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Celebrities on Social Media and Their Effect on Shareholder Wealth

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An Undergraduate Thesis Presented For

Global Leadership Scholars Program

The University of Tennessee, Knoxville

Celebrities on Social Media and Their Effect on Shareholder Wealth

March 2020

"The term 'influencer marketing' increased by 325% in Google searches over 2017. Making this the fastest-growing online acquisition method of the year."[2]

Key Words: Social Media, Stock Price, Celebrity, Event Study, Shareholder Wealth Effects

[1]The author would like to thank Dr. Laura Seery Cole, who served as Thesis Advisor, and the Masters Investment Learning Center for the use of Bloomberg terminals to obtain proprietary data.

[2]Fastenau, Jelle. "Under the Influence: The Power of Social Media Influencers." Medium, Crobox, 25 Apr. 2018, medium.com/crobox/under-the-influence-the-power-of-social-media-influencers-5192571083c3.

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I. Introduction

Social media has grown since its humble beginnings in the early 2000s. According to Statista, social media now engages more than 2.65 billion people across the globe[1], proving these platforms have permeated our society. Furthermore, the companies that created these platforms are some of the most lucrative investments in today's market. Companies like Facebook, Twitter, and Snapchat are serious players in the stock market, with Facebook setting records for one of the largest technology IPOs in history in March 2012[2]. As social media has developed and become a part of daily life, it has not only allowed people to share their own personal stories, but also provided them a conduit to view into the lives of others, including celebrities. Within seconds a celebrity can post something on social media that influences the thinking of millions of followers, and this is something that can make or break a brand. However, outside of brand image, could celebrity posts on social media affect the actual stock price of companies?

The motivation to study this question came from Kylie Jenner's tweet about Snapchat in February 2018 and the effect it had on their stock. The star posted a negative comment regarding Snapchat's new update to her 30 million followers, and the company lost 6 percent in firm value. This is interesting since Jenner had no professional ties to Snapchat. She was not on the Board of Directors, an employee, or spokesperson. In addition, this shows the considerable change that has occurred in how news is shared in our society, with many people relying on social media as a news source. In the Kylie Jenner situation, investors saw Twitter as an indication of news and used the platform to inform their trading decisions. Furthermore, a 2018 study by Pew Research found that one in five adults in the U.S. receive their news from social media platforms[3]. Therefore, social media has a large role in how our society interacts with each other, finds news about the world around us, and potentially how investors make trades.

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1 https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/

2 https://www.investopedia.com/articles/markets/081415/if-your-would-have-invested-right-after-facebooks-ipo.asp

3 https://pewrsr.ch/2rsoHtb

The purpose of this study is to determine if celebrities' social media posts have an effect on a firm's stock price. We will perform an event study to determine if a company experiences abnormal returns (whether positive or negative) following a celebrity's social media post about their brand. We will examine the cumulative abnormal returns of a company in 10 different windows of time surrounding when the event occurred: the day the event occurred (0,0), ten days (-10,0) and 3 days prior (-3,0), one to three days after the event (0, +1), (0, +2), (0, +3), ten days after (0, +10), as well as long-term windows one month (0, +30), 9 months (0, +270), and one year (0, +365) after the event. We compare the observed returns in these windows to the company's performance in an earlier benchmark period to determine if they are abnormal and run statistical tests on the values. Our null hypothesis is that the announcement of a celebrity posting about a company on their social media page has no effect on the stock price of a company. Our alternative hypothesis states that the announcement of a celebrity posting about a company on their social media will have an effect on the stock price of a company.

This topic is important because it illuminates another outlet for investors to possibly gain knowledge about the market, and allows companies to see the value of celebrity endorsements. In addition, this research could reveal new areas that may need to be regulated by the SEC and other government agencies. Finally, changes in firm value can be detrimental to stockholder returns, and furthermore can signify the loss of jobs and the livelihood of many employees. This study aims to discover the true impact that social media posts from a celebrity can have on a company's share price, and whether or not their publicity affects firm value. The rest of the paper is presented as follows: Section II reviews literature that has been created on this topic in past years, Section III describes sample construction and data processes, Section IV examines the event study approach, Section V discusses results, Section VI concludes the paper, and Section VII dives into areas for future research.

II. Literature Review

There have been several studies on the relationship between social media and stock prices in the past. Most relevant to our research is Bartov et. al's 2016 study, "Can Twitter Help Predict Firm-Level Earnings and Stock Returns?". Bartov et. al used tweets published around the time of quarterly announcements to determine if Twitter posts can provide information on the future earnings and stock price. The research team sampled over 900,000 tweets published in an 11-day period around quarterly announcements, and overall determined that the sampled tweets did indeed successfully predict a company's earnings for the quarter. In addition, the team found a positive correlation between what they called the "aggregate opinion" on Twitter about a company's anticipated quarterly update, and the immediate response in stock prices. Therefore, they saw stock prices moving in the same direction that Twitter opinions expected.

After the results of the period were released, the team then studied the "immediate abnormal stock prices" and found a positive correlation between the general opinion in the sample of tweets and the market reaction shown by stock price. Finally, the team pointed out that the correlation between Twitter opinions and stock price reaction was actually stronger for smaller companies with less analysts studying it. However, they only studied stock prices within three days of the quarterly announcements, so their findings do not necessarily translate to long-term market trends. The team explained that their findings not only show the role that social media, and specifically Twitter, can have with investors; but also illuminate a new area that regulators need to investigate. Based on this paper, investors can use the general consensus on

Twitter to successfully predict quarterly earnings and market reactions, so lawmakers may need to study social media as an information platform regarding investing in order to prevent unfair advantage.

The 2011 study titled, “Twitter Mood Predicts the Stock Market” by Bollen, Mao, and Zeng discussed the impact that general public sentiment can have on the stock market. They observed this by monitoring the overall emotional state of Twitter through online mood tracking tools and daily closing values of the Dow Jones Industrial Average (DJIA). Overall, the study found that mood tracking tools can indicate changes in the DJIA closing values.

The team looked at tweets from February 28, 2008 to December 19, 2008 that contained phrases like “I feel”, “I am”, or “makes me”. Their data included over 9 million tweets with which the team used two different mood trackers to analyze the general sentiment of the post: Opinion Finder and Google-Profile of Mood States (GPOMS). The Opinion Finder analyzed whether a post was generally positive or negative, while GPOMS measured the mood of tweets according to six different categories: Calm, Alert, Sure, Vital, Kind, and Happy. Each software created a multidimensional time series regarding the general mood of posts, which was then tested for correlation with the DJIA closing prices. In the end, the team determined that the general sentiment on Twitter can be correlated to the DJIA closing values and standard stock prediction models can significantly improve their accuracy through the addition of certain mood inputs.

Miles Osborne and Mark Dredze looked at the effectiveness of different social media platforms in posting news in their 2014 paper, “Facebook, Twitter and Google Plus for Breaking News: Is there a winner?”. Their team solely focused on Twitter, Facebook, and Google Plus while comparing their timeliness at news reporting. The data came from posts created in a threeweek period during December 2013, and demonstrated how each platform reported 29 different "major" news events in this time frame. Ultimately the study found that though there may be differences in how users can interact with the information, Facebook, Twitter, and Google Plus report on the same news events. In addition, Twitter was found to be the quickest reporter of news, though it still falls behind what Osborne and Dredze refer to as "newswire."

Osborne and Dredze covered three specific questions regarding how social media interacts with news: whether all three platforms in the study cover the same news events, on which platform news appears first, and what "data differences" exist between sites. The study found that in general each platform covered the same news events, but Twitter typically had the first posts. In addition, they noted that posts on Twitter were much shorter than news posts that were added to Facebook and Google Plus, who frequently re-posted newswire articles.

Siikanen et al. specifically examined Facebook data, and its effect on individual Finnish investors' trading decisions regarding Nokia stock in their 2018 paper, "Facebook Drives Behavior of Passive Households in the Stock Market." Their decision to study Finnish investors came from the availability of individual trading data, and they chose to focus on Nokia stock due to its liquidity in the Finnish stock market. Their results showed that decisions to buy versus sell were correlated to Facebook data and have a particularly strong correlation for passive household investors and nonprofit organizations (Siikanen et. al, 1). This correlation was more prevalent among less "sophisticated" investors, while more experienced organizations like insurance companies or financial institutions were unphased by social media.

Their research cited Facebook as the "most widely used social media platform, with 2.2 billion monthly users." In addition, another study referenced in the work shows that in January 2013, "about 45% of S&P1500 firms [used social media] to communicate… information about their business" (Jung et al., 2017). This same paper found companies are "less likely to disseminate information in Twitter when the news is bad" (Jung et al., 2017). This shows that investors who allow social media to influence their buying and selling decisions could be relying on biased information.

The 2013 study "Social Media and Firm Equity Value" conducted by Luo et al. examines the predictive relationship between social media and firm equity value by looking at data from both online consumer ratings as well as blogs. Overall, Luo et al. found social media metrics to be a strong predictor of firm equity value, and determined it as an even stronger indicator of future equity value than web-based metrics like *Google* searches. In addition to its effectiveness as a predictor, the team also found that social media is faster than web searches since posts are instantaneous and have the ability to go viral.

Luo et al. described the importance of their findings and mentioned that executives could use this information to determine the current success of their company. In addition, companies could apply these findings to influence marketing, sales, future investments, and more. The team cites a statistic from *eMarketer* to prove this point stating, "companies with an extensive social media presence reported a return on investment that was more than 4 times that of their counterparts" (eMarketer 2012). This alone shows the impact that social media can have on firm value.

McAlister et al.'s 2011 study, "The relationship between online chatter and firm value" examined the relationship between online activity regarding a firm or product, and the stock price of the corresponding company. The team discussed that though a connection has already been made between online chatter and sales, they sought to determine whether financial markets acknowledge this link as well. Ultimately, the study found that there is indeed a correlation between online communication about a firm and the firm's stock price or market performance.

McAlister et al. examined "online chatter" that they received from a third-party technical firm that used web scanners to record the amount a firm was mentioned on the internet. They sought to determine if higher levels of casual online chatter were "associated with higher stock returns." Overall, they found that changes in total weekly chatter as well as neutral chatter correlated to stock returns.

The 2013 study, "Wisdom of Crowds: The Value of Stock Opinions Transmitted through Social Media" by Chen et al. examined the influence social media comments have on the prediction of future stock prices and returns. The team specifically investigated this connection through posts and comments on the website *Seeking Alpha*, which they cited as being one of the largest "investment-related social-media sites" in the country. Though not the typical format of more "mainstream" social media sites, *Seeking Alpha* allows users to submit personal opinion articles to their review board for publishing on the website as well as gives users the chance to interact with articles through commentaries. In their research, the team found that you can predict future stock returns or what they call "earnings surprises" from the views discussed in articles and commentaries on *Seeking Alpha*.

Chen et al. determined the fraction of negative words in user-generated articles and commentaries on Seeking Alpha to predict the stock returns of companies discussed, and found that both articles and comments "negatively predict stock returns over… three months." However, it is possible that *Seeking Alpha* users may not represent enough capital to have a tangible influence on the market prices. The paper also studied "earnings surprise" which they defined as being the difference between the recorded earnings-per-share (EPS) and the average

EPS forecasts from financial analysts. The team found that just as with stock prices, surprise earnings also demonstrated evidence that information on Seeking Alpha indeed provided "value-relevant" information for investors.

Paul Tetlock's study, "Giving Content to Investor Sentiment: The Role of Media in the Stock Market" was completed in March 2005, before the phenomena of social media truly exploded. Tetlock's team looked at the impact of print media on stock prices, and investigated the influence outside news sources can have on the buy or sell decisions of investors.

The paper mentioned this research was the "first to find evidence that news media content can predict movements in broad indicators of stock market activity." Therefore, this ground-breaking study showed that stock price movements are not necessarily 100% random and unpredictable, but that news can be used to predict future values of stocks. This study specifically focused on the news outlet called "Abreast of the Market" which was published in the Wall Street Journal (WSJ).

There were three major findings from this study: first, it found that "high levels of media pessimism robustly predict downward pressure" on stock prices as a whole. This demonstrates the relationship that negative news sentiment can have on the overall market. In addition, Tetlock found that "unusually high or low values of media pessimism forecast high market trading volume." Finally, the study showed that "low market returns lead to high media pessimism." Overall, this study addressed the effect the media can have on the market and vice versa, which provided a foundation for later studies that focused on social media.

III. Data and Summary Statistics

III.A. Sample Construction

The objective of our sample was to find thirty different instances where public figures mentioned a company in a social media post. We solely focused on examples that were mentioned in the news, and found articles through Factiva and Google by using keywords such as "celebrity" and "stock price". In addition, we looked at articles within one-year time frames, beginning in 2019 and working back to 2009.

We had to determine what criteria qualified someone as a "celebrity" in regard to our research, and what features we wanted to capture about each social media post. For this project, a "public figure" is generally defined to be anyone that has a "verified" badge on their social media accounts. According to Instagram, this verified badge shows users that "an account is the authentic presence of the public figure, celebrity or global brand it represents." Therefore, it is an adequate indicator of a celebrity, as it is used by social media platforms themselves to denote authentic public figures online. This badge is depicted by a blue circle with a checkmark, and is displayed directly after someone's username. There is one instance in our dataset that is not verified, but is still included because this figure was widely known to have very close ties to the company he discussed.

After defining 30 events, we used Wharton Research Data Services (WRDS) to find each company's unique PERMNO identification code. Due to the international status of two companies, we omitted two events, leaving the final data set with 28 total instances.

III.B. Database Collection

To analyze stock price reaction to celebrities' social media posts about companies, we used the Eventus software through Wharton Research Data Services (WRDS). This software performs event studies by using past stock price data from the Center for Research in Security Prices (CRSP). Using WRDS, we found the unique PERMNO identification code for each company in our sample. Once in Eventus, we changed the date format for social media posts into CRSP trading day numbers. Finally, our team used SAS software to pull the corresponding market returns in Eventus for the event windows specified: (-10, 0), (-1, 0), (0, 0), (0, +1), (0, +2), (0, +3), (0, +10), (0, +30), (0, +270), and (0, +365).

We measured the event's impact by looking at its abnormal return (observed return compared to expected return). Expected return is calculated by either the Market Model—which assumes a linear relationship between market and company return, using each company's individual beta value, or the Market Adjusted Model—which uses actual market return to "control" for potential influences of the event on the general market and does not include the beta of each specific company. These models are included in Section VIII Tables. A portion of the SAS code entered into Eventus can be viewed in Appendix A.

IV. Event Study Methodology

Measuring the stock price reaction to celebrities' social media posts about companies could provide insight into a possible emerging driver of company value and future shareholder wealth. This information can impact both investors' decisions and a firm's market strategy in the future.

An event study is performed by creating windows of time that are centered on the event date (called day 0), and includes days both before and after the event date. For this study, we created both an estimation window and an event window. The estimation window represents the window of time that we referenced for a benchmark of a company's normal return. The estimation window for this study ranges from 301 days before an event, until 46 days before, marked as (-301, -46). The event window includes the event date, and is used to encompass any abnormal returns that occurred in this time frame due to the event. In total, we created 10 different time frames ranging from short term windows 10 days before the event occurred, to longer term windows 365 days after. Within each window, we then compared observed market returns to both the CRSP value-weighted returns and CRSP equally-weighted returns to determine if any abnormal returns were statistically significant. The following table displays the time windows:

Event Window	**Estimation Window**
(-10,0)	(-301,-46)
(-1,0)	(-301,-46)
(0,0)	(-301,-46)
(0,+1)	(-301,-46)
(0,+2)	(-301,-46)
(0,+3)	(-301,-46)
(0,+10)	(-301,-46)
(0,+30)	(-301,-46)
(0,+270)	(-301,-46)
(0,+365)	(-301,-46)

We used both the Market Model and the Market Adjusted in this study, with each being equally weighted as well as value weighted. In general, the Market Model Equally Weighted proved to be the most useful in this study as it generated statistically significant results most frequently. Therefore, this is the model utilized most in our analysis and included most frequently in tables. A table of the four model types is shown below:

Model	**Index**
Market Model	Equally Weighted
Market Model	Value Weighted
Market Adjusted	Equally Weighted
Market Adjusted	Value Weighted

V. Results

Null Hypothesis: The announcement of a celebrity posting about a company on their social media page has no effect on the stock price of a company. There are no cumulative abnormal returns for shareholders.

Alternative Hypothesis: The announcement of a celebrity posting about a company on their social media page has an effect on the stock price of a company. There are either positive or negative cumulative abnormal returns for shareholders.

Full Sample

Table 1 reports the results of the Market Model with an Equally Weighted Index for all 28 events included in our dataset, as shown by the "N" column. This model is shown in Table 1 because it provided the most conclusive and useful results in our analysis. In addition, the table displays statistical results for each time window, focusing on the mean cumulative abnormal return, as well as two Z-tests to examine statistical significance. The p-values of each output is written below the value in parentheses and for this study, we considered any output with a p-value less than 0.10 significant. There are two general times we observe significant abnormal returns: immediately following the event (one and three days after) as well as approximately one-year post event. The day after an event has a mean cumulative abnormal return of 1.13 percent and is statistically significant according to the Generalized Sign Z-test. Furthermore, after an initial effect on the market, the returns one year after an event prove to be significant as well. The window (0, +365) is highly significant, as shown by all three Z-tests, with a mean cumulative abnormal return of 34.39 percent. This means that, on average, one year after an event the returns in our sample were 34.39 percent higher than expected. We will dive deeper into the implications and explanation of these results later.

Instagram Subset

Table 2 displays results of the Market Model with an Equally Weighted Index for the events that occurred on Instagram in our dataset. We decided to segment events by social media platform, and overall Instagram only makes up three events in our data. Table 2 is formatted the same way as the Full Sample table. There are two statistically significant windows in this subset: (0, +2) and (0, +3) which have negative mean cumulative abnormal returns of -3.68 percent and -4.68 percent, respectively. These returns were found to be statistically significant by the Boehmer Standardized Cross-sectional Z-test. We chose to display the Market Model, Equally Weighted Index because it produced the most significant and useful results with this data subset.

Twitter Subset

Table 3 is a Market Adjusted model with an Equally Weighted Index that shows results of all Twitter-based events in our data. It is formatted similar to Tables 1 and 2, but uses a different model. The majority of the sample came from Twitter, so this subset has 23 firms included. There are four different time windows that are statistically significant. The first is (-10, 0) with a mean cumulative average return of 3.62 percent and is proven as significant by the Boehmer Standardized Cross-sectional Z-test. The window (0, +1) is also significant as shown by the Generalized Sign Z test and has a mean cumulative abnormal return of 0.98 percent. Long-term windows are also found to be significant such as (0, +270) with a mean cumulative abnormal return of 14.92 percent and is proven significant by the Boehmer Standardized Cross-sectional Z-test. Finally, the one-year window, (0, +365), is proven highly significant in all three Z-tests and has a mean cumulative abnormal return of 31.75 percent. This means that one year after the Twitter event, firms performed an average of 31.75 percent higher than expected.

Facebook Subset

Similar to the Instagram subset, there are very few firms that have events on Facebook, but **Table 4** displays results of the Market Model with an Equally Weighted Index for the 2 events that occurred on Facebook in our dataset. There are two statistically significant windows in this subset: (0, +270) and (0, +365) which are both long-term windows, and have mean cumulative abnormal returns of 160.58 percent and 195.84 percent, respectively. These returns were found to be statistically significant by the Boehmer Standardized Cross-sectional Z-test. We chose to display the Market Model, Equally Weighted Index because it produced the most significant and useful results with this data subset.

VI. Conclusion

This study builds upon previous literature that examined social media's effect on a firm's stock price. However, instead of using an aggregate of all social media posts at a certain time, our research differs from previous studies in that we investigated individual social media events from a specific demographic: public figures and celebrities. Overall, our research found that abnormal cumulative stock returns occur immediately following a social media event (+1 and +3 days after) and again about one year later (+270 and +365 days after). The mean cumulative abnormal return was about one percent shortly after an event, while it was much larger one year later at 34.39 percent. Therefore, our data found that one year after a social media event, stock returns were about 34 percent higher than expected. This could be for many reasons including the increase in press or "damage control" done by the company's Public Realtions, and is an area for future research.

By splitting our data into categories by media platform, we found Twitter to have the most time windows with abnormal returns, though this could be affected by its large sample size compared to the other two platforms. Twitter closely followed the abnormal returns trends in the full sample. Instagram was the only platform to have significant negative effects on stock price with negative abnormal returns occurring two and three days after the social media post which could be an area for future research. Finally, Facebook showed significant returns in the long run at 270 and 365 days after the event, though not in the short term. The difference between these platforms could be an area for future research.

VII. Areas for Future Research

As mentioned, investigating returns one year after the event could be an area for future research. Specifically looking at why firms have such a large spike of mean cumulative abnormal return at the one-year mark, and how much this rise has to do with the social media events from the prior year. This increase could be due to the company's response to the event, the increase in press following the post, or other variables within the year.

Further investigation into each media platform would be useful, as our results could be influenced by the sample size of our subsets. Finding more examples of both Facebook and Instagram events could produce new results and provide investors with valuable information regarding how social media can affect their investment decisions. Finally, further investigation into Instagram events could be interesting as it was the only platform in our dataset to have negative cumulative abnormal returns.

VIII. Tables

Table 1: Market Model, Equally Weighted Index on Full Sample

FULL SAMPLE										
Market Model Equally Weighted										
	(-10,0)	**(-1,0)**	**(0,0)**	**(0,+1)**	**(0,+2)**	**(0,+3)**	**(0,+10)**	**(0,+30)**	**(0,+270)**	**(0,+365)**
N	28	28	28	28	28	28	28	28	28	28
Mean Cumulative Abnormal Return	2.94%	1.03%	0.78%	1.13%	0.32%	-0.06%	0.77%	-0.41%	18.55%	34.39%
Std Csect Z	1.433 (0.152)	-0.042 (0.967)	-0.419 (0.675)	-0.058 (0.954)	-0.478 (0.633)	-0.644 (0.520)	-0.1666 (0.868)	-0.389 (0.697)	1.284 (0.199)	**1.624** **(0.104)**
Generalized Sign Z	-0.258 (0.796)	-0.636 (0.525)	-1.393 (0.164)	**-1.771** **(0.077)**	-1.393 (0.164)	**-1.771** **(0.077)**	0.120 (0.905)	-1.014 (0.310)	**2.010** **(0.044)**	**2.766** **(0.006)**
Signed Rank	28.000 (0.534)	-5.000 (0.912)	-31.000 (0.490)	-44.000 (0.325)	40.000 (0.372)	-44.000 (0.325)	-7.000 (0.877)	-38.000 (0.397)	64.000 (0.148)	**95.000** **(0.028)**

Statistically significant values are shown in bold. P-values are stated beneath in parentheses.

Table 2: Market Model, Equally Weighted Index for Instagram Events

INSTAGRAM SUBSET										
Market Model Equally Weighted										
	(-10,0)	**(-1,0)**	**(0,0)**	**(0,+1)**	**(0,+2)**	**(0,+3)**	**(0,+10)**	**(0,+30)**	**(0,+270)**	**(0,+365)**
N	3	3	3	3	3	3	3	3	3	3
Mean Cumulative Abnormal Return	-0.57%	-0.39%	0.44%	-1.20%	-3.68%	-4.68%	4.97%	7.25%	-34.94%	-41.91%
Std Csect Z	0.018 (0.985)	-0.586 (0.558)	0.148 (0.882)	-0.701 (0.483)	**-2.192 (0.028)**	**-2.377 (0.017)**	0.584 (0.559)	0.418 (0.676)	-0.579 (0.563)	-0.438 (0.661)
Generalized Sign Z	-0.451 (0.652)	-0.451 (0.652)	-0.451 (0.652)	-0.451 (0.652)	1.608 (0.108)	1.608 (0.108)	-0.451 (0.652)	-0.451 (0.652)	0.707 (0.479)	0.707 (0.479)
Signed Rank	-1.000 (0.750)	-1.000 (0.750)	0.000 (1.000)	-1.000 (0.750)	-3.000 (0.250)	-3.000 (0.250)	0.000 (1.000)	0.000 (1.000)	0.000 (1.000)	0.000 (1.000)

Statistically significant values are shown in bold. P-values are stated beneath in parentheses.

Table 3: Market Adjusted, Equally Weighted Index for Twitter Events

TWITTER SUBSET										
Market Adjusted Equally Weighted										
	(-10,0)	**(-1,0)**	**(0,0)**	**(0,+1)**	**(0,+2)**	**(0,+3)**	**(0,+10)**	**(0,+30)**	**(0,+270)**	**(0,+365)**
N	23	23	23	23	23	23	23	23	23	23
Mean Cumulative Abnormal Return	3.62%	0.60%	0.42%	0.98%	0.32%	0.15%	-0.29%	-1.49%	14.92%	31.75%
Std Csect Z	**1.922 (0.055)**	-0.256 (0.798)	-0.696 (0.486)	-0.197 (0.844)	-0.412 (0.681)	-0.441 (0.659)	-0.366 (0.715)	-0.435 (0.663)	**1.894 (0.058)**	**2.852 (0.004)**
Generalized Sign Z	1.177 (0.239)	-0.492 (0.623)	-0.909 (0.363)	**-1.743 (0.081)**	-1.326 (0.185)	-0.909 (0.363)	0.343 (0.732)	-0.909 (0.363)	0.760 (0.447)	**2.846 (0.004)**
Signed Rank	41.000 (0.220)	-2.000 (0.953)	-31.000 (0.357)	-7.000 (0.837)	-17.000 (0.616)	-17.000 (0.616)	-7.000 (0.837)	-35.000 (0.297)	37.000 (0.270)	**97.000 (0.001)**

Statistically significant values are shown in bold. P-values are stated beneath in parentheses.

Table 4: Market Model, Equally Weighted Index for Facebook Events

FACEBOOK SUBSET										
Market Adjusted Equally Weighted										
	(-10,0)	**(-1,0)**	**(0,0)**	**(0,+1)**	**(0,+2)**	**(0,+3)**	**(0,+10)**	**(0,+30)**	**(0,+270)**	**(0,+365)**
N	2	2	2	2	2	2	2	2	2	2
Mean Cumulative Abnormal Return	6.73%	9.21%	6.46%	7.18%	7.96%	6.80%	8.46%	10.45%	160.58%	195.84%
Std Csect Z	0.310 (0.757)	0.838 (0.402)	0.737 (0.461)	0.793 (0.428)	0.739 (0.460)	0.656 (0.512)	0.468 (0.640)	1.160 (0.246)	**1.598 (<0.001)**	**74.070 (<0.001)**
Generalized Sign Z	-0.072 (0.942)	-0.072 (0.942)	-0.072 (0.942)	-0.072 (0.942)	-0.072 (0.942)	-0.072 (0.942)	-0.072 (0.942)	1.344 (0.179)	1.344 (0.179)	1.344 (0.179)
Signed Rank	0.500 (1.000)	0.500 (1.000)	0.500 (1.000)	0.500 (1.000)	0.500 (1.000)	0.500 (1.000)	0.500 (1.000)	1.500 (0.500)	1.500 (0.500)	1.500 (0.500)

Statistically significant values are shown in bold. P-values are stated beneath in parentheses.

IX. Appendix A

SAS Code for Eventus

```
/****************************************************************************************
********************
  EVENTUS 9.0
   USING PC SAS CONNECT
   ENVIRONMENTAL EVENT STUDY, DAILY RETURNS
   AUTHOR: Dr. Laura Cole, University of Tennessee
   This information was compiled by the author and is provided as a public service.
The author is not
   responsible for any errors or omissions, or for any consequential problems that
might result.
   USE AT YOUR OWN RISK.
   GLS THESIS FOR BRENNA LOGAN
****************************************************************************************
*******************/

/****************************************************************************************
********************
 STEP 1:
   You will need to use PROC IMPORT to transfer your Excel spreadsheet into a SAS
Dataset.
    Set LIBNAME to your local windows directory.
       If working from APPS@UT then you need to assign your H: drive to READ & WRITE,
and then the libname is:
       '\\Client\H$\Documents\ …. '
****************************************************************************************
********************/
libname edata '\\Client\C$\Users\lscole\Dropbox\THESES\BRENNA LOGAN\Eventus';

proc import
  datafile = '\\Client\C$\Users\lscole\Dropbox\THESES\BRENNA LOGAN\Eventus\Stock Price
Social Media'
  dbms = xls
  out = edata.eventus replace;
  *The SAS dataset created is now in your temporary WORK directory.
  *Also, issues with SAS 9.4 and Windows 64, need to use XLS filetype instead of XLSX.
   You could change this to a local directory.;
run;

/****************************************************************************************
********************
 STEP 2:
   You need to subset and "clean" your SAS dataset and format it for Eventus.
   The general variable order should be:

    PERMNO (or 8-digit CUSIP) EVENTDAT EVENTDAT2 ID GROUP GRPWEIGHT

   In the following datastep, you need to complete the following:
     (1) EVENTDAT & EVENTDAT2 will need to be in the format YYMMDD6.
     (2) DELETE variables other than those above.
     (3) Variables should be in the order above.
     (4) If either PERMNO (or CUSIP) or EVENTDAT is missing, the observation needs to
be DELETED.

   However, when uploading a SAS dataset the variable names do matter, but the
EVENTDAT format can be
   relaxed.  As of Eventus 9.0, we CAN upload a SAS dataset using PC SAS Connect.
/****************************************************************************************
*********************/
```

```
/*  EVENTUS_ANNOUNCE:  Base model includes all data for Announce Date */
/*************************************************************************************
********************/
* This will reorder the variables (not necessary, but makes it easier to analyze);

data edata.eventus_base;
  retain permno event media_code;
  set edata.eventus;  *the SAS dataset of the original Excel spreadsheet;
run;

/*************************************************************************************
********************/
/*  FULL SAMPLE */
data edata.eventus0 (KEEP = newpermno event RENAME= (newpermno=permno
event=eventdat));
set edata.eventus_base;
  format event YYMMDD6.;
  if permno = . or event=. Then delete;
  newpermno = permno*1;  *Or you can add 0;
run;

/* SUBSAMPLE: MEDIA [1=FB, 2=TWTR, 3=INSTA]  */
data edata.eventus1 (KEEP = newpermno event media_code RENAME= (newpermno=permno
event=eventdat));
set edata.eventus_base;
  format event YYMMDD6.;
  if permno = . or event=. Then delete;
  newpermno = permno*1;  *Or you can add 0;
  if media_code=1;
run;

/* SUBSAMPLE: MEDIA [1=FB, 2=TWTR, 3=INSTA]  */
data edata.eventus2 (KEEP = newpermno event media_code RENAME= (newpermno=permno
event=eventdat));
set edata.eventus_base;
  format event YYMMDD6.;
  if permno = . or event=. Then delete;
  newpermno = permno*1;  *Or you can add 0;
  if media_code=2;
run;

/* SUBSAMPLE: MEDIA [1=FB, 2=TWTR, 3=INSTA]  */
data edata.eventus3 (KEEP = newpermno event media_code RENAME= (newpermno=permno
event=eventdat));
set edata.eventus_base;
  format event YYMMDD6.;
  if permno = . or event=. Then delete;
  newpermno = permno*1;  *Or you can add 0;
  if media_code=3;
run;

/*************************************************************************************
*******************
■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■
 STEP 3:
   Run the EVENTUS program through PCSASConnect which allows us to avoid UNIX
programming.  You will be
   prompted for your WRDS username and password.

■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■
Please consult the EVENTUS manual for specific options.

REQUEST Statement:
```

AUTODATE Specifies that a calendar date in the request file that is not a trading day thus be converted to the following trading day.

EST The absolute value of the argument of EST determines how many trading periods (days, months, etc.)
the estimation period is offset from the event date. The sign of the argument determines whether the estimation period is pre-event or post-event.
EST=SPECIFIC selects an estimation period ending on the calendar or trading date specified in the estimation date column of the request file (immediately after the event date in an ASCII request file, e.g. EVENTDAT2), of length ESTLEN.

ESTLEN Specifies the length of the estimation period in trading days, weeks, months, quarters, or years,depending on the return interval being used for estimation in the current run. Default=255.

MINESTN Specifies the minimum number of usable trading days in the estimation period (default=3).
Will remove firm if fewer than n days of return data.

WINDOWS Statement:
For a single event date event study, use WINDOWS to list up to 200 event windows for which cumulative/
compounded abnormal returns and test statistics are to be reported on the output. The earliest and
latest possible dates are determined by the value of the PRE and POST options respectively.

If WINDOWS statement is omitted, Eventus reports 3 windows: (-PRE, -2), (-1,0), (+1, +POST)

EVTSTUDY Statement:
PRE Specifies the number of trading days or months immediately preceding the event date for which to compute abnormal returns.

POST Specifies the number of trading days or months immediately following the event date for which to compute abnormal returns.

MAR Market-adjusted returns benchmark method. The default is not to compute MAR.

MM Market-model benchmark method. This is the default (because it's the most popular method used in the literature).

STACK Selects an alternative event study report format in which medians are printed below means and numeric p-values are printed below test statistics.

VALUE|BOTH By default, Eventus uses only equally weighted market index returns in MM and MAR.
Specify VALUE to change to value weighted index or BOTH to produce separate event studies using both indexes.

Statistical Tests (PATELL and GENSIGN are default):

PATELL Specifies the Patell (1976) test. The Patell Z test is an example of a standardized abnormal return approach, which estimates a separate standard error for each security-event and assumes cross-sectional independence.

GENSIGN The generalized sign test is a nonparametric test that adjusts the fraction of positive abnormal returns in the estimation period instead of assuming 0.5. The null hypothesis for this test is that the fraction of positive returns is the same as in the estimation period.

STDCSECT Specifies the standardized cross-sectional test (Boehmer, Musumeci, and Poulsen 1991).

```
  WSR  The Wilcoxon signed-rank test for medians.

  TAIL=1|2  Specifies the significance levels of the reported test statistics is based
on 1 or 2-tailed tests.  The default is TAIL=1.

/*****************************************************************************************
********************/
/*  EVENTUS0:  ALL DATA */
/*****************************************************************************************
********************/

%let wrds=wrds.wharton.upenn.edu 4016;
options comamid=TCP remote=WRDS;
signon username="lwallis" password="1f2fRfBf";

libname edata '\\Client\C$\Users\lscole\Dropbox\THESES\BRENNA LOGAN\Eventus';

rsubmit;
options fullstimer ps=60;
libname mywrds '/home/utk/lwallis';

proc upload data=edata.eventus0 out=mywrds.eventus0;

eventus;
  title1  'EVENTUS0: FULL SAMPLE';
request insas=mywrds.eventus0 autodate est=-46 estlen=255 minestn=3 ;
windows (-10,0) (-1,0) (0,0) (0,1) (0,2) (0,3) (0,10) (0,30) (0,270) (0,365);
evtstudy noplist pre=10 post=365 mm mar both stack stdcsect patell wsr gensign tail=2;
run;

proc upload data=edata.eventus1 out=mywrds.eventus1;

eventus;
  title1  'EVENTUS1: MEDIA=1';
request insas=mywrds.eventus1 autodate est=-46 estlen=255 minestn=3 ;
windows (-10,0) (-1,0) (0,0) (0,1) (0,2) (0,3) (0,10) (0,30) (0,270) (0,365);
evtstudy noplist pre=10 post=365 mm mar both stack stdcsect patell wsr gensign tail=2;
run;

proc upload data=edata.eventus2 out=mywrds.eventus2;

eventus;
  title1  'EVENTUS2: MEDIA=2';
request insas=mywrds.eventus2 autodate est=-46 estlen=255 minestn=3 ;
windows (-10,0) (-1,0) (0,0) (0,1) (0,2) (0,3) (0,10) (0,30) (0,270) (0,365);
evtstudy noplist pre=10 post=365 mm mar both stack stdcsect patell wsr gensign tail=2;
run;

proc upload data=edata.eventus3 out=mywrds.eventus3;

eventus;
  title1  'EVENTUS3: MEDIA=3';
request insas=mywrds.eventus3 autodate est=-46 estlen=255 minestn=3 ;
windows (-10,0) (-1,0) (0,0) (0,1) (0,2) (0,3) (0,10) (0,30) (0,270) (0,365);
evtstudy noplist pre=10 post=365 mm mar both stack stdcsect patell wsr gensign tail=2;
run;
endrsubmit;
```

X. References

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