**Does social-media sentiment predict stock returns? Evidence from Twitter**

**Author:** Dr. Konpanas Dumrongwong

**Affiliation:** Department of Finance, Thammasat University, Bangkok, Thailand

**Corresponding Author:** Dr. Konpanas Dumrongwong

**Email address:** konpanas@tbs.tu.ac.th

**Does social-media sentiment predict stock returns? Evidence from Twitter.**

**Abstract**

Using a novel Twitter-based investor sentiment index, this research investigates whether investor sentiment, as expressed in Twitter daily messages, contain predictive power with respect to the US stock returns. Based on conventional linear framework, the empirical results show that Twitter sentiment index has additional predictive power toward the US stock returns, not captured by traditional factors such as market risk premium, firm size, book-to-market ratio or momentum. The results suggest that investor sentiment, as expressed in Twitter messages, is “relevant” for asset pricing.

**JEL Classification**: G12, G40

**Keywords**: behavioral finance, investor sentiment, empirical asset pricing

**1. Introduction**

A long-running debate among finance academia concerns the possible effect of investor sentiment on asset prices. Traditional theorical asset pricing model such as the capital asset pricing model (CAPM) are generally unreliable in explaining the movement of real-world stock returns and pose many challenges in practice. Many versions of empirical asset pricing models exist and some of them are arguably better at explaining realized equity returns. The famous Fama-French 3 factor model (Fama and French, 1993), Carhart 4 factor model (Carhart, 1997) and Fama-French 5 factor model (Fama and French,2015) are good examples of such models. Although these models are more successful at explaining equity returns, it is still unclear what are the risk (or risks) truly represented by the empirical factors in these models. For example, it is unclear what risk(s) are actually represented by the book-to-market ratio (B/M, the ratio of the book value of a common stock to its market value). Similar arguments apply to other empirical factors such as firm size or momentum. Therefore, it remains inconclusive if these are the only factors relevant to stock returns or there are other unknown factor(s) which contain additional predictive power not contained by aforementioned factors.

As the search for a “better” empirical model continues, instead of relying on rationality assumption, some academia has shifted the academic focus to investigate the relations between asset prices and investor sentiment. The existence of noise traders and psychological biases are primary subjects of investigating the impact of investor sentiment on stock prices. For instance, De Long *et al*. (1990) show that irrational noise traders could not be offset by limited arbitrageurs and with diverse sentiment, they could affect the stock prices and earn higher expected returns. However, since it was not possible to directly observe investor sentiment without an intrusive survey, many studies relied on indirect proxies, such as closed-end fund discounts (Lee *et al*., 1991), bid-ask spread and turnover (Baker and Stein, 2004), consumer confidence (Lemmon and Portniaguina, 2006; Schmeling 2009) or a combination of these indirect proxies (Baker and Wurgler, 2006). Although these traditional measures of investor sentiment provide some useful insights into the relationship between asset prices and investor sentiment, they have their disadvantages. For instance, the market-based proxies have many confounding factors, and the survey-based proxies cannot guarantee response quality.

The present research shed a new light on the issue of investor rationality by bringing new data and new techniques to the question. Specifically, a direct online measure of investor sentiment was employed instead of relying on indirect proxies. The measure, which are observed passively, allows for a direct estimate of investor sentiment while minimizing the problem of response quality. The primary distinction between the present paper and prior studies is two folds. First, this research employs a novel proxy for investor sentiment constructed from Twitter, with the advantage of avoiding the endogeneity and directly capturing investor sentiment at a high frequency. Unlike survey-based proxy, an online-search-based measures *reveal* attitudes rather than *inquire* about them. This makes the measure less prone to biases compared to survey-based measure of sentiment. Second, the empirical results presented in this study support recent empirical theories that investor sentiment index constructed from social-media has predictive power with respect to the US stock returns. This predictive power is not previously explained by popular risk factors in financial literature such as market risk premium, firm size, book-to-market ratio or momentum.

The remainder of the paper is structured as follows. The following section presents a review of the literature regarding investor sentiment and its implications for stock return. The next section describes the research hypotheses, data and methodology. The empirical results are then presented and discussed. Finally, the conclusions are given, along with research limitations and suggestions for future research.

**2. Literature review**

Traditional risk-based asset pricing model such as the capital asset pricing model (CAPM) established that prices reflect the consensus investor’s expectation of risks associate with their investment and assume the existence of a theoretical market portfolio, which is unobservable and perfectly diversified (see, Markowitz, 1952; Sharpe, 1964; Litner, 1965; Fama, 1970; Black 1972; among others for the theoretical underpinnings). However, the practicality of the CAPM is largely debatable because the model requires many strict assumptions such as all investors are required to be rational and the informational efficiency of both market and investors must be perfect, among other assumptions. In practice, it is very challenging to reconcile these unrealistic conditions in real world applications.

Many scholars argue strongly against the validity of the CAPM. Many empirical studies document the existence of trends in stock returns as well as model limitations, contradicting the CAPM prediction. For example, Banz (1981) documents that when stocks are sorted on market capitalization, average returns on small stocks are higher than predicted by the CAPM. Stambaugh (1982) argue that the tests of the CAPM are not sensitive to expanding the market proxy beyond common stocks, which contradict the definition of market portfolio in the CAPM. Rosenberg *et al*. (1985) show that stocks with high book-to-market ratios have high average returns that are not captured by betas. These contradicting evidences ultimately lead Fama and French (2004) to conclude in their literature that “the failure of the CAPM in empirical tests implies that most applications of the model are invalid” (pp. 26).

Some academia proposed an idea of arbitrage-free equilibrium as an alternative model for CAPM. (see Ross (1976), among others, for the arbitrage pricing theory: APT). The APT allow each investor to hold a unique portfolio with its own particular array of betas, as opposed to the identical market portfolio required in CAPM. In addition, according to the APT, although some investors may not be rational, their irrationalities should be quickly offset by arbitrageurs. However, behavioral finance theory consistently suggests the presence of noise traders in the stock market with correlated behavior as well as limits on arbitrage as limiting conditions that can lead investor sentiment to influence asset prices (Shleifer and Summers 1990; Lee *et al*. 1991; Shleifer and Vishny, 1997; Baker and Wurgler, 2006, among others). Notable among the literatures includes De Long *et al*. (1990) who models the influence of noise trading on equilibrium prices and show that noise trading affects stock prices and noise traders can earn higher expected returns. Shleifer and Vishny (1997) show that there are limits on risky arbitrage positions which can cause changes in security prices. And Baker and Wurgler (2006) document that investor sentiment contains functional predictive content about stock returns.

Overall, stock market prediction had been the topic of long debates among academia for decades, and the true set of drivers behind the stock returns movement still remain inconclusive. One of an important aspect of such question is whether investor sentiment predicts stock returns. Several theoretical studies offer various behavioral-based models establishing the linkage between asset prices and investor sentiment. For example, it has been documented that investors may form erroneous beliefs, either with excessive optimism or pessimism, and therefore incorrectly evaluate asset values, causing asset prices movements (Black, 1986; De Long *et al*., 1990; Baker *et al*., 2012; among others).

Notable among the literature is a prior study by Baker and Wurgler (2007) who shows that investor sentiment predictive content in relation to the future market movements can act as a valuable information for the traders in forming profitable trading strategies. They broadly define investor sentiment as “investors belief about future cash flows and risk not justified by the facts at hand” and note that “Now, the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects.” (p.130). The present research employs these definitions and further analyze the link between investor’s sentiment and stock returns, using a new data and new methodology of measuring sentiment.

A growing body of research document the relationship between investor sentiment and asset prices. For example, Baker *et al*. (2012) investigate stock prices in Canada, France, Germany, Japan, the UK, and the US and found that sentiment is correlated with stock prices of listed companies in these major stock markets. Dergiades (2012) study the US stock index during 1965 to 2007 and show that investor sentiment embodies significant predictive power with respect to stock returns. And Kaplanski *et al.* (2015) use a survey to investigate sentiment among 900 investors and found that, on average, more positive investor’s sentiment is accompanied by higher return expectations and higher intention to buy stocks. In their study, they also find that investors sentiment affects expected returns more intensely than expected risk.

In this context, prior researches also reveal that online sources are known to contain information regarding the investor’s sentiment, which is corelated to stock returns. For instance, Siganos *et al*. (2014) examine investor sentiment, as expressed in Facebook posts, and find that sentiment has a positive contemporaneous relation to stock returns, and there exists a one-way causality from online sentiment to stock returns. Da *et al.* (2015) document a sentiment index constructed from Google search volume and show a correlation between sentiment as expressed in google search and asset prices. It was found, in their study, that negative words expressed in google search correspond with low market-level returns in the same day. Finally, Zhang *et al*. (2018) study the daily Twitter-based sentiment during 2008 to 2017 and find a one-way causality that the Twitter-based sentiment index Granger cause index returns in their linear causality test. These prior literatures lay an important foundation for the hypothesis in this research as they established the correlation between social-media investor sentiment index and stock returns, discovered a one-way causality from social-media sentiment to stock returns, as well as implying that investor sentiment constructed from social-media should be a “relevant” factor for explaining stock returns.

Although prior evidences established that social-media sentiment can cause stock returns movement, it is unclear if it contains any additional explanatory power toward stock returns (For example, it is possible that the explanatory power of social-media sentiment is already captured by the well-known factors documented in finance literature, such as market risk premium, firm size, book-to-market ratio or momentum). Prior studies (Signanos *et al*. 2014, Da *et al*. 2015 Zhang *et al*. 2018, among others) utilized causality tests and correlation tests while focusing solely on the relation between stock prices and investor sentiment but ignore the correlation between online investor sentiment and the aforementioned well-known risk factors documented in financial literature, which are consistently documented to have predictive power with respect to stock returns and stock return expectations. Given prior discoveries by Zhang *et al.* (2018) who prove that Twitter-based sentiment index Granger-cause index returns and Kaplanski *et al.* (2015) who show that investor’s sentiment can drive stock returns, the study regarding the explanatory power of Twitter-based sentiment relative to the predictive power of known risks factors become paramount. Accordingly, the main hypothesis in the present study is formalized in order to fill out this research gap.

Since A) sentiment such as mood or happiness, as expressed in Twitter messages, are unlikely to be explained by systematic factors in popular asset pricing models such as market-risk premium, firm size or book-to-market ratio. And B) prior researches consistently established that Twitter-based sentiment index Granger cause stock returns (Zhang *et al*. 2018 among others). Therefore, it is hypothesized that Twitter-based sentiment index should have predictive power with respect to stock returns in addition to those systematic factors. This is the main hypothesis being investigated in the present study. Unlike, prior researches (Baker and Stein, 2004; Baker and Wurgler, 2006 among others) which employ indirect proxies for investor sentiment, this study bringing new techniques by utilizing a novel Twitter-based sentiment index. This measure provides unique advantages as it allows for a direct estimate of investor sentiment, at high frequency, while minimizing the problem of response quality.

To the extent that this research also involves the investigation of asset prices, it is particularly important to note not only the theoretical asset pricing model (CAPM), but also prior contributions in the field of empirical asset pricing. Notable among the empirical asset pricing models is a prior research by Fama and French (1993) who proposed Fama-French 3 factor models. According to Fama and French (1993), the stock returns can be “empirically explained” by three factors: market risk premium, book-to-market ratio (High-minus-low: HML) and firm size (Small-minus-big: SMB). This model gains much attention among academia and several studies extend the model by including various additional factors. Notable among such extensions is a prior research by Carhart (1997) who argue that market sentiment should also be an important factor for determining asset prices. According to Carhart (1997) asset prices can be explained empirically by 4 factors: the 3 factors from Fama-French 3 factor models and momentum factor. And Fama and French (2015) who extend their own 3 factor model with profitability and investment as additional factors. It is important to note that although many other versions of empirical asset pricing models exist, this research primarily focus on the former two models (Fama-French 3 factor model and Carhart 4 factor model) because they are among the most widely known models among academia.

**3. Hypothesis, Data and Methodology**

*Data*

Twitter happiness index are observed from <http://hedonometer.org/index.html>, which is generated from the Twitter’s Decahose API feed database of over 50 million daily twitter post observations. The daily index is formulated from scoring nearly 10,000 sentiment-related words found in the database. Each of these words are then scored on a nine-point scale of happiness: (1) sad to (9) happy, following Dodds *et al*. (2011)’s methodology. Due to data availability, the study period ranges from September 2008 to January 2021. All daily risk factors (market risk premium, risk-free rate, high-minus-low (HML) and small-minus-big (SMB)) are observed from the French data library (French 2021). All data sources are kelp in line with prior researches (Zhang *et al*., 2016; Zhang *et al*., 2018 among others), providing a solid base for comparisons.

*Methodology & Hypothesizes*

Since prior studies consistently established that online sentiment Granger-cause stock returns and there exists linear relationship between Twitter-based investor sentiment index and stock returns (Siganos *et al*. ,2014; Zhang *et al*., 2016; Zhang *et al*. ,2018; among others). Therefore, the present study utilizes conventional linear framework to investigate the relationship, following prior researches. Accordingly, Twitter-based investor sentiment are treated as an independent variable in conventional linear regression, consistent with prior researches. Since Da *et al*. (2015) show that daily negativity (or positivity) in online posts corresponds to low (high) market-level returns in the same day, the effect of Twitter-based sentiment toward stock returns is therefore assumed to be observable within the same day. The Standard & Poor’s 500 index (S&P500) and the Dow Jones Industrial Average index (DJIA) are selected to represent the US stock market because the former is one of the most commonly followed indexes while the latter is the oldest US stock index. Additional tests using Gibbons *et al*. (1989) methodologies (henceforth GRS) on US portfolios (2x3 and 5x5 formed on size and book-to-value ratios) are also conducted and reported in robustness checks section.

As discussed previously, the main investigation of this study is the predictive power of Twitter-based sentiment, in addition to the well-known factors documented in finance literature. This involves testing for the significance of the coefficient (β) of the Twitter-based sentiment (DHt) in the following time-series models. It is important to note here that although the following models are not in their natural form, they provide a better context and more straightforward method to examine the research questions compared to GRS tests commonly used in the literature. GRS tests on 2x3 and 5x5 portfolios are briefly discussed in robustness checks section to conserve space. (see also Fama and French 2020 for an alternative method).

(1)

(2)

(3)

; where Rt represent the daily stock returns at the end of day t, DHt represent the Twitter-based sentiment index on day t, MRPt represent the market-risk-premium on day t, SMBt represent the size premium on day t (small-minus-big), HMLt represent the value premium on day t (high-minus-low), UMDt represent the momentum factor on day t, Rft represent the risk-free rate and αt represent the intercept of the regression.

Accordingly, the hypothesizes are stated as,

***H1***: Twitter-based sentiment contain additional predictive power with respect to stock returns which is not explained by factors in Fama-French 3 factor model

***H2***: Twitter-based sentiment contain additional predictive power with respect to stock returns, which is not explained by factors in Carhart 4 factor model

The above hypothesizes are employed because they involve investigating the empirical factors from Fama-French 3 factor model and Carhart 4 factor model, which are among the most popular asset pricing models in finance literature. Although none of them are related to CAPM, the main tests also include a test using CAPM to provide basic contexts for the investigation. (Kaplanski *et al.* (2015) point out that sentiment can drive stock returns expectation, however, the expected returns at the time of writing Twitter messages cannot be precisely measured and therefore no testable hypothesis for CAPM). Tests for newer empirical models (such as Fama-French 5 factor models: Fama and French 2015) and GRS tests on additional portfolios are also conducted, and are reported in robustness check section.

**4. Results and analysis**

All considered time-series were tested for their stationary using Augmented Dickey–Fuller (Dickey and Fuller, 1979) and Phillips–Perron (Phillips and Perron, 1988) methodologies (henceforth, ADF and PP, respectively). The null hypothesis of a unit root for all considered series were rejected at 1% significant level. Table 1 presents the summary statistics for stock returns, independent variables and happiness sentiment index to give an overview of the data.

Table 1 : Summary statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | mean | median | SD | ADF | PP |
| S&P 500 | 0.0003 | 0.0006 | 0.01 | -64.11\*\*\* | -64.25\*\*\* |
| DJIA | 0.0003 | 0.0006 | 0.01 | -21.14\*\*\* | -62.68\*\*\* |
| MRP | 0.047 | 0.085 | 1.34 | -63.17\*\*\* | -63.38\*\*\* |
| SMB | -0.002 | 0.000 | 0.63 | -57.80\*\*\* | -58.02\*\*\* |
| HML | -0.022 | -0.035 | 0.78 | -55.70\*\*\* | -55.93\*\*\* |
| UMD | 0.003 | 0.050 | 1.06 | -50.00\*\*\* | -49.84\*\*\* |
| DH | 1.794 | 1.794 | 0.01 | -4.89\*\*\* | -23.62\*\*\* |

\*,\*\*,\*\*\* represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Since investor sentiment (such as mood or happiness, expressed in Twitter messages) are unlikely to be explained by systematic factors such as book-to-market ratio, firm size or momentum, it is intuitively expected that the correlation between the aforementioned empirical factors and the Twitter-based sentiment index (DH) should be zero or a near zero value. The results in Table 2 indeed confirms this intuition and show that the Pearson correlation between Twitter-based sentiment (DH) and other explanatory variables are very low: size premium (SMB) show the highest correlation with DH at a marginal magnitude r=0.03. This evidence is broadly supportive of the main hypothesis because it shows that Twitter-based sentiment are almost uncorrelated with the known empirical factors used in popular empirical asset pricing models. Therefore, if the explanatory power of *DH* in respect to stock returns exists, it is not likely to be captured by any known risk factors within CAPM, Fama French 3 factor model or Carhart 4 factor model.

In terms of model orthogonality, the value premium (HML) and momentum (UMD) show relatively high correlation at r=-0.62. However, it is not necessary to exclude either of this factor from the main analysis because they are empirically identified as “relevant” factors in accordance with prior empirical researches (Fama and French, 1993; Carhart, 1997 among others). In addition, Equation 1 and Equation 2 naturally exclude momentum factor (UMD), already giving a clear view of what results will be without the UMD.

Table 2: Pearson correlation matrix

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | MRP | SMB | HML | UMD | DH |
| Marker risk premium (MRP) | 1.00 |  |  |  |  |
| Small-minus-big (SMB) | 0.23 | 1.00 |  |  |  |
| High-minus-low (HML) | 0.34 | 0.22 | 1.00 |  |  |
| Momentum (UMD) | -0.30 | -0.21 | -0.62 | 1.00 |  |
| investor sentiment index (DH) | 0.02 | 0.03 | 0.03 | -0.02 | 1.00 |

The primary subject of investigation involves examining the “relevance” of DH factor in Equation (1)-(3). The results are presented in table 3, 4 and 5. Table 3,4 and 5 show the explanatory power of Twitter-based sentiment index, in addition to risks factors stated in CAPM, Fama-French 3 factor model and Carhart 4 factor model, respectively.

Table 3: Regression results: additional explanatory power of Twitter-based sentiment in CAPM

|  |  |  |
| --- | --- | --- |
|  | S&P 500 | DJIA |
| Marker risk premium (MRP) | 1.00  (698.44\*\*\*) | 0.93  (237.79\*\*\*) |
| Investor sentiment (DH) | 0.32  (1.65\*) | 1.19  (2.23\*\*) |
| Intercept | -0.59  (-1.69\*) | -2.15  (-2.24\*\*) |
|  |  |  |
| Adj. R2 | 0.99 | 0.95 |
| Durbin-Wattson | 2.12 | 1.92 |

\*,\*\*,\*\*\* represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Results presented in table 3 reveal that the investor sentiment, as expressed in daily Twitter messages, contain predictive power with respect to US index returns. The coefficient of investor sentiment is found to be positive, and statistically significant at 5% and 10% significance for DJIA and S&P500, respectively. The results are consistent with Da *et al*. (2015)’s position that that daily negativity (or positivity) in online posts corresponds to low (high) market-level returns in the same day. The other factor (the market risk premium, MRP) are found to be positive and statistically significant at 1% significant level. These results are to be expected, as they are in line with CAPM prediction. The Durbin-Watson statistics were found to be very close to 2, suggesting no evidence of auto correlation in the considered cases.

However, it is important to note here that the CAPM results are provided only for simpler illustrating the framework of this study. However, it can be argued theoretically that CAPM is not an appropriate model to examine stock returns because it is the theoretical model for explaining equilibrium *expected* returns, not a model for explaining realized stock returns. The literatures on empirical asset pricing models have been consistently suggests that firm size, book-to-market ratio and momentum are correlated with realized stock returns. (Fama and French 1993, Carhart 1997 among others). Therefore, additional tests using these empirical models are required before stating any inference regarding the hypothesizes. Accordingly, tests using Fama-French 3 factor model and Carhart 4 factor model are conducted and are presented in Table 4 and Table 5.

Table 4: Additional explanatory power of Twitter-based sentiment in Fama-French 3 factor model

|  |  |  |
| --- | --- | --- |
|  | S&P 500 | DJIA |
| Marker risk premium (MRP) | 1.00  (952.76\*\*\*) | 0.93  (236.79\*\*\*) |
| Small-minus-big (SMB) | -0.13  (-58.30\*\*\*) | -0.16  (-20.29\*\*\*) |
| High-minus-low (HML) | 0.03  (16.12\*\*\*) | 0.07  (10.96\*\*\*) |
| Investor sentiment (DH) | 0.47  (3.52\*\*\*\*) | 1.31  (2.62\*\*\*) |
| Intercept | -0.86  (-3.58\*\*\*) | -2.36  (-2.63\*\*\*) |
|  |  |  |
| Adj. R2 | 0.99 | 0.96 |
| Durbin-Wattson | 1.95 | 1.91 |

\*,\*\*,\*\*\* represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 show results from Fama-French regression with Twitter sentiment as an augmented variable. It was found that the coefficients of Twitter sentiment (DH) are statistically significant at 1% for all considered cases (S&P500 and DJIA). This suggest that investor’s sentiment can drive stock returns, in line with Kaplanski *et al.* (2015) prediction. The signs of the coefficients are found to be positive, suggesting that the higher sentiment expressed in Twitter is associated by the higher returns, and vice versa. This finding is consistent with Da *et al.* (2015)’s posit that daily negativity (or positivity) in online messages corresponds to low (high) market-level returns in the same day.

Other factors show results consistent with Fama-French (1993): the market risk premium (MRP), the size premium (SMB) and the value premium (HML) are found to be significant predictors of stock returns. All coefficients of the aforementioned factors are statistically significant at 1% significant level, in line with Fama-French (1993). Since Twitter sentiment (DH) is a statistically significant factor in describing stock returns and its correlation with the others explanatory variables are marginal (as shown in Table 2), the results in Table 4 infer that Twitter sentiment (DH) is a predictor for stock returns which is not explained by market risk premium, firm size or book-to-market ratio, confirming *H1*. Finally, the Durbin-Watson statistics were found to be very close to 2, suggesting no evidence of auto correlation in all considered models.

Table 5: Additional explanatory power of Twitter-based sentiment in Carhart 4 factor model

|  |  |  |
| --- | --- | --- |
|  | S&P 500 | DJIA |
| Marker risk premium (MRP) | 1.00  (946.41\*\*\*) | 0.94  (236.55\*\*\*) |
| Small-minus-big (SMB) | -0.13  (-58.12\*\*\*) | -0.16  (-20.09\*\*\*) |
| High-minus-low (HML) | 0.03  (13.13\*\*\*) | 0.08  (10.05\*\*\*) |
| Momentum (UMD) | 0.00  (-0.16) | 0.01  (1.84\*) |
| Investor sentiment (DH) | 0.47  (3.52\*\*\*) | 1.30  (2.61\*\*\*) |
| Intercept | -0.86  (-3.58\*\*\*) | -2.35  (-2.63\*\*\*) |
|  |  |  |
| Adj. R2 | 0.99 | 0.99 |
| Durbin-Wattson | 1.95 | 1.91 |

\*,\*\*,\*\*\* represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 present the results from Carhart 4 factor model regression (Carhart 1997) with Twitter sentiment as an augmented variable. Once again, it was found that the coefficients of Twitter sentiment (DH) are positive and statistically significant at 1% significant for all considered US stock indexes. These results suggest that investor sentiment, as expressed in Twitter messages, have significant predictive power with respect to US stock returns in addition to the four factors (market risk premium, firm size, value premium or momentum) stated in Carhart 4 factor model, confirming *H2*. Once again, the signs of the coefficients are found to be positive, supporting Da *et al.* (2015)’s posit that daily negativity (or positivity) in online posts corresponds to low (high) market-level returns in the same day. Other factors [market risk premium (MRP), size premium (SMB), value premium (HML)] are found to be significant predictors of stock returns, in line with and Fama and French (1993): All of the coefficients of the aforementioned factors are statistically significant at 1%. The coefficient of momentum (UMD) is found to be significant in explaining DJIA daily returns, albeit at a lower significance level (10%). Finally, the Durbin-Watson statistics were found to be very close to 2, suggesting no evidence of auto correlation for all considered models.

Overall, the results from all tests conducted confirm the main hypothesizes *H1 and H2*: that investor sentiment, as expressed in Twitter daily messages, contain predictive power with respect to the US stock returns. These results are consistent with the position proposed by Kaplanski (2015), and also supportive of prior researches in the field (Signanos *et al*. 2014 Zhang *et al*. 2018, among others) which established that Twitter-based sentiment Granger-cause stock returns. All signs of the coefficients of Twitter sentiment in all considered cases are found to be positive and statistically significant at 1%, in line with Da *et al*. (2015)’s prediction. The results are consistent with the empirical theories that investor sentiment predicts stock returns (De Long *et al*., 1990; Baker and Wurgler, 2007; Baker *et al*., 2012; Zhang *et al*., 2018; among others).

**5. Robustness checks**

Since some professionals and academia consider the S&P500 and DJIA indexes to be a representative of large-cap stocks, it is possible that the results could be biased by firm size differences. To address the argument that the sample used in the study could possibly bias toward large-cap stocks, this study also performs additional tests to investigate the Wilshire 5000, the S&P Midcap 400, Russell 2000 and NASDAQ composite index. These additional indexes are systematically chosen as some professionals considered them (the Wilshire 5000, the S&P Midcap 400 and Russell 2000 indexes) to be a reprehensive of the “total” US stock market, Mid-cap stocks and Small-cap stocks, respectively. The results confirm the initial findings that Twitter sentiment has significant predictive power with respect to stock returns, albeit with lower significance.

This study also experimented with newer asset pricing model such as Fama and French 5 factor model (Fama and French, 2015). The results show no material difference from the main analysis, with similar significance. More importantly, to address concerns that the main models used in this research is not corresponds to their natural form, additional GRS tests (Gibbons *et al*., 1989) are conducted on 2x3 and 5x5 portfolios formed on size and book-to-market ratios in order to compare the performance of the models with Twitter sentiment index as an augmented variable with the performance of its traditional model counterparts. It was found that models with Twitter sentiment index as an augmented variable show lower absolute alphas compared to the absolute alphas of its original models, for all considered case (Fama-French 3 factor model, Carhart 4 factor model and Fama-French 5 factor model on 2x3 and 5x5 portfolios). This suggest that Twitter sentiment index contain explanatory power able to explain stock returns consistent with the initial findings.

In summary, robustness tests support the initial findings from the main analysis that Twitter-based sentiment has an additional explanatory power toward US stock returns. This finding is robust against changes in asset pricing model used in the study (Fama French 3 factor model, Carhart 4 factor model or Fama French 5 factor model) as well as changes in type of stocks (large, medium or small market-capitalization portfolios).

6. **Conclusion**

In classical finance theory, investor sentiment cannot play any role in stock prices, expected returns or realized returns. Based on behavioral framework documented in prior researches, this paper shows contradicting evidence contradicting to that view. This study uses a simple and straightforward model to show that Twitter sentiment index is able to explain deviation of US stock returns from the “rigorous” model’s prediction. It was found that a direct survey measure of investor sentiment, as expressed in Daily Twitter messages, predicts stock returns within the same day and this measure has the ability to explain deviations from intrinsic value as predicted by popular asset pricing models. In all considered cases, the significance of the sentiment index is found to be significant and robust to changes in asset pricing models (Fama-French 3 factors model, Carhart 4 factors model or Fama-French 5 factors model) and are also found to be significant for all considered equity portfolios. In addition, the Twitter sentiment index was found to be almost uncorrelated with popular risk factors, suggesting that the predictive power of Twitter sentiment index is unlikely to be captured by any known risk factors such as market risk premium, firm size or momentum.

At least two possible interpretations are possible for these findings. As the explanatory power of Twitter sentiment is not captured by known risk factors, a conservative interpretation is that this study identified a new factor (or a new proxy for unknown risks) related to asset valuation. Another possible interpretation is that the measure of investor sentiment used in this study is actually a reasonably accurate measure of investor sentiment and this investor sentiment directly related to the level of stock prices as documented in behavioral theories.

Regardless of the interpretation, the results consistently suggest that the employed sentiment variable forecasts daily market returns and helps to explain deviations from popular valuation models, in line with prior researches (De Long *et al*., 1990; Baker and Wurgler, 2007; Baker *et al*., 2012; Siganos *et al*. ,2014; Kaplanski *et al*. ,2015; Da *et al.*, 2015; Zhang *et al*., 2018 among others). This finding has several important implications. First, the results support the behavioral theories that predict the irrational sentiments of investors do in fact affect asset price levels. Second, the results suggest that asset pricing models should consider the possible role of investor sentiment. Besides academics, the practical implications for this research are clear, that market regulators and government officials should be concerned about the potential for market biases or ‘‘irrationalities’’ caused by investor sentiment. Since the Twitter sentiment index and stock returns are found to be corelated, the results presented in this study infer that a sudden change in sentiment could translates into a large wealth shock that potentially depresses stock market. Ultimately, individual investors and fund managers should also be aware of the impact sentiment can have on both their own portfolios and fund managers’ investment.

**6.1 Research Limitations and possible future research**

One of the limitations of this study is that this research focuses primarily on the US stocks while the emerging-market stocks are largely ignored. This limitation arises from of the lack of online sentiment data and social media user demographics, mainly due to the limitations of natural language processing technique for non-English languages. For example, current algorithm in artificial intelligence cannot correctly understand ambiguous words in Japanese and Chinese; hence, the sentiment observations from non-English investors are largely ignored due to this technological constraint. For the same reason, this research therefore systematically focusses primarily on the US stock market because according to Twitter usage statistics (Kemp 2020) the largest number of English Twitter users are from the US, by far. Accordingly, the investigation of the relationship in non-English stock markets, particularly in emerging markets, are recognized as one of the limitations in this study and are identified as promising area for future research should the data become available.

Another minor topic worth mentioning is that the results from the present study do not distinguish between the effect on stock prices caused by volatility and the effects on stock prices caused by investor sentiment. This is because of two main reasons. First, prior researches document that investor sentiment is more relevant to returns than to risks. For instance, Kaplanski *et al*. (2015) argue that that investors sentiment affects expected returns more intensely than expected risk. This position is also consistent with Da *et al*. (2015)’s position and also broadly consistent with recent research by Ding *et al*. (2019) who show that the effect of sentiment on the return is not related to systematic risk. Second, it is plausible that some risk factors may already captured the effects of volatility (For example, market-risk premium tend to be higher during highly volatile market, and vice versa), making this issue less relevant to the present study.

**Declarations of interest**: none

**References**

Baker, M. and Stein, J.C. (2004), Market liquidity as a sentiment indicator. *Journal of Financial Markets*, 7 (3), 271-299.

Baker, M. and Wurgler, J. (2006), Investor sentiment and the cross-section of stock returns. *Journal of Finance,* 61 (4), 1645–1680.

Baker, M. and Wurgler, J. (2007), Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21 (2), 129–152.

Baker, M., Wurgler, J. and Yuan, Y. (2012), Global, local, and contagious investor sentiment. *Journal of financial economics*, 104 (2), 272–287.

Banz, R.W. (1981), The Relationship Between Return and Market Value of Common Stocks. *Journal of Financial Economics*, 9(1), 3–18.

Black, F. (1986), Noise. *Journal of Finance*, 41 (3), 529–543.

Black, F. (1972), Capital Market Equilibrium with Restricted Borrowing. *Journal of Business*, 45(3), 444–54.

Carhart, M. (1997), On Persistence in Mutual Fund Performance. *Journal of Finance*, 52, 57–82.

Da,Z., Engelberg, J. and Gao, P. (2015), The Sum of All FEARS Investor Sentiment and Asset Prices, *The Review of Financial Studies*, 28 (1), 1–32.

Daniel, K., Hirshleifer, D. and Subrahmanyam, A. (1998), Investor psychology and security market under- and overreactions, *Journal of Finance*, 53 (6), 1839–1885.

De Long, J.B., Shleifer, A., Summers, L.H. and Waldmann, R.J. (1990), Noise trader risk in financial markets. *Journal of political economy*, 98 (4), 703–738.

Dergiades, T. (2012), Do investors’ sentiment dynamics affect stock returns? Evidence from the US economy. *Economics Letters*, 116 (3), 404-407.

Dickey, D.A. and Fuller, W.A. (1979), Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74 (366), 427–431.

Ding, W., Mazouz, K. and Wang, Q. (2019), Investor sentiment and the cross-section of stock returns: new theory and evidence. *Review of Quantitative Finance and Accounting*, 53, 493–525.

Dodds P.S., Harris K.D., Kloumann I.M., Bliss C.A. and Danforth C.M. (2011), Temporal patterns of happiness and information in a global social network: hedonometrics and Twitter. *PLoS One*, 6(12) :doi: 10.1371/journal.pone.0026752

Fama, E. (1970), Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*, 25 (2), 383–417.

Fama, E.F. and French, K.R. (1993), Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3–56.

Fama, E. F. and French, K. R. (2004), The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives,* 18 (3), 25–46.

Fama, E.F. and French, K.R. (2015), A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22.

Fama, E.F. and French, K.R., (2020), Comparing Cross-Section and Time-Series Factor Models. *The Review of Financial Studies*, 33(5), 1891–1926.

French, K.R. (2021), *French data library*, retrieved from: <https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html> (accessed 20 January 2021)

Gibbons, M.R., Ross, S. and Shanken, J. (1989), A Test of the Efficiency of a Given Portfolio. *Econometrica*, 57(5), 1121-52.

Kaplanski, G., Levy, H., Veld, C., and Veld-Merkoulova, Y. (2015), Do Happy People Make Optimistic Investors?. *The Journal of Financial and Quantitative Analysis*, 50(1/2), 145-168.

Kemp, S. (2020), *Global Report 2020*, retrieved from: <https://www.hootsuite.com/pages/digital-2020> (accessed 3 February 2021)

Kim S. and Kim, D. (2014), Investor sentiment from internet message postings and the predictability of stock returns. *Journal of Economic Behavior & Organization*, 107, 708-729.

Lee, C.M.C., Shleifer, A. and Thaler, R.H. (1991), Investor sentiment and the closed-end fund puzzle. *Journal of Finance*, 46 (1), 75–109.

Lemmon, M. and Portniaguina, E. (2006), Consumer confidence and asset prices: some empirical evidence. *Review of Financial Studies*, 19 (4), 1499–1529.

Lintner, J. (1965), The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 47 (1), 13-37.

Markowitz, H.M. (1952), Portfolio Selection.  *Journal of Finance*, 7 (1), 77–91.

Phillips, P.C.B. and Perron, P. (1988), Testing for a Unit Root in Time Series Regression. *Biometrika*, 75 (2), 335–346.

Rosenberg, B., Reid, R. and Lanstein, R. (1985), Persuasive Evidence of Market Inefficiency. *Journal of Portfolio Management*, 11, pp. 9–17.

Ross, S. A (1976), The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13 (3), 341–360.

Sharpe, W.F. (1964), Capital Asset Prices – A Theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance*, 19 (3), 425–442.

Shleifer, A. and Summers, L.H. (1990), The noise trader approach to finance. *Journal of Economics Perspectives*, 4 (2), 19–33.

Shleifer, A. and Vishny R.W. (1997), The limits of Arbitrage. Journal of Finance, 52 (1), 35-55.

Siganos, A., Vagenas-Nanos, E. and Verwijmeren, P. (2014), Facebook’s daily sentiment and international stock markets. *Journal of economic behavior & organizations*, 107 (B), 730–743.

Stambaugh, R.F. (1982), On the Exclusion of Assets from Tests of the Two-Parameter Model: A Sensitivity Analysis. *Journal of Financial Economics*, 10(3), 237–68.

Zhang, W., Li, X., Shen. D. and Teglio, A. (2016), Daily happiness and stock returns: Some international evidence, *Physica A: Statistical Mechanics and its Applications*, 460 (C), 201-209.

Zhang, W., Wang, P. Li, X. and Shen, D. (2018), Twitter’s daily happiness sentiment and international stock returns: Evidence from linear and nonlinear causality tests. *Journal of Behavioral and Experimental Finance*, 18, 50-53.