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Facebook Sentiment Communication and its impact on the Stock Market Returns

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Abstract— The ability of Facebook reaction to anticipate investor sentiment and explain stock market swings has drawn a lot of interest. This study investigates how the investor sentiment index affects stock market performance in the context of Tunisia. We investigate if shifts in stock market activity are a result of investor attention as measured by Facebook reaction (Like, Unlike). We use 156 weeks to test the stocks of 12 banks between 2019 and 2021.

Keywords- Facebook, sentiment polarity, stock market

I. INTRODUCTION

The current technology revolution, which has led to a widespread use of computers and the Internet, has produced an unparalleled data flood and fundamentally altered how we view the social and economic sciences. An equal increase in online activity was brought about by the continuously rising usage of the Internet as a source of information, such as business or political news. Massive databases are being created by interaction with technological systems, documenting collective behaviour in ways that were previously unthinkable. We might eventually discover the interests, worries, and intents of the world's population about a number of economic, political, and cultural events in this enormous archive of Internet activity. According to Ali (2018), social media is essential in overcoming the "information asymmetry" that exists between investors and markets. According to Dyck et al. (2008), the existence of media outlets reduces information asymmetries and the cost of information for businesses and investors. However, the media may use sentimental language in reporting, exaggerate or ignore certain points of view in order to garner attention or because of its own editorial preferences. This can lead to investors developing cognitive biases, which can then affect their investment decisions and behaviours (Hermida et al., 2012). In light of this, media sentiment must be taken into account when analysing asset prices and investor behaviour. This is particularly true in the initial public offering (IPO) market, where investors lack historical data to refer to when making decisions and are subject to highly asymmetric information (Guldiken et al., 2017). Scholars have begun to focus on how media sentiment affects asset pricing in the last few years (Sadique et al., 2008; Tetlock et al., 2008; Loughran and McDonald, 2011; Yang et al., 2022). A few of these academics decide to use a dictionary-based method for media sentiment analysis.

II. LITERATURE REVIEW

The academic communities of computer science and finance have different bodies of prior work. We begin by reviewing financial studies. Tetlock (Tetlock, Saar-Tsechansky, and Macskassy 2007) looks into whether we can predict a firm's cash flows by looking for negative terms in news articles about that firm, as well as whether stock market prices effectively take linguistic information into account. They contend that the negative information underpinning news items causes corporations' stock prices to underreact. More specifically, stock market prices reflect bad news information about a day after it appears in the media. Chan (Chan 2003) studies the monthly returns of a selection of equities following the revelation of public news about them and discovers that investors respond slowly to information, particularly negative news. A further noteworthy discovery is that stocks often see a reversal in the following month following significant price swings that aren't supported by the media. These patterns also have statistical significance. This study's use of course, monthly granularity is one of its limitations. In their study, Antweiler and Frank (Antweiler and Frank 2004) examine over 1.5 million postings from the two most prominent Internet stock message boards, Raging Bull and Yahoo! Finance. They evaluated the "bullishness" of the content of these stock communications using Naive Bayes and Support Vector Machine classifiers. They demonstrate the wealth of information available on these message boards and the strong positive correlation between bullishness and returns. From the computer science perspective, the machine learning and text mining communities provide very influential research. Their core concept is to use text mining techniques to calculate linguistic information, obtain a preset set of features from the training data, and then use statistical learning algorithms or classical statistical methodologies to construct different models. The relationship between online investor sentiment and stock movements has gained increasing attention as more and more investors use network forums and social media platforms to voice their opinions. Individual investors are increasingly turning to these online spaces not only to find stock information but also to share their thoughts and observations. These platforms' individual investor-generated content (IIGC) is related to stock fluctuations in two different ways. First, individual investors' emotional reflections in online stock comments impact their decision-making. Second, some investors might include remarks made about stocks on the internet in their selections. Because of this, academics and industry professionals are becoming increasingly interested in the function of social media and online stock forums in the stock market. Additionally, IIGC has emerged as a significant new source of investor sentiment, which is significant information that many experts believe can influence market movements.

There is a complicated link between stock return and investor emotion. Behavioral finance theory holds that emotions and reasoning play a role in investors' decision-making, and that a high concentration of emotionally charged investors can cause price deviations from underlying value. Most of the evidence supports the idea that investor attitude can impact stock return. According to Lee et al. (2002), who looked at how investor sentiment affected excess earnings and market volatility, a shift in mood had a positive correlation with excess returns and a negative correlation with market volatility. Schmeling (2009) discovers that the average returns of the stock market are negatively impacted by investor sentiment. Additionally, Huang et al. (2015) show that stock return is significantly impacted negatively by investor attitude. However, Hu and Tripathi (2016) discover that investor sentiment has a favorable impact on stock return by mining investor sentiment from an online stock market forum. Using investor sentiment indices extracted from Twitter, Sul et al. (2017) discover that both positive and negative sentiment have a significant impact on stock return. According to Dimpfl and Kleiman (2019), investor pessimism increases trade volume and volatility but decreases market return. According to Bouteska (2019), investor conservatism is the primary element driving the positive correlation between the cumulative abnormal return and the investor sentiment standard deviation.

Antweiler and Frank (2004) draw the conclusion that social media messages contribute to market volatility forecasting and have a statistically significant but economically insignificant impact on stock returns based on their examination of over 1.5 million messages on Yahoo!. This was among the first investigations on the connection between social media-based investor sentiment and the stock market. The use of social media investor sentiment to help forecast stock market returns is still a hot topic in finance today (McGurk et al., 2020). One distinct benefit of gauging investor sentiment using social media and natural language processing is its high regularity. Renault (2017) and Sun et al. (2016) claim that social media can be used to anticipate stock market returns by looking at investor mood half an hour in advance and half an hour after it occurs. This implies a causal relationship between investor sentiment and the stock market as well as a relationship between the stock market and social media.

Behrendt and Schmidt (2018) found that although investor sentiment is statistically strongly correlated with stock returns, it cannot be practically used to predict stock returns. This is because they used a higher-frequency measure of sentiment at 5-min intervals.

Wang et al. (2022) investigate the impact of stock returns on the mood of online message boards through a new type of controlled experiment. They discover a strong causal relationship between the mood on social media and same-day stock returns. Future day stock returns are unaffected by sentiment, and messages that are positive are the main source of this effect.

By gathering investors' optimistic and pessimistic expectations about the stock market through surveys, such as the Consumer Confidence Index (Brown & Cliff, 2005), the UBS/GALLUP Investor Optimism Index (Lemmon & Portniaguina, 2006), and the Investment Newsletter (Qiu & Welch, 2004), sentiment proxies based on survey indices quantify investor sentiment. The method based on unique occurrences, of which COVID-19 is arguably the most notable current example, frequently uses unique social events as emotion proxies. The impact of COVID-19 on investor psychology and how this affects the stock market are the subjects of an investigation by Naseem et al. (2021). The literature provides a full explanation of the fundamental traits of these three sentiment proxy techniques (Baker & Wurgler, 2007; Hu et al., 2021). Applying these methods to real-time research on investor sentiment and high-frequency stock market forecasting is challenging due to data acquisition limitations that cause investor sentiment found by these methods to have a certain lag and cannot be measured in real time. Technology related to natural language processing (NLP) presents a fresh way to measure investor sentiment. NLP offers a research foundation for investor sentiment research on social media because it can access investor sentiment that is contained in language and social networks. It also has the advantages of easy data availability, real-time access, and high credibility. High-frequency sentiment measurement has been feasible due to his meteoric rise and the advancement of NLP approaches (Kleinnijenhuis et al., 2013; Sun et al., 2016; Xing et al., 2020). Furthermore, several researchers have examined the intricate impacts of COVID-19 on the stock market and investor mood in light of the virus' ongoing presence (Eachempati et al., 2021; Fallahgoul, 2021; Hoang & Syed, 2021; Naseem et al., 2021; Sun & Shi, 2022). Social media platforms are now great sources of data for sentiment analysis, customer behavior, and market analysis. Studies have indicated that opinions posted on social media might foretell future developments. Asur and Huberman (2010), for instance, confirmed that the sales of upcoming films might be predicted by the interactions between friends on social networking sites. Moreover, textual analysis of sentiment on the social media platform Twitter was done by Bollen et al. (2011) in order to forecast market mood. Furthermore, Howard et al. (2011) asserted that social media discussions regarding revolutions came before the 2010 Arab Spring revolt. However, there isn't much research on the potential links between social media sentiment and corporate institutions' financial stability during times of financial crisis and market turbulence.

III. Information and technique

The stock price index had a 21% decrease in value at the start of 2011 over the prior year. As a result, 2011 is seen as the start of political unrest in the history of the Tunisian currency. We think that foreign direct investment returns could help the Tunisian stock exchange recoup its 13% growth in 2012. Moreover, the Tunis Stock Exchange survived 2013 despite a challenging climate brought on by political rifts, social unrest, economic challenges, and the threat of terrorism. The Tunis Stock Exchange concluded 2014 with a good assessment of the democratic transition process's rate of advancement. By the end of 2014, the benchmark index of the Tunis Stock Exchange had risen by 16.17% to 5089.99 points.

On March 2, 2020, Tunisia declared that it has confirmed its first instances of the virus. The Elyes Fakhfakh government attempted to control the pandemic during its initial wave by taking a novel yet practical method. To stop the coronavirus from spreading throughout the country, the government implemented some preventative containment measures on March 13, 2020. Furthermore, the Central Bank of Tunisia decided to lower the interest rate on the money market to 6.75%. Nonetheless, the stock exchange market, which is known for its fragility and shock susceptibility, was unavoidably impacted by the COVID-19. To be more precise, the Tunisian Stock Index (TUNINDEX) had a severe decline of 4.10% on March 16, 2020. In the first quarter of this year, booking cancellations for hotels in Tunisia reached 45%, indicating that the tourism industry was already feeling the consequences of COVID-19. Elyes Fakhfakh responded by requesting that the people of Tunisia evaluate the most recent measures taken by the government to strengthen the country's plan for containing the disease's spread. The government launched more programs to assist unemployed people and businesses focused on exports while also attempting to strike the best possible balance between economic and health hazards. In addition, the World Health Organization (WHO) and the International Monetary Fund provided US$745 million in help to bolster the health sector, along with assistance from nations including China, Qatar, Algeria, and Turkey (Karamouzian and Madani, 2020).

Model to be calculated.

Based on the conditional mean, the conventional Linear Regression (OLS) illustrates the link between the dependent variable (Y) and the independent variables (X). It is unable to explain the link at various Y levels. Quantile regression minimizes the sum of the absolute residuals in this context by using conditional media functions rather than mean functions. Both over- and under-dispersion of the data can be handled by it. The outcomes of QR estimations are more resilient to anomalies and non-normal data.

Rather than using just the conditional mean of y, a quantile regression model also takes into account the connection between x and the conditional Quantile of y.

The following equation characterizes the Quantil regression:

$$Y_{i,t} = x'_{i,t} B_q + e_{i,t}$$

where Bq is the vector of unknown parametres associated with the qth Quantile.

The OLS minimizes $\Sigma e2_{i,t}$, the sum of squares of the model prediction error $e_{i,t}$,the Quantile regression minimizes $\Sigma q |e_{i,t}|+\Sigma(1-q) |e_{i,t}|$

A sum that gives the asymmetric penalties $q|e_{i,t}|$ for underprediction and $(1-q) |e_{i,t}|$ for overprediction, where $\Sigma|e_{i,t}|$ is the median regression called least absolute deviation regression minimizes.

The qth Quantile regression estimator, $\hat{B}q$ minimizes over Bq the objective functions.

$$Q(B_q)=\Sigma n_{yi>x'B} \quad q|y_i-x'_iB_q| + \Sigma n_{yi<x'B} \ (1-q)|y_i-x'_iB_q| \quad 0<q<1$$

The standard conditional Quantile is specified to be linear

$$Q_q (y_i/x_i)= x'_i B_q$$

For the Jth regression , the marginal effect is the coefficient for the qth Quantile.

$$(\sigma Q_q(y/x))/ \sigma x_j =B_{qj}$$

A Quantile regression parameter Bqj estimates the change in a specified Quantile q of the dependent variable y produced by a one unit change in the independent variable xj.

Measures of variables

Sentiment polarity (SP)= (like – unlike)/(like + unlike)

Like = volume of like per week

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Unlike= volume of unlike per week
Score p = (Like – $\overline{\text{Like}}$)/ σLike
Score n = (Unlike- $\overline{\text{Unlike}}$)/ σUnlike
S1 index= score p - $\overline{\text{score}}$ n
S2 index=(Like-Unlike)/(Like+Unlike)

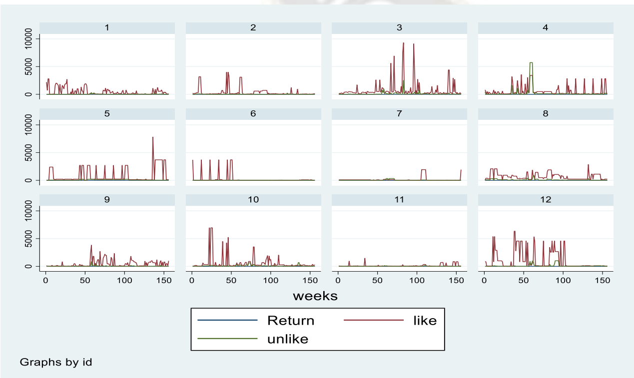
A. *Descriptive Statistics*

We initially show the descriptive statistics and then the series stationary tests prior to reporting the results.

We discovered that the return has a mean of approximately -0;00012, with a minimum value of -0,8953 and a maximum value of 1,18142. The mean values of like and unlike are 527,523 and 69,3052, respectively. As a result, the score p has a mean value of 0,0005645 between -0,326288 and 11,95905, and the score n has a mean value of 0,0010482 between -0,23711 and 10,42612; additionally, the mean values of sent1 and sent2 are -0,600048 and 0,659, respectively. In addition, the average of logvt is 4,172, with a minimum value of 0,876 and a maximum value of 6,595.

We note that the null hypothesis of normality is rejected for the sentiment polarity series. Initially, the Kurtosis coefficient—the Kurtosis theoretical coefficient under a normal distribution—is extremely high, either significantly higher than or different from 3. The series distribution's discernible leptokurtic shape is confirmed by excess kurtosis. Secondly, the theoretical skewness coefficient under a normal distribution is not equal to 0. For like, unlike, score p, and score n returns, the skewness coefficients are positive.

This suggests that each series' distribution is spreading to the right. Consequently, for the examined series, the null hypothesis of normalcy is rejected. Consequently, the emotion polarity, a common characteristic of financial series, is not normally distributed.



It can be concluded that like influences stock market returns more strongly than unlike. We found that the like peak occurred during the Covid period (week between 52 and 150), showing up in the Attijari bank, BT, and UIB (figs. 3,5 and 12), while the unlike peak only appears for BIAT (fig. 4). In most banks, we notice that the like fluctuations are not smooth with the returns, while the unlike follows the stock market fluctuations.

Tests for panel data unit roots

The Harris-Tzavalis (1999) panel unit root tests are used henceforth. The null hypothesis of the model states that there is a unit root in each panel. The test assumes a balanced panel and homogenous variance.

B. *Panel Test*

The Harris-Tzavalis (1999) panel unit root tests are used henceforth. The null hypothesis of the model states that there is a unit root in each panel. The test assumes a balanced panel and homogenous variance.

rho	Coeficient	Z	P-value
return	-0.0699	-1.8e+02	0.0000
Transaction Volume	0.1906	-1.4e+02	0.0000
scoren	0.7037	-47.3732	0.0000
scorep	0.1837	-1.4e+02	0.0000
sent1	0.4541	-90.0525	0.0000
Sent 2	0.6632	-54.2978	0.0000

The Harris-Tzavalis rho statistics is significant for the entire variable at all the usual testing levels. Therefore, we reject the null hypothesis and conclude that the series is stationary.

Using a 25 quantile and median regression to assess the effect of return on logvt, scorep, and scoren, we discovered that scoren is significant and modifies the sign in the two regressions. Positive emotions lead to more optimistic decision-making by investors, who are more likely to invest in the stock market because they tend to overestimate the potential return of a company while underestimating the associated risks. An optimistic outlook for the market will make investors keen to purchase equities. Additionally, when investor sentiment is negative, investors tend to be more cautious or even avoid making investment decisions because they are more concerned about the dangers associated with equities and tend to undervalue them. In summary, favorable investor sentiment in the market will raise stock prices in the near run, which will increase stock returns, and vice versa. As a result, investor mood may be somewhat predictive of stock movement.

IV. CONCLUSION

Our conclusion that investor sentiment has a favorable effect on stock return is consistent with the findings of Hu and Tripathi [32] and Bouteska [33]. Regression 3 demonstrates that the sent 1 has a positive impact on return. demonstrates that the first-day returns of new shares are significantly and favorably impacted by media mood; Wang X. et al. (2022) provide the following theory as a potential explanation for this phenomenon: a large number of noise traders, particularly on the first day of trading, participate in the secondary market. Individual investors are informationally disadvantaged and can only receive useful information through third-party intermediaries like the media, in contrast to professional institutional investors who have access to private information. Furthermore, individual investors are more susceptible to the effect of the media because of their relative lack of skills to assess information. Asset prices inevitably diverge from their underlying basic values due to the irrationality of individual investors.

Regression 4 shows that the unlike has a detrimental effect on the return.

Our findings suggest that sentiment polarity can predict returns. This demonstrates how important emotions are in understanding how stock values change. They're frequently described as a mental condition. According to conventional financial theory, a project can only be viable if investors base their decisions purely on their ultimate objectives. Behavioral finance, often known as emotional finance, differs from this standard viewpoint by assuming that investors make better decisions the more aware they are of their emotions. This implies that feelings aid a person's capacity for logical decision-making.

The question remains, nonetheless, whether the mood of investors affects various stock kinds equally and potently. According to Lee, Shleifer, and Thaler (1991), individual investors, who are more susceptible to sentiment, are the owners of tiny stocks. Therefore, the prices of tiny stocks may be more affected than the prices of large stocks when the sentiment of individual traders changes.

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