Social Media and Firm Equity Value

Xueming Luo (luoxm@uta.edu)

Jie Zhang (jiezhang@uta.edu)

The University of Texas at Arlington

Wenjing Duan (wduan@gwu.edu)

The George Washington University
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Abstract

Companies have increasingly advocated social media technologies and platforms to improve and ultimately transform business performance. This study examines whether social media has a predictive relationship with firm equity value, which metric of social media has the strongest relationship, and the dynamics of the relationship. The results derived from the vector autoregressive models suggest that social media-based metrics (blogs and reviews) are significant leading indicators of firm stock market performance. We also find a faster predictive value of social media, i.e., a shorter “wear-in” effect compared with conventional online behavior metrics, such as web traffic and search. Interestingly, conventional digital user metrics (Google search and web traffic), which have been widely adopted to measure online consumer behavior, are found to have significant yet substantially weaker predictive relationships with firm equity value than social media. The results provide new insights for social media managers and firm equity valuations.

Keywords: Social Media, Word of Mouth, Online Reviews, Web Blogs, Vector Autoregression, Firm Equity Value, Stock Market Performance
“Executives who said their companies had established an extensive social media presence reported a return on investment that was more than four times that of companies with little or no social network engagement activity” (eMarketer 2012).

1. Introduction

Senior leaders in companies are increasingly convinced of the value of harnessing social media to improve and ultimately transform business performance (Divol et al. 2012). The past decade has witnessed the dramatic change of the media landscape with digital social media channels for word-of-mouth (WOM) supplementing and replacing traditional media channels. Consumers engage in more spontaneous activities in information seeking, generation and sharing in faster, more open and more efficient ways. Those popular activities leave digital footprints regarding the users’ behaviors and attitudes toward products and firms. Engaging with their customers on social media platforms is becomingly a key business strategy for c-suite executives (eMarketer 2012). Significant social media investment and engagement are expected to increase firm value by creating critical brand assets, increasing market share, and facilitating business transformation through improvements in many areas including customer and brand management, research and development (R&D), budget allocation, and business processes reengineering.

Given the vast amount of social media information readily available, managers are increasingly measuring and monitoring metrics of various digital social media to collect customer feedback and brand buzz. Many companies’ c-level managers are interested in evaluating the financial value of social media to justify the significant resources input in social media (Deans 2011, Divol et al. 2012). Social media reflects independent opinion of the public, i.e., the wisdom of the crowd. Each individual consumer’s action and decisions drive the bottom line and ultimately the equity value of the firm. With the support of the online social media
platforms enabled by IT productivity (Hall 2000, Brynjolfsson et al. 2002, Gao and Hitt 2012), information relevant to consumer decisions but not obtainable from other sources is revealed. More importantly, social media content is updated instantly and spreads virally at an unprecedented speed, providing first-hand information to investors ahead of any other sources. As such, social media content can provide a timely assessment of the firm’s product and brand performance when sales are not available. In this sense, social media metrics of the firm may allow investors to monitor the firm’s customer sentiment and brand performance and predict its future business value. Social media could provide new information to investors about the most updated firm performance much more frequently. That is, social media may act as a leading indicator of firm equity value.

This study is among the first to examine whether social media has a significant predictive relationship with firm equity value. Prior finance research has suggested that to predict firm equity value, investors use the information from Internet message boards (Das and Chen 2007), print news (Tetlock 2007), customer feedback (Luo 2009), search attention (Da et al. 2011), and online chatter (Tirunillai and Tellis 2012). Extending this line of literature, our study is particularly interested in the predictive value of two forms of social media, the online product reviews and blogs, after accounting for the firm’s other fundamental information and alternative explanations (due to product quality, new product announcements, merger and acquisition, R&D investment, IT-related intangible assets, firm size, revenue, leverage, liquidity, ROA, industry competitiveness, and external economic environment). Considered by marketers and financial analysts to be the most effective channels among new social media (eMarketer 2011), online user reviews and blogs provide product- and brand-specific information compared with other popular forms of social media such as videos and networking sites (Tirunillai and Tellis 2012). Different
from conventional online consumer behavior metrics, social media metrics are featured by their ability to generate, share, and spread information virally, which creates a social contagious effect largely driving the unprecedented speed of information diffusion through the Internet (Aral and Walker 2011). Our study also compares the strength of the predictive value of social media versus conventional online consumer behavior metrics, i.e., web traffic and search volume.

More specifically, this study aims to answer the following research questions:

- Is there a significant predictive relationship between social media, particularly online user reviews and blogs, and firm equity value?
- Is social media a relatively stronger indicator, compared with conventional online consumer behavior metrics, of firm equity value?
- What are the dynamics of the relationship between social media and firm equity value?

In the remainder of the paper, we first present the theoretical background and hypotheses in Section 2. Section 3 introduces the measures and data sample. Section 4 describes the time-series model. The findings are presented in Section 5. The last section discusses the implications.

2. Theoretical Background and Hypotheses

2.1 Social Media as a Leading Indicator of Firm Equity Value

In the finance literature, the efficient market hypothesis holds that any new information that changes market expectations will move firm stock price (Fama 1970, Samuelson 1970). No price movement should be expected unless new information arrives. Finance studies also suggest the notion of information asymmetry in the stock market (Healy and Palepu 2001, Hirshleifer and Teoh 2009). To overcome this asymmetry and better evaluate firm value, investors seek additional sources of information beyond sales to predict firm equity value. New information that changes market expectations among investors will have an impact on firm equity value.
Prior to the social media era, information resources include firms’ reports and announcements of sales, new products, R&D, and other assets (Chen et al. 2011, Tirunillai and Tellis 2012). This source of information is usually only available at a low frequency such as monthly or quarterly. Social media and web 2.0 applications are fundamentally changing interactions between consumers and firms (Gallaugher and Ransbotham 2010). With the popularity of social media and the accompanying creation and consumption of user-generated content, online WOM, such as consumer opinions and user experiences in product reviews and blogs, is becoming a major source of new information for consumer opinion and brand performance prospects (Chen and Xie 2008, Chen et al. 2012, Gu et al. 2012).

More specifically, social media would predict firm equity value for several reasons. First, social media currently accounts for almost a quarter of user online time, ranking well before gaming and email (Gallaugher and Ransbotham 2010). The heavily decentralized and largely independent thoughts voiced through social media best represents and amplifies the “wisdom of the crowd”, which fundamentally contribute to the explosion of social media. There is a great deal of evidence that customers and investors pay attention to what other users are sharing thorough various social media communication paths (Chen et al. 2011, Deans 2011). Empirical evidence also suggests that peer-based advice through social media has increasing influence in facilitating less informed or undecided consumers for purchasing decisions (Tirunillai and Tellis 2012). Social media may amplify user opinions and actions that would shape product success and molds investor expectations and prospects of the firm equity value.

Second, social media content is generated and diffused in the widest adopted media, the Internet, and in an open style, that is, any consumers can read and write reviews and blogs. Therefore, the content represents and influences a broader consumer population. Moreover, the
Internet technologies truthfully and accurately record consumers’ self-revealed content with an altruismistic intention (Dellarocas and Wood 2008). Social media content in terms of online product reviews and blog is expected to be less biased and much more acceptable and absorbed by consumers and investors. As a result, social media metrics of online ratings and blogs may embody social impressions and represent a significant WOM channel that has high credibility, trustworthiness, and likeability among customers (Hanson and Kalyanam 2007). Therefore, social media may enable investors to effectively monitor the firm’s customer sentiment and brand performance prospects of the firm and predict its future equity value. That is, social media metrics can have a significant predictive relationship with firm equity value.

Moreover, investment and engagement in social media is part of intangible assets of firms and organizations. When estimating the value of firms, investors often attempt to incorporate their intangible assets. Previous detailed investigation of some of these types of assets, especially the IT-related intangible assets, has found that they are often large in magnitude and have important productivity benefits (Brynjolfsson et al. 2002). Stock market valuation of firms has been increasingly influenced by the growing application of IT and the associated investment (Hall 2000, Matolcsy and Wyatt 2008). The stock market value of a firm that has leveraged the extensive social media investment and presence should be substantially greater than companies with little or no social media engagement activity (Brynjolfsson et al. 2002, Wyatt 2005). Thus,

\[ H_1: \text{Social media metrics, online product reviews and blogs in particular, have a significant predictive relationship with firm equity value.} \]

2.2 Social Media as a Stronger Indicator in Predicting Firm Equity Value Compared with Conventional Online Consumer Behavior Metrics
Before the emergence of Web 2.0 social media applications, online consumers are largely involved in browsing firm and product webpages and exploring information in search engines and platforms. The interactions between consumers to consumers and consumers to firms are limited to either mass communication (e.g., web advertising) or asynchronous media (e.g., email) (Gallaugher and Ransbotham 2010). Individual consumers have limited ability to observe or influence other consumers’ purchasing and investing decisions. Web traffic and the Internet search metrics are conventional measurements of online consumer behavior in both industry applications and academic research. Website visits (traffic) refers to the number of visitors to a website and the number of web pages they visit or browse. When users search product and service information on a search engine such as Google, attention is paid to the brand and company, and brand exposure is stimulated regardless of the final decision of buying or not (Davenport and Beck 2001). Prior studies suggest that conventional consumer behavior metrics such as web visits directly gauge the popularity of a company’s website (Moe 2003). Financial accounting research reports that web visits are related to firm value (Trueman et al. 2000, Demers and Lev 2001, Dewan et al. 2002), though not in Gupta et al. (2004). Regarding Internet search, Da et al. (2011) provide evidence that search frequency of stock tickers in Google is a strong indicator of stock trading by retail investors. Table 1 compares and contrasts the social media and conventional consumer behavior metrics.

--------Table 1 about Here--------

We expect social media metrics have a stronger predictive relationship with firm equity value than convention metrics for several reasons. Social media is more socially “contagious” than web traffic and search. Blogs and reviews are more visible and available. They appear on the websites and are shared to the public or in a community, thus generating external WOM effects, whereas
web traffic and search tend not to be communicated, exchanged, or spread directly among users. Finance literature has recognized that social influence is central to how information is transmitted and that information contagion should play an important role in examining investor behavior (Hirshleifer and Teoh 2009). Such contagion often leads to the herd behavior (Duan et al. 2009).\(^1\) Herd behavior could be particularly prominent on the Internet, because social media’s broadcast and interactions provide much more information about other users’ choices and preferences. Facing vast amounts of information on the Web and virtually unlimited choices of products, online shoppers and investors often find it could be the most efficient and rational way to follow others’ choices and suggestions, especially facilitated by the viral spread of social media connections (Hirshleifer and Teoh 2009).

Further, social media represents a higher degree of customer engagement and a deeper level of connections with the brand and firm, more so than traffic and search metrics. Social media currently accounts for the large majority of user online time (Gallaugher and Ransbotham 2010). Consumers who spend considerable more time and effort in social media interactions, i.e., writing reviews and posting blogs, are those with higher commitment levels to a brand and presumably are more loyal consumers and contribute more to the firm’s equity value (Gupta et al. 2004). Hence, social media metrics are expected to have a stronger predictive relationship with firm equity value than the more conventional metrics.

\[ H_2: \text{Social media metrics have a stronger predictive relationship with firm equity value than the conventional online consumer behavior metrics.} \]

2.3 Dynamics of the Predictive Value of Social Media

\(^1\) Herd behavior may lead to suboptimal social allocation (Bikhchandani et al. 1998). Readers are encouraged to consult Hirshleifer and Teoh (2009) for a thorough review of contagious behavior in capital market.
Previous marketing literature has shown the dynamics of stock market responses to WOM and online user-generated content. Luo (2007, 2009) uncovers the short- and long-term effects of WOM on cash flows and stock prices. Tirunillai and Tellis (2012) show that negative user reviews have a significant relationship with stock returns with “wear-in” effect, which is defined as how long time it takes before the stock market response of social media reaches the peak point.

Consistent with this line of research, we expect that the predictive relationship between social media and firm equity value may demonstrate significant dynamics, more so than conventional online consumer behavior metrics. This is because information transmits and diffuses at the unprecedented speed facilitated by the viral spread features (wide subscription, wide access, and wide reach) of social media channels (Datamonitor 2010). As shown in Table 1, compared with conventional online consumer behavior metrics, social media metrics have much higher visibility and availability due to the wide subscription, access, and reach of social media platforms. Social media content is updated on a daily, even hourly basis and spread virally. Customer attention and engagement is also higher in social media channels, which accounts for the dominant amount of user online time.

Moreover, social media content can be voted, linked, reproduced, broadcast and spread virally, hence creating richness of information and speed of diffusion not matched by conventional online behavior metrics (Aggarwal et al. 2011, Gu et al. 2011). Social media content travels much faster and can be easily and instantly obtained by investors at the highly frequent temporal level, which makes the “wear-in” effect of stock market response to social media much shorter compared with the effect of conventional website browsing and the Internet search. Thus, we propose the following hypothesis.
**H2: Social media metrics have a shorter “wear-in” effect in predicting firm equity value compared with conventional online behavior metrics.**

3. Data and Measures

In this study, we selected the computer hardware and software industries for two reasons. First, as described by Moore’s Law, computing products have experienced rapid technology advancements and greatly reduced product life cycles. Hence, companies in the computer industry frequently introduce and promote new products (Goeree 2008). Second, customers of computer products are more likely to participate in and be influenced by various digital media. As such, companies in this industry tend to more heavily leverage on social media to engage customers and promote products online. Indeed, most literature on social media has focused on one industry. For example, Dellarocas et al. (2007), Liu (2006), and Chintagunta et al. (2009) examined movies; Forman et al. (2008) and Chevalier and Mayzlin (2006) on books; Dhar and Chang (2009), and Dewan and Ramaprasad (2011) on music; Godes and Mayzlin (2004) on TV; Zhu and Zhang (2010) on video games; and Luo (2009) on airline services.

Within these two industries, we select those firms that are publicly traded (for stock price data availability), and that serve the consumer markets to ensure the availability of consumer product reviews. Nine firms which are all major industry leaders satisfy the above criteria. The selected computer hardware companies (HP, Dell, Acer, Toshiba, Apple, and Sony) are top PC sellers in the industry with a total of more than 80% of the U.S. market share. The software companies included (Microsoft, Adobe, and Corel) are also popular consumer software brands.

The daily data were collected from multiple sources (Google search, Alexa, CNET, Lexis/Nexus, CRSP, COMPUSTAST and Yahoo Finance) during the period of August 1, 2007
to July 31, 2009. The merged data set contains 4,518 observations, representing the nine firms over 505 trading days (Acer has only 478 days of data due to some missing traffic data).

3.1 Data and Measures for Firm Equity Value

Prior studies in information systems, marketing, and finance (Dewan and Ren 2007, Luo 2009, Srinivasan and Hanssens 2009) suggest the two most common measures of firm value: stock return and risk. Return or abnormal return is firm equity value beyond what is expected by the average stock market derived from the extended Fama-French Model widely used in finance (Fama and French 1993, 1996, Carhart 1997). Risk or idiosyncratic risk refers to the vulnerability or volatility of firm equity value, measured as standard deviation of the residuals of the extended Fama-French model (Goyal and Santa-Clara 2003, p. 980).

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

(1)

where \(R_{it}\) = returns for firm \(i\) on time \(t\), \(R_{mt}\) = average market returns, \(R_{ft}\) = risk-free rate, \(SMB_t\) = size effects, \(HML_t\) = value effects, \(MOM_t\) = Carhart’s momentum effects, \(\beta_{0i}\) = the intercept, and \(e_{it}\) = model residual. Stock price data are obtained from the Center for Research in Security Prices (CRSP) database and Yahoo Finance (http://finance.yahoo.com). Data for Fama-French factors and momentum (\(R_{mt}\), \(R_{ft}\), \(HML_t\), \(SMB_t\), \(MOM_t\)) are available at Error! Hyperlink reference not valid. We run model (1) for a rolling window of 250 trading days prior to the target day to get the estimated factor coefficients. Abnormal returns (\(AR_{it}\)) is then calculated as the difference between the observed returns and the expected returns:

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

(2)

Risk is the standard deviation of the model residuals (Dewan and Ren 2007, McAlister et al. 2007). The mean value of firm daily return ranges from -0.053% to 0.023%, while the mean value of daily stock risk ranges from 1.47 to 3.57.
3.2 Data and Measures for Social Media Metrics

For social media metrics, we collect product rating data from the consumer technology product website CNET.com and blog posts from the Lexis/Nexus web blogs database at the daily level.

Data and Measures for Online Product Ratings

We measure product ratings with both level and volume. The level of rating assesses the average rating score of consumer reviews of all products of a firm. Increases in the levels represent greater customer acceptance and advocacy for the firm. Further, volume gauges the total number of consumer reviews. A higher volume may indicate greater consumer resonance with products and brands of the firm. While some argue differential impacts of positive vs. negative ratings (Liu 2006), others hold that “any publicity is good publicity and better than none at all” (Berger et al. 2010).

We collect consumer product ratings from the website CNET.com, following Gu et al. (2011). CNET lists consumer reviews on products of most major consumer electronics firms. We design a software agent in PERL to search all products of sampled firms on CNET.com. The program parses HTML codes of each product review page to collect review dates and ratings and saves those data into a file. This technique of crawling data with an automated software agent from public websites has been applied in IS research (Ghose and Yang 2009, Aggarwal et al. 2011, Gu et al. 2011). Consumers post their reviews on CNET.com on a scale of 0.5 (the worst) to 5 stars (the best). The resulting data include 17,486 consumer reviews for 1,939 unique products of the targeted firms.

Data and Measures for Web Blogs

We measure the web blog posts related to the targeted firms and their products via Lexis/Nexis web blogs database. Specifically, the Lexis/Nexis source includes general web blogs
from thousands of sources on the web. It includes all the top twenty technology blogs ranked by Technorati.com, including Techcrunch, Mashable, Engadget, Gizmodo, and others. The literature on blogs has used the sources ranging from a single blog platform (Aggarwal et al. 2011), a blog aggregator website (Evens 2009, Chen et al. 2011, Dewan and Ramaprasad 2012), a number of major blogs of the same topics (Droge et al. 2010), to a blog search engine like Google blog search (Stephen and Galak 2012). According to the Lexis/Nexis web blogs database, blog posts from those popular blogs attract more attentions and citations, and therefore are weighed more heavily than other less popular blogs (Aggarwal et al. 2011). We collect all blog posts related to the targeted firms and their products for our data sample.

As in Liu (2006) and Aggarwal et al. (2011), we employed two graduate students to categorize each blog post based on the sentiment of blog content as positive and negative. The inter-rater reliability for the coding of blog posts is 0.92, suggesting a high level of agreement. Following Stephen and Galak (2012), we also collected blog volume data for each firm on a daily basis from Google blog search.

### 3.3 Data and Measures for Conventional Online Consumer Behavior Metrics

Conventional online consumer behavior metrics, traffic and search, are collected from Alexa.com and Google search at the daily level, respectively.

**Data and Measures for Web Traffic**

We collect web traffic data from Alexa.com. Alexa is a popular source for traffic data. It is widely adopted by academic and practical research (Palmer 2002, Krishnamurthy et al. 2005, Animesh et al. 2010). We download the traffic data for the selected companies on the domain level with a PERL program, which makes query requests to the Alexa Web Information Service (AWIS) through the URLInfo action. We obtain three traffic measures from Alexa: total
pageviews that measure the total volume of web traffic, pageviews per user that measure the average number of pages browsed by a visitor, and reach that reflects the number of web visitors. The definitions of the three measures imply that total pageviews is the product of the other two measures. Therefore, we use only pageviews per user and reach to measure web traffic for the empirical model, consistent with the financial accounting literature (Trueman et al. 2000). Total pageview metric will be used in the robustness test in Section 5.6. Pageviews per user reflects the site “stickiness” (how long consumers stay to view more pages or visit the site repeatedly over time) or customer loyalty (Demers and Lev 2001). Multiple page views made by the same user on the same day are counted only once. Reach is gauged by the number of visitors who browse a given website (by the rate of visitors per one million Internet users tracked by Alexa). A larger number of visitors may be caused by a greater pool of potential consumers for the firm. Compared with the other metric of audience size “unique visitors,” reach is typically expressed as a percentage in a relative sense, and is therefore more comparable across firms. A user visits an average of 1.31 to 5.24 pages of a targeted firm’s website a day, while a firm’s average daily reach ranges from 228.7 to 49,108.5 per million Internet users.

Data and Measures for Search Engine Queries

We obtain search engine query data from the service Google Insights for Search (Error! Hyperlink reference not valid.) by the popular search engine Google (Varian and Choi 2010, Da et al. 2011). In our study, search has two dimensions assessing brand attention and popularity in digital media. One is search intensity over time, or mean of firm keywords search frequencies at google.com. The key words for each firm are based on the top ten query keywords from search engines provided by Alexa. For example, according to Alexa, the top ten queries driving traffic to adobe.com are “adobe,” “adobe reader,” “flash player,” “flash,” “adobe flash player,”
“photoshop,” “adobe flash,” “adobe air,” and “acrobat reader.” The other dimension is search instability over time, or volatility of firm keywords search frequencies at google.com every day. It is measured as the conditional stochastic volatility ($h_t$) via the auto-regressive conditional heteroskedasticity in mean (GARCH-M) model.

$$LogSearch_t = c + \sum_{i=1}^{k} \rho_i LogSearch_{t-i} + \varphi Log(h_t) + \epsilon_t \quad (3)$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} \quad \epsilon_t \mid (\epsilon_{t-1}, \epsilon_{t-2}, \ldots) \sim N(0, h_t),$$

where $\alpha_0$, $\alpha_1$, and $\gamma_1$ are parameters of the GARCH(1,1) model. The mean value of search intensity ranges from 0.39 to 11.65, while the mean of search instability ranges from 0.001 to 0.017.

### 3.4 Data for Exogenous Control Variables

Following the widely used firm valuation models in the IS and accounting literature (Trueman et al. 2000, Brynjolfsson et al. 2002, Ferreira and Laux 2007), we control the following exogenous controls: product quality, IT-related intangible assets, R&D expenditures, new product announcement events, revenue (sales), firm size, financial leverage, liquidity, return on asset (ROA), industry competitive intensity, Merger and Acquisition (M&A), and economic crisis.

We control for product quality because it can influence both digital user metrics and firm value and therefore may introduce endogeneity bias in data analyses. Product quality is measured by the rating of an unbiased third party -- CNET editors, who conduct independent industry-standard benchmark tests, assess product specifications and company support polices, and use their expert judgment to impartially evaluate technology products based on such key aspects as design, features, performance, service and support (Tellis and Johnson 2007, Duan et al. 2009). IT-related intangible assets measure the IT investment of those technology firms that
can potentially create value in the future, collected from the 10Q forms of firms’ financial reports. *R&D expenditure* is measured as research and development expenses (*XRDQ*) scaled by total assets from COMPSTAT. New product announcements (which reflect IT capabilities of the firm) are collected from the Lexis/Nexis news search. Prior marketing study has also used Lexis/Nexis news search to measure new product announcements (Sood and Tellis 2009). *Firm size* is measured by total assets of the firm (variable *ATQ*). *Revenue* is the *REVTQ* variable in the COMPSTAT database. *Financial leverage* is the ratio of long-term book debt (*DLTTQ*) to total assets. *Liquidity* is the current ratio of a firm (*LCTQ/ACTQ*). *Return on assets* measures firm profitability and is calculated as the ratio of a firm’s operating income to its book value of total assets, which are variables *OIBDPQ* and *ATQ* from COMPSTAT. In addition, industry and economy conditions are also controlled with variables of competitive intensity and economic crisis. *Competitive intensity* is gauged by the Hirschmann-Herfindahl index measure of industry concentration, which is the sum of squared market shares of firms in the industry derived from sales revenue, \( \sum_{i=1}^{N} s_i^2 \), where \( s_i \) is the market share of firm \( i \) in each of the computer hardware and software industries (Hou and Robinson 2006). To match those quarterly financial variables with our daily social media and digital user metrics, we follow Hamilton (1994), Statman et al. (2006) and Luo (2009) by adopting the VAR-bootstrapping scheme with 5000 simulated databases to generate the values of those variables for each observed day.

Also, we construct a dummy variable *events* to control the M&A and new product announcements (from Lexis/Nexis news search), and a dummy variable *economic crisis* indicated by the financial market crash in October 2008.

4. **VARX Model Specification**

4.1 **Rationale for VARX**
We employ a time-series technique, namely, vector-autoregressive model with exogenous covariates (VARX). This modeling approach allows us to capture dynamic interactions and feedback effects (Dekimpe and Hanssens 1999, Luo 2009, Adomavicius et al. 2012). For our study, VARX has several advantages over alternative models. Specifically, it can track the short-term (immediate) and long-term (cumulative) value of social media metrics in predicting firm equity value (direct effects). In addition, it accounts for biases such as endogeneity, auto correlations, and reversed causality. The endogenous treatment in VARX model implies that search, traffic, ratings, and blogs are explained by both past variables of themselves (autoregressive carry-over effects) and past variables of each other (cross effects). VARX models also capture complex feedback loops that may include the reversed impact of firm equity value on future social media metrics (feedback effects). For example, an increase in firm stock return can raise the firm’s brand recognition and interests so that consumers are more likely to blog its products and brand experience information. Thus, VARX can model complex chained effects in a full cycle, uncovering the full predictive value of user metrics. Our empirical time-series analysis proceeds in the following steps that are applied to each firm separately (Srinivasan et al. 2010). Recently, VAR models have been adopted by information systems researchers (Adomavicius et al. 2012).

4.2 Step 1: Model Specification on the Predictive Value of Social Media Metrics

We estimate a ten-equation VARX model, where endogenous variables are two firm equity value metrics (return and risk), two online product rating variables (level and volume), two blog sentiment variables (positive and negative), two Google search variables (intensity and volatility), and two web traffic variables (pageview per user and reach). We also have eleven exogenous control variables: product quality, R&D, IT-related intangible assets, new product
announcements, firm size, revenue, financial leverage, liquidity, ROA, M&A, industry competition intensity, and economy crisis dummy. The VARX model is specified as:

$$
\begin{bmatrix}
RTN_t \\
RSK_t \\
AVR_t \\
NUR_t \\
POS_t \\
NEG_t \\
PGV_t \\
REC_t \\
GSI_t \\
GSV_t
\end{bmatrix} =
\begin{bmatrix}
\alpha_r + \delta_r t \\
\alpha_s + \delta_s t \\
\alpha_3 + \delta_3 t \\
\alpha_4 + \delta_4 t \\
\alpha_5 + \delta_5 t \\
\alpha_6 + \delta_6 t \\
\alpha_7 + \delta_7 t \\
\alpha_8 + \delta_8 t \\
\alpha_9 + \delta_9 t \\
\alpha_{10} + \delta_{10} t
\end{bmatrix} + \sum_{k=1}^{K} \begin{bmatrix}
\phi_{1,1}^k & \ldots & \phi_{1,10}^k \\
\phi_{2,1}^k & \ldots & \phi_{2,10}^k \\
\phi_{3,1}^k & \ldots & \phi_{3,10}^k \\
\phi_{4,1}^k & \ldots & \phi_{4,10}^k \\
\phi_{5,1}^k & \ldots & \phi_{5,10}^k \\
\phi_{6,1}^k & \ldots & \phi_{6,10}^k \\
\phi_{7,1}^k & \ldots & \phi_{7,10}^k \\
\phi_{8,1}^k & \ldots & \phi_{8,10}^k \\
\phi_{9,1}^k & \ldots & \phi_{9,10}^k \\
\phi_{10,1}^k & \ldots & \phi_{10,10}^k
\end{bmatrix} \begin{bmatrix}
RTN_{t-k} \\
RSK_{t-k} \\
AVR_{t-k} \\
NUR_{t-k} \\
POS_{t-k} \\
NEG_{t-k} \\
PGV_{t-k} \\
REC_{t-k} \\
GSI_{t-k} \\
GSV_{t-k}
\end{bmatrix} + \begin{bmatrix}
\tau_{1,1} & \ldots & \tau_{1,11} \\
\tau_{2,1} & \ldots & \tau_{2,11} \\
\tau_{3,1} & \ldots & \tau_{3,11} \\
\tau_{4,1} & \ldots & \tau_{4,11} \\
\tau_{5,1} & \ldots & \tau_{5,11} \\
\tau_{6,1} & \ldots & \tau_{6,11} \\
\tau_{7,1} & \ldots & \tau_{7,11} \\
\tau_{8,1} & \ldots & \tau_{8,11} \\
\tau_{9,1} & \ldots & \tau_{9,11} \\
\tau_{10,1} & \ldots & \tau_{10,11}
\end{bmatrix} \begin{bmatrix}
x_{1t} \\
x_{2t} \\
x_{3t} \\
x_{4t} \\
x_{5t} \\
x_{6t} \\
x_{7t} \\
x_{8t} \\
x_{9t} \\
x_{10t}
\end{bmatrix} + \begin{bmatrix}
e_{1t} \\
e_{2t} \\
e_{3t} \\
e_{4t} \\
e_{5t} \\
e_{6t} \\
e_{7t} \\
e_{8t} \\
e_{9t} \\
e_{10t}
\end{bmatrix}
$$

where $RTN =$ firm return, $RSK =$ risk, $AVR =$ rating level, $NUR =$ rating volume, $POS =$ number of positive blog posts, $NEG =$ number of negative blog posts, $PGV =$ pageviews per user, $REC =$ reach, $GSI =$ Google search intensity, $GSV =$ Google search instability, $t =$ time, $\alpha_i$ ($i = 1, 2…10$) = constant, $\delta_i, \phi_{ij}, \tau_{ld}$ ($i, j = 1, 2…10, l = 1, 2…11$) = coefficients, $K =$ the lag length, $x_i$ ($i = 1, 2…11$) = an exogenous variable, and $\epsilon_i$ ($i = 1, 2…10$) = white-noise residual.

The lag order in VAR is selected by the criteria of Schwartz’s Bayesian Information Criterion (SIC) and final prediction error (FPE). Specifically, we allow for various lag lengths in the model and select the lag order for the VARX model while minimizing these criteria (Dekimpe and Hanssens 1999, Luo 2009, Adomavicius et al. 2012). We choose the optimal lag order of two as suggested by these criteria for our models. We test various assumptions of VARX residuals including multivariate normality, omission-of-variables bias, White heteroskedasticity tests, and Portmanteau autocorrelation with the results available upon request. We find no violations of these assumptions at the 95% confidence level.

### 4.3 Step 2: Short-term and Long-term Predictive Value of Social Media Metrics
In the next step, we use the estimated parameters of the full VARX model $\phi^i_{ij}$ to generate the Generalized Impulse Response Functions (GIRFs), $\psi_{ij}(t)$, which is the net result of a one-unit shock to digital user metrics $i$ on firm value metric $j$ at time $t$ (Dekimpe and Hanssens 1999). 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 still be contemporaneously correlated and thus generate misleading results, we apply an orthogonal transformation to correct this bias (Luo 2009).

We derive the following summary statistics from each GIRF: (1) short-term, immediate predictive value; (2) long-term, total cumulative value that combines all effects across “dust-settling” periods; (3) dynamics as measured by wear-in time, that is, the lag number of periods before peak predictive relationship is reached. We obtain wear-in time of each user metric as days with the largest (in absolute value) impulse response coefficients (Pauwels 2004). To report the findings, we average results across firms as in Srinivasan et al. (2010).

4.4 Step 3: Variance of Return and Risk Explained by Digital User Metrics

Based on the VARX parameters, we derive Generalized Forecast Error Variance Decomposition (GFEVD) estimates to examine which user metric explain more variance of firm equity value than the others in a systematic model. Like a dynamic $R^2$, GFEVD gauges the relative power over time of shocks initiated by each metric in explaining the variance of firm value, without assuming a causal ordering (Dekimpe and Hanssens 1999). GFEVD estimates are derived from:

$$\theta_{ij}(t) = \frac{\sum_{k=0}^t (\psi_{ij}(k))^2}{\sum_{k=0}^t \sum_{j=0}^m (\psi_{ij}(t))^2}, \quad i, j = 1, \ldots, m. \quad (5)$$
GFEVD attributes 100% of the forecast error variance in firm equity value to all endogenous variables. That is, it estimates the extent to which social media and conventional online behavior metrics explain the variance of firm value. This relative importance of endogenous variables is established based on GFEVD values at twenty days, which reduces sensitivity to short-term fluctuations. To establish the statistical significance of GFEVD estimates ($p = 0.05$), we obtain standard errors using Monte Carlo simulations with 1,000 runs.

5. Findings

5.1 Test for Stationarity in Time Series

The process of estimating VARX models begins with unit-root tests to check whether variables are evolving or stationary. Stationarity implies that, although a shock to endogenous variables in VARX can cause fluctuations over time, its effects diminish ultimately. Then, endogenous variables revert back to the deterministic (mean + trend + seasonality) pattern without a permanent regime lift. The variance of stationary variables is finite and time-invariant. We conduct augmented Dickey-Fuller (ADF) tests to check stationarity (Dekimpe and Hanssens 1999). The ADF tests of almost all metrics across firms are less than the critical value -2.89 and can reject the null hypothesis of a unit root with a 95% confidence level except for seven firms’ risk metric series and four firms’ search instability series. We use the first difference of the series of those two metrics. The ADF test results for the corrected data series range from -187.39 to -2.93, suggesting that the series do not cointegrate in equilibrium (Hamilton 1994).

5.2 Test for Granger Causality

We conduct Granger Causality test following Tirunillai and Tellis (2011). Results suggest that social media metrics have significant temporal-based causal relationships with firm equity value. Almost all social media metrics significantly “Granger cause” stock return and risk:
positive and negative blogs, and rating volume “Granger cause” firm stock return ($p = 0.03, 0.04$ and $0.03$, respectively), and negative blog, rating level and rating volume “Granger cause” stock risk ($p = 0.03, 0.04$ and $0.04$, respectively). The reverse feedback from return and risk to the social media metrics is not significant (median $p$ value ranging from $0.08$ to $0.29$). These results confirm the temporal predictive relationship between social media metrics and firm equity value, providing initial evidence for $H_1$.

Regarding conventional online behavior metrics, pageview per user is the only one behavior metric that significantly “Granger causes” stock return and risk ($p = 0.04$ and $0.05$, respectively). The reverse feedback from stock return to traffic and search is not significant but stock risk is found to significantly “Granger cause” search intensity, pageview per user and reach ($p = 0.03$, $0.05$ and $0.05$, respectively).

### 5.3 Short-term and Long-term Predictive Value of Social Media Metrics

Table 2 reports the immediate and cumulative impulsive response elasticities, as well as the wear-in time from the VARX results. The magnitude of elasticity results reflects the change in basis point (1 basis point = one hundredth of a percentage) of stock return or percentage of stock risk in response to one unit shock in a social media or conventional online behavior metric (1% shock in traffic). These results largely support the hypotheses in this study. Next, we present the details.

----- Table 2 about Here -----

**Web Blog**

As shown in Table 2, social media metrics in terms of positive blog posts show a significant positive predictive relationship with firm return (3.01 and 4.38 basis points respectively, $p<0.01$) for both the short- and long- term and significantly reduce short-term risk of the firm (-0.019 percent, $p<0.01$). That is, an increase in positive blog posts will predict a boost of daily stock
return up by 0.0003 and stock intra-day risk down by 0.00019 in the short term. Negative blog posts are negatively related to firm short-term return (-1.55 basis points, \( p<0.01 \)) and predict an increase of intra-day risk for both the short and long term (0.06 and 0.086 percent, respectively, \( p<0.01 \)). Thus, the results largely suggest that blog posts are significant leading indicator of firm equity value.

**Online Product Ratings**

In addition, results in Table 2 suggest that the rating level has a significant long-term relationship with firm return (3.37 basis points, \( p<0.01 \)), though insignificant in the immediate. This suggests that a change in rating is associated with an increase of firm return in the long run. The volume of rating shows a strong positive predictive value with returns in both the short-term (2.09 basis points, \( p<0.01 \)) and long-term (4.70 basis points, \( p<0.01 \)). As such, these results suggest strong empirical evidence for \( H_1 \), that social media metrics, online product reviews and blogs in particular, have a significant predictive relationship with firm equity value.

Interestingly, the findings suggest that though predicting a boost in stock returns, review ratings also have some dark effects, in that the rating level is associated with a higher stock risk (0.089 percent, \( p<0.1 \)) in the long run, and the volume of ratings is significantly (\( p<0.01 \)) associated with stock risks in both short- and long- term.

**Search and Traffic**

As shown in Table 2, all search and web traffic metrics can (at least \( p<0.05 \)) predict firm return in both short- and long-term, which conforms to the theory and literature. For example, more Google searches are associated with higher stock returns (Da et al. 2011). Also, more pageviews per user and/or wider reach of the firm website predict higher firm returns.

**5.4 Dynamics of the Predictive Value of Social Media Metrics**
We recall that wear-in time measures the time it takes for a shock in each social media to reach the peak of the predictive relationship with firm equity value. We obtain the wear-in time results from the impulse response functions (Figure 1 shows the impulse response functions of some social media metrics for Hewlett-Packard). The results reported in Table 2 show that social media metrics (blogs and reviews) demonstrate significantly shorter wear-in time for both firm stock return (parametric $F = 11.02$ and non-parametric Kruskal-Wallis = 7.09, both $p < 0.01$) and risk ($F = 32.25$ and Kruskal-Wallis = 10.98, both $p < 0.001$). As for firm return, negative blogs have the shortest wear-in time (2.4 days), followed by rating volume (2.9 days), while both traffic metrics have the longest wear-in time (7.7 days). These results consistently support $H_3$, in that social media metrics have a shorter “wear-in” effect in predicting firm equity value compared with conventional online behavior metrics.

----- Figure 1 about Here -----

5.5 Relative Strength of the Predictive Value of Social Media versus Conventional Online Consumer Behavior Metrics

The variance decomposition of GFEVD results in Table 3 provides the relative power of each metric in explaining the variance of firm equity value. All of the metrics explain non-trivial portions of the variance. The results suggest the order of ratings (3.12%), blogs (2.75%), then search (2.43%) and traffic (1.28%) in predicting long-term firm return, and the order of rating (2.61%), blogs (2.26%), then traffic (1.32%) and search (0.89%) in predicting long-term firm risk. Further, social media metrics account for a significantly greater proportions of the variance than conventional online behavior metrics (5.87% vs. 3.71% in return and 4.87% vs. 2.21% in risk, see Table 3). Thus, the findings support our expectation that social media metrics are more effective in predicting firm return and risk. They contribute to 9.58% and 7.08% of the total
explained variance of firm stock return and risk, respectively. These differences are statistically significant according to both $F$ statistics and Kruskal-Wallis statistics as shown in Table 3. Thus, the data support our $H_2$, suggesting that social media metrics have a stronger predictive value than the conventional online consumer behavior metrics.

---- Table 3 about Here -----

6. Discussion

As social media grows rapidly in terms of popularity and consumer adoption, recent business practices now seek to transform businesses with social media and capitalize the financial value of social media. This study intends to investigate the predictive power of social media and the dynamics of the predictive relationship between social media and firm equity value. Our results indicate that social media is a leading indicator of firm equity value (supported by Granger Causality tests) and has a stronger predictive value than conventional online consumer behavior metrics. In particular, our findings suggest that product reviews have the highest predictive power for firm returns and risks. Google search and web traffic have significant but only moderate predictive value. Our results also show that social media metrics have shorter “wear-in” time than web traffic and search. Negative blogs have the shortest wear-in time in predicting firm equity value.

Theory Implications

This research contributes to literature in multiple disciplines and has important implications for academic researchers. It is the first to reveal empirical knowledge concerning social media as a leading indicator in predicting business financial value. Our results divulge new insights on the predictive value of social media metrics beyond sales. The strong predictive relationship between social media and firm equity value demonstrates that firms should no longer treat social media as
a cost. Rather, social media metrics can be a significant leading indicator of firm equity value, justifying the importance of investing in social media and new IT initiatives to transform organization and create shareholder value.

In this sense, our study adds to the IS literature in studying IT productivity and the impact of IT intangible assets (Hall 2000, Brynjolfsson et al. 2002, Gao and Hitt 2012) on business performance and transformation. Social media investment is an indispensable asset for firms and organizations not only for short-term performances, but also for long-term budget allocations for business strategies and IT support in a social media platform. Our findings suggest that social media, as a growing indispensable part of IT asset, has important productivity benefits inherently connected to firm equity value. Our results suggest that social media investments pay off best in terms of firm future return if focused on increasing product review ratings and reducing variation of the ratings. Also, in terms of risk management, social media investments pay off best if focused on increasing positive blogs and reducing both neutral and negative blogs. While certainly not abandoning investments in online search and traffic, companies should be aware of the relative larger power of social media in predicting firm future equity value. Thus, managers must better prioritize and allocate appropriately the IT budgets among various social media platforms according to their abilities to predict and affect business financial value.

In addition, some finance and marketing studies have shown that web traffic and search have a significant relationship with firm financial performance (e.g., Moe and Fader 2004, Da et al. 2009). We agree with them and extend this stream of research by showing that social media is a much stronger indicator of firm financial return than the simple “eyeball effect”. This is important because social media provides managers a better measurement of customer attention and product performance as well as prospects of firm future equity value in the social digital age.
Indeed, this is the first study to show the association between web blogs and business stock performance across the IS, marketing, and finance disciplines. Positive blog posts can increase trust, affection, and advocacy of the consumers or investors and therefore result in more demand, higher firm value, and lower risk. Negative blog posts can damage the reputation of the firm and are negatively related to firm performance. An interesting finding is that positive impacts are relatively more enduring and negative impacts are quick. Therefore, firms should monitor and respond quickly to negative blog posts by taking corrective actions to mitigate the potential adverse effects on future performance. For example, Kryptonite announced a lock exchange plan five business days after a video started circulating in the blogosphere about opening a Kryptonite bike lock with a Bic-pen in September 2004.

This study develops time-series models that can gauge the long-term, accumulative value and, therefore, avoid the danger of underestimating the power of digital user metrics because solely focusing on short-term value would neglect the enduring and buzz effects of social media. Web analytics and social media research should pay more attention to time-series models and long-term, cumulative effects. In addition, we benchmark with shareholder value-based business performance because shareholder value is the ultimate concern of the firm and is available at the daily level, which allows for finer-grained analyses for managers and stock investors.

**Managerial Implications**

This research also has important implications for managers. The new social media platforms allow managers to drive personalized relations with individual users for higher firm equity value. Some managers may still hold mixed views of using new media to transform organizations and are quite puzzled because they do not know which online media strategy pays off the highest or the lowest. It is noted that “many corporations took the plunge into social media and now are
sitting on loads of uninstalled software” with wasted IT resources (Baker 2009, p. 57). Our results suggest that social media are relevant to firm equity value, because social media metrics can predict firm return and risk in the short and long runs.

Analyzing the immediate time effects of social media will alert managers to the urgency of the predictive relationships so as to prioritize responsive actions. As noted, wear-in time measures the number of days before peak impact is reached according to the VARX models. As reported in Table 2, the dynamic wear-in times have several implications for managers. First, wear-in times can provide an early warning signal to managers about future damages to firm value. Because negative blog posts have the shortest wear-in time (2.4 days) in predicting firm return, when observing a surge in the leading indicator of negative blog posts, managers should pull the plug and take immediate actions in reversing the negative blogs so as to mitigate the potential damage on future performance (i.e., in cases of recent Southwest Airlines flight incidents and Toyota car recalls).

Second, the wear-in times indicate how soon or how late a shock in each user metric will reach the peak of the predictive value. Managers can act upon the results to better allocate resources. For example, the wear-in time of traffic measures for firm return responses is the longest --7.7 days. Thus, to boost firm return, managers should allocate more IT resources for other metrics such as ratings, blogs, or search queries. On the same token, to more quickly reduce firm risk, managers should shift more IT resources for web blogs and review ratings because they have relatively shorter weak-in times.

In conclusion, this study is an initial step in examining the predictive relationship between social media and firm equity value. Given the importance of social media in transforming
business organizations, we strongly encourage future research to develop more scientific time series and econometric models to discover more insights into the value of social media.
Table 1. Compare and Contrast of Different Digital Metrics

<table>
<thead>
<tr>
<th>Digital Metrics</th>
<th>Visibility and Availability</th>
<th>Trustworthiness</th>
<th>Customer Engagement</th>
<th>Social Influence (contagious effect)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Social Media</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online Product Reviews</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Very High</td>
</tr>
<tr>
<td>Blogs</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Very High</td>
</tr>
<tr>
<td><strong>Conventional Online Consumer Behavior Metrics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Web Traffic</td>
<td>Low</td>
<td>Low (can be easily manipulated)</td>
<td>Low</td>
<td>Very low</td>
</tr>
<tr>
<td>Internet Search</td>
<td>Medium</td>
<td>Low (can be easily manipulated)</td>
<td>Low</td>
<td>Very Low</td>
</tr>
</tbody>
</table>

Table 2: Impulse Responses of Firm Equity Value to Social Media Metrics

<table>
<thead>
<tr>
<th>Return</th>
<th>Immediate</th>
<th>Accumulative</th>
<th>Wear-in Time</th>
<th>ΔRisk</th>
<th>Immediate</th>
<th>Accumulative</th>
<th>Wear-in Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blog Positive</td>
<td>3.01***</td>
<td>4.38***</td>
<td>3.0 days</td>
<td>-0.019***</td>
<td>-0.036</td>
<td>3.1 days</td>
<td></td>
</tr>
<tr>
<td>Blog Negative</td>
<td>-1.55***</td>
<td>-5.84</td>
<td>2.4 days</td>
<td>0.060***</td>
<td>0.086***</td>
<td>3.9 days</td>
<td></td>
</tr>
<tr>
<td>Web Blogs</td>
<td></td>
<td></td>
<td>2.7 days</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rating Level</td>
<td>3.01</td>
<td>3.37***</td>
<td>3.3 days</td>
<td>0.017</td>
<td>0.089***</td>
<td>3.9 days</td>
<td></td>
</tr>
<tr>
<td>Rating Volume</td>
<td>2.09***</td>
<td>4.70***</td>
<td>2.9 days</td>
<td>0.032***</td>
<td>0.041***</td>
<td>3.3 days</td>
<td></td>
</tr>
<tr>
<td>Review Ratings</td>
<td></td>
<td>3.1 days</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pageview</td>
<td>1.18***</td>
<td>1.76</td>
<td>7.7 days</td>
<td>-0.002</td>
<td>0.204***</td>
<td>6.1 days</td>
<td></td>
</tr>
<tr>
<td>Reach</td>
<td>1.30***</td>
<td>8.64***</td>
<td>7.7 days</td>
<td>-0.016</td>
<td>-0.183***</td>
<td>8.0 days</td>
<td></td>
</tr>
<tr>
<td>Web Traffic</td>
<td></td>
<td>7.7 days</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Search Intensity</td>
<td>0.57**</td>
<td>4.43</td>
<td>6.9 days</td>
<td>-0.021***</td>
<td>-0.101***</td>
<td>8.6 days</td>
<td></td>
</tr>
<tr>
<td>ΔSearch Instability</td>
<td>-1.96***</td>
<td>-1.39</td>
<td>3.3 days</td>
<td>0.039***</td>
<td>0.076***</td>
<td>5.2 days</td>
<td></td>
</tr>
<tr>
<td>Google Search</td>
<td></td>
<td>5.1 days</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: (1) The coefficients of returns are in basis points (1 basis point = one hundredth of a percentage).
(2) The coefficients of risk are percentage values.
(3) ** p < 0.05, *** p < 0.01.
Table 3: Variance Decomposition of Firm Equity Value Explained by Digital User Metrics

<table>
<thead>
<tr>
<th>Variance Explained by</th>
<th>Return</th>
<th>ΔRisk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blog Positive</td>
<td>1.21%</td>
<td>0.85%</td>
</tr>
<tr>
<td>Blog Negative</td>
<td>1.54%</td>
<td>1.41%</td>
</tr>
<tr>
<td><strong>Total Web Blog</strong></td>
<td><strong>2.75%</strong></td>
<td><strong>2.26%</strong></td>
</tr>
<tr>
<td>Rating Level</td>
<td>1.53%</td>
<td>0.79%</td>
</tr>
<tr>
<td>Rating Volume</td>
<td>1.59%</td>
<td>1.82%</td>
</tr>
<tr>
<td><strong>Total Review Rating</strong></td>
<td><strong>3.12%</strong></td>
<td><strong>2.61%</strong></td>
</tr>
<tr>
<td><strong>Total social media</strong></td>
<td><strong>5.87%</strong></td>
<td><strong>4.87%</strong></td>
</tr>
<tr>
<td>Pageview</td>
<td>0.80%</td>
<td>0.77%</td>
</tr>
<tr>
<td>Reach</td>
<td>0.48%</td>
<td>0.55%</td>
</tr>
<tr>
<td><strong>Total Web Traffic</strong></td>
<td><strong>1.28%</strong></td>
<td><strong>1.32%</strong></td>
</tr>
<tr>
<td>Search Intensity</td>
<td>1.23%</td>
<td>0.42%</td>
</tr>
<tr>
<td>ΔSearch Instability</td>
<td>1.20%</td>
<td>0.47%</td>
</tr>
<tr>
<td><strong>Total Google Search</strong></td>
<td><strong>2.43%</strong></td>
<td><strong>0.89%</strong></td>
</tr>
<tr>
<td><strong>Total user behavior</strong></td>
<td><strong>3.71%</strong></td>
<td><strong>2.21%</strong></td>
</tr>
</tbody>
</table>

Testing Review + Blog > Search + Traffic

Kruskal-Wallis statistic | 6.79*** | 8.75***
F statistic              | 9.37*** | 13.84***

Note: *** p < 0.01.
Figure 1: Accumulated Impulse Response Functions of Key Social Media Metrics
References


