Information Systems Research
Vol. 24, No. 1, March 2013, pp. 146–163
ISSN 1047-7047 (print) | ISSN 1526-5536 (online)
http://dx.doi.org/10.1287/isre.1120.0462

Social Media and Firm Equity Value

Xueming Luo
College of Business, University of Texas at Arlington, Arlington, Texas 76019;
and Fudan University, Shanghai, China 200433, luoxm@uta.edu

Jie Zhang
College of Business, University of Texas at Arlington, Arlington, Texas 76019, jiezhang@uta.edu

Wenjing Duan
School of Business, George Washington University, Washington, DC 20037, wduan@gwu.edu

Companies have increasingly advocated social media technologies to transform businesses and improve organizational performance. This study scrutinizes the predictive relationships between social media and firm equity value, the relative effects of social media metrics compared with conventional online behavioral metrics, and the dynamics of these relationships. The results derived from vector autoregressive models suggest that social media-based metrics (Web blogs and consumer ratings) are significant leading indicators of firm equity value. Interestingly, conventional online behavioral metrics (Google searches and Web traffic) are found to have a significant yet substantially weaker predictive relationship with firm equity value than social media metrics. We also find that social media has a faster predictive value, i.e., shorter "wear-in" time, than conventional online media. These findings are robust to a consistent set of volume-based measures (total blog posts, rating volume, total page views, and search intensity). Collectively, this study proffers new insights for senior executives with respect to firm equity valuations and the transformative power of social media.

Key words: social media; word of mouth; online reviews; Web blogs; vector autoregression; firm equity value; stock market performance
History: Chris Dellarocas, Senior Editor. This paper was received on January 15, 2012, and was with the authors 4 months for 2 revisions. Published online in *Articles in Advance* December 20, 2012.

> Companies with an extensive social media presence reported a return on investment that was more than four times that of their counterparts.
> (*eMarketer* 2012).

1. Introduction

As social media explodes in popularity among consumers, companies seek to transform businesses with social media and capitalize on its financial value (Divol et al. 2012). Social media captures the "wisdom of the crowd." For executives, social media platforms can facilitate business transformation in terms of managing customer relationships, brand assets, and business processes. Executives may monitor the metrics of various digital social media in order to gauge customer feedback and brand buzz and ultimately improve firm performance. No wonder that firms have committed momentous investments in social media (*eMarketer* 2012).

However, to justify the significant resources and investments in social media, executives need to empirically quantify social media's financial value (Deans 2011). Intuitively, customer decisions drive the firm's bottom line and equity value. Enabled by information technology (IT) advances (Hall 2000, Brynjolfsson et al. 2002, Gao and Hitt 2012), social media platforms reveal information that is pertinent to consumer decisions and unobtainable from traditional media. More importantly, social media content is updated rapidly and spreads virally at an unprecedented speed, providing first-hand information to investors ahead of other sources. Thus, social media content provides a timely assessment of the firm's product and brand performance when sales are not available. In this sense, social media metrics may allow investors to not only monitor the firm's customer sentiment and brand performance but also predict its future business value. Because social media can equip investors with the most updated information about the prospects of firm future performance, it may serve as a leading indicator of firm equity value.

Therefore, this study examines whether social media has a significant predictive relationship with firm equity value. Prior finance literature suggests that to predict firm equity value, investors rely on information from the 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 stream of research, our study investigates the prognostic value of two forms of social media—online consumer ratings and blogs–after accounting for the firm's other fundamental information and alternative explanations (such as product quality, new product announcements, merger and acquisition, R&D investment, IT-related intangible assets, firm size, revenue, leverage, liquidity, return on investment (ROA), industry competitiveness, and the external economic environment). Online ratings and blogs can furnish more relevant product- and brand-specific information to marketers and investors, more so than other forms of social media such as videos and networking sites (Tirunillai and Tellis 2012). Also, diverging from conventional online media (websites and search engines), social media is unique in their ability to generate, share, and spread information virally. These distinguishing characteristics create a social contagion effect that drives the unparalleled speed of digital information diffusion (Aral and Walker 2011). Thus, our study also compares the strength of the predictive value of social media metrics versus conventional behavioral metrics such as Web traffic and search volume. Specifically, this study aims to answer the following research questions:

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

This study contributes to the literature in several ways. First, prior studies (e.g., Moe and Fader 2004, Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Dhar and Chang 2009, Ghose and Yang 2009) examine the relationship between digital user metrics and product sales. A summary of how this study relates to and differs from the literature is reported in Table A1 in the appendix (available at http://dx.doi.org/10.1287/isre.1120.0462).[1] Different from prior studies, this paper demonstrates how social media has a predictive relationship with firm equity value. This manner of examining firm equity value beyond sales can reveal new insights. For example, equity value is the ultimate measure of firm market performance, and executives are concerned about firm stock prices that may define their job compensation and career projections. Echoing this, equity value has been used as the measure of firm financial performance and shareholder wealth (Chen et al. 2012, Dewan and Ren 2007). Although sales revenue indicates top line performance, it does not represent shareholder wealth. Also, compatible with social media content, firm equity value can be monitored and recorded at a higher frequency than daily or even hourly level. However, sales are usually available only at a much lower frequency such as monthly or quarterly levels. Further, because of the viral diffusion of social media content, the stock market can respond faster to the information transmitted through social media than to actual product sales. The unparalleled diffusion speed of social media content offers a unique opportunity to examine dynamics of the predictive value of social media. Thus, executives concerned about shareholder wealth would be interested in examining the magnitude and timing of the predictive value of social media in terms of firm equity value, over and beyond sales.

Note that we measure firm equity value with not only the *first* moment (return) but also the *second* moment (risk) of stock prices, because both moments determine shareholder wealth. Whereas return captures the increase or decrease of shareholder wealth, risk is inherently related to a company's corporate bankruptcy rates, capital cost, and shareholder wealth vulnerability (Ang et al. 2006, Luo 2009, Tirunillai and Tellis 2012). Thus, by simultaneously linking social media to both return and risk, we unveil more mechanisms in understanding the predictive relationship between social media and firm equity value.

The second contribution of this research is our focus on investigating the multiple sources of digital user metrics and the relative effects. Although almost all prior studies are limited to a single source, we investigate two sources of social media (blogs and ratings) and contrast their value implications. Further, we compare the relative strength of social media versus conventional online behavioral metrics (Web traffic and Google searches) in predicting firm equity value. Beyond valence- and level-based measures, we also employ the consistent volume-based measures (total blog posts, rating volume, total page views, and search intensity) to validate the relative predictive value of social media metrics compared with that of conventional online behavioral metrics.

The third major contribution is that this study examines the enduring effects of social media. Previous research has focused solely on the short-term value impact, potentially underestimating the power of social media. Our research models the long-term accumulative value of digital user metrics with

[1] In line with IT productivity literature, prior studies show that online consumer ratings influence consumer product choices and purchase decisions (Godes and Mayzlin 2004; Chevalier and Mayzlin 2006; Liu 2006; Dellarocas et al. 2007; Duan et al. 2008a, b; Zhu and Zhang 2010; Gu et al. 2012). Also, blogs in richer formats such as pictures and videos are found to influence sales (Dewan and Ramaprasad 2012; Dhar and Chang 2009; Droge et al. 2010; Aggarwal et al. 2012a, b).

a time-series technique: the vector autoregressive model with exogenous covariates (VARX). VARX is a flexible time-series approach that can estimate the long-term, accumulative effects of social media and test whether such effects unfold nonmonotonically over time (Luo 2009, Adomavicious et al. 2012). Our modeling approach is paramount for dynamically monitoring social media strategies, tracking the effectiveness of e-commerce systems over time, and making early corrections in IT investments when necessary.

Further, this research is particularly relevant in terms of demonstrating the transformative power of social media for several reasons. From an academic perspective, this study is among the first across information systems (IS), marketing, and finance disciplines to appraise the predictive relationships between social media and firm equity value, the relative effects between social media metrics and conventional online behavioral metrics, and the dynamics of these relationships. Without explicit evidence to corroborate social media's value, academics could only implicitly presume that social media could transform organizations with improved equity value. There is an urgent need to substantiate how social media adds shareholder value. A lack of accountability might undermine social media's credibility and threaten the existence of social media and IS commitment as a distinct capability within the firm. To the extent that social media predicts firm equity value better, faster, and more accurately than conventional online media, it may revolutionize entire organizational processes. Organizations can leverage social media to facilitate consumer blogs, manage brand buzz, and respond to product ratings online, which may ultimately influence investors and firm performance in the stock market.

From a managerial perspective, we underline the predictive value of social media that executives have been struggling to quantify. Social media-based technologies may redefine how firms approach Internet marketing, customer targeting, and online brand engagement for higher firm equity value. Our results indicate that social media investments would pay off the best in terms of firm future return when they focus on increasing consumer review ratings and reducing variation of the ratings. Also, in terms of risk management, social media investments are more productive when tailored to increasing positive blogs and curtailing negative blogs, rather than boosting Web page views and search intensity. Without forsaking investments in Web search and traffic, firms should heed the relatively stronger power of social media in predicting firm equity value. Further, the wear-in effects (how soon or how late each metric will reach the peak of the predictive value) enable managers to timely terminate ineffective practices and allocate IT budgets to more productive ones across social media and traditional online media. For example, wear-in time can signal early warnings of imminent decreases in firm equity value when consumer ratings decline. Remedial actions with social media, such as real-time customer relationship management and online complaint handling, may stunt or reverse declines in firm value. In this sense, social media can reform how managers prioritize business strategies and IT budgets so that boosting returns and reducing risks can be balanced.

In the remainder of this paper, we first depict the theoretical background and hypotheses in §2. Section 3 introduces the measures and data sample. Section 4 describes the time-series model. The findings are presented in §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 states that new information may change market expectations and thus move a firm's stock prices (Fama 1970, Samuelson 1965). No price movement would occur without new information. Financial studies also suggest the notion of information asymmetry in the stock market (Healy and Palepu 2001, Hirshlerfer and Teoh 2009). To overcome this asymmetry, investors seek additional sources of information beyond sales to determine firm equity value. Prior to the social media era, information sources included product quality, new product announcements, profits, R&D, and other assets (Chen et al. 2012). These information sources are usually only available at a low frequency of monthly or quarterly level. 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 its accompanying user-generated content, online word-of-mouth (WOM) such as consumer review ratings and blogs can be a prominent source of new information for investors regarding firm future performance prospects (Chen and Xie 2008, Gu et al. 2012).

We expect that social media may predict firm equity value for several reasons. First, social media currently accounts for almost a quarter of users' online time, grossly surpassing gaming and email (Gallaugher and Ransbotham 2010). Research supports the notion that customers and investors heed what other users share through social media communications (Chen et al. 2012, Deans 2011). Scholars also suggest that peer-based advice (wisdom of the crowd) from the social media influences consumers who are less informed or undecided in their purchasing decisions (Tirunillai and Tellis 2012). Thus, social media can not only reflect user opinions and actions to shape product success but also mold investor prospects of firm equity value.

Second, social media metrics of ratings and blogs may represent credible WOM channels. The Internet technologies can truthfully and accurately record customer feedback and recommendations that are self-revealed by consumers with an altruistic intention (Dellarocas and Wood 2008). Thus, social media content may not only manifest less biased customer sentiment such as satisfaction of the brands and company but can also be more absorbed by consumers and investors (Hanson and Kalyanam 2007). Through monitoring consumer feedback and WOM reflected by social media, firms can take proactive actions to respond to consumer requests and address their concerns, thus likely increasing customer satisfaction. Prior marketing research also reveals that customer satisfaction improves firm equity value (Anderson et al. 2004, Luo et al. 2010), i.e., leading to higher returns and lower risks (Fornell et al. 2006, p. 3). Therefore, as dependable WOM channels with less biased customer sentiment, social media may enable investors to both effectively scrutinize customer satisfaction and brand buzz and timely update their prospects for firm future performance.[2] This stream of research suggests that social media metrics can have a significant predictive relationship with firm equity value.

Moreover, investment in social media may help foster IT intangible assets of the firm. For example, investments in business processes that facilitate firm interactions with consumers online (i.e., publishing blogs, sense-making consumer blogs, enabling product ratings, and responding to consumer complaints online) may represent valuable IT intangible assets. Prior studies note that IT-related intangibles provide productivity benefits and performance advantages to the firm (Brynjolfsson et al. 2002), thus signaling a stronger future financial health of the firm to investors. Indeed, it has been found that the stock market valuation of firms can be influenced by IT applications and intangible assets (Hall 2000, Matolcsy and Wyatt 2008). As such, this line of research also suggests that firms with extensive social media engagement should possess more IT intangible assets and stronger prospects of future equity value than counterparts with less or little social media engagement (Brynjolfsson et al. 2002, Wyatt 2005). Hence, we have the following:

Hypothesis 1 (H1). *Social media metrics, online consumer ratings 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 Behavioral Metrics

Before the emergence of social media applications, consumers were restricted to browsing Web pages and seeking information through search engines. Interactions between consumers and firms were limited to either mass communication (e.g., Web advertising) or asynchronous media such as email (Gallaugher and Ransbotham 2010). Individual consumers had limited ability to observe or influence other consumers' purchase decisions. Therefore, Web traffic and Internet search metrics are conventional measurements of online consumer behavior in both industrial applications and academic research. Website visits (traffic) refer to the number of visitors to a website and the number of Web pages they browse. When users search product information on a search engine such as Google, attentions are paid to the brand and company, and thus brand exposure is stimulated regardless of the final purchase decision (Davenport and Beck 2002). Prior studies suggest that conventional online behavioral metrics such as Web visits are related to firm value (Trueman et al. 2000, Demers and Lev 2001, Dewan et al. 2002). Regarding Internet searches, Da et al. (2011) demonstrate that search frequency of stock tickers on Google is an indicator of stock trading of retail investors. Table 1 compares and contrasts the social media and conventional online consumer behavioral metrics.

We expect that social media metrics have a stronger predictive relationship with firm equity value than conventional metrics for several reasons. First, social media metrics tend to be more socially "contagious" than Web traffic and Internet searches.[3] Blogs and product ratings appear on the websites and are shared with the public, thus generating external WOM effects. In stark contrast, Web traffic and searches tend not to be communicated, exchanged, or spread directly among users. The finance literature indicates

[2] Indeed, according to the branding literature, positive changes in customer-based brand ratings also enhance shareholder value by increasing returns and reducing risks of the firm (Morgan and Rego 2006, Rego et al. 2009).

[3] Recent studies (e.g., Aral and Walker 2011, Duan et al. 2009, Hirshleifer and Teoh 2009) have inferred or measured social contagion. Our study is not intended to infer or measure social contagion. Rather, we use social contagion (supported by prior studies) as theoretical underpinnings for the stronger predictive value of social media.

Table 1 Compare and Contrast of Different Digital Metrics

Digital metrics	Social influence (contagion effect)	Visibility and availability	Customer engagement
Social media metrics			
Consumer ratings	Very high	High	High
Web blogs	Very high	High	High
Conventional online consumer behavioral metrics			
Web traffic	Very low	Low	Low
Google search	Very low	Medium	Low
Supporting literature	Hirshleifer and Teoh (2009), Duan et al. (2009)	Tirunillai and Tellis (2012), Animesh et al. (2010)	Gallaugher and Ransbotham (2010), Gupta et al. (2004), Fornell et al. (2006)

that social influence is central to information diffusion and that information contagion plays an important role in influencing investor responses (Hirshleifer and Teoh 2009).[4] Because social media content is more contagious with stronger social influence than conventional online media, investors may have a stronger response to social media.

Further, social media is more visible than conventional online media. Social media content is generated and diffused on the Internet in an open and visible style. Consumers can read and write reviews and blogs publicly with easy access online (Animesh et al. 2010, Tirunillai and Tellis 2012). On the other hand, conventional behavioral metrics are less visible because Web traffic and search intensity are only reported by third-party companies (e.g., Alexa) or Web-hosting servers that are not directly visible or easily accessible to the public. Finance scholars suggest that investors have limited attention and respond asymmetrically to more visible information (Barber and Oden 2008, Hirshleifer and Teoh 2009). That is, when the information is more visible and accessible, investors are more likely to respond to it. As such, this line of research suggests that investors would have stronger responses to social media metrics than conventional behavioral metrics because of the relatively higher visibility of the former.

Moreover, social media metrics can denote a higher degree of customer engagement with the firm than do traffic and search metrics. Social media occupies a large portion of users' online time (Gallaugher and Ransbotham 2010). Consumers who spend considerably more time and effort in social media interactions (i.e., writing reviews and posting blogs) presumably have higher brand commitment and loyalty, thereby contributing more to firm equity value (Gupta et al. 2004, Fornell et al. 2006, Luo et al. 2010, Tirunillai and Tellis 2012). Therefore, social media metrics are expected to have a stronger predictive relationship with firm equity value than conventional online behavioral metrics such as Web traffic and searches.

Hypothesis 2 (H2). *Social media metrics have a stronger predictive relationship with firm equity value than conventional online consumer behavioral metrics.*

2.3. Dynamics of the Predictive Value of Social Media

Previous marketing literature has demonstrated the dynamics of stock market responses to WOM and online user-generated content. For example, Luo (2007, 2009) reveals the short- and long-term effects of WOM on cash flows and stock prices. Tirunillai and Tellis (2012) show that negative user reviews are related to stock returns with wear-in effects, which are defined as how much time it takes before the predictive value of user-generated content peaks. The wear-in time is useful for managers to timely adjust social media strategies because it indicates the urgency of the predictive relationships. For example, wear-in time can signal early warnings of imminent decreases in firm equity value when customer ratings decline. Remedial actions with social media, such as real-time customer relationship management and service recovery, may stunt or reverse firm value's decline. Further, wear-in time can help managers decide when to retire apparently ineffective practices, thus allowing managers to efficiently allocate IT resources across social media and conventional online media.

We expect that social media metrics have a shorter wear-in time (faster predictive value) in predicting firm equity value than conventional online behavioral metrics. Our expectations stem from the unparalleled speed at which information is transmitted and diffused through the wide reach of social media (Datamonitor 2011). As shown in Table 1, compared with conventional online behavioral metrics, social media metrics boast higher visibility and availability because of the wide subscription, access, and reach of social media platforms. In addition, social media content is updated on a daily and even hourly basis and, thus, can be disseminated more quickly than traditional media content (Gallaugher and Ransbotham 2010).

Moreover, social media content can be voted on, linked, reproduced, broadcast, and spread more quickly, creating information richness and diffusion speed unmatched by conventional online behavioral

[4] Herding 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 markets.

metrics (Aggarwal et al. 2012a, Gu et al. 2012). Because social media content travels faster and can be instantly obtained by investors at the highly frequent temporal level, the wear-in effect of the stock market response to social media should be shorter compared with that of conventional online media. As such, we have the following:

Hypothesis 3 (H3). *Social media metrics have a faster predictive value, i.e., shorter wear-in time, than conventional online behavioral metrics.*

3. Data and Measures

In this study, we selected the computer hardware and software industries as our research context for two reasons. First, according to Moore's Law, computing products have experienced rapid technological advancements with reduced life cycles. Hence, companies in the computer industry frequently introduce new products (Goeree 2008). Second, customers of computer products are more likely to participate in and be influenced by various digital media. As such, firms in these industries intensively leverage social media to engage customers and promote products online. Indeed, most literature on social media has focused on one industry. For example, Liu (2006), Dellarocas et al. (2007), Duan et al. (2008a, b), and Chintagunta et al. (2010) examined movies. Forman et al. (2008) and Chevalier and Mayzlin (2006) examined books. Dhar and Chang (2009) and Dewan and Ramaprasad (2012) examined music. Godes and Mayzlin (2004) examined TV shows. Zhu and Zhang (2010) examined video games. Finally, Luo (2007, 2009) examined airline services.

Within the computer hardware and software industries, we selected publicly traded firms (for stock price data availability) that serve the consumer markets to ensure the availability of consumer reviews. Nine firms that are major industry leaders satisfied these criteria. The selected computer hardware companies (HP, Dell, Acer, Toshiba, Apple, and Sony) are top PC sellers in the industry, garnering 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 (Alexa, CNET, Lexis/Nexus, Google search, CRSP, COMPUSTAT, 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 because of missing data on Web traffic). The descriptive statistics for each firm are summarized in Table 2. We also report the descriptive statistics and correlation matrix for the entire sample in Table A3 (in the online appendix).

3.1. Data and Measures for Firm Equity Value

Prior studies in IS, marketing, and finance (Dewan and Ren 2007, Luo 2009, Srinivasan and Hanssens 2009) suggest two common measures of firm equity value: stock return and risk. Return or *abnormal return* is firm equity value beyond what is expected by the average stock market via the extended Fama-French model from the finance literature (Fama et al. 1993,

Table 2 Data Descriptive Statistics by Firm

Firm	Return	Risk	Rating level	Rating volume	Blog pos.	Blog neg.	Traffic page view	Traffic reach	Google search intensity	Google search instability	Google blog posts
Acer	−0.017	2.53	2.97	0.70	0.41	0.050	1.31	1,754.0	1.36	0.0011	1,299.0
	(2.75)	(0.27)	(0.96)	(1.11)	(0.93)	(0.24)	(0.23)	(916.5)	(0.06)	(0.001)	(731.8)
Adobe	−0.022	1.72	2.90	0.37	0.30	0.053	2.37	13,796.5	8.43	0.0078	7,452.1
	(2.04)	(0.39)	(0.78)	(0.65)	(0.67)	(0.28)	(0.12)	(1,160.0)	(0.82)	(0.008)	(7,450.4)
Apple	0.053	2.22	3.64	5.60	0.29	0.055	4.00	11,787.8	11.65	0.0127	97,514.3
	(2.39)	(0.26)	(0.79)	(4.81)	(0.72)	(0.28)	(0.39)	(2,272.0)	(1.48)	(0.024)	(18,677.2)
Corel	−0.032	3.58	2.95	0.37	0.06	0.031	3.14	406.2	0.39	0.0020	342.4
	(5.46)	(1.62)	(0.89)	(0.64)	(0.28)	(0.21)	(0.49)	(63.36)	(0.06)	(0.002)	(170.3)
Dell	−0.008	2.04	2.78	1.53	0.33	0.125	5.24	5,472.2	2.58	0.0079	4,478.8
	(2.51)	(0.62)	(1.22)	(1.51)	(0.61)	(0.36)	(0.79)	(631.3)	(0.29)	(0.005)	(2,217.5)
HP	0.009	1.48	2.75	3.89	0.12	0.049	4.82	4,563.6	4.40	0.0128	9,827.3
	(1.78)	(0.44)	(1.00)	(2.35)	(0.38)	(0.25)	(0.47)	(371.1)	(0.45)	(0.009)	(10,798.6)
Microsoft	−0.009	1.47	3.13	4.76	0.25	0.121	2.53	49,066.9	44.43	0.0105	34,906.5
	(1.81)	(0.40)	(0.94)	(3.66)	(0.54)	(0.36)	(0.09)	(6,005.1)	(4.07)	(0.012)	(22,456.9)
Sony	−0.005	1.93	3.54	6.65	0.40	0.078	3.68	649.1	5.84	0.0171	13,586.1
	(2.26)	(0.45)	(0.68)	(3.30)	(1.20)	(0.30)	(0.57)	(96.2)	(0.76)	(0.016)	(14,664.2)
Toshiba	0.002	2.81	3.03	0.73	0.31	0.056	4.57	228.3	1.52	0.0151	1,501.8
	(3.43)	(0.76)	(1.02)	(0.97)	(0.68)	(0.37)	(0.80)	(41.4)	(0.25)	(0.0171)	(694.7)

Notes. Standard deviation in parenthesis. See Table A3 (in the online appendix) for data descriptive for the whole sample.

Fama and French 1996, Carhart 1997). Risk or *idiosyncratic risk* refers to the vulnerability or volatility of firm equity value. Idiosyncratic risk captures 80% of the firm's total risk and can be measured as the standard deviation of the residuals of the extended Fama-French model (Goyal and Santa-Clara 2003, p. 980):

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

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, β_{0i} = the intercept, and e_{it} = the 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, and MOM_t) are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We ran model (1) for a rolling window of 250 trading days prior to the target day. *Abnormal returns* (AR_{it}) is then calculated as the difference between the observed returns and the expected returns:

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

Risk is the standard deviation of the model residuals. As shown in Table 2, the mean value of firm daily returns ranges from −0.032% to 0.053%, and the mean value of daily stock risk ranges from 1.47 to 3.58.

3.2. Data and Measures for Social Media Metrics

For social media metrics, we collected consumer rating data from the consumer technology product website CNET.com. In addition, we collected data for blog posts from the Lexis/Nexus Web blogs database at the daily level.

3.2.1. Data and Measures for Online Consumer Ratings. We collected data for *consumer ratings* from the website CNET.com, following Gu et al. (2012). CNET lists consumer reviews on products of major consumer electronics firms. We design a software agent in PERL to search all products of the sampled firms on CNET.com. The program parses HTML codes of each product review page to collect review dates and ratings. This technique of crawling data with an automated software agent from public websites has been widely applied in IS literature (e.g., Ghose and Yang 2009, Aggarwal et al. 2012a, 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.

We measure consumer ratings with both level and volume (Gu et al. 2011). The *level* of rating assesses the average rating score of consumer reviews for all products of the firm. An increase in the rating level represents greater overall customer satisfaction and advocacy for the firm. *Volume* measures the total number of consumer reviews. A higher volume may indicate greater consumer resonance and brand buzz about products of the firm. Although some argue differential impacts of positive versus negative ratings (Liu 2006), others hold that "any publicity is good publicity and better than none at all" (Berger et al. 2010, p. 815).

3.2.2. Data and Measures for Web Blogs. We collected data for *Web blogs* about 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 Internet. It includes all the top 20 technology blogs ranked by blog search engine Technorati.com, including Techcrunch, Mashable, Engadget, Gizmodo, and others. The literature on blogs has used various sources ranging from a single blog platform (Aggarwal et al. 2012a); a blog aggregator website (Evens 2009, Chen et al. 2012, 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 much more attention and, therefore, are more heavily weighed than other less popular blogs (Aggarwal et al. 2012a, b).

Following Liu (2006) and Aggarwal et al. (2012a), we employed two graduate students to categorize each blog post based on the sentiment of blog content as positive or 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. We provide the detailed analysis on the Google blog data in the robustness tests of §5.6.

3.3. Data and Measures for Conventional Online Consumer Behavioral Metrics

For conventional online consumer behavioral metrics, we collected Web traffic data from Alexa.com and search data from Google at the daily level.

3.3.1. Data and Measures for Web Traffic. We collected Web traffic data from Alexa.com, a popular source widely adopted by academic and practical research (Palmer 2002, Krishnamurthy et al. 2005, Animesh et al. 2010). We downloaded 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 obtained three measures of Web traffic from Alexa: *total page views* that can assess the total volume of Web traffic, *page views per user* that capture 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 page views is the product of the other two measures. Therefore, we use only page views per user and reach to measure Web traffic for the empirical model, consistent with the financial accounting literature (Trueman et al. 2000).[5] The total page view metric is used in the robustness test discussed in §5.6. *Page views per user* reflects the "stickiness" (how long consumers stay to view more pages or visit the site repeatedly over time) or customer loyalty to the website (Demers and Lev 2001). To avoid data redundancy, 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 reflect a greater pool of potential customers for the firm. Compared with another commonly used metric of "unique visitors" that also measures audience size, *reach* is typically calculated as a percentage in a relative sense, thus more comparable across firms. As shown in Table 2, on average, a user visits about 1.31 to 5.24 Web pages of a targeted firm per day. Also, daily reach ranges from 228.3 to 49,066.9 per million Internet users.

3.3.2. Data and Measures for Internet Search. We obtained Internet search data from the Google Insights for Search (http://www.google.com/insights/search) provided by the most popular search engine of Google (Varian and Choi 2009, 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 the mean of "firm key words" search frequencies at google.com.[6] The key words for each firm are based on the top 10 query key words from search engines provided by Alexa. For example, according to Alexa, the top 10 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 key words search frequencies at google.com each day. It is measured as the conditional stochastic volatility (h_t) via the auto-regressive conditional heteroskedasticity in mean (GARCH-M) model:

$$\mathrm{Log}\,Search_t = c+\sum_{i=1}^{L}\rho_i \,\mathrm{Log}\,Search_{t-i}+\varphi \mathrm{Log}(h_t)+\epsilon_t \quad (3)$$

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

where α_0, α_1, and γ_1 are parameters of the GARCH(1, 1) model. As shown in Table 2, the mean value of search intensity ranges from 0.39 to 44.43, and the mean of search instability ranges from 0.001 to 0.017.

3.4. Data for Exogenous Control Variables

Following the firm valuation models widely used in IS, marketing, and accounting literature (Trueman et al. 2000, Brynjolfsson et al. 2002, Ferreira and Laux 2007, Tirunillai and Tellis 2012), we control for a comprehensive set of exogenous covariates. The controls include product quality, IT-related intangible assets, R&D expenditures, new product announcement events, merger and acquisition (M&A), revenue (sales), firm size, financial leverage, liquidity, ROA, industry competitive intensity, and economic crisis.

We control for product quality because it can influence both digital user metrics and firm equity value and, therefore, may introduce endogeneity bias in data analyses. *Product quality* is measured by the expert rating from an unbiased third party (CNET), whose professional editors conduct independent industry-standard benchmark tests and impartially evaluate products based on such key aspects as design, features, performance, service, and support. *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 expenditure* is measured as research and development expenses (*XRDQ*) scaled by total assets from COMPUSTAT. New product announcements (which reflect IT capabilities of the firm) are collected from the Lexis/Nexis news search. Prior marketing studies have also used Lexis/Nexis news search to measure new product announcements (e.g., Sood and Tellis 2009). Similarly, we collected *M&A* announcements from Lexis/Nexis news search as well. *Revenue* is the *REVTQ* variable in the COMPUSTAT database. *Firm size* is measured by total assets of the firm (variable *ATQ*). *Financial leverage* is the ratio of long-term book debt (*DLTTQ*) to total assets. *Liquidity* is the current ratio of a firm (*LCTQ/ACTQ*). *Return on assets* measures firm profitability and is calculated as the ratio of a firm's operating income (*OIBDPQ*) to its book value of total

[5] We could have another traffic metric of duration, or average time spent at the site per visit. However, Alexa's AWIS does not provide this data. We checked a different source with ComScore. Yet, ComScore 2006 database had a sparse browsing history for our targeted firms, and the clickstream data for our research period was not available when the research was conducted.

[6] Google normalizes and scales the absolute query values to remove regional effects (thus can allow for direct comparison).

assets. To match those quarterly financial variables with our daily social media and conventional metrics, we adopted the VAR-bootstrapping scheme, which uses 5,000 simulated databases to generate the values of those variables for each observed day (Hamilton 1994, Statman et al. 2006, Luo 2009). In addition, we control for industry and economic conditions with competitive intensity and economic crisis. *Competitive intensity* is gauged by the Hirschmann-Herfindahl index measure of industry concentration. It is the sum of squared market shares of firms in the industry derived from 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). Finally, we construct a dummy variable *economic crisis* indicating the financial market crash in October 2008.

4. VARX Model Specification

4.1. Rationale for VARX

We employ a time-series technique, namely, 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 not only the short-term, immediate but also the long-term, cumulative effects 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 blogs, ratings, search, and traffic 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. Thus, VARX can model complex chained effects in a complete cycle, uncovering the full predictive value of social media metrics. Our empirical time-series analysis proceeds in the following steps (Table A2 in the online appendix) that are applied to each firm separately (Srinivasan et al. 2010). Recently, VARX models have been adopted by IS researchers (Adomavicius et al. 2012).

4.2. Step 1: Model Specifications on the Predictive Values of Social Media Metrics

We estimate a 10 equation VARX model, where endogenous variables are firm equity value metrics (return and risk), consumer rating variables (level and volume), blog sentiment variables (positive and negative), Google search variables (intensity and volatility), and Web traffic variables (page view per user and reach). We also have a set of 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

$$\begin{bmatrix} RTN_t \\ RSK_t \\ AVR_t \\ NUR_t \\ POS_t \\ NEG_t \\ PGV_t \\ REC_t \\ GSI_t \\ GSV_t \end{bmatrix} = \begin{bmatrix} \alpha_1+\delta_1 t \\ \alpha_2+\delta_2 t \\ \alpha_3+\delta_3 t \\ \alpha_4+\delta_4 t \\ \alpha_5+\delta_5 t \\ \alpha_6+\delta_6 t \\ \alpha_7+\delta_7 t \\ \alpha_8+\delta_8 t \\ \alpha_9+\delta_9 t \\ \alpha_{10}+\delta_{10} t \end{bmatrix} + \sum_{k=1}^{K} \begin{bmatrix} \phi_{1,1}^k & \cdots & \phi_{1,10}^k \\ \phi_{2,1}^k & \cdots & \phi_{2,10}^k \\ \phi_{3,1}^k & \cdots & \phi_{3,10}^k \\ \phi_{4,1}^k & \cdots & \phi_{4,10}^k \\ \phi_{5,1}^k & \cdots & \phi_{5,10}^k \\ \phi_{6,1}^k & \cdots & \phi_{6,10}^k \\ \phi_{7,1}^k & \cdots & \phi_{7,10}^k \\ \phi_{8,1}^k & \cdots & \phi_{8,10}^k \\ \phi_{9,1}^k & \cdots & \phi_{9,10}^k \\ \phi_{10,1}^k & \cdots & \phi_{10,10}^k \end{bmatrix}$$

$$\cdot \begin{bmatrix} RTN_{t-k} \\ RSK_{t-k} \\ AVR_{t-k} \\ NUR_{t-k} \\ POS_{t-k} \\ NEG_{t-k} \\ PGV_{t-k} \\ REC_{t-k} \\ GSI_{t-k} \\ GSV_{t-k} \end{bmatrix} + \begin{bmatrix} \tau_{1,1} & \cdots & \tau_{1,11} \\ \tau_{2,1} & \cdots & \tau_{2,11} \\ \tau_{3,1} & \cdots & \tau_{3,11} \\ \tau_{4,1} & \cdots & \tau_{4,11} \\ \tau_{5,1} & \cdots & \tau_{5,11} \\ \tau_{6,1} & \cdots & \tau_{6,11} \\ \tau_{7,1} & \cdots & \tau_{7,11} \\ \tau_{8,1} & \cdots & \tau_{8,11} \\ \tau_{9,1} & \cdots & \tau_{9,11} \\ \tau_{10,1} & \cdots & \tau_{10,11} \end{bmatrix}$$

$$\cdot \begin{bmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \\ x_{4t} \\ x_{5t} \\ x_{6t} \\ x_{7t} \\ x_{8t} \\ x_{9t} \\ x_{10t} \\ x_{11t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \\ \varepsilon_{8t} \\ \varepsilon_{9t} \\ \varepsilon_{10t} \end{bmatrix}, \tag{4}$$

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 = page views per user, REC = reach, GSI = Google search intensity, GSV = Google search instability, t = time, α_i ($i = 1, 2, \ldots, 10$) = constant, δ_i, ϕ_{ij}^k, $\tau_{i,l}$ ($i, j = 1, 2, \ldots, 10$, $l = 1, 2, \ldots, 11$) = coefficients, K = lag length, x_i ($i = 1, 2, \ldots, 11$) = an exogenous variable, and ε_i ($i = 1, 2, \ldots, 10$) = white-noise residual.

The lag order in VARX is selected by 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 with the minimized SIC and FPE (Dekimpe and Hanssens 1999, Luo 2009, Adomavicius et al. 2012). The optimal lag order was two according to these criteria for our models (Table A5 in the online appendix). We test various assumptions of VARX residuals including multivariate normality, omission-of-variables bias, White heteroskedasticity tests, and portmanteau autocorrelation. As reported in Tables A6–A9 (in the online appendix), results suggest no violations of these assumptions at the 95% confidence level.

4.3. Step 2: Short- and Long-Term Predictive Values of Social Media Metrics

In the next step, we use the estimated parameters of the full VARX model ϕ_{ij}^k to generate the generalized impulse response functions (GIRFs) with $\psi_{ij}(t)$, which can gauge the net effects of one unit of unexpected change in digital user metric 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 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, or number of periods before the peak predictive value is reached. The largest (in absolute value) impulse response coefficients determine the peak predictive value (Pauwels 2004, Srinivasan et al. 2010).

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

Based on the VARX parameters, we derive generalized forecast error variance decomposition (GFEVD) estimates to examine which user metric explains more or less variance of firm equity value in a systematic model. Like a dynamic R^2, GFEVD gauges the relative predictive power of each metric in explaining the variance of firm equity value over time, without assuming a causal ordering (Dekimpe and Hanssens 1999, Nijs et al. 2001). GFEVD estimates are derived from

$$\theta_{ij}(t) = \frac{\sum_{k=0}^{t} (\psi_{ij}(k))^2}{\sum_{k=0}^{t} \sum_{j=0}^{m} (\psi_{ij}(t))^2}, \quad i, j = 1, \ldots, m. \tag{5}$$

GFEVD attributes 100% of the forecast error variance in firm equity value to all endogenous variables. Thus, it can identify the relative predictive value of social media versus conventional media. This relative value of endogenous variables is established based on GFEVD in 20 days (to reduce sensitivity to short-term fluctuations, see Tirunillai and Tellis 2012). To establish the statistical significance of GFEVD estimates ($p = 0.05$), we obtain standard errors using Monte Carlo simulations with 1,000 runs (Luo 2009).

5. Findings

5.1. Test for Stationarity in Time Series

The process of estimating VARX models begins with the unit-root tests to check whether variables are evolving or stationary. Stationarity implies that, although an unexpected change in endogenous variables in VARX can induce fluctuations over time, its effects dissipate ultimately. Then, endogenous variables revert back to the deterministic (mean + trend + seasonality) pattern without a permanent regime shift. The variance of stationary variables is finite and time invariant. We conduct the augmented Dickey-Fuller (ADF) tests to check stationarity (Dekimpe and Hanssens 1999). The ADF tests 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* series and four firms' *search instability* series. We thus use the first differences for these two metrics. As reported in Table 3, the ADF test results for the corrected data series range from -187.39 to -2.93, suggesting that the variable series do not cointegrate in equilibrium (Hamilton 1994).

5.2. Test for Granger Causality

Following Tirunillai and Tellis (2012), we conduct Granger causality tests (Granger 1969) and report the results in Table 4. Our results suggest that social media metrics have significant temporal-based causal relationships with firm equity value. Almost all social media metrics significantly "Granger cause" firm equity value. Positive blogs, negative blogs, and rating volume Granger cause firm stock return ($p =$ 0.03, 0.04, and 0.03, respectively). In addition, 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 H1.

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

Table 3 Stationarity Test of the Endogenous Variables

Firm	Return	ΔRisk	Rating level	Rating volume	Blog pos.	Blog neg.	Traffic page view	Traffic reach	Google search intensity	ΔGoogle search instability	ΔGoogle blog posts
Acer	−22.90	−19.52	−22.28	−14.27	−6.95	−4.05	−2.93	−5.20	−15.10	−24.02	−11.38
Apple	−22.25	−21.76	−21.15	−11.02	−18.12	−23.06	−9.16	−9.02	−6.81	−12.63	−6.72
Dell	−22.07	−22.65	−7.00	−3.17	−21.08	−18.82	−4.87	−26.42	−8.28	−4.13	−11.92
HP	−21.92	−22.62	−21.04	−18.33	−22.32	−18.22	−17.23	−4.13	−5.21	−4.60	−14.79
Sony	−21.00	−22.02	−19.07	−6.17	−20.99	−22.44	−3.22	−29.97	−53.82	−14.66	−5.97
Toshiba	−28.37	−22.82	−21.66	−8.02	−17.58	−20.86	−3.18	−5.60	−12.84	−8.29	−17.29
Adobe	−22.94	−22.57	−14.76	−18.55	−22.22	−21.20	−12.77	−23.50	−9.98	−17.25	−7.84
Corel	−23.35	−18.50	−21.72	−20.12	−19.32	−22.15	−16.21	−22.85	−187.39	−9.27	−582.09
Microsoft	−21.40	−22.52	−22.64	−7.20	−20.69	−20.20	−16.76	−20.53	−11.67	−13.22	−23.12

Note. Augmented Dickey Fuller (ADF) test statistic critical value: −2.89 (5% level confidence interval).

5.3. Short- and Long-Term Predictive Values of Social Media Metrics

Table 5 reports the immediate and cumulative impulsive response elasticities, as well as the wear-in time from the GIRFs results. The magnitude of elasticity results reflects the change in basis point (one basis point = one hundredth of a percentage) of stock return or percentage of stock risk in response to one unit of unexpected change in social media metrics. These results largely support the hypotheses. We discuss more details of the results below.

5.3.1. Web Blog. As shown in Table 5, social media metrics in terms of positive blog posts have 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 terms and significantly reduce the short-term risk (−0.019%, $p < 0.01$). That is, an unexpected increase in positive blog posts will predict a surge in daily stock return by 0.0003 and a drop in stock intraday risk by 0.00019 in the short term. Negative blog posts are negatively related to the short-term return (−1.55 basis points, $p < 0.01$) and predict an increase of intraday risk for both the short term and long term (0.060 and 0.086%, respectively, $p < 0.01$). Thus, the results suggest that blog posts are a significant leading indicator of firm equity value. We calculate the economic impact of each social media metric. Consistent with Tirunillai and Tellis (2012), we find that holding other factors constant, for the sampled firm of Acer, one unit of unexpected increase in positive blog posts will translate into an increase of approximately $0.93 million market capitalization in the short run, and an accumulated value of $1.40 million over 20 days.

Table 4 Summary of the Results of Granger Causality Tests

Response to	Return	ΔRisk
Web blog		
Blog positive	0.03**	0.06
Blog negative	0.04**	0.03**
Consumer rating		
Rating level	0.06	0.04**
Rating volume	0.03**	0.04**
Web traffic		
Page view	0.04**	0.05**
Reach	0.07	0.06
Google search		
Search intensity	0.11	0.07
ΔSearch instability	0.07	0.06

Note. The estimates of the Granger causality are the mean of the *p*-values of the joint Wald statistics.
$^{**}p < 0.05$.

5.3.2. Online Consumer Ratings. Results in Table 5 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 term. This suggests that a change in rating is associated with an increase of firm return in the long run. The rating volume 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 H1, that social media metrics, online consumer reviews and Web blogs in particular, have a significant predictive relationship with firm equity value.

Interestingly, the findings suggest that though predicting a boost in stock returns, consumer ratings also have some negative effects, because the rating level is associated with a higher stock risk (0.089%, $p < 0.1$) in the long run, and the rating volume is significantly ($p < 0.01$) associated with stock risks in both short and long terms.

5.3.3. Search and Traffic. As shown in Table 5, most metrics of Web search and traffic can predict firm return both in the short term and in long term (at least $p < 0.05$), which conforms to the theory and literature. For example, Google searches are associated with higher stock returns (Da et al. 2011). Also, more page views by a user and/or wider reach of the firm website can significantly predict higher firm returns, which is in line with prior literature (Trueman et al. 2000, Demers and Lev 2001).

Table 5 Impulse Responses of Firm Equity Value to Social Media Metrics

	Return			ΔRisk		
	Immediate	Accumulative	Wear-in time (days)	Immediate	Accumulative	Wear-in time (days)
Blog positive	3.01***	4.38***	3.0	−0.019***	−0.036	3.1
Blog negative	−1.55***	−5.84	2.4	0.060***	0.086***	3.9
Web blogs			2.7			3.5
Rating level	3.01	3.37***	3.3	0.017	0.089***	3.9
Rating volume	2.09***	4.70***	2.9	0.032***	0.041***	3.3
Consumer ratings			3.1			3.6
Page view	1.18***	1.76	7.7	−0.002	0.204***	6.1
Reach	1.30***	8.64***	7.7	−0.016	−0.183***	8.0
Web traffic			7.7			7.1
Search intensity	0.57**	4.43	6.9	−0.021***	−0.101***	8.6
ΔSearch instability	−1.96***	−1.39	3.3	0.039***	0.076***	5.2
Google search			5.1			6.9

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

5.4. Relative Strength of the Predictive Value of Social Media versus Conventional Online Consumer Behavioral Metrics

The variance decomposition of GFEVD results in Table 6 provides the relative power of each metric in explaining the variance of firm equity value. All of the metrics explain nontrivial 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. Also, the data support the order of rating (2.61%), blogs (2.26%), then traffic (1.32%) and search (0.89%) in predicting long-term firm risk. Further, total social media metrics account for a significantly greater proportion of the variance than total conventional online behavioral metrics (5.87% versus 3.71% in return and 4.87% versus 2.21% in risk). These differences are statistically significant according to both parametric F statistics and nonparametric Kruskal-Wallis statistics as shown in Table 6 ($F = 9.37$ and Kruskal-Wallis = 6.79, both $p < 0.01$ for return, and $F = 13.84$ and Kruskal-Wallis = 8.75, both $p < 0.01$ for risk). Thus, these results support H2, that social media metrics have a stronger predictive value than the conventional online consumer behavioral metrics.

Table 6 Variance Decomposition of Firm Equity Value as Explained by Digital User Metrics

Variance explained by	Return (%)	ΔRisk (%)
Blog positive	1.21	0.85
Blog negative	1.54	1.41
Total Web blog	2.75	2.26
Rating level	1.53	0.79
Rating volume	1.59	1.82
Total consumer rating	3.12	2.61
Total social media	5.87	4.87
Page view	0.80	0.77
Reach	0.48	0.55
Total Web traffic	1.28	1.32
Search intensity	1.23	0.42
ΔSearch instability	1.20	0.47
Total Google search	2.43	0.89
Total conventional media	3.71	2.21
Testing rating + Blog > Search + Traffic		
Kruskal-Wallis statistic	6.79***	8.75***
F statistic	9.37***	13.84***

*** $p < 0.01$.

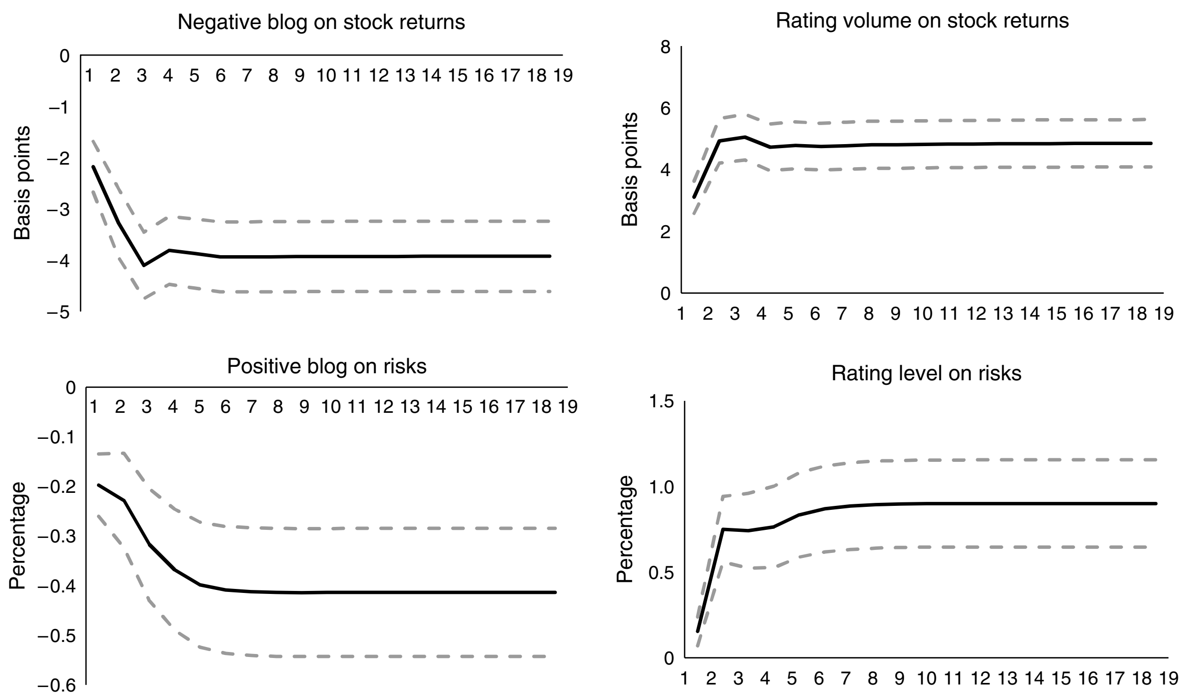
5.5. Dynamics of the Predictive Value of Social Media Metrics

Recall that wear-in time gauges how long it takes for 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 responses to social media metrics for Hewlett-Packard). The results reported in Table 5 show that social media metrics (blogs and reviews) demonstrate significantly shorter wear-in time for both firm stock return ($F = 11.02$ and 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), and Web traffic metrics have longer wear-in time (7.7 days). A similar pattern exists for firm risk. Thus, these results consistently support H3, that social media metrics have a faster predictive value or shorter wear-in time than conventional online behavioral metrics.

5.6. Robustness Tests

We conduct several additional tests to ascertain the robustness of the results. For example, we use a

Figure 1 **Accumulated Impulse Response Functions of Key Social Media Metrics**



uniform measure for all metrics, alternative measure of Web blogs, and different subsamples of firms.

5.6.1. Consistent Measures for Social Media Metrics and Conventional Online Behavioral Metrics. To remove the bias with different measures, we conduct additional analyses with a consistent set of measures with *volume* of each metric (total blog posts, rating volume, total page views, and search intensity). The variance decomposition and impulse response results are shown in panel A of Tables 7 and 8. Again, all three hypotheses are supported. Thus, our conclusion is robust to the uniform volume-based measure of social media and conventional online behavioral metrics. Social media metrics can predict firm equality value (panel A of Table 7) and explain significantly greater proportions of the variance than conventional online behavioral metrics (4.10% versus 1.98% in return and 4.23% versus 1.94% in risk; see panel A of Table 8). Social media metrics also have significantly shorter wear-in time than conventional online behavioral metrics: 3.28 versus 5.78 days in return ($F = 4.24$ and Kruskal-Wallis $= 3.65$, both $p < 0.05$), and 2.89 versus 6.28 days ($F = 4.95$ and Kruskal-Wallis $= 4.38$, both $p < 0.05$).

5.6.2. Alternative Measure of Web Blogs. Following Stephen and Galak (2012), we collect blog posts about the firms and brands from another blog search engine—Google blog search. Because of the large variance and scale of this variable, we take the natural log of it. For stationarity test, we cannot reject the hypothesis of a unit root in this blog variable for Acer, Adobe, Dell, HP, and Microsoft, but can significantly reject the unit root hypothesis after we take the first differences. We replace the blog volume variable in the previous VARX model with this alternative variable. The results are reported in panel B of

Table 7 **Impulse Responses of Firm Equity Value to Social Media Metrics (Volume Only)**

	Panel A: From Lexis/Nexis blog search				Panel B: From Google blog search			
	Return		Risk		Return		Risk	
	Immediate	Accumulative	Immediate	Accumulative	Immediate	Accumulative	Immediate	Accumulative
Blog posts	2.57***	4.58***	−1.39***	−2.15**	1.95***	4.06**	−4.31***	−5.41***
Rating volume	2.12**	2.58**	3.49	5.33***	4.23***	6.91***	6.99***	11.09***
Page view	1.52***	4.78***	0.95***	1.15	1.04***	1.49***	−0.65***	−3.98
Search intensity	0.41	4.26***	−1.98***	−0.20	1.31	9.10***	−3.07***	−2.09

Notes. The coefficients of returns are in basis points (one basis point = one hundredth of a percentage). The coefficients of risk are percentage values.
$^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8 Variance Decomposition of Firm Equity Value to Social Media Metrics (Volume Only)

	Panel A: From Lexis/Nexis blog search (%)		Panel B: From Google blog search (%)	
Variance explained by	Return	Risk	Return	Risk
Blog posts	2.12	1.58	1.32	1.11
Rating volume	1.98	2.66	2.55	3.03
Total social media	4.10	4.23	3.87	4.14
Page view	1.05	1.05	0.95	0.84
Search intensity	0.94	0.89	0.90	0.87
Total conventional media	1.98	1.94	1.85	1.71
	Testing rating + Blog > Search + Traffic			
Kruskal-Wallis statistic	6.79***	4.68**	6.33***	10.39***
F statistic	11.10***	6.49**	4.31**	5.78**

** $p < 0.05$, *** $p < 0.01$.

Tables 7 and 8. These results are qualitatively similar to the previous VARX model and consistently support the three hypotheses. Social media metrics can predict firm equity value (panel B of Table 7) and account for significantly greater proportions of the variance than conventional online behavioral metrics (3.87% versus 1.85% in return and 4.14% versus 1.71% in risk; see panel B of Table 8). Social media metrics also have significantly shorter wear-in time than conventional online behavioral metrics: 1.67 versus 4.83 days in return ($F = 6.12$ and Kruskal-Wallis $= 6.51$, both $p < 0.05$), and 2.33 versus 5.11 days in risk ($F = 5.01$, $p < 0.05$ and Kruskal-Wallis $= 6.65$, $p < 0.01$).

5.6.3. Firm Level Variation. To control for outliers in our sample and check if our results are not driven by one particular firm, we take out the sampled firms, one at a time on a rolling basis, and then examine the hypotheses. Once again, all of our three hypotheses are still supported. For ease of exploration and journal space issue, we illustrate the consistent variance decomposition results with the subsample excluding Microsoft in Table 9.

Table 9 Variance Decomposition of Firm Equity Value for the Data Sample Excluding Microsoft

Variance explained by	Return (%)	ΔRisk (%)
Blog positive	1.29	0.73
Blog negative	1.57	1.35
Total Web blog	2.85	2.08
Rating level	1.33	0.77
Rating volume	1.48	1.71
Total consumer rating	2.81	2.48
Total social media	5.66	4.56
Page view	0.87	0.74
Reach	0.52	0.58
Total Web traffic	1.39	1.33
Search intensity	1.34	0.47
Search instability	1.19	0.38
Total Google search	2.53	0.85
Total conventional media	3.92	2.18
Testing rating + Blog > Search + Traffic		
Kruskal-Wallis statistic	6.89***	7.46***
F statistic	9.38***	12.91***

*** $p < 0.01$.

6. Discussion

This study was intended to investigate the predictive power of social media and dynamics of the relationship between social media metrics and firm equity value. The results suggest 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 behavioral metrics. Consumer ratings have the highest predictive power for firm returns and risks. Google searches and Web traffic have significant but only moderate predictive value. Social media metrics in terms of blogs and ratings have shorter wear-in time than Web traffic and search, and negative blogs have the shortest wear-in time in predicting firm equity value. These findings are robust to a consistent set of measures using the *volume* of each metric (total blog posts, rating volume, total page views, and search intensity). These findings proffer novel and important implications for the theory and practice of social media.

6.1. Theoretical Implications

This research contributes to the literature across IS, marketing, and finance disciplines. Social media is indispensable for organizations to achieve not only short-term performance but also long-term productivity benefits inherently connected to firm equity value. Firms should no longer treat social media investments as net costs. Rather, social media can be a significant leading indicator of firm equity value, thus helping justify the investments in social media and new IT initiatives for organizational transformation and shareholder value creation. In this sense, our research adds to the literature on IT productivity (Hall 2000, Brynjolfsson et al. 2002, Gao and Hitt 2012). Specifically, our results indicate that social media investments on increasing consumer ratings and reducing variation of the ratings would be most fruitful in terms of firm future return. Also, investments on increasing positive blogs and curtailing negative blogs would be more effective in terms of firm risk management, more so than investments on increasing Web page views and search intensity. Although investments on Web search and traffic are still important, companies should attend to the relatively larger power of social media in predicting firm future equity value. Thus, managers should prioritize and allocate IT budgets appropriately among various social media platforms according to these platforms' ability to predict business financial value.

Furthermore, our study is the first to unveil the association between Web blogs and business stock performance among IS, marketing, and finance literature. Positive blog posts can improve trust and advocacy of the consumers or investors and, thus, result in higher firm value and lower risk. Negative blogs can damage corporate reputations and impair firm performances. Interestingly, we found that the harm of negative blogs kicks in faster than the benefits of positive blogs. Thus, firms should respond quickly to negative blog posts by adopting corrective actions to mitigate the potential adverse effects on future performance. For example, Kryptonite announced a lock exchange plan *five* business days after a negative video began circulating the blogosphere in September 2004 that showed how to pick a Kryptonite bike lock with a Bic pen.

Also, prior finance and marketing studies have demonstrated the relationship between Web traffic/search and firm performance (Moe and Fader 2004, Da et al. 2011, Demers and Lev 2001). We agree and extend this stream of research by showing that social media can be a much stronger indicator of firm performance than the pure "eyeball effects" of Web traffic. Thus, social media metrics can equip organizations with more potent measures of online customer engagement and brand buzz, as well as prospects of firm equity value in the social digital age.

Finally, we develop time-series models that can gauge the long-term and accumulative value of digital user metrics. Our models prevent underestimating the power of digital user metrics because focusing solely on short-term value would neglect the enduring effects of social media. Web analytics research should therefore pay more attention to time-series models and the long-term, cumulative effects of social media. Also, we benchmark with shareholder value-based business performance because shareholder value is the ultimate concern to senior executives. Moreover, shareholder value of the firm is available at the daily level, which permits managers and investors to conduct more refined time-series analyses.

6.2. Managerial Implications

This research also informs managers in several ways. Social media allows managers to nurture customer relationships and brand buzz for higher firm equity value. Still, some managers are perplexed by not knowing which online media strategy pays off the most or the least. Indeed, "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). This may threaten the accountability and credibility of social media investments as a distinct capability within the organization. However, our results support that social media is germane to firm equity value because social media metrics can predict firm return and risk in the short and long terms.

Analyzing the wear-in effects of social media will alert managers to the urgency of the predictive relationships so as to prioritize responsive actions. As reported in Table 5, the dynamic wear-in times can provide an early warning signal to managers about future damages in 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 take immediate actions to reverse negative blogs so as to stem the potential damage on future performance (i.e., in cases of Southwest Airlines airplane incidents and Toyota car recalls).

Moreover, managers can act upon the wear-in effects to better allocate resources across social media and conventional online media. For example, the wear-in time of Web traffic for firm return responses is the longest at 7.7 days. Thus, to boost firm return, managers should allocate more IT resources for other metrics such as ratings, blogs, or search queries. Also, to more quickly reduce firm risk, managers should shift more IT resources for Web blogs and consumer ratings because they have relatively shorter wear-in times.

6.3. Limitations and Future Research

This study has several limitations that serve as avenues for future research. First, our research design cannot assure the causality of the predictive value of social media. One fruitful direction for future research is the use of field experiments (Aral and Walker 2012).

Second, differences between the measures of conventional online behavioral metrics and social media metrics may constitute a possible alternative explanation for the differences in the effects and, thus, a potential limitation of the paper. Even though we have conducted robustness tests using a consistent volume-based measure, future research could test the results with more harmonious and comprehensive metrics.

Third, the social media content in our sample may vary in the level of trustworthiness given the various sources. Strategically manipulating user-generated content on the Internet is not uncommon

(Dellarocas 2006). An interesting extension to our study is to investigate the effects of various sources of social media content on brand performance outcomes, including brand recommendation, brand feeling among customers, and brand reputation among employees.

Fourth, processing social media content is time consuming. We therefore call for more efficient procedures, such as the applications of text mining and sentiment analyses in this area. These procedures are especially pivotal for managers and practitioners to monitor, process, and analyze social media in real time.

Finally, the generalizability of the results could be assessed by extending our research to industries other than PC and software, such as books, videos, and healthcare industries. Indeed, to advance the burgeoning IS-finance interface (Aggarwal et al. 2012b, Dewan and Ren 2007), we call for future research that further explores the relationships between IT-related metrics (e.g., social media, electronic WOM, and user networks) and financial metrics (e.g., analyst recommendations, investor attention, initial public offerings, and venture financing).

6.4. Conclusion

In conclusion, this study provides an initial step toward examining the predictive relationship between social media and firm equity value. Given the significance of social media for transforming business organizations, we hope future research will develop more scientific time-series models to discover novel insights into the business value of social media.

Electronic Companion

An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/isre.1120.0462.

Acknowledgments

The authors gratefully acknowledge the insightful and constructive comments from the senior editors; the area editors; anonymous reviewers; marketing colleagues (Peter Fader, Eric Bradlow, Yuxin Chen, K. Sudhir, Catherine Tucker, Michelle Andrews, and Kris Floyd); IS colleagues (Yunjie Xu, Zhiwei Peng, and Tuan Phan); seminar participants at Fudan University and the University of Texas at Arlington, as well as participants in the ISR special issue workshop at the University of Maryland.

References

Adomavicius G, Bockstedt JC, Gupta A (2012) Modeling supply-side dynamics of IT components, products, and infrastructure: An empirical analysis using vector autoregression. *Inform. Systems Res.* 23(2):397–417.

Aggarwal R, Gopal R, Sankaranarayanan R, Singh RV (2012a) Blog, blogger, and the firm: Can negative employee posts lead to positive outcomes? *Inform. Systems Res.* 23(2):306–322.

Aggarwal R, Gopal R, Gupta A, Singh H (2012b) Putting money where the mouths are: The relation between venture financing and electronic word-of-mouth. *Inform. Systems Res.* 23(3-Part-2):976–992.

Anderson EW, Fornell C, Mazvancheryl SK (2004) Customer satisfaction and shareholder value. *J. Marketing* 68(4):172–185.

Ang A, Hodrick RJ, Xing Y, Zhang X (2006) The cross-section of volatility and expected returns. *J. Finance* 61(1):259–299.

Animesh A, Ramachandran V, Viswanathan S (2010) Quality uncertainty and the performance of online sponsored search markets: An empirical investigation. *Inform. Systems Res.* 21(1):190–201.

Aral S, Walker D (2011) Creating social contagion through viral product design: A randomized trial of peer influence in networks. *Management Sci.* 57(9):1623–1639.

Aral S, Walker D (2012) Identifying influential and susceptible members of social networks. *Science* 337(6092):337–341.

Baker S (2009) Beware social media snake oil. *Business Week* (December 3). http://www.businessweek.com/magazine/content/09_50/64159048693735.htm.

Barber BM, Odean T (2008) All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Rev. Financial Stud.* 21(2):785–818.

Berger J, Sorensen AT, Rasmussen SJ (2010) Positive effects of negative publicity: When negative reviews increases sales. *Marketing Sci.* 29(5):815–827.

Bikhchandani S, Hirshleifer D, Welch I (1998) Learning from the behavior of others: Conformity, fads, and informational cascades. *J. Econom. Perspect.* 12(3):151–170.

Brynjolfsson E, Hitt L, Yang S (2002) Intangible assets: Computers and organizational capital. *Brookings Papers on Economic Activity: Macroeconomics* 2002(1):137–181.

Carhart M (1997) On persistence in mutual fund performance. *J. Finance* 52(1):57–82.

Chen Y, Xie J (2008) Online consumer reviews: A new element of marketing communications mix. *Management Sci.* 54(3):477–491.

Chen Y, Liu Y, Zhang J (2012) When do third-party product reviews affect firm value and what can firms do? The case of media critics and professional movie reviews. *J. Marketing* 76(2):116–134.

Chevalier JD, Mayzlin D (2006) The effect of word of mouth on sales: Online book reviews. *J. Marketing Res.* 43(3):345–354.

Chintagunta PK, Gopinath S, Venkataraman S (2010) Online word-of-mouth effects on the offline sales of sequentially released new products: An application to the movie market. *Marketing Sci.* 29(5):944–957.

Da Z, Engelberg J, Gao P (2011) In search of attention. *J. Finance* 66(5):1461–1499.

Das SR, Chen MY (2007) Yahoo! for Amazon: Sentiment extraction from small talk on the Web. *Management Sci.* 53(9):1375–1388.

Datamonitor (2011) Social media in financial services: The customer as the advisor. http://www.marketresearch.com/Datamonitor-v72/Social-Media-Financial-Services-Customer-6424875.

Davenport TH, Beck JC (2002) *The Attention Economy: Understanding the New Currency of Business*. (Harvard Business School Press, Boston).

Deans PC (2011) The impact of social media on C-level roles. *MIS Quart. Executive* 10(4):187–200.

Dekimpe M, Hanssens DM (1999) Sustained spending and persistent response: A new look at long-term marketing profitability. *J. Marketing Res.* 36(4):397–412.

Dellarocas C (2006) Strategic manipulation of Internet opinion forums: Implications for consumers and firms. *Management Sci.* 52(10):1577–1593.

Dellarocas C, Wood C (2008) The sound of silence in online feedback: Estimating trading risks in the presence of reporting bias. *Management Sci.* 54(3):460–476.

Dellarocas C, Zhang X, Awad N (2007) Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *J. Interactive marketing* 21(4):23–45.

Demers E, Lev B (2001) A rude awakening: Internet value drivers in 2000. *Rev. Accounting Stud.* 6(2–3):331–359.

Dewan R, Friemer M, Zhang J (2002) Management and evaluation of advertisement-supported websites. *J. Management Inform. Systems* 19(3):87–98.

Dewan S, Ramaprasad J (2012) Music blogging, online sampling, and the long tail. *Inform. Systems Res.* 23(3, Part 2):1056–1067.

Dewan S, Ren F (2007) Risk and return of information technology initiatives: Evidence from electronic commerce announcements. *Inform. Systems Res.* 18(4):370–394.

Dhar V, Chang E (2009) Does chatter matter? The impact of user-generated content on music sales. *J. Interactive Marketing* 23(4):300–307.

Divol R, Edelman D, Sarrazin H (2012) Demystifying social media. *McKinsey Quart.* (April). http://www.mckinseyquarterly.com/Demystifying_social_media_2958.

Droge C, Stanko M, Pollitte W (2010) Lead users and early adopters on the Web: The role of new technology product blogs. *J. Product Innovation Management* 27(1):66–82.

Duan W, Gu B, Whinston AB (2008a) Do online reviews matter?—An empirical investigation of panel data. *Decision Support Systems* 45(4):1007–1016.

Duan W, Gu B, Whinston AB (2008b) The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *J. Retailing* 84(2):233–242.

Duan W, Gu B, Whinston AB (2009) Informational cascades and software adoption on the Internet: An empirical investigation. *MIS Quart.* 33(1):23–48.

eMarketer (2012) For brands, social media shows returns but measurement hurdles remain. (May 1), http://www.public.site2.mirror2.phi.emarketer.com/Article.aspx?R=1009011.

Evens M (2009) The aggregator blog model: How a blog leverages long tail economics. *J. Inform. Sci. Tech.* 6(2):3–21.

Fama E (1970) Efficient capital markets: A review of theory and empirical work. *J. Finance* 25(2):383–417.

Fama E, French K (1996) Multifactor explanations of asset pricing anomalies. *J. Finance* 51(1):55–84.

Fama E, French F, Kenneth R (1993) Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* 33(1):3–56.

Ferreira MA, Laux PA (2007) Corporate governance, idiosyncratic risk, and information flow. *J. Finance* 62(2):951–989.

Fornell C, Mithas S, Morgeson III FV, Krishnan MS (2006) Customer satisfaction and stock prices: High returns, low risk. *J. Marketing* 70(1):3–14.

Forman C, Ghose A, Wiesenfeld B (2008) Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Inform. Systems Res.* 19(3):291–313.

Gallaugher J, Ransbotham S (2010) Social media and customer dialog management at starbucks. *MIS Quart. Executive* 9(4):197–212.

Gao G, Hitt LM (2012) Information technology and trademarks: Implications for product variety. *Management Sci.* 58(6):1211–1226.

Ghose A, Yang S (2009) An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Sci.* 55(10):1605–1622.

Godes D, Mayzlin D (2004) Using online conversation to study word of mouth communications. *Marketing Sci.* 23(4):545–560.

Goeree MS (2008) Limited information and advertising in the U.S. personal computer industry. *Econometrica* 76(5):1017–1074.

Goyal A, Santa-Clara P (2003) Idiosyncratic risk matters! *J. Finance* 58(3):975–1007.

Granger C (1969) Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37(3):424–438.

Gu B, Park J, Konana P (2012) The impact of external word-of-mouth sources on retailer sales of high-involvement products. *Inform. Systems Res.* 23(1):182–196.

Gupta S, Lehmann DR, Stuart JA (2004) Valuing customers. *J. Marketing Res.* 41(1):7–18.

Hall R (2000) E-Capital: The link between the stock market and the labor market in the 1990s. *BPEA* 2(2000):73–102.

Hamilton J (1994) *Time Series Analysis* (Princeton University Press, Princeton, NJ).

Hanson W, Kalyanam K (2007) *Internet Marketing and e-Commerce* (Thomson South-Western, Mason, OH).

Healy P, Palepu K (2001) Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *J. Accounting Econom.* 31(1–3):405–440.

Hirshleifer D, Teoh SH (2009) Thought and behavioral contagion in capital markets. Hens T, Schenk-Hoppe KR, eds. *Handbook of Financial Markets: Dynamics and Evolution* (North Holland, Amsterdam), 1–56.

Hou K, Robinson DT (2006) Industry concentration and average stock returns. *J. Finance* 61(4):1927–1956.

Krishnamurthy S, Patel R, Kaushal A (2005) Online competition. *Marketing Res.* 17(4):20–25.

Liu Y (2006) Word-of-mouth for movies: Its dynamics and impact on box office revenue. *J. Marketing* 70(3):74–89.

Luo X (2007) Consumer negative voice and firm-idiosyncratic stock returns. *J. Marketing* 71(3):75–88.

Luo X (2009) Quantifying the long-term impact of negative word of mouth on cash flows and stock prices. *Marketing Sci.* 28(1):148–165.

Luo X, Homburg C, Wieseke J (2010) Customer satisfaction, analyst stock recommendations, and firm value. *J. Marketing Res.* 47(6):1041–1058.

Matolcsy Z, Wyatt A (2008) The association between technological conditions and the market value of equity. *Accounting Rev.* 83(2):479–518.

Moe WW, Fader PS (2004) Dynamic conversion behavior at e-commerce sites. *Management Sci.* 50(3):326–335.

Morgan NA, Rego LL (2006) The value of different customer satisfaction and loyalty metrics in predicting business performance. *Marketing Sci.* 25(5):426–439.

Nijs VR, Dekimpe MG, Steenkamp JEM, Hanssens DM (2001) The category demand effects of price promotions. *Marketing Sci.* 20(1):1–22.

Palmer JW (2002) Website usability, design, and performance metrics. *Inform. Systems Res.* 13(2):151–167.

Pauwels KH (2004) How dynamic consumer response, competitor response, company support and company inertia shape long-term marketing effectiveness. *Marketing Sci.* 3(4):596–610.

Rego LL, Billett MT, Morgan NA (2009) Consumer-based brand equity and firm risk. *J. Marketing* 73(6):47–60.

Samuelson PA (1965) Proof that properly anticipated prices fluctuate randomly. *Indust. Management Rev.* 6(2):41–49.

Sood A, Tellis GJ (2009) Do innovations really payoff? Total stock market returns to innovation. *Marketing Sci.* 28(3):442–456.

Srinivasan S, Hanssens D (2009) Marketing and firm value: Metrics, methods, findings and future directions. *J. Marketing Res.* 46(3):293–312.

Srinivasan S, Vanhuele M, Pauwels K (2010) Mind-set metrics in market response models: An integrative approach. *J. Marketing Res.* 47(4):293–312.

Statman M, Thorley S, Vorkink K (2006) Investor overconfidence and trading volume. *Rev. Financial Stud.* 19(4):1531–1565.

Stephan AT, Galak J (2012) The effects of traditional and social earned media on sales: A study of a microlending marketplace. *J. Marketing Res.* 49(5):624–639.

Tetlock PC (2007) Giving content to investor sentiment: The role of media in the stock market. *J. Finance* 62(3): 1139–1168.

Tirunillai S, Tellis G (2012) Does chatter matter? The impact of online consumer generated content on a firm's financial performance. *Marketing Sci.* 31(2):198–215.

Trueman B, Wong F, Zhang X-J (2000) The eyeballs have it: Searching for the value in internet stocks. *J. Accounting Res.* 38(Supplement):137–170.

Varian HR, Choi H (2009) Predicting the present with google trends. Google research blog, http://googleresearch.blogspot.com/2009/04/predicting-present-with-google-trends.html.

Wyatt A (2005) Accounting recognition of intangible assets: Theory and evidence on economic determinants. *Accounting Rev.* 80(3):967–1003.

Zhu F, Zhang X (2010) Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *J. Marketing* 74(2):133–148.