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Twitter's Relationship with Overreaction in Individual Security Returns

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Abstract

Using stock market return data from 2007 to 2019 from The Center for Research in Security Prices, I inquire into the impact that Twitter has on the overreactions of individual stock returns by breaking down returns into pre and post-Twitter periods. I examine negative serial correlation, demonstrating return reversals, between a lag crossed Twitter dummy variable and initial returns. With stock reversals serving as an indicator of initial overreaction and assuming stationarity of overreactions over time, I find that the presence of Twitter results in significantly more overreactions for highly followed companies when using monthly returns. However, when assessing Twitter's influence using weekly returns, the results suggest the possibility of return momentum. Similarly, Twitter's influence on overreaction is a highlighted when evaluating only negatively or positively large returns, producing greater significance despite a decrease sample size. While these promising results are not economically significant and thus do not reveal a viable contrarian investment strategy, my paper lays the foundation for a predictive model based of Twitter's influence on company returns.

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I. Introduction

Twitter has appeared in the forefront of how politicians communicate with their constituents, companies communicate with their shareholders and customers, and how the people and major media gather news. As such, Twitter is a reasonable measure of broad social media following and retail investor interest which in turn may impact the stock market. The question is how it will impact the stock market. While I do not doubt the ability for professionals to correctly analyze and use Twitter breaking news, which appears in waves and consensus of retweets, retail investors may lack this expertise, especially considering that Twitter is an information pushing platform. Though increased information is supposed to enhance market efficiency, the unreliable sources on Twitter and the false consensus that Twitter depicts through the wave of information it pushes, may decrease market efficiency. Hence, I argue that companies with large social media audiences should experience overreactions in their returns, because of unreliable information, pseudo-consensus, and social media's retail investor audience.

Examining the literature regarding market inefficiencies, Shleifer and Summers (1990) discuss how "noise traders" who rely on pseudo-signals, have a herded reaction which contributes to irrational shifts in the market that are not compensated for by arbitrageurs. Barber, Odeon, and Zhu (2009) connect these ideas with retail investors, demonstrating their ability to affect individual stock returns and produce subsequent rebounds. Shifting gears towards social media, Antweiller and Frank (2007) demonstrate that internet message boards help predict returns and volatility of the market, while Zhang, Fuehres, Gloor (2011) and Sul, Dennis, Yuan (2014) illustrate social-media-predicted returns can originate simply from general emotional sentiment on Twitter. Finally Tetlock(2007; 2010) proves that these broad market return shifts are inefficient and caused partially by investor reaction to stale information. Despite the breadth of the current literature, it fails to address how social media impacts individual stocks.

This paper connects the literature on retail investor overreaction on particular stocks and broad market overreaction due to social media. By examining if Twitter causes overreaction amongst its most followed brands, I fill in the gap that represents the cross-section of these two topics. Specifically, I test Twitter's impact on individual stocks, attempting to demonstrate a causal relationship that could be subject to arbitrage. Furthermore, I also examine whether this overreaction is more prevalent in large stock shifts in particular, which other papers do not specifically test. The next logical steps of future studies, on the condition that this study yields significant findings, would be research that examines if trending news on social media causes overreaction as well.

In order to fill in the gaps and expand previous literature, I examine 19 of the 50 most followed brands on Twitter from 2007 to the end of 2019. I regress the returns of the current period on the previous period, creating a lag variable. This study focuses on a Twitter dummy variable(crossed with the initial lag returns) in order to demonstrate that after these companies became popular on Twitter their returns in the next period are predictable through overreactions. In a separate regression, I use the same methods; however with only monthly stock shifts greater than (+/-) 0.1.

Through testing multiple dates to signify the start of the Twitter period, I find that the monthly returns of the most followed companies, with respect to their previous returns, are significantly negatively affected by Twitter's rising influence in 2013, especially when large return shifts are isolated. Therefore, after Twitter, these companies are more prone to overreactions during an initial month period and corrections in the next month period, despite return momentum when returns were analyzed weekly. My findings are consistent with the pattern of individual stock reversals in Barber, Odeon, and Zhu (2009).

The remainder of the paper is as follows. Section II discusses the development and execution of my hypothesis. I then address the previous literature that can be connected with the potential impact that social media may have on individual stock returns in Section III. The literature review section is essentially split into two parts, addressing how individual stock returns are affected by retail investor overreaction and social media's inefficient impact on the market in general. Section IV outlines the data: stock market returns, company sizes and retail investor percentage data from the beginning of 2007 to the end of 2019 from Wharton Research Data Services for 19 different companies. The empirical strategy and results are presented in Section V and VI. Section VII conveys information about unincluded tests run for robustness. The final section concludes.

II. Hypothesis

In this paper my testable hypothesis remains that companies with large Twitter audiences should experience more overreactions in their stock returns than before Twitter's popularity. In order to measure overreactions, I test for serial correlation. In the event that I discover significantly negative serial correlation compared to the before Twitter period, this indicates that Twitter stocks have become more susceptible to stock reversals. Consistent, or the significant presence of, reversals would signal that these stocks are regularly overreacting and then correcting in the post-Twitter period.

This testable hypothesis originates from a broader hypothesis that Twitter causes overreactions in individual stocks. I also believe that companies with large Twitter audiences should experience more overreactions in their returns than those that have small Twitter audiences. Furthermore, companies that commonly trend on Twitter should also experience overreactions. However, testing the effects of large versus small Twitter audiences and the effects of trending on Twitter is rather difficult. These limitations for testing my broader hypothesis are discussed more extensively in the concluding section. Therefore, in order to examine the possible impact that Twitter could have towards individual stock overreactions, this paper compares the degree of overreactions before and after Twitter's rise to popularity.

I argue that Twitter's propensity for spreading, or almost pushing information, leads investors to rely on pseudo-signals and believe in a false consensus regarding a company's future stock returns. Thus, I do not believe that it is only Twitter following that causes overreaction, but also company interests across the Twittersphere; however, I think that Twitter following acts as a proxy for broad company interest on Twitter. It is with this belief in mind, that I also think that companies on Twitter should experience more overreactions on average when examining large stock shifts only. To explain, these large shifts most likely occur with greater Twitter buzz surrounding the highly followed company.

Nevertheless, when attempting to prove my testable hypothesis, I assume that if popularized companies experience more overreactions after Twitter than before, this indicates that Twitter causes these overreactions. However, this does not take into account the possibility of time-based effects, but instead assumes stationarity in the amount of overreaction in the market. In order to corroborate my assumption of overreaction stationarity, I turn to Jegadeesh(1989). Jegadeesh(1989) tests for negative serial correlation in stock returns by assembling a contrarian portfolio for the months between 1934 and 1987, finding significant evidence of overreactions. More importantly for my corroborating my assumptions, Jegadeesh(1989) finds a similar amount of serial correlation across subperiods of 1934 to 1987. Consistent with other literature on monthly returns, these historic results substantiate my claim that any major difference in serial correlation between 2007 and 2019 results from Twitter's impact rather than time or market-based effects.

III. Literature Review

In their influential paper, Shleifer and Summers (1990) revisit the efficient markets approach and present a case for inefficient markets, citing “noise traders”. Their approach incorporates two main assumptions. First, the authors argue that not all market demand changes are rational. The beliefs and sentiments of these investors rest on spurious signals of future returns, such as the advice of brokers or financial gurus. The authors continue by arguing that experimental subjects are overconfident, chase trends, and rely too heavily on new information, respectively. The trading spurred by pseudo-signals is correlated and aggregated to form meaningful demand shifts; this contrasts with the null hypothesis which states that these trades should be random and cancel each other out.

Their second assumption argues that arbitrage, which involves trading by rational investors, does not entirely counter the inefficiencies caused by noise traders. They argue that the riskiness of arbitrage serves to limit it and its ability to direct markets towards efficiency. Their approach, noise traders/limited arbitrage, provides more accurate descriptions of the market and data-consistent implications about asset prices. Thus, they surmise that investor sentiment can shift prices away from fundamentals.

Parlaying off of Shleifer and Summers (1990) and its case for inefficient markets, Barber, Odeon, and Zhu (2009) address the idea that incorrect investor sentiment from pseudo-signals originates from retail trades. Thus, this begs the question if retail trades move markets, specifically in the direction of inefficiency. In order to incorporate retail trades into their model, the authors rationalize the use of small trade size as a proxy for individual investor trades. However, in order to appraise the effectiveness of this proxy, the authors evaluate the correlation between trading patterns for small signed trades in TAQ/ISSM database and trades of individual investors at different brokers in the 1990s. Upon finding reliable correlation, the authors look at tick-by-tick transaction data from 1983 to 2001 from the ISSM and TAQ.

The authors observe that, in addition to the correlation between small trades and individual investor trades, individual investing exhibits dependable evidence of herding. Though herding constitutes an indication of inefficiency alone, the researchers uncover that stocks heavily bought by individual investors earn strong returns the following week (or vice versa); this pattern persists for a few weeks and then reverses. Finally, stocks heavily bought by individual investors underperform heavily sold stocks by 4.4 percentage points the following year. The subsequent return reversals that accompany these individual investor favorites, establish the possibility for retail investor-oriented platforms to cause temporary market inefficiencies.

Shifting gears, the following few sources serve to illustrate the effect that social media has on returns and the market in general, in order to lead the way for discussion and research on social media and its relationship to noise traders and inefficiency. As one of the foundations for research on social media's impact on returns, Antweiller and Frank (2004) analyze internet stock messages across Yahoo Finance and Raging Bull in 2000. They compare these messages to financial data from the TAQ database of the 45 stocks that make up the DIA and XLK and an exchange-traded fund that served as a proxy for the market. Their hypothesis involves the ideas that the message volume and their bullishness predict returns or volatility and that disagreements between posts results in higher trading volume. Through contemporaneous regressions, the study affirms that greater bullishness is significantly positively related to returns and message volume serves as an indicator of volatility for both the DIA and XLK, even when accounting for the volatility caused by increased trading volume. While Antweiller and Frank (2004) support the argument that retail investors and social media (message posts) have significant impacts on the market, they do not indicate if this impact originates from efficient rational investing, such as decreased information asymmetry, and inefficient investing, such as that of noise investors.

Antweiller and Frank's work led to further research regarding social media's impact on markets, examining if they detract or contribute to efficiency. Zhang, Fuehres, Gloor (2011) assess if non-fundamental social media information affects returns. Through March 2009 and September 2009, the authors collect between 8100 and 43040 tweets per day. By measuring the emotional composition of these tweets, hope or fear, and comparing those sentiments to various indices, the researchers demonstrate significant correlations between the emotions of tweets and the DIA, S&P500, NASDAQ, and VIX. Thus, simply analyzing emotional developments on Twitter can be used as a predictor of future stock movement. While these results could indicate that non-fundamental information causes inefficient returns for the companies within these indices, the indices are also highly correlated with the overall movement of the market. Thus, public sentiment could be correlated with greater macroeconomic factors, meaning there could be no direct causation between tweet emotions and returns.

Building upon Zhang, Fuehres, Gloor (2011), alternative research corroborates the idea that emotional sentiment on Twitter has a legitimate causal relationship with market returns. Sul, Dennis, Yuan (2014) match emotional tweets about a firm specifically to the returns of that firm's stock. Through analyzing tweets and stocks in the S&P 500 between March 2011 and February 2012, the researchers find significant evidence that overall emotional valence is related to a firm's stock returns. Therefore Sul, Dennis, Yuan (2014) demonstrate that the correlation between public sentiment and macroeconomic factors does not account for the impact that emotional tweets have on the market. By narrowing down previous studies, focusing on comparisons for individual firms, the authors present a strong argument that irrational information could predict next day stock returns. However, to illustrate that the irrational impact that social media has on the markets is indeed inefficient, overreactions should be observable through return reversals.

Hence, related research also looks at the possibly inefficient relationship between the media and the stock market. Using General Inquirer to analyze the pessimism in the WSJ "Abreast of the Market" column from 1984 to 1999, Tetlock (2007) finds that pessimism not only precedes downward prices but also a subsequent reversal to the original "fundamentals". In accordance with the assumption that reversals indicate initial inefficient movements, Tetlock's tests confirm that the analyzed media information does not provide anything new regarding asset prices. However, Tetlock (2007) fails to describe why media sentiment predicts reversals, whether that be from unjustified indications of consensus, or saturation of topic news that would make pinpointing reliable or meaningful sources difficult.

Accordingly, Tetlock (2010) later performs research that more closely lines up with the hypothesis of this paper. To clarify, he tries to pinpoint what mechanisms cause the inefficiency and reversals. Tetlock (2010) investigates if stock market investors are able to differentiate between new and old information. His study's results provide significant evidence that while stocks react less to stale news (news that has cycled ten times), the reaction and reversal are statistically substantial. Therefore, Tetlock (2007; 2010) provides grounds and reasoning behind an inefficient market hypothesis due to the media.

By connecting Barber, Odeon, and Zhu's (2009) results regarding pseudo-signals and retail investor overreactions towards individual stocks, with Tetlock's (2007; 2010) results regarding social media's tendency to cause overreactions in the market in general, this paper explores a cross section, or gap, between these two branches of literature. Unlike Barber, Odeon, and Zhu (2009), this paper focuses on social media popularity as a particular cause of overreactions, and unlike Tetlock(2007; 2010), this paper tests if social media causes overreaction in individual stocks. As a general summary, by examining next period returns in comparison to previous period returns, before and after Twitter and for specific companies, this paper tests if Twitter popularity causes overreaction in its most popular stocks. Lastly, this paper also tests whether overreactions associated with Twitter are more prevalent within large return shifts. To the best of my knowledge, no literature has explicitly addressed this intersection, social media and individual stock overreaction, or if the individual stock overreaction from social media is more prevalent in large return shifts.

IV. Data

The data I use for my analysis of overreactions in the stock market due to Twitter originates from CRSP (The Center for Research in Security Prices), provided by WRDS, from January 2007 to December 2019. This data period is optimal because it stretches early enough to account for a period before Twitter became popular/influential, allowing period comparisons. This forces me to include the volatility that originated from the 2008 Great Recession. However, based on the previously mentioned study, Jegadeesh(1989), looking at monthly data, there was a similar pattern of serial correlation from 1934 to 1987. Therefore, serial correlation or overreaction in the stock market seems to be fairly chronologically stationary. Thus, it is reasonable to assume that the increased volatility during 2008/2009 should not bias my regression results, but simply add to my sample size. Furthermore, CRSP's available data restricts my analysis to the end of 2019.

The initial scope of my data examines the 50 most followed brands, using live Twitter statistics from a social media tracker, SocialBakers. However, despite the original 50 companies considered, there are a number of restrictions for the companies that I could use to test my hypothesis, leaving my data to consist of the returns of 19 different companies rather than 50 for a regression. While I believe 19 companies is a small sample size, expanding the scope of my data to the top 100 or even 200 most followed brands could dilute the significance of my regressions. To explain, the number of followers of the 50th to the 100th most followed companies drops dramatically, and I would expect that Twitter's impact on the stock of the 100th most followed company drops accordingly.

Next, I will discuss the restrictions placed the companies included in my dataset. Amongst these 50 companies, there are multiple subsidiaries of the same firm and also private companies. Also, the remaining companies need to be widely traded and need enough historical data. I find it pertinent to only include stocks that are majorly traded on the NYSE to ensure adequate trade volume, maintain consistency in the data, guarantee retail activity (as opposed to OTC trades), and finally to keep the data within my US-centric analysis.

Lastly, an important criterion for this study is that the stock has enough relevant data before Twitter's influence appeared to produce an efficient sample size. Not only could newly created/IPO'd companies exhibit more overreaction and skew results, they also do not allow for this study's period comparison. On that note, two of the 19 companies, Tesla and Michael Kors, do not have public data going back to 2007; however, they have enough data to be usable. In the end, the data consists of 19 different companies. Following these restrictions and analyzing stock returns by weekly and monthly periods, the sample sizes are 12,406 and 2,864, respectively.

To explore Twitter as a potential cause of overreaction in the company stocks, I create a continuous variable that captures the stock returns of these companies measured either weekly or monthly. Previous literature has demonstrated that before stock reversals, there is often a period of continued momentum in which irrational stock returns persists. Thus in order to successfully detect investor overreactions, it is important to observe stock returns monthly and weekly. Returns are calculated as the change in the company's stock over the week or month long period divided by the average stock price during that same period of time. Whereas the average stock price is the mean of the average between the bid and ask price of the stock. One of the primary independent variables in my dataset is lag returns, which is the returns of the previous week or month relative to current returns.

Moving forward, in order to directly compare overreactions in these stocks before and after Twitter, I create a set of indicator variables for Twitter. First, I create a Twitter indicator variable equal to 1 if it is after 2010 and 0 if it is before 2010. 2010 represents a year of massive Twitter growth and usage milestones such as signing a 100 million new users in a given year. Because there is some debate over what the correct timing for the indicator variable should be, I create two analogous indicator variables for 2013 and 2016. 2013 marks a significant turning point for Twitter because Twitter performed its initial public offering in November 2013, gaining much wider public and media attention. 2016 signifies the year that Twitter gained extensive financial, economic, and most prominently political impact.

My data includes the market cap in billions as of December 31, 2019, of each of the companies in the regression, which I take the natural log of, to represent the natural log of firm size. Using market cap and the natural log in my regression is consistent with other literature. The percentage of each company owned by retail investors, as stated on CNN Business as of October 2020, represents another important control variable. Each of these two variables, size and retail percentage, are continuous across the companies included in my data; however, these variables are constant over time within each company within my dataset.

I present summary statistics by month and week in Tables 1 and 2, respectively. There are several noteworthy results. Looking at monthly returns first, the returns of the before Twitter period are consistently lower than the returns of the after Twitter period, and they also have a larger standard deviation. The lower returns in the first major period are explained by the Great Recession and the slow recovery period, which also explains the volatility. The lower average returns is especially noticeable when compared to the positive returns experienced during the last 10 years of bull market.

Looking at weekly returns, the standard deviation of weekly returns in Table 2 are just as large, if not larger than those found in Table 1's monthly returns. Finally turning focus towards the other variables of Table 1 and 2, the mean size differs between the before and after Twitter period, even though size is kept constant over time for each company because of the few companies in the data that became public later than 2007.

V. Empirical Strategy

To examine the possibility of overreactions in the stock market due to Twitter and retail investor activity, this study utilizes the following regression model:

$$Y_{t+1,c} = \alpha + \beta_1 Y_{t,c} + \beta_2 Tw_c + \beta_3 \left(Y_{t,c} * Tw_c\right) + \delta_1 Size_c + \delta_2 \left(Y_{t,c} * Size_c\right) + \delta_3 RetailPerc_c + \delta_4 (Y_{t,c} * RetailPerc_c) + \varepsilon_{c,t}$$

where $Y_{t+1,c}$ measures the returns in the period immediately after the initial period(t). $Y_{t,c}$ represents the lag returns, that is, the returns in the period prior to $Y_{t+1,c}$. As stated, the returns of $Y_{t+1,c}$ and $Y_{t,c}$ are grouped weekly or monthly depending on the regression specification. Tw_c is the post-Twitter indicator variable, which categorizes the dataset into two main time periods, before and after Twitter. In separate regression specifications, Tw_c indicates shifts after 2010, 2013, and 2016, and the Twitter indicator variable is crossed with the lag returns, $\left(Y_{t,c} * Tw_c\right)$. The beta associated with the interaction variable is the main parameter of interest. Significant results would indicate that lag returns influence returns in the post-twitter period relative to the pre-twitter period. A positive coefficient demonstrates that heavily followed companies on Twitter exhibit momentum within their returns, while a negative coefficient exhibiting reversals, or overreactions. Though I suspect in population that a negative coefficient exists, detecting it may be difficult because I am unsure how long reversals normally occur after an initial overreaction. Thus, I have no priors on whether the coefficients will be positive or negative based on monthly and weekly returns.

Furthermore, for a separate regression, I only include previous period returns, $Y_{t,c}$, that are larger in absolute value than 0.1 for monthly returns. This threshold represents roughly the 10th and 90th percentiles of monthly stock returns. By specifically examining the relationship between Twitter crossed lag returns and initial period returns after a large stock shift, I test if

Twitter's impact on stock returns is more or less noticeable in large movements. In other words, are large stock return shifts more likely to be the result of an overreaction from Twitter?

Next, I explain the rationale and reasoning for the inclusion of the (S) size and retail percentage (RP) variables (in addition to crossing them with lag returns) in my regression framework. For some background information, a potentially prominent source of error that this study faces is how to account for subsidiaries in my regression. Because this paper focuses on how Twitter helps predict returns of the stock market in a future period, it is reasonable to assume that when a popular Twitter brand is only a subsidiary of a larger company, Twitter should not have as large of a relationship with the stock market movement. While data regarding each of these company's subsidiaries is publicly available, the subsidiaries would need to be deeply analyzed in order to understand how to record the sensitivity of a parent organization's stock to news on its subsidiary. This, however, is beyond the scope of this study. With this potentially unaccounted error in mind, my regression framework includes a firm size variable, S_c, and its cross with lag returns, $(Y_{t,c} * S_c)$. To explain, by identifying a company as extremely large, this could communicate that the popular brand on Twitter is part of a larger organization.

The other variable with the potential to impact returns when crossed with lag returns is the percent of retail ownership for each of these companies, RP_c and $(Y_{t,c} * RP_c)$. I argue that Twitter, and even social media as a whole, causes overreactions in the stocks of its highly followed companies because it pushes information on retail investors. It is their lack of experience that could potentially cause retail investors to believe unreliable information, detect nonexistent stock trends, and overlook the relatively small hints of useful information. Therefore, companies that have high retail ownership should be more susceptible to overreaction. Because social media presence and high retail investor interest are most likely highly correlated, the inclusion of this variable isolates the impact that social media has on the market from retail investor effects.

Though I have not included variables in my regression framework that account for time-based differences in the overreactions of these stocks, I rely on the Jegadeesh(1989) to indicate that time-based variables are unnecessary. Finally I have not included other variables that are, unrelated to my hypothesis, but may help build a predictive model based on inefficient stock market movement. Isolating for all possible causes of inefficiency in the market is beyond the scope of this paper. This study aspires to narrow down on an inefficient model rather than complete it. With that said, the robust regression yielded the following.

VI. Results

The results for monthly returns when Twitter is measured as post-2010, 2013, and 2016 are presented in columns 1,2, and 3 of Table 3, respectively. There are several noteworthy results. The cross-term between Twitter and lag returns is negative for all Twitter measurements; however it has the largest magnitude for 2013. As expected, late 2013 represents the most significant shift between a before Twitter time and an after period time. In other words, a time when Twitter had no financial market impact to a time when Twitter could stir up overreaction in the stock market. Twitter's 2013 is marked by further user growth (200 million monthly users), maturation of Twitter's influence in media and across other forms of social media, and finally its IPO. *LagXTwitter* for 2013 has a beta that is slightly over 3 robust standard errors away from the null, indicating that with over 99% confidence *LagXTwitter* can predict future returns.

This signifies that when associated with the returns of the previous month, the presence of Twitter causes stock reversals in the next period. Highly followed companies experience these reversals with greater frequency after Twitter than before. Because I find significant results through the regression of monthly reversals, this presents the argument that stock reversals occur a month after overreaction from Twitter.

Second, the regression of monthly returns using a 2016 Twitter dummy variable conveys similar, yet slightly less significant results. Casual empiricism dictates that *LagXTwitter*, using 2016, is not significant at conventional levels because Twitter had already gained notable influence by late 2013. However, considering 2016's dummy variable is still considerable, this suggests that the tendency for Twitter to generate overreactions amongst its most followed brands is growing. It seems like Twitter's economic, financial, and political reach is expanding since 2013 especially after the 2016 election.

Furthermore, Table 4 displays a positive serial correlation between *LagXTwitter* and initial period returns when using weekly returns. Though these coefficients are insignificant by conventional standards, their signum suggests that Twitter causes stock return momentum before monthly reversals occur. This is consistent with the pattern of individual stock reversals in Barber, Odeon, and Zhu (2009).

Discussing the other variables of Table 3 and 4, the only other significant variable is *Size*. The positively significant *Size* variable indicates that when lag equals 0, large companies on Twitter have experienced positive returns on average. This result is logically reasonable when I consider that companies that have become popular on Twitter and have large market caps have probably grown significantly during the recent bull market period. All other variables are insignificant; however the signum of variables such as *LagXSize* and *LagXRetail* are consistent with my rationale for including these variables in my regression, as described above in the empirical strategy section.

Table 5 displays the results of a similar regression of monthly returns however this time only using large lag return datapoints(+/- 0.1). The cross-term between Twitter (2013) and lag returns is very statistically significant. It has a t-statistic of approximately -3.4 with a coefficient of -0.17. Furthermore, unlike the previous regressions which use all return data, this regression yields a statistically significant beta for the cross between Twitter (2016) and lag returns. This indicates that Twitter's tendency to cause overreactions in the returns of the most followed companies is more pronounced with large return shifts. My interpretation for these more significant results is as follows. As companies draw attention on Twitter, the event that the attention is focused around becomes more widely known and frequently retweeted. Therefore, Twitter causes this buzz to exponentially expand, overemphasizing the event importance on the overall value of a company. Logically, this exponential effect occurs more with larger events, which cause larger initial market reactions.

As a final concluding, compared to all other factors that contribute to the direction of a stock's price, the relationship that I have found is still economically insignificant. This intuition is corroborated by my regression's very small R-squared, meaning that the majority of next day returns are explained by other unknown variables or are even unexplainable. Thus researching other outside information about a company, such as its financial or strategy, is needed to make *LagXTwitter*'s beta useful for investment strategy.

VII. Robustness Tests

I also perform a number of robustness tests. First, as seen in Table 5, in order to measure the effect that large market shifts have on next period returns after Twitter, I only include lag returns that are below the 10th and above the 90th percentiles of returns in the period between 2007 and 2019. Table 5 depicts a regression that includes monthly returns and 2013 & 2016 Twitter dummy variables. However, I actually test the effect of large market shifts in 4 other regressions. In addition to using monthly returns and a 2010 Twitter dummy variable, I also use large weekly returns and 2010, 2013, and 2016 dummy variables. However, because only the regression with monthly returns and 2013 and 2016 Twitter dummy variables yield significant results, I elect to only include these two regressions. In my view, this allows for clear comparison between the regressions that use all return data and the regression that only used data on large return shifts. However, these additional results are available upon request.

Second, I re-estimate equation 1 adding two additional control variables: a cross-term between size, lag returns, and Twitter, and a cross-term between retail, lag returns, and Twitter. I hypothesize that these triple cross-term variables may demonstrate how much Twitter's tendency to cause overreaction is because of a company's size or retail ownership. However, the coefficients on these additional cross-terms are statistically insignificant at conventional levels. This suggests that a company's size or retail ownership do not noticeably affect Twitter's tendency to cause overreactions amongst its most followed companies. Thus, just as the stock reactions that Twitter causes are inefficient, the reasons behind these inefficient reactions are unexplainable as well. Results are available upon request

VIII. Conclusion

In the current political and financial age, Twitter has arisen as an important tool for politicians and companies to speak with their constituents and customers/investors. Twitter has thus become viable information hub because of the previously mentioned direct connection that it allows. However, within this hub, third parties constantly exchange ideas, facts, rumors, and falsehoods. Oftentimes, rumors appear first on Twitter because of Twitter's easy and immediate disbursement of information, leaving it up to investors to decide if the information that they are receiving is true, false, or overexaggerated. Because retail investors most likely are highly impressionable, rely on Twitter for information, and are probably unable to differential between meaningful trustworthy news and irrelevant unreliable news, Twitter and social media in general may instigate inefficient markets. Following this logic, companies with large social media audiences experience overreactions in their stock returns.

Regarding current knowledge on this topic, the literature can be split into two main branches: how retail investor's contribute to overreactions in the returns of individual stock returns and how social media sentiment produces overreactions in the market in general. First, Shleifer and Summers (1990) represents the foundation of this first branch of literature; in their research, they discuss how "noise traders" react based on pseudo-signals as a herd, and that arbitrageurs do not leverage this irrational shift because of the risk involved. Barber, Odeon, and Zhu (2009) build off of the hypothesis of inefficient markets by relating retail investor activity with subsequent rebounds. Thus, the authors support the argument that stocks targeted by retail investor activity experience overreactions. Following the branch of literature focused specifically on social media's impact on the market, current knowledge ends with Sul, Dennis, Yuan (2014) and Tetlock(2007; 2010). Sul, Dennis, Yuan (2014) demonstrates that current emotional sentiment on Twitter predicts future returns. Tetlock(2007; 2010) proves that market shifts resulting from social media are inefficient by recording rebounds.

This paper attempts to connect the first branch of literature which states that stocks with large retail investor interest experience overreactions and the second branch of knowledge that points out that social media causes inefficient shifts of the market. Thus, there is a gap in existing knowledge regarding if overreaction due to social media can be predicted in the returns of individual stocks. In order to fill this gap, this study focuses on the returns of 19 of the 50 most followed brands on Twitter from 2007 to the end of 2019. With the objective to test if Twitter can be predictor of future returns, I set up a lag regression, consisting of a Twitter dummy variable interacted with previous period returns. The Twitter dummy variable serves to indicate a shift from before Twitter's influence in the stock market to after.

When the Twitter dummy variable marks 2013 as this shift, my regression results indicate that the monthly returns of the most followed companies are negatively predicted by the presence of Twitter, when the returns of the previous month are taken into account. I detect a negative relationship with 99% certainty. The negative coefficient of this relationship reveals that Twitter, and by assumption social media in general, initiates overreactions in the monthly returns of its most followed companies. Interestingly, though the relationship between the Twitter dummy and future returns in the weekly regression is insignificant, it is positive. This corroborates the findings of Barber, Odeon, and Zhu (2009) by indicating that before returns reverse to demonstrate overreaction, there could be a period of return momentum. Finally, when only large return shifts are used for regression analysis, Twitter's impact on the overreactions of individual stocks is even more pronounced.

As discussed at the end of my results section, due to the economically insignificance of the serial correlation between present day returns and the Twitter dummy interacted with lag returns, the results of this regression do not substantiate invest strategy changes. This is one of the main shortcomings of this paper. In other words, forming an investment strategy to take advantage of the discovered overreactions would not result in a positive alpha, especially if this strategy were to replace investments based on more comprehensive background research on a stock. Another shortcoming to be aware of is the limited amount of companies that could be analyzed, because as explained in my data section, few of the top followed companies qualified for my regression and the lesser followed companies may not have significant overreactions in the market.

A logical next step after this paper would be a regression that compares companies with little or no Twitter following to those that have large Twitter following. Though I initially perceived this regression as a more valuable indicator of the effect that Twitter has on individual stock returns, I immediately approached roadblocks during my research. It is very difficult to find non-Twitter companies that are even slightly comparable to the top followed Twitter companies, especially in the US. I discovered a pattern of differences in size, popularity in normal media, retail investor following, and financial ratios and reasonably assumed there are many more differences between Twitter and non-Twitter companies that would need to be controlled for. However, given amble time and resources, this seems like a reasonable step.

Another path for further research would be to analyze if the degree that stocks trend on Twitter after a certain event or incident could dictate how much an individual security's returns overreacted to said event. This could uncover actionable investment strategies for positive alpha, given that statistically significant results were found. I believe that a hypothesis surrounding this idea would be extremely interesting but difficult to explore. Researchers would need to have data on when a company trended on Twitter because of a specific event and the company's stock returns that followed. For a reasonable sample size, this would involve the events of numerous different companies. To my knowledge, this data does not currently exist, at least publicly.

Nevertheless, despite the difficulties that I suspect for further research, I believe that examining the relationship between social media and stock returns to identify investment strategies should be a continued area of focus.

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X. Appendix

Table 1: Monthly Summary Statistics

VARIABLES	Before Twitter			After Twitter		
2010 Twitter	Obs.	Mean	S.D.	Obs.	Mean	S.D.
Retail (%)	823	6.982	6.550	2,041	6.652	6.256
Size (billions)	823	252.3	367.8	2,041	232.8	355.6
Returns	823	-0.00110	0.132	2,041	0.00821	0.107
	Before Twitter			After Twitter		
2013 Twitter	Obs.	Mean	S.D.	Obs.	Mean	S.D.
Retail (%)	1,496	6.860	6.427	1,368	6.621	6.246
Size (billions)	1,496	244.7	362.9	1,368	231.6	355.1
Returns	1,496	0.00369	0.124	1,368	0.00755	0.103
	Before Twitter			After Twitter		
2016 Twitter	Obs.	Mean	S.D.	Obs.	Mean	S.D.
Retail (%)	2,180	6.784	6.370	684	6.621	6.249
Size (billions)	2,180	240.6	360.5	684	231.6	355.2
Returns	2,180	0.00366	0.121	684	0.0115	0.0901

Table 2: Weekly Summary Statistics

VARIABLES	Before Twitter			After Twitter		
2010 Twitter	Obs.	Mean	S.D.	Obs.	Mean	S.D.
Retail (%)	3,563	6.983	6.550	8,843	6.653	6.255
Size (billions)	3,563	252.5	367.8	8,843	232.9	355.6
Returns	3,563	-0.000347	0.0658	8,843	0.00176	0.0513
	Before Twitter			After Twitter		
2013 Twitter	Obs.	Mean	S.D.	Obs.	Mean	S.D.
Retail (%)	6,478	6.861	6.428	5,928	6.621	6.244
Size (billions)	6,478	244.8	362.9	5,928	231.6	355.0
Returns	6,478	0.000672	0.0616	5,928	0.00168	0.0489
	Before Twitter			After Twitter		
2016 Twitter	Obs.	Mean	S.D.	Obs.	Mean	S.D.
Retail (%)	9,442	6.785	6.371	2,964	6.621	6.245
Size (billions)	9,442	240.7	360.5	2,964	231.6	355.0
Returns	9,442	0.000695	0.0595	2,964	0.00261	0.0423

Table 3: Monthly Returns Regression

VARIABLES	(1) Twitter 2010	(2) Twitter 2013	(3) Twitter 2016
Lag Returns	0.0793	0.0796	0.0448
	(0.0942)	(0.0852)	(0.0810)
Twitter Dummy	0.00735	0.00157	0.00707
	(0.00573)	(0.00485)	(0.00495)
LagXTwitter	-0.0928	-0.154***	-0.111*
	(0.0587)	(0.0461)	(0.0580)
Size	1.09e-05**	1.08e-05**	1.12e-05**
	(5.48e-06)	(5.49e-06)	(5.49e-06)
LagXSize	0.00916	0.0102	0.00438
	(0.0138)	(0.0136)	(0.0141)
Retail	3.71e-05	1.75e-05	8.30e-06
	(0.000344)	(0.000345)	(0.000346)
LagXRetail	-0.00173	-0.00184	-0.000358
	(0.00417)	(0.00422)	(0.00414)
Constant	-0.00349	0.00117	0.000330
	(0.00627)	(0.00520)	(0.00481)
Observations	2,225	2,225	2,225
R-squared	0.006	0.009	0.006

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Weekly Returns Regression

VARIABLES	(1) Twitter 2010	(2) Twitter 2013	(3) Twitter 2016
Lag Returns	-0.0844**	-0.0505	-0.0454
	(0.0400)	(0.0350)	(0.0336)
Twitter Dummy	0.00182	0.000392	0.00167
	(0.00139)	(0.00114)	(0.00113)
LagXTwitter	0.0733***	0.0184	0.00889
	(0.0281)	(0.0242)	(0.0279)
Size	2.98e-06**	2.88e-06**	2.90e-06**
	(1.28e-06)	(1.28e-06)	(1.27e-06)
LagXSize	-0.00101	0.000819	0.00124
	(0.00634)	(0.00624)	(0.00629)
Retail	8.21e-06	7.00e-06	8.13e-06
	(8.30e-05)	(8.31e-05)	(8.33e-05)
LagXRetail	-0.000272	-0.000507	-0.000668
	(0.00223)	(0.00230)	(0.00229)
Constant	-0.00114	4.14e-05	-0.000187
	(0.00155)	(0.00126)	(0.00115)
Observations	9,687	9,687	9,687
R-squared	0.004	0.002	0.002

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Large Returns Regression

VARIABLES	(1) Twitter 2013	(2) Twitter 2016
Lag Returns	0.0608	0.0336
	(0.0927)	(0.0898)
Twitter Dummy	0.0195*	0.0131
	(0.0106)	(0.0118)
LagXTwitter	-0.170***	-0.143**
	(0.0506)	(0.0684)
Size	2.00e-06	2.31e-06
	(1.27e-05)	(1.30e-05)
LagXSize	0.0185	0.00936
	(0.0152)	(0.0163)
Retail	0.00119	0.00116
	(0.000852)	(0.000853)
LagXRetail	0.000790	0.00302
	(0.00495)	(0.00485)
Constant	-0.0126	-0.00735
	(0.0118)	(0.0106)
Observations	513	513
R-squared	0.046	0.028

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1