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

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**Abstract**

Using a novel Twitter-based investor sentiment index, this research investigates whether investor sentiment, as expressed in daily Twitter messages, has predictive power with respect to US stock returns. Based on a conventional linear framework, the empirical results show that the Twitter sentiment index has additional predictive power for US stock returns, which is 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.

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

**JEL Classification**: G12, G40

**1. Introduction**

A long-running debate among academics concerns the possible effect of investor sentiment on asset prices. Traditional theoretical asset pricing models 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. Good examples include the famous Fama-French three-factor model (Fama and French, 1993), the Carhart four-factor model (Carhart, 1997) and the Fama-French five-factor model (Fama and French, 2015).. Although they are more successful at explaining equity returns, it is still unclear what risk (or risks) the empirical factors truly represent in these models. For example, what are the actual risk factors of a book-to-market (B/M) ratio (i.e., 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 as to whether these are the only factors relevant to stock returns or whether there are other unknown factor(s) with additional predictive power not contained in the aforementioned factors.

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

The present research sheds new light on the issue of investor rationality by bringing new data and techniques to bear on the question. Specifically, a direct online measure of investor sentiment was employed instead of relying on indirect proxies. The measure, 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 twofold. First, this research employs a novel proxy for investor sentiment constructed from Twitter, with the advantage of avoiding endogeneity and directly capturing high-frequency investor sentiment. Unlike survey-based proxies, online-search-based measures *reveal* attitudes rather than *inquire* about them. This makes the measure less prone to biases compared to survey-based measures of sentiment. Second, the empirical results presented in this study support recent empirical theories that an investor sentiment index constructed from social media has predictive power with respect to US stock returns. This predictive power has not previously been explained in the finance literature by popular risk factors 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, conclusions are given, along with research limitations and suggestions for future research.

**2. Literature review**

Traditional risk-based asset pricing models such as the capital asset pricing model (CAPM) are based on the premise that prices reflect the consensus investor’s expectation of risks associated with their investment; such models assume the existence of a theoretical market portfolio, which is unobservable and perfectly diversified (for the theoretical underpinnings, see Markowitz, 1952; Sharpe, 1964; Litner, 1965; Fama, 1970; and Black, 1972; among others). However, the practicality of the CAPM is highly debatable becauseit requires many strict assumptions: for example, all investors are required to be rational, and the informational efficiency of both market and investors must be perfect. 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. Indeed, a number of empirical studies have identified the existence of trends in stock returns as well as model limitations, contradicting the CAPM prediction. For example, Banz (1981) documented that when stocks are sorted on market capitalization, average returns on small stocks are higher than predicted by the CAPM. Stambaugh (1982) argued that the tests of the CAPM are not sensitive to expanding the market proxy beyond common stocks, which contradicts the definition of market portfolio in the CAPM. Rosenberg *et al*. (1985) showed that stocks with high book-to-market ratios have high average returns that are not captured by betas. These contradictory findings ultimately led Fama and French (2004) to conclude that “the failure of the CAPM in empirical tests implies that most applications of the model are invalid” (p. 26).

Some academics have proposed the idea of arbitrage-free equilibrium as an alternative model to the CAPM. Ross (1976), among others, developed the arbitrage pricing theory (APT). The APT allows for 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). De Long *et al*. (1990), notably, modelled the influence of noise trading on equilibrium prices and showed that noise trading affects stock prices and that noise traders can earn higher expected returns. Shleifer and Vishny (1997) demonstrated that there are limits on risky arbitrage positions which can cause changes in security prices. Furthermore, Baker and Wurgler (2006) documented that investor sentiment contains functional predictive content about stock returns.

For decades, stock market prediction was the topic of long debates among academics, and yet the true set of drivers behind stock returns still remains inconclusive. An important aspect of the debate is the question of whether investor sentiment predicts stock returns. Several theoretical studies offer various behavioral-based models establishing the link between asset prices and investor sentiment. For example, it has been documented that investors may form erroneous beliefs, through either excessive optimism or pessimism, and may therefore incorrectly evaluate asset values, causing asset price movements (Black, 1986; De Long *et al*., 1990; Baker *et al*., 2012; among others).

Baker and Wurgler (2007) showed that investor sentiment predictive content in relation to future market movements can act as valuable information for traders in forming profitable trading strategies. They broadly defined investor sentiment as “investors’ belief about future cash flows and risk not justified by the facts at hand” and noted 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 analyzes the link between investor sentiment and stock returns, using new data and a new methodology for measuring sentiment.

A growing body of research has documented the relationship between investor sentiment and asset prices. For example, Baker *et al*. (2012) investigated 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) studied the US stock index from 1965 to 2007 and showed that investor sentiment embodies significant predictive power with respect to stock returns. And Kaplanski *et al.* (2015) used a survey to investigate sentiment among 900 investors and found that, on average, more positive investor sentiment is accompanied by higher return expectations and higher intention to buy stocks. In their study, they also found that investor sentiment affects expected returns more intensely than expected risk.

In this context, prior research has also revealed that online sources are known to contain information regarding investor sentiment, which is correlated with stock returns. For instance, Siganos *et al*. (2014) examined investor sentiment, as expressed in Facebook posts, and found that sentiment has a positive contemporaneous relation to stock returns, and that there exists a one-way causality from online sentiment to stock returns. Da *et al.* (2015) documented a sentiment index constructed from Google search volume and showed a correlation between sentiment as expressed in google searches and asset prices. It was found that negative words expressed in google searches correspond with low market-level returns on the same day. Finally, Zhang *et al*. (2018) studied daily Twitter-based sentiment from 2008 to 2017 and found that the Twitter-based sentiment index Granger-causes index returns in their linear causality test. These prior studies have provided an important foundation for the hypothesis in this research in three principal ways: first, they established the correlation between social-media investor sentiment index and stock returns; second, they discovered one-way causality from social-media sentiment to stock returns; and third, their findings implied that investor sentiment constructed from social-media should be a “relevant” factor for explaining stock returns.

Although prior evidence has 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 well-known factors documented in the 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 ignored the correlation between online investor sentiment and the aforementioned well-known risk factors documented in the finance 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 proved that a Twitter-based sentiment index Granger-causes index returns and Kaplanski *et al.* (2015) who showed that investor sentiment can drive stock returns, there is a need to study the explanatory power of Twitter-based sentiment relative to the predictive power of known risk factors. Accordingly, the main hypothesis in the present study is formalized in order to fill this research gap.

Since A) sentiment such as mood or happiness, as expressed in Twitter messages, is 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 research has consistently established that a Twitter-based sentiment index Granger-causes stock returns (Zhang *et al*. 2018, among others); it is therefore hypothesized that a 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 research (Baker and Stein, 2004; Baker and Wurgler, 2006, among others) which employed indirect proxies for investor sentiment, this study brings in 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.

Insofaras this research also involves the investigation of asset prices, it is particularly important to considernot 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 prior research by Fama and French (1993) who proposed Fama-French three-factor models. According to the authors, 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 academics, and several studies have extended the model by including various additional factors. For instance, Carhart (1997) argued that market sentiment should also be an important factor for determining asset prices. According to Carhart (1997) asset prices can be explained empirically by four factors: the three factors from Fama-French three-factor models and momentum factor. Moreover, Fama and French (2015) extended their own three-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 focuses on the former two (the Fama-French three-factor model and the Carhart four-factor model) because they are among the most widely known models in academia.

**3. Hypothesis, data, and methodology**

*Data*

The Twitter happiness index was observed from <http://hedonometer.org/index.html>, which is generated from Twitter’s Decahose API feed database of over 50 million daily twitter post observations. The daily index is formulated by 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*.’s (2011) 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, HML and SMB measures) are observed from the French data library (French, 2021). All data sources are in line with prior research (Zhang *et al*., 2016; Zhang *et al*., 2018, among others), providing a solid base for comparisons.

*Methodology & Hypotheses*

Prior studies have consistently established that online sentiment Granger-causes stock returns and that there exists a linear relationship between a 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 a conventional linear framework to investigate the relationship, following prior research. Accordingly, Twitter-based investor sentiment was treated as an independent variable in conventional linear regression, again consistent with prior research. Since Da *et al*. (2015) showed that daily negativity (or positivity) in online posts corresponds to low (high) market-level returns on the same day, the effect of Twitter-based sentiment toward stock returns is therefore assumed to be observable on the same day. The Standard & Poor’s 500 index (S&P 500) and the Dow Jones Industrial Average index (DJIA) were 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) were also conducted and are reported in the robustness checks section.

As discussed previously, the main focus of investigation of this study was the predictive power of Twitter-based sentiment, in addition to the well-known factors documented in the finance literature. This involved 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 a more straightforward method for examining the research questions compared to the GRS tests commonly used in the literature. GRS tests on 2x3 and 5x5 portfolios are briefly discussed in the robustness checks section (see also Fama and French, 2020 for an alternative method).

(1)

(2)

(3)

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

Accordingly, the two following hypothesizes were formulated:

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

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

The above hypotheses were employed because they involve investigating empirical factors from the Fama-French three-factor model and the Carhart four-factor model, which are among the most popular asset pricing models in the finance literature. Although none of them are related to CAPM, the main tests also included a test using CAPM to provide basic contexts for the investigation. (Kaplanski *et al.* (2015) pointed 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 there is no testable hypothesis for CAPM). Tests for newer empirical models, such as Fama-French five-factor models (Fama and French, 2015) and GRS tests on additional portfolios were also conducted, and are reported in the robustness checks section.

**4. Results and analysis**

All considered time series were tested for being 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 was rejected at 1% significance level. Table 1 presents the summary statistics for stock returns, independent variables, and the 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) is unlikely to be explained by systematic factors such as book-to-market ratio, firm size, or momentum, it was intuitively expected that the correlation between the aforementioned empirical factors and the Twitter-based sentiment index (DH) would be zero or near zero. The results in Table 2 indeed confirm this intuition and show that the Pearson correlation between Twitter-based sentiment (DH) and other explanatory variables is very low: size premium (SMB) shows 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 is 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 the CAPM, Fama-French three-factor or Carhart four-factor models.

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

Table 2. Pearson correlation matrix

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | MRP | SMB | HML | UMD | DH |
| Market 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 involved examining the “relevance” of the DH factor in Equations (1)-(3). The results are presented in tables 3, 4 and 5, showing the explanatory power of the Twitter-based sentiment index, in addition to the risk factors stated in the CAPM, Fama-French three-factor and Carhart four-factor models, respectively.

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

|  |  |  |
| --- | --- | --- |
|  | S&P 500 | DJIA |
| Market 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-Watson | 2.12 | 1.92 |

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

Results presented in Table 3 reveal that investor sentiment, as expressed in daily Twitter messages, contains predictive power with respect to US index returns. The coefficient of investor sentiment was found to be positive, and statistically significant at 5% and 10% significance for DJIA and S&P 500, respectively. The results are consistent with Da *et al*.’s (2015) conclusion that daily negativity (or positivity) in online posts corresponds to low (high) market-level returns on the same day. The other factor (market risk premium, MRP) was found to be positive and statistically significant at 1%. These results were expected, as they are in line with CAPM prediction. The Durbin-Watson statistic was found to be very close to 2, suggesting no evidence of autocorrelation in the considered cases.

It is important to note here that the CAPM results are provided only to more simply illustrate the framework of this study. However, theoretically it can be argued that CAPM is not an appropriate model for examining stock returns because it is a theoretical model for explaining equilibrium *expected* returns, not realized stock returns. The literature on empirical asset pricing models has consistently suggested 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 hypotheses. Accordingly, tests using the Fama-French three-factor and Carhart four-factor models were conducted and the results are presented in Table 4 and Table 5.

Table 4. Additional explanatory power of Twitter-based sentiment in the Fama-French three-factor model

|  |  |  |
| --- | --- | --- |
|  | S&P 500 | DJIA |
| Market 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-Watson | 1.95 | 1.91 |

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

Table 4 show results on Fama-French regressions 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&P 500 and DJIA). This suggests that investor sentiment can drive stock returns, in line with Kaplanski *et al.*’s (2015) prediction. The signs of the coefficients were found to be positive, suggesting that higher sentiment expressed in Twitter is associated with higher returns, and vice versa. This finding is consistent with Da *et al.* (2015) who posited that daily negativity (or positivity) in online messages corresponds to low (high) market-level returns on the same day.

The results for other factors are consistent with Fama and French (1993): market risk premium (MRP), size premium (SMB), and value premium (HML) were 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 and French (1993). Since Twitter sentiment (DH) is a statistically significant factor in describing stock returns, and since its correlation with the other explanatory variables is marginal (as shown in Table 2), the results presented in Table 4 infer that Twitter sentiment (DH) is a predictor for stock returns which is not explained by the 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 autocorrelation in all considered models.

Table 5. Additional explanatory power of Twitter-based sentiment in the Carhart four-factor model

|  |  |  |
| --- | --- | --- |
|  | S&P 500 | DJIA |
| Market 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-Watson | 1.95 | 1.91 |

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

Table 5 presents the results from the Carhart four-factor regression model (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% 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, and momentum) stated in the Carhart four-factor model, confirming *H2*. Once again, the signs of the coefficients were found to be positive, supporting Da *et al.* (2015) who posited that daily negativity (or positivity) in online posts corresponds to low (high) market-level returns on the same day. Other factors (MRP, SMB and HML) were 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) was found to be significant in explaining DJIA daily returns, albeit at a lower significance level of 10%. Finally, the Durbin-Watson statistics were found to be very close to 2, suggesting no evidence of autocorrelation for all considered models.

Overall, the results from all of the tests conducted confirmed the main hypotheses *H1 and H2*: that investor sentiment, as expressed in Twitter daily messages, contains predictive power with respect to US stock returns. These results are consistent with Kaplanski (2015), and also support prior research in the field (Signanos *et al*., 2014; Zhang *et al*., 2018, among others) which established that Twitter-based sentiment Granger-causes stock returns. All signs of the coefficients of Twitter sentiment in all considered cases were found to be positive and statistically significant at 1%, in line with Da *et al*.’s (2015) prediction. The results are consistent, too, with 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 academics consider the S&P 500 and DJIA indexes to be representative of large-cap stocks, it is possible that firm size differences could be a source of bias. To address the argument that the sample used in the study could be potentially biased toward large-cap stocks, additional tests were performed to investigate the Wilshire 5000, the S&P Midcap 400, the Russell 2000 and the NASDAQ composite index. These additional indexes are systematically chosen as some professionals consider them (the Wilshire 5000, the S&P Midcap 400, and Russell 2000 indexes) to be representative 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 models such as the Fama and French five-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 did not correspond to their natural form, additional GRS tests (Gibbons *et al*., 1989) were 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 those of the original models, for all considered cases (the Fama-French three-factor model, the Carhart four-factor model, and the Fama-French five-factor model on 2x3 and 5x5 portfolios). This suggests that the Twitter sentiment index has explanatory power for stock returns, which is consistent with the initial findings.

In summary, the robustness tests supported the initial findings from the main analysis that Twitter-based sentiment has additional explanatory power toward US stock returns. This finding is robust against changes in asset pricing models used in the study (Fama French three-factor model, Carhart four-factor model or Fama French five-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 does not play any role in stock prices, expected returns, or realized returns. Based on the behavioral framework documented in prior research, this paper provides evidence that contradicts that view. This study used 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 on the same day, and that this measure has the ability to explain deviations from intrinsic values as predicted by popular asset pricing models. In all cases, the significance of the sentiment index was found to be significant and robust to changes in asset pricing models (Fama-French three-factor model, Carhart four-factor model or Fama-French five-factor model) and significant for all considered equity portfolios. In addition, the Twitter sentiment index was 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 can be suggested for these findings. As the explanatory power of Twitter sentiment is not captured by known risk factors, a conservative interpretation would be 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 reasonably accurate and 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 actually forecasts daily market returns and helps to explain deviations from popular valuation models, in line with prior research (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 behavioral theories that predict that the irrational sentiments of investors do in fact affect asset price levels. Second, the findings suggest that asset pricing models should consider the possible role of investor sentiment. Besides academics, the practical implications for this research are clear: 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 were found to be correlated, the results presented in this study infer that a sudden change in sentiment could translate into a large wealth shock with the potential to depress the 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 US stocks while emerging-market stocks are largely ignored. This limitation arises from the lack of online sentiment data and social media user demographics, mainly due to the limitations of natural language processing techniques for non-English languages. For example, current algorithms 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 systematically focused primarily on the US stock market because according to Twitter usage statistics (Kemp, 2020) by far the largest number of English Twitter users are from the US. Accordingly, the investigation of the relationship in non-English stock markets, particularly in emerging markets, is recognized as one of the limitations in this study and identified as a 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 effects on stock prices caused by volatility and investor sentiment. This is because of two main reasons. First, prior research has documented that investor sentiment is more relevant to returns than risks. For instance, Kaplanski *et al*. (2015) argued that investor sentiment affects expected returns more intensely than expected risk. This position is also consistent with Da *et al*.’s (2015) position and broadly in line with recent research by Ding *et al*. (2019) who showed that the effect of sentiment on return is not related to systematic risk. Second, it is plausible that some risk factors may already be captured in the effects of volatility (for example, the market-risk premium tends to be higher during times of high volatility, and vice versa), making this issue less relevant to the present study.

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