Measuring the Dynamic Predictive Relationship of Social Media Metrics with Firm Equity Value: A Time Series Analysis

Zeshan Ahmad	Assistant Professor, Business Administration, Air University Multan Campus, Pakistan
Imran Khan	Senior Lecturer, Department of Management Sciences, The Islamia University of Bahawalpur, Pakistan.
Muhammad Abbas	Associate Professor, Business Administration, Air University Multan Campus, Pakistan. Email; mam@aumc.edu.pk

Abstract

In the online environment, social media metrics offer a credible basis of customer feedback in anticipating the firm performance. This study verifies the association of social media metrics of Face-book and Twitter to financial market performance. Data were collected from official Facebook pages and Twitter accounts of 3 fast-food companies over the time period of 6 months. Then established multiple metrics for respective social media platforms and develop outcomes using Vector Autoregressive time series models to evaluate the instantaneous and continuing relationship between social media metrics and financial market performance of the firms in terms of unusual returns and idiosyncratic risk. Results indicated that FB metrics are significant leading indicators of firm equity value. However, Twitter metrics, have a weaker relationship with firm value as compared to FB metrics. Collectively, current research extends new visions for organizational top executives and investors concerning organizational equity valuation and the social media power transformation.

Key Words

Firm Equity Value, Social Media Metrics, Facebook, Twitter, Social Media Marketing.

Introduction

Prior literature of finance provides evidence that in addition to firm fundamentals, investors depend on information acquired from internet (Das & Chen, 2007), search attention (Da, Engelberg & Gao, 2011), customer feedback (Luo, 2009), print media (Tetlock, 2007), and online chatters (Tirunillai & Tellis, 2012). Social media tools are attaining fame and these are part of regular operations of a large sum of companies of all sizes: start-ups, small, medium and large corporations (Osimo, 2008). Companies using social media technologies have outperformed their competitors which are not using these technologies and have achieved benefits of low cost and higher efficiency (Harris & Rae, 2009). Companies are capitalizing on their financial value through social media transformation in business because of the increasing popularity of social media among consumers (Divol, Edelman, & Sarrazin, 2012). This transformation can be in the form of customer relationship management, corporate business processes and brand building. Quantitative analysis of social media's financial value to the organization is crucial to justify the investment of scarce resources in it (Deans, 2011). Social media enables the organization to utilize rich information about consumer decisions with the help of information technology advancement which is inaccessible through traditional media. Furthermore, social media has an unprecedented speed of content spread and continuously updating contents that provide the primary information to organizations and their investors. Social media contents are the source of timely assessment of an organization's products and brands while sales information is not available at this frequency. Thus, social media not only enables the investors to perform sentiment analysis of a firm's contents but also to analyze the brand performance and its future value. As social media can arm the investors with unceasingly updating information regarding the future performance of their prospective firm, it may be the most important predictor of the firm equity value function.

Social Media Metrics and Equity Value of The Firm

Previous researches evaluated the association among product sales and digital user metrics (e.g., Dhar & Chang, 2009; Ghose & Yang, 2009), while current research focuses on new insights by highlights the predictive association between firms' equity value and social media metrics. Shareholder wealth and firms' financial performance can be measured through firm equity value(Chen, Liu, & Zhang, 2012; Dewan & Ren, 2007). While sales revenue cannot represent shareholder wealth but it is a prime

indicator of top-line performance. Firm equity value is compatible with social media metrics as it can be recorded and monitored at a high frequency than sales revenue. Moreover, the stock market could respond quicker to the social media contents which are diffused virtually than actual product sales. Because of this dynamics executive concerned about shareholder wealth beyond and over the sales. By keeping in mind that shareholder wealth determined by two moments of stock prices (risk and return), we measure firm equity value with both moments. Whereas risk is associated with the capital cost, corporate bankruptcy and wealth vulnerability of shareholders and return apprehends the fluctuation in shareholders' wealth (Luo, 2009; Tirunillai & Tellis, 2012). Because of this simultaneous linkage between social media and two moments of stock prices (risk and return), we highlight the new mechanism in the evaluation of the predictive relationship between the firm equity and social media by focusing on multiple investigation sources of social media

Social media popularity and its convoying user-generated content can be a protuberant source of fresh information for managers and investors concerning firms' future performance (Gu, Park, & Konana, 2012). Social media is an essential information source as literature supports the belief how investors and consumers notice about the information shared by others on social media (Chen et al., 2012; Deans, 2011). Less informed customers or customers with the indecision of their product choice get influence from the wisdom of the crowd (Tirunillai & Tellis, 2012). Customer's feedback and recommendations are accurately and truthfully recorded by the internet technologies that are altruistic intentions of consumers (Dellarocas & Wood, 2008). So that user-generated content on social media like satisfaction and positive word-of-mouth are perceived more reliable by the customers and investors (Hanson & Kalyanam, 2007). Social media metrics of Facebook and Tweeter engagement may have a noteworthy predictive relationship with value of firm. Current research explores that among the two social media metrics (Facebook metrics and Twitter metrics), which is a strong indicator in predicting firms' equity value.

Data and its Measures

In the current study, we chose, for several reasons, the fast-food sector for our research context. First, consumers of the fast-food industry are the participants in our research and supposed to be affected by various digital media. Second, organizations in this industry leverage social media for promotion and engagement online as 57% of consumers view a restaurant's website before dining there. Third, global fast-food industry sales increased over two trillion dollars and 13 million employees are associated with this industry(Statisticsbrain, 2016).

Within the fast-food industry, we selected three firms that function as the consumer markets to ensure the readiness of social media contents and reviews. The selected companies are among the top 5 players of the industry, generating more than 70% of the United States market share.

The daily data were collected from the official Facebook fan pages and twitter account of the companies from July 1, 2017, to December 31, 2017. The collected data set contains 384 observations, representing the 3 companies over 128 trading days. The descriptive statistics of the firms are available in Table 1.

Table 1. Firm wise descriptive statistics

	RTRN	FPST	FBE	PINT	PST	RTWT	RSK	TWT	TWTE	TWTI
Dominos	0.13 (0.012)	35.64 (35.55)	0.0087 (0.0057)	0.858 (0.0071)	1.15 (0.58)	235.98 (222.33)	0.96 (0.08)	127.65 (40.12)	0.0912 (0.0664)	0.0007 (0.0005)
KFC	-0.06 (0.011)	2538.52 (1374.65)	0.016 (0.0071)	0.0266 (0.0099)	0.5 (0.58)	564.7 (191.26)	1.1324 (0.07)	26.27 (20.92)	0.0632 (0.0991)	0.0204 (0.0056)
McDonald	-0.03 (0.007)	12.48 (7.14)	0.0637 (0.0602)	0.2275 (0.1010)	0.79 (0.68)	683.59 (363.74)	0.6112 (0.02)	55.26 (48.32)	0.0401 (0.0608)	0.0032 (0.0018)

where RTRN = firm return, FPST = fan posts, FBE = Facebook engagement, PINT = post interaction, PST = number of posts, RTWT = retweets, RSK = risk, TWT = number of tweets, TWTE = Twitter engagement, TWTI = tweet interaction. Note: Standard deviation in parenthesis

Measurement of Firm Equity Value

Firm equity value can be measured through two different methods: stock risk and return as suggested by the literature of information system, finance, and marketing (Luo, 2009; Srinivasan & Hanssens, 2009). According to finance literature return/ab-normal return is the equity value of firm yonder what's anticipated by the typical capital market by the extended Fama-French model (Fama & French, 1993, 1996). Volatility or vulnerability of organization equity value is denoted as risk or idiosyncratic risk. It can be measured as the extended Fama-French model residual's standard deviation that can measure the 80% of the total firm risk (Goyal & Santa-Clara, 2003).

$$Rit - Rft = \beta 0i + \beta 1i\ (Rmt - Rft) + \beta 2iSMBt + \beta 3i\ HMLt + \beta 4i\ MOMt + eit \quad (1)$$

Where returns for firm i on time t is given by Rit , Rmt shows average market returns, Rft is the risk-free rate, $SMBt$ is size effects, $HMLt$ = value effects, $MOMt$ = Carhart's momentum effects, $\beta 0i$= the intercept, and eit = the model residual. The first model was run for a 250 trading day rolling window earlier than the day of the target.

In finance theory, abnormal returns (ARit) are measured by the difference of returns observed and the expected returns:

$$ARit = (Rit - Rft) - (\hat{\beta}0i + \hat{\beta}1i\ (Rmt - Rft) + \hat{\beta}2iSMBt + \hat{\beta}3i\ HMLt + \hat{\beta}4i\ MOMt) \quad (2)$$

At this stage, the standard deviation of the residuals represents a risk. The average range of firms' daily return lies between -0.06 % to 0.13 %. Whereas, the average value of daily stock risk is expected to remain between 0.02 and 1.13.

Data and Measure of the Social Media Metrics

We gathered the data for Face-book metrics from the brand fan page of each firm. Software agents were developed in Python language for data crawling on the pages of firms in Face-book and the timeline of Twitter. This program collected data by crawling in Facebook pages exploring moderator posts, likes, fan posts, shares and comments recording with reference to the date and time of the posts. Data crawling from Twitter was done based on the firm's official account names and hashtags about tweets, retweets, mentions, replies and likes. It is generally useful to use automated software for data crawling on public websites (Gu et al., 2012).

Facebook Metrics

A number of posts are the total posts posted by a relevant firm moderator and fan post are the posts posted by fans of the relevant company on the fan page on a given day. Post interaction shows the brand fans' reaction to the moderator post while sharing, commenting or liking the posts. Facebook engagement is the overall reaction of brand fans to the moderators' all posts and fan posts on a given day (Facebook-Developers, 2016).

Twitter Metrics

Twitter engagement is the sum of the four components including replies, mentions, retweets and likes of moderator all tweets on a given day. Retweets are the number of times users share tweets of firm moderators with their followers in a given day. A number of tweets are the total number of tweets posted by a firm on a given day and tweet interaction is the reaction of users to a specific firm's tweet in terms of replies, mentions, retweets and likes on a given day.

Exogenous Control Variables

Certain exogenous variables are kept as control variables. These variables include revenue (sales) for firm equity value calculation, firm size (firm's total assets), liquidity (current ratio) financial leverage (ratio of long-term book debt to total assets), and ROA (ratio of the firm operating income to book value of the total asset). Data of these variables are extracted from the financial statements of the firms in the given period. These variable data is available on quarterly bases but social media data is collected on daily bases, authors adopt the VAR-bootstrapping scheme as a remedy, which uses 5000 simulated databases to make the value of said variables for a respective observed day (Statman, Thorley, & Vorkink, 2006).

VAR Model Specification

Vector Autoregressive, a time series technique, is employed to evaluate the feedback and dynamic interaction effects (Adomavicius et al., 2012; Luo, 2009). We selected this approach for several reasons. First, with the help of this model we can predict the direct effect of firm equity value, by tracking, not only instant but similarly the long-term growing influence of social media metrics. Second, it accounts for biases, for instance, reversed causality,

autocorrelation and endogeneity. Third, with the help of this model, we can capture the complex feedback loops like a feedback effect that is firm equity value's reverse impact on future social media metrics.

Model Specification

In VAR model endogenous variables are Face-book metrics (Face-book engagement, number of posts, post-interaction and fan posts), Twitter metrics (Twitter engagement, number of tweets, tweet interaction and retweets) and firm equity value metrics (risk and return). Exogenous control variables include firm size, liquidity, financial leverage, ROA and revenue. The specification of the VAR model is as under:

$$
\begin{bmatrix}
RTRN_t \\ RSK_t \\ FBE_t \\ PST_t \\ PINT_t \\ FPST_t \\ \varepsilon_{6t} \\ TWTE_t \\ \varepsilon_{7t} \\ TWT_t \\ \varepsilon_{8t} \\ TWTI_t \\ \varepsilon_{9t} \\ RTWT_t \\ \varepsilon_{10t}
\end{bmatrix}
=
\begin{bmatrix}
\alpha_1+\delta_1 t \\ \alpha_2+\delta_2 t \\ \alpha_3+\delta_3 t \\ \alpha_4+\delta_4 t \\ \alpha_5+\delta_5 t \\ \alpha_6+\delta_6 t \\ \alpha_7+\delta_7 t \\ \alpha_8+\delta_8 t \\ \alpha_9+\delta_9 t \\ \alpha_{10}+\delta_{10} t
\end{bmatrix}
+ \sum_{k=1}^{K}
\begin{bmatrix}
\phi_{1,1}^k \cdots \phi_{1,10}^k \\ \phi_{2,1}^k \cdots \phi_{2,10}^k \\ \phi_{3,1}^k \cdots \phi_{3,10}^k \\ \phi_{4,1}^k \cdots \phi_{4,10}^k \\ \phi_{5,1}^k \cdots \phi_{5,10}^k \\ \phi_{6,1}^k \cdots \phi_{6,10}^k \\ \phi_{7,1}^k \cdots \phi_{7,10}^k \\ \phi_{8,1}^k \cdots \phi_{8,10}^k \\ \phi_{9,1}^k \cdots \phi_{9,10}^k \\ \phi_{10,1}^k \cdots \phi_{10,10}^k
\end{bmatrix}
\begin{bmatrix}
RTRN_{t-k} \\ RSK_{t-k} \\ FBE_{t-k} \\ PST_{t-k} \\ PINT_{t-k} \\ FPST_{t-k} \\ TWTE_{t-k} \\ TWT_{t-k} \\ TWTI_{t-k} \\ RTWT_{t-k}
\end{bmatrix}
+
\begin{bmatrix}
\tau_{1,1} \cdots \tau_{1,11} \\ \tau_{2,1} \cdots \tau_{2,11} \\ \tau_{3,1} \cdots \tau_{3,11} \\ \tau_{4,1} \cdots \tau_{4,11} \\ \tau_{5,1} \cdots \tau_{5,11} \\ \tau_{6,1} \cdots \tau_{6,11} \\ \tau_{7,1} \cdots \tau_{7,11} \\ \tau_{8,1} \cdots \tau_{8,11} \\ \tau_{9,1} \cdots \tau_{9,11} \\ \tau_{10,1} \cdots \tau_{10,11}
\end{bmatrix}
\begin{bmatrix}
x_{1t} \\ x_{2t} \\ x_{3t} \\ x_{4t} \\ x_{5t} \\ x_{6t} \\ x_{7t} \\ x_{8t} \\ x_{9t} \\ x_{10t}
\end{bmatrix}
+
\begin{bmatrix}
\varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t}
\end{bmatrix}
\quad (3)
$$

where *RTRN* = firm return, *RSK* = risk, *FBE* = Facebook engagement, *PST* = number of posts, *PINT* = post interaction, *FPST* = fan posts, *TWTE* = Twitter engagement, *TWT* = number of tweets, *TWTI* = tweet interaction, *RTWT* = retweets, t = time, α_i (i = 1,2,3…,10) = constant, δ_i, ϕ_{ij}, $\tau_{i,l}$ (*I and* ,*j* are from 1,2,3,…,10) co-efficients, k = lag length, x_i (i = 1,2,3,…,11) and ε_i shows white noise residual.

Social Media: Short Term and Long-term Predictive Values

Generalized impulse response functions (GIRFs) was generated through estimated parameters ϕ_{ij}^k of full VAR model with $\psi_{ij}(t)$, that can measure the total influence of one unit of un-expected variation in social media metric i at time t and organizational value metric j as taken by (Dekimpe & Hanssens, 1999). We also used 5000 simulations of Monte Carlo to drive standard errors for statistical significance testing of parameters at 5% level (p=0.05). Note that an orthogonal transformation was applied to correct the bias of white-noise residuals that can correlate contemporaneously and produce ambiguous results (Luo 2009). Each GIRF generate multiple summary statistics: first, temporary and instant predictive value; and second, lasting, the overall aggregate value that pools all properties through "dust-settling" periods.

Risk and Return Variance Explained by Social Media Metrics

We measured Generalized Forecast Error Variance Decomposition (GFEVD) estimates on VAR parameters to evaluate which social media metric explains the relative variance of equity in a systemic model (Dekimpe & Hanssens, 1999). GFEVD in 20 days was used in the establishment of these relative values of endogenous variables for the reduction in sensitivity to short-term fluctuation (Tirunillai & Tellis, 2012). Standard errors were obtained through Monte Carlo simulation with 5000 runs for the establishment of GFEVD estimates significance (p=0.05) (Luo 2009).

Findings

Variable Stationarity in Time Series

VAR model estimation starts with checking of variables stationarity with unit-root tests through Augmented Dickey-Fuller (ADF) (Dekimpe & Hanssens, 1999). The result of ADF test was less than critical value -2.89 for almost all metrics across firms and could discard the null hypothesis of a unit root (p=0.05), except for all firms Facebook engagement and Risk series, two firm's fan post series and one firm's number of tweets series. Thus, we used the

first difference in these metrics. As shown in Table 2, the ADF test outcomes suggest no cointegration as the adjusted data series ranged from -3.78 to -16.07(Hamilton, 1994).

Table 2. Endogenous variables stationarity test

	FBE	TWTE	PST	TWT	TWTI	PINT	FPST	RTWT	RTRN	RSK
KFC	-11.67	-12.62	-5.29	-5.00	-7.78	-12.13	-3.78	-11.78	-10.80	-9.30
Dominos	-16.07	-10.53	-9.54	-7.32	-9.83	-8.00	-16.72	-11.07	-11.97	-14.17
McDonalds	-8.92	-12.11	-12.13	-9.06	-6.00	-8.64	-6.88	-11.94	-11.59	-11.47

Note: The critical value of ADF is – 2.89 with a 5% confidence level.

Granger Causality Test

Following Luo et al. (2013) and Tirunillai & Tellis's (2012) Grangér Causality test has been applied and Table 3 exhibits the outcomes. Findings propose that Facebook metrics have temporal based significant causal relationships through firms' equity value. Nearly all Facebook metrics *Grangér cause* significantly to the equity value of the firm. Facebook engagement, number of posts, fan posts and post-interaction granger cause stock risk. Moreover, Facebook engagement and fan posts result in stock returns. From stock return to Facebook metrics reverse feedback is insignificant, although post-interaction is significantly granger caused by stock risk.

Table 3. Grangér causality test results summary

	Return	ΔRisk
Facebook Engagement	0.01*	0.01*
Fan Posts	0.02*	0.02*
Post Interaction	0.19	0.03*
Number of Posts	0.28	0.02*
Retweets	0.23	0.46
Number of Tweets	0.04*	0.53
Twitter Engagement	0.03*	0.02*
Tweet Interaction	0.41	0.23

Twitter engagement considerably both risk and return. A number of tweets also causes return significantly. from a stock return to Twitter metrics reverse feedback isn't significant, although stock risk cause significantly with tweet interaction.

Predictive Values of Social Media Metrics in Short Run and Long Run

Cumulative/immediate impulsive response elasticities from the GIRFs outcomes are reposted in Table 4. The elasticity outcomes magnitude identify the change in basis point of stock return where one base point equals to one hundredth (1/100) of a percentage. Moreover, the stock risk percentage is in reaction to a unit change in social media metrics.

Table 4. Firm equity value to social media metrics: Impulse responses

	Return		Risk	
	Immediate	Accumulative	Immediate	Accumulative
Facebook Metrics				
Facebook Engagement	1.79**	3.49**	-0.031**	-0.089*
Number of Posts	0.87*	1.86	-0.014*	-0.054*
Post Interaction	0.69**	2.98**	-0.022**	-0.048*
Fan Posts	0.43	2.60*	-0.012*	0.052
Twitter Metrics				
Twitter Engagement	1.24*	3.05**	-0.028*	-0.093**
Number of Tweets	0.22	2.64*	-0.017*	0.042
Tweet Interaction	0.21	1.90	0.011	-0.045*
Retweets	0.16	2.76*	-0.03*	-0.091

Facebook metrics

Facebook metrics in terms of Facebook engagement, as shown in Table 4, have a significantly positive (+ve) predictive relationship with a firm return for both short- and long-terms and significantly shrink the both short- and long-term risk. It shows that an unexpected surge in Facebook engagement will predict an increase in everyday stock return by 0.000179 and reduce intraday stock risk by 0.00031 in the short-term. A number of posts possess a significantly encouraging predictive relationship with a firm return for short-terms and shrink significantly the both short- and long-term risk. Post interaction has a significantly positive predictive relationship with a firm return for both short- and long-terms and shrinks significantly the both short- and long-term risk. Fan posts possess a significantly encouraging predictive relationship with a firm return for long-terms and shrink expressively the short-term risk.

Twitter Metrics

Results in Table 4 suggest that Twitter metrics in terms of Twitter engagement have a significant positive predictive temporary and lasting relationship with firm return and significantly shrink both short and long-term risk. A number of tweets have a long-term significant relationship with firm return and reduce significantly the short-term risk. Tweet interaction has reduced the long-term risk, though insignificant in temporary and lasting return and short-term risk. Retweet has a long-term significant predictive relationship with firm return and significantly shrink the short-term risk. Facebook and Twitter metrics have a noteworthy predictive relationship with the equity value of the firm. Remarkably, the results propose that Facebook engagement is at the top in predicting a boost in stock returns in long-term and Twitter engagement is at a peak in the reduction of long-term risk.

Relative Strength of the Predictive Value of Facebook versus Twitter Metrics

Table 5 provides the variance decomposition of GFEVD result that is the relative strength of individual metric in illustrating the firms' equity value variance. All FB and Twitter metrics describe nontrivial variance portions. According to findings the order of FB engagement (1.84%), a number of posts (1.63%), post-interaction (1.31%) and fan posts (0.62%) in predicting firm returns in the long-run. Moreover, the results support the order of FB engagement (1.91%), post-interaction (1.80%), number of posts (1.51%) and fan posts (1.51%) in predicting firm risk in long-run. The results suggest the order of Twitter interaction (1.60%), a number of tweets (0.96%), tweet engagement (0.61%) and retweets (0.49%) in predicting a firm return in long-run. Also, the results suggest the order of Twitter engagement (1.36%), number of tweets (1.35%), retweets (1.30%) and tweet interaction (1.24%) in predicting firm risk in long-run. Total Facebook metrics account for a considerably higher amount of the difference than total Twitter metrics (5.41% versus 3.66% in return and 6.75% versus 5.25% in risk). Results in table 5 also propose that these dissimilarities are statistically significant ($F=10.85$, p <0.05 for return and $F=13.45$, p <0.05 for risk). So that these findings support RQ2, that FB metrics have stronger predictive value than the Twitter metrics.

Table 5. Variance de-composition of firm equity value as described by social media metrics

Variance Explained by	Return (%)	ΔRisk (%)
Fan Posts	0.62	1.51
Facebook Engagement	1.84	1.91
Post Interaction	1.31	1.80
Number of Posts	1.63	1.53
Total FB Metrics	5.41	6.75
Retweets	0.49	1.30
Number of Tweets	0.96	1.35
Twitter Engagement	0.61	1.36
Tweet Interaction	1.60	1.24
Total Twitter Metrics	3.66	5.25
F Statistics	10.85*	13.45*

* $p < 0.05$

Discussion

The current research was trying to evaluate the social media's predictive power and changing aspects of relationships among social media metrics and firms' equity value. The findings indicate that Facebook metrics are primary indicators of firms' equity value (proved through Granger causality tests) and takes a higher predictive

value than Twitter metrics. Facebook engagement has the highest predictive strength for firm risks and returns. Twitter engagement also shows significant predictive power for firm risks and returns. The findings of the current research proffer important and novel inferences for the theoretical and managerial absorbers of social media.

Our findings prove that investment in social media on increasing Facebook and Twitter engagement would be most rewarding related to organizational future risk and return. Top management should prioritize and allot marketing communication budgets properly among numerous social media platforms according to the ability to predicted financial value for the firm. The engagement of consumers in Facebook posts and Twitter tweets provide the factor of trust to the consumers and reduce negative valence on social media.

Social media metrics could furnish firms with more effective processes of online engagement of consumers, in addition to improving the organizational equity value during this social media era. Centering on only short-term value would ignore the persistent effects of these digital user metrics. Our findings support that social media metrics can effectively predict organizational risk and return not only in the short-term but also in the long-term.

Our results suggest that managers have to prioritize these metrics for the enduring long-term returns of their social media investment. Managers have to develop strategies to enhance customer engagement in social media specifically Facebook and Twitter to increase firm value and reduce risk.

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