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THE EFFECT OF SOCIAL MEDIA ON STOCK MARKET EVIDENCE FROM TWITTER

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Abstract

In this study, we investigate the sentiment of social media to predict stock market performance. In particular, we test the relationship between the twitter activity, number of tweets and followers, and the stock return, volume, and volatility of top 82 companies listed on ASX. We obtain a data set of number of tweets and followers from each company's twitter account at end of the fiscal year 2019. Our results indicate that stock return is positively associated with the number of organizations' twitter followers, suggesting firms with high returns are likely to have significant number of followers. Moreover, stock trading volume is positively (negatively) associated with the number of organizations' tweets (twitter followers). These findings suggest that firms with high liquidity tend to have significant flow of tweets information rather than many followers with few tweets. However, we find no evidence suggesting that twitter followers and tweets are associated with stock volatility. This study will assist regulators in understanding to what extent the information on major social media platforms can help investors in their investment decision-making.

***Keywords*:** Social media, Twitter, Stock market, Efficient Market Hypothesis, Behavioral Finance.

1. Introduction

Social media plays a crucial role in today's business world (Kim & Ko 2010). In a rapid changing society and evolving consumer behavior, Twitter remains a key player these days. It influences the decisions of different users such as individual, companies, businesses and public and private services by presenting a wide range of news and information and reaching millions of people in short period of time with less cost (Nisar & Yeung 2018). Twitter's simplicity, openness, and uniqueness make it very successful. Just by 140 characters, followers can spread valuable content and information at anytime and anywhere. Similarly, crucial events and emergency news could spread easily through its dynamic firehose and micro blogs as a public information channel used by authorities (Burns 2012). Social media has a great influence on the organizations' stock prices and returns (Luo Zhang & Duan 2013). Bartov Faurel and Mohanram (2018) mention that years ago, organizations have relied on traditional financial intermediaries such as financial analysts and financial advisors, the business press, short sellers, auditors, and credit rating agencies to acquire updates and valued information on stock returns. However, now a days, with the development of the Internet and specifically social media platforms such as Twitter, Facebook, Instagram, etc., companies depend heavily on each other as peer to peer dissemination of information regarding the prospects of stocks in which users post instantly their views about stocks to a wide audience (Kim & Ko 2012; Parveen Jaafar & Ainin 2016) with less cost (Hsu 2012; Schniederjans Edita & Schniederjans 2013). This report investigates whether there is a relationship between the social media sentiment and stock market performance in the Australian context. Specifically, we are testing for relationships between the number of organizations' Twitter followers and tweets associated with stock returns, volume, and volatility of top 82 companies listed on ASX. We are particularly asking the following main research question, whether the number of organizations' Twitter followers and tweets is associated with stock market performance of top 82 companies listed on ASX? The report will help investors to understand the impact of social media on stock market and influence their investment decision making. The results will guide organizations and stakeholders to implement strategies related to social media and stock market in order to gain a competitive advantage. Likewise, this report will be useful to fill the gap in Australian context of research and literature study.

2. Literature Review

2.1. Neoclassical Versus Behavioural Finance

It is extremely hard to be able to prove whether the stock market is predictable or not. There are myriad of models that have been developed for this aim. Some researchers' findings eventually led to the development of the Efficient Market Hypothesis (EMH) which states that stocks already reflect all available information, making it impossible to predict their movement based on past data. While, others believed in conventional financial theory which assumes full rationality and efficiency, consensus in behavioral finance and that psychology and emotions are important factors in determining how investors behave (Subrahmanyam 2010). Market Efficiency was created in 1970 by the famous economist Eugene Fama, whose EMH states that investors can't outflank the market, and that market anomalies should not exist because they will immediately be arbitraged away. Fama later won the Nobel Prize for his hard work (Sewell 2011). Market efficiency refers to how well current prices reflect all available, relevant information about the actual value of the underlying assets. It indicates how much market prices react to all relevant information. In the event that markets are efficient, at that point all data is as of now consolidated into prices, thus it's absolutely impossible to beat the market in light of the fact that there are no undervalued or overvalued securities available (Fama 1970; Fama 1998). Moreover, a study by Fama and French (1996) show that the stock return is related to firm characteristics like the size, earnings price, cash flow price, book to market equity, and short- and long-term return. It was argued that "Many of the CAPM average return are related and they are captured by the three-factor model in Fama and French (1993). The model says that the expected return on a portfolio in excess of the risk-free rate is explained by the sensitivity of its return to three factors. Ramiah Xu and Moosa (2015) show the difference between Neoclassical and Behavioral Finance. It was mentioned that EMH is the main pillar of neoclassical finance. This theory assumes that financial asset prices reflect all available data because market participants are rational processors of all information. It is believed that the market value and fundamental value of an asset should both be aligned, financial markets react rapidly to new information or data, prices follow unsystematic process resulting from a haphazard arrival of data, and investors cannot earn return in excess of what is steady with risk. However, many articles did not agree with Fama and French's EMH theory and all other authors that support their studies. Unlike EMH, the conventional financial theory believes that investors are noise traders who make decisions without the use of finance fundamentals, exhibits poor market timing, follows trends and tends to overreactor underreact to good and bad news. Investor' decisions are influenced by taste, preference and other psychological factors and not only by statistical characteristics such as mean-variance configurations to make investment decisions. Inadequate information flows in the existence of trader heterogeneity. Different investors might have different investment opportunities. This will all depend on investors' tastes and preferences. In some cases, this herding behavior may result in a common taste. And investors may be subject to market sentiment while arbitrage opportunities exist. Thus, market is not necessarily in equilibrium (Ramiah et al. 2015) and (Subrahmanyam 2010). According to Shiller (2003), an increase in speculative prices encourages investors to invest and attract the public attention. This will also promote the word-of-mouth enthusiasm, and rise the expectations for further price increases. All these articles contradict the EMH model that emphasized on the idea of investors can't outflank the market, and that market anomalies should not exist because they will immediately be arbitraged away. We can see that recently it was proved through many models that studies merged psychology and finance and proved that stock prices and investors decisions are influenced by external psychological biases factors that in return affect the decision-making process and the stock prices (Ritter 2003; Fung 2006). Similarly, another study by Engelberg and Parsons (2016) reveal that there is a positive relationship between the stock price change and investors' psychology. Engelberg and Parsons (2016, p. 1228) mention that 'The more quickly that changes in stock prices impact an investors' instantaneous well-being, the more likely the effect is coming through expectations over future consumption, rather than through current consumption, that is, the budget constraint'.

2.2. Information-Based Theories

Stock market efficiency is associated with news being spread immediately in the market. Asymmetric information among market participants is also key to understand the formation of market prices. According to Shiller (1987) investors do not react immediately to any information during the market crash; however, they do respond to each other. Unlike the EMH, De Bondt and Thaler (1985) postulate that in an event of new information, shareholders overreact by trading more, especially when receiving news about the asset value. They added that this overreaction is due to a purely biased behavior. Hence, considering extreme events, transaction volumes are then expected to be even more positively correlated with market returns. Kyle (1985) presents model that indicates a positive correlation between stock prices and stock market volumes. When traders are informed about the liquidation value of the asset, they will increase their demands for the asset proportionally to the information received. Thus, they will trade more aggressively in the event of this particulate news, an extreme change in the liquidation value of the asset. Additionally, Miller (1977) who presented the Visibility Hypothesis (VH) proposes that a volume shock will lead to an increase in the probability that a trader will investigate a stock. He mentioned that if investors have divergence of opinions and short-sale constraints exist, the stock price will tend to increase after attracting investors' examination. Alternately, Merton's (1987) present Investor Recognition Hypothesis (IRH) which extends the standard CAPM model and postulates that the stock price and visibility are positively correlated because the required rate of return may decrease as the investor base increases. Boehme Danielsen Kumar and Sorescu (2009, p. 439) stated that 'Investors only hold securities whose risk and returns characteristics they are familiar with. Because these investors hold under-diversified portfolios, they demand compensation for idiosyncratic risk. Accordingly, ex-post returns are positively related to firms' idiosyncratic risk'. Information disseminated in the market affect directly the stock market efficiency and many studies conducted by famous authors proved that true. For example, the Mixture of Distribution (MDH) developed by Epps and Epps (1976) shows that traders and investors are exposed to all information arriving to the market simultaneously, so that a new equilibrium is reached directly with the new data impounded in prices. According to the MDH, contemporaneous trading volume explains stock price volatility. On the other hand, Copeland (1976) had developed Sequential Information Arrival Hypothesis (SIAH) which competes with Epps and Epp's model. It has another explanation of the volume volatility relationship, at the beginning not all traders are informed or exposed to the news, so a series of intermediate equilibria are attained. Later, after the development of the internet especially social media, information becomes complete and a full equilibrium is established. Copeland theorized that trading volume will be abnormally high during the same periods in which absolute returns are serially correlated.

3. Hypothesis

Based on the above theory and previous studies, the main hypothesizes are developed as follows:
[H1]. Stock market performance is associated with the numbers of organizations' number of tweets.

[H2]. Stock market performance is associated with the numbers of organizations' Twitter followers.

[H3]. Stock market performance is associated with organizations' size.

[H4]. Stock market performance is associated with organizations' price-to-earnings ratio.

[H5]. Stock market performance is associated with organizations' book-to-market ratio.

4. Methodology and Models

In this section, we will outline the statistical tests and methods we will use to test our hypothesis. We have chosen the Linear Regression approach for the following reason: the purpose of this study is to investigate if the number of organizations' Twitter followers and tweets are associated with stock returns, volume, and volatility of top 82 companies listed on ASX. This is a correlational research based on secondary sources. According to Curtis Comiskey and Dempsey (2015), in this type of non-experimental research method, a researcher measures two variables through a Linear Regression approach, that is used to determine the extent to which there is a linear relationship between a dependent variable and one or more independent variables. Furthermore, we will use quantitative research. It will definitely help to answer the research question that was stated in the previous section. Moreover, we are modeling the relationship between stock returns and number of Tweets and Twitter followers and control for firm size, PE ratio and PB ratio. We also use trading volume and volatility as dependent variable respectively and model its association with number of Tweets and followers and the control variables of frim size, PE ratio, and PB ratio. Thus, the following is a mathematical representation of our Linear Regression Models:

$$VOL = \alpha + \beta_1 TWEETS + \beta_2 FOLLOWERS + \beta_3 SIZE + \beta_4 PE + \beta_5 PB + \varepsilon_t \text{ (Equation 1.1)}$$

$$RET = \alpha + \beta_1 TWEETS + \beta_2 FOLLOWERS + \beta_3 SIZE + \beta_4 PE + \beta_5 PB + \varepsilon_t \text{ (Equation 1.2)}$$

$$S.D = \alpha + \beta_1 TWEETS + \beta_2 FOLLOWERS + \beta_3 SIZE + \beta_4 PE + \beta_5 PB + \varepsilon_t \text{ (Equation 1.3)}$$

Where the dependent variable is shares' trading volume, return and volatility respectively, the main variable of interest are Tweets and Followers and we control for firm size, PE ratio and PB ration. The trading volume (VOL) is measured as the log form of share trading volume. We calculated stock returns (RET) as the difference between the ending price and the beginning price plus the dividends distributed and divide by the beginning price. The volatility (S.D) is obtained by retrieving the closed price of the share for the last three months and it is calculated as the standard deviation of the last three months share price. The tweets (TWEETS) and followers (FOLLOWERS) are measured as the log form of number of tweets and followers at the end of the fiscal year 2019. The firm size (SIZE) is measured as the log form of market capitalization. The price-to-earnings ratio (PE) is measure as price divided by earnings per share. The book-to-market ratio (PB) is measured by dividing the book value equity by the common shareholder equity. All the financial data we hand collected from Yahoo! Finance at the end of fiscal year 2019.

5. Data

We chose to focus on the Australian market mainly. Particularly, the top 82 companies listed on Australian Stock Exchange. All the data was at the end of the fiscal year 2019. This will give us advantage to study accurately the influence of numbers of organization's tweets and twitter followers and tweets on stock returns, volume, and volatility. We have collected the independent variables, number of tweets and followers, from each of the company's Twitter account. Plus, we have gathered and calculated the dependent variables such as the volume, return rate, and volatility of shares, and control variables such as the market capital, price- earnings ratio, and book-to-market ratio from Yahoo! Finance.

6. Empirical Findings

6.1. Descriptive Statistics

Table 1 below provides descriptive statistics for volume, return, volatility, tweets, followers, size, PE, and PB. It is clearly shown below that the mean and median are almost the same. Consistent with the study done by Grob König and Ebner (2019), the mean return in our results is equal to 4%. It is approximately equal to the mean return (3%) of companies listed on ASX 100 (Grob et al. 2019). The study examines the long-term relationship between signals derived from nine years of unstructured social media microblog text data such as Twitter and financial market developments such as ASX 100 in five major economic regions. Therefore, the return in our research is slightly different as the sample size and industries were different. Furthermore, the standard deviation for VOLUME (VOL) is equal to .52. It is low and clustered around the mean and it shows that there is no much volatility in the VOL variable. Our result is similar to standard deviation VOL (1.43) in a study conducted by Paul (2015). We can see a small difference as the sample size was *n=176* bigger than our sample size *n=82*. The standard deviation for TWEETS is equal to .8 approximately similar to standard deviation of number of tweets (.6) found in Prokofieva (2015) for ASX companies. Moreover, the mean FOLLOWERS equal to 20,451 is equivalent to 3.6 in the log form of the number of followers. This mean is similar to the mean followers found in one article by Mauder (2018) that investigate the relationship between the firm's social media activities on Facebook, LinkedIn and Twitter and corporate value. The mean followers found in the article was equal to 24,521 with sample size *n*= 1329. The study was done in 2018 and investigated Australian companies in general regardless if they were listed on ASX.

6.2. Regression Analysis

The results in table 2 below show that VOL and TWEETS are positively and moderately correlated with β= .363 and *p*-value = .068. For every 1% increase in number of Tweets the stock return will increase 36.3%. These findings are consistent with Prokofieva (2015) where twitter activities such as number of tweets posted by organizations and stock volume were positively and significantly correlated. The study suggests that number of tweets and followers contribute to the increase or decrease of investors' attention and influence investors during stock trading activity. It was found that tweeting good news affects the stock market and investors' decision positively while vice versa for bad news. Another study by Wysoki (1998) show a strong positive correlation between the volume of messages posted on the discussion boards during the hours that the stock market is closed and the next trading day's volume. VOL and FOLLOWERS are negatively and strongly correlated with β= -.557 and *p*-value= .01. The result was consistent with Nofer and Hinz (2015) who investigate the relation between the Social Mood Index (SMI) mood and the stock trading volume. The SMI was calculated based on the number of followers on Twitter and other external factors such as negative and positive mood. The results show negative and moderate correlation with β= -.002 and *p*-value = 0.1. It was mentioned that the correlation was negative as the majority of followers fell under the bad mood category when collecting the data. The weight of bad mood calculated in SMI was higher than the weight of good mood. Many articles such as Cazzoli Sharma Treccani and Lillo (2016) believe that it is the quantity of users, wisdom of crowd, that influence the stock market performance, however; it is the quality of users, important ones, that affect the stock market performance. Cazzoli et al. (2016) state that this could be explained as well that companies sometimes tweet existing followers. These findings suggest that firms with high liquidity tend to have significant flow of tweets information rather than many followers with few tweets. Similarly, Nofer and Hinz (2015) and Zhang et al. (2011) showed in their studies that mood plays a crucial role in investors' decision making which will affect directly the stock market performance. Thus, it was mentioned that bad mood followers affect the stock volume negatively and good mood followers influence the stock market liquidity positively. The values of the control variables were significant and in the expected direction except for PB. VOL and SIZE positively correlated with $\beta = .419$ and significant at p-values .001. This was consistent with Lischewski and Voronkova (2012) who mentioned a combination of size, and price to earnings effect is better able to capture the cross-section of stock volume and return. The study showed that there is a correlation between the stock market liquidity (volume) and return and the size. Therefore, the stock volume is influenced by the size indicating the bigger the size of the company the higher the trading volume of share. On the other hand, VOL and PE were negatively correlated with $\beta = -.282$ and p-values= .008 respectively. The results were similar to one article by Mugwagwa et al. (2012) who investigated the impact of stock return and volatility on the buy-write strategy in the Australian market and proved that price earnings ratio have an impact the stock return, volume, and volatility. The study shows high price- earnings ratio indicates that a company's stock is over-valued. This could lead to decrease in share's trading volume. Investors will be hesitant to invest in the company and buy shares, leading to decrease in the stock return. For RET and FOLLOWERS were a significant regressors. This means that all else held constant, firm-initiated followers made a difference in stock return. RET and FOLLOWERS are positively and moderately correlated with $\beta = .454$ and significant at p-value =.035. In other words, for every 1% increase in number of followers the stock return will increase 45.5%. This was consistent with Mauder (2018). The findings showed that Twitter measured as the number of firms' Twitter followers was strongly and positively correlated with stock return with p-value = .003. There is a supported relationship between the numbers of organization's Twitter followers and stock returns. According to Paul (2015) social media such as Twitter motivate investors to buy more shares by overemphasizing the positive aspects of investing in the company though the communication "Tweeting". Hence, Twitter became a significant channel for companies to communicate with investors and disseminate the information. It also serves as a convenient mechanism to capture market sentiment and influence stock prices which will simultaneously affect positively the stock returns. This shows that there is a positive relationship between number of organizations' Twitter followers and stock return. Our result contradicts the EMH theory developed by Farma and French (1970) which states that that investors can't outflank the market, and that market that market anomalies should not exist because they will immediately be arbitraged away. While, it supports the Behavioral theory that was studied in many articles such as Shiller (2003), Ritter (2003) and Fung (2006) and proved that psychology affects stock market especially stock prices. Investors decisions are influenced by external psychological biases factors that in return affect the decision-making process and the stock prices. Not surprisingly, we note a correlation between RET and PE. Both were negatively and strongly correlated with $\beta = -.281$and highly significant at p-value = .009. This implies a high price-earnings ratio could mean that a company's stock is over-valued. Therefore, investors will hesitate to invest in the company and buy shares thus, negatively affecting the stock return (Mugwagwa et al. 2012). No correlation found between RET and the remaining control variables SIZE and PB. Our findings were consistent with (Mauder 2018), stock returns were not correlated with PE. The study shows that p-value was equal to .198. For S.D, FOLLOWERS and

TWEETS were a not significant regressors, however, SIZE and PE were significant ones. Thus, firms' size and price earnings ratio made a difference in stock volatility. For S.D, SIZE, and PE it was a positive and strong correlation with β= .345 and .283 and highly significant at *p*-values = .004 and .008. This was consistent with Nazir Nawaz Anwar and Ahmed (2010) who showed that firm size has significant impact on stock price volatility. Their results demonstrated strong and positive correlation between firm size and stock volatility with β= .14 and *p*-value = .005. Likewise, our findings for S.D and PE were constant with Afza and Tahir (2012) who postulate that stock volatility and PE ratio are strongly and positively correlated with β= .14 and *p*-value = .032. Moreover, Henry and Sharma (1999) and Farag and Cressy (2012) argue that prices changes are related to the flow of new information to the market. The more investors are exposed to information the more the stock volatility and return are affected. They added that mainly large firm portfolios are affected more than small firm portfolio by the flow of bad or good news. In other words, stock volatility is higher in organization with higher market capitalization. Furthermore, Drechsler (2013) and Mugwagwa et al. (2012) mentioned that high PE ratio can lead to low stock return and high stock volatility. They stated that an acceptable PE ratio is equal to 19. Anything higher than that would not attract investors as high price- earnings ratio indicates that a company's stock is over-valued. Hence, investors will be hesitant to invest in the company and buy shares, leading to decrease in the stock return. In addition to that, no correlation was found between S.D and PB.

7. Conclusion and Limitations

In a rapid changing society and evolving consumer behavior, Twitter remains a key player now a days. It influences the decisions of different users such as individual, companies, businesses and public and private services by presenting a wide range of news and information and reaching millions of people in short period of time with less cost. Twitter's simplicity, openness, and uniqueness make it very successful. Our results indicate that stock return is positively associated with the number of organizations' twitter followers, suggesting firms with high returns are likely to have significant number of followers. Moreover, stock trading volume is positively (negatively) associated with the number of organizations' tweets (twitter followers). These findings suggest that firms with high liquidity tend to have significant flow of tweets information rather than many followers with few tweets. Thus, the results were supportive to the behavioral finance theory which states that investor' decisions are influenced by taste, preference and other psychological factors. Finally, the current research has several limitations. The sample size and the time frame were narrow. It was not enough to study top 82 companies to find the correlation between Twitter sentiment and stock market performance. Similarly, this report demands more than eight weeks to extend our investigation. All these important notes were noted to expand more the work in my future PhD studies that will include a bigger data set to examine the relationship between social media specifically Twitter and the stock market performance.

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Appendix:

Table 1: Summary Statistics

	VOL	RET	S.D	TWEETS	FOLLOWERS	SIZE	PE	PB
Mean	5.954	4.072	.696	3.416	3.6911	10.072	26.022	.553
Median	5.962	3.854	.386	3.285	3.641	10.038	22.050	.404
Std. Dev.	.522	2.546	1.034	.806	.734	.402	19.267	.899
Skewness	-.259	-.441	3.632	.419	.129	.780	3.323	7.494
Kurtosis	-.337	3.190	15.575	.391	-.131	.259	15.764	63.184
Minimum	4.640	-6.570	.040	1.480	2.110	9.480	7.400	.000
Maximum	6.980	11.170	6.340	5.87	5.690	11.160	139.300	8.110
Sum	488.30 0	333.94 0	57.090	280.170	302.670	825.920	2133.81 0	45.410
Percentile 25%	5.582	2.591	.147	2.940	3.244	9.728	14.125	.217
Percentile 75%	6.347	5.575	.950	3.887	4.212	10.260	30.625	.746
Observations	82	82	82	82	82	82	82	82

Note: This table provides the results of descriptive statistics on stock return, volume, and volatility in relation to number of Tweets and followers and control variables using the data of top 82 companies listed on ASX. The data relate to the end of fiscal year December 2019. Where VOL is the trading volume measured in log form. RET is the stock return rate measured in percentage. S.D is the volatility measured in percentage. TWEETS is the number of tweets measured in log form. FOLLOWERS is the number of followers on firms' twitter account and measured in log form. SIZE is representing the market capitalization and measured in the log form. PE is the price earnings ratio. PB is the book market ratio.

Table 2: Regression Results

$$VOL = \alpha + \beta_1 Tweets + \beta_2 Followers + \beta_3 Size + \beta_4 PE + \beta_5 PB + \varepsilon t \text{ (Equation 1.1)}$$

$$RET = \alpha + \beta_1 Tweets + \beta_2 Followers + \beta_3 Size + \beta_4 PE + \beta_5 PB + \varepsilon t \text{ (Equation 1.2)}$$

$$S.D = \alpha + \beta_1 Tweets + \beta_2 Followers + \beta_3 Size + \beta_4 PE + \beta_5 PB + \varepsilon t \text{ (Equation 1.3)}$$

	VOL			RET			S.D.		
	β	t-stat	P-value	β	t-stat	P-value	β	t-stat	P-value
Constant α	-	.920	.360	-	.076	.940	-	-3.024	.003
β_{Tweets}	.363	1.852	.068*	-.256	-1.294	.199	-.196	-.989	.326
$\beta_{Followers}$	-.557	-2.650	.010***	.454	2.142	.035**	.184	.870	.387
β_{Size}	.419	3.592	.001***	.019	.159	.874	.345	2.939	.004***
β_{PE}	-.282	-2.720	.008***	-.281	-2.697	.009***	.283	2.715	.008***
β_{PB}	.018	.171	.865	.167	1.591	.116	-.070	-.673	.503
Adjusted R-squared		.181			.167			.169	
N		82			82			82	

Note: *, **, *** Indicate significance at the 10 percent, 5 percent, and 1 percent or lower levels. This table provides the results of linear regressing on Twitter-related and control variables using the data of top 82 companies listed on ASX. The data relate to the end of fiscal year December 2019. Where Y is the dependent variable, α is the constant, β is the beta coefficient, Tweets and Followers are the independent variables, Size, PE, PB are the control variables, and ε is the error.