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Verbal Qualitative Information from Social Networks and Stock Performance of Tunisian Financial Companies

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Abstract: Social networks have invaded our world and changed the way we communicate. Even the financial world has turned to social media, with Twitter leading the way. As a result, social media is becoming an undeniable tool that affects the stock market. In this study, we consulted the articles published on the facebook page ilboursa of Tunis. The published articles contain an announcement of the news of the movements of the shares of the listed companies by using negative and positive words. Our database is composed by a manual counting of these qualitative verbal information. We used the list of words of the psychological dictionary "Harvard-IV-4". Our research focuses on 26 Tunisian financial companies listed on the Tunis Stock Exchange, over a one-year horizon, from 01 January 2015 until 31 December 2015. We used the GMM (Generalized Method of Moment) on dynamic panel. The generalized method of moments analyzes two models in which five days of delay of the dependent variable appear as explanatory variable. The results of the study are twofold. First, the Tunis stock exchange seems to react positively to positive qualitative information. Second, it reacts negatively to negative qualitative information. Among other things, the impact of stock returns on information is quite important. It is always necessary to master the tool of social networks to disseminate good and relevant qualitative financial information on the financial market.

Keywords: Verbal Qualitative Information, Social Media, Positive Information, Negative Information

1. Introduction

Today, social networks are part of the daily life of economic agents both personally and professionally. It is a tool that allows to easily exchange with customers, prospects, and develop one's business. This innovative tool aims to leverage the efforts of listed companies to diversify and rejuvenate their shareholder base, but also to federate the community of individual investors.

Social networks have invaded our world and changed the way we communicate. Even the world of finance has turned to social media, with Twitter in the lead. Indeed, the little blue bird delivers its information and makes the financial market go crazy. Despite the strong regulatory constraints on the stock market and listed companies, Twitter is increasingly becoming an indispensable tool for the financial world.

Schaupp and Belanger [9] define the use of social media in a business context as the deployment of a network to develop a community of users who collectively create, know, like, and trust relevant issues of the business entity. Blume and Keim [1] demonstrated that using social media to control the flow of information can benefit the company in explicit or even subtle ways, leading to broader interest and larger stakes in the company's stock.

This paper is organized into three sections. Section 1 presents the literature review of the relationship between financial information published on social networks and the stock market. Section 2 is devoted to the methodology. Section 3 presents the results obtained. Finally, we conclude in Section 4 and present our future work.

2. Literature Review

Bollen et al. [5] examined whether measures of collective mood states derived from large-scale Twitter social network feeds are correlated with the value of the Dow Jones Industrial Average (DJIA) over time. The authors analyzed the textual content of daily Twitter social network feeds by two mood tracking tools, namely OpinionFinder which measures positive versus negative mood and the GoogleProfile of Mood States (GPOMS) which measures mood in terms of 6 dimensions (Calm, Alert, Sure, Vital, Kind, and Happy).

Ranco et al [4], studied the relationship between a well-known microblogging platform on Twitter and the financial markets. This analysis is conducted on 30 blocks of the Dow Jones Industrial Average stock index. The stock data is collected for a 15- month period between 2013 and 2014. Following this study, the researchers investigated the relationship between price data in the financial market and data published on the social network Twitter.

Smailović et al [15] investigated whether social network Twitter feeds, expressing public opinion about companies and their products, are a suitable data source for predicting changes in closing prices. The researchers used the term predictive sentiment analysis to refer to the approach in which sentiment analysis is used to predict changes in the phenomenon of interest.

Puri [12] focuses on the relationship, if any, between Twitter "s public mood and stock returns by analyzing Tweets about four major U.S. consumer discretionary companies, namely Amazon, Walt Disney, Home Depot, and Comcast. The duration of this study is approximately one month. The author found a causal relationship between sentiment on the social network Twitter and the volume of Tweets for a given stock and stock price returns.

Kumbure et al [11] studied machine learning techniques applied to stock market prediction. The authors examined 138 journal articles published between 2000 and 2019. They provided a bibliometric analysis of these journal articles, highlighting the most influential work and articles. The researchers conducted an extensive review of the data, specifically the markets and stock indices covered by the forecasts, as well as the 2173 unique variables used for stock market predictions, including technical indicators, macroeconomic variables, and fundamental indicators.

Ruochen Lu and Muchao Lu [13] focus on the problem of predicting the trend of stocks based on deep learning. The researchers classified the sentiment of the stock market forum remarks and calculate it to get the investor sentiment index. Based on the sentiment dictionary, a stock market sentiment dictionary is formed by adding the specialized vocabulary of the stock market. A sentiment classification model is built based on the simple Bayesian algorithm to classify the sentiments of stock market forum comments. Experiments show that the classification effect is better by using this model, and the investor's sentiment is obtained more accurately, and the accuracy rate can reach 85%, which lays the foundation for the establishment of the whole stock trend prediction model.

Wang. J and Yan. Z [6] proposes a new prediction method based on machine learning technology that incorporates traditional stock index variables and social media text features as inputs to the prediction model. First, they found that the new stock price prediction method, which combines the textual features of social media, improves the performance of traditional methods. Social media content contains a lot of important information about stocks. The variables of the stock financial index can only represent the development trend of the stock price, but the sentiment of investors can describe the potential trend of the stock price. Second, we use SAE to address the imbalance between stock features and text features, there by improving the accuracy of stock price prediction methods.

Hu. Z et al [16] provided a detailed review of 88 papers from 2015 to 2021 on predicting stock price movements/Forex using deep learning methods. They categorized the papers according to different deep learning methods, which include: Convolutional neural network (CNN), Long Short-Term Memory (LSTM), Deep neural network (DNN), Recurrent Neural Network (RNN), Reinforcement Learning, and other deep learning methods such as HAN, NLP, and Wavenet. The researchers examined the key performance measures of all models. These are RMSE, MAPE, MAE, MSE, precision, Sharpe ratio and Return rate.

Ardia et al [2] conducted a tone-based event study to examine the overall anomalous tone dynamics in news articles around earnings announcements. They tested whether they convey additional information useful for price discovery for nonfinancial S&P 500 firms. The researchers found that the relationship between abnormal tone and abnormal returns suggests that news articles provide additional information compared to the information in press releases.

Lu et al. [10] measure abnormal media tone based on new text data in China and study its predictive power in cross-sectional stock returns. The researchers observe that firms with high abnormal media tone generate lower future returns than those with low abnormal media tone. This negative relationship is robust when controlling for common risk factors. These results are more pronounced among low-investment, high short-term reversal, and value firms. They found that the negative premium induced by abnormal media tone is related to poor valuation. The results show that investors tend to overreact to the abnormal tone of the media, even though the media does disseminate competing information about the companies. Furthermore, the media's following exacerbates this investor overreaction.

Hanyu et al [3] classified news articles into positive, neutral, and negative sentiment to test the anomaly of media sentiment in cross-sectional stock returns. The authors found that firms without positive or negative news have significant positive returns. Portfolios constructed by buying companies with no negative information and shorting companies with a lot of the negative information can achieve the highest abnormal return after controlling for well-known risk factors. In addition, the researchers tested different combinations of portfolio formation and holding period. They found that excess return exists for holding periods longer than three months with different portfolio formation periods based on current sentiment. The authors concluded that the news sentiment anomalies are not caused by the short-term momentum effect and are robust in the Chinese stock market.

3. Empirical Study

Our study focuses on 26 Tunisian financial companies listed on the Tunis Stock Exchange, over a one-year horizon, from January 01, 2015 until December 31, 2015. The period of the study is weekly. We will use two types of data, the first is the site of the Facebook page: facebook.com/ilboursa. The second type is the website of the stock exchange of Tunis bvmt.com.tn.

The articles published in the facebook page ilboursa, contain an announcement of the news of the movements of the shares of the quoted companies using negative and positive words. Our database is composed by manual counting of this qualitative verbal information. We will use the word list from the Harvard Psychological Dictionary-IV-4. The models of our research are used to test the impact of verbal qualitative information from social networks and the stock performance of Tunisian financial companies.

The models are estimated by K. Ahmad et al [7]:

$$\boldsymbol{R_i} = \boldsymbol{\alpha_{1,i}} + \sum_{k=0}^{1} (\boldsymbol{\beta_{1k} R_{i,t-k}}) + \sum_{k=0}^{1} (\boldsymbol{\delta_{1k} M_{i,t-k}}) + \boldsymbol{\Theta_1 DRam_t} + \boldsymbol{\varepsilon^R_{i,t}} \tag{1}$$

$$\boldsymbol{M_i} = \boldsymbol{\alpha_{2,i}} + \sum_{k=0}^{1} (\boldsymbol{\beta_{2k} R_{i,t-k}}) + \sum_{k=0}^{1} (\boldsymbol{\delta_{2k} M_{i,t-k}}) + \boldsymbol{\Theta_2 DRam_t} + \boldsymbol{\varepsilon^M_{i,t}} \tag{2}$$

With:

$R_{i,t}$ = The stock return variables of company i at time t.

$M_{i,t}$ = The media information variables of the social network face book.

Ramt = Ramadan effect.

$\varepsilon_{i,t}$ = The error term.

Variables

The model of the study is based on three variables of stock returns of financial companies, three variables of verbal qualitative information of the social network facebook and a control variable:

Table 1. *Variables.*

Variables	Measure
	Number of articles: Takes the value 1 if there are published articles otherwise 0.
Social network	Number of positive words: We manually count the number of positive words for each article.
	Number of negative words: We manually count the number of negative words for each item.
	Stock return: is the difference between the natural logarithm of P_t and P_{t-1}.
Market performance	Market capitalization: (BVMT website)
	Volume of transactions: (BVMT website)
Control variable	Ramadan effect: Takes the value 1 if the day is in the month of Ramadan otherwise 0.

With: Pt and Pt-1: are the stock prices at time t and t-1.

4. Results

We used a dynamic model using STATA 12 software for our model estimation. We used the GMM (Generalized Method of Moment) on dynamic panel. In our study, the generalized method of moments analyzes two models in which five days of lag of the dependent variable appear as an explanatory variable. The effectiveness of GMM estimation relies on the validity of two tests: the Arellano Bond test and the Hansen/Sargan test.

In the estimation results, we notice that the number of observations for the different variables is not identical. This is explained by the number of missing data for the main variables retained. We notice that the probability of the variable number of items with a day delay is (0.000). This variable is significant at the 1% level. With probabilities of (0.019) and (0.039) the variable number of articles with two and four days of delay is significant at the 5% threshold. In addition, with a probability of (0.067) the variable number of items with three days delay is significant at the 10% threshold.

4.1. The First Model

We find that the delayed variable number of articles published on the facebook page ilboursa affects the performance of shares of Tunisian financial companies. The Ramadan effect control variable has a probability of (0.000). This variable is negatively significant at the 1% level. The Ramadan effect variable affects the stock returns of Tunisian financial companies. We find that the probabilities of the lagged variable and the probability of the control variable are above the significance level. On the other hand, the lagged variable number of items and Ramadan effect are not significant. We find that the variation of the lagged variable number of items does not affect the transaction volume of Tunisian financial firms. The set of probabilities for the lagged variable number of items and Ramadan effect is (0.000). The lagged variable and the control variable are significant at the 1% level.

The number of articles published on the facebook page ilboursa affects the market capitalization of Tunisian financial companies. The control variable Ramadan effect affects the market capitalization of Tunisian financial companies. We notice that the probabilities of all the variables are (0.000) and (0.010). The lagged variable number of positive words and Ramadan effect are significant at the 1% level. The variable number of positive words affects the return on shares of Tunisian financial companies. Similarly, the Ramadan effect variable affects the stock performance of Tunisian financial companies.

We notice that the probability of the variable number of positive words with one day delay is (0.004). The variable delayed by one day is negatively significant at the 1% level. In addition, the probability of the variable number of positive words with five days delay is (0.073). This variable is positively significant at the 10% level. The variable number of positive words delayed by five days affects the trading volume of Tunisian financial companies' shares. We notice that the probabilities of the variable delayed by five days number of positive words and the probability of the control variable Ramadan effect amounts to (0.000).

Indeed, we find that the lagged variable number of positive words and the Ramadan effect variable are significant at the 1% threshold. The variable delayed by five days number of positive words affects the market capitalization of shares of Tunisian financial companies. In addition, the Ramadan effect variable affects the market capitalization. We note that the probabilities of the variable number of negative words with three and four days delay are (0.066) and (0.055). We find that this variable is significant at the 10% level. In addition, the probability of the variable number of negative words with a delay of five days is (0.009). The variable delayed by five days is negatively significant at the 1% level.

We find the probability of the control variable Ramadan effect amounts to (0.000). The Ramadan effect variable is negatively significant at the 1% level. We find that the variable delayed number of negative words by three, four and five days affects the stock returns of Tunisian financial firms. In addition, the Ramadan effect variable affects the stock performance of Tunisian financial firms. From the probabilities of the lagged variable number of negative words, we find that this variable is not significant. The variable number of negative words does not affect the volume of transactions of Tunisian financial companies. The control variable Ramadan effect notes a probability of (0.029), this variable is negatively significant at the 5% level. The variation of the Ramadan effect variable affects the transaction volume of Tunisian financial companies.

The statistical results of the estimation of the impact of the variable number of negative words on market capitalization are shown in the Appendix. We notice that the probabilities of the variable number of negative words with a delay of one, two, three and five days are (0.000). This variable is significant at the 1% level. The Ramadan effect control variable has a probability of (0.000). This variable is significant at the 1% level. The lagged variable number of negative words and the variable Ramadan effect affect the market capitalization of Tunisian financial companies.

4.2. The Second Model

We focus on analyzing the impact estimates of lagged stock performance variables on the verbal qualitative information variables posted on the ilboursafacebook page. From the probabilities of the variables delayed return on shares and Ramadan effect, we find that these variables are not significant. The variation of the lagged variable stock return of Tunisian financial companies does not affect the number of articles published on the Facebook page ilboursa. From the probabilities of the lagged stock return variable and the probability of the Ramadan effect control variable. We find that these two variables are not significant. The lagged variable of five days stock return of Tunisian financial companies does not affect the number of positive words used in the articles published on the facebook page ilboursa.

We note that the probabilities of the variable stock return with one, two and five days delay are (0.000) and (0.008). This variable is significant at the 1% level. In addition, the probability of the stock return variable with a four-day delay is (0.018). This variable is significant at the 5% level. The probability of the Ramadan effect control variable is (0.000). This variable is significant at the 1% level. The variable delayed stock return and the variable ramadan effect affect the number of negative words used in the articles published on the facebook page ilboursa.

From the probabilities of the variable volume of transactions with a delay of one, four and five days (0.000) and (0.002), we find that this variable is significant at the 1% threshold. The probability of the variable volume of transactions with a delay of three days is (0.026), this variable is significant at the 5% level. The variable delayed volume of transactions of shares of Tunisian financial companies affects the number of articles published on the facebook page ilboursa. We note that the probabilities of the variable volume of transactions with a delay of one, three and five days are (0.000) and (0.001).

This variable is significant at the 1% level. The probability of the variable volume of transactions with four days delay is (0.018). This variable is significant at the 5% level. The variable delayed volume of transactions of shares of Tunisian financial companies affects the number of positive words of the articles published on the page facebookilboursa. We note that the probabilities of the transaction volume variable with two, four and five days delay are (0.010) and (0.000). This lagged variable is significant at the 1% level.

The probability of the Ramadan effect control variable is (0.000), so this variable is significant at the 1% level. The variable delayed volume of transactions of shares of Tunisian financial companies affects the number of negative words of the articles published on the Facebook page ilboursa. We note that the mentioned probabilities are above the significance level. The lagged variable stock market capitalization of Tunisian financial companies and the control variable Ramadan effect do not have significant impacts. The variation of the variable delayed market capitalization does not affect the variable number of articles published on the page facebookilboursa. From the probabilities of the lagged variable market capitalization and the control variable Ramadan effect, we find that these variables do not have significant impacts. The variable delayed market capitalization of shares of Tunisian financial companies does not affect the number of positive words used in the articles published on the facebook page ilboursa.

We note that the probabilities of the market capitalization variable are (0.000), (0.005) and (0.053). We find that the variable lagged by five days is significant at the 1% and 10% level. The probability of the Ramadan effect control variable is (0.016). This variable is significant at the 5% level. The variable delayed market capitalization of shares of Tunisian financial companies affects the number of negative words used in the articles published on the facebook page ilboursa. In addition, the Ramadan effect variable affects the number of negative words variable.

4.3. Validation Tests

From the probabilities of validation tests (Arellano Bond test and Sargan test), we reject the null hypothesis. The instruments used in our regression are valid.

4.4. Similar Results

Our result is similar to the work of a number of researchers.

Siganos et al [14], examined the relationship between daily sentiment and trading behavior in 20 international markets by leveraging Facebook's Gross National Happiness index. They found that sentiment has a positive contemporaneous relationship with stock market returns. Furthermore, Sunday sentiment affects stock returns on Monday, suggesting causality from sentiment to stock markets. The authors observed that the relationship between sentiment and returns reversed in subsequent weeks. In addition, they also showed that negative sentiment is related to increased trading volume and volatility of returns.

Bollen et al. [5] and Karabulut [8] proposed measures of investor sentiment based on the content of Internet posts on the social networks Twitter and Facebook respectively. These studies design their sentiment measures to capture investors' moods. Bollen et al. [5] argue that the "Calm" and "Happy" dimensions of public mood extracted from the social network Twitter have strong predictive power for weekly returns of the Dow Jones index in 2008. Karabulut [8] shows that Facebook's Gross National Happiness index updated status - positively predicts next day stock returns, followed by a partial price reversal. These results underscore the promise of proxies for social network data-based sentiment.

5. Conclusion

The results found on the Tunisian market are corroborated with previous studies testing international markets (American, Japanese, German etc....). The results demonstrated the importance of social networks for the dissemination of financial information. As a result of its significant impact on stock returns, trading volume and market capitalization. Among other things, the impact of stock returns on information is quite important. It is always necessary to master the tool of social networks to disseminate good and relevant qualitative financial information on the financial market.

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