

An Empirical Pilot Event Study of Popularity and Performance: How Social Media
Consumer Brand Fan Count Predicts Stock Prices

By ARTHUR J. O'CONNOR

41 W. 82nd Street
New York, New York 10024 USA
E-mail: ao19153n@pace.edu

Arthur J. O'Connor is an IT management consultant serving the financial services industry and is currently enrolled in the executive doctoral program in business at Pace University in New York City.

ACKNOWLEDGEMENT

Daniel Dearlove, founder of Famecount.com – a web site that tracks brands that are receiving the greatest number of Facebook fans, the number of Twitter followers, and the number of YouTube views – was instrumental to this study in providing data used in the test study and all three pilot event regression analyses.

ABSTRACT

This innovative study explores the power of social media “electronic word of mouth” or popularity on consumer behavior and brand performance. Pilot longitudinal event studies were conducted on three major brands – Starbucks, Coke and Nike – comparing their respective fan counts on social media networks with their respective corporate stock prices, along with two independent variables representing exogenous stock market and mass media environments, to better isolate the effects of popularity. The independent variables demonstrated an extremely high correlation between predicted and observed stock prices, and notably, the independent variables were found to reliably predict the daily stock prices over a 10 month period – during which the stocks experienced radically different returns, with Starbucks climbing 29%, Nike appreciating by 14%, and Coke declining by nearly 6% – even when the fan counts were lagged by as much as 30 days.

OBJECTIVE/INTRODUCTION

This innovative study integrates the literature on consumer behavior and investor sentiment and attempts to link social media activity with consumer behavior or demand and ultimately brand company competitive performance, using stock prices as a proxy for a daily indicator of financial performance. The study hypothesizes that if brand loyalty is generally believed, and in the academic literature found, to be an important driver of and ultimately competitive performance, brand following as expressed by fan counts on social media networks – as a measure of user-generated content or “audience involvement” – might serve as predictor of increased revenues, earnings and (thus) stock prices of brand companies. The results offer considerable significance in the fundamental analysis and forecasting of brand companies and their stock prices.

Researchers are just beginning to explore the predictive value of social media, and what the volume and tone of messages on social media networks such as Twitter, LinkedIn, Facebook, Flickr, and YouTube can reveal about cognitive processes, knowledge and memory, categorization, motivation, attitude formation, affect, and decision-making. In an age of behavioral marketing, in which major brands target social media campaigns to drive business goals, consumer banks embed electronic discount coupons in their customers’ online bank statements (<http://www.cardlytics.com>), and as new types of content analysis tools are being used to “machine-read” news by Wall Street – to either generate buy or sell orders ahead of overall market reaction to either positive or negative news or divine changes in investor mood – this pilot event study will explore the statistical relationship between social media popularity of three major consumer

brands – Starbucks, Coke and Nike – and the respective performance of their stock prices, as a proxy for a daily indicator for performance, given company fundamentals, industry competition and economic conditions, consistent with a reasonable (if imperfect) efficient market theory. To the best knowledge of this researcher, this multidisciplinary research study is the first event study that combines social media information processing, attitude formation, decision-making and buying behavior of brands with investor behavior and corporate performance.

THEORETICAL DEVELOPMENT

As user-generated material, social media content regarding consumer brands could be considered a reliable indicator of audience involvement, defined in the context of advertising (Krugman 1966) as "...the number of conscious 'bridging experiences,' connections, or personal references per minute that the viewer makes between his own life and the stimulus." In this sense, brand chatter over the social media networks, as a repeated incidental exposure, influences consumer product evaluation and choice (Berger and Fitzsimmons 2008). Consistent with this view are classic studies that found increased frequency of advertising (or messages) can influence perceptions of attribute importance (Mackenzie 1986); audience involvement has a moderating impact of on the effectiveness of advertising messages (Greenwald and Leavitt 1984), and incidental ad messages affects on subconscious consumer behavior (Shapiro 1999).

In consumer marketing, social media has become "electronic word of mouth" regarding what consumers talk about products and brands, and its predictive powers help marketers design and execute promotional and ad campaigns (Jansen, Zhang, Sobel and

Chowdury 2009). Studies have shown a relationship between on-line activity and consumer behavior. The volume of on-line chat has been found to predict book sales (Gruhl, Kumar, Nova and Tomkins 2005), and assessments of blog sentiments were found to predict movie theater sales (Mishne and Glance 2006).

In a study of differences between traditional and electronic word of mouth mechanisms of information dissemination (Romero, Meeder, Kleinberg 2011), Cornell University researchers found significant variation in the ways widely-used subject-headings known as hashtags on different topics spread on a network defined by the interactions among Twitter users. The researchers found that hashtags on politically controversial topics were particularly “persistent,” meaning that repeated exposures resulted in unusually large marginal effects on adoption. The researchers concluded that their findings were analogous to complex contagion principle from sociology (repeated exposures to an idea are particularly crucial when the idea is in some way controversial or contentious) – an interesting observation given the reported effects of social media in the recent political upheavals in many Arab countries.

In a 2010 study (Asur and Huberman) with HP Labs in Palo Alto, researchers counted some 3 million tweets about film over three months found that the rate at which people produce tweets about movies can accurately forecast the short-term box office revenue of the film after the films are released. An earlier study by Zhang and Skiena (2009) used a data aggregation model to predict box office sales.

The Role of Volume vs. Tone of Content

In the context of brand awareness and interest, mere popularity may play a powerful role in the way information spreads in cyberspace (electronic word-of-mouth,

online chatter, and other user-generated content), adding a new dimension to the study of behavioral mimicry, or how people often influence one another's behavior, in the context of behavioral finance and corporate performance.

Interestingly, in two recent studies using sophisticated content analysis tools and mood variables to measure sentiment, only one variable or set of moods were found to be significant, suggesting that mere popularity may be a powerful influence in behavior and performance. In a 2010 study (Bollen, Mao, Zeng) the tone of micro-blogs (known as "tweets"), analyzed using two mood tracing tools from large-scale Twitter feeds, were found, in one instance, to accurately predict the direction of the stock market in the days that followed. The study used (among other techniques) an algorithm developed by Google, the Google-Profile of Mood States (GPOMS), which measures six mood levels – happiness, kindness, alertness, sureness, vitality and calmness – through people's text on the internet. From its analysis of 9.7 million tweets posted over ten months in 2008 by 2.7 million twitter users, the results showed that only one mood (calmness) was predictive, with a 87.5% accuracy whether the market would close up or down between 2 and 6 days after a calmness reading was logged on Twitter.

An earlier study of how media coverage affects investor sentiment (Tetlock 2007) used the General Inquirer (GI) quantitative content analysis program to analyze the words for each day of the "Abreast of the Market" column in the Wall Street Journal over a 16-year period from 1984 to 1999. Despite the robustness of the GI tool, with 77 pre-determined categories from the Harvard psychosocial dictionary, the study consolidated all 77 categories into one single media factor – a "pessimism factor" – that was strongly related to pessimistic words in the newspaper column. In standard return predictability

regressions, Tetlock found that changes in this pessimism factor predicted statistically significant and economically meaningful changes in the distribution of daily U.S. stock returns and volume.

Supporting Tetlock's 2007 study findings are two studies examining the effect of stock prices by the investment advice doled out by TV personality Jim Cramer on his CNBC show, "Mad Money." The first study (Engelberg, Sasseville, Williams 2009) revealed that stocks mentioned on Cramer's show (notably, the show does not provide breaking news, but Cramer's personal opinions and reflections upon information that is already disseminated) were found to undergo a significant price change before reverting back to the original price range over a period of 30 days.

Another study (Aral, Ipeirotis, Taylor 2009) examined the relationship of investor sentiment to different themes or topics in Cramer's investment advice. By parsing the show's transcripts into vectors to extract 20 topics and associated keywords, the researchers performed a regression of unexplained/excess or "abnormal" returns using the Fama-French three factor of return model (Fama and French 1986). Interestingly the study found that while the substance of comments (positive or negative) explained a significant amount of the variance in abnormal returns following a recommendation, two other factors were also significant: 1) the length of Cramer's advice was correlated with the magnitude of "the Cramer effect", 2) certain types of topics in and of themselves have a significant explanatory power (eight of the 20 topics were statistically significant at the 10% level).

Fang and Peress (2007) approached the issue of information efficiency differently, in measuring the relative return on stocks that are widely covered by

newspapers versus those that are not – to measure what might be termed “the publicity effect.” The study found a portfolio of stocks with no media coverage outperforms a portfolio with high media coverage by 3% a year after adjusting for market, size, book-to-market valuation, momentum and liquidity (using the Pastor-Stambaugh proxy for liquidity risk). The study suggests that added awareness from publicity results in a consistent bias of relative over-valuation, reminiscent of the classic growth vs. value stock debate (Shiller 1984).

HYPOTHESIS

This study hypothesizes that, as brand following on social media networks becomes more established as a barometer of cognitive processes, knowledge and memory, categorization, motivation, attitude formation, affect, and consumer decision-making, mere popularity, or fan counts, may be a reliable indicator of consumer behavior, and in fact, may serve as a leading indicator of brand performance.

The study explores three hypotheses

H #1: Daily social media popularity of a consumer brand is positively correlated with the common stock price performance of the brand company

H #2: Daily social media popularity of a consumer brand on a 10 day lagged basis is positively correlated with the common stock price performance of the brand company

H #3: Daily social media popularity of a consumer brand on a 30 day lagged basis is positively correlated with the common stock price performance of the brand company

METHODOLOGY

Population and Data Collection

For the measure of popularity or “electronic word of mouth,” this study used the fan counts of brands by Famecount.com, which identifies and tracks those people, products or topics – in the categories of politics, video games, brands, athletes, non-profits, films, actors, TV shows, education/schools, sports teams and musicians – that are receiving the greatest number of Facebook fans, the number of Twitter followers, and the number of YouTube views in given time periods.

Daily stock price data on the three brands were sourced from Yahoo finance and market index data was based on the PowerShares S&P SmallCap Consumer Discretionary Portfolio. The fund is based on the S&P SmallCap 600 Cap Consumer Discretionary Index, and normally invests at least 90% of its total assets in common stocks that comprise the index. The index is designed to measure the overall performance of common stocks of U.S. consumer discretionary companies. These companies are principally engaged in providing consumer goods and services that are cyclical in nature, including retail, automotive, leisure and recreation, media and real estate.

The keyword search trend data were sourced and scaled by Google Trends to the average traffic for during a fixed point in time (typically January 2004). Thus, a value of 1.0 represents the average traffic for “Starbucks” (or any brand) relative to that traffic level at January 2004, thus helping normalize the data. Moreover, Google Trends normalizes its sets of data by a common variable to cancel out the variable’s effect on the data and allow the underlying characteristics of the data sets to be compared.

Pre-Test

In a pre-test to measure the power of social media as a measure of audience involvement and information accessibility and processing, and its correlation with stock price as a daily indicator of performance, fan counts for the Starbucks brand on three social media networks (Facebook, Twitter, and YouTube) were regressed along with two other variables with two independent variables to isolate the effects of social media popularity: 1) an index of consumer discretionary common stocks – composed of the share prices of publicly owned firms that provide consumer goods and services that are cyclical in nature, including retail, automotive, leisure and recreation, media and real estate – was used to reflect the overall stock market performance (or beta, the single most significant exogenous factor on market volatility or systemic risk), and 2) keyword search trends reflecting variations in a average keyword searches for Starbucks as a broader user-generated or general public interest in the mass media environment during the timeframe of the study to reflect major announcements or news (for example, Starbuck’s re-design of its logo, roll out of Via instant coffee line, etc).

The sample for the pre-test event study (n) included 210 observations, representing daily data from 4-07-10 (the first available date for an index of consumer discretionary common stocks) to 2-02-11. The 10-month sample size for the longitudinal event study was selected to improve the internal validity of the study, as markets as known to exhibit unusual correlations over short-term periods.

To normalize the data, daily fan counts from Facebook, Twitter and YouTube from non-trading days such as weekends and holiday were excluded to synchronize the

daily data. Also, weekly average keyword search trends were repeated for each day of the week following their respective weekly point-in-time value.

Model Estimations

The pre-test regression equation to estimate the relationship was as follows...

$$\Sigma [\text{CSP}]_{1 \text{ to } n} = a_0 + \Sigma [\text{FF}]_{1 \text{ to } n} + \Sigma [\text{TF}]_{1 \text{ to } n} + \Sigma [\text{YTV}]_{1 \text{ to } n} + \Sigma [\text{KSI}]_{1 \text{ to } n} + \Sigma [\text{CDSI}]_{1 \text{ to } n}$$

...in which dependent variable, common stock price (CSP), was expressed as a function of five independent variables – number of Facebook fans (FF), number of Twitter followers (TF), and number of YouTube views (YTV), along with a keyword search index (KSI) to reflect general public interest and brand visibility and consumer discretionary stock index (CDSI) to reflect general equity market conditions during the period – plus a constant error value/y-intercept (a) – for each of the 210 observations.

For the three pilot events regressions, only one social media variable was used (Facebook fan count) to mitigate the high inter-correlation (mutlicollinearity) of the three social media fan count variables), hence the regression model for the three pilot event studies was reduced to the following...

$$\Sigma [\text{CSP}]_{1 \text{ to } n} = a_0 + \Sigma [\text{FF}]_{1 \text{ to } n} + \Sigma [\text{KSI}]_{1 \text{ to } n} + \Sigma [\text{CDSI}]_{1 \text{ to } n}$$

...in which dependent variable, common stock price (CSP), was expressed as a function of three independent variables – number of Facebook fans (FF), along with a keyword search index (KSI) to reflect general public interest and brand visibility and consumer

discretionary stock index (CDSI) to reflect general equity market conditions during the period – plus a constant error value/y-intercept (a) – for each of the 210 observations.

In both the pre-test and pilot event studies, IBM’s PASW Statistics, version 18 was used to perform the statistical analyses.

RESULTS

At a time when researchers are just beginning to explore the predictive powers of social media metrics, the results shows that social media popularity can predict brand performance (in the proxy form of daily stock prices), suggesting a clear link between consumer behavior and brand performance. In the pre-test correlation analyses [see Table 1: Pearson and Spearman Correlations], both Pearson and Spearman correlations matrices show that all variables were statistically significant.

Insert Table 1 approximately here

In the ANOVA and linear regressions [see Table 2: ANOVA and Regression Results], the coefficients of determination was 93.6%, indicating considerable linear strength – but not necessarily appropriateness – of the model; however, statistical significance was found for the relationship (f value less than .05) and for each independent variable (t value less than .05).

Insert Table 2 approximately here

In the pre-test, Starbucks brand fan counts from the most popular users on three social networks were found to be statistically significant indicators of stock price.

In the three following pilot longitudinal event studies [see Table 3, 4 and 5: Results of Starbucks, Coke and Nike Event Study Results], the proportions of variability in the data sets accounted for by the models (coefficients of determination) were found to be surprisingly large, suggesting considerable linear strength of the models. Statistical significance was found for all three regressions (f value less than .05) and for each independent variable (t value less than .05). That is, the independent variables were found to reliably predicted stock prices over the 10 month period - during which the market returns for the three consumer brand companies exhibited radically different results, with Starbucks climbing 29%, Nike appreciating by 14% yet Coke declining by nearly 6%. Moreover, the resulted showed that the independent variables reliability predicted these returns, even when the fan counts were lagged by as much as 30 days.

Insert Table 3 approximately here

Insert Table 4 approximately here

Insert Table 5 approximately here

The only exception to variable statistical significance in all the analyses was the key word search index variable in the 10-day lagged regression of the Nike brand, suggesting timing differences of the effect between general public interest and brand popularity and stock performance.

DISCUSSION AND CONCLUSIONS

The results of the study suggest the powerful effect of social media “electronic word of mouth” on consumer behavior and corporate brand performance. While the causal statistical significance of social media popularity with corporate performance has significant practical applications in investment management, securities trading and financial engineering – not to mention implications to classic assumptions of stock market information efficiency and “random walk” theory (Fama 1995) – the focus of this research study was to discover a link between audience involvement and performance, given the rise of social media as a new type of user-generated content on brands. It is hoped that the success of this pilot event study will inspire further investigation on the implications of social media on consumer brand performance.

Limitations

The study has many limitations, perhaps foremost a relatively crude assumption about the correlation of brand popularity with corporate performance and investor behavior: that popularity favorably impacts performance. Perhaps contrary to the old saying, “there’s no such thing as bad publicity,” the results of the event studies would have been much different if any of the brands were the focus of scandal, as at least

intuitively, one would expect lower performance or valuation with greater public discourse or criticism that might damage the image or reputation of the respective brand or corporation. That is, the findings support the theory that mere popularity can result in higher performance but does not directly address the issue of volatility – the process by which “bad publicity” impedes performance or drives down values or the process by which either (presumably) less rational investors cause temporal changes in valuations and (presumably) more rational investors counteract these abnormalities and thus drive security prices to revert to the mean or their intrinsic values.

The extremely high correlation between predicted and observed stock prices, suggest considerable linear strength – but not necessarily appropriateness – of the models. Moreover, at least some degree of correlation may be attributed to the growth bias in fan counts, which is partly a function of promotional campaigns by brand companies to acquire followers. However, these campaigns only partly influence the overall trend, and fan count is more likely a function of the overall reputation of the brand and its competitive standing in the consumer market. Anecdotally, a couple of years ago, Coca Cola became the most popular brand on Facebook when the page was unofficial, not managed by Coke, and thus its following on social media had nothing to do with any marketing initiatives by the brand company.

The general bias of fans counts and stock market prices was also considered, but the statistical significance of the fan counts to Coke common stock prices, which declined nearly 6% of the study period, provides some evidence against spurious correlation.

The index used as an indicator of the general media environment regarding brand names, relative average keyword search traffic, has some inherent limitations. Foremost

is that Google Trends shows users' propensity to search for a certain topic on Google on a relative basis; it is not a direct measure of public interest, awareness or involvement. There are also inherent imprecision of web analytics in general and Google's disclosed inaccuracies to consider which include data-sampling issues and approximations that are used to compute keyword search results.

While the study's sample size ranged over a multi-month period – to mitigate the effect of invalid short-term correlation effects – a longer-term longitudinal study, with a statistically valid sample of 30 or more consumer brand stocks, would have greater internal and external validity.

REFERENCES

- Aral, Sinan and Panos Ipeirotis and Sean Taylor (2009), "Cramer's Rule: How Information Content Moves Markets" October 8, 2010 Winter Conference on Business Intelligence
- Asur, Sitaram and Bernardo A. Huberman (2010). "Predicting the Future With Social Media." HP Labs, Palo Alto, CA. National Science Foundation Grant #0937060. Report issued Mar 29, 2010
- Berger, Jonah and Grainne Fitzsimons (2008), "Dogs on the Street, Pumas on Your Feet: How Cues in the Environment Influence Product Evaluation and Choice," *Journal of Marketing Research*, 45 (February), 1-14
- Bollen, Johan, Huina Mao and Xiao-Jun Zeng (2010). "Twitter Mood Predicts the Stock Market," University of Indiana
- Engelberg, Joseph and Caroline Sasseville and Jared Williams (2009), "Market Madness? The Case of Mad Money" January 23rd, SSRN
- Fama, Eugene and Kenneth French (1986), "The Cross-Section of Expected Stock Returns," *The Journal of Finance*, Vol. 47, No. 2 (Jun., 1992), pp. 427-465
- _____ (1995), "Random Walks in Stock Market Prices," *Financial Analysts Journal*, Jan/Feb 1995, Vol 51. Issue 1 pg 75, 6 pgs
- Fang, Lily and Joel Peress (2007) "Media Coverage and the Cross-Section of Stock Returns"
- Greenwald, Anthony and Clark Leavitt (1984), "Audience Involvement in Advertising: Four Levels," *Journal of Consumer Research*, 11 (June), 581-592
- Gruhl, Daniel R., Ravi Kumar Guha, Jasmine Novak and Andrew Tomkins (2005). "The Predictive Power of On-Line Chatter," *ACM*, New York, NY pp. 78-87
- Jansen, B, M. Zhang, K. Sobel and A. Chowdury (2009). "Twitter Power: Tweets as Electronic Word of Mouth." *Journal of Science and Technology*
- Krugman, Herbert E. (1966-1967), "The Measurement of Advertising Involvement," *Public Opinion Quarterly*, 30 (Winter), 583-596
- Mackenzie, S.B. (1986), "The Role of Attention in Mediating the Effect of Advertising on Attribute Importance," *Journal of Consumer Research*, 13 (Sep), 174-195

- Mishne, G and N. Glance (2006). "Predicting Movie Sales from Blogger Sentiment"
AAAI 2006 Spring Symposium on Computational Approaches to Analyzing Web
Logs
- Romero, Daniel M., Brendan Meeder and Jon Kleinberg (2011). "Differences in the
Mechanics of Information Diffusion Across Topics: Idioms, Political Hashtags,
and Complex Contagion on Twitter." International World Wide Web Conference
Committee (IW3C2). WWW 2011, March 28–April 1, 2011, Hyderabad, India.
ACM 978-1-4503-0632-4/11/03
- Shapiro, Stewart (1999), "When an Ad's Influence is beyond our Conscious Control:
Perceptual and Conceptual Fluency Effects Caused by Incidental Exposure,"
Journal of Consumer Research, 26 (Jun), 16-36
- Shiller, Robert (1984), "Stock Prices and Social Dynamics," *Brookings Papers on
Economic Activity*, The Brookings Institutions pp. 457-570
- Tetlock, Paul (2007) "Giving Content to Investor Sentiment: The Role of Media in the
Stock Market" *Journal of Finance* 62: 3: 1139-1168
- Zhang, Wenbin and Steven Skiena (2009), "Trading Strategies to Exploit News
Sentiment." SSRN 1-11, Stony Brook University

Table 1: Pearson and Spearman Correlations**Pearson Correlation**

		Correlations					
		CSP	CDSI	FF	TF	YTV	KWS
CSP	Pearson Correlation	1	.807**	.773**	.790**	.756**	.807**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	210	210	210	210	210	210
CDSI	Pearson Correlation	.807**	1	.421**	.404**	.346**	.585**
	Sig. (2-tailed)	.000		.000	.000	.000	.000
	N	210	210	210	210	210	210
FF	Pearson Correlation	.773**	.421**	1	.988**	.987**	.815**
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	210	210	210	210	210	210
TF	Pearson Correlation	.790**	.404**	.988**	1	.996**	.798**
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	210	210	210	210	210	210
YTV	Pearson Correlation	.756**	.346**	.987**	.996**	1	.788**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	210	210	210	210	210	210
KWS	Pearson Correlation	.807**	.585**	.815**	.798**	.788**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	210	210	210	210	210	210

** . Correlation is significant at the 0.01 level (2-tailed).

Spearman Correlation

		Correlations						
		CSP	CDSI	FF	TF	YTV	KWS	
Spearman's rho	CSP	Correlation Coefficient	1.000	.799**	.695**	.695**	.695**	.664**
		Sig. (2-tailed)		.000	.000	.000	.000	.000
		N	210	210	210	210	210	210
	CDSI	Correlation Coefficient	.799**	1.000	.402**	.401**	.401**	.533**
		Sig. (2-tailed)	.000		.000	.000	.000	.000
		N	210	210	210	210	210	210
	FF	Correlation Coefficient	.695**	.402**	1.000	1.000**	1.000**	.841**
		Sig. (2-tailed)	.000	.000		.000	.000	.000
		N	210	210	210	210	210	210
	TF	Correlation Coefficient	.695**	.401**	1.000**	1.000	1.000**	.841**
		Sig. (2-tailed)	.000	.000	.000		.000	.000
		N	210	210	210	210	210	210
	YTV	Correlation Coefficient	.695**	.401**	1.000**	1.000**	1.000	.841**
		Sig. (2-tailed)	.000	.000	.000	.000		.000
		N	210	210	210	210	210	210
	KWS	Correlation Coefficient	.664**	.533**	.841**	.841**	.841**	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.000	
		N	210	210	210	210	210	210

** . Correlation is significant at the 0.01 level (2-tailed).

Table 2: ANOVA and Regression Results

ANOVA

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
CDSI	Between Groups	898.704	187	4.806	3.882	.000
	Within Groups	27.235	22	1.238		
	Total	925.939	209			
FF	Between Groups	4.200E15	187	2.246E13	4.839	.000
	Within Groups	1.021E14	22	4.641E12		
	Total	4.302E15	209			
TF	Between Groups	2.829E12	187	1.513E10	4.826	.000
	Within Groups	6.895E10	22	3.134E9		
	Total	2.898E12	209			
YTV	Between Groups	1.569E8	187	838921.743	4.366	.000
	Within Groups	4227306.167	22	192150.280		
	Total	1.611E8	209			
KWS	Between Groups	21.966	187	.117	6.126	.000
	Within Groups	.422	22	.019		
	Total	22.388	209			

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.967 ^a	.936	.934	.8046

a. Predictors: (Constant), KWS, CDSI, YTV, FF, TF

ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1927.210	5	385.442	595.385	.000 ^a
	Residual	132.066	204	.647		
	Total	2059.276	209			

a. Predictors: (Constant), KWS, CDSI, YTV, FF, TF

b. Dependent Variable: CSP

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-30.768	2.656		-11.583	.000
	CDSI	.940	.049	.631	19.121	.000
	FF	-8.013E-7	.000	-1.158	-8.949	.000
	TF	1.825E-5	.000	.685	2.324	.021
	YTV	.003	.001	.895	2.890	.004
	KWS	1.261	.341	.131	3.694	.000

a. Dependent Variable: CSP

Table 3: Starbucks Event Study Results
Regression A Results: Current Day

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	.941 ^a	.885	.883	1.0736	

a. Predictors: (Constant), KWS, CDSI, FF

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1821.821	3	607.274	526.830	.000 ^a
	Residual	237.455	206	1.153		
	Total	2059.276	209			

a. Predictors: (Constant), KWS, CDSI, FF
 b. Dependent Variable: CSP

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.656	.909		.721	.472
	CDSI	.814	.044	.546	18.593	.000
	FF	3.014E-7	.000	.436	10.601	.000
	KWS	1.274	.441	.133	2.889	.004

a. Dependent Variable: CSP

Regression B Results: 10- Day Lagged Social Media

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	.940 ^a	.884	.882	1.0320	

a. Predictors: (Constant), KWS, CDSI, FF

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1595.319	3	531.773	499.346	.000 ^a
	Residual	209.793	197	1.065		
	Total	1805.112	200			

a. Predictors: (Constant), KWS, CDSI, FF
 b. Dependent Variable: CSP

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.298	.873		.341	.734
	CDSI	.813	.044	.569	18.480	.000
	FF	2.679E-7	.000	.395	9.371	.000
	KWS	1.582	.445	.173	3.558	.000

a. Dependent Variable: CSP

Regression C Results: 30-Day Lagged Social Media

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	.922 ^a	.849	.847	1.0033	

a. Predictors: (Constant), KWS, CDSI, FF

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1003.459	3	334.486	332.291	.000 ^a
	Residual	178.169	177	1.007		
	Total	1181.627	180			

a. Predictors: (Constant), KWS, CDSI, FF
 b. Dependent Variable: CSP

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.822	.974		-.844	.400
	CDSI	.842	.048	.639	17.481	.000
	FF	2.672E-7	.000	.429	9.104	.000
	KWS	1.590	.504	-.167	3.153	.002

a. Dependent Variable: CSP

Table 4: Coke Event Study Results
Regression A Results: Current Day

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	.890 ^a	.792	.789	1.53481	

a. Predictors: (Constant), KWS, CDSI, FF

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1846.852	3	615.617	261.337	.000 ^a
	Residual	485.263	206	2.356		
	Total	2332.115	209			

a. Predictors: (Constant), KWS, CDSI, FF
b. Dependent Variable: CSP

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	29.908	1.887		15.847	.000
	FF	1.168E-7	.000	.210	5.297	.000
	CDSI	1.089	.060	.686	18.112	.000
	KWS	-4.792	.926	-.178	-5.174	.000

a. Dependent Variable: CSP

Regression B Results: 10- Day Lagged Social Media

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	.901 ^a	.812	.809	1.48013	

a. Predictors: (Constant), KWS, CDSI, FF

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1868.128	3	622.709	284.240	.000 ^a
	Residual	431.585	197	2.191		
	Total	2299.713	200			

a. Predictors: (Constant), KWS, CDSI, FF
b. Dependent Variable: CSP

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	28.880	1.825		15.829	.000
	FF	1.425E-7	.000	.251	6.823	.000
	CDSI	1.107	.057	.887	19.544	.000
	KWS	-4.582	.894	-.170	-5.124	.000

a. Dependent Variable: CSP

Regression C Results: 30-Day Lagged Social Media

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	.912 ^a	.832	.829	1.40148	

a. Predictors: (Constant), KWS, CDSI, FF

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1717.769	3	572.590	291.522	.000 ^a
	Residual	347.653	177	1.964		
	Total	2065.421	180			

a. Predictors: (Constant), KWS, CDSI, FF
b. Dependent Variable: CSP

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	24.855	1.824		13.629	.000
	FF	1.825E-7	.000	.277	8.562	.000
	CDSI	1.295	.055	.744	23.463	.000
	KWS	-5.337	.844	-.203	-6.325	.000

a. Dependent Variable: CSP

Table 5: Nike Event Study Results
Regression A Results: Current Day

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.944 ^a	.890	.889	2.07307

a. Predictors: (Constant), KWS, FF, CDSI

ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7151.326	3	2383.775	554.675	.000 ^a
	Residual	881.009	205	4.298		
	Total	8032.334	208			

a. Predictors: (Constant), KWS, FF, CDSI
b. Dependent Variable: CSP

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	37.673	2.488		15.141	.000
	CDSI	1.054	.088	.358	12.006	.000
	FF	4.045E-6	.000	.663	22.283	.000
	KWS	3.264	1.042	.073	3.134	.002

a. Dependent Variable: CSP

Regression B Results: 10- Day Lagged Social Media

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.953 ^a	.907	.906	1.91343

a. Predictors: (Constant), FF, KWS, CDSI

ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7026.981	3	2342.327	639.766	.000 ^a
	Residual	717.800	196	3.661		
	Total	7744.582	199			

a. Predictors: (Constant), FF, KWS, CDSI
b. Dependent Variable: CSP

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	36.685	2.265		16.196	.000
	CDSI	1.211	.077	.410	15.695	.000
	KWS	1.236	.988	.028	1.251	.213
	FF	4.025E-6	.000	.657	24.955	.000

a. Dependent Variable: CSP

Regression C Results: 30-Day Lagged Social Media

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.983 ^a	.966	.965	1.12053

a. Predictors: (Constant), FF, CDSI, KWS

ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6252.846	3	2084.282	1660.013	.000 ^a
	Residual	220.982	176	1.256		
	Total	6473.829	179			

a. Predictors: (Constant), FF, CDSI, KWS
b. Dependent Variable: CSP

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	30.920	1.309		23.620	.000
	CDSI	1.641	.046	.533	35.895	.000
	KWS	-2.604	.636	-.062	-4.093	.000
	FF	4.232E-6	.000	.789	46.648	.000

a. Dependent Variable: CSP