9-2018

Paying attention to social media stocks

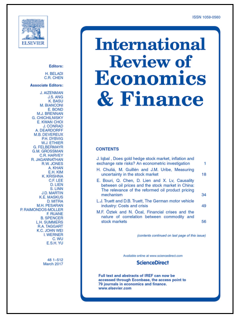
Wan-Jiun Paul Chiou
Northeastern University

Heather Knewtson
Michigan Technological University, knewtson@mtu.edu

John R. Nofsinger
University of Alaska, Anchorage

Follow this and additional works at: https://digitalcommons.mtu.edu/business-fp
Part of the Business Commons

Accepted Manuscript



Paying attention to social media stocks

Wan-Jiun Paul Chiou, Heather S. Knewtson, John R. Nofsinger

PII: S1059-0560(18)30204-1

DOI: 10.1016/j.iref.2018.08.009

Reference: REVECO 1667

To appear in: *International Review of Economics and Finance*

Received Date: 18 April 2016

Revised Date: 7 April 2018

Accepted Date: 15 August 2018

Paying Attention to Social Media Stocks

Wan-Jiun Paul Chiou[*]

Heather S. Knewtson[†]

John R. Nofsinger[‡]

Abstract:

Social media has reshaped business models, economies, politics, and culture around the world. In this paper, we identified social media stocks from various sectors by using a strict, academic definition and then studied their performance and return characteristics. Multivariate regression results demonstrate that being recognized as a social media firm yields extra return. The performance of social media stocks is not associated with macro-level sentiment, but rather with firm-level attention paid by potential investors. Causality tests indicate that the default risk premium and volatility have incremental power in explaining the performance of social media stocks.

Keywords: Social media, social gaming, social networking, sentiment, investor attention

Acknowledgements
The authors would like to thank Carl Chen (the editor), anonymous referees, and participants at seminars in Boston University, National Chung-Hsin University, the Financial Management Association Annual Meeting in Nashville, and Global Conference on Business and Finance, San Jose, Costa Rica, for helpful comments and suggestions. The usual disclaimer applies.

[*] Wan-Jiun Paul Chiou (Corresponding author): Finance Group, Northeastern University, 360 Huntington Avenue, Boston, MA 02115, Phone number: 617-373-8374; Fax number: 617-373-8374; *Email: w.chiou@neu.edu*.
[†] Heather S. Knewtson: School of Business & Economics, Michigan Technological University, 124 Academic Office Building, 1400 Townsend Drive, Houghton MI 49931, Phone: 906-774-2771, *Email: knewtson@mtu.edu*.
[‡] John R. Nofsinger: Accounting and Finance Department, College of Business & Public Policy, University of Alaska Anchorage, 3211 Providence Drive, Anchorage, AK 99508, *Email: john.nofsinger@uaa.alaska.edu*.

Paying Attention to Social Media Stocks

Abstract:

Social media has reshaped business models, economies, politics, and culture around the world. In this paper, we identified social media stocks from various sectors by using a strict, academic definition and then studied their performance and return characteristics. Multivariate regression results demonstrate that being recognized as a social media firm yields extra return. The performance of social media stocks is not associated with macro-level sentiment, but rather with firm-level attention paid by potential investors. Causality tests indicate that the default risk premium and volatility have incremental power in explaining the performance of social media stocks.

Keywords: Social media, social gaming, social networking, sentiment, investor attention

Acknowledgements:

The authors would like to thank Carl Chen (the editor), anonymous referees, and participants at seminars in Boston University, National Chung-Hsin University, the Financial Management Association Annual Meeting in Nashville, and Global Conference on Business and Finance, San Jose, Costa Rica, for helpful comments and suggestions. The usual disclaimer applies.

"It took 38 years for the radio to attract 50 million listeners, and 13 years for television to gain the attention of 50 million viewers. The Internet took only four years to attract 50 million participants, and Facebook reached 50 million participants in only one-and-a-half years."

(Nair 2011)

1. Introduction and Motivation

Social media firms have drawn much attention from investors and the financial press. The initial public offerings of Facebook and Twitter represent examples of this intense investor interest. Facebook set several market records by its IPO on May 18, 2012, including: (1) the largest venture-backed IPO debuting at over $100 billion, (2) the largest venture capital raised with $2.2 billion in equity financing acquired prior to IPO, and (3) the most active pre-IPO acquirer (Facebook acquired 13 venture-backed enterprises prior to its IPO).[1] Facebook facilitates social networking around the globe and is ubiquitous with the term "social media." In November 2013, the IPO of Twitter also drew a lot of attention as its stock rose from the IPO price of $26 to a first trading day closing price of $44.90. Additionally, social media firms have become increasingly significant to the economy. In May 2017, for instance, two out of the top ten multi-billion-dollar "unicorns" ranked by Fortune magazine were social media startups that may be publicly-traded in the future.[2]

Given this intense investor interest, we conducted this study to learn about the performance and return characteristics of social media stocks. Specifically, does being recognized as a social media firm yield extra value when controlling for possible pricing anomalies? Are social media firms merely a subset of dot-coms in terms of the stock price behavior? Is the performance of social media stocks related to market-wide sentiment or investor attention at the firm level? What factor loadings drive social media firm value? We explored the impact of various market risks, forward market volatility, investor attention, and investor sentiment on the performance of social media stocks. Though social

[1] See http://venturebeat.com/2012/05/16/record-breaking-facebook-ipo/.
[2] See http://fortune.com/unicorns/.

media has been widely recognized as a specialized economic sector, the stocks currently are categorized across several industries. To answer these questions, we manually collected data on all publicly-listed social media firms using the definition proposed by Kaplan and Haenlein (2010).

Social media has changed and reshaped business models, economies, politics, and culture throughout the world. The McKinsey Global Institute estimates that widespread use of social media technologies will transform communications from one-to-one interactions into many-to-many interactions, resulting in productivity gains of 20-25% amongst workers in knowledge-intensive professions. It was further estimated that this shift could result in a $900 billion to $1.3 trillion increase in economic surplus annually, if industries fully embrace the benefits offered by the adoption of social technologies throughout their business models.[3] Clearly, the anticipated impact of social media as a new industry is more than a mere social matter. For instance, Cohen (2013) documented the impact of innovation on economic growth on long-term corporate performance and on security returns. Understanding the factors that are associated with the performance of social media stocks is useful to evaluating these assets for possible portfolio inclusion.

The buzz surrounding the social media craze is reminiscent of that of the dot-com era from the late 1990s to the early 2000s. Ofek and Richardson (2003), Griffin *et al.* (2011), and Yu and Yuan (2011) analyzed how markets priced technology stocks through the previous wave of strong investor interest. Customer-to-customer feedback about experiences gave rise to the phrase "going viral." By monitoring the social media posts of their customers, firms can respond to customers more quickly, accelerating both the pace of product response and obsolescence.

The infrastructure used to support socialization provides opportunities for business, ranging from data analytics (e.g., Palantir and IBM-Watson), e-commerce (e.g., Amazon, Alibaba, and Flipkart), to the sharing economy (e.g., Uber and Airbnb). The business model of social media

[3] http://www.mckinsey.com/insights/high_tech_telecoms_internet/the_social_economy.

service also leaves challenges for valuation. What drives corporate value? Is it the overall market sentiment or firm-level investor attention? Since the definition and scope of social media is not completely clear, even for financial regulators, a study on their stock performance remains uncharted territory. Given the fact that large, private social media companies, such as the aforementioned unicorns Snapchat and Pinterest, are becoming publicly-listed, a study of social media stock price behavior seems timely and relevant to both academia and Wall Street.

In any era, investors can identify a group of investments that outperformed the market such as the concept stocks described by Hsieh and Walkling (2006). As an emerging technology sector, social media firms may be experiencing outperformance as predicted in the hype cycles. Gartner suggested that this is associated with a new business model advancing through various phases of development as entrepreneurial ventures.[4] An *ex ante* expectation of this outperformance is rooted in investor-driven interest in the firms offering new technology formats. The "going viral" effect has quickly gained widespread adoption by users. Therefore, it is important to question whether social media stocks are influenced by behavioral factors that are beyond the risk factors documented by asset pricing models.

To conduct our study, we thoroughly analyzed publicly-listed firms and identified the population of social media firms trading on the NYSE, Amex, and Nasdaq. The population includes obvious firms such as Facebook and LinkedIn. Missing from our population are several high-profile social media firms such as Snapchat, Linden Labs, and Wooga, which remain privately-held. For example, Pinterest, an online photo-sharing bulletin board, was valued at $2.5 billion in February 2013, three years after its launch, following an injection of capital by Valiant. This is larger than the market value of some current public companies such as Zynga, Yelp, and Pandora.[5]

[4] See http://www.gartner.com/technology/research/methodologies/hype-cycle.jsp.
[5] http://www.bloomberg.com/news/2013-02-21/pinterest-gets-200-million-in-funding-at-2-5-billion-valuation.html.

We applied various models to evaluate the relation of behavioral measures, specifically those including attention and sentiment, with the performance of social media stocks, controlling for other known risk factors. We found that social media stocks outperformed the market by providing a positive abnormal return while controlling for various risk factors. Unlike the technology stocks of the previous dot-com era, social media stocks appear to be unaffected by market-level sentiment. Our results indicate that market sentiment does not appear to be priced in social media stocks. Rather, investors show firm-level interest in social media stocks, as captured by the abnormal Google search volume index (SVI), proposed by Da *et al.* (2011).

This rest of the paper is organized as follows. Section 2 contains a literature review and theoretical development. In Section 3, we explain our data and methodology. Section 4 analyzes the performance of social media stocks and their relation to investor attention and investor sentiment. In Section 5, we study how various macroeconomic factors are associated with social media outperformance. Section 6 provides our conclusions.

2. Literature Review and Theoretical Development

Social media, as a new communication platform, has had a tremendous impact on the world economy. As more users enter into virtual gathering places, information delivery and communication have transitioned from traditional media (television, radio, and print media) to user-generated social media platforms. The impact of social media on business is wide ranging, as noted by scholars in information systems (Luo *et al.* 2013), marketing (Kim & Ko 2012), law (Janoski-Haehlen 2011; Bellin 2012), supply chain management (O'Leary 2011), and across the business disciplines (Trainor *et al.* 2014).

Finance research on social media firms is also new. Social media stocks can be classified as concept stocks after 2000, according to the definition of Hsieh and Walkling (2006). Sornette and Cauwels (2012) suggest that Facebook and Groupon were overpriced according to their fundamental value-based model of social media firms. Larcker *et al.* (2014) investigate the role that social media can play in assisting boards of directors with monitoring customer experiences. Specifically, they consider the word-of-mouth offered freely by customers as an early warning system before poor customer experiences go viral and damage a firm's reputation. Chen *et al.* (2014) conduct a textual analysis of social posts and investigate its relation to stock returns and earnings surprises. Karabulut (2013) and Heimer and Simon (2015) study a proprietary database of retail investors that share a common social platform. They find that communications over social media platforms by active, professional investors led to more active trading. Most of the current research has focused on how the information revealed by social media affected market behavior, but has not investigated the investment value of social media stocks.

Some of the firms in our population have their origins in the dot-com era; thus, we considered similarities and differences between the findings of the dot-com era and our study of social media companies. The mania for dot-coms was followed by a crash. Ofek and Richardson (2003) attribute the selloff of stocks to lockup expirations. In contrast, Griffin *et al.* (2011) attribute the selloff to institutions exiting the sector in a coordinated fashion. Ljungqvist and Wilhelm (2003) study the relation between severe IPO underpricing (as recently seen with Twitter) and firm characteristics unique to the dot-coms. Overall, Hendershott (2004) finds that value was created in his sample of venture-backed dot-coms, with 19% annual return, even after controlling for the known price surge and correction of the dot-com era.

DeMarzo *et al.* (2007) provide a theoretical model that explains how technological firms tend to overinvest, resulting in synchronized mispricing of technology stocks. The prediction of their model is for overinvestment to arise from an impulse for investors to herd into these stocks, creating price pressure beyond the prediction of rational pricing models. This model explains why a new type of industry creates heightened investor interest in the markets and how asset price bubbles result.

Like the preceding technology firms, social media firms may therefore be experiencing outperformance due to the hype associated with this new business model. It is natural to question whether the factors affecting social media stock returns are the risk factors from asset pricing models or more behaviorally focused factors. Fama and French (1993) establish the three-factor model which includes risk factors for an asset's covariablility with market returns, a size effect and a value effect. Their model extended the single-factor capital asset pricing model appreciating that smaller firms exhibit higher returns than larger firms do and that the firms with high book-to-market ratios exhibit higher returns than low book-to-market firms do. Recently, Fama and French (2015) expanded the Fama-French three-factor model to include two new factors that capture profitability (RMW) and investment (CMA).

With respect to behaviorally focused factors, Baker and Wurgler (2006) demonstrate that sentiment plays a role in explaining the cross section of equity returns. Using principal components analysis (PCA), they built an index of six factors thought to capture the overall sentiment in the equity markets: the closed-end fund discount, NYSE turnover,[6] the number and average first-day returns of initial public offerings (IPOs), equity share in new issues, and the dividend premium. Baker and Wurgler (2006) found that periods of low sentiment were followed by higher than normal returns for certain stocks: those that were small, young, highly-volatile, unprofitable, non-dividend paying, fast-growing, and distressed. Yu and Yuan (2011) then considered the mean-variance relation of sentiment, demonstrating that sentiment is unrelated to the mean-variance relation during the periods of high sentiment. Tsukioka, Yanagi, and Takada (2018) find excessive optimism leads to the high initial returns and long-run underperformance of IPO by using text data on message boards.

[6] NYSE turnover was removed from the index in 2015, because NYSE turnover now captures more than investor trading based on sentiment (high frequency trading artificially inflates turnover.)

Da *et al.* (2011) suggest using Google search volume index (SVI) of stock tickers as a measure of retail investor attention. Retail investors are thought to be susceptible to irrational, noise trading, and SVI is a direct revealed preference measure of investor attention. They found that changes in weekly search volume was a leading measure of investor attention which predicted future stock prices over the subsequent two week period.

Social media offers a new business paradigm that may be attractive to investors interested in new investment opportunities. We therefore considered whether social media stocks have generated superior performance over our sample period. An *ex ante* expectation of this outperformance is rooted in demand driven interest by firms offering new technology formats which have quickly gained widespread adoption by users. Our first hypothesis is:

(H1) Controlling for known risk factors, social media stocks exhibit outperformance.

Finding outperformance would be consistent with interest in social media stocks early in their introduction. The attention pushes prices beyond the levels justified by fundamentals. It could also be consistent with heightened sentiment in the market as a whole. If sentiment was influential over the sample period, outperformance could be attenuated by the effect of sentiment. Our second hypothesis is therefore:

(H2) Social media stock performance is influenced by sentiment.

We expect sentiment to be significantly negative (outperformance associated with low sentiment) given that Baker and Wurgler (2006) found that sentiment exhibited stronger effects for firms with highly subjective valuations and stocks difficult to arbitrage. Given their newness, social media firms are likely more difficult to value and therefore to arbitrage.

While sentiment offers a top-down view of how emotions can enter into investment selections, a more direct measure of firm-level scrutiny is captured by investor attention. Social media is a young industry intricately related to the technology industry. The hype cycles for technologies retailed by Gartner indicated distinct phases of the maturity of a technology industry as it relates to their visibility.[7] Gartner proposed that the visibility of a new technology product or service rapidly rises as it is introduced. After visibility peaks, expectations for the industry are brought back to normal levels as visibility returns to more sustainable levels. Then, as the technology gains widespread adoption and the industry matures, a more normal growth pattern emerges. We consider investor attention as a proxy for heightened visibility. Our third hypothesis is:

(H3) Social media stock performance is influenced by investor attention.

Consistent with the findings of Da *et al.* (2011), we expect greater attention to be focused on social media stocks and for that attention to be a significant factor in explaining outperformance.

3. Materials and Methods

Identifying social media firms that satisfy both investor intuition and academic precision was the first challenge of our study. An interesting event illustrates this ambiguity even to regulators. In July 2012, Netflix CEO, Reed Hastings, posted material information about Netflix to his personal page on Facebook. The Securities and Exchange Commission (SEC) brought charges of improper disclosure against Hastings in December 2012 for failing to make full disclosure through approved outlets. Following its investigation, the SEC ruled in April 2013 that news could flow into social media venues if investors are notified that announcements are routinely made through these venues. The SEC recognized the shift of information into social media spaces. However, it did not attempt to define social media outlets in its guidance.

We first identified the population of social media firms. Facebook seemed to be an obvious social media firm, but whether to include others, such as Angie's List or Groupon, was less clear. We applied the definition proposed by Kaplan and Haenlein (2010) to set the population. They are webspaces: (1) operating in a Web 2.0 environment (that is, real-time and dynamically updateable to

[7] http://www.gartner.com/technology/research/methodologies/hype-cycle.jsp.

make online communication feasible), (2) of user-generated content defined by the Organization for Economic Cooperation and Development(Vickery & Wunsch-Vincent 2007), and (3) demonstrating features of social presence, media richness, self-presentation, and self-disclosure. For the period January 1, 2004 – December 31, 2014, we identified 43 social media firms traded on the NYSE, Amex and Nasdaq. Global X Management Company LLC debuted a social media ETF on November 11, 2011. Its portfolio includes non-social media firms, such as Angie's List, Groupon, and Nutrisystem. We selected this sample period to enable the tests of investor attention that rely on Google search volume index (SVI) available from January 1, 2004. See the appendix for further details on population identification.

Table 1 contains the list of firms that form the social media population. A fair number of these social media firms are international enterprises that are traded in the U.S. markets as American Depository Receipts (ADRs). As such, it is appropriate to include them in the population and to use the U.S. market risk loadings to test their asset pricing behaviors. Furthermore, their membership as social media firms reflects the increasingly global nature of business.[8] The population was further split into two main types of social media firms. The first type, most typically identified to be social media, is social networking, including Facebook and Twitter. The second type is social gaming in which a game is the forum for socializing. One might equate these to their face-to-face counterparts of a coffee klatch (social networking) and socializing over a game of dominos (social gaming). We also include the U.S. based online dating service providers in this study.

<Insert Table 1 about here>

We considered possible differences within the population between social gaming firms and social networking firms. Although both types fit the broad definition of social media, Kaplan &

[8] We conducted robustness tests with and without international domiciled firms. Their presence or absence in the population did not change the results throughout this study. It is necessary to allow these international firms to remain in the population, given that they reflect the trade-off portfolio selections for investments in social media firms.

Haenlein (2010) differentiate between social networking and virtual gaming spaces along two dimensions. Social networking spaces are believed to have a higher degree of self-presentation than social gaming spaces. For example, posting in a Facebook news feed offers highly personalized information about the author (and possibly the friends who the author chooses to include in the post), whereas participating in multi-player online gaming has less flexibility for specific personalization. Your picture sends different information than does your avatar. Conversely, social gaming spaces offer a higher degree of media richness than social networking spaces. This is due to the intention of drawing the player into the game through a high degree of apparent realism of the gaming space.

To compare social media firms to the industry in which they are members, we constructed industry benchmark returns and collected monthly returns for all firms in the same 4-digit SIC code of the identified social media firms. We used monthly returns from the Center for Research in Security Prices (CRSP), for the data to compute the market value of equity, and for industry membership codes (SIC). We then formed an industry return by averaging the monthly returns within each SIC grouping.[9]

Table 2 reports summary statistics of monthly returns and firm size between 2004 and 2014 for social media firms, their industry peers, and all U.S. stocks. Panel A shows that social media firms had slightly lower average raw returns than the industries they came from, but that they were higher than the broader U.S. stock market. Risk, as captured by the standard deviation of returns, was stronger for social media than either their industry peers or the broader U.S. stock market. Panel B shows that the size of social media firms is generally larger than both their industries and the average U.S. stock. If we find abnormal returns for social media firms, it is not merely a firm size effect.

[9] For robustness, we also conducted tests with daily and weekly returns. Results are consistent with our findings using monthly returns.

<Insert Table 2 about here>

Figure 1 plots the cumulative returns of an equal-weighted social media index plotted against benchmark cumulative returns for the S&P 500 and Nasdaq from 2004 - 2014. Social media firms outperformed both these benchmarks in terms of raw return, but also exhibited greater fluctuations.[10] This seems to be consistent with a general impression about the outperformance of social media stocks.

<Insert Figure 1 about here>

We computed abnormal returns by controlling for risk factors. Using the monthly return measure, we apply (1) the Fama and French (1993) three-factor model and (2) the Fama and French (2015) five-factor model to detect abnormal returns:

$$R_{it} - R_{ft} = \alpha_{pt} + \beta_1\left(R_{mt} - R_{ft}\right) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_t \ , \quad (1)$$

and

$$R_{it} - R_{ft} = \alpha_{pt} + \beta_1\left(R_{mt} - R_{ft}\right) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \epsilon_t \ , \quad (2)$$

where R_{it} is firm *i*'s return, R_{ft} is the risk-free rate, R_{mt} is the market benchmark return, *SMB* is the size premium, *HML* is the value/growth premium, *RMW* is the robust minus weak profitability factor, *CMA* is the conservative minus aggressive investment factor, and α_{pt} is the abnormal return from the regression.

For our tests of investor attention, we gathered Google search volume index (SVI) arrays for the tickers that are part of our social media population and for the firms in the industries from which social media firms come. We followed Da *et al.* (2011) and collected the SVI, available from January 1, 2004, for tickers from Google Trends. If the frequency of searching was strong enough, data was available weekly. Less frequently searched tickers were available monthly, while some

[10] Social media does not fit neatly into either the S&P 500 or the Nasdaq.

tickers resulted in null searches. Because our tests were conducted using monthly returns, we converted SVI from weekly to monthly. We began by taking the natural logarithm of SVI plus one as ln(SVI) to keep firms without adequate search volume indexes from exiting the sample. Based on the methodology in Da *et al.* (2011), we used the prior two months of data as the benchmark of attention to generate abnormal SVI, ln(aSVI). Specifically, ln(aSVI) was constructed by taking the difference between current ln(SVI) and the mean of the previous two month's ln(SVI). We used consumer sentiment from monthly surveys conducted by the University of Michigan.[11]

For our mean-variance tests, we constructed Sharpe ratios to investigate the time-variation in the risk-return behavior of social media stocks. For each month, we formed Sharpe ratios by using the past 52 weekly returns. The yield for the 3-month Treasury bill was used as the proxy for the risk-free rate. We computed the expected return and standard deviation from the weekly returns of social media stocks and their corresponding industries. We then formed the average Sharpe ratio for the social media firms by taking the mean Sharpe ratio each week, *t*, for all of the firms, *i*, in our sample:

$$SR_t = \frac{1}{N}\sum_{i=1}^{N} SR_{i,t} \quad . \tag{3}$$

Figure 2 demonstrates the time-series behavior of the Sharpe ratio and its long-term smoothing curve (H-P) proposed by Hodrick and Prescott (1997). It shows no specific trend in the long term, but it is volatile over time. The time-variation of the mean-variance efficiency was particularly significant in the first half of the sample period. The pattern seems to follow the business cycle, which suggests that performance may be associated with macroeconomic factors.

<Insert Figure 2 about here>

[11] When our empirical work was being conducted, the Baker and Wurgler (2006) factors were not available to match our sample period. Because Baker and Wurgler (2006) noted the high degree of correlation between their measure and the University of Michigan sentiment measure, we conducted our study with the University of Michigan data.

4. Empirical Results

4.1. Performance of social media index returns

We formed both an equal-weighted and a value-weighted social media index by including all the social media stocks and examined their performance. Table 3 presents the regression analysis for the social media indexes. We control for risk factors by estimating the Fama and French (1993) three-factor model and the Fama and French (2015) five-factor model. Earlier enthusiasm for social media as a new business paradigm does not imply outperformance of social media stocks. Indeed, DeMarzo *et al.* (2007) predict that strong investor interest in technology firms can erode their performance through investors herding into the new investment opportunities. Hsieh and Walkling (2006) found overpricing of concept stocks after controlling for factors such as glamour, IPO, industry, or contrarian effects. Panel A presents the results for equal-weighted returns. For the period 2004 - 2014, the index showed a 12.7% abnormal annualized return for the three-factor model and a 16.3% abnormal annualized return for the five-factor model, both significant at the 1% level.

<Insert Table 3 about here>

We also present the results of social gaming and social networking. Consistent with the results from the broader population, the social gaming index outperformed on a risk-adjusted basis, showing a 13.3% abnormal annualized return for the three-factor model and 17.0% abnormal annualized return for the five-factor model, statistically significant at the 5% and 1% levels. The coefficient on the investment aggressiveness factor (CMA) indicates that more aggressive investments had been made in social gaming than in either social media or social networking. Column 3 shows the results for social networking. There was marginal evidence of outperformance between 2004 and 2014 with a 12.0% abnormal annualized return for the three-factor model (significant at the 10% level) and a 15.6% abnormal return for the five-factor model (significant at the 5% level).

In Panel B, we show the results for the value-weighted indices, which are economically and statistically insignificant. The adjusted R^2 is lower for the value-weighted returns (48.8%) than for the equal-weighted returns (61.3%), based on the five-factor model. Baker and Wurgler (2006) note that theory indicates that large firms will be less effected by sentiment; therefore, they do not conduct their tests of sentiment using value-weighted returns. We follow their approach, and, as a result, the rest of the paper will use equal-weighted indices in further statistical tests.

The evidence from Table 3 is consistent with our first hypothesis that social media firms outperformed on a risk-adjusted basis. The null hypothesis, that the widely applied asset pricing models efficiently price social media stocks, is rejected. In the next section, we will investigate the effects of sentiment on and attention to social media stocks.

4.2. Investor sentiment and attention in social media firms

We considered whether abnormal returns of the social media index were associated with the sentiment of the overall market or investor attention to individual stocks. Over any particular period, one may observe a subset of firms outperforming or underperforming on a risk-adjusted basis. Rather than merely knowing the outperformance of social media stocks over the sample period, we were interested in what type of behavioral factors most likely affected the social media performance. Since the triumph of social media depends on "going viral," what kind of behavioral measures affected its returns? Is social media stock performance associated with a *macro* level of interest captured by market-wide sentiment (Baker & Wurgler 2006)? Alternatively, did a *micro* level measure, as captured by investor attention (Da *et al.* 2011), better reflect the interest? Given that social media firms have generated intense interest from the market, it is worthwhile to understand which factors were most influential for social media stocks.

In Table 4, we report firm-level regression results investigating how sentiment affected social media stock returns. We show results for both the Fama and French three-factor and five-factor models. For each column we considered social media stocks, non-social media stocks from the same 4-digit SIC code, and the combination of the two groups.

<Insert Table 4 about here>

In the full sample shown as Column 1, we have conflicting evidence across the three-factor and five-factor models. The three-factor model shows insignificance of sentiment and a statistically insignificant intercept. The five-factor model shows a significantly positive abnormal return, coupled with a significantly negative coefficient on sentiment. The coefficients on RMW and CMA are significantly negative, having reduced explanatory power from the HML factor, which captures the value premium. The evidence in Column 3 for peer firms of social media firms echoes Column 1, with sentiment acting as a drag during the period 2004 – 2014. Column 2 shows the results for the social media firms. The coefficients on the intercept and sentiment are not statistically different from zero. Interestingly, the coefficients on profitability (RMW) and investment (CMA) are more significantly negative, indicating that social media stocks were weaker in profit margins, presumably due to more aggressive investments captured by a negative CMA coefficient. Column 2 shows the five-factor model fits the best capturing 17.61% of the variation, higher than adjusted R^2 for Columns 1 or 3. Sentiment did not appear to be a priced factor for social media stocks, which rejects our hypothesis that sentiment was influential for social media stocks (H2).

To ensure that we had the power to detect a relation between social media performance and sentiment, we considered the level of sentiment during our sample period. Yu and Yuan (2011) found that sentiment was time dependent. In periods of low sentiment, the mean-variance tradeoff holds, while during high sentiment, it is not apparent. For our sample period, the average University of Michigan consumer sentiment level from 1978 - 2014 was 85.1. During the period 2004 - 2014, average sentiment was 78.7, reflecting lower than average sentiment for our sample period. Of the 132 months in the sample window, only 39 of these months were characterized by high sentiment (above the 85.1 average). Therefore, we believe that we had the power to detect the relation with sentiment, had there been one for social media stocks, which strengthens our findings.

Recent studies by Barber and Odean (2008) and Da *et al.* (2011) indicated that investor attention can affect asset pricing. Given the interest in social media over the past decade, how are these attention-grabbing stocks associated with investor interest? We followed Da *et al.* (2011) and used the search volume index (SVI) data published by Google Trends as a direct measure of investor attention. We collected the SVI arrays for social media firms and their peer companies that shared the same 4-digit SIC code and compared their behavior. For our population, univariate results showed that social media firms had an average SVI and average abnormal SVI of 2.853 and 0.021, respectively. Their industry peers had a lower average SVI, but a slightly higher average abnormal SVI of 2.605 and 0.029, respectively. Note that the abnormal SVI represents the change in investor attention.

Table 5 replaces sentiment with investor attention as a possible explanatory variable for explaining the outperformance of the social media stocks and non-social media stocks from the same 4-digit SIC code. We also studied the results of the combination of the two groups. Unlike the results for sentiment, investor attention appears to be an important factor across all groups for both three-factor and five-factor results, significant at the 1% level for all tests. Social media stocks on average received greater investor attention, and the return impact was slightly more economically significant than it was for peer firms in the same sectors with a lower statistical significance. Consistent with the results from the previous table, the coefficients on profitability (RMW) and investment (CMA) factors were also significantly negative. The results suggest weaker profitability and stronger investment in social media firms relative to their industry peers. The model significance as captured by adjusted R^2 is substantially higher for social media stocks (19.6%) than for their peer firms (12.5%).

<Insert Table 5 about here>

In Table 6, we show the relative significance of the factors driving asset prices by putting both sentiment and investor attention together in the model. Sentiment represents a market-wide excitement, while investor attention is a firm-level factor. Including both factors offers evidence as to which is more important in the pricing of social media stocks. On the one hand, mispricing of social media stocks may arise, as it did in the dot-com era, because investors were rushing to purchase a new generation of concept stocks. On the other hand, investors may be responding to firm information as captured by investor attention, which is a micro level variable.

Tables 6 presents the findings of both three-factor and five-factor models for social media stocks, stocks of peer firms from the same 4-digit SIC code, and for each group separately between 2004 and 2014. For social media stocks, the model intercepts disappear. Sentiment, while statistically insignificant, has driven out the remaining unexplained variation. Attention has a significantly positive association with the performance of social media firms. The adjusted R^2 in the model was slightly lower when sentiment was included (18.4%) than when it was not included in Table 5 (19.6%). Column 3 in Table 6 shows both market-wide sentiment and firm-level attention effects for the pricing of the peer firms. Sentiment acts as a drag on pricing for peer firms, and the result shows it is offset by the impact of investment attention.

<Insert Table 6 about here>

We showed that the micro level measure of investor behavior, attention (ASVI), influenced social media stocks and their peers. This finding is consistent with the finance literature (Da *et al.* 2011). The effect of sentiment on returns, however, varied between social media stocks and their peer firm stocks. Specifically, unlike their peer stocks in the same industries, social media stocks were not associated with the general emotion of the market as captured by investor sentiment. We also found a major difference in the source of asset pricing in Tables 5 and 6. The finding that the investment coefficient (CMA) for social media is about four times higher than those of peer stocks suggests that social media stocks are more sensitive to investment than their peers, which is perhaps more reflective of their innovative nature as social media firms.

5. What Macroeconomic Factors Drive Social Media Performance?

Our previous analysis showed that social media stocks outperformed the market and that investor attention was a significant pricing factor, providing support for our third hypothesis (H3). We then extended our analysis of social media firms to analyze the macroeconomic factors that drove this performance. In this section, we examine the relation between risk-adjusted returns of social media stocks and macroeconomic factors.

5.1. GARCH regression analysis

We initially considered risk premiums from Chen *et al.* (1986) and forward volatility captured by the *VIX* (the CBOE S&P 500 Volatility Index) of Fleming *et al.* (1995). Prior research suggests that the maturity risk premium (*MRP*) can be important in determining the equity premium (Fama & Gibbons 1982; Campbell 1987; Rapach *et al.* 2005). We measured *MRP* as the difference in yield between the 20-year Treasury bond and the 3-month Treasury bill. Campbell *et al.* (2008) and Vassalou and Xing (2004) found the economic importance of default risk in asset pricing. We set the default risk premium (*DRP*) as the difference in the average interest rate between Moody's Baa and Aaa corporate bonds.

We also considered the impact of sentiment on performance. Yu and Yuan (2011) showed the relation between investor sentiment and the mean-variance relation.[12] They found variation in the risk-return relation when investors had different attitudes about prospects. There is a positive tradeoff between risk and return during periods of low investor sentiment. However, the mean-variance relation appeared to weaken during periods of high investor sentiment. Due to the time-rolling nature of the Sharpe ratio calculation, it is appropriate to include a one-lag error in the regression. The dependent variable is the Sharpe ratio (SR_t) of social media stocks[13]. To control the time-variation in error, we used the following GARCH model (Engle 1982):

$$SR_t = (\beta_{0,t} + \sum_{j=1}^{J} \beta_i x_{j,t}) + u_t + \theta u_{t-1}, \text{ and}$$

$$h_t = \omega + \alpha u_{t-1}^2 + \delta h_{t-1} \,, \tag{6}$$

where x_j's are the macroeconomic variables. In addition to equation (6), we considered single-variable regressions.

Table 7 reports the regression results. The GARCH regression results in Column 1 show statistically significant estimates for *DRP* and *VIX*. The findings are consistent with the risk-adjusted returns for social media firms being associated with stress in credit markets, as modeled by the default risk premium. As credit markets required greater risk premiums for liquidity and default, the Sharpe ratio for social media stocks decreased. The negative estimate on the *VIX* suggests that investors of social media stocks in general were inversely sensitive to higher forward risk environments. This may be because social media stocks provided investors new opportunities for those who were sensitive to market volatility. The single-variable regressions showed similar results

[12] Yu and Yuan (2011) use the Baker and Wurgler (2006) investor sentiment measure and check for robustness with the University of Michigan Consumer Sentiment Index. Results were similar with both measures; therefore, we elected to use the index more readily available to us.
[13] We computed the monthly Sharpe ratio of social media stocks by converting the weekly data to match the frequency of the control variables in the GARCH regressions.

to the multiple-variable regression. Consistent with our prior findings, sentiment was not an important factor for social media asset pricing.

<Insert Table 7 about here>

5.2. Causality tests

We further applied Granger (1969) model to test whether these variables were associated with the risk-adjusted returns of social media stocks. We first confirmed that the series was stationary by using augmented Dickey–Fuller (1979) and Phillips–Perron (1988) tests. Using both the Akaike (1974) and the Schwarz (1978) criteria, we set 12 lags as the optimum in the time-series to test whether these variables Granger-cause the Sharpe ratio (*SR*) of the social media stocks.

In Table 8, the *F*-statistics show that the null hypotheses cannot be rejected for the Granger causality test only for sentiment and the maturity risk premium. The regression results from Table 7 suggest a statistical correlation between the Sharpe ratio and two risks: default risk and *VIX*. Granger causality tests further support the possibility that the changes in these variables determine the performance of social media stocks. Interestingly, it appears that projected risk captured by the *VIX* lends Granger causality to the performance of social media stocks. The performance of social media stocks appears to be associated with forward-looking risk and investor attention.

<Insert Table 8 about here>

Our empirical results showed that the return behavior of social media stocks was different from that of the dot-coms in terms of the influence of the overall-economy sentiment. Yu and Yuan (2011) considered the mean-variance implications of sentiment, demonstrating that sentiment seems to be a significant factor only during periods of low sentiment, with the relation decoupling during high sentiment. They suggest that dot-com stock pricing was associated with investor confidence. Our results showed that the risk factors in the economy, including default risk premium and forward volatility, appear to determine the performance of this new group of stocks. We further confirmed the statistical correlation of these risk factors by showing Granger causality tests, which supported the notion that many of these factors influenced the relation for social media firms.

6. Conclusion

Social media has accelerated the pace at which people communicate, socialize, learn, and conduct business. A study of the performance and pricing factors of social media firms has become important to both academia and Wall Street. We studied the performance of social media stocks by following the definition proposed by Kaplan and Haenlein (2010) to set the population of social media firms.

We found that social media firms generated abnormal returns of about 13% to 16% annually over the sample period. All five factors in the Fama-French (2015) model contribute to expected return, as well as investor attention. We also investigated various groups of social media: social networking and social gaming. Outperformance of social media stocks was related to and Granger-caused by default risk premiums and forward volatility, but not investor sentiment. Our findings suggest the pricing behavior of social media stocks differs from their dot-com peers.

Social media stocks should not be simply viewed as a subset of dot-com stocks because their stock prices behave differently. The results regarding the impact of macroeconomic factors on the excess industry-adjusted performance of social media stocks are insightful to understating their pricing behavior.

References

Akaike, H., 1974. A new look at the statistical model identification. IEEE Transactions on Automatic Control 19, 716-723
Baker, M., Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. The Journal of Finance 61, 1645-1680
Barber, B.M., Odean, T., 2008. All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. The Review of Financial Studies 21, 785-818
Bellin, J., 2012. Facebook, Twitter, and the Uncertain Future of Present Sense Impressions. University of Pennsylvania Law Review 160, 331-375
Campbell, J.Y., 1987. Stock Returns and the Term Structure. Journal of Financial Economics 18, 373-399
Campbell, J.Y., Hilscher, J., Szilagyi, J.A.N., 2008. In Search of Distress Risk. The Journal of Finance 63, 2899-2939
Chen, H., De, P., Hu, Y., Hwang, B.-H., 2014. Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media. Review of Financial Studies 27, 1367-1403
Chen, N.-F., Roll, R., Ross, S.A., 1986. Economic Forces and the Stock Market. The Journal of Business 59, 383-403
Cohen, A.J., 2013. Innovation and portfolio management. In: Journal of Portfolio Management, pp. 1-2
Da, Z.H.I., Engelberg, J., Gao, P., 2011. In Search of Attention. The Journal of Finance 66, 1461-1499
DeMarzo, P., Kaniel, R., Kremer, I., 2007. Technological innovation and real investment booms and busts. Journal of Financial Economics 85, 735-754
Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association 74, 427-431
Engle, R.F., 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation Econometrica 50, 987-1007
Fama, E., French, K., 2015. A five-factor asset pricing model. Journal of financial economics 116, 1-22
Fama, E.F., French, K.R., 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33, 3-56
Fama, E.F., Gibbons, M.R., 1982. Inflation, real returns and capital investment. Journal of Monetary Economics 9, 297-323
Fleming, J., Ostdiek, B., Whaley, R.E., 1995. Predicting stock market volatility: A new measure. Journal of Futures Markets 15, 265-302
Granger, C.W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: Journal of the Econometric Society 37, 424-438
Griffin, J.M., Harris, J.H., Shu, T.A.O., Topaloglu, S., 2011. Who Drove and Burst the Tech Bubble? The Journal of Finance 66, 1251-1290
Heimer, R., Simon, D., 2015. Facebook Finance: How Social Interaction Propagates Active Investing. Federal Reserve Bank of Cleveland Working Paper No. 15-22
Hendershott, R.J., 2004. Net value: wealth creation (and destruction) during the internet boom. Journal of Corporate Finance 10, 281-299
Hodrick, R.J., Prescott, E.C., 1997. Postwar U.S. business cycles: An empirical investigation. Journal of Money, Credit, and Banking 29, 1-16

Hsieh, J., Walkling, R.A., 2006. The history and performance of concept stocks. Journal of Banking & Finance 30, 2433-2469
Janoski-Haehlen, E.M., 2011. The Courts are all a'Twitter': The Implications of Social Media Use in the Courts. Valparaiso University Law Review 46, 43-68
Kaplan, A.M., Haenlein, M., 2010. Users of the world, unite! The challenges and opportunities of Social Media. Business Horizons 53, 59-68
Karabulut, Y., 2013. Can Facebook Predict Stock Market Activity? AFA 2013 San Diego Meetings Paper. Available at SSRN: http://ssrn.com/abstract=2017099
Kim, A.J., Ko, E., 2012. Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. Journal of Business Research 65, 1480-1486
Larcker, D.F., Larcker, S.M., Tayan, B., 2014. Monitoring Risks Before They Go Viral: Is it Time for the Board to Embrace Social Media? Working Paper: Rock Center for Corporate Governance at Stanford University - CGRP-25. Available at SSRN: http://ssrn.com/abstract=2035072.
Ljungqvist, A., Wilhelm, W.J., Jr., 2003. IPO Pricing in the Dot-Com Bubble. The Journal of Finance 58, 723-752
Luo, X., Zhang, J., Duan, W., 2013. Social Media and Firm Equity Value. Information Systems Research 24, 146-163
Nair, M., 2011. Understanding and measuring the value of social media. Journal of Corporate Accounting & Finance 22, 45-51
O'Leary, D.E., 2011. The Use of Social Media in the Supply Chain: Survey and Extensions. Intelligent Systems in Accounting, Finance and Management 18, 121-144
Ofek, E., Richardson, M., 2003. DotCom Mania: The Rise and Fall of Internet Stock Prices. The Journal of Finance 58, 1113-1137
Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335-346
Rapach, D.E., Wohar, M.E., Rangvid, J., 2005. Macro variables and international stock return predictability. International Journal of Forecasting 21, 137-166
Schwarz, G., 1978. Estimating the Dimension of a Model. The Annals of Statistics 6, 461-464
Sornette, D., Cauwels, P., 2012. The Illusion of the Perpetual Money Machine. In: White Paper Series Academy N (Ed.), pp. 1-27. ETH Zurich
Trainor, K.J., Andzulis, J., Rapp, A., Agnihotri, R., 2014. Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM. Journal of Business Research 67, 1201-1208
Tsukioka, Y., Yanagi, J., Takada, T., (2018). Investor sentiment extracted from internet stock message boards and IPO puzzles. International Review of Economics and Finance, forthcoming.
Vassalou, M., Xing, Y., 2004. Default Risk in Equity Returns. The Journal of Finance 59, 831-868
Vickery, G., Wunsch-Vincent, S., 2007. Participative web and user-created content: Web 2.0, wikis and social networking. Organisation for Economic Co-operation and Development.
Yu, J., Yuan, Y., 2011. Investor sentiment and the mean–variance relation. Journal of Financial Economics 100, 367-381

Table 1. Social media firms
The table reports social media firms that form the population. We follow the definition of social media firms from Kaplan and Haenlein (2010) to manually identify the 43 social media firms. Column A lists the name of the firm. Column B classifies the firm as either social networking (N) or social gaming (G). Column C describes the rationale for membership as a social media firm. Columns D and E show the beginning and ending dates for membership as social media firms, listed by year and then month.

(A) Company Name	*(B) Social*	*(C) Description*	*(D) Begin*	*(E) End*
A O L INC	N	media platform, social networking (bebo and about.me)	200912	201412
ANCESTRY COM INC	N	genealogy community	200911	201212
BAIDU COM INC	N	news service, content, and social chat	200508	201412
FACEBOOK INC	N	social networking	201205	201412
GEEKNET INC	N	technology social networking and news	200401	201412
GOOGLE INC	N	social networking (Orkut, Google Blog, Picasa, Google+)	200408	201412
IAC INTERACTIVECORP	N	search applications, online dating, vimeo, ask.com	200401	201412
JIAYUAN COM INTL LTD	N	Chinese online dating social network space	201105	201412
LINKEDIN CORP	N	professional social networking	201105	201412
REDIFF COM INDIA LTD	N	Indian news; social networking (Rediff MyPage)	200401	201412
RENREN INC	N	Chinese social networking service	201105	201412
SINA CORP	N	Chinese social networking (personal and professional)	200401	201412
SOHU COM INC	N	Chinese content community and social networking	200401	201412
TWITTER	N	real-time conversation - social expression	201311	201412
UNITED ONLINE LTD	N	social networking and Internet provider	200401	201412
WEIBO CORPORATION	N	social media in support of Chinese language acquisition	201404	201412
YAHOO INC	N	news and social chat (Flickr, Tumblr, Yahoo 360)	200401	201412
YANDEX N V	N	Russian social network and search engine	201105	201412
YELP INC	N	business reviews and online yelper social space	201203	201412
YOUKU COM INC	N	Chinese video content library; Internet television & video	201012	201412
YY INC.	N	Chinese social networking	201211	201412

ACTIVISION BLIZZARD INC	G	social gaming	200401	201412
ANSWERS CORP	G	user generated answers + reference materials	200410	201104
CHANGYOU COM LTD	G	Chinese social gaming	200904	201412
CHINA MOBILE GAMES	G	Chinese social gaming	201209	201412
ELECTRONIC ARTS INC	G	social gaming and software services	200401	201412
GIANT INTERACTIVE GROUP	G	Chinese social gaming	200711	201407
GIGAMEDIA LIMITED	G	Taiwanese social gaming and cloud computing	200401	201412
GLU MOBILE INC.	G	social gaming	200703	201412
GRAVITY CO. LTD	G	social gaming	200502	201412
KING DIGITIAL ENTERTAINMENT	G	social gaming	201403	201412
KONGZHONG CORP.	G	Chinese social gaming	200407	201412
MAJESCO ENTERTAINMENT CO	G	social gaming	200501	201412
NETEASE COM INC	G	Chinese social gaming	200401	201412
PERFECT WORLD CO LTD	G	Chinese social gaming	200707	201412
PHEONIX NEW MEDIA LTD	G	Chinese social gaming	201105	201412
SHANDA GAMES LTD	G	Chinese social gaming	200909	201412
TAKE TWO INTERACTIVE	G	social gaming and video gaming	200401	201412
TAOMEE HOLDINGS LTD	G	Chinese social gaming	201106	201412
THE9 LIMITED	G	Chinese social gaming	200412	201412
WEBZEN INC	G	South Korean social gaming	200401	201007
XUNLEI LTD	G	Chinese social gaming and cloud services	201406	201412
ZYNGA INC	G	social gaming	201112	201412

Table 2. Summary statistics
The table reports the number of firm-month observations, minimum, median, maximum, mean, and standard deviation of the monthly returns and market value of equity of social media stocks, industries in which social media firms are members (peer firms), and the universe of U.S. stocks from CRSP (excluding penny stocks). Panel A includes the monthly returns. Panel B contains the natural logarithm of market value of equity (in millions). The time period for the population is January 1, 2004 – December 31, 2014. We follow the definition of social media firms from Kaplan and Haenlein (2010) to manually identify the 43 social media firms.

Firm type	*N*	*Min*	*Median*	*Max*	*Mean*	*Standard Deviation*
			Panel A: Monthly returns			
Social Media	2,127	-0.4802	0.0113	1.1907	0.0212	0.1376
Peer Firms	37,726	-0.8562	0.0121	3.8594	0.0219	0.1288
US Stocks	611,024	-0.8686	0.0096	13.4951	0.0136	0.1037
			Panel B: Natural logarithm of market value of equity (except N)			
Social Media	2,127	16.7140	21.6712	26.5482	21.8234	1.8816
Peer Firms	37,726	13.9043	20.5247	26.6930	20.4704	1.9680
US Stocks	611,024	11.1211	20.3179	27.2640	20.2997	2.0117

Table 3. Regression results for social media indexes

This table contains regression results for indices of social media firms for the period January 1, 2004 - December 31, 2014. The indices are formed by equal weighting (Panel A) or by value weighting (Panel B) monthly raw returns to form three indices: social media (43 firms) and its two subgroups of social gaming (22 firms) and social networking (21 firms). The index returns are regressed on risk factors (excess market return (Mkt - R_f), size (SMB), value (HML), profitability (RMW) and investment patterns (CMA)) for the Fama-French three-factor (1993) and five-factor (2015) models. The coefficients shown reflect the coefficient on the intercept and their associated *t* statistics. Monthly returns are calculated by subtracting the adjusted stock price from CRSP from the previous month's adjusted stock price and by dividing by the previous month's adjusted stock price. Panel A shows results for equal-weighted index returns for social media (Column 1), social gaming (Column 2), and social networking (Column 3) indices. Panel B shows results for value-weighted index returns for social media (Column 4), social gaming (Column 5), and social networking (Column 6) indices. The risk factors are obtained from Ken French's website. Tests of significance at traditional levels of 1%, 5%, and 10% are indicated with ***, **, and *.

Dependent Variable - Monthly Returns

	Panel A: Equal weighted					
	Column 1: Social Media		*Column 2: Social Gaming*		*Column 3: Social Networking*	
Variables	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*
Intercept	0.0106***	0.0136***	0.0111**	0.0142***	0.0100*	0.0130**
	(2.42)	(3.04)	(2.07)	(2.61)	(1.86)	(2.32)
Mkt - R_f	1.3257***	1.1827***	1.2983***	1.1414***	1.3602***	1.2301***
	(11.07)	(9.26)	(8.85)	(7.33)	(9.28)	(7.69)
SMB	0.5694***	0.4540**	0.3803	0.2801	0.6839***	0.5515**
	(2.67)	(2.10)	(1.45)	(1.06)	(2.62)	(2.04)
HML	-0.8038***	-0.6242***	-0.4770**	-0.1648	-1.0965***	-1.0310***
	(-4.08)	(-2.93)	(-1.98)	(-0.63)	(-4.55)	(-3.86)
RMW		-0.7181**		-0.6958*		-0.7436*
		(2.16)		(-1.71)		(-1.78)
CMA		-0.8616***		-1.3150***		-0.4473
		(-2.41)		(-3.02)		(-1.00)
Adjusted R^2	0.5895	0.6130	0.4598	0.4966	0.5138	0.5209

Panel B: Value weighted

	Column 4: Social Media		Column 5: Social Gaming		Column 6: Social Networking	
Variables	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*
Intercept	-0.0007**	-0.0006*	-0.0005	-0.0002	-0.0004	-0.0002
	(-2.04)	(-1.72)	(-0.52)	(-0.25)	(-0.56)	(-0.23)
$Mkt - R_f$	0.0940***	0.0892***	0.1858***	0.1728***	0.1712***	0.1586***
	(9.69)	(8.38)	(7.15)	(6.06)	(8.25)	(6.99)
SMB	0.0130	0.0106	0.0228	0.0161	0.0210	0.0132
	(0.75)	(0.59)	(0.49)	(0.33)	(0.57)	(0.34)
HML	-0.0774***	-0.0668***	-0.1016***	-0.0762	-0.1485***	-0.1228***
	(-4.84)	(-3.76)	(-2.38)	(-1.60)	(-4.35)	(-3.24)
RMW		-0.0197		-0.0568		-0.0559
		(-0.71)		(-0.76)		(-0.95)
CMA		-0.0452		-0.1040		-0.1038
		(-1.52)		(-1.30)		(-1.64)
Adjusted R^2	0.4850	0.4878	0.3285	0.3294	0.4033	0.4095

Table 4. Stock pricing and sentiment

The table reports regression results of sentiment in asset pricing for the period January 1, 2004 – December 31, 2014, for the Fama- French three-factor (1993) and five-factor (2015) models, and shows results for social media stocks and stocks from the same 4-digit SIC code combined (Column 1) and for each group separately (Columns 2 and 3). Returns are regressed on risk factors (excess market return (Mkt - R_f), size (SMB), value (HML), profitability (RMW), and investment patterns (CMA)) for the Fama-French three-factor (1993) and five-factor (2015) models. The coefficients shown reflect the coefficient on the intercept and their associated *t* statistics. We use monthly stock return data for 43 social media stocks and 1,299 non-social media stocks that share the 4-digit SIC code. The risk factors are obtained from Ken French's website. Tests of significance at traditional levels of 1%, 5%, and 10% are indicated with ***, **, and *.

Dependent Variable - Monthly Returns

	Column 1: All		*Column 2: Social Media*		*Column 3: Peer Firms*	
Variables	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*
Intercept	0.00036	0.0886***	-0.05049	0.09659	0.00512	0.08877***
	(0.01)	(3.73)	(-0.55)	(1.01)	(0.22)	(3.62)
Mkt - R_f	0.9916***	0.9229***	1.3759***	1.2645***	0.9664***	0.8994***
	(47.19)	(42.40)	(15.72)	(13.71)	(44.65)	(40.15)
SMB	0.7520***	0.5757***	0.5746***	0.4054***	0.7642***	0.5892***
	(23.28)	(16.59)	(4.13)	(2.79)	(23.02)	(16.49)
HML	-0.4467***	-0.3780***	-0.8058***	-0.4837***	-0.4247***	-0.3754***
	(-13.26)	(-9.64)	(-5.82)	(-3.07)	(-12.23)	(-9.27)
RMW		-0.6577***		-0.7674***		-0.6487***
		(-12.67)		(-3.35)		(-12.17)
CMA		-0.3672***		-1.1738***		-0.3115**
		(-6.11)		(-4.73)		(-5.03)
ln(Sentiment)	0.0058	-0.04006***	0.03118	-0.04534	0.00340	-0.04004***
	(0.48)	(-3.19)	(0.64)	(-0.90)	(0.27)	(-3.09)
Adjusted R^2	0.1130	0.1177	0.1640	0.1761	0.1102	0.1146

Table 5. Stock pricing and attention

The table reports regression results of investor attention in asset pricing for the period January 1, 2004 – December 31, 2014, for the Fama-French three-factor (1993) and five-factor (2015) models, and shows results for social media stocks and stocks of peer firms from the same 4-digit SIC code combined (Column 1) and for each group separately (Columns 2 and 3). Returns are regressed on risk factors (excess market return (Mkt - R_f), size (SMB), value (HML), profitability (RMW), and investment patterns (CMA)) for the Fama-French three-factor (1993) and five-factor (2015) models. The coefficients shown reflect the coefficient on the intercept and their associated *t* statistics. We use monthly stock return data for 43 social media stocks and 1,299 non-social media stocks that share the 4-digit SIC code. Abnormal Search Volume Index (*ln* (ASVI)) is defined by Da *et al.* (2011) to directly measure the change in investor attention. The risk factors are obtained from Ken French's website. Tests of significance at traditional levels of 1%, 5%, and 10% are indicated with ***, **, and *.

Dependent Variable - Monthly Returns

	Column 1: All		*Collumn 2: Social Media*		*Column 3: Peer Firms*	
Variables	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*
Intercept	0.0110***	0.0127***	0.0101***	0.0130***	0.0111***	0.0128***
	(16.71)	(19.01)	(3.62)	(4.49)	(16.44)	(18.57)
Mkt - R_f	0.9911***	0.9215***	1.3573***	1.2242***	0.9665***	0.9000***
	(51.28)	(45.96)	(17.26)	(14.49)	(48.47)	(43.59)
SMB	0.6767***	0.5304***	0.5353***	0.4145***	0.6868***	0.5407***
	(21.46)	(15.74)	(3.93)	(2.93)	(21.20)	(15.59)
HML	-0.4486***	-0.4026***	-0.8324***	-0.5667***	-0.4247***	-0.3964***
	(-13.87)	(-10.62)	(-6.26)	(-3.74)	(-12.74)	(-10.12)
RMW		-0.5779***		-0.6570***		-0.5705***
		(-11.84)		(-3.06)		(-11.39)
CMA		-0.3214***		-1.0206***		-0.2712***
		(-5.42)		(-4.18)		(-4.43)
ln(ASVI)	0.0115***	0.0113***	0.0142***	0.0140***	0.0113***	0.0111***
	(11.41)	(11.31)	(3.22)	(3.18)	(10.93)	(10.84)
Adjusted R^2	0.1250	0.1292	0.1866	0.1963	0.1214	0.1253

Table 6. Stock pricing, sentiment, and attention
The table reports regression results of sentiment and attention in asset pricing for the period January 1, 2004 – December 31, 2014, for the Fama-French three-factor (1993) and five-factor (2015) models, and shows results for social media stocks and stocks of peer firms from the same 4-digit SIC code combined (Column 1) and for each group separately (Columns 2 and 3). Returns are regressed on risk factors (excess market return (Mkt - R_f), size (SMB), value (HML), profitability (RMW), and investment patterns (CMA)) for the Fama-French three-factor (1993) and five-factor (2015) models. The coefficients shown reflect the coefficient on the intercept and their associated *t* statistics. We use monthly stock return data for 43 social media stocks and 1,299 non-social media stocks that share the 4-digit SIC code. Abnormal Search Volume Index (*ln* (ASVI)) is defined by Da *et al.* (2011) to directly measure the change in investor attention. The risk factors are obtained from Ken French's website. Tests of significance at traditional levels of 1%, 5%, and 10% are indicated with ***, **, and *.

	Dependent Variable - Monthly Returns					
	Column 1: All		*Column 2: Social Media*		*Column 3: Peer Firms*	
Variables	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*	*Three-factor*	*Five-factor*
Intercept	-0.00385	0.08686***	-0.07217	0.08423	0.00230	0.08766***
	(-0.16)	(3.54)	(-0.76)	(0.85)	(0.09)	(3.46)
Mkt - R_f	1.00502***	0.9329***	1.3858***	1.2763***	0.9800***	0.9092***
	(47.14)	(41.82)	(15.59)	(13.45)	(44.63)	(39.61)
SMB	0.7222***	0.5722***	0.5383***	0.4053***	0.7348***	0.5853***
	(21.84)	(16.36)	(3.78)	(2.76)	(21.61)	(16.26)
HML	-0.4831***	-0.3913***	-0.8277***	-0.4646***	-0.4615***	-0.3909***
	(-14.00)	(-9.67)	(-5.84)	(-2.87)	(-12.97)	(-9.35)
RMW		-0.6154***		-0.6673***		-0.6103***
		(-11.52)		(-2.82)		(-11.14)
CMA		-0.3843***		-1.2457***		-0.3243***
		(-6.19)		(-4.87)		(-5.07)
ln(Sentiment)	0.00798	-0.03924***	0.04305	-0.03877	0.00484	-0.0396***
	(0.64)	(-3.03)	(0.86)	(-0.74)	(0.38)	(-2.96)
ln(ASVI)	0.0112***	0.01107***	0.01442***	0.01460***	0.01096***	0.01083***
	(10.73)	(10.64)	(3.21)	(3.27)	(10.23)	(10.13)

Adjusted R^2	0.1193	0.1237	0.1720	0.1842	0.1163	0.1203

Table 7. GARCH regression of macroeconomic factors on Sharpe ratios of social media stocks
The table reports the GARCH regression results of the variables affecting the Sharpe ratio of social media stocks (*SR*) using monthly data for January 1, 2004 - December 31, 2014. The regression models are $SR_t = (\beta_{0,t} + \sum_{j=1}^{J} \beta_i x_{j,t}) + u_t + \theta u_{t-1}$, and the variance equation is $h_t = \omega + \alpha u_{t-1}^2 + \delta h_{t-1}$, where x_j's are the macroeconomic variables. The maturity risk premium (*MRP*) is the difference in yield between the 20-year Treasury bond and the 3-month Treasury bill; the default risk premium (*DRP*) is the difference in the average interest rate between Moody's Baa and Aaa corporate bonds; and *VIX* is the CBOE S&P 500 Volatility Index. *Sentiment* is taken as the University of Michigan Consumer Sentiment Index. Panel A shows the results of the regressions. The variance equations are reported in Panel B. Tests of significance at traditional levels of 1%, 5%, and 10% are indicated with ***, **, and *.

Panel A: GARCH Regression					
Variable	*Column 1*	*Column 2*	*Column 3*	*Column 4*	*Column 5*
Constant	0.030	0.035***	0.027***	0.042***	0.039
	(0.34)	(2.34)	(2.54)	(3.07)	(0.99)
MRP	0.884*	0.720			
	(1.73)	(1.15)			
DRP	4.483***		0.522***		
	(3.46)		(3.76)		
VIX	-0.004***			-0.005***	
	(-3.28)			(-3.83)	
Sentiment	-0.001				-0.001
	(-0.09)				(-0.15)
Durbin-Watson	0.304	0.306	0.307	0.304	0.306
Panel B: Variance Equation					
ω	0.003**	0.002***	0.002***	0.002***	0.002***
	(2.24)	(2.46)	(2.53)	(2.48)	(2.50)
α	0.853***	0.723**	0.710*	0.736*	0.716**
	(3.42)	(2.02)	(1.93)	(1.95)	(1.99)
δ	-0.230	0.039	0.073	0.011	0.054
	(-1.36)	(0.28)	(0.56)	(0.09)	(0.41)

Table 8. Granger causality tests
The table reports the results of pairwise Granger (1969) causality tests. The null hypotheses are the variables (*MRP, DRP, ln(VIX),* ln(*aSVI*), and ln(*Sentiment*)) do not Granger cause the Sharpe ratio of social media stocks (SR_{SM}). We first check that the series are stationary by using augmented Dickey–Fuller (1979) and Phillips–Perron (1988) tests and find that all series are stationary. Using both the Akaike (1974) and the Schwarz (1978) criteria, we set 12 lags as the optimum in the time-series to test whether these variables Granger-cause *SR*. The *F*-statistics and probabilities are shown.

	F value	*Prob.*
MRP does not Granger cause SR_{SM}	0.895	0.555
DRP does not Granger cause SR_{SM}	2.028	0.030
VIX does not Granger cause SR_{SM}	2.346	0.011
ln(*aSVI*) does not Granger cause SR_{SM}	2.248	0.021
ln(*Sentiment*) does not Granger cause SR_{SM}	1.333	0.213

Figure 1. Social media index vs. S&P 500 and Nasdaq
The social media index plotted against the returns on the S&P500 and the Nasdaq Index. Returns were computed monthly for the period January 1, 2004 - December 31, 2014. The social media index was computed as an equal-weighted index of the 43 social media firms that comprise the population.

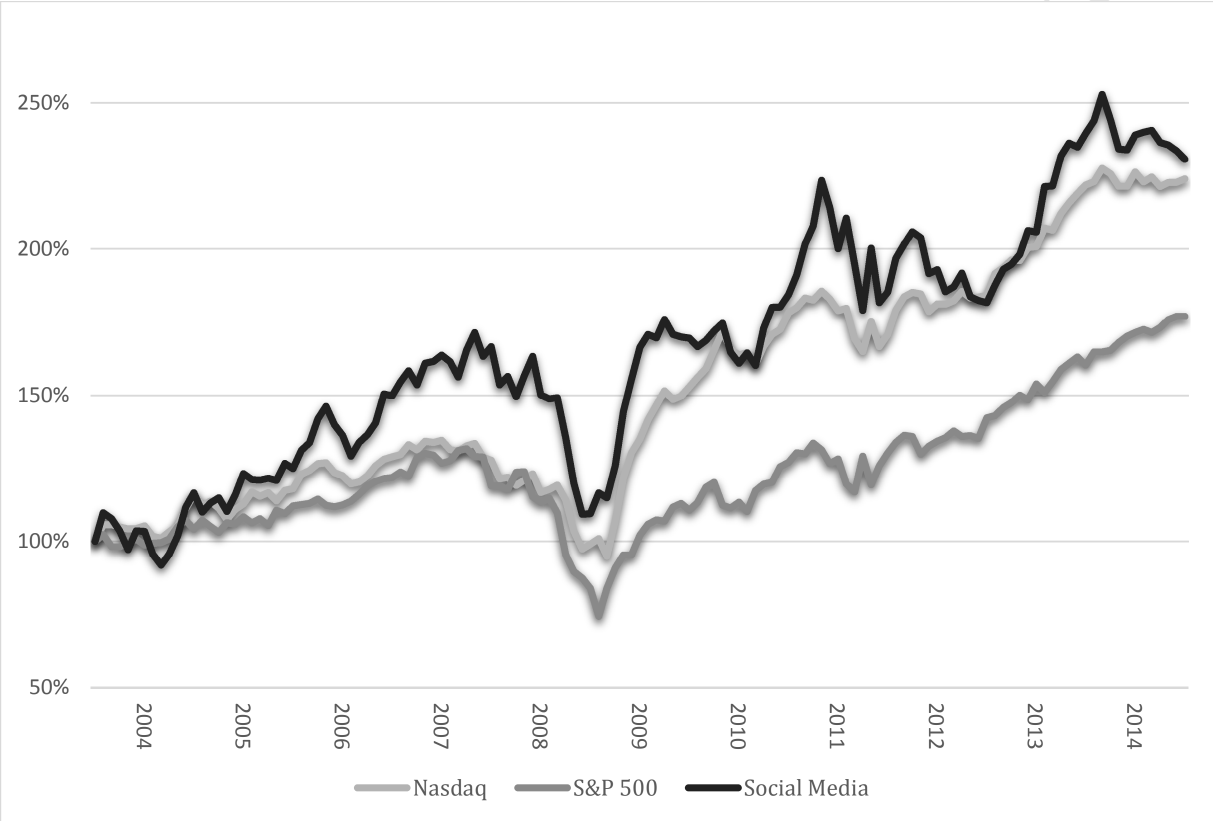
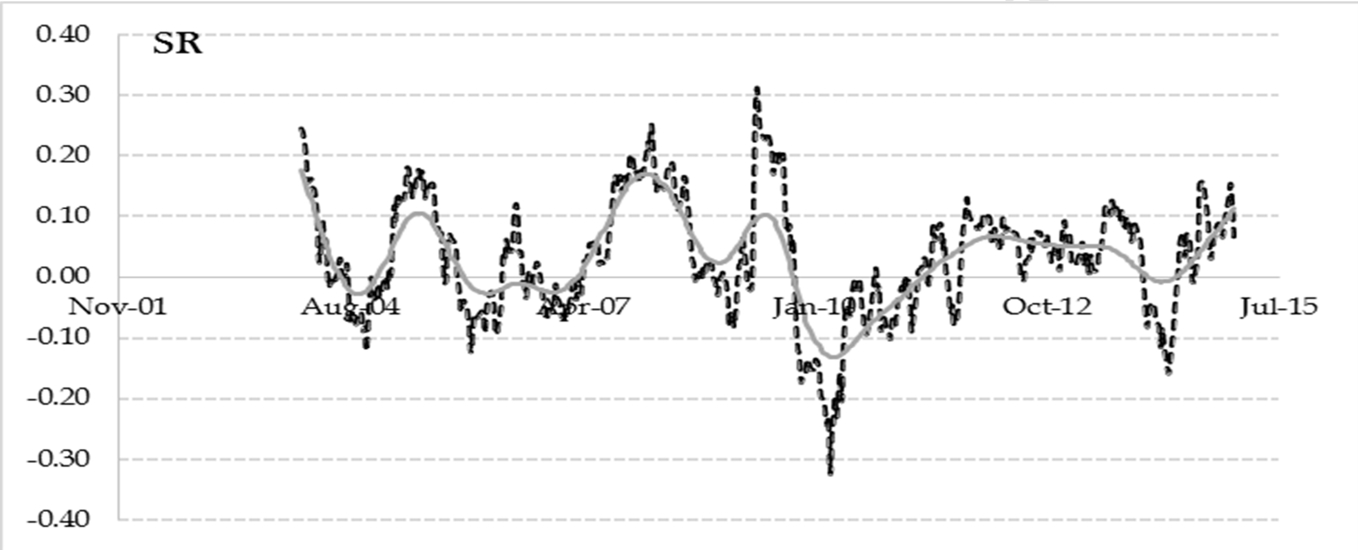


Figure 2. Sharpe ratio of social media stocks
The mean of Sharpe ratios of social media stocks between the period January 1, 2004 - December 31, 2014, and its smoothing curve are presented. The Sharpe ratio is computed by using the 52 weekly returns. The long-term trend is illustrated and smoothed by the filter proposed by Hodrick and Prescott (1997) for the actual time-series (H-P) which is the gray curve.



Appendix: Population Identification

The social media firms do not emanate from a common SIC or NAICS industry code. Thus, setting the population was a laborious process of searching firms and testing stocks against an objective, academic definition. In this study, we applied the definition proposed by Kaplan and Haenlein (2010) to a subpopulation of firms that we deemed unequivocally to be members of the social media industry, such as Facebook, Google, and Yelp. The common Yahoo! industry category for these firms was Internet Information Providers. Each of the 217 firms from the Yahoo! list for this industry, downloaded on May 2015, was considered as a potential member of social media (whether or not the firm was public). In addition, Global X Funds retails a social media ETF (SOCL) with 29 firms as of December 31, 2014. From these initial lists of candidate firms, we eliminated firms that did not meet the social media definition. Given the requirements of a web-based platform, we also searched the 1,000 most active websites by web traffic from the Alexa List of Top Million websites based on one-month average traffic, downloaded on May 14, 2015.

We then searched for additional candidate firms by identifying the competitors of our initial list of social media firms and testing these firms against the objective social media definition using Mergent Online, Lexis Nexis, and Value Line. These databases provided a list of competitors, which we added to our list as potential firms of the population. We compiled a list of industry codes and searched all CRSP-listed firms within these 18 sectors defined by 4-digit SIC codes traded on the NYSE, Amex, and Nasdaq. We considered each firm that appeared in these SIC codes as a candidate for the social media population.

We manually investigated whether and when the firm had a user interface that fit the three criteria defined by Kaplan and Haenlein (2010). These sites could also have a more enhanced, fee-based model (like LinkedIn), but they needed to host a platform beyond merely a comment portal in support of a normal product line for the firm. For example, Amazon.com has a very active user-generated comment interface, but the portal exists to complement Amazon's business model of retailing products. Thus, Amazon.com was not deemed to be a social media firm. On the other hand, Google has a very active search interface that is widely used. It also offers a social media interface known as Google+. The presence of the Google+ social space merits Google's inclusion in the social media population. Many firms fit the definition of a social media firm, but remained either privately-held, traded on an exchange outside the United States, or traded as penny stocks. We list them in Table A1. Our final population consists of 43 social media firms between the years 2004-2014.

Table A1 Social media firms not in the population

We present social media companies that were not included in the current study. We report their type (privately-held, publicly-traded, or penny stocks), country of firm headquarters, exchange that shares are traded on, and category (social networking or social gaming).

Firm Name	Type	Country	Exchange	Category
Arkadium	private	United States	N/A	SG
Linden Labs	private	United States	N/A	SG
Peak Games	private	Turkey	N/A	SG
Pinterest	private	United States	N/A	SN
Pretty Simple	private	France	N/A	SG
Socialpoint	private	Spain	N/A	SG
Supercell	private	Finland	N/A	SG
Wooga	private	Germany	N/A	SG
Com2uS Corp	public	Korea	KRX	SG
Cupid	public	London	LSE	SN
CyberAgent, Inc.	public	Japan	TYO	SN
Daum Kakao Corp.	public	South Korea	KRX	SG
Dena Co. Ltd.	public	United States	OTC	SG
Forgame Holdings Ltd	public	Hong Kong	SEKH	SG
Gameloft SE	public	France	EPA	SG
Gree	public	Japan	Shenzen	SN
Mail.Ru Group Limited	public	United Kingdom	LSE	SN
Snapchat	public	United States	OTC	SN
Tencent Holdings Limited	public	Hong Kong	SEKH	SG
Xing AG	public	Germany	FWB	SN
Mixi Inc	public	Japan	TYO	SN
MeetMe, Inc.	penny	United States	Nasdaq	SN
Spark Networks	penny	United States	NYSE	SN