The relationship between public sentiment on Twitter and share price performance of South African retail banks

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ABSTRACT

Social media growth in South Africa is exponential. South African society has embraced the concept and adopted social media as a part of their everyday lives. They feel empowered by its reach and connected to people with similar ideas and interests. This gives society the ability to have their sentiments and opinions heard and they feel a sense of community and self-worth. They now have the power to punish those that they feel have done them wrong with very little consequence. They can influence mainstream and non-mainstream media debate and have a material impact on the prevalent sentiment in the country. This influence over sentiment affects the share price performance of South African retail banks, among other. Recent research proves that share price performance can be predicted by establishing sentiment on social media.

The theoretical framework crosses behavioural finance with linguistics. Behavioural finance illustrates the influence of public sentiment on investor sentiment and in turn, the influence of investor sentiment on share price performance. Methods from the area of linguistics are applied to establish public sentiment as expressed on social media. The purpose of the study is to assess the significance of the relationship between public sentiment, as expressed on South African Twitter and the share price performance of South African retail banks on the JSE.

Social media sentiment data was collected from Twitter via the Twitter API. Polarity and emotional sentiment was deduced from the text using NLP techniques. The closing balances of the share price data for the top five South African retail banks (ABSA, Nedbank, Standard Bank, Capitec and FNB) was collected over the same period. The data was analysed using Pearson's correlation coefficient to establish a correlation between the social media sentiment explanatory variables and the retail banking share price performance dependant variable. Multiple linear regression was applied to these variables to establish if sentiment is an accurate predictor of share price performance.

The key findings from the study is that social media sentiment on Twitter has a correlation with share price performance for several scenarios, at a 95% confidence interval. Polarity sentiment has a positive correlation, where negative sentiment on Twitter predicts a decrease in retail banking share prices three days after its observation. The emotional mood state of confusion is an accurate predictor of the next day's share price performance, where an increase in confusion predicts a decrease in the next days' retail banking share price performance.

Social media sentiment is an accurate representation of public sentiment and public sentiment has a significant impact on investor sentiment. Research shows that positive sentiment in the markets specifically result in a decline in retail banking deposits. Questions that management in the retail banking sector must ask revolve around how much should be invested in protecting the corporate brand against social media sentiment, and what opportunities there are to harness the real-time capabilities of social media to predict the markets.

DECLARATION

I, ___________, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Jaco Taute

Signed at ……………………………………………………

On the …………………………….. day of ………………………… 20…..

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To my supervisor, Dr Yvonne Saini. Thank you for your guidance and patience throughout this process.

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CHAPTER 1. INTRODUCTION

1.1 Purpose of the study

The purpose of this study is to make use of sentiment analysis as discussed in Liu (2012), measuring public sentiment on Twitter while examining the effect that this sentiment has on the share price performance of South African retail banks. Arafat, Habib and Hossain (2013) as well as other authors (Arafat, Habib, et al., 2013; Fang & Peress, 2009; Tetlock, Saar-Tsechansky, & MacSkassy, 2008), all set out to analyse the ability to predict stock markets using social media, with a specific focus on the performance of the Dow Jones All Share Index (ASI) in America. Gussenhoven (2014), as well as Johnston & Maree (2015), applied the methodologies from the works of Bollen, Mao and Zeng (2011) in their research to assess the effect of Twitter sentiment on the Johannesburg Stock Exchange (JSE) in South Africa, with a specific focus on the ASI. The purpose of this study is to apply the same approach as the authors discussed above to explore the effect that South African public sentiment, as measured on Twitter, has on the JSE share price performance of the major retail banks in South Africa.

1.2 Context of the study

The study approaches the research topic from two different perspectives. Firstly, by exploring the effect of media on public sentiment with a specific focus on social media sentiment on Twitter in South Africa. Secondly, it investigates the effect of public and investor sentiment on financial markets, with a specific focus on the share price performance of the retail banking sector in South Africa

For many years, the leading theory for stock market prediction was the efficient market hypothesis (EMH) (Brown & Cliff, 2004). This theory state that new information affects stock market price movements, and that the development of new information happens randomly, which makes the stock market unpredictable. Recent studies conclude that stock markets can be predicted to a certain extent and that, contrary to EMH theory, do not follow a random walk (Arafat, Habib, et al., 2013). Emerging behavioural finance theories point to the importance of psychology and sentiment in financial decision making

(De Bondt, Muradoglu, Shefrin, & Staikouras, 2008). Studies on the effect of Twitter sentiment on the DIJA have proven to predict movements with a 86.7% accuracy (Bollen et al., 2011), opposed to the unpredictable accuracy of EMH due to its random walk theory.

The measurement and management of sentiment on social media is critical for all organisations. Liu (2012), as well as other authors (Arafat, Halimu, Habib, & Hossain, 2013; Fang & Peress, 2009; Tetlock et al., 2008), discuss the measurement of social media sentiment using opinionated data recorded in different digital forms, also known as "opinion mining". Sentiment analysis, using natural language processing, is widely applied by many organisations in their quest to gauge what their customers think and feel about them. The advantage of using this approach is the high volume of social media activity that can give organisations real-time feedback through quantitative measures upon which they can act. Bollen, Mao, and Pepe (2012) found that the use of SM improves the accuracy of measuring public sentiment, compared to more traditional large scale surveys.

Social media use in South Africa is growing exponentially. In his article on SA Social Media by the numbers, Gareth van Zyl (2015) analyses research conducted in August 2015 by WorldWideWorx.com regarding social media use in South Africa. The two main social media platforms used in South Africa is Facebook and Twitter. Twitter specifically has been growing at an average rate of 52% per year since 2012. The profile of South African social media users differs vastly from that of first world countries like America. Osunkunle (2010) describes the reason for this digital divide as the lack of information and communication technology infrastructure in the rural areas of South Africa. Despite the digital divide, we find that South African's are actively participating on Twitter, setting main stream news agendas and shaping the public debate, evident in the case of #Rhodemustfall as an example (Bosch, 2016). The conclusion is that South Africans have adopted the use of social media platforms in all aspects of their lives, and it is currently a voice that cannot be ignored.

In their analysis of the major banks in South Africa (SA), Price Waterhouse Cooper (PWC) (2016) concludes that the SA Banking industry tradtionaly report consistent and reliable performance over time and has shown strong results despite the recent financial crisis of 2008. Besides the makro-economic volatility, the key threats to the industry from a SA customer perspective are regulation and criminality, which differs from the rest of the global industry risks where technology ranks at the top. All the major banks in SA believe that customer relationship and the use of social media will see the biggest changes in future. The major South African banks according to (BASA, 2014) consists of "Barclays Africa Group, FirstRand, Nedbank and Standard Bank". Capitec has shown the most aggressive market share growth in recent years and is noted as a strong competitor in the unbanked market, making them part of the top five elite group of major banks in South Africa (Coetzee, Van Zyl, & Tait, 2012). Hirtle and Stiroh (2009) suggests that there is no clear definition that differentiates retail banking financial activities from that of other financial institutions. The activities may be similar, but Saunders and Cornett (2011) propose a definition where the income generating activities of retail banks are unique compared to other financial businesses. Retail banking shares are typically less susceptible to market volatility and noise trading and it could be argued that public opinion and investor sentiment has little impact on the share price performance.

This study will branch across the disciplines of behavioural finance, linguistics, information science, as well as econometrics to explore the SM trends observed on Twitter and how these affect share price performances. The relationship between the "sentiment" and "share price performance" variables will give insight into the impact that Twitter has on the share price performance of the retail banking sector in South Africa.

1.3 Problem statement

1.3.1 Main problem

To assess the significance of the relationship between public sentiments as expressed on South African Twitter and the share price performance of South African retail banks on the JSE.

The theory of "informational cascade" and its relation to herding in the discipline of behavioural finance explains the impact of public sentiment on share price performance (Bikhchandani, Hirshleifer, & Welch, 1998). Sentiment can be classified as either emotional sentiment (Tension, Depression, Anger, Fatigue, Confusion) or polarity sentiment (positive, negative, neutral) (Kozareva, Navarro, Vasquez, & Montoyo, 2007; Wang et al., 2016). Public sentiment can be derived by utilising NLP techniques from the discipline of linguistics to determine the emotional and polarity classifications of a text message (Arafat, Halimu, et al., 2013; Q. Li et al., 2014a, 2014b). Twitter, as a social media platform, can be successfully used to survey a large sample of the population (O 'Connor, Balasubramanyan, Routledge, & Smith, 2010).

The public sentiment on Twitter will be derived using Profile of Mood States (PMOS) and sentiment polarity, with a specific focus on results generated from Twitter as a social media platform (Arafat, Habib, et al., 2013; Bollen et al., 2011). The closing share price balances of the big five banks in South Africa will be tracked over time to assess their performance on the JSE.

1.4 Significance of the study

"Exploring implications of peer-based advice and, more generally, using social media outlets as a laboratory to investigate the effects of social interactions on investment behaviour should prove to be interesting avenues for future research." (Chen, De, Hu, & Hwang, 2011)

There is a significant amount of research that focus on the effects of media on the stock markets (Tetlock et al., 2008). Bollen, Mao and Zeng's (2011) research on the impact that public sentiment has on the performance of the stock market is limited to Twitter as a social media tool and the Dow Jones as a financial institution. South African social media is at a different phase in its lifecycle compared to that of more developed countries (West, 2015). West (2015) explains that this is largely as a result of the digital divide currently existing in South Africa. Most of the available research has a distinct focus on the performance of stock markets in developed countries (Arafat, Habib, et al., 2013; Fang & Peress, 2009; Tetlock et al., 2008). Research done by Baker and Wurgler (2007) show that younger stocks that are volatile will be more sensitive to investor sentiment than more established stocks and propose a more focused approach of measuring the effect of sentiment on individualised stocks (i.e. retail banking stocks as opposed to the ASI). The South African studies observed have a particular focus on the

JSE ASI (Gussenhoven, 2014; Johnston & Maree, 2015). There is no available research that addresses the relationship between public sentiment on Twitter and retail bank share price performance from a South African context.

The significance and existence of a correlation between sentiment on Twitter and financial performance may guide retail banking leadership in South Africa to make informed decisions on what resource investment is sufficient to manage online public sentiment, while avoiding the potential negative effect it might have on the organisation. Finding that there is no significant correlation between sentiment and share price movements could avoid gross overinvestment in an area that has little impact on performance. The results from this study may also be generalised to the wider financial sector in South Africa, and could potentially also be applied to other retail sectors such as food and clothing retail.

1.5 Delimitations of the study

- The retail banking sector in South Africa has 17 registered banks (BASA, 2014). The major retail banks in South Africa are generally accepted as ABSA, Nedbank, Standard Bank, FNB and Capitec. Other retail banks will be excluded from the study.
- Media and digital media are broad concepts that include many aspects. This research will be limited to the impact of social media as a sub-branch of digital media
- There are many SNS in the social media market today. The focus of this study will only be on Twitter. All other SNS will be excluded from the study.
- Retail Bank performance can be measured from various perspectives using a vast number of measures. The research will only measure the share price performance of retail banks on the JSE. All other financial measures (such as Return on Equity (ROE)) will be excluded.

1.6 Definition of terms

Retail banking – “Retail banking is the cluster of products and services that banks provide to consumers and small businesses through branches, the Internet, and other channels.” (Clark, Dick, Hirtle, Stiroh, & Williams, 2007)

Return on equity (ROE) – “Return on Equity is the profit after interest but before taxation.” (Shoesmith, 2004)

Social media (SM) – “...web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system.” (Ellison, 2012)

1.7 Assumptions

- The tool used to measure social media sentiment gives a true reflection of actual sentiment. Sentiment in text messages are subjective and open to interpretation.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

Our theoretical framework (refer to Figure 1) for the conducting of a literature review crosses the disciplines of behavioural finance with that of linguistics. The informational cascade theory from the behavioural finance discipline states that individual investors will disregard their own private opinions when public opinion becomes more informative (Bikhchandani et al., 1998). This then starts a sequence of cascading that causes investors to react to what their predecessors are doing and results in an "informational cascade" that affects investor sentiment in general and ultimately the financial performance of the stock exchange (Bikhchandani et al., 1998). Public opinion can be determined by conducting surveys on a sample of the population, however this is not very affective, can be prone to bias and is limited in its coverage (Schweidel, Moe, & Boudreaux, 2012). With the advent of social media and the influx of public opinion on SNS like Twitter, we can deduce the public sentiment using natural language processing techniques (opinion mining and sentiment analysis) from the area of linguistics. This determines the polarity and emotional classification of the text (Arafat, Habib, et al., 2013; Jain & Nemade, 2005; O 'Connor et al., 2010). The sentiment detected in the public domain can be cross referenced against the financial performance of the local stock exchange (in our case the JSE) to determine the significance of the relationship (Bollen et al., 2011).

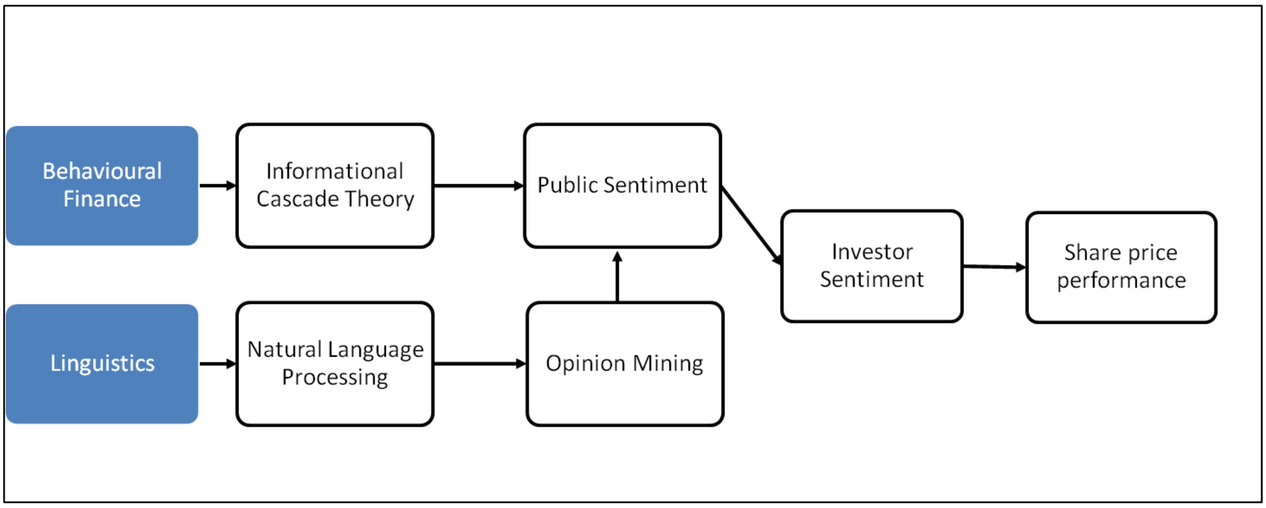

Figure 1: Theoretical Framework

The basis of our literature review starts with the early works of Bollen et al. (2011), published in the Journal of Computational Science, where their research found that stock market movements can be predicted using sentiments expressed on Twitter. We start by explaining the state of the social media landscape in South African society and investigate the role that it plays, as well as the extent that it is embraced with a specific focus on Twitter as a SNS platform. The review further progresses to a deeper understanding of sentiment on Twitter; how it is measured and how sentiment is analysed using various technical enablers. The literature review concludes by investigating previous works that explore the relationship between sentiment on Twitter and the performance of financial institutions, and provides a framework of research hypotheses, against which the research will be conducted.

2.2 Behavioural Finance: The effects of public sentiment on investor sentiment

"Behavioural finance is the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets." (Sewell, 2010, p. 1)

The literature review investigates the relationship between public sentiment and investor sentiment to determine the causal affects that each has on the other. Public sentiment affects investor sentiment, which in turn affects financial markets (Q. Li et al., 2014a).

2.2.1 Public Sentiment

"In this and like communities, public sentiment is everything. With public sentiment, nothing can fail; without it nothing can succeed. Consequently he who moulds public sentiment, goes deeper than he who enacts statutes or pronounces decisions. He makes statutes and decisions possible or impossible to be executed" (Abraham Lincoln(1858) as cited in Zarefsky,1994, p.24). Zarefsky (1994) explains how Abraham Lincoln understood the power of public sentiment and the reality that sentiment often carries more weight than actual fact. Lincoln believed that public sentiment affects everything and that it represents society's source of legitimacy. An important point noted by Zarefsky (1994) is that it is "sentiment" that is emphasised, not just rational opinion. Sentiment is more encompassing and includes culture, beliefs, emotion, as well as intellectual reason. Public sentiment is not just an aggregate of individual opinions, but an entity on its own that can be measured and understood. A study done by Mutz and Soss (1997) describes the effect of media on public sentiment. Mainstream media often attempts to move the publics' sentiment regarding specific issues in a certain direction. They find that although media is not very successful in influencing opinion, it is very affective in moulding the publics' perception about the importance of an issue. In other words, they find that media can successfully change public sentiment regarding the importance of a specific topic by the content that gets publish in the various media channels. The "influentials hypotheses", as described by Watts and Dodds (2007), is the idea that a minority of influential people will influence a larger number of their peers, and thus form public sentiment. This two-step flow of communication states that influence flows from the media, through opinion leaders ("influentials"), to their followers (Katz and Lazarsfeld (1955), as cited in Watts and Dodds, 2007, p.441). Watts and Dodds (2007) found that there are circumstances under which the "influentials hypothesis" holds true, but that these are the exception rather than the norm and that opinion leaders are only slightly more influential than the average person. Another important finding is that the biggest extent of influence is driven by the large masses of easily influenced individuals, i.e. public sentiment is influenced more by the opinions of many other easily influenced people. This correlates with what can be seen in today's Twitter trending phenomenon where certain topics will become important (or "trending") purely because large numbers of people comment on it. The source of the opinion does not have to follow the two-step

flow of communication (i.e. from media, through "influentials", to followers) and will often start trending by sheer mass amounts of people reacting to something in the media with no "opinion leader" involved. A 20 year study on the theory of emotional contagion done by Fowler and Christakis (2008) show that happiness and unhappiness spread in social networks. Emotions are contagious and spread via social interactions within social networks, of which social media play an increasingly important role. These emotions can be aggregated to reflect the public sentiment.

2.2.2 Investor Sentiment

Investor sentiment, as defined by Baker and Wurgler (2007), is "a belief about future cash flows and investment risks that is not justified by the facts at hand." (Baker & Wurgler, 2007, p. 129). Thaler and De Bondt (1985) published an article in the Journal of Finance called "Does the stock market overreact?"(Thaler & De Bondt, 1985), effectively announcing what is now known as behavioural finance. Their research sets out to measure and explain the occurrence of overreaction in the financial markets. They propose that investors do not follow Bayes' rule of correct reaction to new information (i.e. investors will react appropriately to new information) and that individuals will overweight the importance of new information and underweight the importance of historical base data. There is a tendency for investors to overreact to unexpected and dramatic news events that are available in the public domain. They use the monthly return data of common stocks on the New York Stock Exchange (NYSE) and find that movements in the opposite direction directly follow extreme movements in stock prices, also that the adjustment will be directly proportional to the extremity of the initial movement. These findings violate rational market efficiency and point to investor overreaction. Barberis, Shleifer, and Vishny (1998) test the causes of investor overreaction and under-reaction and find that their behaviour is directly related to investor sentiment. Public news and opinion affects the sentiment of the investor and investors overreact to good and bad news, which impacts on stock prices. The strength of the news (a series of very good or very bad news) is also found to generate a bigger reaction from investors. They find that investors under-react to news such as earnings announcement and that this challenges the efficient market theory. Bikhchandani, Hirshleifer, and Welch (1998) describe how information cascades between investors and that the information that is in the public domain takes preference, as the investor follow the actions of his predecessor. This informational cascade will typically be stopped by information that is deemed more valuable, which make these cascades unpredictable, i.e. the cascade can stop at any moment, or turn from ascending to descending. The behaviour of imitating the decisions of others is commonly referred to as "herding" and serves as an explanation why investors follow their predecessors in the informational cascade theory.

Nofsinger (2003) argues that social mood, or in other words public sentiment , affects the emotions of financial decision-makers, including consumers, investors and corporate managers. His review of literature points to the fact that the economy is a system of "human interactions" and should not be modelled from the perspective of economic fundamentals only. His findings are that an optimistic society leads to optimistic investors that overestimate success and underestimate risk. This optimism also leads to consumer spend increases, as well as a correlated corporate sector that invests, lends, borrows and acquires more. All of this leading to increased activities on the stock market and a growth in the economy. This scenario may result in stock prices exceeding their real value for long periods.

Baker and Wurgler (2007) proposes a top down macroeconomic model for sentiment measurement, where the investor sentiment is aggregated and the effects traced to the performance of individual stocks. Their argument for this approach is that some stocks (stocks of low capitalization, younger, unprofitable, high-volatility, non–dividend paying, firms in financial distress etc.) will be disproportionately more sensitive to investor sentiment and that stocks where the true value of the stock can be determined, are much less speculative and not as sensitive to sentiment. De Bondt et al. (2008) discuss the future of behavioural finance in their article "Behavioral Finance: Quo Vadis?", published in the Journal of Applied Finance. Here they state that the assumption that investors make rational decisions based on the information available is unrealistic. Behavioural finance introduces elements from psychology (judgmental heuristics, biases, mental frames etc.), to explain decision-making and why it is not always rational. They find that the big difference between traditional (neoclassical finance) and behavioural finance is "sentiment" and that sentiment impacts all asset prices. Li et al. (2014a) discuss the effects of public sentiment on stock markets and identify news and public sentiment as the two main areas that has an impact on investor sentiment. They propose a framework of the electronic media aware quantitative trader (eMAQT) that highlights the important role of media in defining public sentiment and in turn affecting investor decision making and sentiment. Their research reitterates the concensus that both economic fundamentals (as described in the EMH) as well as emotion play a role on investor decision making, and that sentiment can be a predictor of market performance.

2.3 Linguistics: Natural Language Processing

Natural Language Processing (NLP) refers to the use of computers to explore and understand natural language text or speech (Chowdhury, 2003). The area of statistical NLP is particularly fast growing. It applies a wide range of statistical methodologies to text to automate the categorisation and definition of the text, i.e. to determine the meaning of the text (Manning & Schutze, 1999). Their book on the foundations of Statistical NLP, authored by Manning and Schutze (1999), is regarded as the first comprehensive introduction of modern NLP theories (Eugene Charniak as cited in Manning & Schutze (1999)). Their work describes the use of statistical tools and techniques to analyse words and grammar to understand their meaning and context. The biggest challenge they identify in NLP is related to the ambiguity of language. The structure and context of the text is important in understanding the meaning and NLP must effectively make disambiguation decisions to achieve this contextual understanding. This can be done through human intervention where an individual will manually categorise and create rules to define the meaning of vague sentence structures. The problem highlighted with this approach is that there are too many permutations in natural language and humans cannot program rules fast enough to cover all the permutations. The accuracy of this approach is also poor. This gave way to statistical methods where robust statistical models will identify trends in data and make use of automatic learning. Manning and Schutze (1999) list the following reasons why they believe statistical NLP are more trustworthy and a better solution to dealing with disambiguation in large scale systems: “statistical models are robust, generalize well, and behave gracefully in the presence of errors and new data” (Manning & Schutze, 1999, p. 19). Some of the areas of application mentioned in Chowdhury (2003) where statistical NLP is used include “machine translation, natural language text processing and summarization, user interfaces, multilingual and cross language information retrieval (CLIR), speech recognition, artificial intelligence and expert systems etc.”(Chowdhury, 2003, p. 1).

2.3.1 Opinion mining

“An important part of our information-gathering behavior has always been to find out what other people think.” (Pang & Lee, 2008, p. 1).

Opinion mining, according to Selvam and Abirami (2013), is the use of NLP techniques to track the sentiment of the public in general, or related to a specific topic/product. Their opinion mining framework (depicted in Figure 2) describes the collection of data sources (blogs, review site, microblogging etc.), cleaning up the data in the pre-processing phase, processing these datasets through a feature extraction algorithm that identifies feature types (frequency, co-occurrence, part of speech tokens, opinion words, negations, syntactic dependency), presenting the targeted aspects that will be used for opinion mining in a vector space (words, sentences, phrases). Sentiment analysis is applied to the vector space to classify sentiment in terms of polarity (positive, negative) and the summarisation of the polarity serves as the overall sentiment.

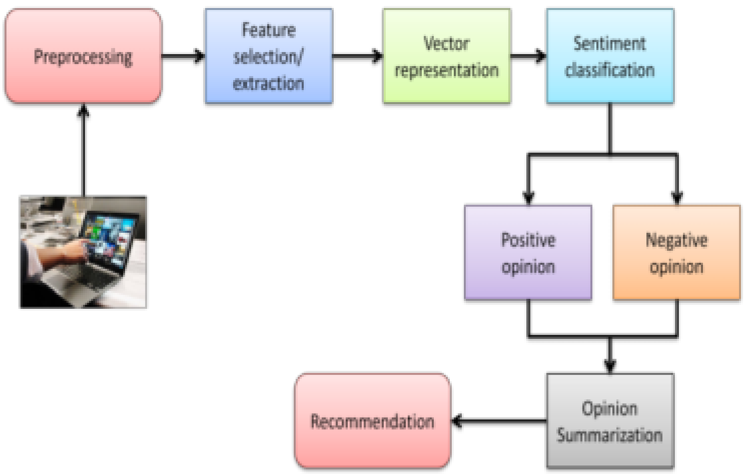

Figure 2: Opinion Mining Framework

Source: From “A survey on opinion mining framework" by Selvam and Abirami, 2013, p.3545

Selvam and Abirami (2013) identify document, sentence and word/phrase classification as the three approaches for deriving sentiment from text. Where document classification makes use of machine learning to predict the overall sentiment of the document, sentence classification extracts opinion bearing terms from subjective sentences to determine the polarity of the sentence, and word/phrase classification use the basic semantic orientation of the word. Either the process of classification can happen by machine learning based approaches, or lexicon based approaches. The machine learning-based approaches discussed are: naïve Bayes - using Bayes' theorem to determine the probability of a text belonging to a category, supports vector machine - using statistical classification algorithms to classify a vector. Bayes classifier, groups the results of several Bayes classification models and neural networks, which divides the corpus into positive or negative based on prior human decision making results. The lexicon based approaches are the corpus based approach, which determines the emotional affinity of words by comparing them to a predefined list from the same domain such as Affective Norms for English Words (ANEW) (Bradley & Lang, 1999). The other is the Profile of Mood States (POMS) (Douglas M. McNair, Lorr, & Droppleman, 1971)); and dictionary based approach which matches the word to a synonym in a dictionary to determine polarity. The semantic orientation of text can be analysed either by its polarity only (positive, negative or neutral), or by its intensity (the degree of positivity or negativity).

Pang and Lee (2008) identifies a clear shift in momentum towards the area of opinion mining and sentiment analysis at the turn of the century. Prior to 2000 research in this area was very much focused on the semantic orientation of words. The semantic orientation of a word is basically the meaning of the word when studied within the context of the sentence structure it appears in (Hatzivassiloglou & McKeown, 1996). Hatzivassiloglou and McKeown (1996) achieved a more than 90% accuracy in predicting the semantic polarity of a word, i.e. labelling the word as positive or negative in its context. Their study was focused on adjectives only but could be replicated for nouns. Israel (1996) identifies the lack of universal understanding due to the complexity of the data as a major challenge in the field. He proposes that polarity sensitive items (PSI) can be measured and described as positive or negative based on their degree of emphasis and understanding (refer to Figure 3 below).

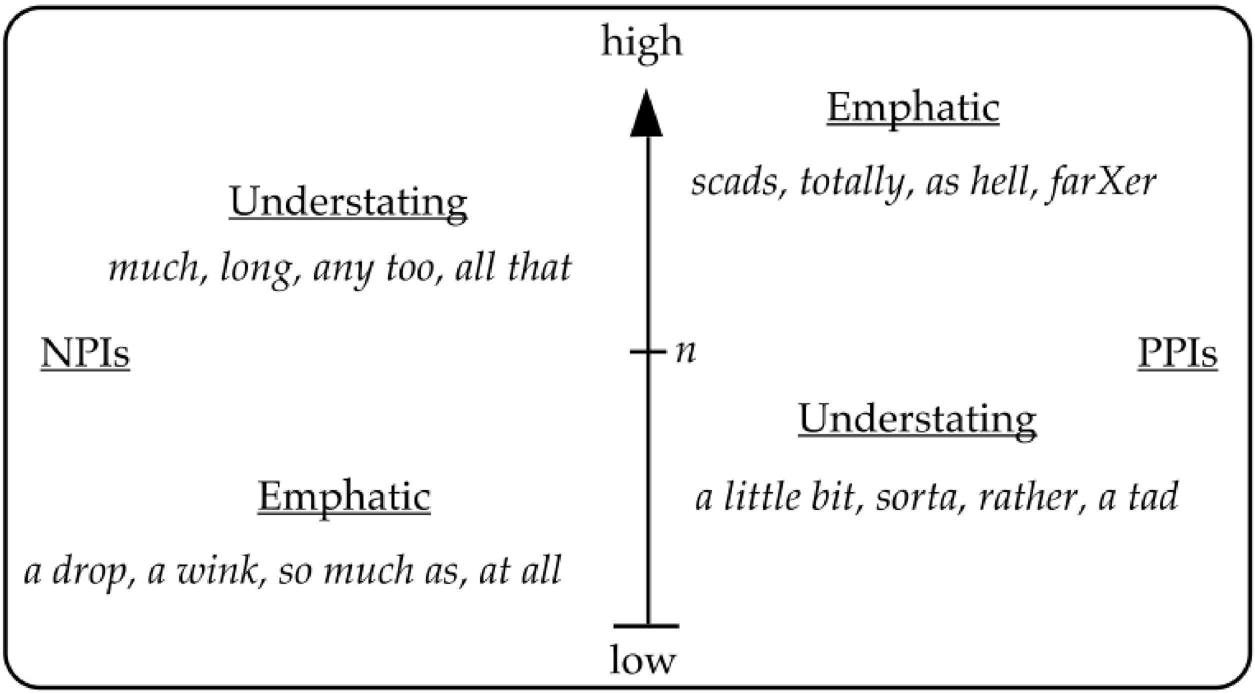

Figure 3: PSI Scales

Source: From "Polarity sensitivity as lexical semantics" by M. Israel, 1996, p.8.

The popularity of Social Media platforms resulted in an influx in social interaction and the opportunity to derive sentiment from this came to the forefront. Examples of research using natural language processing methodologies to derive sentiment are abundant post 2000. Pang and Lee (2008) note the reasons for this increase as the rise in machine learning methods in NLP, the increased availability of large amounts of data to apply machine learning to (Twitter, Facebook), and the obvious commercial benefit of sentiment analysis. Liu and Zhang (2013) wrote a chapter in the book "Mining Text Data" where they surveyed tools and methodologies used for opinion mining and sentiment analysis. They describe the five components that influence a regular opinion as 1) the entity about which the opinion is made (person, car, phone, etc.), 2) a specific aspect about the entity (location, gender, sound etc.), 3) the orientation of the opinion (positive, negative, neutral), 4) the opinion holder, 5) the time of the opinion. This approach creates structure to the free format text. The five components can be extracted from the text and stored in a database to enable efficient data mining. Although the five elements are essential to create the appropriate context for the text, analysis can also be done on single components, depending on the purpose of the research. The example they use is that component 4 (opinion holder) is not needed if the purpose is to summarise the opinions of all the people (Liu & Zhang, 2013, p. 418).

2.3.2 Sentiment Analysis

The third component in the process of opinion mining as discussed in Liu and Zhang (2013) and explained in section 2.3.1 above, is orientation. The orientation of the opinion is positive, negative or neutral. The section below will explore previous sentiment analysis research to identify the different approaches used to determine the polarity of the opinion. This will be addressed under the two sections of polarity classification and emotion classification. Polarity classification is defined as "the binary classification task of labelling an opinionated document as expressing either an overall positive or an overall negative opinion" (Pang & Lee, 2008, p. 25). Emotion classification is the use of NLP techniques to link the subjective text to an emotional category that explains the overall emotion of the text (Rao, 2016).

a. Polarity classification

Jain and Nemade (2005) made use of a two-step approach to determine the contextual polarity at a phrase level. Their research differed from previous works that only focused on determining sentence or document level polarity. The first step was to identify all neutral phrases in a sentence by defining the polarity of the previous word, the word itself and the next word. This gave them an accurate indication of the phrase polarity. The second step was to determine the polarity classification of the phrases that were not identified as neutral in step one. A phrase would be classified as positive, negative, or both. This pointed to the fact that a single phrase can have both positive and negative polarity, e.g. *"they supported+ the people and that the killings were —not tolerable−.*" (Jain & Nemade, 2005, p. 12). Their findings were that by using the two-stepped approach for determining the polarity of a phrase, they could aggregate sentiment at a more granular level compared to sentence or document sentiment, as well as provide more context than merely determining sentiment on a word level. By using a combination of factors (complex classifiers) to determine sentiment, they achieved a 65.7% accuracy, which is a 4.3% improvement on simpler classifiers (sentence or word level).

Hassan and Radev (2010) made use of the Markov random walk model to automatically identify the polarity of words. A simple explanation of this approach is that the polarity of a word will be the same as the polarity of a synonym for that word. This way when the polarity is unknown, the algorithm will seek for the polarity of a synonym of the word and assign the same polarity. They used WordNet (Miller, 1995) as a corpus for synonyms. Their findings are that this method outperforms the best approaches in semi-supervised settings and though it performs equal to other unsupervised approaches, it produces faster results from a smaller set of labelled words (corpus). Their comparison against four other models (spin-model, bootstrap model, short-path model) show 88.8% accuracy on adjectives, with the next best model 5.2% lower (spin model: 83.6%).

Speriosu, Sudna, Upadhyay, and Baldridge (2011) compare three different approaches to polarity classification. The first approach explores the use of label propogation algorythms (LPA) to determine the polarity of specific text words, sentences or entire documents. A basic explanation of LPA is that a node(in this case a message on Twitter) takes on the label of the majority of its neighbours. The polarity of messages in a network will be propogated across the network, i.e. if preceeding messages by an author are positive, the messages that follow adopts the same label. The author will also be influenced by those he follows. Maximum entropy classification as the second approach is based on attempts to address the challenges that are associated with messages on social media platforms– "they are short and include informal/colloquial/abbreviated language" (Speriosu et al., 2011, p. 53). It makes use of noisy labels to identify polarity of a message by categorising the emoticons (smiley face☺, frowning face ☹, or neutral face 😐) within the text message into positive, negative or neutral opinion. Lastly they compare lexicon-based classification which is the simple count of possitive and negative terms in a message and categorise the message based on the highest occurance. The results show that the per-Tweet accuracy of label propogation (84.7%) outperforms lexicon based (72.1%) and maximum entropy (83.1%) classifiers.

In their research on multiple-domain sentiment analysis, Yoshida, Hirao, Iwata, Nagata, and Matsumoto (2011) highlight the importance of recognising that the meaning of a word is directly related to its domain. The example they use is that "long" has a different meaning when the domain refers to that of "battery life", compared to when the domain refers to the length of a “service interaction”. The challenge is that when a polarity dictionary for a sentiment lexicon is created, it is only applicable to the domain that was used when constructing the model and that such model is not transferrable to other domains. Transfer learning has been used in previous research (Blitzer, McDonald, and Pereira (2006), as cited in Yoshida et al., 2011) to apply what was learnt in one domain to that of another. The problem is that this approach cannot be used in multi-domain sentiment analysis where the polarity classification needs to be applied on text from various domains. They propose a Bayesian probabilistic model where each word is associated to the domain it belongs to (whether the meaning of the word is dependent on its domain or not) and what the polarity of the word is. The results show that their model can improve the accuracy of polarity classification within a domain by increasing the number of source domains, but that increasing the number of target domains has an adverse effect on accuracy.

Ortega, Fonseca, and Montoyo (2013) found 50.17% accuracy in their research using unsupervised machine learning techniques to define the polarity of message on Twitter. The importance of their findings is that this accuracy was obtained using completely unsupervised techniques by implementing WordNet (Miller, 1995) for word sense disambiguation and SentiWordNet (Baccianella, Esuli, & Sebastiani, 2010) as a sentiment inventory. Nandi and Agrawal (2016) use a hybrid approach to determine the sentiment of text posted on Twitter during a political campaign. They combine the Lexical Dictionary based approach with support vector machine (SVM) learning. The lexical approach matches words from the text against a predefined dictionary to establish and categorise the sentiment of the word. SVM learning refers to the application of statistical machine learning algorithms to automate the classification and word polarity. Nandi and Agrawal (2016) used supervised machine learning techniques (where a training dataset is used to classify polarity of sentences), as well as a lexical based approach that statistically determines the polarity of words and phrases and assumes the sentiment of the document as the aggregate of the measured polarity. Their results show 93% accuracy in determining sentiment and that machine learning takes a fraction of the time to produce results.

b. Emotion classification

Kozareva, Navarro, Vasquez, and Montoyo (2007) test the hypothesis that words that co-occur across many documents with a given emotion, are likely to express the same emotion. Their example is that “birthday” co-occurs with “joy” across documents that express a positive emotion and “war” co-occurs with “fear” across documents that express a negative emotion. They make use of part of speech (POS) tags to derive the emotion baring words from the headlines that appear on internet search engines (Yahoo, MyWay, AlltheWeb) and then match those words to an emotion category using SentiWordNet (Baccianella et al., 2010). They can predict the dominant emotion in a document with an 85% and above accuracy for negative emotions. Shehata, Karray, and Kamel (2007) used machine learning techniques to establish the emotions that can be found in web blogs on the internet. These emotions derived from the blogs were categorised against four emotion areas (happy, joy, angry, sad). They used three different criteria to assign an emotion to a blog: 1) the emotion that appears the most, 2) the emotion that appears in the longest series of sentences, 3) the last emotion in the blog. Their results show that both support vector machine (SVM) and conditional random field (CRF) approaches get better results than Bayesian classifiers. CRF has the highest accuracy in determining emotion and the final emotion in the blog outperforms the other categories. This implies that humans summarise their emotions in the final sentences of a text.

Tokuhisa, Inui, and Matsumoto (2008) built an emotion-provoking event corpus that assigned the emotion words in a dictionary to 10 emotion classes. The emotion classes are then assigned to a positive or negative sentiment polarity (refer to Table 1).

Table 1: Emotion provoking event corpus

Sentiment Polarity	10 Emotion Classes	Emotion lexicon (349 Japanese emotion words)	
		Total	Examples
Positive	happiness	90	嬉しい (happy)，狂喜 (joyful)，喜ぶ (glad)，歓ぶ (glad)
	pleasantness	7	楽しい (pleasant)，楽しむ (enjoy)，楽しめる (can enjoy)
	relief	5	安心 (relief)，ほっと (relief)
Negative	fear	22	恐い (fear)，怖い (fear)，恐ろしい (frightening)
	sadness	21	悲しい (sad)，哀しい (sad)，悲しむ (feel sad)
	disappointment	15	がっかり (lose heart)，がっくり (drop *one's* head)
	unpleasantness	109	嫌 (disgust)，嫌がる (dislike)，嫌い (dislike)
	loneliness	15	寂しい (lonely)，淋しい (lonely)，わびしい (lonely)
	anxiety	17	不安 (anxiety)，心配 (anxiety)，気がかり (worry)
	anger	48	腹立たしい (angry)，腹立つ (get angry)，立腹 (angry)

Source: From “Emotion classification using massive examples extracted from the web" by Tokuhisa, Inui, and Matsumoto, 2008, p.883.

They collected 1.3 million emotion-provoking event instances from the internet and matched that to 349 emotion words, which are related to the 10 emotion classes. Their findings are that following the approach of first determining the sentiment polarity of the text, significantly increases the accuracy of determining the emotional class that the text belongs to, by as much as 17%.

In their research on modelling public mood and emotion using Twitter sentiment, Bollen et al. (2012) make use the of the six emotional dimensions of the POMS (Douglas M. McNair et al., 1971) psychometric instrument to classify the emotions expressed on Twitter. Their approach made use of the extended version of POMS (POMS-ex) where 739 emotion words have been assigned to the six POMS mood states (Tension, Depression, Anger, Vigour, Fatigue, and Confusion). They compare their findings against a timeline of important political, cultural, social, economic, and natural events that occurred during the same period. Their findings show that the fluctuations in the mood curve accurately reflect that of the socio-economic environment at the time, such as the U.S Election Day (“Tension” increased over +2 standard deviations) and Thanksgiving (“Vigour” increased by +4 standard deviations). They conclude that a syntactic term based approach that requires no training or machine learning can sufficiently explain the emotions found in Twitter text and suggest that sentiment spreads across the Twitter network, implying that Twitter has an impact on public sentiment.

The research done by S. Li, Huang, Wang, & Zhou (2015) sets out to address the challenges experienced with sentence-level emotion classification. With the growth of

SNS, the use of short text messages has become much more prevalent than that of long paragraphs in documents such as blogs. It is difficult to determine emotion from a short text sentence that might contain multiple emotions. These short sentences have little content and are prone to data sparseness problems where the limited information makes it difficult to detect emotion accurately. They propose modelling both the label and context dependence to determine the emotional category, where label dependence is explained as the likelihood that two positive emotions (love, joy) appear in one text is more than two contradicting emotions (love, hate). Context dependence alludes to the likelihood that two sentences in the same text will have the same emotional categories. From the comparison of the three approaches (maximum entropy, Bayesian network, and dependence factor graph (DFG)), they find that the DFG-label approach (where two words in a sentence will likely have the same emotion category) has 62.1% accuracy and outperforms the others by more than 20%. Similar results were recorded for the DFG-context approach (where two sentences in the same text will have the same emotional category) with the DFG-context (neighbour) results showing the best accuracy. Applying both label and context improves the accuracy by 1.3% to 63.4%.

2.4 Social media

Our aim in this section is to define the social media landscape from a South African context. We identify the various platforms and look at current usage on these platforms to assess the relevance of Twitter as a SNS in South Africa. It is important to assess how South African's engage on SM platforms to determine their willingness to spread electronic word-of-mouth. The literature review explores previous research on social media with a specific focus on how social media effects public sentiment and what methods are used to measure this sentiment.

2.4.1 A South African perspective

Social media is the interaction between the key elements of the "social media triangle" namely communities, content and Web 2.0 (Ellison, 2012). A simplified interpretation of this definition could be that social media communities create and share content using social media applications (Web 2.0 technology). From a social media context, “communities” are viewed as people that are interested in the same things sharing their ideas, thoughts and opinions through online communication. These interactions generate different types of “content”. Community members will post content such as videos, photos, comments and opinions. Social media applications will generate references to people’s whereabouts and community members will post comments and contribute to the interaction in different ways. All of this creates social media content and is done using social media applications (i.e. “Web 2.0”) such as Facebook, Twitter, Pinterest, to name a few.

“Third World countries with emerging economies are embracing social media even more enthusiastically than are mature markets, which has exciting implications for business in these emerging economies” (Erasmus, 2012, p. 5). Chaffey (2015) reported 10% worldwide growth in internet users. In the Fin24 report (Fin24, 2015) on “Social media by the numbers”, the global growth for social media use is estimated at 50%, compared to the growth in South Africa of 65%. We can conclude that South African consumers are embracing social media at a rapid rate. This growth is likely to continue in the long term with the expansion of access to internet connectivity. The growth in internet connectivity in South Africa is positive, but there still remains a large digital divide in sub-Saharan Africa (West, 2015). West (2015) indicates that 29% of the 2.2 billion unconnected users reside in sub-Saharan Africa and that the main reason for this is the combination of high levels of poverty and high accessibility costs. Devices are expensive and telecommunication fees are high. There are many other complex factors contributing to the digital divide in South Africa including infrastructure, literacy etc. For the reasons listed, a large segment of the population cannot access the internet and thus, do not participate in the social media sphere.

Cheung & Lee (2012, p. 219) defines word-of-mouth (WOM) as *“an oral form of interpersonal non- commercial communication among acquaintances”*. They conclude that there are three key differences between WOM and eWOM. With eWOM, the information spreads quicker, lasts longer and lacks credibility. It spreads quicker than WOM due to multiple people exchanging the content in real-time. The content is theoretically archived and can be referenced indefinitely and therefore persists much longer than WOM. The source of the eWOM content is often unknown and thus, it is difficult to judge its credibility. In their study to assess the willingness to engage in negative eWOM, Beneke & Wickham (2015) revealed that South African consumers, in general, are willing to engage in negative eWOM after service failure. They also found that this had a negative impact on the consumer's attitude towards the brand. The main reasons why consumers participate in eWOM behaviour is due to the desire for social interaction and the feeling of increased self-worth. Consumers feel empowered by their ability to warn other people of the breakdown in service, as well as to hurt the company that failed them. This correlates with the statement in the PWC report that social media gives customers the "power to punish" (PWC, 2015).

2.4.2 Twitter in South Africa

Twitter is a social media site where users can post or read short 140 character messages called Tweets. Twitter was launched in March 2006 and today has 317 million users that Tweet more than 500 million messages per day (World Wide Worx, 2016). The South African Social Media Landscape 2016 conducted by World Wide Worx (2016) and Fuseware indicates that Facebook has the most users (13 million) and Twitter is second (7.4 million). Usage on Twitter is more extensive than Facebook with 68% of Twitter users accessing Twitter at least once a day. Nearly 100% of Twitter users are 16 years old and above. 53% of Twitter users in South Africa range between 24 and 44, which means most Twitter users are adults that will directly influence the economy, or be influenced by the economy.

2.4.3 Public sentiment on Twitter

In their research, sponsored by the Association for the Advancement of Artificial Intelligence (AAAI), O 'Connor, Balasubramanyan, Routledge, & Smith (2010) find an 80% correlation between public sentiment (derived from surveys conducted by polling organisations) and Twitter sentiment. They tried to determine if publicly available data could be used to measure public sentiment in the same way that public opinion is assessed using polls. They made use of NLP techniques to calculate the sentiment from Twitter messages and match them against the results from consumer confidence and political polls conducted during the same period. The conclusion of their research is that accurate public sentiment can be mined from freely available public data (such as on

Twitter). It can be done in real time, with a focus on any topic broadcasted on Twitter, which makes for much greater variety and comes at a fraction of the cost of traditional polls. There has been rapid growth in the use of Twitter as a tool to measure political campaigns and public sentiment regarding political parties. Tumasjan, Sprenger, Sandner, and Welpe (2010) use text analysis software to analyse the content of Tweets that contain a reference to a political party during the German federal election in 2009. They find that the public sentiment expressed on Twitter accurately predicts the election results. Furthermore, they could predict coalitions between political parties after the election with significant accuracy. They conclude that Twitter is a valid indicator of public sentiment and can be used to reflect the official political landscape. Twitter is found to be more accurate than other internet blogging sites used during the 2005 federal elections in Germany. The main reasons stated for this is the fact that “opinion leaders” do not have the same power to impose their opinion on Twitter due to the sheer size of the Twitter community, which makes the distribution larger and more representative of the public. The research done by Bollen et al (2012) on modelling public sentiment from Twitter indicate that an accurate public sentiment can be derived from the aggregated sentiment on Twitter. Their findings show a significant correlation between Twitter sentiment and the public sentiment as extracted from macroeconomic and social indicators. Nguyen, Varghese, and Barker (2013) highlight the limitations of traditional methods for measuring public sentiment, such as surveys, questionnaires and polls. The first obvious issue is the fact that the sample is not a sufficient representation of the public. They also mention the cost of implementing these methods as a big limitation, but specifically highlight the complexity of acting on results from out-of-date public sentiment that does not reflect current opinions. Their research concludes that Twitter as an alternative can deliver current public sentiment, from a much greater representative sample of the public, at a much better cost.

2.5 The effect of Twitter sentiment on the stock exchange

In their analysis of the effect of social media on firm equity value, Luo et al. (2013) and others (Bollen et al., 2011; Hoteit, 2015; Zheludev, Smith, & Aste, 2014) find that changes in social media sentiment can predict changes in stock market performance with significant accuracy.

Luo et al. (2013) concludes that the time it takes for stock markets to respond to changes in social media sentiment is shorter compared to conventional media such as newspapers, television and internet search volumes. The instant dissemination of information can serve as a valuable substitute measure of brand performance in the case where other financial information such as sales is only available periodically. They propose that executives consider making significant resource investment in social media structure in their organisations. This is supported by the 2012 results in the eMarketer (eMarketer, 2012) publication indicating that companies with social media presence can gain large positive returns compared to those without. Luo et al (2013) and Hoteit (2015) agree that there is only a significant relationship between negative financial performance and negative social media sentiment. A positive change in social media sentiment does not necessarily result in positive financial performance.

Hoteit (2015) investigated if financial distress (i.e. bankruptcy) of an organisation can be predicted using investor sentiment on social media as a lead indicator. His conclusion was that there is no significant relationship between company bankruptcy and negative investor sentiment on social media. The factors listed that could directly lead to bankruptcy include "reduced sales, excessive debt, and little analysts' coverage", where indirect or external factors are listed as "macroeconomic conditions and financial market turmoil. They stress the point that negative information on social media attracts attention and can do damage to corporate reputation and brand by amplifying the internal and external factors that drive financial performance.

Fang and Peress (2009) researched the effects of general media coverage on the stock exchange. They find that stock with no media coverage earn higher returns, concluding that stocks with high media coverage perform between 0.65% and 1% worse. Combined with other research that find only negative sentiment has an effect on financial performance (Hoteit, 2015; Luo et al., 2013), one can conclude that the existence of a social media presence, although it may have an upside in positive returns (eMarketer, 2012), has an inherent risk factor that must be considered.

Where most authors focus on how social media sentiment affect financial performance (Bollen et al., 2011; Fang & Peress, 2009; Hoteit, 2015; Luo et al., 2013), Zheludev et al (2014) specifically focus on asking "when" financial performance is affected. They find from analysis of Twitter messages in the UK, that changes in social media sentiment cannot accurately predict returns on the FTSE100. Conversely, changes in social media sentiment on the US Twitter feed significantly correlates to returns on the S&P500. They conclude that a combination of variables impact the ability to predict changes in security returns. Social media sentiment can serve as a lead indicator of expected returns for companies with a large social media presence and a high value brand such as "Apple Inc., Amazon.com Inc. and Google Inc."

Research done by Bollen et al (2011) on the relationship between the mood on Twitter and the performance of the Dow Jones Industrial Average (DIJA) indicate that only some moods has an effect on financial performance. Their findings show a 4-day delay between sentiment or mood change and the movement in financial performance. Another interesting finding is that the "calm" dimension measured by GPOMS is more accurate in predicting movements in DJIA than the positive or negative sentiment measured by OpinionFinder.

2.6 Conclusion of Literature Review

From the theoretical framework of behavioural finance we find that psychology has a significant impact on financial decision making (De Bondt et al., 2008). The key difference between neoclassical theories (such as EMH) and behavioural science is sentiment (Beckett & Howcroft, 2000). The literature indicates that social mood affects the emotions of financial decision makers (Nofsinger, 2003) and that news and public sentiment are the two main factors that influence social mood (Q. Li et al., 2014b). Although SM in developing countries experience a digital divide (West, 2015), SM in SA is on the rise (Fin24, 2015) and SA consumers are willing to engage in eWOM, especially when it is negative (Beneke & Wickham, 2015).

The sentiment on social media can be measured using two NLP approaches, polarity sentiment (Liu, 2012) and emotional sentiment (Bollen et al., 2011). The literature review established that although there is a strong correlation between sentiment on social media and share price performance, there are variable factors that impact on the extent of the influence. Negative sentiment has a larger correlation to performance than positive (Hoteit, 2015; Luo et al., 2013), amplifies the external and internal factors that drive the performance (Hoteit, 2015) and introduces more risk to the organisation compared to not having any social media presence(Fang & Peress, 2009). The country where the sentiment originates and its related stock exchange will be affected different and at different levels (Zheludev et al., 2014) as will the dimension used to categorise the mood of the country where results will vary between different moods and measurement approaches (Bollen et al., 2011). The type of stock is also a variable that needs to be considered. Stocks where the true value of the stock can be determined are much less speculative and not as sensitive to sentiment (Baker & Wurgler, 2007).

A conceptual framework drawn from our study reveals that sentiments expressed on social media have an effect on share price performance (Bollen et al., 2011; Hoteit, 2015; Luo et al., 2013). The response (or dependant) variable is ***share price performance*** and the explanatory (or predictor) variable is ***sentiment on Twitter*** (Chatterjee & Hadi, 2015). The correlation between these variables can be measured to confirm if sentiment on Twitter has a significant effect on the share price performance, if all other variables are consistent. Other research that focused on the effect of Twitter sentiment from a South African context, focused on the impact it has on the JSE All Share Index. This study aims to further develop this research by focusing on specific stock types (i.e. retail banking) to ascertain its sensitivity to social media sentiment (Baker & Wurgler, 2007).

Hypothesis 1_0: There is no relationship between negative social media sentiment and the share price performance of South African retail banks

Hypothesis 1_a: There is a positive relationship between negative social media sentiment and the share price performance of South African retail banks

Hypothesis 2_0: There is no relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

Hypothesis 2_a: There is a positive relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

Hypothesis 3_0: There is no relationship between a combination of mood state profiles (POMS) on social media and the share price performance of South African retail banks

Hypothesis 3_a: There is a positive relationship between a combination of mood state profiles (POMS) on social media and the share price performance of South African retail banks

CHAPTER 3. RESEARCH METHODOLOGY

Crotty as cited in Creswell (2003) state that research should consider the four questions of epistemology, theoretical perspective, methodology and methods. Our research is conducted from an epistemology of empirical knowledge through the observation and measurement of demonstrable objective facts. The post positivist theoretical perspective of examining the causes that influence share price movements is held as our philosophical stance.

The research methodology and its design describe the use of quantitative methods to determine the correlation between sentiment and performance from a social media and retail bank share price perspective. The aim of the research is to provide a valid and reliable indication of the significance and extent to which social media sentiment, as expressed on Twitter, affects the share price performance of South African retail banks.

3.1 Research methodology / paradigm

The research aims to test the theory that social media sentiment expressed on Twitter has a significant effect on the share price performance of retail banks in South Africa. Our hypothesis is derived through the means of a deductive study of the literature per the theoretical framework (refer to Figure 1). From this, we can identify the variables to study as ***a) social media sentiment on Twitter*** and ***b) share price performance on the JSE***, which in turn relates to our research propositions stated in paragraph 2.6. The social media sentiment and share price performance information will be measured and observed numerically, and statistical procedures will be applied to the data to accept or reject our hypothesis.

The conditions described above lend itself to a post positivist knowledge claim that employs a quantitative research approach as prescribed by Creswell (2003) in Similar research conducted on social media sentiment and the effect it has on share price performance of institutions outside of South Africa, also made use of quantitative methodologies to answer their research questions (Bollen et al., 2011; Fang & Peress, 2009; Gilbert & Karahalios, 2010; Hoteit, 2015; Luo et al., 2013; Zheludev et al., 2014).

The study will benefit from previous research by adopting and adapting existing research tools that have extensive use in other studies, such as NLP and POMS (Arafat, Habib, et al., 2013; Bollen et al., 2011; Johnston & Maree, 2015). This ensures the validity and reliability of the study and such tools can be re-used for replication of the study (Bennett, 2004; Golafshani, 2003).

Table 2: Research Approach Selection below. Similar research conducted on social media sentiment and the effect it has on share price performance of institutions outside of South Africa, also made use of quantitative methodologies to answer their research questions (Bollen et al., 2011; Fang & Peress, 2009; Gilbert & Karahalios, 2010; Hoteit, 2015; Luo et al., 2013; Zheludev et al., 2014). The study will benefit from previous research by adopting and adapting existing research tools that have extensive use in other studies, such as NLP and POMS (Arafat, Habib, et al., 2013; Bollen et al., 2011; Johnston & Maree, 2015). This ensures the validity and reliability of the study and such tools can be re-used for replication of the study (Bennett, 2004; Golafshani, 2003).

Table 2: Research Approach Selection

Table 1.4 Qualitative, Quantitative, and Mixed Methods Approaches

Tend to or Typically	*Qualitative Approaches*	*Quantitative Approaches*	*Mixed Methods Approaches*
Use these philosophical assumptions Employ these strategies of inquiry	Constructivist/Advocacy/ Participatory knowledge claims Phenomenology, grounded theory, ethnography, case study, and narrative	Postpositivist knowledge claims Surveys and experiments	Pragmatic knowledge claims Sequential, concurrent, and transformative
Employ these methods	Open-ended questions, emerging approaches, text or image data	Closed-ended questions, predetermined approaches, numeric data	Both open- and closed-ended questions, both emerging and predetermined approaches, and both quantitative and qualitative data and analysis
Use these practices of research, as the researcher	Positions himself or herself Collects participant meanings Focuses on a single concept or phenomenon Brings personal values into the study Studies the context or setting of participants Validates the accuracy of findings Makes interpretations of the data Creates an agenda for change or reform Collaborates with the participants	Tests or verifies theories or explanations Identifies variables to study Relates variables in questions or hypotheses Uses standards of validity and reliability Observes and measures information numerically Uses unbiased approaches Employs statistical procedures	Collects both quantitative and qualitative data Develops a rationale for mixing Integrates the data at different stages of inquiry Presents visual pictures of the procedures in the study Employs the practices of both qualitative and quantitative research

Source: From "Research Design: Qualitative, Quantitative and Mixed methods approaches" by J.W. Creswell, 2003, p.19.

3.2 Research Design

Strategies associated with quantitative research include experiments and surveys, where experiments are defined as "random assignment of subjects to treatment conditions" and surveys as "using questionnaires or structured interviews for data collection, with the intent of generalizing from a sample to a population" (Creswell, 2003, p. 14). Our research will be conducted by use of a survey approach for data collection. The two survey approaches that are identified include longitudinal studies and cross sectional surveys. Longitudinal research is defined by Ployhart & Vandenberg (2010) as a study of change containing repeated observations (minimum of three) on one or more constructs, whereas a cross-sectional survey analyses data from a population (or subset) at a specific point in time.

Our research will focus on the ability of sentiment on Twitter to predict share price movements at a specific point in time. The data is collected over a three-month period, but we are interested in the effect of sentiment on share price at a specific point in time and not on its ability to predict how movements changed over a period. The study is therefore cross-sectional. Axiology is defined as "the researcher's view of the role of values in research" (M. Saunders, Lewis, & Thornhill, 2009, p. 119). From a positivist philosophy, this implies that the researcher is independent of the data and will not influence the data in any way and that data collection techniques are mostly for large datasets with quantitative measures. The data collection approach in our research will use predetermined instruments to gather observations from Twitter users as well as retail bank share price information extracted from the JSE. Other than the construction of the sampling method, none of these datasets can be influenced by the researcher and research is seen to be conducted in a value-free way (M. Saunders et al., 2009).

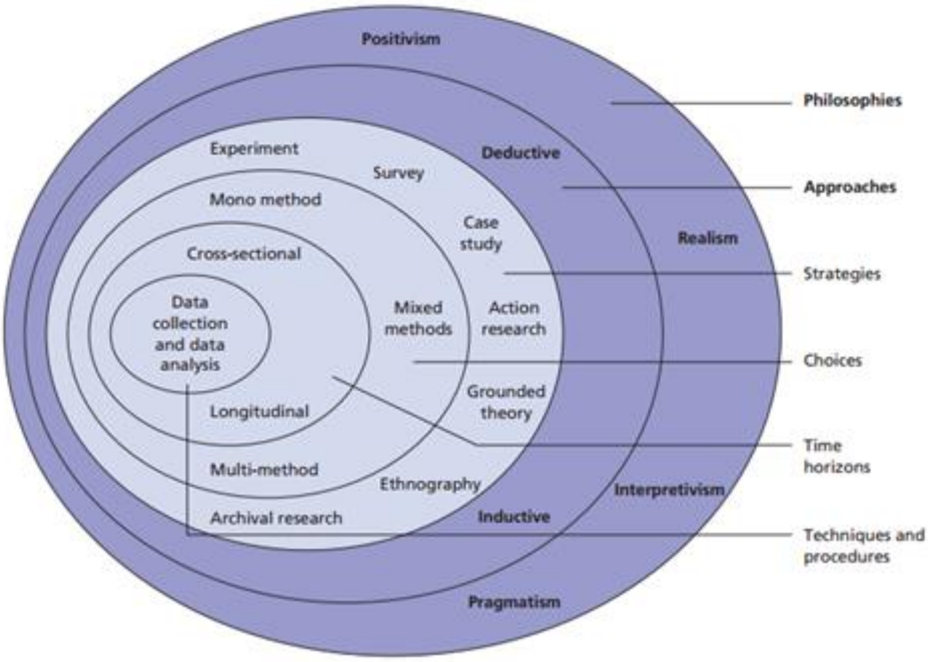

Figure 4: The research 'onion'

Source: From "Research Methods for Business Students" by M. Saunders, Lewis, & Thornhill, 2009, p.108.

The research design follows the same approach as that of other authors that conducted quantitative research using NLP extraction methods to survey Twitter and conduct cross-sectional studies to determine the extent to which Twitter sentiment can influence stock price movements at a specific point in time (Bollen et al., 2011; Gussenhoven, 2014; Johnston & Maree, 2015)

3.3 Population and sample

3.3.1 Population

The population is “the full set of cases from which the sample is taken” (M. Saunders et al., 2009).

The population we will target as part of our study includes all messages on Twitter with a place_id attached to it that falls within the borders of South Africa, as collected over a 60-day period, and the daily closing share price information of the top 5 retail banks in South Africa (ABSA, Nedbank, Capitec, Standard Bank, First National Bank), as collected over a 60-day period. The share price information will include an additional 5 days to test for the lag effect. The lag effect can be explained as the time it takes for the markets to react to sentiment expressed on Twitter and is discussed in more detail in paragraph 3.3.2. This approach follows the population definition method used by other researchers conducting research on Twitter users in South Africa (Gussenhoven, 2014; Johnston & Maree, 2015).

SNS: Twitter

Geo Location: South Africa

3.3.2 Sample and sampling method

Saunders et al.(2009) explains that a census will gather all information about the entire population, whereas a sample is a subset of the population that represents the entire population. A sample should be used when it is impractical to survey the entire population due to sheer size of the data, or the budget and time constraints for analysing the data. "Probability sampling (or representative sampling) is most commonly associated with survey-based research strategies where you need to make inferences from your sample about a population to answer your research question(s) or to meet your objectives" (M. Saunders et al., 2009).

Our study follows a cross-sectional survey-based research strategy that will typically make use of probability based sampling as discussed by Saunders et al.(2009). The sampling frame from which statistical inferences are made includes all South African Tweets from the entire population, as well as share price results of retail banks on the JSE (as discussed in paragraph 3.3.1). The proposed minimum sample size where the mean of the sampling distribution is close to that of the normal distribution of the population, is generally more than 30 (Stutely (2003) as cited in Saunders, 2009, p.218).

i. Twitter sentiment sampling

Twitter will expose random Tweets from a sample of recent Tweets published in the past 7 days to the Twitter search API. The sampling is done based on relevance where the Tweets that are most relevant to the filter criteria is returned in the result set (Twitter API Developers, 2014). Tweets that contain a subjective opinion on Twitter is defined as any text that contain the words ”I feel”, “I am feeling”, “I’m feeling”, “I dont feel”, “I don’t feel”, “I’m”, “Im”, “I am”, “makes me”. These are the exact same terms used by Bollen et al. (2012) and also adopted by other authors (Arafat, Habib, et al., 2013; Bollen et al., 2012, 2011; Johnston & Maree, 2015) to identify opinionated Tweets. As the research is only interested in the sentiment expressed on Twitter, there will be no need for Tweets that do not contain sentiment. The sample will further be limited to only include text that contain either English as a language (this is only logical based on the opinion words that the study will be filtered on), or an “emoticon” (☺, ☹, etc.) that can be referenced to a specific emotion or sentiment polarity. Based on these filters we estimate a sample size of approximately 1.5 million Tweets (25,000 Tweets per day) that will form part of the study which is 21.7% of the estimated total South African Twitter population of 115,000 Tweets per day (Kapuria, 2014).

ii. Share price performance sampling

The retail banking sector in South Africa has 17 registered banks (BASA, 2014). The major retail banks in South Africa, as measured by market share and market capitalisation, are generally accepted as ABSA, Nedbank, Standard Bank, FNB and Capitec (BASA, 2014).

Zhang, Fuehres, and Gloor (2011) tested the lag effect on the Dow Jones and found that emotional sentiment on Twitter could be observed in the markets the same day as the event as well as the next day. Johnston & Maree (2015) tested “fatigue” mood on Twitter with a 5 day lag and found that the JSE ASI could predict “fatigue” as a mood on Twitter with a 1 day lag.

Our sample will be limited to the share price performance of ABSA, Nedbank, Standard Bank, FNB and Capitec, as measured over a 60-day period, plus an additional 5 days for lag.

iii. Sample period

The sample period will be a 60-day period ranging from 1 October 2016 to 30 November 2016 (including an additional 5 days from 1 December to 5 December to accommodate lag).

3.4 The research instrument

The research instrument is the data collection instrument that will be used to extract the information needed to conduct the research (M. Saunders et al., 2009). Saunders et al.(2009) defines secondary data as data that have already been collected that are either in its raw form (where there has been little or no processing), or that has been compiled using some form of selection or aggregation. This study uses survey based secondary data that has been collected through continuous/regular surveys of Tweets posted on Twitter.

The advantages of using secondary data are discussed by Saunders et al.(2009). The ability to analyse bigger datasets because of fewer resource requirements is evident. The Twitter and share price data already exist in the public domain and time and money will not be needed to create new data. The unobtrusive nature of the secondary data approach is also a great advantage. Secondary data is likely to be of higher quality as it is not obtained by collecting it on your own, and could not be influenced by your biases. For example, the share price information is recorded on the JSE and is a highly regulated dataset that is supervised by the Financial Services Board (FSB) (JSE, 2016). Some of the disadvantages related to the study are that access to the data may be difficult and that there is no real control over the data quality. The Twitter dataset is complex to access without the necessary technical skills and the data mining process require certain expertise to ensure necessary data quality.

This study aims to measure ***public sentiment*** as measured on Twitter and its effect on retail banking ***share price*** performance. A research instrument will be utilised to assess the general sentiment expressed on Twitter (discussed in paragraph 3.4.1). The values of the retail banking share price information will be extracted from the relevant sources (refer to paragraph 3.5).

3.4.1 Twitter sentiment research instrument

The area of linguistics has a multitude of approaches towards determining the semantic orientation of words (Hatzivassiloglou & McKeown, 1996; Liu & Zhang, 2013; Selvam & Abirami, 2013), as deducted from our literature review in paragraph 2.3. Pang and Lee (2008, p. 25) identify the "polarity classification" of a Tweet as a method for measuring sentiment. Rao (2016) and others (Arafat, Habib, et al., 2013; Bollen et al., 2012, 2011) improve on this by analysing the different emotions expressed in Tweets and describe this as "emotional classification". Gonçalves, et al. (2014) improve results significantly by combining both polarity and emotional classification techniques. The research instrument used specific to this study combines three different approaches as discussed below:

a) Polarity classification

The first step to identify the polarity of a message is to categorise the emoticons (smiley face☺, frowning face ☹, or neutral face 😐) within the text message into positive, negative or neutral opinion. The next step is to compare lexicon-based classification which is the aggregation of possitive and negative terms in a message and categorising the message based on the highest occurance (Speriosu et al., 2011). The study will reference the emoticon variation list proposed by Gonçalves, Araújo, Benevenuto, and Cha (2014) to extend the emoticons that are used to determine polarity. The final step is to determine the polarity of the remaining Tweets using the SentiWordNet (Baccianella et al., 2010) lexicon. SentiWordNet is a research tool used in many research studies involved with analysing social media sentiment on Twitter (Liu, 2012; Liu & Zhang, 2013; Ortega et al., 2013; Pang & Lee, 2008; Selvam & Abirami, 2013). The polarities of the social media messages are determined by parsing the text through the SentiWordNet lexicon, which places text in the positive, negative or neutral category.

b) Emotional classification

The POMS psychometric assessment test (Douglas M. McNair et al., 1971) is used as the emotional sentiment instrument to determine the "mood" state of the specific Tweet. The full-length version of the POMS assessment tool has 65 items that all relate to a specific emotional class (Depression, Tension, Anger, Vigour, Fatigue and Confusion) –

refer to APPENDIX B – Extended Profile of Mood States Instrument. The participants' "feeling" about the specific item is rated on a 5 point Likert scale (0 = Not at all to 4 = Extremely.) by asking the question "How do you feel right now". The POMS assessment is normally completed by the participant either online or manually. The scores for each mood state can be calculated by adding up the Likert scale rating for each of the key words related to the mood. The Total Mood Disturbance (TMD) is then calculated by using the following formula: TMD = (Tension + Depression + Anger + Fatigue + Confusion) – Vigour

POMS2 is an established research utility and has well documented psychometric qualities. Some of them are listed below, as recorded in the International Journal of Psychology (Heuchert & McNair, 2012):

Internal consistency

"For the POMS 2-A Cronbach's alphas range from .76 to .95 for the normative sample, and from .83 to .97 for the clinical sample." (Heuchert & McNair, 2012)

Test-retest reliability:

"Coefficients for the POMS 2-A over a 1 week period range from .48 to .72, and over a 1 month period range from .34 to .70." (Heuchert & McNair, 2012)

Convergent validity

"Correlations between the POMS 2-A and the PANAS-X range from .57 to .84 (median = .73). Tension-Anxiety correlated with Fear (.57), Anger-Hostility correlated with Hostility (.84), Depression-Dejection correlated with Sadness (.70), Fatigue-Inertia correlated with Fatigue (.73), and Vigour-Activity correlated with Positive Affect (.79)." (Heuchert & McNair, 2012)

Construct validity

"The factor structure of the original sample was confirmed by Boyle (1987) in an Australian student sample. Heuchert & McNair (2012) more recently confirmed the factor structure of the POMS 2-A in a sample of 1,000 normal and 215 clinical patients." (Heuchert & McNair, 2012)

The POMS assessment tool has more recently been introduced as part of the opinion mining and NLP disciplines around linguistics to assess the “mood” contained in natural language. This study utilises the POMS2 psychometric assessment tool to derive the “mood state” of Tweets on Twitter in the same manner as previous research done by other authors (Arafat, Habib, et al., 2013; Bollen et al., 2012, 2011; Johnston & Maree, 2015).

The words in the Twitter text is matched against the 65 words represented in POMS to determine the mood category that it falls in (Depression, Tension, Anger, Vigour, Fatigue and Confusion). The synonyms of the 65 POMS words are retrieved from the SentiWordNet lexicon and assigned to the original words’ mood category to extend POMS. Each POMS mood is scored daily by dividing the number of Tweets that are assigned to a mood by the total number of Tweets that have opinion, sentiment or emotion attached to it (Johnston & Maree, 2015). The POMS assessment is further extended by assigning an overall polarity to the 6 different mood states. The instrument will filter the Tweets according to polarity and then assign a mood state based on the polarity of the Tweet, as proposed in the research done by Tokuhisa, Inui, and Matsumoto (2008).

3.5 Procedure for data collection

Twitter as a source for secondary data is used to survey all opinionated texts with a place_id within the borders of South Africa, over a regular and continuous period of 60 days. The results are stored in a database in its raw format where data processing is applied through data cleansing procedures and NLP techniques to obtain emotional and polarity sentiment.

The Twitter Search API (Twitter API Developers, 2014) is queried using the data collection procedure discussed below to extract all Tweets that have an opinion, sentiment or emotion attached to it. The filter criteria, as discussed in paragraph 3.3, are applied to the search API and stored in a database. This constitutes the base data that carries the opinions of South African Twitter users. The approach described in the research of Speriosu et al. Is followed (2011, p. 53).

Step 1: Twitter sentiment: Data extraction process

The data extraction process implements a REST API that passes the search term parameters into the Twitter Search API. The Twitter Search API returns a result set of the most relevant Tweets based on the search criteria. The REST API in turn stores the dataset in an XML schema that is imported into a Microsoft SQL Database. The parameters passed into the Twitter Search API are constructed as follows:

Country context- South Africa: The metadata of the "place" object in the Twitter API is referenced to where the "country" variable is equal to 'South Africa'. This country variable can be reverse-geocoded into latitude and longitude.

Sentiment context – "Feeling": The Get search/tweets function in the Twitter Search API accepts a 'q' parameter that contains the search terms. The filters defined for identifying feeling on Twitter ("I feel", "I am feeling", "I'm feeling", "I dont feel", "I don't feel", "I'm", "Im", "I am", "makes me") are passed into the 'q' parameter

Step 2: Twitter sentiment: Data clean-up process

The dataset that exists in the Microsoft SQL Database is analysed for inconsistencies (check that all Tweets are about South Africa, all Tweets have the "feeling" keywords in their text, all Tweets either express emotional or polarity sentiment or contain an emoticon). Special attention must be paid here to ensure that the "cleanse" process does not introduce personally orientated discrepancies as a result of the researcher's subjective choice of what to cleanse (Winter, 2000).

Step 3: Twitter sentiment: Assigning polarity sentiment

The first step in the process will be to filter all the Tweets that contain emoticons per the emoticon sentiment instrument (refer to APPENDIX A – Emoticon Sentiment Instrument).

In the second step, the SentiWordNet (Baccianella et al., 2010) lexicon is implemented to define the positive, negative or neutral polarity of each Tweet by determining the semantic orientation of the text.

Step 4: Twitter sentiment: Assigning emotional sentiment

The polarity sentiment from the previous step is referenced to determine the qualifying mood states linked to that polarity. The extended POMS research instrument is used to match the Tweet to a POMS word and relate it to a mood state with the same polarity as the Tweet (refer to APPENDIX B – Extended Profile of Mood States Instrument).

Step 5: Twitter sentiment: Calculate aggregated sentiment results

Polarity sentiment calculation: The different polarity types (positive, negative, neutral) are aggregated on a daily basis (Liu, 2012).

Emotional sentiment calculation: Each POMS mood is scored daily by dividing the number of terms that are assigned to a mood by the total number of terms that have POMS mood attached to it (Johnston & Maree, 2015)

Step 6: Share price: data extraction

The Morningstar.com website (MonringStar.com, 2017) is referenced to extract the retail banking share price information of the defined retail banks (ABSA, Nedbank, Standard Bank, FNB, Capitec) over the same 60-day period, including an additional 5-day period to cater for the effects of lag. The following share codes are utilised to extract the share price information (refer to Table 3: Banking Sector - Share Codes).

Table 3: Banking Sector - Share Codes

Name	Full Name	Code	Sector
FIRSTRAND	FirstRand Limited	FSR	8355
B-AFRICA	Barclays Africa Grp Ltd	BGA	8355
NEDCOR	NEDBANK GROUP LTD	NED	8355
STANBANK	STANDARD BANK GROUP LIMITED	SBK	8355
CAPITEC	CAPITEC	CPI	8355

3.5.1 Data security and confidentiality

The Microsoft SQL Server (MSS) development environment that exists in FNB Business Intelligence will conform to FNB Information Security Services (ISS) standards. Access to the MSS environment is governed and controlled by FNB's internal lightweight directory access protocol (LDAP) that grants profile based access linked to a user's network domain credentials (Zeilenga, 2006).

Sensitivity of customer information is governed by the POPI Act (Parliament of the Republic of South Africa, 2013). No customer information deemed sensitive per the act would be stored or used during the research analysis. All secondary data used in the proposed research is publicly available.

3.6 Data analysis and interpretation

The study will make use of regression analysis to investigate the functional relationship among variables (Chatterjee & Hadi, 2015). The two key variables from our research propositions stated in paragraph 2.6 are share price performance and social media sentiment on Twitter. The aim of the research is to relate the share price performance of the South African Banking Sector to the changes in public sentiment as expressed on Twitter. The response (or dependant) variable is ***share price performance*** and the explanatory (or predictor) variable is ***sentiment on Twitter*** (Chatterjee & Hadi, 2015).

Correlation analysis will be used to assess the confidence level for interpretation of the results, i.e. accepting or rejecting the hypothesis that there is no significant relationship between fluctuations in banking sector share prices and sentiment on Twitter in the South African retail banking sector, at a certain level of confidence (Marsh, Hau, & Wen, 2000). The data points of the measured variables will be plotted on a trend graph illustrating the fluctuations over the period measured.

Johnston and Maree (2015) made use of four rounds of tests to determine the correlation between Twitter mood and JSE ALSI movement. The first test used statistical analysis to determine the reliability and validity of the data. The second test uses Spearman's rank correlation coefficient to test the strength of the correlation between Twitter sentiment and retail bank share prices on the JSE. The third test uses the Granger causality test to determine if Twitter causes retail bank share price movement on the JSE. This study will implement a similar process, but will substitute Spearman's rank correlation with Pearson's correlation coefficient (Lee, 2016) to determine correlation between the dependant and explanatory variables. It will then apply linear regression modelling as well as multiple linear regression modelling to establish if the explanatory variables, or a combination thereof, are statistically significant predictors of the dependant variable behaviour (Lee, 2016). The study will not include the fourth test of creating a neural network to test the actual ability to predict share price movement as that is not the purpose of this research. Figure 5 below depicts the process followed to measure the variables as well as the data analysis techniques applied to determine the correlation.

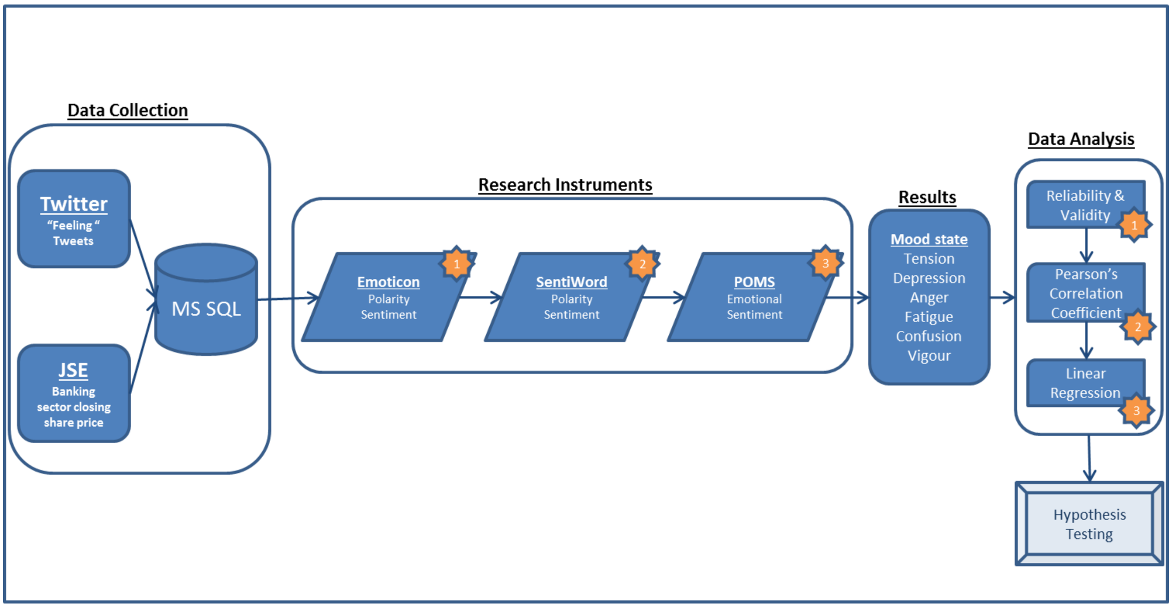

Figure 5: Research process

3.7 Limitations of the study

- The sample period may have to be revised, depending on the availability of social media data history
- Only Twitter will be used as a source to measure social media sentiment. Facebook and other social media platforms will be excluded.

3.8 Validity and reliability

The **validity** of the research instrument relates to its ability to measure what is set out to measure in the research proposition. “Is the relationship between the two variables a causal relationship?”(M. Saunders et al., 2009). In this study, validity relates to the ability of Twitter sentiment to explain share price movements. **Reliability** refers to the consistency of the research results and its ability to be reproduced (Bennett, 2004; Golafshani, 2003). The section below will discuss the ability of the proposed research instrument to measure share price performance and sentiment on Twitter, as well as how reliably the study and results can be reproduced.

Saunders et al.(2009) discuss the threats to validity under the following headings.

History: There might be external factors that impact the research results. Share price movements may occur because of external political factors and not because of Twitter sentiment. In this case, the research is specifically designed to consider external socio-economic factors that influence public sentiment.

Testing: The research respondents might manipulate the results if they believe that it might disadvantage them. The research conducted in this study is completely unobtrusive and the Twitter users have no idea that their Tweets are being analysed. The research makes use of secondary Twitter data that is part of the public domain and accessible to anyone.

Mortality: Participants in a study might drop out during the study. The individuality of the participant is of no concern to the research conducted in this study. The research is focused on the overall sentiment of the entire Twitter population at a specific point in time (cross-sectional).

Ambiguity about causal direction: There must be clarity about what the explanatory variable is and what the response variable is. It needs to be clear if the sentiment on Twitter is causing change in share price performance, or if the share price performance is causing a change in Twitter sentiment. Our problem statement is clear that the purpose of the research is to test the former.

3.8.1 External validity/Generalisability

Winter (2000) refers to external validity as "generalisability" and defines it as "the ability to generalise findings to wider groups and circumstances" (Winter, 2000).

There are many similarities between the retail banking sector and the financial services sector. These sectors are in many cases referred to interchangeably as some group the retail banking sector under financial services and retail banks are regulated by the Financial Services Board (FSB) (BASA, 2014). The research conducted in this study categorise the different sectors as they appear on the JSE. The JSE lists the financial services and banking sectors separately. The point is that the findings made regarding the banking sector in this study can be generalised to the financial services sector on the JSE. The maturity levels of SNS in many of the developing countries in Africa are similar (West, 2015). The information and communication technology (ICT) infrastructure in many of the developing countries are also similar. Such developing countries have similar educational challenges and literacy levels as South Africa (Osunkunle, 2010). This research could potentially be generalised and applied in the banking sector of other developing countries in Africa, or to the wider financial industry.

3.8.2 Internal validity

Cooper and Schindler (2008), (as cited in Saunders et al., 2009, p.373) refer to three areas that depict the validity of the research instrument.

a. Content validity

The research instrument must measure the important aspects of the concept defined in the proposition to ensure content validity (Patrick et al., 2011). The POMS psychometric assessment has been used in numerous studies to determine the **emotional sentiment** of a research participant (Cheung & Lam 2005; McNair, Heuchert, and Shilony 2003; Pepe and Bollen 2008 (as cited in Bollen et al. (2012, p. 452)). **Polarity sentiment** is measured in research using research instruments such as WordNet, SentiWordNet and Opinion Finder (OF) (Nandi & Agrawal, 2016; Pang & Lee, 2008).

Share price results are recorded on the JSE and is a highly regulated dataset that is supervised by the Financial Services Board (FSB) (JSE, 2016)

b. Construct validity

Heale & Twycross (2015) define construct validity as "whether you can draw inferences about test scores related to the concept being studied" (Heale & Twycross, 2015). Heale & Twycross (2015) propose homogeneity, convergence and theory evidence as methods to ensure construct validity.

i. Homogeneity

All research instruments employed measure a single construct (Heale & Twycross, 2015). Polarity classification is measured using the SentiWordNet lexicon. Emotional classification is measured using the POMS2 psychometric assessment test, and share price information is measured and reported on by the JSE.

ii. Convergence

Opinion Finder (OF) and GPOMS (Hutto & Gilbert, 2014) can be used to converge with SentiWordNet and POMS2 respectively. The historical share price results extracted from the Morningstat.com website can be cross-referenced against the results reported by the JSE (Heale & Twycross, 2015).

iii. Theory evidence

POMS2 Twitter mood results can be validated against findings from similar research on Twitter sentiment (Bollen et al., 2011). Share price results on the JSE are regulated by the FSB. The study can assume internal validity.

c. Criterion validity

Creterion validity can be determined by assessing the extent of correclation between different research instruments measureing the same variable (Heale & Twycross, 2015).

i. Convergent validity

Convergent validity can be confirmed by matching sentiment measured by SentiWordNet to the overall Twitter sentiment reported by Twitter.com.

3.8.3 Reliability

"Reliability relates to the consistency of a measure" (Heale & Twycross, 2015, p. 66). For example, the sentiment findings must be approximately the same if the same set of Twitter results are parsed through the SentiWordNet lexicon twice.

a. Internal consistency

Internal consistency can be gauged by using the split-half method (Heale & Twycross, 2015) where the Twitter result set is split in two equal halves. The text messages for both halves are parsed through the SentiWordNet lexicon and correlations between the sentiment results of the two halves are compared. A strong correlation would indicate high reliability (Heale & Twycross, 2015). The commonly used Cronbach's Alpha reliability coefficient will be applied to the sentiment results with a minimum score of 0.7 indicating sufficient reliability (Heale & Twycross, 2015).

b. Stability

The test-retest reliability approach will be used to measure stability (Heale & Twycross, 2015). The Twitter messages will be parsed through the SentiWordNet lexicon more than once and the results statistically compared. A correlation coefficient of more than 0.5 will be used as a benchmark for high stability (Heale & Twycross, 2015).

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

The results derived from the conduction of this research will be described and illustrated in three sections. The first section will focus on analysing the results as obtained from the various source systems, namely Twitter and the JSE. The next sections will discuss the reliability and validity of the results. The final section will discuss the results obtain from the statistical analysis applied to the data, to test the three hypotheses specified:

$H1_0$: There is no relationship between negative social media sentiment and the share price performance of South African retail banks

$H2_0$: There is no relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

$H3_0$: There is no relationship between a combination of mood state profiles (POMS) on social media and the share price performance of South African retail banks

4.2 Twitter

The Twitter results used as part of the research analysis contains daily data from the period between 10 October 2016 and 7 December 2016. The data is filtered by Tweets that originate from within the borders of South Africa and contains the “feeling” keywords (”I feel”, “I am feeling”, “I’m feeling”, “I dont feel”, “I don’t feel”, “I’m”, “Im”, “I am”, “makes me”) as specified by Bollen et al. (2012). The data files for the 15th October and 16th October were corrupt and excluded from the result set. The corrupt data has no significant impact on the accuracy and validity of the study as the aim of the research is not to measure sentiment over time, but rather the impact of sentiment on retail banking share price performance at a specific point in time, i.e. a cross-sectional study. The total number of Tweets with the feeling keywords in South Africa for the period equates to 1,720,248 at an average of 30,180 Tweets per day. The maximum number of Tweets containing feeling keywords is recorded as 24th October with 56,991 Tweets. This corroborates with the peak of the highly emotional and tense #feesmustfall protest that occurred during that period (Madibogo, 2016).

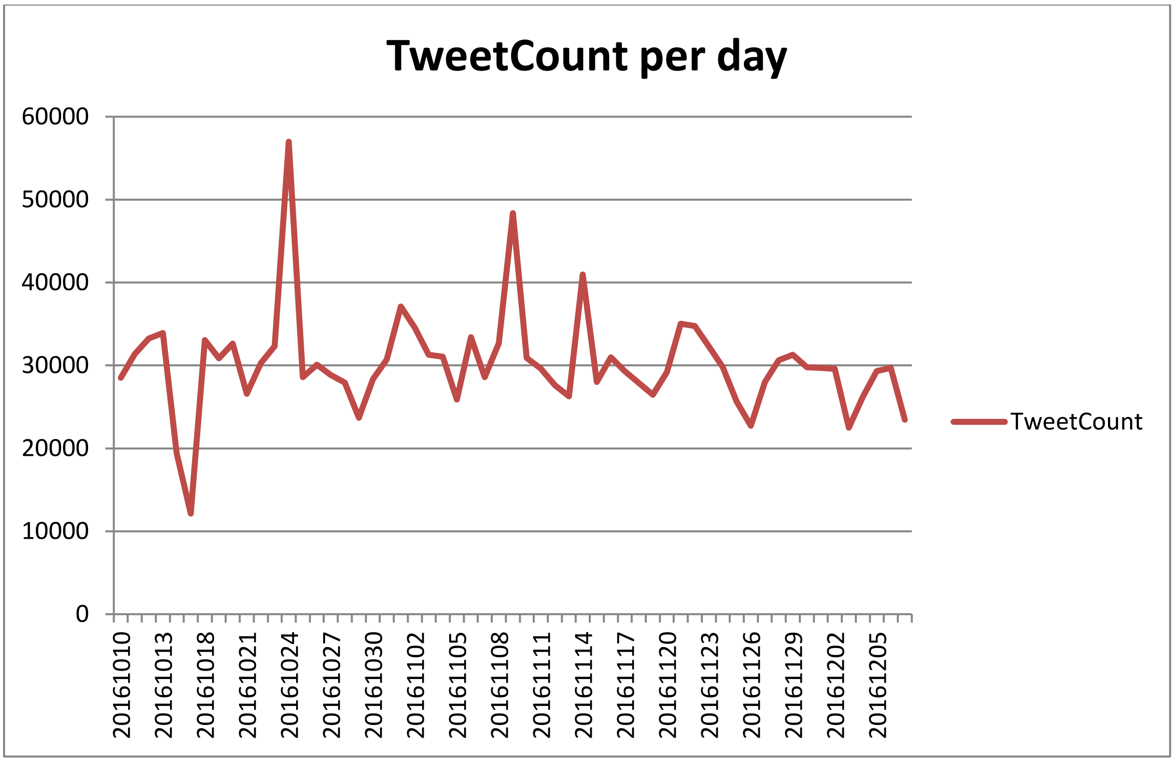

Figure 6: TweetCount per day

Source: Data extracted via Twitter API (Twitter API Developers, 2014)

4.2.1 Polarity classification

The polarity classification process gives preference to emoticons within the Tweets. The sentiment polarity is set for all Tweets that contain emoticons. Only 858 of the 1,720 million Tweet base contained emoticons that could be referenced against our list in APPENDIX A – Emoticon Sentiment Instrument. After investigation, it became clear that the emoticon images that occur in text are stored as special characters via the Twitter API. Only emoticons that users typed without using images were successfully mapped to the emoticon reference list. A special Twitter API function would have to be used to convert the Tweet images into usable text. This approach may be considered for future research in the area.

The remainder of the Tweets that could not be successfully mapped to the emoticon reference list were all parsed through the SentiWordNet (Baccianella et al., 2010) lexical resource, which assigns a fractional waiting to the Tweet based on the strength of the sentiment in a range between -1 and 1. Everything between -1 and less than 0 are deemed negative sentiment and everything more than 0 and less than or equal to 1 is deemed positive sentiment. A score of 0 is classified as neutral sentiment. The polarity sentiment results are aggregated each day and the result represents the power of the overall sentiment of the population.

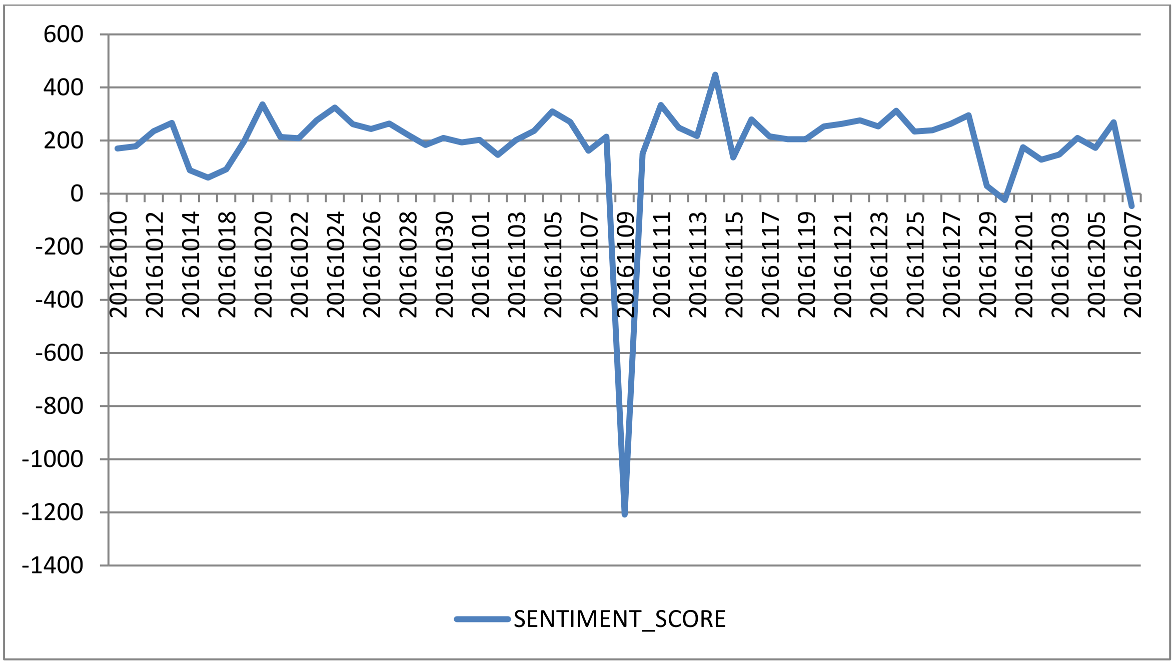

Figure 7: Polarity Sentiment from SentiWordNet

Source: Data extracted via Twitter API (Twitter API Developers, 2014)

Figure 7 illustrates the trend of the polarity sentiment recorded and aggregated over the timeframe. The mean score for polarity sentiment over the period is 187.07, indicating a generally positive sentiment prevailing. A clear outlier is the negative sentiment spike observed on the 9th of November 2016. We also find that this is the second highest day in terms of Tweet volumes (refer to Figure 6). The 9th of November 2016 is the day that Donald Trump was announced as the winner of the presidential election in the USA (Democracy Now, 2016).

4.2.2 Emotional classification

The results from 0 above were used to categorise the Tweets as having an overall positive or negative sentiment. This polarity is in turn mapped to the POMS synonyms in APPENDIX B – Extended Profile of Mood States Instrument. The key terms from the positive or negative mood state are extracted from the Tweets and a count of their occurrence stored for each Tweet. The number of times that a mood state term occurs is aggregated on a daily level, and the proportional contribution of that term towards the total number of POMS terms recorded, is stored as the POMS score for that term. Of the 1,720 million Tweets, 761,656 are found to contain one or more mood state term. 1,039 million individual mood state terms were extracted from these Tweets with an average of 18,228 per day and a maximum day 48,311 on the 9th of September 2016.

Table 4: POMS Contributions

Row Labels	Polarity	Sum of Score	% Contr
Vigour	Positive	379,436	37%
Depression	Negative	187,968	18%
Fatigue	Negative	177,517	17%
Anger	Negative	132,308	13%
Tension	Negative	109,989	11%
Confusion	Negative	51,788	5%

Source: Data extracted via Twitter API (Twitter API Developers, 2014)

Positive terms related to “Vigour” are the most popular of the six mood states and contribute 37% of the total terms measured. This aligns with the generally positive polarity sentiment observed in section 0 above.

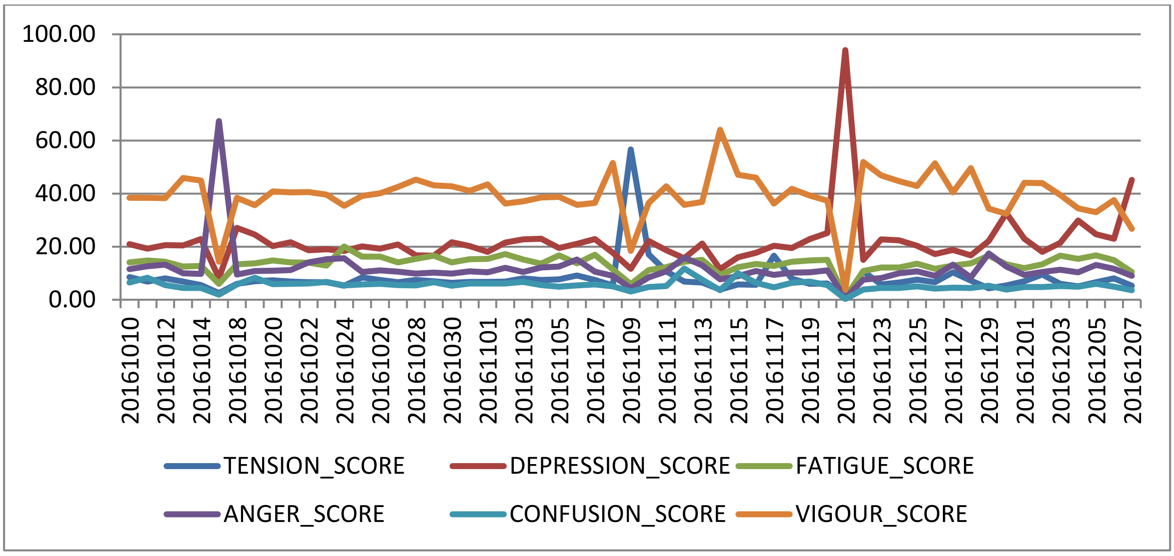

Figure 8: POMS trend line

Source: Data extracted via Twitter API (Twitter API Developers, 2014)

Figure 8 above illustrates the trend of the POMS variables over the timeframe. The generally positive trend can be seen from the Vigour variable. The outliers are the obvious spikes in Anger (2016/10/17), Tension (2016/11/09) and Depression (2016/11/21). The Anger spike is explained by the Pravin Gordhan vs. Oakbay saga (News24, 2016a), the Tension spike is the same negative sentiment spike we discussed under Source: Data extracted via Twitter API (Twitter API Developers, 2014)

Polarity classification in 00 above, that resulted from Donald Trump winning the US elections. The causes and validity of these spikes are discussed in further detail in the The closing values of the five retail banks identified as part of our research (ABSA, Nedbank, FirstRand, Standarbank and Capitec) were retrieved from the Morningstar.com (MonringStar.com, 2017) website. An additional five days of data, over and above the specified research period, was extracted to cater for the lag variables identified in our research methodology. The JSE is not open for trade on Saturdays, Sundays and public holidays (JSE, 2016). The closing values of the previous days' retail banking share prices are populated in any instance where we find a missing value because of weekends or public holidays. For example, the closing value on Friday afternoon is populated as the share price for the following two days (Saturday and Sunday). This is a true reflection of the actual share price as the Friday closing value is used by the JSE as the Monday opening value for the share (JSE, 2016).

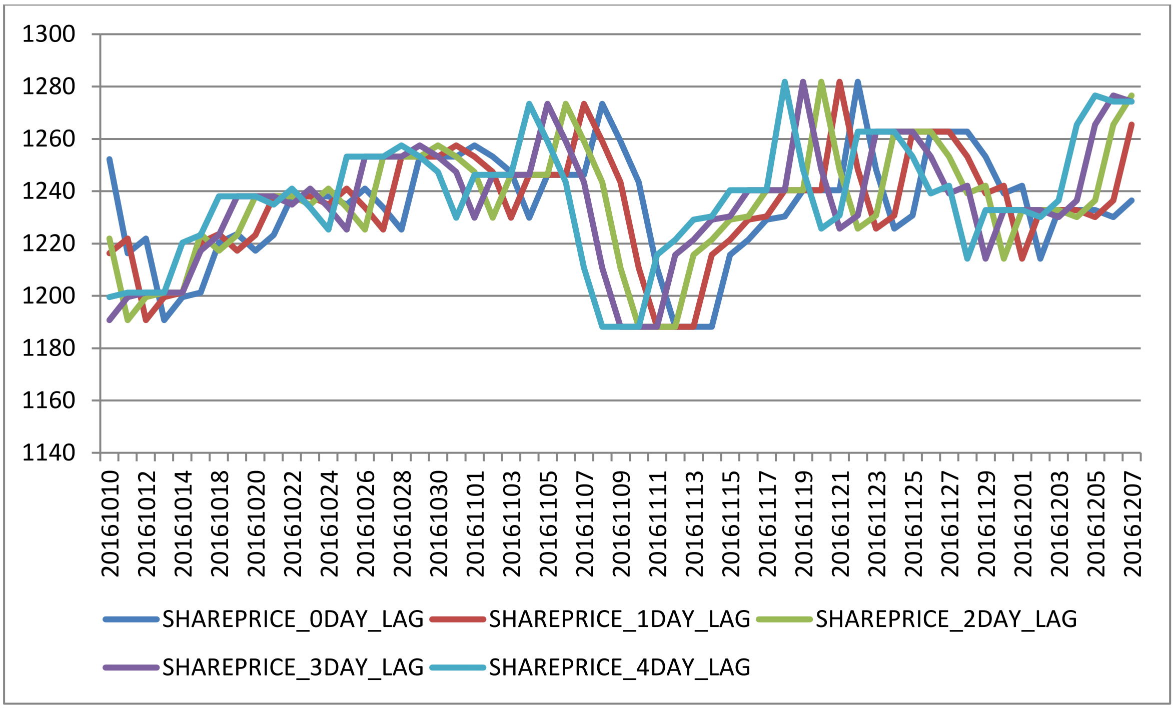

Figure 9: JSE Trend with lag

Source: Data extracted from Morningstat.com (MonringStar.com, 2017)

The effect of the explanatory POMS variables on the dependant share price variable is measured over a period of 5 days, i.e. 5-day lag. The exact trend repeating itself five times, as illustrated in Figure 9, is what is expected for the share price variables, indicating the validity of the share price lag measure.

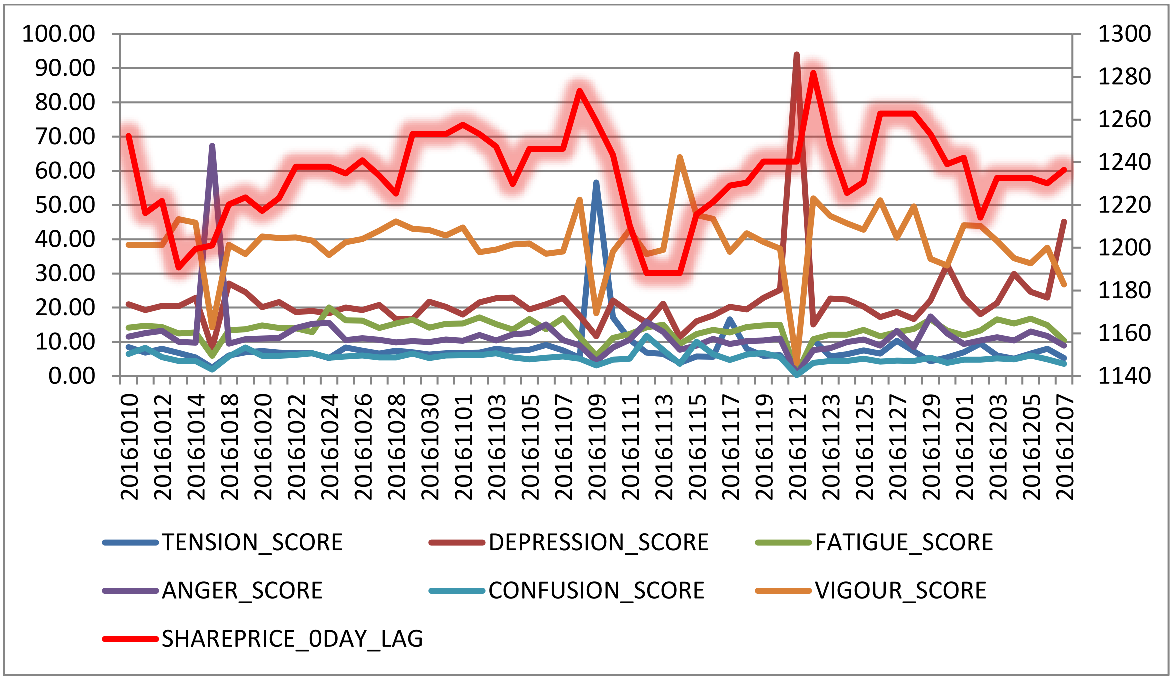

Figure 10: POMS trend vs. JSE trend

Source: Data extracted from Morningstat.com (MonringStar.com, 2017)

The trend in Figure 10 is an illustration of how the retail banking share price trend relates to the six different POMS variables. It is evident that the causal relationship may exist in both directions. As much as the different mood states may predict the movements in the share price (as per our hypothesis), the share price appears to also have a significant effect on the different mood states. Investigating the causal relationship from a different point of view is a subject for future research and discussed in more detail in paragraph 6.3. Another observation is the existence of lag. There appears to be a lag in effect where the share price reacts to the POMS variable with a slight delay. The significance of what is derived from the analysis of the data and its visual illustration is tested and explained in the hypothesis results in paragraph 4.5.

Validity and reliability paragraph in 0 below. There are however, obvious similarities between the polarity trends illustrated in paragraph 0, the emotional mood state trends discussed in this paragraph, and the news events discussed in paragraph 0.

4.3 JSE – Retail banking share price

The closing values of the five retail banks identified as part of our research (ABSA, Nedbank, FirstRand, Standarbank and Capitec) were retrieved from the Morningstar.com (MonringStar.com, 2017) website. An additional five days of data, over and above the specified research period, was extracted to cater for the lag variables identified in our research methodology. The JSE is not open for trade on Saturdays, Sundays and public holidays (JSE, 2016). The closing values of the previous days' retail banking share prices are populated in any instance where we find a missing value because of weekends or public holidays. For example, the closing value on Friday afternoon is populated as the share price for the following two days (Saturday and Sunday). This is a true reflection of the actual share price as the Friday closing value is used by the JSE as the Monday opening value for the share (JSE, 2016).

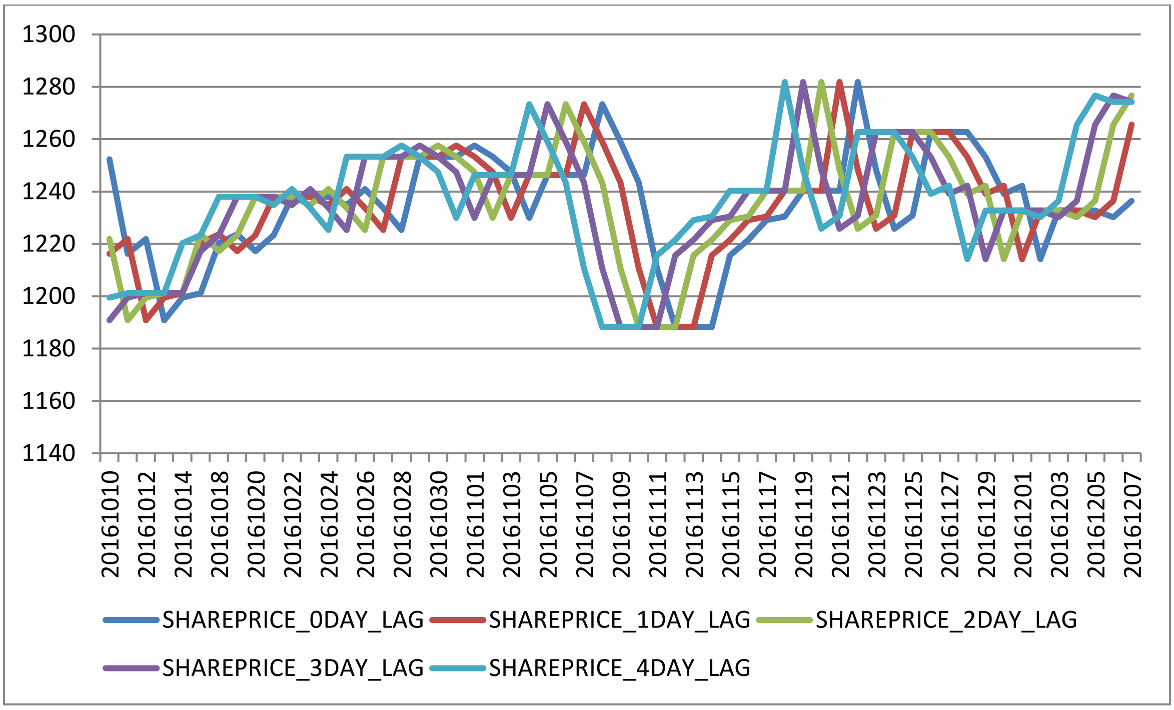

Figure 9: JSE Trend with lag

Source: Data extracted from Morningstat.com (MonringStar.com, 2017)

The effect of the explanatory POMS variables on the dependant share price variable is measured over a period of 5 days, i.e. 5-day lag. The exact trend repeating itself five times, as illustrated in Figure 9, is what is expected for the share price variables, indicating the validity of the share price lag measure.

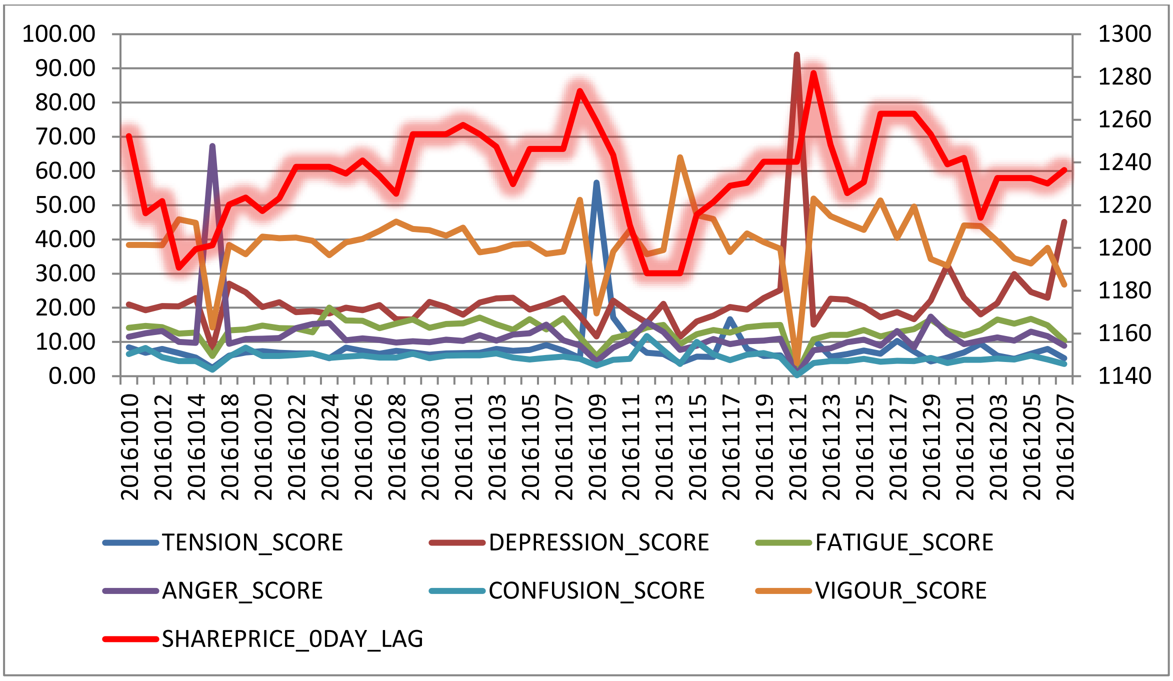

Figure 10: POMS trend vs. JSE trend

Source: Data extracted from Morningstat.com (MonringStar.com, 2017)

The trend in Figure 10 is an illustration of how the retail banking share price trend relates to the six different POMS variables. It is evident that the causal relationship may exist in both directions. As much as the different mood states may predict the movements in the share price (as per our hypothesis), the share price appears to also have a significant effect on the different mood states. Investigating the causal relationship from a different point of view is a subject for future research and discussed in more detail in paragraph 6.3. Another observation is the existence of lag. There appears to be a lag in effect where the share price reacts to the POMS variable with a slight delay. The significance of what is derived from the analysis of the data and its visual illustration is tested and explained in the hypothesis results in paragraph 4.5.

4.4 Validity and reliability

The results of the two predictive variables from the SentiWordNet (Baccianella et al., 2010) sentiment polarity tool, as well as the POMS scores were stored in a dataset on a daily level with the correlating JSE results aggregated for the five South African banks. Table 1 below is a sample of the dataset.

Table 5: Source Data Sample

TWEET DAY	SENTIMENT SCORE	TENSION SCORE	DEPRESSION SCORE	FATIGUE SCORE	ANGER SCORE	CONFUSION SCORE	VIGOUR SCORE	SHAREPRICE 0DAY_LAG	SHAREPRICE 1DAY_LAG	SHAREPRICE 2DAY_LAG	SHAREPRICE 3DAY_LAG	SHAREPRICE 4DAY_LAG
20161010	170.1084	8.48	20.99	14.11	11.51	6.50	38.42	1252.25	1216.28	1221.87	1190.76	1199.46
20161011	179.3045	6.83	19.26	14.73	12.58	8.26	38.34	1216.28	1221.87	1190.76	1199.46	1201.19
20161012	235.5953	8.01	20.53	14.34	13.26	5.56	38.29	1221.87	1190.76	1199.46	1201.19	1201.19
20161013	266.8005	6.77	20.40	12.51	10.00	4.42	45.91	1190.76	1199.46	1201.19	1201.19	1201.19
20161014	88.68993	5.46	22.83	12.71	9.75	4.40	44.84	1199.46	1201.19	1201.19	1201.19	1220.27

The validity and reliability of the data was examined using SAS Studio®. Results are displayed in Table 6.

Table 6: Analysis of variance results

Variable	Label	Mean	Std Dev	Minimum	Maximum	Median	N	Variance
SENTIMENT_SCORE	SENTIMENT_SCORE	187.0788341	206.6739636	-1208.20	448.2357400	214.6948790	57	42714.13
TENSION_SCORE	TENSION_SCORE	7.9592439	7.0305668	0.6113000	56.5988000	6.8042000	57	49.4288701
DEPRESSION_SCORE	DEPRESSION_SCORE	21.9665053	10.9966259	8.1568000	94.0403000	20.3968000	57	120.9257801
FATIGUE_SCORE	FATIGUE_SCORE	13.5427684	2.9917866	0.7229000	20.0482000	13.9303000	57	8.9507873
ANGER_SCORE	ANGER_SCORE	11.7492667	7.9379445	0.5285000	67.3065000	10.6258000	57	63.0109635
CONFUSION_SCORE	CONFUSION_SCORE	5.4617526	1.6945373	0.2652000	11.7466000	5.3839000	57	2.8714566
VIGOUR_SCORE	VIGOUR_SCORE	39.3201632	8.8067620	3.8314000	64.0127000	39.4903000	57	77.5590561
SHAREPRICE_0DAY_LAG	SHAREPRICE_0DAY_LAG	1234.36	20.7757300	1188.16	1281.83	1236.46	57	431.6309570
SHAREPRICE_1DAY_LAG	SHAREPRICE_1DAY_LAG	1234.67	20.8582982	1188.16	1281.83	1238.00	57	435.0686034
SHAREPRICE_2DAY_LAG	SHAREPRICE_2DAY_LAG	1235.24	20.6271835	1188.16	1281.83	1238.00	57	425.4807001
SHAREPRICE_3DAY_LAG	SHAREPRICE_3DAY_LAG	1235.28	21.3066656	1188.16	1281.83	1238.00	57	453.9739979
SHAREPRICE_4DAY_LAG	SHAREPRICE_4DAY_LAG	1235.12	22.0526153	1188.16	1281.83	1239.10	57	486.3178420

Variable	Label	Coeff of Variation	Skewness	Lower Quartile	Upper Quartile
SENTIMENT_SCORE	SENTIMENT_SCORE	110.4742632	-5.6756121	172.2109430	263.5765700
TENSION_SCORE	TENSION_SCORE	88.3320949	6.1587093	5.9634000	7.7110000
DEPRESSION_SCORE	DEPRESSION_SCORE	50.0608801	5.3141104	18.3483000	22.7137000
FATIGUE_SCORE	FATIGUE_SCORE	22.0913963	-1.7735724	12.5071000	15.1425000
ANGER_SCORE	ANGER_SCORE	67.5611914	6.2761619	9.7507000	12.1477000
CONFUSION_SCORE	CONFUSION_SCORE	31.0255221	0.6784767	4.6850000	6.0773000
VIGOUR_SCORE	VIGOUR_SCORE	22.3975723	-1.3174285	36.4255000	43.4567000
SHAREPRICE_0DAY_LAG	SHAREPRICE_0DAY_LAG	1.6831180	-0.3999869	1223.28	1247.37
SHAREPRICE_1DAY_LAG	SHAREPRICE_1DAY_LAG	1.6893865	-0.4171534	1223.28	1248.28
SHAREPRICE_2DAY_LAG	SHAREPRICE_2DAY_LAG	1.6698959	-0.4063445	1223.28	1252.25
SHAREPRICE_3DAY_LAG	SHAREPRICE_3DAY_LAG	1.7248443	-0.4365405	1223.28	1252.25
SHAREPRICE_4DAY_LAG	SHAREPRICE_4DAY_LAG	1.7854578	-0.5072380	1223.28	1252.25

The results indicate that the mean and median of most of the variables are relatively close except for the sentiment score variable where the difference is large. The reason for this is that the sentiment is largely positive but has instances of very negative polarity on specific days (2016/11/09, 2016/11/30, 2016/12/07). Four of the variables show significant skewness (i.e. a skewness score larger than 2 (Lee, 2016)). The sentiment score has a negative skewness of -5.68 where the mean of 187 is less than the median of 214. This is because of the three low negative scores mentioned above. Tension, depression and anger are all significantly positively skewed. The tension score observed on the 2016/11/09 was abnormally large at 56.6 compared to the observed mean of 7.9 which results in the positive skewness with a long tail to the right (Lee, 2016). The same is true for depression with a maximum score of 94 (observed on the 2016/11/21) and a mean score of 21.97, as well as anger with a maximum score of 67.3 (observed on the 2016/10/17) and a mean of 11.75. The validity of these abnormal findings that cause skewness in the distribution of the data is analysed below using event study analysis (Barberis et al., 1998; Gussenhoven, 2014; Johnston & Maree, 2015; Q. Li et al., 2014a; Tan et al., 2014). Cronbach's alpha, used to measure the reliability of the same construct, is not an applicable measure as the seven variables are all separate constructs (Salkind (2004), as cited in Johnston and Maree, 2015, p.59).

Table 7 below is a mapping of news events that occurred on the days where skewness in one or more variables was observed.

Table 7: Event Study Analysis

Variable	Date	Score	News Event
SENTIMENT_SCORE	2016/11/09	Score: -1208.2 Mean: 187.01	Donald Trump is announces as winner of presidential election (Democracy Now, 2016) Announcement of investigation and possible charges against Pravin Gordhan (BizNews.com, 2016)
SENTIMENT_SCORE	2016/11/30	Score: -23.366 Mean: 187.01	Rand vs Dollar exchange rate drop by 4% (Moneyweb, 2016) Massive heatwave hit majority of South Africa. >40degrees

SENTIMENT_SCORE	2016/12/07	Score: -46.812 Mean: 187.01	Controversial SABC enquiry starts (iafrica.com, 2016d)
TENSION_SCORE	2016/11/09	Score: 56.6 Mean: 7.96	Donald Trump is announces as winner of presidential election (Democracy Now, 2016) Announcement of investigation and possible charges against Pravin Gordhan (BizNews.com, 2016)
DEPRESSION_SCORE	2016/11/21	Score:94 Mean:21.97	Springboks rugby team loose against Italy (iafrica.com, 2016a) Water restrictions introduced(iafrica.com, 2016b) Minimum wage decision outrage (iafrica.com, 2016c) ANC Veterans call for Zuma to step down (iafrica.com, 2016e)
ANGER_SCORE	2016/10/17	Score:67.3 Mean:11.75	Pravin Gordhan revealed R6billion suspicious Oakbay transactions (News24, 2016a) SABC board members resign. Chairperson refuses (News24, 2016d) State Capture report revelations (News24, 2016c) Fees must fall protests and arrests (News24, 2016b)

4.5 The main problem: Assess the relationship between social media sentiment and the share price performance of South African retail banks

The purpose of this study is to assess the significance of the relationship between public sentiments as expressed on South African Twitter and the share price performance of

South African retail banks on the JSE. The two variables identified as ***a) social media sentiment on Twitter*** and ***b) share price performance on the JSE.*** The response (or dependant) variable is ***change in share price*** and the explanatory (or predictor) variable is ***change in sentiment on Twitter*** (Chatterjee & Hadi, 2015). Statistical analysis is conducted on the results described in previous sections of chapter 4 using the University Edition of SAS Studio®. We use Pearson correlation (p) at a confidence level of 0.05 to identify obvious correlation between the dependant share price variables and the explanatory sentiment and mood variables. Linear regression models are then applied to further analyse the significance of the relationship and if the explanatory variables are accurate predictors of the dependant variable. The slope of the correlation is explored by discussing the standardised (B) and unstandardized (β) parameter estimates and interpreting the strength and practical business implication of the correlation. Adjusted R-Square (Adj R^2) values are analysed to determine what proportion of the variance are explained by the model and to what extend other factors outside the model influence the retail banking share price as a dependant variable.

4.5.1 Results pertaining to Hypothesis 1: The relationship between negative social media sentiment and the share price performance of South African retail banks

$H1_0$: There is no relationship between negative social media sentiment and the share price performance of South African retail banks

$H1_a$: There is a positive relationship between negative social media sentiment and the share price performance of South African retail banks

Table 8 below show the correlation between the banking sector share price values for the five days (i.e. to take lag into consideration) and the sentiment score as measured by SentiWordNet (Baccianella et al., 2010)

Table 8: H1: Pearson Correlation

Pearson Correlation Coefficients, N = 57					
	SHAREPRICE 0DAY_LAG	SHAREPRICE 1DAY_LAG	SHAREPRICE 2DAY_LAG	SHAREPRICE 3DAY_LAG	SHAREPRICE 4DAY_LAG
SENTIMENT SCORE	0.2019	0.5113	0.2383	**0.0259**	**0.0362**

The results show a correlation between polarity sentiment and the retail banking sector with 3-day lag (p = 0.0259) and 4-day lag (p = 0.0362) at a 95% confidence interval. Regression analysis is done with polarity sentiment as the explanatory variable and both the 3-day lag and 4-day lag dependant variables to determine how well the sentiment score predicts retail banking sector share price movements three and four days after its observation.

Table 9: H1 - Linear Regression - 3-day lag

Parameter Estimates						
Variable	**B**	**P**	**β**	**SE**	**95% Confidence Limits**	
Intercept	1229.7122	<.0001	0	3.96736	1221.76152	1237.66303
SENTIMENT_SCORE	0.03275	0.0259*	0.29507	0.01430	0.15853	1.68278
F	5.25					
Adj R^2	0.0705					

Notes: B = unstandardized parameters, β = standardised parameters, SE = Standard Error, p<0.05*

Table 10: H1 - Linear Regression - 4-day lag

Parameter Estimates						
Variable	**B**	**P**	**β**	**SE**	**95% Confidence Limits**	
Intercept	1231.66172	<.0001	0	3.93435	1223.77711	1239.54633
SENTIMENT_SCORE	0.03045	0.0362*	0.27806	0.01418	0.00202	0.05887
F	4.61					
Adj R^2	0.0605					

Notes: B = unstandardized parameters, β = standardised parameters, SE = Standard Error, p<0.05*

The results in Table 9 and Table 10 are very similar. Polarity sentiment has a correlation with both 3 day and 4-day lag. The p-values are close and the adjusted R-square values indicate that the model explains 6% and 7% of the share price dependant variable behaviour respectively. The strongest correlation appears to be between sentiment and retail banking share price with a 3-day lag. This correlation has a relatively large positive standardised slope of β = 0.295 where β>0.2 is used as a guide (Lee, 2016). The small unstandardized slope of B = 0.03 indicates a small impact. A sentiment score movement of 1 predicts a share price movement of R0.03, three days after it is observed. Although the impact is small, the p-value of 0.0259 shows a correlation at a 0.05 confidence level, resulting in the rejection of the null hypothesis **$H1_0$: There is no relationship between negative social media sentiment and the share price performance of South African retail banks.**

4.5.2 Results pertaining to Hypothesis 2: The relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

$H2_0$: There is no relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

$H2_a$: There is a positive relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

Table 11 below shows the correlation between the banking sector share price values for the five days (i.e. to take lag into consideration) and the six different POMS mood state variables.

Table 11: H2: Pearson Correlation

Pearson Correlation Coefficients, N = 57					
	SHAREPRICE 0DAY_LAG	SHAREPRICE 1DAY_LAG	SHAREPRICE 2DAY_LAG	SHAREPRICE 3DAY_LAG	SHAREPRICE 4DAY_LAG
TENSION SCORE	0.1268	0.9645	0.1357	**0.0195**	**0.0199**
DEPRESSION SCORE	0.6456	**0.0137**	0.1815	0.5134	0.4099
FATIGUE SCORE	0.6322	0.5904	0.3462	**0.0317**	0.0769
ANGER SCORE	0.06	0.1968	0.5856	0.5755	0.6991
CONFUSION SCORE	0.0764	**0.0045**	0.1002	0.9729	0.9757
VIGOUR SCORE	0.9505	0.2718	0.993	0.422	0.5909

The results show a correlation between the Tension, Depression, Fatigue and Confusion as explanatory variables and the banking sector share price as the dependant variable (refer to values highlighted in red in Table 11 above). P-values for Tension and 3-day lag ($p = 0.0195$) as well as 4-day lag ($p = 0.0199$) are below the 0.05 confidence level. The P-values for Depression and 1 day lag ($p = 0.0137$), Fatigue and 3-day lag ($p = 0.0317$), as well as Confusion and 1 day lag ($p = 0.0045$) are below the 0.05 confidence level.

Further regression analysis is done using linear regression with the combinations of banking sector share price with lag as the dependant variable and the different POMS mood states as continuous variables. Only the combinations where correlation was observed (as discussed above) are included in the linear regression results.

Table 12: H2 - Linear Regression – Tension - 3-day lag

Parameter Estimates						
Variable	B	P	β	SE	95% Confidence Limits	
Intercept	1243.85651	<.0001	0	4.42719	1234.98422	1252.72879
TENSION_SCORE	-1.00724	0.0195*	-0.30868	0.4185	-1.84592	-0.16855
F	5.79					
Adj R^2	0.0788					

Notes: B = unstandardized parameters, β = standardised parameters, SE = Standard Error, p<0.05*

The parameter estimates from the regression analysis indicate that Tension, based on standardised estimates, has a relatively large negative slope (β = -0.31), where β>0.2 is used as a guide (Lee, 2016). The unstandardized slope of -1.01 indicates that the share price will decrease by R1.01 three days after a 1 point increase in the Tension score is observed. The adjusted R-Square of 0.0788 indicate that the model only explains 8% of the behaviour of the share price (dependant variable) and that 92% is affected by factors not included in the model. If we consider the fact that the size (mean = 7.95) of the Tension variable is relatively small compared to other POMS mood state variables (refer to Table 6), we can conclude that although there is a correlation between Tension and Share Price (P-value = 0.0195 at 0.05 confidence), there may be other factors that influence share price movement.

Table 13: H2 - Linear Regression - Depression - 1 day lag

Parameter Estimates						
Variable	B	P	β	SE	95% Confidence Limits	
Intercept	1220.93924	<.0001	0	5.98689	1208.94124	1232.93724
DEPRESSIO_SCORE	0.62151	0.0137*	0.32466	0.24414	0.13223	1.11078
F	6.48					
Adj R^2	0.0891					

Notes: B = unstandardized parameters, β = standardised parameters, SE = Standard Error, p<0.05*

The parameter estimates from the regression analysis indicate that Depression, based on standardised estimates, has a relatively large positive slope (β = 0.32), where β>0.2

is used as a guide (Lee, 2016). The unstandardized slope of 0.62 indicates that the share price will increase by R0.62 the day after a 1 point increase in the Depression score is observed. The adjusted R-Square of 0.0891 indicate that the model only explains 9% of the behaviour of the share price (dependant variable) and that 91% is affected by factors not included in the model. Depression is the second largest variable in size (mean = 21.97) compared to other POMS mood state variables (refer to Table 6), but the small unstandardized slope suggests that the business impact will be less than that of Tension (B = 1.01).

Table 14: H2 - Linear Regression - Fatigue - 3-day lag

Parameter Estimates						
Variable	B	P	β	SE	95% Confidence Limits	
Intercept	1206.2451	<.0001	0	13.73974	1178.71004	1233.78015
FATIGUE_SCORE	2.18527	0.0317*	0.28499	0.99106	0.19913	4.1714
F	4.86					
Adj R^2	0.0645					

Notes: B = unstandardized parameters, β = standardised parameters, SE = Standard Error, p<0.05*

The parameter estimates from the regression analysis indicate that Fatigue, based on standardised estimates, has a relatively large positive slope (β = 0.28), where β>0.2 is used as a guide (Lee, 2016). The unstandardized slope of 2.19 indicates that the share price will increase by R2.19 three days after a 1 point increase in the Depression score is observed. The adjusted R-Square of 0.0645 indicate that the model only explains 6.5% of the behaviour of the share price (dependant variable) and that 93.5% is affected by factors not included in the model. Fatigue has an average mean size (mean = 13.54) compared to other POMS mood state variables (refer to Table 6), but could potentially have a large business impact considering the size of the unstandardized slope (B = 2.19) being larger than that of other share price and mood state correlations observed.

Table 15: H2 - Linear Regression - Confusion - 1 day lag

Parameter Estimates						
Variable	B	P	β	SE	95% Confidence Limits	
Intercept	1259.78722	<.0001	0	8.88739	1241.9765	1277.59794
CONFUSION_SCORE	-4.61311	0.0045	-0.37134	1.55532	-7.73004	-1.49617
F	8.8					

Adj R^2	0.1222

Notes: B = unstandardized parameters, β = standardised parameters, SE = Standard Error, $p<0.05$*

The parameter estimates from the regression analysis indicate that Confusion, based on standardised estimates, has a considerably larger negative slope (β = -0.37), as well as smaller p-value (p = 0.0045) than the other share price and mood state correlations observed. The unstandardized slope of -4.61 indicates that the share price will decrease by R4.61 the day after a 1 point increase in the Confusion score is observed. The adjusted R-Square of 0.1222 indicates that the model explains 12.2% of the behaviour of the share price (dependant variable) and that 87.8% is affected by factors not included in the model. The adjusted R-Square value for Confusion is larger than any of the other share price and mood state correlations observed, but is the smallest variable in size (mean = 13.54) compared to other POMS mood state variables (refer to Table 6).

There is however, a correlation between Tension, Fatigue, Depression, Confusion and retail banking share price values with lag. We therefore reject the null hypothesis of **$H2_0$: There is no relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks.**

4.5.3 Results pertaining to Hypothesis 3: The relationship between a combination of mood state profile (POMS) on social media and the share price performance of South African retail banks

$H3_0$: There is no relationship between a combination of mood state profiles (POMS) on social media and the share price performance of South African retail banks

$H3_a$: There is a positive relationship between a combination of mood state profiles (POMS) on social media and the share price performance of South African retail banks

Different permutations of multiple linear regression analysis are executed to establish if a combination of POMS mood states are predictors of any of the 5 days of share price results (dependant variables). Table 16 below only records the significant results for further discussion.

Table 16: H_3 - Pearson Correlation Values

Explanatory variables	0DAY_LAG	1DAY_LAG	2DAY_LAG	3DAY_LAG	4DAY_LAG
All mood states	**P = 0.0253**	**P = 0.0121**	**P = 0.0494**	**P = 0.0436**	P = 0.1045
FATIGUE, CONFUSION	**P = 0.0386**	**P = 0.0076**	**P = 0.0166**	**P = 0.0305**	P = 0.1047

As illustrated by the numbers highlighted in red in Table 16 above, the tests found that by including all six POMS mood states in the model, the model produces statistically significant predictors of retail banking share prices, with the day after the mood state observations being the most significant (P-value = 0.0121 at 1DAY_LAG). By excluding other POMS variables, the Fatigue and Confusion combination proved to have the smallest p-value (p = 0.0076) and the strongest correlation to the retail banking share price with 1 day lag. Table 17 below explains the effect of each individual mood state on this model.

Table 17: H3 - Multiple Linear Regression – All mood states – 1 day lag

Parameter Estimates						
Variable	**B**	**P**	**β**	**SE**	**95% Confidence Limits**	
Intercept	1226.7733	<.0001	0	27.01847	1172.5314	1281.0151
TENSION_SCORE	0.17142	0.7109	0.05725	0.45984	-0.75174	1.09458
DEPRESSION_SCORE	0.50958	0.1403	0.2662	0.34014	-0.17327	1.19244
FATIGUE_SCORE	2.05359	0.097	0.29186	1.21473	-0.38509	4.49227
ANGER_SCORE	-0.25515	0.5228	-0.09621	0.39652	-1.0512	0.5409
CONFUSION_SCORE	-5.41095	0.0064*	-0.43556	1.90177	-9.22891	-1.593
VIGOUR_SCORE	0	.	.	.	.	.
F	3.28					
Adj R^2	0.1691					
Pr > F	0.0121					

Notes: B = unstandardized parameters, β = standardised parameters, SE = Standard Error, p<0.05*

Note: The following parameters have been set to 0, since the variables are a linear combination of other variables as shown.

VIGOUR_SCORE =	99.9998 * Intercept - 1 * TENSION_SCORE - 1.00001 * FATIGUE_SCORE - 0.99999 * CONFUSION_SCORE - 1 * DEPRESSION_SCORE - 1 * ANGER_SCORE

Confusion is found to be the only predictor of retail banking share prices with 1 day lag when other mood state variables are kept at a constant. Confusion has a relatively large negative slope (β = -0.43), where a 1 point increase in Confusion predicts a R5.41 decrease in the next day's retail banking share price. The adjusted R-square value of this model (Adj R^2 = 0.1691) is higher than the 0.1222 observed when only the Confusion mood is included in the model. The inclusion of the other five mood states thus improved the model.

Table 9: H3 - Multiple Linear Regression –Fatigue & Confusion – 1 day lag

Parameter Estimates						
Variable	**B**	**P**	**β**	**SE**	**95% Confidence Limits**	
Intercept	1248.36782	<.0001	0	12.31334	1223.681	1273.055
FATIGUE_SCORE	1.4088	0.1891	0.20022	1.05926	-0.71489	3.5325
CONFUSION_SCORE	-6.01553	0.0022	-0.48423	1.87018	-9.76501	-2.26604
F	5.34					
Adj R^2	0.1343					
Pr > F	0.0076					

Notes: B = unstandardized parameters, β = standardised parameters, SE = Standard Error, p<0.05*

From the various permutations of mood states tested, the highest correlation was found to be in the instance where only Fatigue and Confusion are included in the multiple linear regression model. A p-value of 0.0076 is achieved which indicates a stronger correlation compared to the p-value of 0.0121 when all mood states are included. The exclusion of the Vigour, Depression, Anger and Tension mood states improved the model's p-values, but adjusted R-Square values decreased from the 0.1691 observed when all mood states are included to 0.1343. The Fatigue and Confusion variables explain 13.43% of the next day's retail banking share price performance, implying that 86.57% of the behaviour is because of factors not included in the model.

The relationship found in the multiple linear regression test between all six mood states, as well as the combination of Fatigue and Confusion (explanatory variables) and the share price performance with a 1 day lag (dependant variable), leads to the rejection of the null hypothesis. **$H3_0$: There is no relationship between a combination of mood state profiles (POMS) on social media and the share price performance of South African retail banks.**

4.6 Summary of the results

The purpose of the study is to assess the relationship between social media sentiment on Twitter and retail banking share price performance. Retail banking share price performance is identified as the dependant variable against which the movements of social media sentiment as predictors are assessed over a period of 57 days. The result-set consist of 1.72 million Tweets that contain the specified “feeling” keywords. The sentiment derived from these Tweets are specified as either polarity sentiment (positive, negative or neutral), or emotional sentiment categorised by POMS mood states (Tension, Depression, Fatigue, Anger, Confusion). The research process track the polarity and emotional sentiment explanatory variables against the share price performance of the top five South African banks to test the three hypotheses derived in our research.

The first hypothesis ($H1_0$) tests if polarity sentiment on social media is a predictor of retail banking share price performance. The polarity sentiment results tested over the 57-day period showed a positive correlation to retail banking share price values 3 and 4 days after the sentiment was observed. The p-values and standardized slope indicate that polarity sentiment predicts share price movements more accurately and with bigger impact after three days’ lag ($p = 0.0259$, $\beta = 0.295$) compared to 4 days’ lag ($p = 0.0362$, $\beta = 0.278$). The null hypothesis ($H1_0$) was rejected. A 1 point increase in polarity sentiment predicts a R0.03 increase in retail bank share prices, three days later.

Hypothesis 2 ($H2_0$) tests if a single POMS mood state is a predictor of retail banking share price performance. The Pearson correlation coefficient values of each mood state were tested against the share price values with 5 days of lag. The Tension, Depression, Fatigue and Confusion mood states were found to all have correlation to share price performance. The correlation between Confusion and retail banking share prices with 1 day lag ($p = 0.0045$) proved to be the strongest, with a relatively strong standardised negative slope ($\beta = -0.371$). The null hypothesis ($H2_0$) was rejected. A 1 point movement in the Confusion score predicts a -R4.61 decrease in share price performance the day after.

The third hypothesis ($H3_0$) tests if a combination of POMS mood states predict retail banking share price performance. Multiple regression analysis results indicate that a model, which includes all the POMS mood states, has a correlation to share price performance for the first four days after observation. The p-value of this model is improved by excluding four POMS variables (Tension, Depression, Anger, and Vigour) and only including Fatigue and Confusion. By assessing the p-values and standardised slopes of all the different permutations of mood states, we find a combination of Fatigue and Confusion as the most effective model for predicting share price performance. The combination of the three mood states produced the lowest p-values compared to other permutations. Based on this evidence hypothesis 3 ($H3_0$) was rejected.

CHAPTER 5. DISCUSSION OF THE RESULTS

5.1 Introduction

Chapter 5 interprets and describes the research results derived in chapter 4. The approach is to discuss the results obtained in each hypothesis and relate this to the findings of previous research done on similar subjects. The similarities and differences of these are investigated and possible logical explanations or arguments for such are explored.

5.2 Discussion pertaining to Hypothesis 1: The relationship between social media sentiment and the share price performance of South African retail banks

$H1_0$: There is no relationship between social media sentiment and the share price performance of South African retail banks

$H1_a$: There is a positive relationship between social media sentiment and the share price performance of South African retail banks

The results from the correlation analysis conducted show a correlation between social media sentiment and retail banking share price performance. This concurs with previous research done by Bollen et al.(2011), showing a positive correlation between polarity sentiment and Dow Jones closing values. The purpose of this study is to establish if the same results will hold true for a specific sector within the ASI of a specific country, and in our case, the retail banking sector within South Africa on the JSE. Although a correlation was found between social media sentiment on Twitter and the retail banking share price performance on the JSE, the standardised slope ($\beta = 0.29$) and the unstandardized estimate ($B = 0.03$) is small in comparison to other permutations measured. A 1 point movement in the polarity sentiment score only predicts a R0.03 movement in the retail banking share price, three days later. The small impact could be explained by investigating the composition of the banking sector with reference to the JSE. The banking sector is a large role player in the financial industry and is well established and regarded as properly governed and stable (BASA, 2014). The share prices of stocks with these types of composition, where the real value of the share can be accurately calculated are found to be more stable and not as susceptible to sentiment (Baker & Wurgler, 2007). Research in behavioural finance show that the specific mood of the population is a more accurate predictor of investor sentiment, and in turn share price performance (Bollen et al., 2011). Speriosu et al.(2011) found that the accuracy of polarity sentiment algorithms could be improved to levels above most POMS algorithms. This improved accuracy approach must be considered in future research.

Based on the research findings and their discussion above, we find that there is a positive relationship between social media sentiment and the share price performance of South African retail banks. We reject Hypothesis 1 ($H1_0$).

5.3 Discussion pertaining to Hypothesis 2: The relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

$H2_0$: There is no relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

$H2_a$: There is a positive relationship between a specific mood state profile (POMS) on social media and the share price performance of South African retail banks

Results from the correlation analysis between the six different POMS variables and the retail banking share price closing values (with a 5-day lag) show that there is correlation between Tension, Depression, Fatigue and Confusion as predictor variables and retail banking share price performance. Each of these POMS variables, on their own, is an accurate predictor of the next day's retail banking share price results. The strongest correlation is found between Confusion and the next day's retail banking share price. The slope of the correlation is negative (β = -0.37), which indicates that retail banking shares will decrease as Confusion increases. This could be explained by investor behaviour called arbitrage, where rational investors move their investment to safer shares for protection when markets are unstable (i.e. when there is confusion in the market), or opt to be more adventurous when the Confusion in the market decreases by redirecting their investment towards higher risk shares for higher returns (Baker & Wurgler, 2007). Other research using POMS as a tool show that Calmness (which would be categorised as a positive mood state) accurately predict the performance of Dow Jones closing values (Bollen et al., 2011). The Dow Jones in the USA has a different composition to the JSE in South Africa. Johnston & Maree (2015) found that depression had the only correlation to JSE ASI values. This alludes to the premise that both the country where the stock exchange resides (i.e. first world USA, or third world RSA) as well as the composition of the stock on the countries' stock exchange (i.e. financial sector, media sector, telecommunication sector etc.), influence the factors that affect performance. Another factor to consider when comparing this study to any previous study using the POMS variables is the method of extension. POMS is an assessment tool that in its standard form has 65 terms that are matched to the 6 key mood states (Anger, Tension, Depression, Vigour, Confusion) (Heuchert & McNair, 2012). The first problem with comparing it to other studies is that some authors rename the mood states to fit their research problem better (Bollen et al., 2011) which results in mood state descriptions that do not match the original POMS. The second problem is that all authors extend the 65 terms to a more inclusive base by mapping synonyms to the 65 key terms to improve the classification results of the POMS survey tool. The timing of when the mapping was done and what thesaurus was referenced to map the synonyms will also cause differences in findings.

Based on the research findings and their discussion above, we find that there is a negative correlation between the Confusion mood on social media and the share price performance of South African retail banks. We reject Hypothesis 2 ($H2_0$).

5.4 Discussion pertaining to Hypothesis 3: The relationship between a combination of mood state profile (POMS) on social media and the share price performance of South African retail banks

$H3_0$: There is no relationship between a combination of mood state profiles (POMS) on social media and the share price performance of South African retail banks

H3$_a$: There is a positive relationship between a combination of mood state profiles (POMS) on social media and the share price performance of South African retail banks

Multiple linear regression results deduced in chapter 4 are analysed in two sections. The first section looks at including all six mood states in the multiple linear regression model to find the predictor effect this combination will have on the model as well as to investigate the effects of the individual mood states within the model with the condition that other variables are kept at a constant. The second section then attempts to derive the most efficient model for predicting retail banking share price movement by removing POMS variables from the model to ascertain the effect different combinations of POMS variables have on the correlation results.

Results of the first multiple linear regression test produced a correlation between all six POMS variables combined and the retail banking share price closing values for the first 4 days (0-day lag to 4-day lag). This means that a model that combines all six POMS variables is an accurate predictor of the next four day's retail banking share price performance. An interesting finding is that the p-values peak at day 1 and decrease constantly thereafter. This means that the correlation weakens from day 3 to day 5 and is at its strongest on day 1 (i.e. the day after the POMS score is observed). The individual POMS variables in the model that has correlation (where all other variables are kept at a constant) are found to be Tension, Depression, Fatigue and Confusion. Results from the second section of tests found the most effective combination of POMS variables, in terms of predicting retail banking share price performance, to be a combination of Fatigue and Confusion. This combination improved the p-value from 0.021 for all six POMS variables to 0.0076. Once again, the correlation was strongest on the same day (0-day lag) and next day's (1-day lag) retail banking share price performance

Previous research support the finding that correlation decrease as time goes on, but differ on the POMS variable, what day the correlation is strongest and when it starts to decline. Bollen et al.(2011) found that correlation between the Calm mood state and Dow Jones closing values were at its strongest on day 3 (2DAY_LAG variable in our model) and decreased significantly from day 4 onwards, where our findings suggest stronger correlation on the same day and the day after (0DAY_LAG and 1DAY_LAG).

From a South African context, Johnston and Maree (2015) found that the Depression mood state had a negative correlation to JSE ASI closing values on the same day, suggesting that the JSE closing values will decrease the same day that Depression mood increases. Another finding was that Fatigue had a positive correlation for two days after (1DAY-LAG and 2DAY_LAG), suggesting that JSE closing values will increase for two days after the Fatigue mood increases. These differences are all explained against the theoretical framework in the conclusion (paragraph 5.5).

Based on the research findings and their discussion above, we find that there is a positive relationship between a combination of POMS variables (Fatigue and Confusion) on social media and the share price performance of South African retail banks. We reject Hypothesis 3 ($H3_0$).

5.5 Conclusion

The conclusion is that the first hypothesis ($H1_0$) is rejected, as there is a correlation between polarity sentiment on social media and retail banking share prices. Although the correlation is statistically significant, what is evident from this research, as well as research done by others (Bollen et al., 2011), is that the impact of polarity sentiment (positive, negative, neutral) on share price results is not large, and that there are other more complex factors than purely sentiment that affect investor decision making. One of these factors includes the public mood of the country. The results supported the predictions of the second and third hypothesis ($H2_0$ and $H3_0$). There is a correlation between the POMS mood states on Twitter and the retail banking share price performance on the JSE. This relationship is even stronger when specific moods are combined, such as Fatigue and Confusion. The slope of the correlation is positive even though the mood is negative. This can again be explained by rational arbitrageurs (De Long, Shleifer, Summers, & Waldmann, 1990), investor behaviour where investors will choose to invest money in safer shares when there is Confusion or Tension in the market and take more risk when the market shows less Tension or Confusion. The adjusted R-Square values observed for the most effective model, where only Confusion is included as an explanatory variable, indicate that the model only explains 84% of the retail banking share price performance. Other factors that should be considered as explanatory variables in future research include firm size, stability of profit rate, the regulatory framework, and the sector (which is already included in this research as the focus is on the retail banking sector) (Demsetz & Lehn, 1985). The impact of other international stock markets on the JSE is also a factor that will not be explained by the POMS variables in our model. The mood observed on Twitter may be negative, but positive macroeconomic factors in other stock markets will spill over into the JSE (Hamao, Masulis, & Ng, 1990).

A key understanding is that retail banking in South Africa is affected by different factors to the ASI in USA, or even the ASI on the JSE in South Africa. A study done by Flannery and James (1984) found that the retail banking sector was negatively influenced by interest rate changes. Although the findings are interesting, taking into consideration that bad news influence public sentiment (Thaler & De Bondt, 1985), one would expect the POMS variables to reflect the negative sentiment and influence the model accordingly. The JSE seems to be largely affected by negative mood states such as Tension, Fatigue, Depression and Confusion in our study and, Depression and Fatigue in the study done by Johnston and Maree (2015). This differs from key research done on Dow Jones closing values by Bollen et al.(2011), where Calmness had a positive correlation. The theoretical framework of our study explains this behaviour. Figure 1: Theoretical Framework illustrates the influence of public sentiment on investor sentiment and in turn, the influence of investor sentiment on share price performance (Q. Li et al., 2014a). Factors that have a considerable impact on public sentiment is mainstream media (Mutz & Soss, 1997) and "influentials" (Watts & Dodds, 2007). The mainstream media in a country has the ability to influence what the public deem as crucial and move their sentiment in a specific direction (Mutz & Soss, 1997). The "influential hypothesis" claim that specific people in influential positions (leaders, celebrities) as well as large crowds of regular people, has the ability to influence the sentiment of a population (Watts & Dodds, 2007). Nofsinger (2003) finds that an optimistic society will overreact to good news and underreact to bad news. Taking this into account, one can argue that both the mainstream media as well as the "influentials" in USA and RSA are vastly different. It makes sense that if public sentiment has an influence on investor sentiment and public sentiment is different, then investor sentiment will be influenced in a different manner. Our findings indicate that South African investors are more sensitive to negative news than their American counterparts and that they respond faster to a change in sentiment. This ties in with the finding that USA is more optimistic (overreacts to good news and underreacts to bad news (Nofsinger, 2003)), hence the positive correlation with the Calm mood on the Dow Jones ASI closing values compared to RSA that react more to negative moods in our study (Confusion, Fatigue, Tension, Depression) and others (Depression, Fatigue (Johnston & Maree, 2015)).

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

In this chapter, we discuss the culmination of findings from the literature review conducted in chapter two, the subsequent research methodology stipulated in chapter three and its implementation, results and discussion in chapters four and five.

6.2 Conclusions of the study

This study sets out to measure the relationship between social media sentiment on South African Twitter and retail banking share price performance on the JSE. The theoretical framework of behavioural finance explains the impact public sentiment has on investor sentiment and in turn, shares price performance. Public sentiment is derived from Twitter using NLP techniques to measure polarity sentiment and emotional sentiment (POMS mood states). From the literature review we conclude that NLP as a technique for deriving meaning from language has many different applications and is rapidly growing especially in the area of social media (Liu, 2012). The effect of sentiment on share price performance is widely studied and the general consensus is that negative sentiment has a larger impact than positive sentiment (Hoteit, 2015; Luo et al., 2013). The literature review also highlights the type of stock, the country within which the stock exchange reside as well as the sentiment analysis approach as factors that need to be considered when analysing research results in this area (Zheludev et al., 2014).

The results from Twitter and the JSE were captured in a database over a period of 57 days. An analysis of variance (ANOVA) test was conducted to check the consistency of the data. The validity of the results was checked by conducting an event study analysis for days that caused significant skewness and appropriately matched to news events that could potentially explain the results. Events such as the announcement of Donald Trump winning the US election (Democracy Now, 2016) on the 9th of November 2016 was clearly reflected by the spike in negative polarity sentiment on Twitter as well as the majority prevalence of the Anger mood state. The reliability of the research tools are also inherent to SentiWordNet (Baccianella et al., 2010) where the use in other research has been well documented (Kozareva et al., 2007; Liu & Zhang, 2013; Pang & Lee, 2008), as well as POMS (Heuchert & McNair, 2012) where the results for its internal consistency, reliability and validity can be found in paragraph 3.4.

The results show that there is a correlation between polarity sentiment and retail banking share prices. This concurs with research done by Bollen et al.(2011) that also finds a correlation between polarity sentiment and Dow Jones ASI closing values. The Confusion mood state was found to be a predictor of the next day's retail banking share price performance. The most effective models for predicting retail banking share price performance proved to be the Confusion mood state on its own, with a combination of Fatigue and Confusion as a close second. These findings differ from that of Bollen et al.(2011) who found that Calmness has the strongest correlation to Dow Jones ASI closing values, as well as the research of Johnston and Maree(2015) indicating correlations with Depression and Fatigue and the JSE ASI.

It is important to note that the model that combines of Fatigue and Confusion has an adjusted R-Square value of 0.1604, implying that 84% of the retail banking share price performance is not explained by the Fatigue and Confusion variables. The differences in findings with past research as well as the unexplained factors highlighted by the adjusted R-Square values can be explained by the fact that the Dow Jones ASI will be influenced by different factors than the JSE ASI, as will the retail banking sector be influenced by different factors than the JSE ASI. Other factors not included in the model such as firm size, stability of profit rate, the regulatory framework (Demsetz & Lehn, 1985), the impact of other international stock markets on the JSE (Hamao et al., 1990), may also improve the model's fit. Another important factor noticed is the differences in dictionaries used to conduct the sentiment and POMS variable extraction. Bollen et al.(2011) extended the original POMS terms by mapping synonyms obtained from the WordNet (Miller, 1995) dictionary to the POMS categories. Johnston and Maree(2015) used a similar approach, but extended the synonyms further by using google translate to translate the English words into Afrikaans. This highlights the importance of the different behaviours observed because of three factors: the country, the sector, as well as the research tool used to conduct the measurement.

6.2.1 Impact on retail banking

The subprime crisis that occurred in the US during 2007 shows how vulnerable the financial sector, including the retail-banking sector, is to sentiment. In his paper on maintaining stakeholder trust in difficult times, Kai Schanz (2009) tests the vulnerability of the financial industry to a change in trust form its major stakeholders. During 2007, all stakeholders lost trust in the financial sector and the effects were evident in the poor performance of financial sector share prices on stock exchanges across the globe. Schanz (2009) differentiates between the insurance industry and the retail banks within the financial sector. His findings indicate that banks were more susceptible to the negative trust sentiment than the insurance industry. The reason for this is that insurance premiums are paid upfront and that the losses that occurred during the financial crisis, were catered for within their underwriting models. Burdekin and Redfern (2009) found a negative correlation between stock market sentiment and saving deposit growth in the Chinese banking sector. Positive sentiment coincides with a higher preference for stocks outside of banks, like investment funds and a lower preference for saving money in time deposits within banks. They also find that negative sentiment is a more important contributor to the decline in savings deposits at banks than the actual decrease in interest rates. Khatua and Khatua (2015) investigates the reaction of the share prices in specific sectors to major events in the marketplace. Their main event study analysis compares share price performance to sentiment on Twitter after the 2015 budget speech in India. They find that the share prices of stocks in a specific sector increases, as the sentiment on Twitter regarding the budget speech pronouncements for that sector increases. The results from the NLP methods used to mine the Twitter data showed that private sector banking sentiment was highly positive about the budget. This positive sentiment also reflects in the performance of banking sector share prices over the same period.

The impact of social media sentiment (as a representation of public sentiment) on retail banking is evident. Social media sentiment can be a predictor of increases and decreases in savings deposits (Burdekin & Redfern, 2009), which in turn affects relationship revenue and leads to increased or decreased return on equity (ROE). ROE is a primary measure of stakeholder and shareholder value (A. Saunders & Cornett, 2011).

6.2.2 Recommendations

The retail banking sector in South Africa spends large amounts of money on developing social media strategies and implementing real-time measurement tools (PWC, 2016). It is important for senior management to put the impact of social media into perspective. Questions that management must ask revolve around how much should be invested in protecting the corporate brand against social media sentiment, and what opportunities there are to harness the real-time capabilities of social media to predict the markets. This research, as well as others (Bollen et al., 2011; Johnston & Maree, 2015), suggest that the different moods that can be derived from social media are predictors of share price performance, not only for overall share price performance, but very specific to the retail banking sector. Other stakeholders from sectors with similar structures may also find benefit from this model.

6.3 Suggestions for further research

6.3.1 Longer period

The research is conducted on Twitter and share price results over a 57-day period between 10 October 2016 and 7 December 2016. Many interesting political events occurred during this period, including the announcement of Donald Trump as the winner of US election against Hillary Clinton (Democracy Now, 2016). Extending the period over which the results are monitored will allow more data points against which the cross-sectional analysis can be tested, as well as potentially introduce more significant events that may influence both sentiment and share price results. One such event is an increase or decrease of interest rates, which according to Flannery and James (1984) has a significant effect on retail banking performance. The public mood on some of the major holidays such as Christmas day, New Year’s Day and Easter may also see a positive general mood against which our findings in paragraph 5.5 that South Africa is more prone to negative than positive sentiment can be properly tested.

6.3.2 Granger causality

"Correlation does not imply causality, and a statistically significant correlation does not necessarily explain any or all of the cases upon which it is based" (Bennett, 2004). By using Granger causality analysis in a similar fashion as Bollen et al. (2011) and others (Gilbert & Karahalios, 2010; Johnston & Maree, 2015; Q. Li et al., 2014a; Luo et al., 2013; Tetlock, 2007), we will be able to test if the sentiment time series has predictive information about the retail banking share price time series.

6.3.3 Individual share prices of banks

This research aggregates the closing values of the 5 major retail banks in South Africa as a representation of the retail banking sector. There is an opportunity to do linear regression analysis with each individual bank's share price as the dependant variable, and the various POMS mood states as the explanatory variables. The results of this statistical analysis may show the existence of a correlation between individual banks share price and emotional sentiment. It may also highlight that different POMS mood states are predictors of different share price movements. Each individual bank may be influenced by different factors.

6.3.4 Expanding the model – explanatory variables

The accuracy of the model may be improved by including additional explanatory variables such as firm size, stability of profit rate and the regulatory framework (Demsetz & Lehn, 1985) as well as the impact of other international stock markets on the JSE (Hamao, Masulis, & Ng, 1990). The most accurate version of the model is found to be where Confusion is the explanatory variable and the next days' retail banking share price values as the dependant variable. The adjusted R-Squared values for this model is 0.122, which implies that Confusion only explains 87.8% of the next days' share price movements. Introducing the variables above may improve the accuracy of the model.

6.3.5 Change causal variable – Share price effect on Social media

The causal relationship is critically important in linear regression (Lee, 2016). This research tests the effect of emotional and polarity sentiment as explanatory variables on the retail banking share price as dependant variable. From our analysis in paragraph 4.3 we realise that this relationship could work both ways. Figure 10: POMS trend vs. JSE trend illustrate how the POMS mood appears to have a visual correlation with the previous day's upwards and downwards movement of the retail baking share price. This proposition can be tested by doing linear regression analysis with the retail banking share price as the explanatory variable and Twitter sentiment as the dependant variable, thus testing the effect of retail banking share prices on emotional and polarity sentiment. This reversal of the causal relationship seems to be an area that has not been explored in academic literature yet.

6.3.6 Different sectors

This research focuses specifically on the effect that social media sentiment has on the share price performance in the retail banking sector. There are many similarities between the different sectors in the financial industries. Hirtle and Stiroh (2009) concludes that the financial activities in retail banking is much the same as in the insurance industry, and many retail banks even have insurance industry divisions (BASA, 2014). It makes sense to apply this research model to other sectors in the financial industry. An area that lacks research is the effect of social media sentiment on the mining sector. The mining sector employs many people and these employees all have extended families. We have seen recently what effect emotional events in the mining industry, such as the Marikana incident (Wu, 2013), has on public sentiment and the role that social media plays in creating that sentiment. This may in turn, per our theoretical framework (Figure 1: Theoretical Framework), have an influence on investor sentiment and subsequently mining sector share price performance. The correlation between the various POMS mood states and mining sector share price movements may be of significance to mining sector stakeholders. This may also be the case for many other industries and sectors.

APPENDIX A – Emoticon Sentiment Instrument

Table 18: Emoticons and their variations

<table>
<tr><th>Emoticon</th><th>Polarity</th><th>Symbols</th></tr>
<tr><td></td><td>Positive</td><td>:) :] :} :o) :o] :o}
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<tr><td></td><td>Negative</td><td>D: D= D-: D^: D^= :(:[
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<tr><td></td><td>Neutral</td><td>:| =| :-| >.< >< >_< :o
:O =O :@ =@ :^o :^@ -.-
-.-' -_- -_-' :x =X :#
=# :-x :-@ :-# :^x :^#</td></tr>
</table>

Source: From " Comparing and Combining Sentiment Analysis Methods" by Gonçalves, Araújo, Benevenuto, and Cha, 2014, p.3.

APPENDIX B – Extended Profile of Mood States Instrument

The following POMS table was created from the “Scoring for POMS” website (Mackenzie, 2001):

Mood state	Word/Statement	Synonyms
Tension	Tense, Shaky, On Edge, Panicky, Relaxed, Uneasy, Restless, Nervous, Anxious	Extended using synonyms from SentiWordNet
Depression	Unhappy, Sorry for Things Done, Sad, Blue, Hopeless, Unworthy, Discouraged, Lonely, Miserable, Gloomy, Desperate, Helpless, Worthless, Terrified, Guilty	
Anger	Anger, Peeved, Grouchy, Spiteful, Annoyed, Resentful, Bitter, Ready to Fight, Rebellious, Deceived, Furious, Bad Tempered	
Fatigue	Worn Out, Listless, Fatigued, Exhausted, Sluggish, Weary, Bushed	
Confusion	Confused, Unable to Concentrate, Muddled, Bewildered, Efficient, Forgetful, Uncertain About Things	
Vigour	Lively, Active, Energetic, Cheerful, Alert, Full of Pep, Carefree and Vigorous	

The following adjectives are not used in the scoring (Mackenzie, 2001):

- Friendly, Clear Headed, Considerate, Sympathetic, Helpful, Good Natured and Trusting

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