Relationships between social media sentiment, customer satisfaction, and stock price performance

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Abstract

This research tested the relationships between social media sentiment, customer satisfaction and stock price performance. Furthermore, social media sentiment was broken down into global or aggregated social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment. Custom dictionaries were created by the researcher to classify tweets as customer-oriented or financial-oriented. The relationships were also tested for potential differences between utility companies and non-utility companies.

The research methodology employed was quantitative in nature and has been applied in a causal design as part of a longitudinal approach to the study. Secondary data were downloaded for 79 American listed companies for the period of 1 January 2011 – 31 December 2012. The data comprised of end-of-day daily stock prices, customer satisfaction scores from the American customer satisfaction index (ACSI), and tweets from the Twitter network that mentioned the company name or brand. A total of approximately 20 million tweets were downloaded and transformed so that it could be analysed statistically. Due to the large number of tweets that had to be downloaded and analysed, the researcher developed a Twitter scraper and sentiment analysis tool to do this programmatically. Sentiment analysis was performed by using a combination of two well-known dictionaries. Panel data analysis was done on the transformed data.

A statistically significant relationship could be found for the ability of global social media sentiment to predict stock price performance. Furthermore, it was demonstrated that financial-oriented social media sentiment predicts stock price performance more accurately than customer-oriented social media sentiment or even global social media sentiment. Aligned with previous studies, no statistically significant relationship was found between social media sentiment and its ability to predict customer satisfaction. Social media sentiment can however be used to analyse customer satisfaction in real time. Lastly, customer satisfaction is not considered in financial models predicting stock price performance. This supports the debate around the efficient market hypothesis (EMH) and its ability to take all information into account when valuating stock prices.

The researcher's unique contributions to academic research are the way she developed the custom dictionaries, the large amount of tweets that were downloaded and analysed as well as the types of tweets that were tested in this research.

Keywords

Customer satisfaction; Social media sentiment; Stock price performance; Twitter; Marketing; Financial behaviour.

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

11 November 2013

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List of abbreviations

Abbreviation:	Description:
ACSI	American customer satisfaction index
CF = 0	Utility company
CF = 1	Non-utility company
chCSS	Percentage change in customer satisfaction score
chSP	Percentage change in stock price
chTS_cust	Percentage change in customer-oriented social media sentiment
chTS_fin	Percentage change in financial-oriented social media sentiment
chTS_global	Percentage change in global social media sentiment
CSS	Customer satisfaction score
DV	Dependent variable
EMH	Efficient market hypothesis
GLM	General linear model
IV	Independent variable
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York stock exchange
R&D	Research and development
S&P 500	Standard & Poor's 500
SACSI	South African customer satisfaction index
SP	Stock price
TSC	Customer-oriented social media sentiment
TSF	Financial-oriented social media sentiment
TSG	Global social media sentiment
USA	United States of America
VIX	Chicago Board Options Exchange Market Volatility Index

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1. Chapter one: Introduction to research problem

1.1 Background to the research problem

Social media is becoming an increasingly more popular vehicle for businesses to communicate and collaborate with their customers and stakeholders. This includes both internal and external communication. Social media is progressively becoming more effective than traditional marketing communication tools (Diffley, Kearns, Bennett, & Kawalek, 2011). Further to this, customers are also using social media platforms to express their emotions around an organisation's products or services (Zorfas, 2012). One of the most recent focus areas from academia interested in "social media and business" is the role that social media sentiment plays in stock price prediction. Markets are often in a volatile state and any assistance that traders can get in choosing the best performing stocks is of huge benefit to them.

Social media sentiment data can, for example, reveal customer preferences, customer satisfaction, and customer feedback on product ratings. In order to stay competitive, marketers have no choice but to exploit these social media platforms in a way that can add value to their business as well as to their customers and stakeholders through relationship building and social communities. In light of this, it is also important to understand that customer satisfaction will only become a priority for management and shareholders if strong support for a positive association between customer satisfaction, social media, and stock price performance is put in place. Alternatively, management will remain split as to how customer satisfaction can be used to influence how the business performs (Anderson, Fornell, & Mazvancheryl, 2004).

Literature has demonstrated that in some cases customer satisfaction can lead to increased investor rewards. Added to this, strong links can be found between customer satisfaction levels and subsequent stock price returns, with a lag of up to 24 months (Sheridan, 2012). However, the results of various other studies attempting to find a correlation between customer satisfaction and stock price performance have been inconsistent (Ray, 2012). It therefore does seem that satisfied customers tend to result in satisfied shareholders but the circumstances around these occurrences need to be investigated and understood.

Twitter is a popular micro blogging tool and is being used more often in sentiment analysis studies. This is due to a recent study that showed that approximately 80% of Twitter users update their followers with their experiences and also share their opinions on a company, its products or its services, on a daily basis (Mostafa, 2013). Analysing and interpreting social media data for sentiment has led to a new term called "social intelligence" (Bird, 2013). Valuable clues and insights are hidden in online conversations that just need to be found and implemented to a company's benefit.

In a post mortem study done on the impact of various Netflix announcements in 2010 and 2011, it found that sentiment could have been analysed to better understand their customers' opinion on these announcements (De Leo, 2011). Further to this, if the analysis was done in real time by the Netflix marketers, it would have been clear to them the moment that the sentiment became negative. Proactive interventions could have prevented a serious decrease in customer satisfaction. Netflix could have also put measures in place to help cushion the impact on stock price performance. Netflix have learnt the hard way that their customers' voice has become much more influential.

1.2 Research problem definition

The research aims to contribute positively to academic and business knowledge by building on existing theory and allowing any listed organisation to use the resultant academic research and consider the application thereof in their marketing strategy. The results of the study also positively contribute to the growing body of literature on electronic word-of-mouth and customer satisfaction (Mostafa, 2013).

According to the efficient market theory (EMH), stock prices incorporate all information about expected future financial performance (Anderson, *et al.* , 2004). It therefore provides an impartial estimate of the value of a firm (Jacobson & Mizik, 2009). However, the literature does not always support this theory and certain anomalies have been observed. It therefore motivates a repeat of previous studies.

Various studies have been done to test the relationship between social media sentiment and stock price performance as well as customer satisfaction's influence on stock price performance. However, little research could be found where social media sentiment in its decomposed nature (specifically customer-oriented sentiment and financial-oriented sentiment) has been tested to see which aspects of the global or aggregated sentiment predict stock price performance more accurately. Furthermore, no research could be found that was done on this large scale. The researcher analysed approximately 20 million tweets from 79 companies over a period of two years. According to Chowdury, Jansen, Sobel, & Zhang (2009), approximately only 20% of all tweets that mention a company name or brand, can be categorised as tweets containing sentiment, when basic dictionaries are used. The approximately 20 million tweets analysed by the researcher were the tweets that mentioned a company name or brand. Moreover, the large sentiment dictionary used in this research allowed the researcher to classify approximately 90% of all the tweets as tweets containing sentiment. This study also did not use a sample of analysed tweets but rather all tweets. The results of this study are therefore more generalisable and representative of the overall sentiment contained in tweets for listed American companies.

The testing of the relationships between customer satisfaction, social media sentiment and stock price performance across different types of companies and industries is limited in the current literature and was therefore identified as another area the researcher can contribute to. Another shortcoming that was identified is the lack of available research around the possible mediating or moderating effect that social media sentiment has on the relationship between customer satisfaction and stock price performance. It was therefore included in the research.

Evidence exists that supports the identification of the above mentioned shortcomings in existing literature as well as social media's emerging importance in market research. Social media allows for a one-to-many communication with far-reaching consequences for marketers because it is difficult to control (Bhattarakosol, Chamlertwat, Haruechaiyasak, & Rungkasiri, 2012). Technological developments have however made listening to social media users much easier than ever before as they congregate in communities like Facebook and Twitter. Consumers have integrated social media into their daily lives and in doing so have created new opportunities for research (Patino, Pitta, & Quinones, 2012).

Social media platforms and their user bases are increasing daily. This makes it even more sensible to explore to what extent users and the opinions they share represent the general consumer's overall opinion. Therefore, the exploration of large-scale social media data to determine the direction of management decisions based on consumer opinions is critical for any company to solve the associated real-world problems.

1.3 Research objectives

The overarching goal of this research was to determine if customer satisfaction and social media sentiment can be used as accurate predictors of stock price performance and whether or not any other relationships exist between the mentioned variables. The research problem was broken down into a number of research hypotheses. This study was motivated by the researcher's desire to learn more about social media and its use cases, specifically in its' relationship to customer satisfaction and its ability to predict stock price performance. The study seeks not only to contribute to academic research that crosses disciplinary boundaries in the fields of marketing strategy and financial behaviour, but also to determine the implications of the findings to academics, marketers and traders.

The companies used in this research were classified as utility companies and non-utility companies to understand if there are any differences in the findings that could be attributed to characteristics associated with utility companies and non-utility companies. One such characteristic could be the monopolistic nature of utility companies resulting in customer satisfaction being perceived as less important.

Consumer generated opinions on Twitter have been used in this study. Due to the number of tweets posted on Twitter daily, the researcher believes that the Twitter platform provides an unbiased representation of consumers' sentiment towards a company, its products and its services. Data collected from social media sites are construed to be qualitative as they need to be transformed and interpreted before any quantitative analysis can be done. The method used to transform and classify the qualitative data into different categories according to emotion, is called sentiment analysis. Social media effects are clear but the techniques used to get valuable data for marketers are not so clear (Patino *et al*., 2012). Complementing current research techniques in an attempt to understand social media data better will therefore contribute to the marketing body of literature. This research is therefore timely and impactful.

This research build on other researchers' pioneering work by analysing general trends contained in social media sentiment in an aggregated manner and not per company. Moreover, the majority of the statistical tests that could be found by the researcher were conducted at a significance level of 10% while this research study used a significance level of 5% resulting in more reliable results.

1.4 Summary of introduction

In summary, the academic literature has given limited attention to the potential relationships that exist between customer satisfaction, social media sentiment and stock price performance. Given that sentiment analysis on microblogging platforms is a recent phenomenon, it is not surprising that only a few studies have tested the relationship of social media sentiment with other variables from within any academic discipline. To the best of the researcher’s knowledge, no studies exist that examined all the variables within the same study.

Various other studies were found that tested the relationships between customer satisfaction and stock price performance but the results were inconsistent. Similarly, previous researchers also could not agree on the statistical relationship between customer satisfaction and social media sentiment as well as the statistical relationship between social media sentiment and stock price performance. A repeat of previous studies in a slightly different manner is therefore motivated to better understand the relationships and how they have potentially changed based on the increased and changing usage of social media platforms.

In a perfect world, social media platforms provide the ideal toolset for marketers and traders alike to identify trends on customer satisfaction and expected financial performance. By using the hidden insights in tweets, proactive interventions can be put in place to change the direction of negative customer satisfaction or to identify the impact of announcements on potential future financial returns. If this is the case, invaluable information is stored in publicly available forums and this should not be ignored by companies. Social media platforms have allowed companies and investors to enter a whole new world full of new marketing, investment and research opportunities.

Well-known brands were used in this study and no other study could be found that has been done on this scale based on the number of tweets that was analysed. Therefore, the findings are believed to be practical, influential and generalisable.

The next chapter provides a background to the efficient market hypothesis and describes the value of social media sentiment analysis. Furthermore, the importance of customer satisfaction and social media to the marketer is explained. The review also offers a critical evaluation of previous studies that were done to test the relationships between customer satisfaction, social media sentiment and stock price performance.

2. Chapter two: Literature review

2.1. Introduction

The objective of this research study was to identify if any relationships exist between customer satisfaction, social media sentiment and stock price performance. The literature review chapter addresses the main themes aligned with the proposed hypotheses and explains their relevance to the topic.

The literature review starts with a general overview of the efficient market hypothesis, the importance of customer satisfaction and social media to the marketer and an explanation of the value of social media sentiment analysis. Finally, the review examines and critically evaluates literature on the relationships between the mentioned variables, specifically:

a) Customer satisfaction and stock price performance.
b) Social media sentiment and customer satisfaction.
c) Social media sentiment and stock price performance.

2.2. Stock prices and the efficient market hypothesis (EMH)

The concept of "efficient markets theory" comes into play over the debate where the theory states that financial values at all times will reflect all public information. Furthermore, the theory supports the statement that financial assets or stock can be correctly priced even if consumer power is limited for a specific product or market (Fornell, Mithas, Morgeson III, & Krishnan, 2006) as will be the case with monopolies.

The efficient market hypothesis (EMH) suggests that, amongst other things, investors and analysts are coherent and value stock rationally (Lawrence, McCabe, & Prakash, 2007). The underpinning points of view of the EMH are the following:

a) Investors and analysts are rational and will as such price stock coherently.
b) Where investors and analysts are not rational, their transactions are arbitrary and will cancel each other out resulting in stock prices being balanced again.

c) Where investors and analysts are not rational, they will come across other rational analysts and investors and there will once again be a balance in terms of their influence.

Investors and analysts base their opinions on information they research on the overall macroeconomic circumstances of the market as well as the views from other investors and analysts. Their opinions can change over time as conditions change. Financial anomalies can be explained by the lack of balance between high opinions and low opinions of investors and analysts. As an example, a financial bubble can be the result of an equilibrium price being above that predicted by the traditional EMH model because of high opinion-based supply and demand (Lawrence *et al., 2007)*.

2.2.1. Behavioural finance

The study done by Lawrence *et al.* (2007) relaxed the notion of rationality of investors and analysts and explained the financial anomalies using investor sentiment and included that in the existing stock pricing models. The theory behind this study is behavioural finance and it does not assume financial markets to be efficient or methodical because investors and analysts have opinions or sentiment that impact their pricing philosophies. Therefore, the prediction of stock price performance is directed by company characteristics as well as investor opinion.

Social media platforms are used by consumers to express their opinions or sentiment about a company, product or service. Psychological research has shown that decision making is heavily influenced by the availability of information as well as emotions. This has been supported by various studies in behavioural finance. Therefore, it makes sense that users' sentiment and frame of mind could influence stock price changes just as much as any other financial driver (Bollen, Maoa, & Zengb, 2011). This view is supported by Andrejevic (2011) where he states that marketing theory is pursuing a new configuration. In his research he tried to understand what underpins emotional decision making.

2.3. The importance of customer satisfaction to the marketer

Consumers play an important role in how markets function in that they can incentivise sellers that increase their satisfaction and penalise others that do not satisfy them (Fornell *et al.*, 2006). Customer satisfaction decreases when consumers complain. However, when customer satisfaction is positive, it increases loyalty and usage of the product or service and thereby ensures recurring business and future revenues. Satisfied customers will also buy related products from the same brand or company and will spread positive word-of-mouth about their experience with a specific product or service. Customer satisfaction should therefore be seen as an intangible economic asset that can create economic value. This view is shared by Anderson *et al.* (2004) and they further state that there is a definite link between customer satisfaction and customer behaviour as satisfied customers are revenue generating assets. For this reason, firms should consider reporting on their customer satisfaction index scores in their integrated report. Moreover, this view is also supported by Luo, Homburg, & Wieseke (2010).

Similarly, Tuli & Bharadwaj (2009) also suggest that customer satisfaction should be disclosed in integrated reports as it provides non-financial measures that are very useful for financial markets. Aligned with the thinking of Fornell *et al.* (2006) and Morgan & Rego (2006), customer satisfaction is regarded as important to take into consideration when looking at a company's economic strength. This is due to customer satisfaction being perceived as giving a combined view of the size of the customer base as well as how loyal they are. Customer satisfaction is an important factor for investors and analysts because they would rather invest in a company that meets their customer needs better than that of the opposition. Companies that actively drive customer satisfaction have a competitive advantage because satisfied customers stay longer with a company and they also spread more positive word-of-mouth about a company and its products or services.

In the literature it is also argued that satisfied customers lead to a more stable customer base for companies. A more stable customer base allows a company to understand their customers' unique requirements better and to act on them in a more cost effective way because they are more predictable (Tuli & Bharadwaj, 2009). Therefore, increased customer satisfaction decreases the overall and systematic risk. If investors use customer satisfaction changes in their investment decisions they can lower their stock portfolio's exposure to market changes.

Hart (2007) and Aksoy, Cooil, Groening, Keiningham, & Yalcin (2008) suggest that customer service is an important focus point for marketers if they want to increase customer satisfaction. Their studies have shown that high customer satisfaction ratings have a positive influence on the amount of money customers are willing to spend in the future on a specific brand or service, ultimately increasing shareholder value. Customer satsifaction is intangible and therefore it is difficult to quantify the results of initiatives from the marketing department to increase customer experience. However, research from Aksoy *et al.* (2008) has shown that high levels of customer satisfaction can result in abnormal high returns for shareholders and based on this marketers can start to motivate marketing budgets and their value-add. Management and leaders that do not understand the value of investing in increasing customer satisfaction will negatively impact their future income and shareholder value.

Customer satisfaction is measured using different metrics and apart from the overall customer satisfaction values, companies should try and understand which specific measure drives business performance, of which stock performance is part of, the most (Morgan & Rego, 2006). This is important so that the marketing strategy can be adjusted to focus on the high value contributors of customer satisfaction. Morgan & Rego (2006) used the American customer satisfaction index (ACSI) to find correlations with various business performance indicators. They concluded that it is important for a company to keep their customer satisfaction levels high because it plays a key role in determining a company's financial performance.

2.3.1. The evolution of customer satisfaction monitoring

Social media platforms are more cost effective and also more effective as a communication channel compared to the more traditional methods of marketing communication (Castronovo & Huang, 2012). These platforms can be used to build important relationships with consumers and send them personalised information about a company's products or services. If used to a company's advantage, social media can be a powerful mechanism for word-of-mouth marketing where customers can express their opinions to everyone that has access to their posts on the different online platforms. Studies have demonstrated that consumers rely heavily on the opinions of other consumers before they make purhasing decisions (Castronovo & Huang, 2012).

Consumers prefer to express their opinions on social networks freely to answering company surveys. These opinions influence other consumers' opinions on a specific product or service. Marketers should therefore take the sentiment expressed on these social media platforms seriously as it articulates customer satisfaction to a user base beyond their direct customers. This can impact a company's ability to grow and retain their customer base (Bhattarakosol *et al.*, 2012).

Social media platforms allow marketers to listen to their customers in a different way (Andrejevic, 2011). Listening to customers and analysing their satisfaction levels has become easier with tools that automate the analysis of online conversations. These tools are seen as being more accurate than human intuition and can be used for their predictive capabilities with some limitations. Insights on changing customer satisfaction allow marketers to act quickly on complaints and adjust their marketing campaigns appropriately thereby increasing customer satisfaction.

2.4. The role of social media in a marketing context

One of the latest developments arising from Web 2.0 is microblogging (Barnes & Bohringer, 2011). Twitter is the most popular microblogging tool by far even though users complain about its lack of functionality and reliability. Microblogging is a smaller version of a normal blog but it is complimented with social features and can be used on mobile devices thereby increasing its reach. The major reasons identified for people to express themselves on microblogging platforms like Twitter include the following (Chowdury *et al.,* 2009):

(a) Documentation of one's life.
(b) Providing commentary and opinions.
(c) Expressing deeply felt emotions about experiences.
(d) Expressing ideas through writing, forming and maintaining communities.

Approximately 67% of all active Internet users also use social media platforms (Mostafa, 2013) which give marketers access to a wealth of information and inexpensive opportunities to market in modern ways. The proliferation of social media could result in traditional marketing methods not being effective anymore. It is estimated that approximately 20% of all tweets mention a company's name or a product name and it is therefore important for marketers to make online brand reputation management part of their integrated marketing strategy. Mostafa (2013) further states that companies should invest in sentiment analysis tools to be able to analyse consumer trends, identify new target markets and also to be proactive in providing feedback on complaints.

In a study done by Chowdury *et al.* (2009), it was found that social media, in specific microblogging, is a very powerful tool for customer word-of-mouth and that it should therefore form part of any company's overall marketing strategy. Electronic word-of-mouth takes place when information is shared between people on an electronic platform like a social media site. Word-of-mouth marketing is influential and complex as it is based on trust and therefore difficult to influence. Furthermore, electronic word-of-mouth, especially in the form of microblogging, is immediate, has significant reach and is reliable by being in print.

Social media platforms can prescribe the amount of control its users have over the receivers of their posts. For example, Facebook limits its users to post messages only to their friends while Google+ allows its users to create groupings of types of audiences like "public" and "friends". These various channels and the way they are positioned should be used by marketers to do targeted marketing. With the proliferation of various social media platforms, it can be assumed that the user base on a specific platform is a close representation of the total market segment or a portion thereof. Social media platforms play the role of macro informers whereby messages generated by a community are analysed and given to uninformed recipients. Furthermore, social media platforms can also play the role of micro informers where users on the platforms can send messages directly to each other. Marketers can leverage both roles to their advantage by embracing electronic word-of-mouth and also by interacting with the broader user base by pushing information to them and responding on complaints (Evangelopoulos, Magro, & Sidorova, 2012).

Humans are hyper-social beings and social media platforms give them a tool to interact with other consumers and share their opinions. Similarly, marketing departments have started to use social media to broadcast positive word-of-mouth messages about their products and services and to raise awareness of their offerings to prospective customers (Moran & Gossieaux, 2010). It is important for companies to realise the value of investing in these online communities and to sustain them as these online communities have better reach than traditional tools.

In a study done by Deloitte it was found that companies are increasingly using social media to collaborate with consumers (Moran & Gossieaux, 2010). However, marketing departments are facing various challenges to make these online communities that exist on social media, efficient and effective. The major reason given for these challenges is that marketers are focussing too much on the social media tools rather than trying to understand and predict consumer behaviour and their motivation for using these platforms.

Customer complaints as a customer satisfaction measure are suggested to be an important metric to track and react on as it has a high correlation with business performance (Morgan & Rego, 2006). Marketers should therefore ensure that they use all channels where consumers have the ability to give feedback on or complain on in order to react and put corrective measures in place as soon as possible after an event occurs. Contradictory to Chowdury *et al.* (2009), Castronovo & Huang (2012) and Luo, Raithel, & Wiles (2013) argue that word-of-mouth recommendations are significantly overstated in the role they play in increasing business performance.

A total mind-set change is needed where marketers need to ensure that community contributors representing a company are available 24 hours a day to contribute to questions and discussions online. Furthermore, the platform should be user-friendly and allow consumers to not only post comments and opinions, but also to help each other. Marketers should measure community success continuously and put the necessary interventions in place to act on improvements that are identified. (Moran & Gossieaux, 2010).

Social media platforms have allowed consumers to take ownership of after sales product experiences in a collaborative way by interacting with other users and even with the company itself (Harwood & Garry, 2010). Due to the continuous sharing of experiences, the consumers can co-create or enhance a product if marketers take their opinions into account and use it as input into the product development cycle. This ability to co-create products has significant management implications as the previously separate roles played by the consumer and the company have now converged. This is due to consumers having access to more information and collaborative platforms turning them into powerful and active consumers.

2.4.1. Customer satisfaction and social media

Opinions expressed on social networks play a major role in influencing user behaviour. Because of this, social media has become a valuable resource for marketing departments for customer relationship management and increasing customer satisfaction (Mostafa, 2013). Social media is considered useful because millions of opinions or views expressed about a company, product or service are highly unlikely to be biased.

Social media platforms therefore provide an ideal place for consumers to express their satisfaction or dissatisfaction with a company and its products or services (Chowdury *et al.*, 2009). The information being shared plays a major role in customer buying decisions as customers share their experience and satisfaction on these social media sites. The broad reach of electronic word-of-mouth provides consumers with tremendous power to influence a company's brand image as their satisfaction is revealed on these social media sites.

Social media allows companies to build close relationships with their consumers (Sashi, 2012). Social media provides an interactive platform for consumers to communicate with each other and with the brand communities of a product or service. Consumers participate in content generation and the result is that these satisfied consumers create value for a company. Marketers soon realise the potential this has and quickly use the tools available to them to serve customers better. Social media does not only allow transaction specific customer satisfaction monitoring but also cumulative customer satisfaction monitoring. Consumers base their satisfaction levels on their assessment of the purchase experience as well as the service over time. Customers share positive emotions on social media platforms if their expectations have been exceeded. These customers therefore become advocates for the brand. Affective commitment, where consumers trust a specific company, product or service more and form emotional bonds with them, is the result.

Castronovo & Huang (2012) also agree that by using social media platforms, marketers can increase the commitment of a customer to their brand. Consumers participating in these brand communities can be influenced to spread positive information about a product or service and thereby increasing the probability of other potential consumers buying from them. The aim of social media platforms is therefore to encourage communication which in turn will foster relationships.

Social media provides rich functionality and has a superior reach due to its network effect. The rich functionality of social media allows marketers to build up their customer engagement initiatives. This is due to the fact that most of these social media tools store a wealth of information about their consumers and potential consumers. Marketers can extend their existing marketing mix to include a mix of Web 2.0 tools that can assist them in increasing customer experience through bi-directional exchange of information and deep engagement. The result is increased customer satisfaction (Sashi, 2012).

The study done by Sashi (2012) showed that regular interaction between the consumer and the company or brand increases the emotional and physical investment a customer is willing to make in that brand, product or service. By being engaged, consumers become partners that work with sellers in a collaborative fashion to add value to satisfy their own needs as well as that of other consumers. These relationships grow into relationships characterised by trust and committment. Social media makes it easier for companies to connect with consumers and potential customers as it removes barriers associated with traditional methods of connecting with consumers.

2.4.2. The value of sentiment analysis

In a recent study it was found that 80% of Twitter users update their followers on what they are doing and also give their opinions about their experiences with companies, products or services on a regular basis. It is for this reason that Twitter is being used more in sentiment analysis studies (Mostafa, 2013).Twitter is by far the largest and most popular microblogging social network in the world.

The extensive use of social media tools and the information posted by consumers on these platforms make the mining of this data an interesting new phenomenon (Kennedy, 2012). Sentiment analysis is described as the solicitation of technology to conclude what opinions or sentiments are being expressed by consumers about a company's products or services (Andrejevic, 2011). Mostafa (2013) describes sentiment analysis as online opinions that can be analysed using technology with natural language processing capability. These natural language processing applications use computational semantics and text mining to identify the sentiment of text as positive, negative or neutral.

Opinion mining or sentiment analysis is seen as important and necessary by marketers for the following reasons (Kennedy, 2012):

a) Large amounts of data are available in the form of company messages and marketing information.
b) Consumers do not trust traditional advertising as much as they did before.
c) Consumers trust opinions and suggestions from other consumers.

Besides the various commercial products specialising in sentiment analytics, there are also freely available online tools. One such popular free tool that can do basic sentiment analysis is Socialmention and it can be downloaded from http://www.socialmention.com (Kennedy, 2012). Due to companies only recently starting to show interest in sentiment analysis, little academic research has been conducted on this topic.

In the research report from Kennedy (2012), various concerns have been raised about the accuracy of these analyses. This is often due to the inadequate amount of data available to be analysed as well as the readiness of this data to really be viable for a true and accurate analysis. To compound this matter even further the human language, by its very nature, is very complex to analyse. As examples, sarcasm and humour are difficult to analyse if the consumers that shared this information do not explain the original intent and associated sentiment context. Furthermore, due to the large amounts of online information that is analysed, it is impossible to do sentiment analysis manually and marketers and academics need to rely on computers to analyse the information programmatically. Other challenges preventing researchers from doing accurate sentiment analysis include (Kennedy, 2012):

a) The phenomenon where consumers try to show that they are positive in nature. On this note, consumers would rather try balance the positive and negative information they share and not give the true reflection of their experience with a company, product or service. Companies are also not very open to allow consumers to share negative reviews about their products or services.
b) Emotions are psychologically complex and cannot simply be classified as positive, negative or neutral without the context being fully understood.
c) Kennedy (2012) claims that only a very small percentage of information actually contains valuable sentiment data and therefore researchers and companies should be very careful to use sentiment analysis data to make decisions. This view is shared by the author of this research report. Other studies including those done by Chowdury *et al.* (2009) and Bhattarakosol *et al.* (2012) claim that approximately

only 20% of all microblogging posts mention a company or brand and of these posts only about 10-20% actually contain sentiment data that can be classified as positive, negative or neutral.

Affective economics should be extended to include sentiment analysis so that marketers can effectively create strategies that targets their respective audiences. These target market stratergies can then be based not only on demographics but also on the realtime online behaviour of users with other users and groups (Andrejevic, 2011). Marketers must therefore tap into this so-called “emotional capital” as customers are more and more basing their decisions on the opinions and moods of those they interact with on social media platforms. Marketers finally have the ability to influence “emotional capital”.

2.5. Customer satisfaction and stock price performance

Neoclassical economics and marketing theory provide general support for a positive relationship between customer satisfaction and stock price performance. It views customer satisfaction as the material standard for economic progression. Equally, various market factors may contribute to a negative relationship between the above mentioned variables (Fornell *et al*., 2006). The concept of the efficient markets theory comes into play on the debate where the theory states that financial values at all times will reflect all publicly available information.

Anderson & Mansi (2009) argue that significant research exists that explains how customer satisfaction impacts customer behaviour. Financial performance is most certainly impacted by customer behaviour. For example, a satisfied customer will generally buy more from a specific company that he or she is satisfied with. This will allow the company to lower their retention costs and will also give the company great visibility into the customer’s current and potential future purchasing patterns. Even though various studies have been done to suggest a positive association between customer satisfaction and customer behaviour, the findings are much more diverse when the relationship between customer satisfaction and financial markets behaviour is tested. The recommendation from the research done by Anderson & Mansi (2009) was that a new classification of the economic benefits of customer satisfaction can be done by studying the secondary financial impact that customer satisfaction can have on a company.

A study done by Anderson *et al*. (2004) in the 1990's was built on the basic logic that customer satisfaction increases customer retention and that if customer retention can be increased it will secure future revenues. This is most certainly possible as satisfied customers will buy more products or services from the organisation. Positive word-of-mouth is also expected to influence shareholder value as this can lead to new and existing market penetration that will result in accelerated cash flows. Lastly, Anderson *et al*. (2004), claim that satisfied customers have higher price tolerance which may lead to higher income and shareholder value.

Jacobson & Mizik (2009), however, contradict this view by stating that it can take time for the market to correctly price some types of assets and strategic business decisions. Market participants may not take into account the full effects of strategic business decisions in a timely manner and may only do so later when the impact of strategic business decisions is reflected in their financial performance metrics. Another finding documented by Fornell *et al.* (2006) indicates that news about customer performance ratings does not necessarily have an impact on stock price performance. This could be because the information is already incorporated into the stock price as the efficient market hypothesis suggests.

Raithel, Sarstedt, Scharf & Schwaiger (2012) identified and exploited a gap in previous research whereby it was assumed that overall customer satisfaction is important to investors and not the components that make up the calculation of customer satisfaction. The authors of that study saw this as a significant shortcoming as marketers will not focus on the correct customer satisfaction drivers if they base their strategies on this assumption and this could negatively impact the long term success of that company and its products or services.

Brand dispersion has been demonstrated to affect stock price performance (Luo *et al.*, 2013). Brand dispersion is where variance exists across consumer's opinions about a product or service associated with a brand. Their research showed that investors continuously do research on consumers' opinions about brands and those investors then incorporate their findings in their investment decisions.

Luo *et al.* (2013) used BrandIndex data which are available online at http://www.brandindex.com. It is not expected that investors will use this website on a daily basis to track changes in variance. However, the authors state that it is possible that the BrandIndex data can be interpreted as a combination of data from other widely used sources including social media platforms like Twitter. Investors are often careful when buying a company's stock if brand dispersion is high. This can mean that the brand is inconsistent and it is therefore important for marketers to give attention to brand haters just as much as they do to brand lovers.

Interestingly, Luo *et al.* (2013) used BrandIndex to track public perceptions of brands daily. The ACSI used by some other studies in this literature only updates their findings quarterly for various industries and publish them yearly. BrandIndex also uses a different data collection and data analysis method. The frequency of information available on BrandIndex gives investors a more up-to-date insight onto what the perceptions are around a company's brand. This assists them in making crucial investment decisions. Contradictory to other studies reviewed, Luo *et al.* (2013) are of the opinion that investors continuously scan word-of-mouth sentiment on social media platforms and incorporate their findings into stock price performance evaluations.

It is important for companies to focus on the acquisition and retention of customers as shareholder value is calculated on investments focussing on these objectives (Grewal, Chandrashekaran, & Citrin, 2010). In their study, Grewal *et al.* (2010) found that the return on customer satisfaction to shareholder value reduces when customer satisfaction heterogeneity increases. Furthermore, higher levels of customer satisfaction heterogeneity minimise shareholder value instability. The role that customer satisfaction heterogeneity plays in investor perceptions around a brand should therefore be taken into account when developing an integrated marketing strategy.

2.5.1. Mispricing and market imperfections

Even though Fornell *et al.* (2006) found a relationship between customer satisfaction and stock price performance in their study conducted for the period 1994 - 2002, no evidence could be found to support the notion that investors react on changes in customer satisfaction in a timely manner. This finding is aligned with the efficient market hypothesis as an assumption can be made that the information is already factored into the share price, but the evidence showed that the reason was rather market imperfections.

If investors, as previous studies suggest, do not immediately reward companies whose customer satisfaction levels are higher, then marketers will have very little reason to invest in customer satisfaction programs (Raithel *et al.*, 2012). Similarly, investors could potentially not realise that investments in certain components of customer satisfaction are actually the major drivers for increasing the satisfaction of customers. Therefore, investors may not react to news on changes of satisfaction levels around those components immediately. However, when they do react later, they will realise the total impact that customer satisfaction has on a company's long term financial performance. This is called mispricing and indicates that investors do not rapidly and appropriately integrate information related to customer satisfaction with their stock valuation in the long run. This has also been argued by Jacobson & Mizik (2009).

Jacobson & Mizik (2009) agreed that market flaws exist and state that companies lack the ability to use customer satisfaction as an intangible asset to fully assess and impound this into a company's stock price. This results in a mispricing of customer satisfaction by financial markets. Although Aksoy *et al.* (2008) also agree, they state that the market will adjust over a period of time.

To be able to accurately predict or even price stocks, companies need to take their tangible and intangible assets into account. It is getting more difficult for companies to value intangible assets like expertise, brands and customer satisfaction that will lead to increased sales and shareholder value. Furthermore, generally investors do not see the value of customer satisfaction and its importance when evaluating stock price performance. Some investors, however, have started to articulate the need to include customer satisfaction in financial reports as an intangible asset. Analysts have also acknowledged the value of financial and non-financial measures as complimentary to each other when determining stock price performance (Aksoy *et al*., 2008).

Market imperfections result in investors not reacting in predictable ways. Fornell *et al*. (2006) found that there were cases where stock prices declined even though customer satisfaction increased. Various factors could cause this sort of behaviour including:

a) Investors suspecting that companies are giving away too much to customers.
b) Investment in customer satisfaction costs money which could lead to long term declines in stock price value.

c) Unhappy customers are not buying from the company anymore causing the overall satisfaction of existing customers to be higher than expected.

Another potential reason could be that customer satisfaction changes are not visible on a daily basis as measured on the ACSI as they only publish results yearly. Moreover, in the various studies reviewed by East, Lomax & Romaniuk (2011), they revealed that although numerous studies could find correlations between customer satisfaction as defined by the ACSI and stock price performance, that this is only the case when the economy is expanding. The reason, as also supported by Fornell *et al*. (2006) is that the market does not incorporate the impact of customer satisfaction on profit in a timely manner. East *et al.* (2011) argued that the ACSI does not include the view of never-consumers and ex-consumers when evaluating customer satisfaction levels and therefore do not include dissatisfied users' view in their index scores. They further argued that the result of not including negative word-of-mouth in the calculation of customer satisfaction scores is that the ACSI scores could potentially be overrated.

Another reason given by Raithel *et al.* (2012) on why only weak evidence exists that the announcement of customer satisfaction results from the ACSI has an impact on stock price performance is due the announcement being seen as a single event. This gives investors and analysts a limited view of the true value of customer satisfaction. They argue that investors have access to other sources of information in newspapers and online forums and that this information can be related to events that could impact customer satisfaction in real time for example product recalls. Therefore, the weight of the metric announcement is weakened because investors have already formed some opinion around customer satisfaction levels for a company, product or service.

Raithel *et al.* (2012) identified various reasons that explain why investors act on certain information and not on others as the efficient market hypothesis suggests. These include:

a) Investors do not have sufficient marketing skills and therefore do not fully understand the impact of a marketing driver like customer satisfaction on shareholder value.
b) Investors get influenced by other investors, analysts and company representatives and alternative perceptions of performance are formed.

In a study done by Luo *et al.* (2010), it was found that the positive correlation between customer satisfaction and recommendations made by financial analysts are stronger where conditions exist where product market competition is elevated or when financial market uncertainty is significant. Their findings show that customer satisfaction should be seen as an important intangible asset and that often financial analysts underestimate this metric. Moreover, their research suggests that financial analyst recommendations mediate, at least partially, the relationship between customer satisfaction and shareholder value. The reasoning for the relationship between customer satisfaction and analyst recommendations is given by the logic that, changes in a company's customer satisfaction levels provide the financial analyst with information on the forecast of the company's potential future cash flows.

Financial analysts and investors base their predictions on the potential of the company's future cash flows. This is because better prospects are seen to result in more positive recommendations due to the higher probability of increased revenue. Increased revenue can result in increased shareholder value (Luo *et al.,* 2010). Companies with higher customer satisfaction levels also lead to more analysts agreeing with the forecasted stock recommendations. These financial analysts make their opinions known via all types of media, including social media platforms like Twitter. It therefore makes sense that similar results can be found if financial-oriented social media sentiment is analysed separately from global social media sentiment.

2.5.2. Acting on customer satisfaction announcements and abnormal returns

In their study, Aksoy *et al.* (2008) showed that should an investor act based on announcements on changes in customer satisfaction scores, it could result in abnormal returns. However, this is only the case on certain portfolios with high customer satisfaction scores. Companies with low customer satisfaction scores showed a negative return towards the end of the study period. Furthermore, there is reliable evidence, looking at the various academic studies that has been done on this topic, that the market misprices customer satisfaction by not reacting immediately. However, it is important to realise that the market does adjust over time.

The S&P 500 stock price has increased dramatically over the last few years. This has been directly aligned with high customer satisfaction scores and it has produced abnormal high returns while also showing less volatility (Hart, 2007). Contradictory to the efficient market hypothesis that states that it is impossible to continuously outperform the market as the market will adjust over time, research has demonstrated that the stock market fails to include customer satisfaction as described by the ACSI in its valuation models.

2.5.3. Industry differences

Industry and customer factors can reduce or increase the effect of customer satisfaction on shareholder value (Anderson *et al.*, 2004). Anderson *et al.* (2004) concluded that the impact of customer satisfaction on customer behaviour differs across industries. Furthermore, the degree of concentration of customers is also different across industries. The result is a diverse impact of customer satisfaction on shareholder value depending on the industry. Previous studies have shown that the relationship between customer satisfaction and shareholder value is stronger for companies specialising in goods than for companies specialising in services. Fornell *et al.* (2006) support this view by stating that the fact that services companies are very labour intensive may compromise productivity in favour of customer satisfaction. Productivity could have an impact on income and therefore the trade-off between customer satisfaction and productivity can lead to unfavourable market conditions as shareholders see this as a negative move by the company.

Hart (2007) has found that companies with long purchasing cycles including life insurance and durable goods show a longer time lag before stock prices adjust to announcements of customer satisfaction score changes. The opposite is true for service industries. Interestingly, Fornell *et al*. (2006) demonstrated that for services firms, share prices increase irrespective of whether customer satisfaction increase or decrease. A consistent result for all companies could therefore not be shown. Similarly, Jacobson & Mizik (2009) could not find statistically significant results when they tested the relationship between customer satisfaction and abnormal stock price performance when they excluded computer and Internet firms which skewed the overall results. They further found that with computer and Internet firms, the ability of customer satisfaction to predict abnormal returns in these industries were only significant at a 10% significance level which could be supportive of the efficient markets theory.

Jacobson & Mizik (2009) suggest that research and development (R&D) intensive industries, like the computer and Internet industries, show a less positive effect between customer satisfaction and stock price performance. A possible reason for this is that customers and the financial markets alike do not immediately realise the longer term benefit of R&D investments on financial performance. A delayed response is therefore seen between customer satisfaction and stock price performance. However, aligned with the findings of Fornell *et al*. (2006), this causes unusually large positive future period stock returns to the portfolio of top-satisfaction stocks. This is due to the financial markets not fully appreciating the long term value of customer satisfaction when it occurs or even when it is announced.

The study done by Raithel *et al.* (2012) focussed on the automotive industry across the United States of America (USA), United Kingdom (UK) and Germany. The period under investigation was 2004-2008. The car industry was used as previous studies showed that industries that are heterogeneous in nature should not be directly compared. The findings of their study showed that investors react to evidence on customer satisfaction related to product quality while the cost of ownership and after sales service was less important. Another interesting finding was that the information as extracted from the USA market was more positively associated with investor decisions than those from the UK or Germany. This finding verifies the assumption that the USA market is representative of the global market for this industry.

Jacobson & Mizik (2009) specifically tested the ability of customer satisfaction to predict stock price performance for utility companies and compared that to non-utility companies. They did not do the study over all industries due to a concern that the results could be diluted by utility companies. The reason provided for this separation is that utility firms do not need customer satisfaction to have high values for their shares. The utility industry is characterised by high barriers to entry and high levels of consumer captivity and therefore customer satisfaction is less important. The results of the study done by Jacobson & Mizik (2009) showed that there was no difference in the ability of customer satisfaction to predict stock price performance for utility companies and non-utility companies.

2.6. Social media sentiment and customer satisfaction

Previous research has demonstrated that social media sentiment analysis can successfully be used to analyse customer satisfaction using different methods including tracking discussions on discussion boards, identifying Internet hot spots, analysing online advertising promotions and distinguishing between informative and emotional social media content (Mostafa, 2013). Barnes & Bohringer (2011) agree that a microblogging platform like Twitter can be used to analyse and predict user behaviour. Consumers use Twitter to post their daily experiences and share their opinions on brands and it has become a habit for them to do so.

Social media sentiment analysis can predict customer satisfaction in the commercial sector as supported by the study done by Chowdury *et al.* (2009). The industries that they studied included automative, computer hardware, computer software, consumer electronics, food, personal care and sporting goods. Statistically significant differences were found between brands, based on social media sentiment. It was shown that companies that respond to questions in microblogs have higher positive sentiment. Therefore, social media platforms that allow for microblogging are important channels for companies to not only develop their brands but also to improve their customer service thereby improving customer satisfaction (Barnes & Böhringer, 2011).

2.6.1. Changing customer behaviour using sentiment analysis

One of the objectives of social media sentiment analysis is to manipulate a customer's behaviour (Andrejevic, 2011). This is done by collecting posts from social media platforms, analysing the sentiment contained in those posts and then doing experiments on the user base to determine their behaviour. An example of such a study was done by analysing 100,000 Twitter posts related to smartphones to determine the level of customer satisfaction towards all the product features including screen, camera and applications (Bhattarakosol *et al.*, 2012). Valuable information was obtained that, if used correctly, could be given to the product designers to improve on their designs. Consumers have made social media part of their daily lives as it is easier and more convenient to send a message or share information on these platforms. Social media platforms have changed the way consumers communicate with each other as they do not believe information shared from companies on its own. Consumers prefer to share their messages with other consumers and friends and make up their own minds about a company, product or service.

Social media platforms like Twitter reduce the obstacles for users to create content making it uncomplicated to share information about a product, service or even their social lives (Bhattarakosol *et al.*, 2012). Companies can use the information posted by consumers to improve their product characteristics and after sales service or even use it to identify a new target market or product opportunity. Proper customer relationship management is only possible if a company has enough consumer insight. Consumer insights can be transformed to marketing intelligence and can be used as follows:

a) Early warning about an event or condition that is about to occur.
b) Identification of trends on certain topics and new ones that are forming.
c) Opinion mining or sentiment analysis where the cummulative measures of positive and negative sentiment from consumers are extracted and used to push information to these consumers in order to influence customer behaviour and customer satisfaction.

Databases containing information on consumers and their purchasing patterns are important to companies to ensure that they include the correct marketing mix in their market targeting strategies. Social media platforms allow consumers to actively participate with companies and other consumers in discussions. Consequently these exchanges of information play the role of the database for marketers. The social media platforms act as a database since it contains a variety of information on consumer preferences and their behaviour based on certain stimuli (Castronovo & Huang, 2012).

2.7. Social media sentiment and stock price performance

The efficient markets theory states that stock prices are based on new information and not on present and historical stock price trends. However, news is unpredictable and this makes it very difficult to predict stock prices at a significant level of accuracy. Research suggests that although news is unpredictable, early indicators can be extracted from social media sites like Twitter. This information can then be used to predict various economic indicators like stock price performance (Bollen *et al.,* 2011). The study performed by Bollen *et al.* (2011) was based on the theory that emotions can predict decision making. Financial decisions in particular are driven by emotion and mood and therefore a reasonable assumption can be made that social media sentiment can drive stock price performance just as much as news can.

Social media sites contain publically available data about what consumers think about various topics and can be used to reflect the mood and interest of a customer towards a company, product or service. These moods can be used to predict the success of a product or service and even stock market performance if included in existing economic models (Lica & Tuța, 2011). The article published by Lica & Tuta (2011) summarises research done in the area of social media sentiment and its ability to predict performance of products, services as well as economic performance. Like Evangelopoulos *et al*. (2012), they found that the number of tweets plays an important role in predicting performance and that sentiment analysis can improve the predictions.

2.7.1. Results from studies using different sentiment analysis approaches

Bollen *et al.* (2011) found that when macro mood states or global mood states from largescale Twitter feeds are analysed that contained the words “feel” or “feeling”, a positive correlation was found with the value of the Dow Jones Industrial Average (DJIA) over a period of time for one of the six mood groupings called “calm”, they identified. They also found that there is a delay sometimes up to four days for stock price performance to shift along the mood dimensions that were calculated.

Findings like these started a whole new debate around the assumptions of the efficient markets theory. Bollen *et al.* (2011) did however also find that unexpected news not anticipated by sentiment as captured in tweets, is a significant factor in the modeling of the stock market. This unexpected news caused descrepencies in the model where the ability of social media sentiment to predict stock price performance failed. They stated after the study that although the results were interesting and the study successful, they cannot conclude that Twitter sentiment can predict stock price performance. In order to predict stock price performance accurately, various elements need to be taken into consideration (Lica & Tuța, 2011).

Similarly to Bollen *et al.* (2011), Evangelopoulos *et al.* (2012) have found that there could be a delay of up to five days for stock price performance to reflect the sentiment level as expressed on social media platforms. Furthermore, it was found that tweeting about “buying” or “getting” something resulted in an even stronger reflection of future stock price performance while tweeting about “selling” had a weaker reflection as it is potentially seen as a tip off that a company is struggling to sell its products or services.

The study done by Evangelopoulos *et al.* (2012) therefore showed that certain Twitter topics are leading indicators of stock price performance rather than the sentiment itself.

Sentiments or opinions expressed in blogs and microblogs represent public opinion and there is a strong positive correlation between these sentiments and the performance of a company's stock (Tayal & Komaragiri, 2009). Tayal & Komaragiri (2009) also concluded that microblogging sentiments can more accurately predict stock price performance than blogs sentiments can.

Another study was done by Zhang, Fuehres, & Gloor (2011) where they analysed a randomised subsample of a 100^{th} of all tweets they collected over a six month period for four market indicators. They categorised the sentiment in these tweets as "hope" or "fear", and found that the amount of emotion in the tweets negatively correlated with the NASDAQ, Dow Jones and S&P 500 but correlated positively with the VIX. Since the VIX is made up of a spread of stock options, a possible reason for this could be that Twitter users are using emotional words in times of economic uncertainty irrespective of whether the context is positive or negative.

Zhang *et al.* (2011) used a total of five words in their sentiment dictionary and could therefore only classify a small percentage of the total tweets per day as either positive or negative. They took the number of tweets into consideration when comparing the impact of the positive and negative tweets to the performance of the stock market the following day. The majority of the results were statistically significant at a significance level of 10%. Furthermore, certain words like "hope", "fear" and "worry" were found to be better predictors than other words.

Stock markets are unpredictable which makes investing therein risky (Wong, Xia, Xu, & Wu, 2008). Amateurs and seasoned investors alike make investment decisions based on predictions of other investors and analysts. The challenge for investors is trying to understand which analyst or other investor's opinion is more accurate. Instinctively it makes sense to rely on the opinions supported by the majority of analysts and investors. However, Wong *et al.* (2008) showed that investors will get higher returns if they trust the most credible group of analysts and investors. Added to this pattern-based event movements and opinions embedded in daily online stock market reports are more trustworthy than word based events and opinions.

Analysts, investors and other interested parties post summaries or their opinions of financial reports on microblogging sites like Twitter. For this reason, it makes sense that sentiment analysis on a social media platform like Twitter will have similar results than those found by Wong *et al.* (2008). Furthermore, it seems that certain types of opinions like those that are financially oriented could potentially be able to predict stock price performance better than other information that is not related to financial performance.

2.7.2. Industry differences

Evangelopoulos *et al.* (2012) agree that Twitter can be used as a macro informer of stock price performance. In their analysis they found that unique themes such as customer service could be identified. Another significant finding was the differences between industries. Consumer products, banking and investment as well as oil and gas companies had relatively few tweets when compared to other industries. The findings suggest that the number of tweets mentioning the company or its products and services as well as the sentiment, as determined from the sentiment analysis, appear to be predictors of stock performance. Specifically, the number of tweets per day is negatively related to the stock performance during the same trading day while more positive sentiment resulted in higher stock price performance.

2.8. Summary of literature review

The literature review provided a summary and critical evaluation of the academic literature addressing certain aspects of the researcher's study as well as an overview of challenges and shortcomings in various approaches used by the authors of the academic literature.

Table 1 summarises the various academic literature that was reviewed in terms of the topics that were studied, the variables that were used in those studies as well as what their findings were.

Table 1: Summary of literature review

Variables:	Author(s):	Summary of findings:
Customer satsifaction and stock price performance	Anderson *et al.* (2004)	Customer satisfaction increases shareholder value because satisfied customers secure future revenues.
	Jacobson & Mizik (2009)	It takes time for the market to include the impact of strategic decisions like customer satisfaction into the pricing of certain assets. The information is only included much later. No statistically significant relationship was found between customer satisfaction and stock price performance when computer and Internet firms were excluded. No difference were found when utility firms were compared to non-utility firms.
	Fornell *et al.* (2006)	News about customer satisfaction ratings does not impact stock price performance in the immediate future. Stock prices increase even if customer satisfaction decreases for services companies. Therefore, inconsistent results were found in their study.
	Raithel *et al.* (2012)	Certain components of customer satisfaction have a stronger correlation with stock price performance than overall customer satisfaction. For the USA automative industry a correlation was found with certain components of customer satisfaction and stock price performance.
	Luo *et al.* (2013)	Brand dispersion affects stock price performance. Higher dispersion leads to lower stock price performance since these brands are seen to be inconsistent.
	Grewal *et al.* (2010)	The return on customer satisfaction to shareholder value reduces when customer satisfaction heterogeneity increases but higher levels of customer satisfaction heterogeneity minimises shareholder value instability.
	Aksoy *et al.* (2008)	Even though the market does not react immediately on customer satisfaction changes, it does so over time. Acting on customer satisfaction changes can lead to abnormal high returns in the future for companies with high customer satisfaction scores.
	East *et al.* (2011)	A correlation was found between customer satisfaction and stock price performance only when the economy was expanding. Therefore, all information is not included in the valuation of assets in a timely manner.
	Luo *et al.* (2010)	The relationship between customer satisfaction and stock price performance is stronger when conditions exist where product market competition is elevated or financial market uncertainty is significant.
	Hart (2007)	Increased stock price performance aligned with high customer satisfaction scores lead to abnormal returns and these stocks show less volatility.

Variables:	Author(s):	Summary of findings:
Social media sentiment and customer satisfaction	Mostafa (2013)	Social media sentiment can be used to analyse customer satisfaction.
	Barnes & Böhringer (2011)	Microblogging can be used to analyse and predict user behaviour. Companies that respond more on microblogs have higher overall sentiment and this increases customer satisfaction.
	Chowdury *et al.* (2009)	Social media sentiment predicts customer satisfaction in the commercial sector.
Social media sentiment and stock price performance	Bollen *et al.* (2011)	Early indicators from the impact of news or announcements by companies can be extracted from social media sites. This can be used to predict economic indicators including stock price performance. They found a delay of up to four days for stock price performance to align with social media sentiment trends. Inconsistencies were found in their study when unexpected news were released. They concluded that various elements need to be considered to accurately predict stock price performance.
	Lica & Tuța (2011)	Moods contained in social media postings can be used to predict stock price performance if they get included in existing economic models. They could not conclude that social media sentiment can accurately predict stock price performance as various elements are at play.
	Evangelopoulos *et al*. (2012)	The number of tweets plays an important role in predicting stock price performance and social media sentiment can improve these predictions. A delay of up to five days was found for stock prices to reflect social media sentiment trends. Furthermore, it was found that certain topics in tweets can predict stock price performance more accurately than sentiment itself.
	Tayal & Komaragiri (2009)	A strong correlation was found between social media sentiment and stock price performance.
	Zhang *et al.* (2011)	The amount of emotion shared on social media sites correlated postively with stock price performance in three markets and negatively with stock price performance in one market. Consumers use more emotions in time of economic downturn whether the context is positive or negative. Certain sentiment words are better predictors of stock price performance than others.

Based on the reviewed literature and the inconsistent findings as well as the recommendations from the authors of the reviewed academical literature, the author of this research report deemed it necessary to review the relationships between customer satisfaction, social media sentiment and stock price performance using more data and a different approach. The researcher conducted her study over the period of 1 January

2011 – 31 December 2012 in support of Lica & Tuta (2011) where they stated that when you study relationships, the findings will become more relevant and easier to interpret if it is conducted over a period of time.

The next chapter defines the research hypotheses that were studied.

3. Chapter three: Research hypotheses

3.1. Introduction to research hypotheses

The research hypotheses follow firstly from the inconsistent findings of previous studies and secondly, from the identified gaps in terms of the relationships between customer satisfaction, social media sentiment and stock price performance. The researcher was interested in testing the relationships between the mentioned variables using more data and different methods to those used in previous studies. Furthermore, the study seeked to identify any differences that potentially exist between utility companies and non-utility companies when testing the relationships between customer satisfaction, social media sentiment and stock price performance.

Due to the fact that social media usage has increased exponentially, it was important for the study to examine if the relationship between social media sentiment and stockprice performance gets stronger over time. Lastly, social media provides rich content which can be used to further explore the ralationship between social media sentiment and stock price performance over time. It is expected that certain types of social media sentiment could have stronger relationships with customer satisfaction and stock price performance than others. Global social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment and their relationships with customer satisfaction and stock price performance were therefore tested in an attempt to find insights on this topic.

3.2. Research hypotheses

The academic literature demonstrated inconsistent findings when the following relationships were tested:

a) Customer satisfaction and stock price performance.
b) Social media sentiment and customer satisfaction.
c) Social media sentiment and stock price performance.

Based on the extensive literature review, no study has been conducted to date that tested the relationships between all three variables together. Moreover, no study could be found that tested the relationships with customer satisfaction and stock price performance using global social media sentiment, financial-oriented social media sentiment and customer-oriented social media sentiment. Lastly, very few studies were conducted using the mentioned variables and comparing the results between utility companies and non-utility companies.

3.2.1. Customer satisfaction and stock price performance

Anderson *et al.* (2004) recommended that their study be repeated for different classifications of companies and different groupings of industries, including the more strongly oligopolistic or monopolistic industries. Following this reasoning and the conflicting findings in the reviewed literature, a re-examination of the relationship between customer satisfaction and stock price performance is warranted. Different types of companies have different challenges and characteristics at different times that could impact customer satisfaction and stock price performance. The studies in the reviewed literature were done in the 1990's and early 2000's and it is worth repeating the studies to show how changes of industry and company characteristics over time result in different relationships between customer satisfaction and stock price performance. The repetition of this study was also recommended by Jacobson & Mizik (2009).

The following hypotheses are therefore stated:
H1: Customer satisfaction is positively associated with stock price performance.
H1a: The positive relationship between customer satisfaction and stock price performance differs between utility companies and non-utility companies such that it will be more positive for non-utility companies and less positive for utility companies.

3.2.2. Social media sentiment and customer satisfaction

Following the reasoning in the literature, it is apparent that social media plays an important role in providing a platform for consumers to express their opinions and satisfaction. However, a limited number of companies and industries were studied in the available research and all the mentioned studies were conducted in a very limited period of time. This warrants a repeat of previous studies to firstly re-affirm the findings of the research done to date and to then test the relationships between social media sentiment and customer satisfaction in utility companies and non-utility companies. Moreover, customer-oriented social media sentiment's ability to potentially predict customer satisfaction more accurately than other types of social media sentiment could provide valuable insights for marketers.

The following hypotheses are therefore stated:
H2: Global social media sentiment is positively associated with customer satisfaction.
H2a: The positive relationship between global social media sentiment and customer satisfaction differs between utility companies and non-utility companies such that it will be more positive for non-utility companies and less positive for utility companies.
H2b: Customer-oriented social media sentiment is a better predictor of customer satisfaction than global social media sentiment.
H2c: Financial-oriented social media sentiment is a worse predictor of customer satisfaction than global social media sentiment.

3.2.3. Social media sentiment and stock price performance

A very interesting finding by Zhang *et al.* (2011) was that by only analysing a subset of tweets they could not in all cases demonstrate a correlation with stock price performance, even at a significance level of 10%. Zhang *et al.* (2011) concluded that more accurate results could be achieved if all tweets are taken into consideration. However, in their analysis of all the tweets, the actual retweets were excluded. The exclusion of retweets has been identified as a gap in the research and therefore all tweets, including retweets have been analysed in this study. The assumption was that retweets could potentially amplify the results overall as people feel strongly about a specific opinion or issue.

Lawrence *et al.* (2007) suggest that investor sentiment can explain financial anomalies of the traditional EMH model. Furthermore, measuring investor sentiment is challenging and they suggested that future research should attempt to find correlations between investor sentiment or financial-oriented sentiment and stock price performance based on the assumption that investors sometimes perform stock market transactions based on noise and not necessarily reviewed information.

The following hypotheses are therefore stated:

H3: Global social media sentiment is positively associated with stock price performance.

H3a: Customer-oriented social media sentiment is a worse predictor of stock price performance than global social media sentiment.

H3b: Financial-oriented social media sentiment is a better predictor of stock price performance than global social media sentiment.

H3c: The positive relationship between global social media sentiment and stock price performance differs between utility companies and non-utility companies such that it will be more positive for non-utility companies and less positive for utility companies.

3.2.4. Social media sentiment as a moderator

Based on the extensive literature review, no previous studies tested the relationship between all three variables in the same study: customer satisfaction, social media sentiment and stock price performance. This research study therefore attempted to identify any interaction effects that potentially exist between the mentioned variables that could provide valuable insights to academics, investors and marketers.

The following hypotheses are therefore stated:

H4: The positive relationship between customer satisfaction and stock price performance will be positively moderated by global social media sentiment such that the more positive the global social media sentiment the stronger the relationship.

H4a: The positive relationship between customer satisfaction and stock price performance will be positively moderated by customer-oriented social media sentiment such that the more positive the customer-oriented social media sentiment the stronger the relationship.

H4b: The positive relationship between customer satisfaction and stock price performance will be positively moderated by financial-oriented social media sentiment such that the more positive the financial-oriented social media sentiment the stronger the relationship.

3.2.5. Social media sentiment and stock price performance tested over time

Fornell *et al.* (2006) stated that it takes time for markets to include all information in their valuation of assets. However, stock price performance and social media sentiment should eventually move together in the long run. Moreover, the use of social media platforms is increasing incrementally, not only in terms of volumes of posts but also in terms of usage patterns.

The following hypotheses are therefore stated:

H5: The degree to which global social media sentiment is positively associated with stock price performance gets stronger over time.

H5a: The degree to which customer-oriented social media sentiment is positively associated with stock price performance gets stronger over time.

H5b: The degree to which financial-oriented social media sentiment is positively associated with stock price performance gets stronger over time.

3.3. Summary of research hypotheses

The study's research hypotheses examined the different relationships between customer satisfaction, social media sentiment and stock price performance. The relationships between the mentioned variables were also compared between utility companies and non-utility companies. Furthermore, social media sentiment's relationships with customer satisfaction and stock price performance were tested using global social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment. The interaction effects that exist between the three variables were also studied. Lastly, the relationship between social media sentiment and stock price performance was studied over a period of time in order to determine if higher usage of social media platforms resulted in a stronger correlation between social media sentiment and stock price performance.

The next chapter describes the research methodology used to collect the data and test the research hypotheses.

4. Chapter four: Research methodology

4.1. Introduction

The research methodology chapter introduces and explains the methodologies used to collect the data and test the research hypotheses. The research took the form of a deductive casual quantitative study that described the relationships between social media sentiment, customer satisfaction, and stock price performance. The period used for the longitudinal study was 1 January 2011 - 31 December 2012.

Secondary data were collected for all three variables and were downloaded from publicly available sources. The data are seemed to have a high degree of credibility as raw data were downloaded. The researcher programmatically transformed the raw data so that it could be analysed using quantitative methods.

4.2. Choice of methodology

The research methodology employed was quantitative in nature and has been applied in a causal design as part of a longitudinal approach to the study. Quantitative data were collected in a standardised way. The variables were described as numbers and analysed using statistical methods (Saunders & Lewis, 2012, p.165). This method was chosen as it allowed the researcher to analyse the data and test the hypotheses. A longitudinal study is a study of a specific scenario over an extended period of time (Saunders & Lewis, 2012, p. 124). The period chosen was 1 January 2011 – 31 December 2012. A two year period was chosen because secondary data were available and the findings could be supported with higher validity because they were tested over a long period of time.

The approach that was used in the research study was deductive in nature. Deductive research involves the testing of a theoretical proposition or hypothesis by basing it on a previously conceived theory (Saunders & Lewis, 2012, p. 194). This study addresses specific gaps identified in the micro analysis of social media sentiment by testing global social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment and their relationships with customer satisfaction and stock price performance. Furthermore, the study tests the boundaries of the application of social media sentiment as well as the relationships between customer satisfaction, social media sentiment and stock price performance.

4.3. Population

Important factors for this research study were the availability of customer satisfaction data per company over the period of 1 January 2011 – 31 December 2012 as well as the availability of stock price data and social media sentiment for the same period. The American customer satisfaction index (ACSI) is an independent company doing national benchmarking of amongst others, customer satisfaction. The company surveys approximately 70,000 customers each year and benchmarks customer satisfaction with more than 230 companies in 43 different industries. The database can be found at http://www.theacsi.org. Data on the ACSI website are publicly available and were downloaded for all companies for the period of 1 January 2011 – 31 December 2012. The initial population can therefore be defined as all the companies that have customer satisfaction data published on the ACSI website for at least the period 1 January 2011 – 31 December 2012.

The population was further constrained using the following selection criteria:

a) The companies must have been listed on an American stock exchange for at least the period 1 January 2011 – 31 December 2012. This was necessary so that daily stock price data could be downloaded. Companies that merged or changed listing symbols during this period were removed from the population in order to eliminate unusual external factors that could impact stock price performance, customer satisfaction or social media sentiment.
b) The companies must have been mentioned in Twitter feeds over the period 1 January 2011 – 31 December 2012.
c) The companies must have had global sentiment data for at least 50% of the days. Therefore 365 of the 731 days must have global social media sentiment data for the companies to be considered for the analysis. This restriction was added to the criteria to ensure high validity and reliability of the results.

4.4. Unit of analysis

The unit of analysis for this research study is the company. Companies were considered to be the most appropriate unit of analysis as this allowed for testing of the dependent and independent variables within the context of the company. A company's customer satisfaction data could potentially predict its stock price performance and similarly a company's social media sentiment data could potentially predict its stock price performance.

4.5. Sampling method and sampling size

The research study made use of a census sampling technique. This method was chosen since the complete list of the population is known, accounted for and recorded after the application of the selection criteria, making that the sampling frame. The researcher therefore took a census of all companies that met the requirements (Weiers, 2008, p.7).

The automated nature of data collection and data processing provided by social media platforms and the abundance of available secondary data on stock prices and customer satisfaction indexes made the census sampling approach possible. After applying the selection criteria, a total of 79 American listed companies made up the final sample. Daily sentiment data, customer satisfaction scores and stock price values were collected and programmatically transformed for the 731 days that made up the period of 1 January 2011 – 31 December 2012.

4.6. Data collection method

The data collected for stock price performance were the end-of-day values and were raw data that were downloaded from the Yahoo! finance website available at http://finance.yahoo.com/q/hp?s=YHOO. Similarly, the data that were collected for customer satisfaction were also raw data and were downloaded from the ACSI website.

The data that were collected for social media sentiment were downloaded from the Twitter network available at http://www.twitter.com. The data were subject to quantitative sentiment procedures to convert the qualitative data into quantitative data so that the data could be analysed. Twitter was chosen because previous research had been done on Twitter sentiment analysis and its ability to predict stock price performance. Added to this, Twitter is the most popular microblogging platform in the world (Barnes & Bohringer, 2011).

The development of the Twitter scraper program to assist with the automated download of tweets as well as the program used to transform the Twitter data, took ten days. The download of the tweets took place over five weeks and the transformation of this data took a total of 15 days to complete. A total of approximately one terabyte of data were downloaded and analysed from the Twitter network.

All three data sources represent publically available data. The study has employed a longitudinal time horizon which will allow for the collection and analysis of data over time.

Customer satisfaction data were manually downloaded and this secondary data contained the following information:

a) Company name so that the data could be associated with the unit of analysis.
b) Customer satisfaction index score for the last four years (2010-2013) to allow extrapolation of data to determine daily values for the period 1 January 2011 – 31 December 2012. Four years' worth of data needed to be downloaded because the ACSI releases customer satisfaction data quarterly for different industries and publish them yearly.

The secondary data for the stock price data that were manually downloaded included the following information:

a) Company name so that the data could be associated with the unit of analysis.
b) The listing code of the company.
c) Daily end-of-day stock price value for the period 1 January 2011 – 31 December 2012.
d) The date stamp to allow for the analysis and statistical comparison of stock price data with the customer satisfaction and social media sentiment datasets.

English tweets were downloaded from the Twitter network using various algorithms that programmatically extracted the following information on all the tweets that contained any of the search terms, listed in Appendix A, for the 79 companies for the period 1 January 2011 – 31 December 2012:

a) The content of the tweet so that sentiment analysis could be done.
b) The date stamp of the tweet so that the tweet sentiment could be associated with a specific day.
c) Retweets were included in the search results as they assisted the researcher to determine the impact of retweets or repeated tweets on social media sentiment scores. A tweet that is retweeted can increase or decrease the overall sentiment score depending on the number or retweets and is seen as an important indication of Twitter users' opinions at a point in time.
d) The total number of tweets as it could be useful for comparison purposes to explain different results.

4.7. Data analysis method

Quantitative analysis of the hypotheses was performed using a statistical package called SAS. Before this could be done the data were prepared, cleaned and transformed to ensure that all the data collected were in the same format.

4.7.1. The preparation of stock price performance data

An additional column was added to the stock price performance dataset to indicate the percentage change in the stock price compared to the previous day. Stock prices do not change on weekends or public holidays. Therefore, the daily percentage change for these days was calculated based on the last trading day. The public holidays, available at http://www.investmentu.com/nyse-holiday-schedule.html and set out in figure 1 below, were incorporated:

Figure 1: NYSE public holidays

NYSE 2012 – 2013 Holiday Schedule

Normally the hours for the New York Stock Exchange are from 9:30 AM to 4:00 PM (Eastern Time) Monday through Friday. However the stock market does close for certain holidays and occasionally for other extraordinary events.

NYSE Holidays	2011	2012	2013
New Year's Day	January 1	January 2	January 1
Martin Luther King, Jr. Day	January 17	January 16	January 21
Washington's Birthday/ Presidents Day	February 21	February 20	February 18
Good Friday	April 22	April 6	March 29
Memorial Day	May 30	May 28	May 27
Independence Day	July 4	July 4	July 4
Labor Day	September 5	September 3	September 2
Thanksgiving Day	November 24	November 22	November 28
Christmas Day	December 26	December 25	December 25

4.7.2. The preparation of customer satisfaction data

The ACSI provides customer satisfaction index data per company only once a year and the release date is different per industry. Daily values for customer satisfaction were determined by extrapolating values from the previous year to the next year. The researcher is confident that this was an appropriate way to transform the data to daily values based on the assumption that customer satisfaction change gradually over time. Daily lags in customer satisfaction scores were also calculated up to a lag of four days to allow for tests to show any significant effect that could be lagged.

4.7.3. The preparation of social media sentiment data

Due to the qualitative nature of tweets, the data had to be transformed to quantitative data for analysis. To do this, three dictionaries of sentiment constructs were built. The first two dictionaries were built using words available on various websites and books that could be associated with customer-oriented sentiment or financial-oriented sentiment. The original dictionaries created by the researcher contained 188 financial-oriented words and 190 customer-oriented words. The dictionaries were sent to six second year MBA students and six employees at the researcher's company, in various professions, to test. The aim of the testing of the dictionaries was to eliminate words that the testers did not associate with customer-oriented sentiment or financial-oriented sentiment and to prevent any overlap of words between the customer-oriented words and financial-oriented words. The final tested dictionaries contain 125 financial-oriented words and 78 customer-oriented words. The dictionary containing customer-oriented words can be found in Appendix B and the dictionary containing financial-oriented words can be found in Appendix C.

The third sentiment dictionary was built based on previous work done by researchers whose work had been peer reviewed and used in similar research studies. The Affin sentiment dictionary (Nielsen, 2011) contains sentiment words and a weighting per word. This dictionary was used in studies conducted by Hansen, Arvidsson, Nielsen, Colleoni, & Etter (2011). The Affin dictionary was combined with the Loughran and McDonald dictionary (Loughran & McDonald, 2011) that was also statistically developed but more focussed on symbols and financial words. The combined sentiment dictionary contains 6,663 words and symbols with weightings and can be found on the data disk.

The customer-oriented dictionary and financial-oriented dictionary were used to classify every tweet either as a customer-oriented tweet, financial-oriented tweet or other tweet. Global sentiment analysis was performed on all tweets using the sentiment dictionary and applying the weights to all the tweets. Furthermore, customer-oriented sentiment analysis was done by applying the weightings in the sentiment dictionary to the tweets that were classified as customer-oriented tweets using the customer dictionary. Similarly, financial-oriented sentiment analysis was done using the sentiment dictionary and applying the weightings to all the tweets that were classified as financial-oriented tweets using the financial-oriented dictionary. The sentiment analysis was done programmatically using complex algorithms. The three types of sentiment were calculated per company per day. Daily lags in the percentage change of global social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment were calculated up to a lag of four days to be able to test if any significant effects could be found that lagged.

Apart from the preparation and transformation of the mentioned variables, the following information was programmatically calculated per company per day:

a) The total number of tweets per company per day. These were also broken down into the total number of customer-oriented tweets and financial-oriented tweets.

b) The total number of tweets that could be weighted. These tweets contained words that are present in the sentiment dictionary. This was done for global social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment.
c) The variance of the weightings over all tweets as well as the weighted tweets for global social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment.
d) The mean of the weightings over all tweets as well as the weighted tweets for global social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment.

There were days for some companies that did not contain any sentiment data. It was assumed that sentiment stays constant until it changes by means of consumers expressing their opinions through tweets that contained positive or negative sentiment. The missing data were therefore replaced with the values of the previous day.

One of the objectives of the research was to ascertain if there are any differences in the findings between utility companies and non-utility companies. Utility companies and non-utility companies were chosen for comparison as utility companies are seen as state sanctioned monopolies in the USA. Customers therefore do not have a lot of choice if they require services from these companies. Significant differences were expected to be found when utility companies and non-utility companies are compared because non-utility companies are generally more focussed on customer satisfaction.

Once the three datasets were cleaned, transformed and harmonised as explained, they were combined into a single dataset for analysis of the hypotheses. Econometrics panel data analysis was used. Econometrics panel data analysis deals with multi-dimensional data. Panel data is data that is longitudinal and multi-dimensional in nature (Park, 2009).

The following tests were used to conduct the panel data analysis:
a) <u>Univariate analysis</u>: Univariate analysis was done to assist the researcher with descriptive statistics. The descriptive statistics included histograms of the variables.
b) <u>Multivariate analysis</u>: Multivariate analysis was done in order to answer the research hypotheses. The multivariate analysis was done after the variables were winsorised in order to get a more regular distribution. Scatterplots were used to identify the relationship between the dependent and independent variables for each

hypothesis. General linear modeling was used including companies as a repeated measure. General linear modeling is used often when longitudinal data is analysed (Liang & Zeger, 1986). This accounted for the likelihood that data within a company are likely to be more correlated over time than data between companies. The AR(1) covariance model is a linear model that is used to predict the present value of longitudinal data using the immediately prior value in time. AR(1) therefore denotes the first order auto regression model (Liang & Zeger, 1986). The AR(1) covariance model was used for the following reasons:

i) It seemed plausible that in this data set, adjacent observations would be expected to be more highly correlated than observations further apart in time.
ii) The observations are equally spaced in time.
iii) The correlation structure was not expected to change appreciably over time.

The Toeplitz covariance model was also considered for the same reasons, but was found to be computationally too intensive due to the much higher number of parameters required to be estimated

4.8. Limitations

A number of limitations are present that could potentially have impacted the validity and reliability of the study. Validity is defined as the degree to which the data collection method correctly measures what it was intended to measure and the findings are what they confess to be about (Saunders & Lewis, 2012, p. 127). Reliability is defined as the degree to which the collection method and analysis techniques result in consistent findings (Saunders & Lewis, 2012, p. 128).

Validity was potentially compromised as certain historical events like mergers, acquisitions and significant announcements could impact stock price performance that was not related to customer satisfaction or social media sentiment changes. However, the large sample size and time series data allowed for anomalies to show in the analysis which could then be used for further analysis should it be necessary.

Another limitation was that only English tweets were analysed and without demographic information about the person or organisation posting the tweet, data quality cannot be guaranteed. Nevertheless, with regards to this limitation, a large number of tweets were analysed over a period of time which would increase the overall validity.

Furthermore, validity of the data can also be compromised if spam tweets were made part of the analysis. The number of spam tweets was limited by programmatically removing duplicate tweets sent by the same person at the same time. The number of spam tweets and the impact it can have on the validity of the overall results, was further limited due to the large number of tweets that were analysed over the period 1 January 2011 – 31 December 2012. Tweets sent by different people at the same time were included in the final data set because some users' accounts are set to retweet selected people's tweets automatically.

Reliability could potentially be compromised due to the measurements of the three variables taking place at different times, specifically customer satisfaction data. This limitation was minimised by using extrapolation of data and assuming that customer satisfaction changes gradually over time.

Another limitation which was identified is observer bias and could be present in the way that Twitter feeds are classified. This could lead to a different interpretation of the results. The researcher minimised the impact of this limitation by using existing sentiment dictionaries and building on them. Moreover, the researcher also tested the customer-oriented dictionary and the financial-oriented dictionary with six colleagues and six MBA students.

Lastly, reliability could have been compromised due to measurement errors. This could have resulted due to the way people post in Twitter. Twitter's limitation of 140 characters results in consumers using "slang" words which are abbreviations that are not commonly used or documented in formal dictionaries, bad spelling and punctuation as well as no spacing in their tweets. Users can also be sarcastic in what they mean in a tweet which will lead to the sentiment analysis tool classifying the tweet incorrectly as a positive or negative tweet. Also, tweets could have been missed when the customer-oriented and financial-oriented classification was done. Additionally, companies have the ability to delete tweets from their page or to prevent them from being picked up with a search engine. However, due to the large number of tweets that were downloaded and the period of time they were downloaded for, the researcher is confident that the overall results are a close representation of reality.

4.9. Research method conclusion

The research methodology chapter provided an explanation of the collection and analysis of the data that addressed the research hypotheses. The next chapter describes the output of the statistical analysis that was performed on the data.

5. Chapter five: Research results

5.1. Introduction

The research results chapter focusses on a broad description of the sample. This is followed by descriptive statistics and the results of each of the hypotheses that were tested.

5.2. Description of the sample

The final sample was made up of 79 listed American companies. Daily data were gathered and calculated for stock price (SP), customer satisfaction score (CSS) and Twitter sentiments - global social media sentiment (TSG), customer-oriented social media sentiment (TSC) and financial-oriented social media sentiment (TSF) - for the period 1 January 2011 – 31 December 2012. In addition, each company was categorised as a non-utility company (CF = 1) or utility company (CF = 0). The daily percentage change for customer satisfaction score, stock price, global social media sentiment, customer-oriented social media sentiment and financial-oriented social media sentiment was also calculated. For the stock price, which does not change on weekends or public holidays, the daily percentage change was calculated based on the last trading day. These variables are labelled with the prefix "ch". Table 2 summarises the abbreviations of the variables used to test the research hypotheses.

Table 2: Dictionary of abbreviations of variables

Abbreviation:	Description:
SP	Stock price
CSS	Customer satisfaction score
TSG	Global social media sentiment
TSC	Customer-oriented social media sentiment
TSF	Financial-oriented social media sentiment
CF = 1	Non-utility company
CF = 0	Utility company
chCSS	Percentage change in customer satisfaction score
chSP	Percentage change in stock price
chTS_global	Percentage change in global social media sentiment
chTS_cust	Percentage change in customer-oriented social media sentiment

Abbreviation:	Description:
chTS_fin	Percentage change in financial-oriented social media sentiment
DV	Dependent variable
IV	Independent variable

5.3. Descriptive statistics

A total of 18,625,439 tweets were analysed for the period 1 January 2011 – 31 December 2012. Of these, 16,470,921 or 88.43% could be analysed for sentiment and therefore contained words that are listed in the sentiment dictionary. Based on the custom sentiment dictionaries, 10.57% or 1,969,132 of the total number of tweets could be classified as customer-oriented tweets. In this case 81.12% of these tweets contained sentiment words and could be weighted. The financial-oriented tweets that were classified from the dictionary were 17.21% or 3,207,009 of the total number of tweets and of these 89.17% or 2,859,729 could be weighted based on the sentiment dictionary. (See Appendix B and C for the customer-oriented and financial-oriented dictionaries respectively and the data disk for the sentiment dictionary). Table 3 summarises the univariate statistics for the variables used in the analyses.

Table 3: Univariate statistics

Variable	N	Mean	SD	Min	Max	Skew-ness	Kurtosis
CSS	57749	77.62	5.81	54.00	89.00	-1.14	1.32
SP	57749	73.06	198.35	0.24	1848.21	5.88	36.26
TSG	57749	-8	425	-9865	11452	0	107
TSC	57749	16	132	-3699	7321	18	706
TSF	57749	10	185	-8138	7265	-1	305
chCSS	57670	0.00	0.01	-0.09	0.09	0.03	11.55
chSP	57591	0.06	2.26	-83.95	85.27	4.08	232.19
chTS_global	57661	-57.32	5662.38	-200800	1117000	141.23	27257.18
chTS_cust	57670	67.79	2876.44	-46700	447000	108.87	15043.40
chTS_fin	57669	-92.16	2468.97	-399200	63300	-90.65	13169.49

It is furthermore noted that the dataset comprised of a total of 59 or 74.7% non-utility companies but 98.56% of all the tweets came from these companies. This means that more tweets were generated on non-utility companies than on utility companies. It is therefore expected that more accurate results will be observed for non-utility companies.

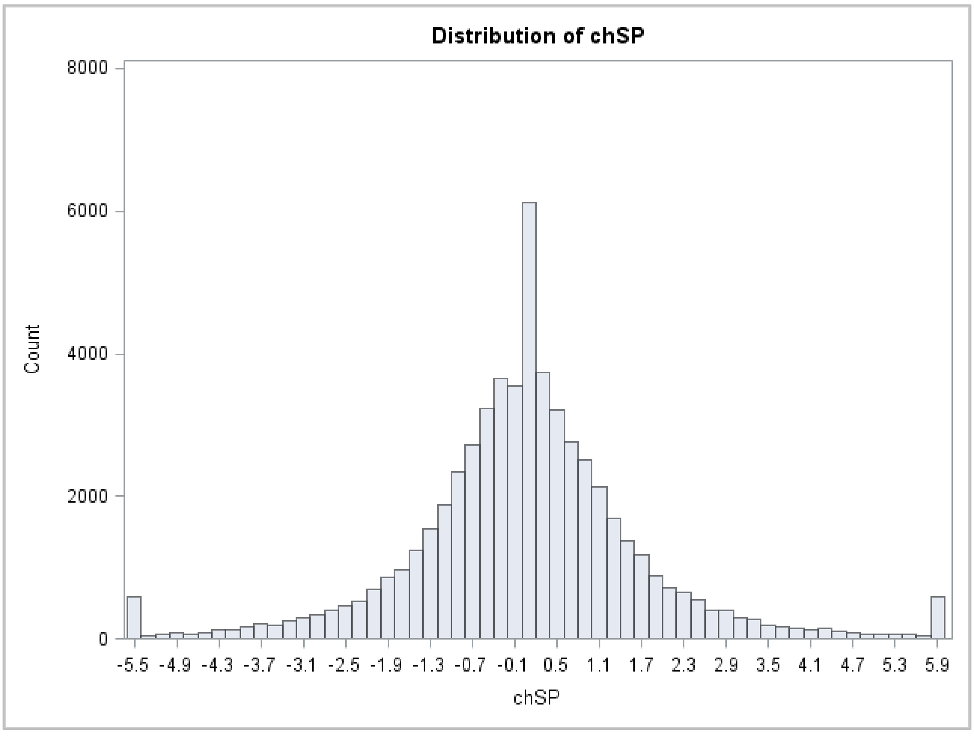
Moreover, the univariate analysis showed that all the data were characterised by extremely leptokurtic distributions, which have been problematic in the later analysis and were most likely in the form of outliers or points with high leverage. Leptokurtic distributions have higher peaks compared to normal distributions (Weiers, 2008, p.90). The five "change" variable were therefore winsorised at the 1% and 99% levels. This is often done with financial data to replace extreme data values with less extreme data values. Table 4 illustrates the univariate statistics for the five winsorised variables.

Table 4: The univariate statistics for the five winsorised variables

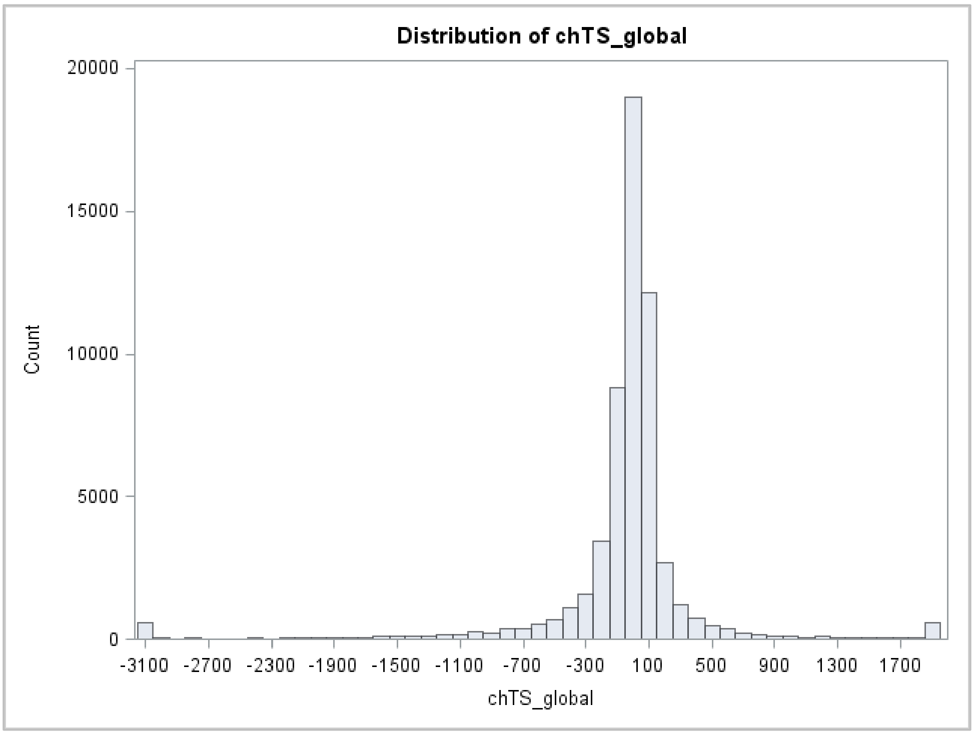
Variable	N	Mean	SD	Min	Max	Skewness	Kurtosis
chCSS	57670	0.00	0.01	-0.03	0.06	1.297	5.238
chSP	57591	0.05	1.69	-5.51	5.86	0.08	2.431
chTS_global	57661	-56.22	527.78	-3133.33	1920	-2.282	15.774
chTS_cust	57670	37.62	405.17	-1500.00	2250	1.804	13.036
chTS_fin	57669	-55.37	503.04	-3000.00	1700	-2.52	15.77

The improvement in the distribution of the variables is apparent in table 4 as well as the histograms in figure 2 to figure 6 that show the distribution of the variables after the winsorisation.

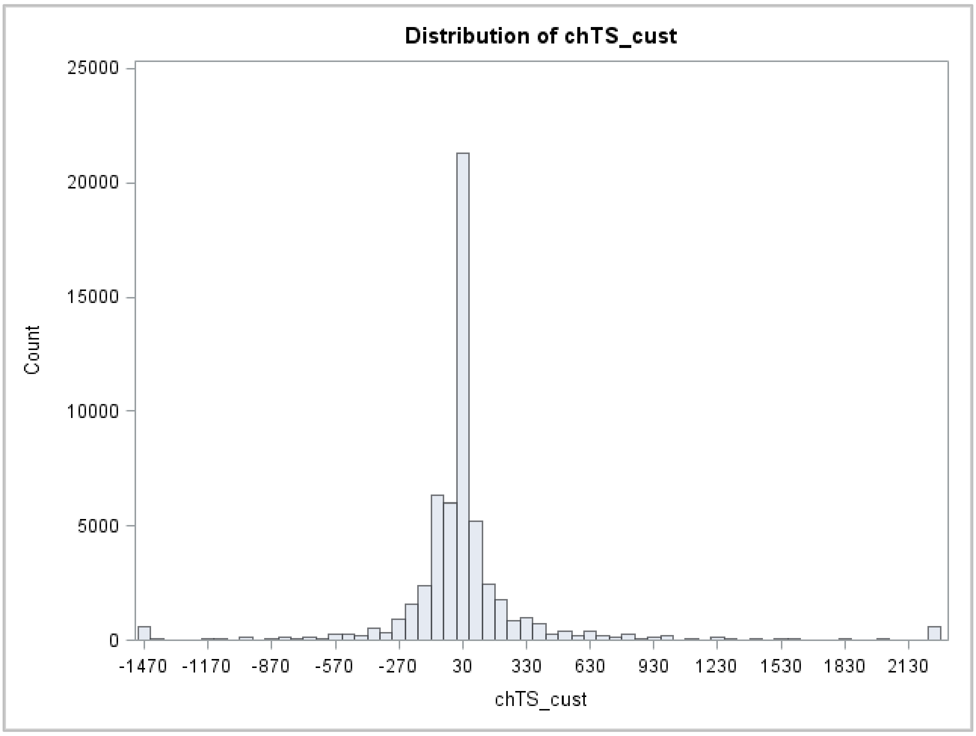
Figure 2: Histogram showing the distribution of chSP after winsorisation



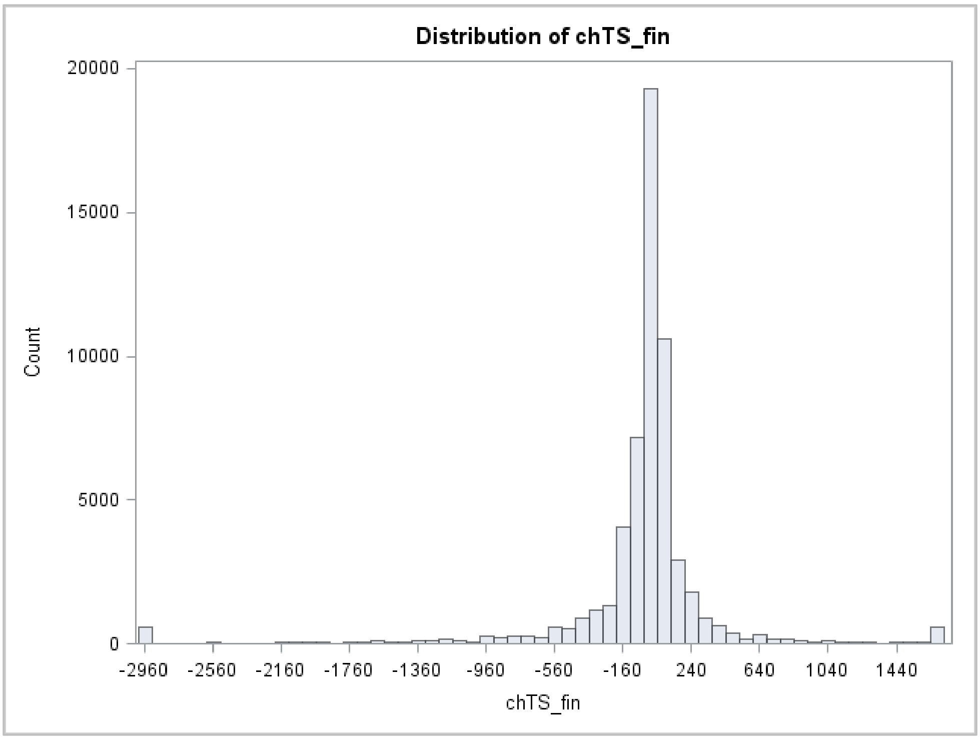
<u>Figure 3</u>: Histogram showing the distribution of chTS_global after winsorisation



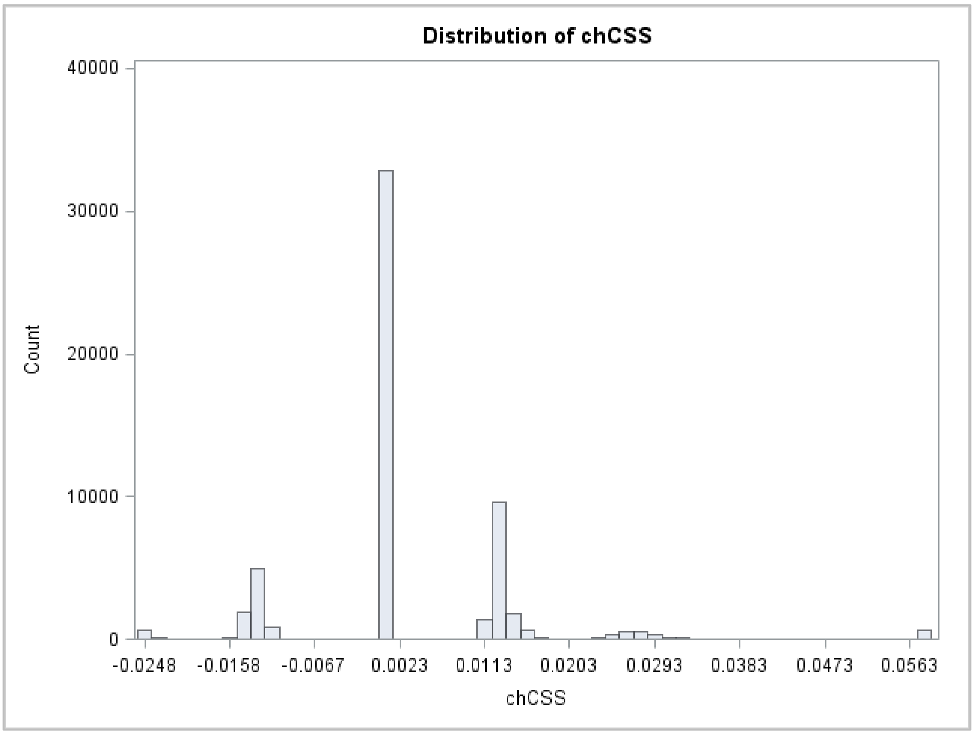
<u>Figure 4</u>: Histogram showing the distribution of chTS_cust after winsorisation



<u>Figure 5</u>: Histogram showing the distribution of chTS_fin after winsorisation



<u>Figure 6</u>: Histogram showing the distribution of chCSS after winsorisation



However, even after the winsorisation of the data, the distribution of chCSS remains irregular. This is due to the extrapolation method used to derive this data. There is also a peak at chSP=0 due to some companies' share prices not changing every day.

5.4. Multivariate analysis

For the multivariate analysis a significance level of 5% was used throughout all the tests, unless specified otherwise. Thus, a p-value below 0.05 means a significant result.

Daily lags for the change in customer satisfaction score, the change in global social media sentiment, the change in customer-oriented social media sentiment and the change in financial-oriented social media sentiment, were calculated, up to a lag of four days. These variables are denoted as chCSS_x where x indicates the lag.

Unless otherwise indicated, the following approach was used throughout the analysis of the hypotheses: The correlation coefficient and scatterplot, between the independent variable (IV) and dependent variable (DV) in each case, for the different lags, were examined to understand the nature of the relationship between the independent variable and dependent variable and to see which lags suggested the strongest relationship between the variables. Thereafter, the data were analysed using a general linear model (GLM), including company as a repeated measure. This accounts for the likelihood that data within a company are likely to be more correlated over time than data between companies. The AR(1) covariance model was used.

5.4.1. Hypothesis 1 (H1)

H1: Customer satisfaction is positively associated with stock price performance.

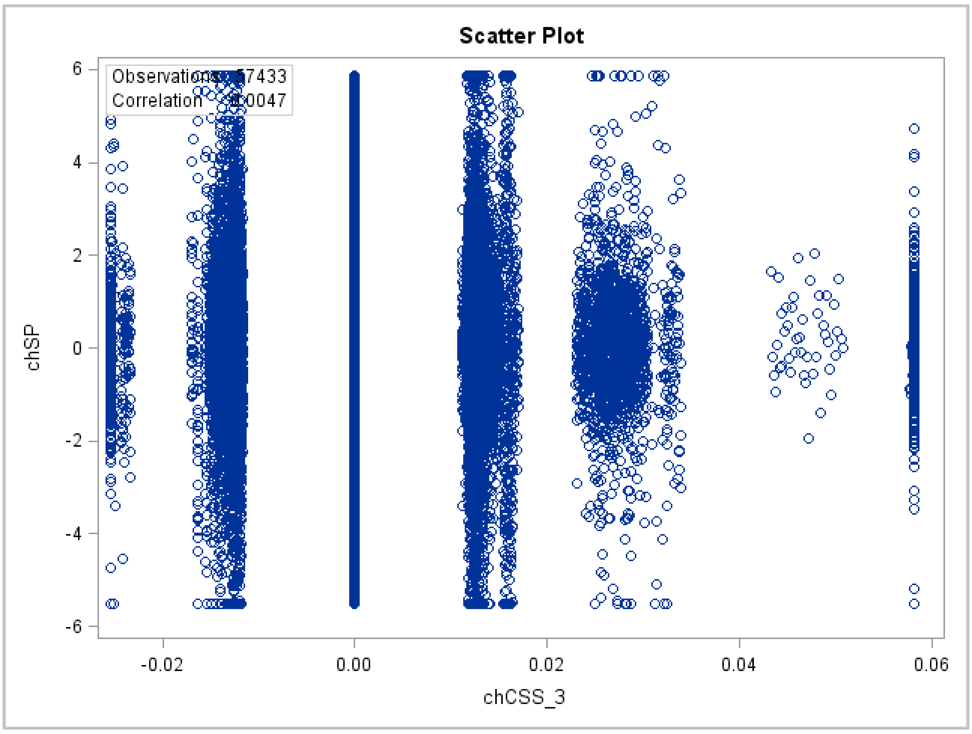
For this hypothesis, the dependent variable is the change in stock price while the independent variable is the change in customer satisfaction score. The hypothesis was tested at lags of zero to four days. None of the correlation coefficients are significant, and the scatterplots do not suggest a relationship between the change in the customer satisfaction score and the change in stock price. The results of the general linear model are shown in table 5.

Table 5: Results of GLM for H1

IV	F	p-value
chCSS_0	0.08	0.78
chCSS_1	0.55	0.46
chCSS_2	0.15	0.69
chCSS_3	1.49	0.22
chCSS_4	0.10	0.75

The coefficient of the change in customer satisfaction score was not significantly different to zero for all lags, which means there is no significant relationship, whether it is positive or negative between the change in customer satisfaction score and the change in stock price. Furthermore, the scatterplots show no evidence of a linear relationship between the change in customer satisfaction score and the change in stock price as can be seen in figure 7.

Figure 7: Scatterplot for H1 at a lag of three days



H1 is thus not accepted.

5.4.1.1. Hypotheses 1a (H1a)

H1a: The positive relationship between customer satisfaction and stock price performance differs between non-utility companies and utility companies such that it will be more positive for non-utility companies and less positive for utility companies.

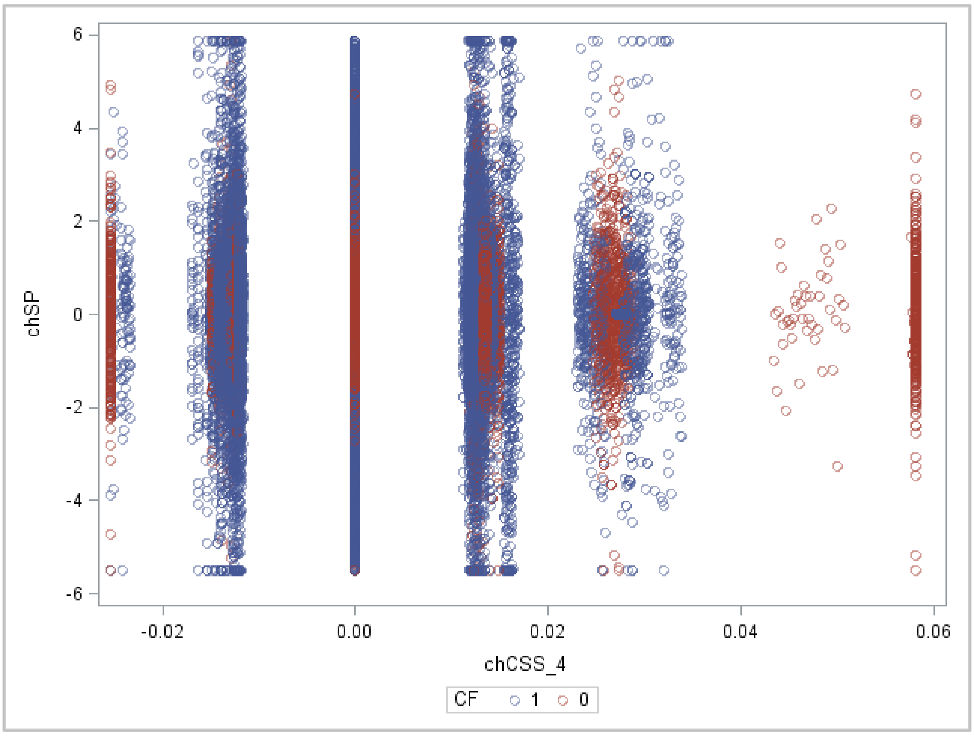
For this hypothesis, the dependent variable is the change in stock price while the independent variables are the change in customer satisfaction score, the company type (utility companies and non-utility companies) and the interaction between the type of company and the change in customer satisfaction score denoted by CF*chCSS. The hypothesis was tested at lags of zero to four days. The CF*chCSS interaction term will show if the slope of the change in stock price versus the change in customer satisfaction score, at a given lag, differs for utility companies where CF = 0 and non-utility companies where CF = 1. The results of the general linear mode are shown in table 6.

Table 6: Results of GLM for H1a

IV	effect	F	p-value
chCSS_0	chCSS_0	0.10	0.76
	CF	0.04	0.84
	chCSS*CF	0.00	0.98
chCSS_1	chCSS_1	0.61	0.44
	CF	0.02	0.90
	chCSS_1*CF	0.39	0.53
chCSS_2	chCSS_2	0.14	0.70
	CF	0.01	0.92
	chCSS_2*CF	0.06	0.81
chCSS_3	chCSS_3	1.62	0.20
	CF	0.13	0.72
	chCSS_3*CF	0.05	0.82
chCSS_4	chCSS_4	0.12	0.73
	CF	0.05	0.82
	chCSS_4*CF	2.75	0.10

The scatterplot at a lag of four days are shown in figure 8.

<u>Figure 8</u>: Scatterplot for H1a at a lag of four days



None of the main effects or interactions were significant at any lag, which means there is no significant relationship, positive or negative, between the change in customer satisfaction score and the change in stock price for utility companies or non-utility companies. H1a is thus not accepted.

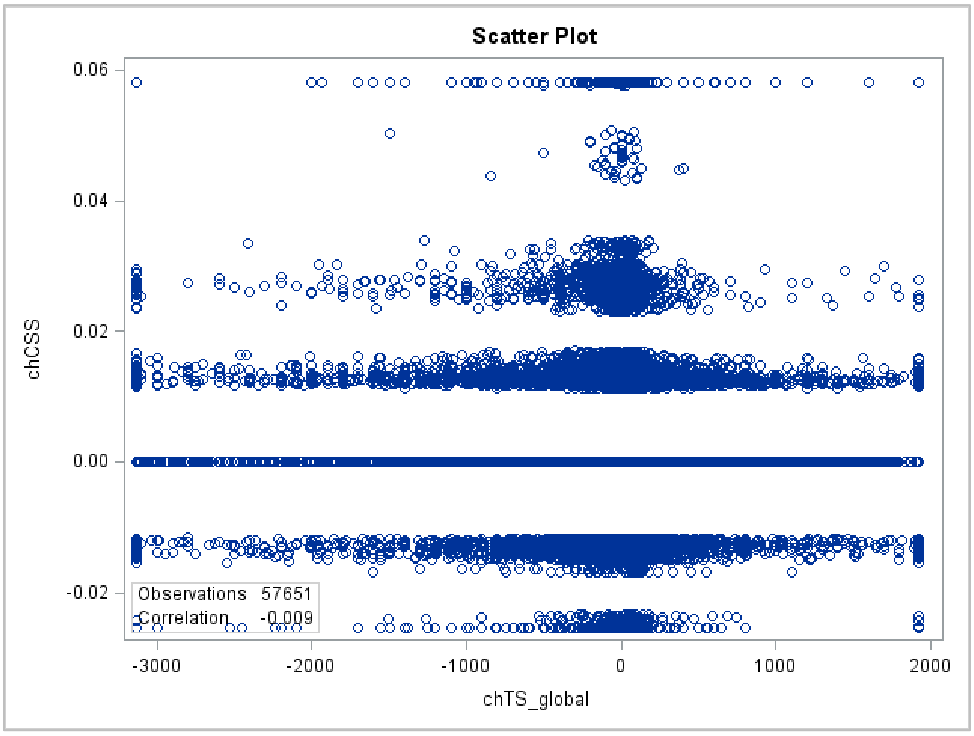
5.4.2. Hypothesis 2 (H2)

H2: Global Social media sentiment is positively associated with customer satisfaction.

For this hypothesis, the dependent variable is the change in customer satisfaction score and the independent variable is the change in global social media sentiment. The researcher assumed that these variables move concurrently and that their effects are not lagged.

Although the correlation coefficient is significant, the magnitude of the correlation coefficient is very small. The scatterplot shows no evidence of a linear relationship between the change in customer satisfaction score and the change in global social media sentiment as can be seen in figure 9.

<u>Figure 9</u>: Scatterplot for H2



The results of the general linear model are shown in table 7.

<u>Table 7</u>: Results of GLM for H2

IV	F	p-value
chTS_global	2.06	0.15

The coefficient of the change in global social media sentiment was not significantly different to zero, which means that there is no significant relationship, positive or negative, between the change in customer satisfaction score and the change in global social media sentiment. H2 is thus not accepted.

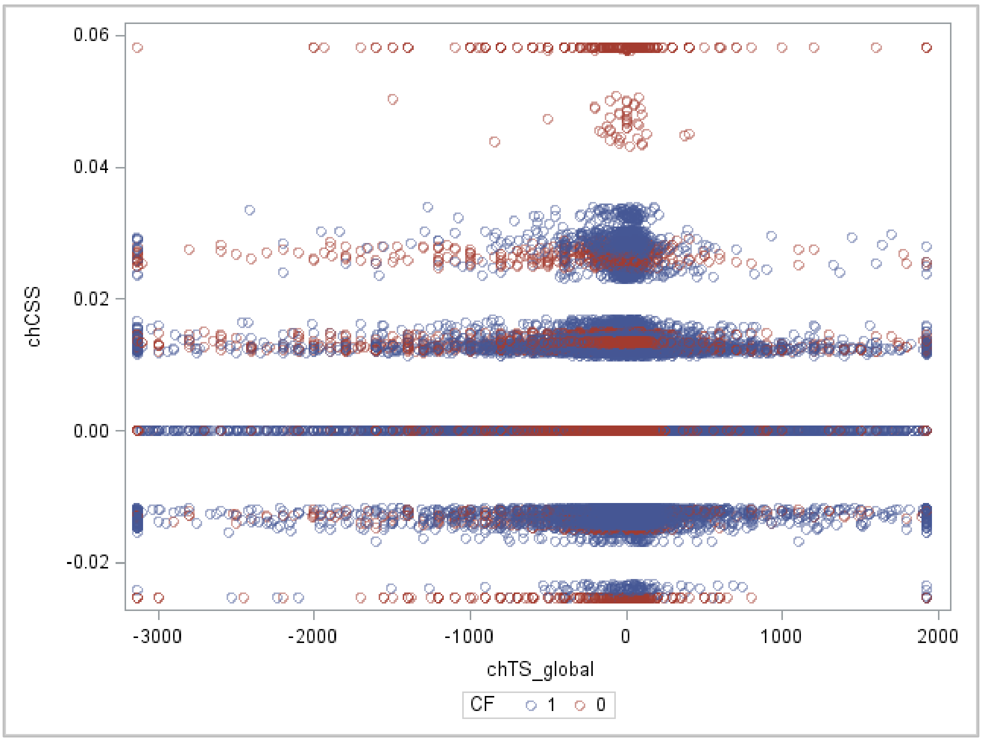
5.4.2.1. Hypothesis 2a (H2a)

H2a: The positive relationship between global social media sentiment and customer satisfaction differs between non-utility companies and utility companies such that it will be more positive for non-utility companies and less positive for utility companies.

For this hypothesis, the dependent variable is the change in customer satisfaction score while the independent variables are the change in global social media sentiment, the type of company (utility companies and non-utility companies) and the interaction of the type of company and the change in global social media sentiment, denoted by CF*chTS_global. The CF*chTS_global interaction term will show if the slope of the change in global social media sentiment versus the change in customer satisfaction score differs for utility companies where CF = 0 and non-utility companies where CF = 1.

Looking at the scatterplot in figure 10, it does not suggest a relationship between the change in customer satisfaction score, grouped by the type of company, and the change in global social media sentiment.

<u>Figure 10</u>: Scatterplot for H2a



The results of the general linear model are shown in table 8.

Table 8: Results of GLM for H2a

IV	effect	F	p-value
chTS_global	chTS_global	1.00	0.32
	CF	16.56	0.00*
	chTS_global*CF	0.22	0.64

The effect of the type of company alone was significant, as shown in table 8. The comparison of the least-squares means shows that the mean change in customer satisfaction score was 0.0059 for utility companies where CF = 0 and 0.0014 for non-utility companies where CF = 1. However, the interactions were not significant, which means that there is no significant relationship, positive or negative, between the change in customer satisfaction score and the change in global social media sentiment for either utility companies or non-utility companies. H2a is thus not accepted.

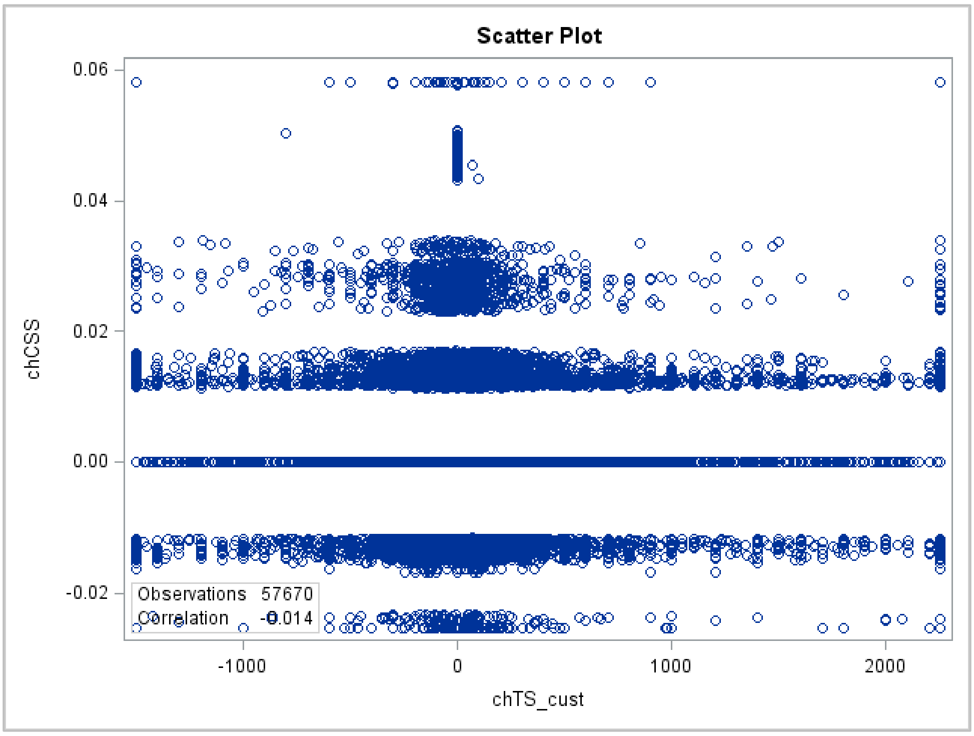
5.4.2.2. Hypothesis 2b (H2b)

H2b: Customer-oriented social media sentiment is a better predictor of customer satisfaction than global social media sentiment.

For this hypothesis, the dependent variable is the change in customer satisfaction score and the independent variable is the change in customer-oriented social media sentiment. The researcher assumed that these variables move concurrently and that their effects are not lagged.

Although the correlation coefficient is significant, the magnitude of the correlation coefficient is very small. Furthermore, the scatterplot in figure 11 shows no evidence of a linear relationship between the change in customer satisfaction score and the change in customer-oriented social media sentiment.

Figure 11: Scatterplot for H2b



The results of the general linear model are shown in table 9.

Table 9: Results of GLM for H2b

IV	F	p-value
chTS_cust	1.61	0.21

The coefficient of the change in customer-oriented social media sentiment was not significantly different to zero, which means there is no significant relationship, positive or negative, between the change in customer satisfaction score and the change in customer-oriented social media sentiment. H2b is thus not accepted.

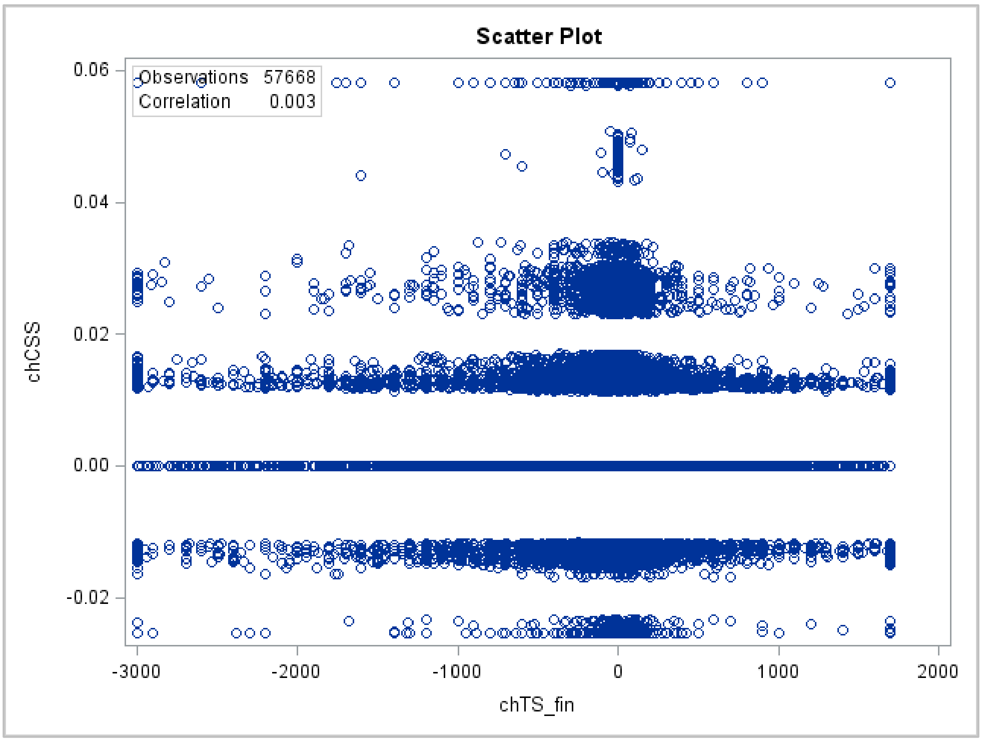
5.4.2.3. Hypothesis 2c (H2c)

H2c: Financial-oriented social media sentiment is a worse predictor of customer satisfaction than global social media sentiment.

For this hypothesis, the dependent variable is the change in customer satisfaction score and the independent variable is the change in financial-oriented social media sentiment. The researcher assumed that these variables move concurrently and that their effects are not lagged.

The correlation coefficient between the change in customer satisfaction score and the change in financial-oriented social media sentiment is not significant. Furthermore, the scatterplot in figure 12 shows no evidence of a linear relationship between the variables.

Figure 12: Scatterplot for H2c



The results of the general linear model are shown in table 10.

Table 10: Results of GLM for H2c

IV	F	p-value
chTS_fin	1.21	0.27

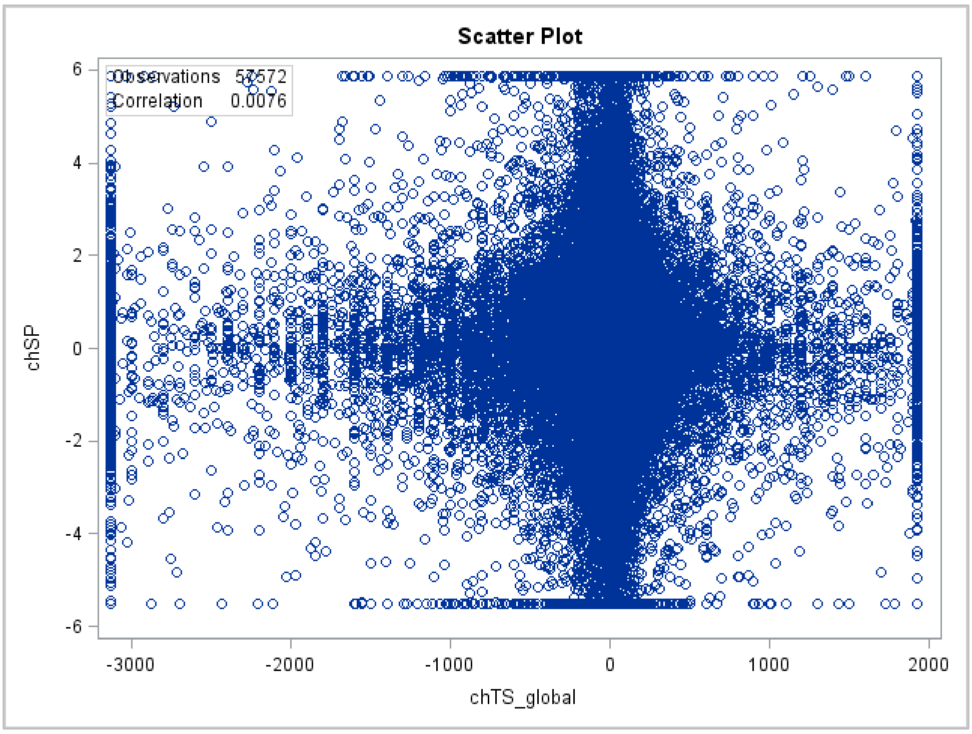
The coefficient of the change in financial-oriented social media sentiment was not significantly different to zero, which means there is no significant relationship, positive or negative, between the change in customer satisfaction score and the change in financial-oriented social media sentiment. H2c is thus not accepted.

5.4.3. Hypothesis 3 (H3)

H3: Global Social media sentiment is positively associated with stock price performance.

For this hypothesis, the dependent variable is the change in stock price while the independent variable is the change in global social media sentiment. The hypothesis was tested at lags of zero to four days. None of the correlation coefficients are significant, and the scatterplots do not suggest a relationship between the change in global social media sentiment and the change in stock price as can be seen in figure 13 for a lag of zero days.

Figure 13: Scatterplot for H3 with chTS_global at lag zero



The results of the general linear model are shown in table 11.

Table 11: Results of GLM for H3

IV	F	p-value
chTS_global_0	3.66	0.05*
chTS_global_1	0.08	0.77
chTS_global_2	0.10	0.75
chTS_global_3	0.00	0.95
chTS_global_4	0.91	0.34

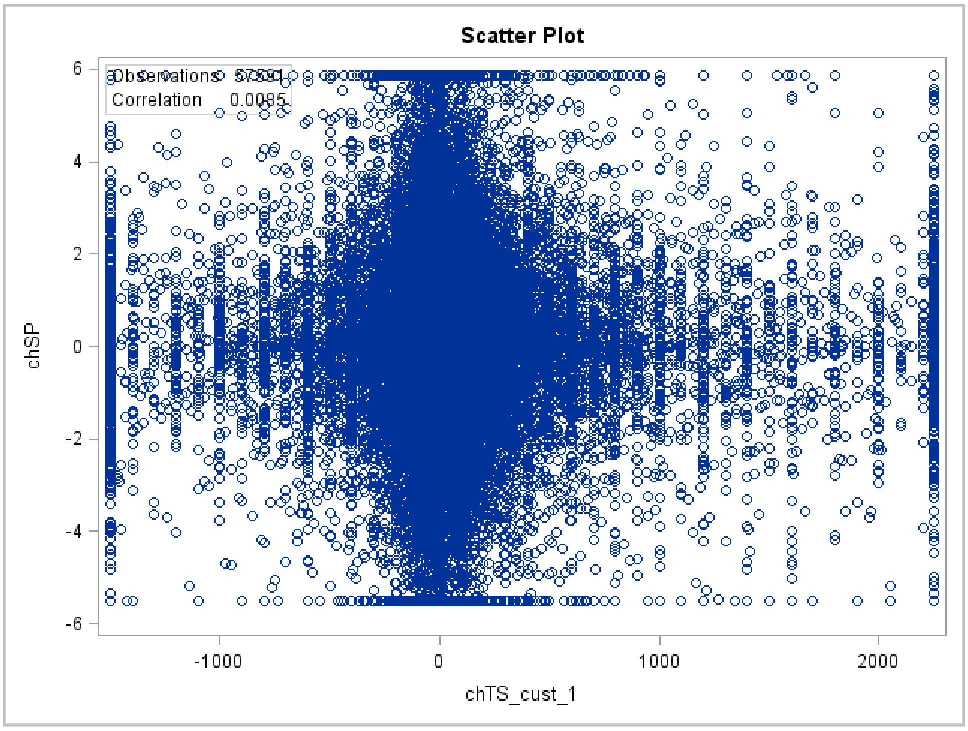
The coefficient of the change in global social media sentiment was not significantly different to zero for all lags, which means there is no significant relationship, positive or negative, between the change in global social media sentiment and the change in stock price. However, p = 0.05 and H3 is thus accepted.

5.4.3.1. Hypothesis 3a (H3a)

H3a: Customer-oriented social media sentiment is a worse predictor of stock price performance than global social media sentiment.

For this hypothesis, the dependent variable is the change in stock price while the independent variable is the change in customer-oriented social media sentiment. The hypothesis was tested at lags of zero to four days. Although the correlation coefficient for the change in customer-oriented social media sentiment at a lag of 1 day is significant, the magnitude of the correlation coefficient is very small. Furthermore, the scatterplot in figure 14 does not suggest a relationship between the change in customer-oriented social media sentiment and the change in stock price.

Figure 14: Scatterplot for H3a with chTS_cust at a lag of one day



The results of the general linear model are shown in table 12.

Table 12: Results of GLM for H3a

IV	F	p-value
chTS_cust_0	0.39	0.53
chTS_cust_1	2.44	0.12
chTS_cust_2	0.16	0.69
chTS_cust_3	0.11	0.74
chTS_cust_4	2.35	0.13

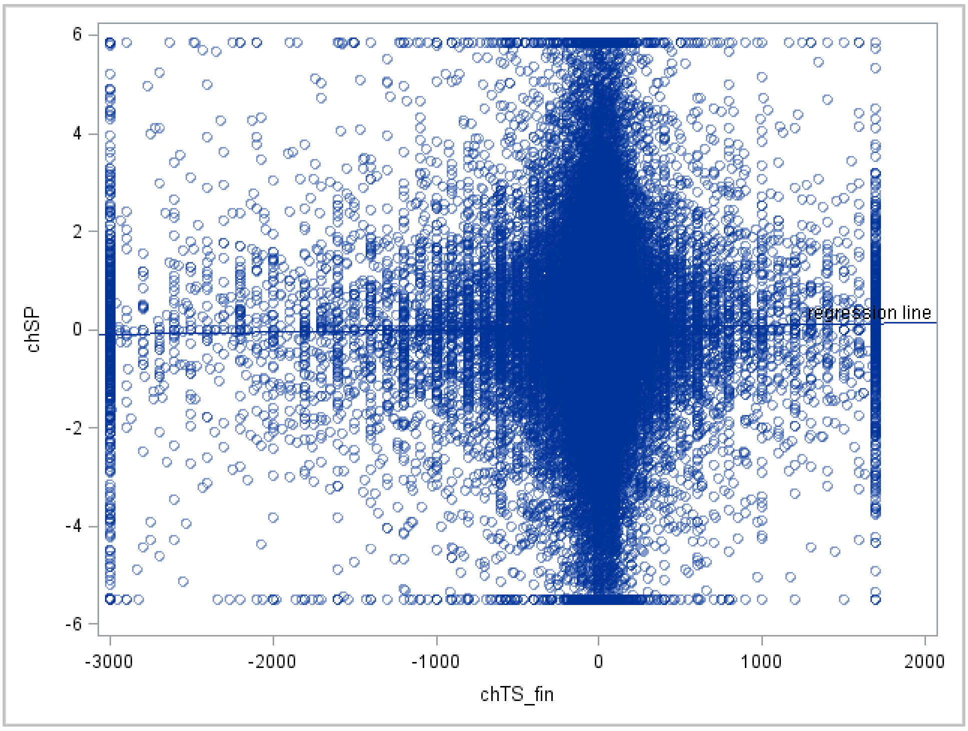
The coefficient of the change in customer-oriented social media sentiment was not significantly different to zero for all lags, which means there is no significant relationship, positive or negative, between the change in customer-oriented social media sentiment and the change in stock price. H3a is thus not accepted.

5.4.3.2. Hypothesis 3b (H3b)

H3b: Financial-oriented social media sentiment is a better predictor of stock price performance than global social media sentiment.

For this hypothesis, the dependent variable is the change in stock price and the independent variable is the change in financial-oriented social media sentiment. The hypothesis was tested at lags of zero to four days. Although the correlation coefficients for the change in financial-oriented social media sentiment for zero and three days are significant, the magnitudes of the correlation coefficients are very small. Furthermore, the scatterplots do not suggest a relationship between the variables as can be seen in figure 15 depicting the scatterplot for the variables at a lag of zero days.

Figure 15: Scatterplot for H3b with chTS_fin at a lag of zero days



The results of the general linear model are shown in table 13.

Table 13: Results of GLM for H3b

IV	F	p-value
chTS_fin	14.8	0.00*
chTS_fin_1	6.07	0.01*
chTS_fin_2	0.94	0.33
chTS_fin_3	3.03	0.08
chTS_fin_4	0.01	0.92

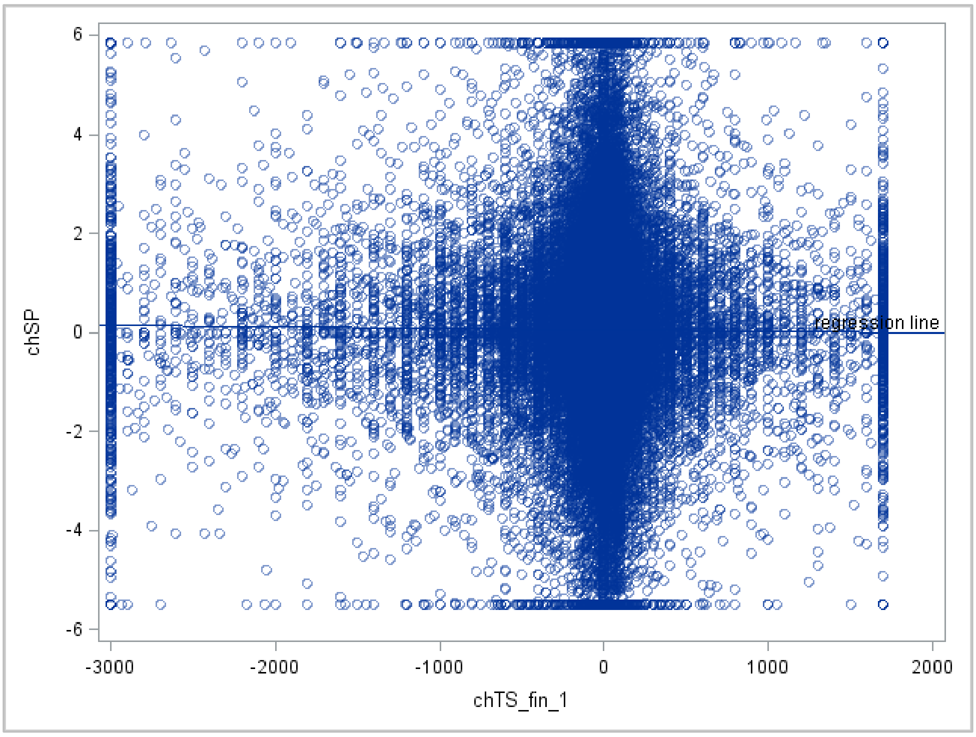
The coefficient of the change in financial-oriented social media sentiment was significant for lags of zero and one days. The model coefficients are shown in table 14.

<u>Table 14</u>: Model coefficients for H3b at lags of zero and one days

Effect	Estimate	Standard Error
Intercept (lag 0)	0.0499	0.0092
chTS_fin	0.00005	0.000013
Intercept (lag 1)	0.0454	0.0092
chTS_fin_1	-0.00003	0.000013

It is evident that the coefficient for the change in financial-oriented social media sentiment is positive at a lag of zero days and negative at a lag of one day. The fit of the model to the data at a lag of one day is shown in the scatterplot in figure 16.

<u>Figure 16</u>: Scatterplot for H3b with chTS_fin at a lag of one day



With $p < 0.05$ for a lag of zero and one days, H3b is accepted.

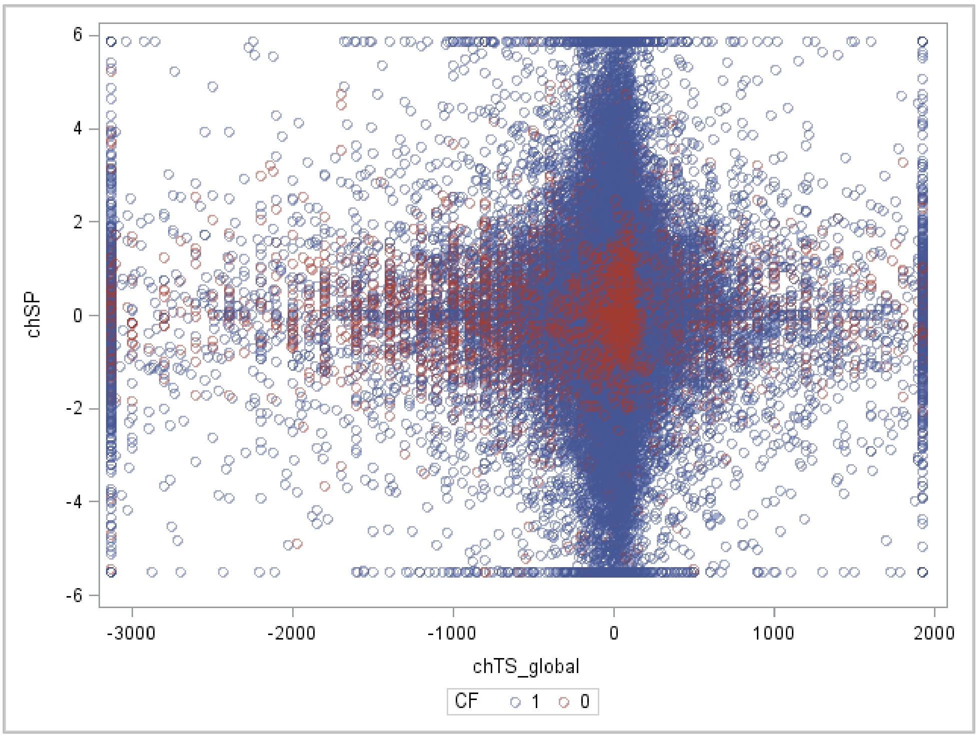
5.4.3.3. Hypothesis 3c (H3c)

H3c: The positive relationship between global social media sentiment and stock price performance differs between non-utility companies and utility companies such that it will be more positive for non-utility companies and less positive for utility companies.

For this hypothesis, the dependent variable is the change in stock price and the independent variables are the change in global social media sentiment, the type of company (utility companies and non-utility companies) and the interaction between the type of company and the change in global social media sentiment, denoted by CF*chTS_global. The hypothesis was tested at lags of zero to four days. The interaction term CF*chTS_global will show if the slope of the change in stock price versus the change in global social media sentiment, at a given lag, differs for utility companies where CF = 0 and non-utility companies where CF = 1, which will answer the hypothesis.

The scatterplots do not suggest a relationship between the change in global social media sentiment, grouped by the type of company, and the change in stock price. This can be seen in figure 17 where the variables are plotted for a lag of zero days.

<u>Figure 17</u>: Scatterplot for H3c at a lag of zero days



The results of the general linear model are shown in table 15.

<u>Table 15</u>: Results of GLM for H3c

IV	effect	F	p-value
chTS_global	chTS_global	1.01	0.31
	CF	0.06	0.80
	chTS_global*CF	1.46	0.23
chTS_global_1	chTS_global_1	0.07	0.79
	CF	0.01	0.94
	chTS_global_1*CF	0.99	0.32
chTS_global_2	chTS_global_2	0.33	0.57
	CF	0.00	0.98
	chTS_global_2*CF	0.35	0.55
chTS_global_3	chTS_global_3	0.18	0.67
	CF	0.01	0.90
	chTS_global_3*CF	0.85	0.36
chTS_global_4	chTS_global_4	0.28	0.60
	CF	0.02	0.88
	chTS_global_4*CF	0.30	0.58

None of the main effects or interactions are significant at any lag, which means there is no significant relationship, positive or negative, between the change in global social media sentiment and the change in stock price for utility companies where CF = 0 or non-utility companies where CF = 1. H3c is thus not accepted.

5.4.4. Hypothesis 4 (H4)

H4: The positive relationship between customer satisfaction and stock price performance will be positively moderated by global social media sentiment such that the more positive the global social media sentiment the stronger the relationship.

For this hypothesis, the dependent variable is the change in stock price performance and the independent variables are the change in customer satisfaction score, the change in global social media sentiment (the moderator) and the interaction between the change in customer satisfaction score and the change in global social media sentiment, denoted by chCSS*chTS_global. The hypothesis was tested at lags of zero to four days. The interaction term chCSS*chTS_global will show if the slope of the change in stock price versus the change in customer satisfaction score at a given lag varies with the change in global social media sentiment, which will answer the hypothesis. The researcher assumed that the change in customer satisfaction score and the change in global social media sentiment move at the same lags.

There are no multi-collinearity concerns, since the change in customer satisfaction score and the change in global social media sentiment are not highly correlated. The results of the general linear model are shown in table 16.

Table 16: Results of GLM for H4

Lag	effect	F	p-value
0	chCSS	0.19	0.66
	chTS_global	2.74	0.10
	chCSS*chTS_global	1.50	0.22
1	chCSS_1	0.63	0.43
	chTS_global_1	0.13	0.71
	chCSS*chTS_global_1	0.22	0.64
2	chCSS_2	0.22	0.64
	chTS_global_2	0.19	0.67
	chCSS*chTS_global_2	0.46	0.50
3	chCSS_3	1.41	0.24
	chTS_global_3	0.00	1.00
	chCSS*chTS_global_3	0.06	0.80
4	chCSS_4	0.08	0.78
	chTS_global_4	0.98	0.32
	chCSS*chTS_global_4	0.07	0.78

None of the main effects or interactions are significant at any lag, which means there is no moderation effect of the change in global social media sentiment on the relationship between the change in customer satisfaction score and the change in stock price. H4 is thus not accepted.

5.4.4.1. Hypothesis 4a (H4a)

H4a: The positive relationship between customer satisfaction and stock price performance will be positively moderated by customer-oriented social media sentiment such that the more positive the customer-oriented social media sentiment the stronger the relationship.

For this hypothesis the dependent variable is the change in stock price and the independent variables are the change in customer satisfaction score, the change in customer-oriented social media sentiment (the moderator) and the interaction between the change in customer satisfaction score and the change in customer-oriented social media sentiment, denoted by chCSS*chTS_cust. The hypothesis was tested at lags of zero to four days. The interaction term chCSS*chTS_cust will show if the slope of the change in stock price versus the change in customer satisfaction score at a given lag varies with the change in customer-oriented social media sentiment, which will answer the hypothesis. The researcher assumed that the change in customer satisfaction score and the change in customer-oriented social media sentiment move at the same lags. There are no multi-collinearity issues, since the change in customer satisfaction score and the change in customer-oriented social media sentiment are not highly correlated. The results of the general linear model are shown in table 17.

Table 17: Results of GLM for H4a

Lag	effect	F	p-value
0	chCSS	0.08	0.78
	chTS_cust	0.36	0.55
	chCSS*chTS_cust	0.02	0.88
1	chCSS_1	0.55	0.46
	chTS_cust_1	2.21	0.14
	chCSS*chTS_cust_1	0.23	0.64
2	chCSS_2	0.13	0.72
	chTS_cust_2	0.23	0.63
	chCSS*chTS_cust_2	0.32	0.57
3	chCSS_3	1.41	0.24
	chTS_cust_3	0.05	0.82
	chCSS*chTS_cust_3	0.67	0.41
4	chCSS_4	0.12	0.73
	chTS_cust_4	1.92	0.17
	chCSS*chTS_cust_4	0.88	0.35

None of the main effects or interactions was significant at any lag, which means there is no moderation effect of the change in customer-oriented social media sentiment on the relationship between the change in customer satisfaction score and the change in stock price. H4a is thus not accepted.

5.4.4.2. Hypothesis 4b (H4b)

H4b: The positive relationship between customer satisfaction and stock price performance will be positively moderated by financial-oriented social media sentiment such that the more positive the financial-oriented social media sentiment the stronger the relationship.

For this hypothesis the dependent variable is the change in stock price and the independent variables are the change in customer satisfaction score, the change in financial-oriented social media sentiment (the moderator) and the interaction between the change in customer satisfaction score and the change in financial-oriented social media sentiment, denoted by chCSS*chTS_fin. The hypothesis was tested at lags of zero to four days. The interaction term chCSS*chTS_fin will show if the slope of change in stock price versus the change in customer satisfaction score at a given lag varies with the change in financial-oriented social media sentiment, which will answer the hypothesis. The researcher assumed that the change in customer satisfaction score and the change in financial-oriented social media sentiment move at the same lags. There are no multi-collinearity issues, since the change in customer satisfaction score and the change in financial-oriented social media sentiment are not highly correlated. The results of the general linear model are shown in table 18.

Table 18: Results of GLM for H4b

Lag	effect	F	p-value
0	chCSS	0.10	0.75
	chTS_fin	13.99	0.00*
	chCSS*chTS_fin	0.25	0.62
1	chCSS_1	0.58	0.45
	chTS_fin_1	6.06	0.01*
	chCSS*chTS_fin_1	0.02	0.89
2	chCSS_2	0.14	0.71
	chTS_fin_2	0.87	0.35
	chCSS*chTS_fin_2	0.04	0.84
3	chCSS_3	1.47	0.22
	chTS_fin_3	2.94	0.09
	chCSS*chTS_fin_3	0.00	0.95
4	chCSS_4	0.08	0.78
	chTS_fin_4	0.02	0.88
	chCSS*chTS_fin_4	0.16	0.69

None of the interactions are significant at any lag, which means there is no moderation effect of the change in financial-oriented social media sentiment on the relationship between the change in customer satisfaction score and the change in stock price. H4b is thus not accepted.

5.4.5. Hypothesis 5 (H5)

H5: The degree to which global social media sentiment is positively associated with stock price performance gets stronger over time.

To test this hypothesis, the model used to test hypothesis 3 was repeated, but separately for the four six-month periods covered by the data for the period 1 January 2011 – 31 December 2012. The results of the general linear model are shown in table 19.

Table 19: Results of GLM for H5

Time period	1 Jan - 30 Jun 2011		1 Jul - 31 Dec 2011		1 Jan - 30 Jun 2012		1 Jul - 31 Dec 2012	
IV	**F**	**p-value**	**F**	**p-value**	**F**	**p-value**	**F**	**p-value**
chTS_global	0.12	0.73	6.66	0.01*	0.32	0.57	1.90	0.17
chTS_global_1	0.83	0.36	1.57	0.21	0.87	0.35	0.29	0.59
chTS_global_2	0.58	0.44	0.59	0.44	0.01	0.90	0.05	0.83
chTS_global_3	6.16	0.01*	0.59	0.44	3.50	0.06	1.36	0.24
chTS_global_4	4.60	0.03*	0.84	0.36	1.42	0.23	0.00	0.95

Although the coefficient for the change in global social media sentiment was significant for isolated six-month periods, there was no consistency over time in this result for any of the lags tested. The coefficients for significant models were extremely small and some were positive while others were negative. H5 is thus not accepted.

5.4.5.1. Hypothesis 5a (H5a)

H5a: The degree to which customer-oriented social media sentiment is positively associated with stock price performance gets stronger over time.

To test this hypothesis, the model used to test hypothesis 3a was repeated, but separately for the four six-month periods covered by the data for the period 1 January 2011 – 31 December 2012. The results of the general linear model are shown in table 20.

Table 20: Results of GLM for H5a

Time period	1 Jan - 30 Jun 2011		1 Jul - 31 Dec 2011		1 Jan - 30 Jun 2012		1 Jul - 31 Dec 2012	
IV	**F**	**p-value**	**F**	**p-value**	**F**	**p-value**	**F**	**p-value**
chTS_cust	0.36	0.55	0.10	0.75	0.75	0.39	0.67	0.41
chTS_cust_1	2.59	0.11	0.61	0.43	0.00	0.99	0.87	0.35
chTS_cust_2	0.69	0.41	0.06	0.81	3.57	0.06	0.54	0.46
chTS_cust_3	1.47	0.23	0.00	0.98	0.12	0.73	2.89	0.09
chTS_cust_4	0.00	0.98	0.67	0.41	1.65	0.20	1.06	0.30

There were no significant coefficients for the change in customer-oriented social media sentiment for any of the lags tested. H5a is thus not accepted.

5.4.5.2. Hypothesis 5b (H5b)

H5b: The degree to which financial-oriented social media sentiment is positively associated with stock price performance gets stronger over time.

To test this hypothesis, the model used to test hypothesis 3b was repeated, but separately for the four six-month periods covered by the data for the period 1 January 2011 – 31 December 2012. The results of the general linear model are shown in table 21.

Table 21: Results of GLM for H5b

Time period	1 Jan-30 Jun 2011		1 Jul-31 Dec 2011		1 Jan-30 Jun 2012		1 Jul-31 Dec 2012	
IV	**F**	**p-value**	**F**	**p-value**	**F**	**p-value**	**F**	**p-value**
chTS_fin	0.25	0.62	9.62	0.00*	3.53	0.06	3.75	0.05*
chTS_fin_1	5.26	0.02*	3.91	0.04*	0.00	0.98	0.13	0.72
chTS_fin_2	1.84	0.17	1.44	0.23	0.12	0.73	1.29	0.26
chTS_fin_3	0.33	0.57	0.84	0.36	3.89	0.04*	1.45	0.23
chTS_fin_4	0.90	0.34	0.10	0.76	2.40	0.12	3.27	0.07

Although the coefficient for the change in financial-oriented social media sentiment was significant for isolated six-month periods, there was no consistency in this result over time for any of the lags tested. The coefficients for significant models were extremely small and some were positive while others were negative. H5b is thus not accepted.

5.5. Summary of results

Table 22 summarises the hypotheses that were tested and their statistical results.

Table 22: Summary of results

Hypothesis:	Accepted:
H1: Customer satisfaction is positively associated with stock price performance.	NO
H1a: The positive relationship between customer satisfaction and stock price performance differs between non-utility companies and utility companies such that it will be more positive for non-utility companies and less positive for utility companies.	NO
H2: Global Social media sentiment is positively associated with customer satisfaction.	NO
H2a: The positive relationship between global social media sentiment and customer satisfaction differs between non-utility companies and utility companies such that it will be more positive for non- utility companies and less positive for utility companies.	NO
H2b: Customer-oriented social media sentiment is a better predictor of customer satisfaction than global social media sentiment.	NO
H2c: Financial-oriented social media sentiment is a worse predictor of customer satisfaction than global social media sentiment.	NO
H3: Global Social media sentiment is positively associated with stock price performance.	YES
H3a: Customer-oriented social media sentiment is a worse predictor of stock price performance than global social media sentiment.	NO
H3b: Financial-oriented social media sentiment is a better predictor of stock price performance than global social media sentiment.	YES
H3c: The positive relationship between global social media sentiment and stock price performance differs between non-utility companies and utility companies such that it will be more positive for non-utility companies and less positive for utility companies.	NO
H4: The positive relationship between customer satisfaction and stock price performance will be positively moderated by global social media sentiment such that the more positive the global social media sentiment the stronger the relationship.	NO
H4a: The positive relationship between customer satisfaction and stock price performance will be positively moderated by customer-oriented social media sentiment such that the more positive the customer-oriented social media sentiment the stronger the relationship.	NO

Hypothesis:	Accepted:
H4b: The positive relationship between customer satisfaction and stock price performance will be positively moderated by financial-oriented social media sentiment such that the more positive the financial-oriented social media sentiment the stronger the relationship.	NO
H5: The degree to which global social media sentiment is positively associated with stock price performance gets stronger over time.	NO
H5a: The degree to which customer-oriented social media sentiment is positively associated with stock price performance gets stronger over time.	NO
H5b: The degree to which financial-oriented social media sentiment is positively associated with stock price performance gets stronger over time.	NO

The results of the research hypotheses are discussed in chapter 6.

6. Chapter six: Discussion of research results

6.1. Introduction

Chapter six discusses the results of the findings presented. This is done within the context of the literature review and critical evaluation presented in chapter two as well as the research objectives. Data on customer satisfaction, social media sentiment and stock price performance were collected from publicly available sources. The data were transformed so that quantitative analysis could be performed. The main objective of the research was to identify the relationships that exist between customer satisfaction, social media sentiment and stock price performance.

6.2. Discussion of research hypothesis H1 findings

H1: Customer satisfaction is positively associated with stock price performance.

Hypothesis H1 examined the relationship between customer satisfaction and stock price performance over the period 1 January 2011 – 31 December 2012 for 79 listed American companies. In table 5 it was shown that no statistically significant relationship could be found between customer satisfaction and stock price performance at any lag.

The findings are supported by Fornell *et al.* (2006) where they could not find any evidence suggesting that investors react on changes in customer satisfaction in a timely manner. The findings also align with the results from Jacobson & Mizik (2009) where they stated that companies lack the ability to incorporate intangible assets, like customer satisfaction into their stock price valuations. Customer satisfaction is therefore still mispriced by financial markets, as supported by this study.

In their discussion of their research report, Aksoy *et al.* (2008) stated that financial markets do adjust over time and incorporate all information, including customer satisfaction, into the valuation of stock prices. This re-emphasises the debate around the efficient market hypothesis (EMH) in that it is still not very successful in taking all information into account when estimating stock prices. Investors do not act as rational as the EMH states and will selectively choose what information to use when making decisions.

Another reason supporting the findings might be that the ACSI used in this and various other studies in the reviewed literature, does not measure customer satisfaction scores on a daily basis. The ACSI publishes results yearly and with a lag of approximately one quarter. Another limitation resulting in the findings could be that the ACSI measures customer satisfaction as a total unit and that certain components thereof could be more important than others in predicting stock price performance. East *et al.* (2011) agrees with this and suggests that the ACSI does not include the view of neve- customers and ex-customers, thereby skewing the results.

The researcher therefore concludes that customer satisfaction is not positively associated with stock price performance at any lag. The results suggest that customer satisfaction is not incorporated in financial models that determine stock price performance and that the impact of customer satisfaction changes could potentially only be reflected in stock prices much later.

6.2.1. Discussion of research hypothesis H1a findings

H1a: The positive relationship between customer satisfaction and stock price performance differs between utility companies and non-utility companies such that it will be more positive for non-utility companies and less positive for utility companies.

Hypothesis 1a examined the relationship between customer satisfaction and stock price performance, but this time the research attempted to find a difference between utility companies and non-utility companies. In table 6 it was shown that no statistically significant relationship could be found between utility companies and non-utility companies when testing the ability of customer satisfaction to predict stock price performance at any lag. However, a weak relationship could be found at a lag of four days where $p = 0.1$. The researcher used a 5% significance level in her tests. However, various researchers, including Jacobson & Mizik (2009) that tested the ability of customer satisfaction to predict stock price performance, used a 10% significance level. Moreover, their results were not always conclusive, even at a significance level of 10%.

Numerous studies were conducted where the differences between industries were tested in terms of the ability of customer satisfaction to predict stock price performance. The findings were not consistent. Fornell *et al.* (2006) for example found that for services firms, share prices increase irrespective of the direction of customer satisfaction. Anderson *et al.* (2004) concluded in their investigation that industry and customer factors can increase or decrease the effect of customer satisfaction on shareholder value and that customers' behaviour are impacted by industry specific factors.

The findings of the study are corroborated by Jacobson and Mizik (2009) which also compared utility companies and non-utility companies. They also found that there is no difference between the ability of customer satisfaction to predict stock price performance for utility companies and non-utility companies. Utility companies are very monopolistic in nature and an assumption could be that customer satisfaction therefore does not matter as much to them as it does for non-utility companies. However, the results show that customer satisfaction plays a similar role in predicting stock price performance for both utility companies and non-utility companies.

The researcher therefore concludes that customer satisfaction is not positively associated with stock price performance at any lag and that there is no difference in the ability of customer satisfaction to predict stock price performance for utility companies and non-utility companies. The results suggest that customer satisfaction is not incorporated in financial models that determine stock price performance and that the impact of customer satisfaction changes could potentially only be reflected in stock prices much later. The extent to which the stock price adjusts at a later point in time according to customer satisfaction score changes needs further investigation.

6.3. Discussion of research hypothesis H2 findings

H2: Global social media sentiment is positively associated with customer satisfaction.

The relationship between global social media sentiment and customer satisfaction, in particular the ability of global social media sentiment to predict customer satisfaction, was examined with hypothesis H2. As per table 7, it was shown that there was no statistically significant relationship between global social media sentiment and customer satisfaction.

Mostafa (2013) found that social media sentiment analysis could be used to successfully analyse customer satisfaction. Barnes & Bohringer (2011) reinforce this view where they demonstrated that Twitter could be used to analyse and predict user behaviour. Marketers can use social media to respond to questions from consumers and push information to them. In this way, marketers improve their customer service, which will result in an increase in customer satisfaction.

The researcher therefore concludes that, aligned with the results from the study, social media sentiment can be used to understand what a customer's opinion is about a company, its products or its services. Social media sentiment can even be used to identify interventions in order to allow customers to spread positive word-of-mouth (Andrejevic, 2011). However, the results suggest that social media provides a platform for reactive analysis or even real time analysis, but cannot predict customer satisfaction levels of the future with significant confidence.

6.3.1. Discussion of research hypothesis H2a findings

H2a: The positive relationship between global social media sentiment and customer satisfaction differs between utility companies and non-utility companies such that it will be more positive for non-utility companies and less positive for utility companies.

The relationship between global social media sentiment and customer satisfaction, in particular the difference between utility companies and non-utility companies and the ability of global social media sentiment for these companies to predict customer satisfaction, was examined with hypothesis H2a. As per table 8, it was shown that there was no statistically significant evidence showing a stronger relationship between global social media sentiment and customer satisfaction for non-utility companies.

Chowdury *et al.* (2009) tested the ability of social media sentiment to predict customer satisfaction in various industries, including automotive, computer hardware, computer software, consumer electronics, food, personal care and sporting goods. They found statistically significant differences between the mentioned non-utility brands. They furthermore showed that companies that respond to online questions have higher positive sentiment. This is contradictory to the findings of the study based on the effect of the company type alone.

An interesting finding was the effect of the type of company alone. The comparison of the least-squares means shows that the mean of the change in customer satisfaction score (chCSS) was 0.0059 for utility companies and 0.0014 for non-utility companies. Therefore, customer satisfaction differs between non-utility companies and utility companies such that it is less positive for non-utility companies and more positive for utility companies.

The researcher therefore concludes that the ability of global social media sentiment to predict customer satisfaction does not differ between utility companies and non-utility companies. The results and literature suggest that this could be related to the low number of tweets analysed for non-utility companies. Aligned with Lica & Tuta (2011) and Evangelopoulos *et al.* (2012), the number of tweets plays an important role in its predictive ability.

6.3.2. Discussion of research hypothesis H2b findings

H2b: Customer-oriented social media sentiment is a better predictor of customer satisfaction than global social media sentiment.

The relationship between social media sentiment and customer satisfaction, in particular the ability of customer-oriented social media sentiment to predict customer satisfaction, was examined with hypothesis H2b. As per table 9, it was shown that there was no statistically significant relationship between customer-oriented social media sentiment and customer satisfaction.

Although no academic literature could be found that analysed different types of tweets in an attempt to understand what information has a better ability to predict customer satisfaction, it makes sense that tweets related to products or services and how customers feel about them, could predict customer satisfaction more accurately than all the social media sentiment aggregated. This could however not be statistically established by this study. The researcher is of the opinion that these tweets can, similarly to global social media sentiment, be used to analyse customer behaviour (Barnes & Bohringer, 2011) and to encourage positive word-of-mouth (Mostafa, 2013).

The researcher therefore concludes that, aligned with the results from the study, customer-oriented social media sentiment can be used to understand what a customer's opinion is about a company, its products, or its services. Customer-oriented social media sentiment can even be used to identify interventions in order to allow customers to spread positive word-of-mouth (Andrejevic, 2011). However, the results suggest that social media provides a platform for reactive analysis or even real time analysis, but cannot predict customer satisfaction levels of the future with significant confidence.

6.3.3. Discussion of research hypothesis H2c findings

H2c: Financial-oriented social media sentiment is a worse predictor of customer satisfaction than global social media sentiment.

The relationship between social media sentiment and customer satisfaction, in particular the ability of financial-oriented social media sentiment to predict customer satisfaction, was examined with hypothesis H2c. As per table 10, it was shown that there was no statistically significant relationship between financial-oriented social media sentiment and customer satisfaction.

No academic literature could be found that analysed different types of tweets in an attempt to understand what type of information has a better ability to predict customer satisfaction. However, it makes sense that tweets posted by investors and analysts or other Twitter users related to financial performance, stock prices or company reports, could not predict customer satisfaction more accurately than tweets that are focused on products and services or alternatively all the sentiment aggregated. This could however not be statistically established by this study. The researcher is therefore of the opinion that social media sentiment, aggregated or broken down, can be used to analyse customer behaviour and sentiment reactively or in realtime, but it cannot be used to predict future customer satisfaction levels (Barnes & Bohringer, 2011).

The researcher therefore concludes that, aligned with the results from the study, social media sentiment can be used to understand what a customer's opinion is about a company, its products or its services. Social media sentiment can also be used to identify interventions in order to allow customers to spread positive word-of-mouth (Andrejevic, 2011). However, the results suggest that social media provides a platform for reactive analysis or even real time analysis, but cannot predict customer satisfaction levels of the future with significant confidence.

6.4. Discussion of research hypothesis H3 findings

H3: Global Social media sentiment is positively associated with stock price performance.

Hypothesis H3 examined the relationship between global social media sentiment and stock price performance over the period 1 January 2011 – 31 December 2012 for 79 listed American companies. In table 11 it was shown that a statistically significant positive relationship could be found between global social media sentiment and stock price performance at a lag of zero days. No statistically significant relationship could be found between global social media sentiment and stock price performance at a lag of one to four days.

The academic literature supports the findings of this study in that global social media sentiment as expressed on microblogging platforms like Twitter, predicts stock price performance (Tayal & Komaragiri, 2009). Bollen *et al.* (2011) also suggested that social media could be analysed for early indicators of future stock price performance. However, their results showed a lag of up to four days before the impact of sentiment expressed on social media platforms reflected in stock prices. Evangelopoulos *et al.* (2012) also found a positive relationship between social media sentiment and stock price performance and in this case, the lag showed that social media sentiment was only reflected in stock prices after approximately five days.

The researcher therefore concludes that global social media sentiment still predicts stock price performance, but does so at a lag of less than one day. This phenomenon could result due to various reasons. One such reason could be that social media sentiment is reflected in stock prices much faster than it was before, aligned with the efficient market hypothesis. Another reason could also be that this study is more accurate than that done by Evangelopoulos *et al*. (2012) as an example due to the fact that all tweets that mentioned a company, and not only a random sample, were used for the analysis, making the results more valid.

6.4.1. Discussion of research hypothesis H3a findings

H3a: Customer-oriented social media sentiment is a worse predictor of stock price performance than global social media sentiment.

Hypothesis H3a examined the relationship between customer-oriented social media sentiment and stock price performance over the period 1 January 2011 – 31 December 2012 for 79 listed American companies. The aim was to show that customer-oriented social media sentiment can predict stock price performance less accurately than what global social media sentiment can. In table 12 it was shown that a statistically significant relationship could not be found to support the hypothesis at any lag. However, a very weak relationship could be found where $p = 0.12$ for a lag of one day and $p = 0.13$ for a lag of four days. Should this study have been conducted with a significance level of 10%, the results would have been marginally accepted.

The study is partially supported by Lica & Tuta (2011) and Evangelopoulos *et al.* (2012). The authors of these studies stated that opinions are used to reflect the mood and interest of a customer towards a company, its products or its services. They further stated that although their results were interesting and successful they cannot conclude that social media sentiment can predict stock price performance as various elements are at play. An example found by Bollen *et al.* (2011) was that unexpected financial news that was shared on Twitter caused discrepancies in their model of the ability of social media sentiment to predict stock price performance. Therefore, financial-oriented information being shared on Twitter, should have a stronger influence in the predictive power of social media sentiment on stock price performance. If the financial-oriented tweets are excluded from the global tweets, less accurate results will be observed.

The researcher however concludes that customer-oriented social media sentiment is not necessarily a worse predictor of stock price performance than global social media sentiment. The researcher is of the opinion that this could be due to the large sample size and the large number of tweets that were analysed and that if companies were to be analysed independently, results showing the impact of financial-oriented tweets could be more visible.

6.4.2. Discussion of research hypothesis H3b findings

H3b: Financial-oriented social media sentiment is a better predictor of stock price performance than global social media sentiment.

Hypothesis H3b examined the relationship between financial-oriented social media sentiment and stock price performance over the period 1 January 2011 – 31 December 2012 for 79 listed American companies. The aim was to show that financial-oriented social media sentiment can predict stock price performance more accurately than global social media sentiment. In table 13 it was shown that a statistically significant relationship could be found to support the hypothesis at a lag of zero days and a lag of one day. Also, a very weak relationship could be found where $p = 0.08$ at a lag of three days. Should this study have been conducted with a significance level of 10%, the results for three days lag would have been accepted.

By investigating the model coefficients in table 14, it is evident that the change in financial-oriented social media sentiment is positive at a lag of zero days and negative at a lag of one day. Although statistically significant findings were shown, this is probably due to a very large sample size as the trend is essentially meaningless. Furthermore, the magnitude of the correlation coefficients is very small.

However, statistically significant results, supporting the statistical findings of this study, were found by Evangolopoulos *et al.* (2012) where they suggested that certain topics like "buying" predicted stock price performance more accurately than topics about "selling". Furthermore, Wong *et al.* (2008) suggested that analysts and investors trust each other's opinions and that these opinions are used to make decisions and to value stock. Analysts and investors share their opinions on microblogging sites like Twitter in the form of financial-oriented tweets. Zhang *et al.* (2011) suggested that consumers use more emotional words in time of economic downturn or financial struggles, irrespective of whether the context is positive or negative.

The researcher therefore concludes that financial-oriented social media sentiment can predict stock price performance more accurately than global or aggregated sentiment.

6.4.3. Discussion of research hypothesis H3c findings

H3c: The positive relationship between global social media sentiment and stock price performance differs between utility companies and non-utility companies such that it will be more positive for non-utility companies and less positive for utility companies.

Hypothesis H3c examined the relationship between global social media sentiment and stock price performance over the period 1 January 2011 – 31 December 2012 for 79 listed American companies. The aim was to show that differences exist in the findings for utility companies and non-utility companies such that non-utility companies show a stronger positive relationship between global social media sentiment and stock price performance than utility companies. In table 15 it was shown that statistically significant evidence of this could not be found to support the hypothesis at any lag.

Few academic studies tested the relationship between social media sentiment and stock price performance across different industries. Evangelopoulos *et al.* (2012) found significant differences between industries. Notable was also the significant difference in the number of tweets for these industries. Consumer products, banking and investment as well as oil and gas companies had significantly less tweets than other industries. Specifically, they found that the number of tweets per day is negatively related to stock price performance during the same trading day while sentiment that is more positive resulted in higher stock price performance.

The researcher found that there are significantly less tweets per day for utility companies compared to non-utility companies. However, testing the number of tweets for correlation with stock price performance was out of scope for this study. The researcher therefore concludes that global social media sentiment does not predict stock price performance more accurately for non-utility companies than for utility companies.

6.5. Discussion of research hypothesis H4 findings

H4: The positive relationship between customer satisfaction and stock price performance will be positively moderated by global social media sentiment such that the more positive the global social media sentiment the stronger the relationship.

The relationship between social media sentiment, customer satisfaction, and stock price performance, in particular the moderating role of social media sentiment, was examined with hypothesis H4. As per table 16, it was shown that none of the main effects or interactions was significant at any lag. Therefore, there is no moderating effect of global social media sentiment on the relationship between customer satisfaction and stock price performance.

The moderating and mediating effects of social media sentiment on the relationship between customer satisfaction and stock price performance are not well documented. Luo *et al.* (2010) suggest that financial analyst recommendations mediate, at least partially, the relationship between customer satisfaction and shareholder value. The reasoning for the relationship between customer satisfaction and analyst recommendation is given by the logic that information around changes in a company's customer satisfaction levels provides the financial analyst with information on the forecast of the company's potential future cash flows.

Financial analysts and investors base their predictions of stock price performance on the basis of the potential of the company's future cash flows. Satisfied customers buy more from a company and will also recommend that company's products or services to other potential customers. Therefore, due to the higher probability of increased revenue, financial analysts and investors believe that satisfied customers could lead to increased shareholder value. These financial analysts make their opinions known through all types of media, including social media platforms. Moreover, consumers will also express their satisfaction with a company, its products or its services on microblogging platforms like Twitter.

Following the logic and findings, it makes sense that global social media sentiment could potentially moderate the relationship between customer satisfaction and stock price performance. Customer satisfaction alone had a weak relationship with stock price performance and global social media sentiment had a weak relationship with customer satisfaction, but global social media sentiment had a statistically significant relationship with stock price performance. However, the moderating effect could not be demonstrated with the statistical tests that were performed and no literature supports or contradicts the findings. Therefore, the researcher concludes that global social media sentiment does not have a moderating effect on the relationship between customer satisfaction and stock price performance.

6.5.1. Discussion of research hypothesis H4a findings

H4a: The positive relationship between customer satisfaction and stock price performance will be positively moderated by customer-oriented social media sentiment such that the more positive the customer-oriented social media sentiment the stronger the relationship.

The relationship between social media sentiment, customer satisfaction, and stock price performance, in particular the moderating role of customer-oriented social media sentiment, was examined with hypothesis H4a. As per table 17, it was shown that none of the main effects or interactions was significant at any lag. Therefore, there is no moderating effect of customer-oriented social media sentiment on the relationship between the customer satisfaction and stock price performance.

The moderating and mediating effects of social media sentiment on the relationship between customer satisfaction and stock price performance are not well documented. Luo *et al.* (2010) suggest that financial analyst recommendations mediate, at least partially, the relationship between customer satisfaction and shareholder value. The reasoning for the relationship between customer satisfaction and analyst recommendation is given by the logic that information around changes in a company's customer satisfaction levels provides the financial analyst with information on the forecast of the company's potential future cash flows.

Financial analysts and investors make their opinions known through all types of media, including social media platforms. Furthermore, customers will also express their satisfaction with a company, its products or its services on microblogging platforms like Twitter.

Following the logic and findings, it does not makes sense that customer-oriented social media sentiment could potentially moderate the relationship between customer satisfaction and stock price performance. Customer satisfaction alone had a weak relationship with stock price performance and customer-oriented social media sentiment had a weak relationship with customer satisfaction. Also, customer-oriented social media sentiment had a weak relationship with stock price performance. This logic supports the results even though no literature was found that supports or contradicts the findings. Therefore, the researcher concludes that customer-oriented social media sentiment does not have a moderating effect on the relationship between customer satisfaction and stock price performance.

6.5.2. Discussion of research hypothesis H4b findings

H4b: The positive relationship between customer satisfaction and stock price performance will be positively moderated by financial-oriented social media sentiment such that the more positive the financial-oriented social media sentiment the stronger the relationship.

The relationship between social media sentiment, customer satisfaction, and stock price performance, in particular the moderating role of financial-oriented social media sentiment, was examined with hypothesis H4b. As per table 18, it was shown that none of the main effects or interactions was significant at any lag. Therefore, there is no moderating effect of financial-oriented social media sentiment on the relationship between the customer satisfaction and stock price performance.

The moderating and mediating effects of social media sentiment on the relationship between customer satisfaction and stock price performance are not well documented. Luo *et al.* (2010) suggest that financial analyst recommendations mediate, at least partially, the relationship between customer satisfaction and shareholder value. The reasoning for the relationship between customer satisfaction and analyst recommendation is given by the logic that information around changes in a company's customer satisfaction levels provides the financial analyst with information on the forecast of the company's potential future cash flows. Furthermore, customers will also express their satisfaction with a company, its products or its services on microblogging platforms like Twitter.

Following the logic and findings, it does make sense that financial-oriented social media sentiment could potentially moderate the relationship between customer satisfaction and stock price performance. Customer satisfaction alone had a weak relationship with stock price performance and financial-oriented social media sentiment had a weak relationship with customer satisfaction but financial-oriented social media sentiment had a statistically significant relationship with stock price performance. However, the results are not supported by the logic and no literature was found that supports or contradicts the findings. Therefore, the researcher concludes that financial-oriented social media sentiment does not have a moderating effect on the relationship between customer satisfaction and stock price performance.

6.6. Discussion of research hypothesis H5 findings

H5: The degree to which global social media sentiment is positively associated with stock price performance gets stronger over time.

Hypothesis H5 examined the relationship between global social media sentiment and stock price performance over the period 1 January 2011 – 31 December 2012 for 79 listed American companies. The objective was to show that the relationship between global social media sentiment and stock price performance gets stronger over time. In table 19 it was shown that although there was a positive relationship between global social media sentiment and stock price performance for isolated six-month periods, there was no consistency over time for any of the lags tested.

An interesting observation is that the six-month periods that did show a significant result were all in 2011. It seems logical that the more users that participate in social media platforms, the more information will be available to analyse and more accurate statistical results will be possible. Twitter usage has grown at an exponential rate (Mostafa, 2013). Twitter has grown from a niche social network in 2009 with only 35 million active users to the fastest growing social platform in the world in 2013. It is estimated that Twitter had 288 million active users by the end of 2012 and this is an increase of over 40% from the previous year. The USA shows the most growth in terms of active users and 34 million of their 59 million accounts were believed to be active users by the end of 2012 (Globalwebindex, 2013).

However, it is also evident from Globalwebindex (2013) that the demographics of users have changed significantly over the last few years and this is leading to different usage patterns. Users are more careful about posting information on social media platforms based on new privacy acts but they also engage more with brands and customer service staff. Twitter is also being used more often as a communication channel.

The researcher therefore concludes that the ability of global social media sentiment to predict stock price performance does not get stronger over time. Even though more tweets are available for analysis over time due to the increased usage of Twitter, results will be somewhat diluted due to the usage patterns of users that has led to more noise. Noise contained in social media platforms is preventing researchers from finding explicit relationships. Sentiment analysis techniques will have to evolve to filter through this noise and to find patterns that can be used to make informed decisions.

6.6.1. Discussion of research hypothesis H5a findings

H5a: The degree to which customer-oriented social media sentiment is positively associated with stock price performance gets stronger over time.

Hypothesis H5a examined the relationship between customer-oriented social media sentiment and stock price performance over the period 1 January 2011 – 31 December 2012 for 79 listed American companies. The objective was to show that the relationship between customer-oriented social media sentiment and stock price performance gets stronger over time. In table 20 it was shown that there is no statistically significant result for any of the six-month periods for any of the lags tested.

It seems logical that the more users contribute on social media platforms, the more information will be available to analyse and more accurate statistical results will be possible. Twitter usage has grown at an exponential rate from a user perspective and from a number of tweets posted per day perspective. However, it is also evident from Globalwebindex (2013) that the demographics of users have changed significantly over the last few years and this is leading to different usage patterns. Users are more careful when posting information on social media platforms based on new privacy acts but on the other hand they also engage more with brands and customer service staff. Twitter has also been used more often as a communication channel.

The researcher therefore concludes that the ability of customer-oriented social media sentiment to predict stock price performance does not get stronger over time. Even though more tweets are available for analysis over time, the results will be somewhat diluted due to the usage patterns of users that has led to more noise preventing researchers to find explicit relationships. Sentiment analysis techniques will have to evolve to filter through this noise and to find patterns that can be used to make informed decisions.

6.6.2. Discussion of research hypothesis H5b findings

H5b: The degree to which financial-oriented social media sentiment is positively associated with stock price performance gets stronger over time.

Hypothesis H5b examined the relationship between financial-oriented social media sentiment and stock price performance over the period 1 January 2011 – 31 December 2012 for 79 listed American companies. The objective was to show that the relationship between financial-oriented social media sentiment and stock price performance gets stronger over time. In table 21 it was shown that although there was a positive relationship between financial-oriented social media sentiment and stock price performance for isolated six-month periods, there was no consistency over time for any of the lags tested.

An interesting observation is that the six-month periods that did show a significant result were randomly spread across 2011 and 2012. It seems logical that the more users participate on social media platforms, the more information will be available to analyse and more accurate statistical results will be possible. Twitter usage has grown exponentially over the last few years but so has the usage patterns (Globalwebindex, 2013). Users are more careful when posting information based on new privacy acts but they also engage more with brands and customer service staff. Twitter is also being used more often as a communication channel.

The researcher therefore concludes that the ability of financial-oriented social media sentiment to predict stock prices performance does not get stronger over time. Even though more tweets are available for analysis, the results will be somewhat diluted due to the usage patterns of users that has led to more noise. This noise is preventing researchers from finding explicit relationships. Furthermore, other factors like sudden financial announcements and financial distress lead to consumers using more emotion in their posts and this can impact the results of the relationship between social media sentiment and stock price performance as have been suggested by Raithel *et al.* (2012) and Zhang *et al.* (2011). Sentiment analysis techniques will have to evolve to filter through the noise and to find patterns that can be used to make informed decisions.

6.7. Conclusion

The study examined the relationships between customer satisfaction, social media sentiment and stock price performance. Table 23 summarises the research results and the academic literature that supported or contradicted the findings.

Table 23: Research results related to academic literature

Hypothesis:	Accepted:	Support:	Contradict:
H1: Customer satisfaction is positively associated with stock price performance.	NO	Fornell *et al.* (2006); Jacobson & Mizik (2009); Aksoy *et al.* (2008); East *et al.* (2011)	N/A
H1a: The positive relationship between customer satisfaction and stock price performance differs between non-utility companies and utility companies such that it will be more positive for non-utility companies and less positive for utility companies.	NO	Jacobson & Mizik (2009); Fornell *et al.* (2006); Anderson *et al.* (2004)	N/A
H2: Global social media sentiment is positively associated with customer satisfaction.	NO	Mostafa (2013); Barnes & Böhringer (2011); Andrejevic (2011)	N/A
H2a: The positive relationship between global social media sentiment and customer satisfaction differs between non-utility companies and utility companies such that it will be more positive for non- utility companies and less positive for utility companies.	NO	Lica & Tuța (2011); Evangelopoulos *et al.* (2012)	Chowdury *et al.* (2009)
H2b: Customer-oriented social media sentiment is a better predictor of customer satisfaction than global social media sentiment	NO	Mostafa (2013); Barnes & Böhringer (2011); Andrejevic (2011)	N/A

Hypothesis:	Accepted:	Support:	Contradict:
H2c: Financial-oriented social media sentiment is a worse predictor of customer satisfaction than global social media sentiment	NO	Barnes & Böhringer (2011); Andrejevic (2011)	N/A
H3: Global social media sentiment is positively associated with stock price performance	YES	Tayal & Komaragiri (2009); Bollen *et al.* (2011); Evangelopoulos *et al.* (2012)	N/A
H3a: Customer-oriented social media sentiment is a worse predictor of stock price performance than global social media sentiment	NO	Lica & Tuța (2011); Bollen *et al.* (2011); Evangelopoulos *et al.* (2012)	N/A
H3b: Financial-oriented social media sentiment is a better predictor of stock price performance than global social media sentiment	YES	Evangelopoulos *et al.* (2012); Wong *et al.* (2008); Zhang *et al.* (2011)	N/A
H3c: The positive relationship between global social media sentiment and stock price performance differs between non-utility companies and utility companies such that it will be more positive for non- utility companies and less positive for utility companies.	NO	N/A	Evangelopoulos *et al.* (2012
H4: The positive relationship between customer satisfaction and stock price performance will be positively moderated by global social media sentiment such that the more positive the global social media sentiment the stronger the relationship.	NO	Not documented	
H4a: The positive relationship between customer satisfaction and stock price performance will be positively moderated by customer-oriented social media sentiment such that the more positive the customer-oriented social media sentiment the stronger the relationship.	NO	Not documented	
H4b: The positive relationship between customer satisfaction and stock price performance will be positively moderated by financial-oriented social media sentiment such that the more positive the financial-oriented social media sentiment the stronger the relationship.	NO	Not documented	
H5: The degree to which global social media sentiment is positively associated with stock price performance gets stronger over time	NO	Not documented	

Hypothesis:	Accepted:	Support:	Contradict:
H5a: The degree to which customer-oriented social media sentiment is positively associated with stock price performance gets stronger over time	NO	Not documented	
H5b: The degree to which financial-oriented social media sentiment is positively associated with stock price performance gets stronger over time	NO	Not documented	

Although many of the research hypotheses were not documented in previous studies, enough literature and logic could be used to give possible explanations for the findings. It seems that the usage patterns of Twitter are progressively causing diluted results due to higher noise levels and that different sentiment analysis techniques will have to be used to filter through this noise to find relationships that are useful for decision making.

7. Chapter seven: Conclusions and recommendations

7.1. Summary of main findings

The majority of the arguments made by previous researchers (Tayal & Komaragiri, 2009; Bollen *et al.*, 2011; Evangelopoulos *et al.,* 2012) regarding the ability of global social media sentiment to predict stock price performance still holds true. Moreover, as part of the unique contribution from the researcher, the study further demonstrated that financial-oriented social media sentiment is a better predictor of stock price performance than customer-oriented social media sentiment or even global social media sentiment. Furthermore, no difference could be found for the ability of social media sentiment to predict stock price performance for utility companies and non-utility companies.

Academics have presented strong arguments that social media sentiment can be used as a strong indicator of customer satisfaction (Mostafa, 2013; Barnes & Böhringer, 2011; Andrejevic, 2011). The study showed evidence that social media sentiment can be analysed to show the level of customer satisfaction at a point in time. However, social media sentiment does not predict customer satisfaction. Furthermore, customer-oriented social media sentiment does not predict customer satisfaction more accurately than global social media sentiment. One potential reason for the findings is that the ACSI does not take never-customers and ex-customers into account when they evaluate customer satisfaction levels. Once again, no differences could be found between utility companies and non-utility companies and the ability of social media sentiment to predict customer satisfaction.

The research results have shown substantial evidence that the debate around the efficient market hypothesis (EMH) and the ability of the market to timeously take all information into account when valuing stock, is still a valid one. The researcher argued that customer satisfaction is not taken seriously enough when shareholders make investment decisions. Customer satisfaction could not be demonstrated to predict stock price performance at any of the lags tested. Furthermore, no differences could be found when the ability of customer satisfaction to predict stock price performance was tested for utility companies and non-utility companies. An interesting argument in the literature was that even though customer satisfaction does not predict stock price performance at any of the lags tested, an investor could get higher returns later, especially if they buy stock of companies that have high customer satisfaction levels (Aksoy *et al.,* 2008).

Another finding by this study was that more users have access to social media platforms through various channels including mobile devices. Furthermore, the amount of information posted on these social media platforms is growing exponentially. It made sense that more posts that are available for analysis would lead to more accurate results over time. However, no consistent positive trend could be found to show that the relationship between social media sentiment and stock price performance gets stronger over time. The researcher argues that social media platforms contain more noise than before due to the demographics of users that have changed as well as their usage patterns. This noise makes it difficult to analyse social media sentiment and to find useful insights.

Consumers express their opinions of a company, its products or its services by using different channels, including social media platforms. Anderson *et al.* (2004) argued that customer satisfaction can predict stock price performance because satisfied customers result in more predictable future revenues and future revenues will increase shareholder value. No study could be found that tested the relationships of customer satisfaction, social media sentiment and stock price performance in the same study. This study attempted to test for any interaction effects that exist between the mentioned variables. The results show that social media sentiment does not have a moderating effect on the relationship between customer satisfaction and stock price performance.

7.2. Recommendations

It is evident from the academic literature and published case studies that social media is widely used by consumers to share their opinions and experiences (Mostafa, 2013). Consumers have become more engaged in brands and they want to actively participate in building these brands. With this, the level of customer satisfaction becomes more visible than before and this can positively or negatively influence various decision-makers, from marketing managers to investors and academics.

7.2.1. Management recommendations

From this study, various management implications and recommendations are formed. One implication that stands out is that traditional marketing methods will not be successful in the future. The face of marketing has changed from information being pushed to consumers to consumers actively participating in brands. The researcher along with Tuli & Bharadwaj (2009) and Luo *et al.,* (2010) recommend that customer satisfaction be measured more proactively by marketing managers. Management should also report on the measurement technique and value thereof in their integrated financial report. This will demonstrate to all stakeholders, including investors, that customer satisfaction is an important focus area for the company and that it is seen as equally important to financial performance.

Furthermore, marketing managers should understand the potential power of social media platforms. Social media platforms and the management of the company's brand on these platforms a well as its communication channel capabilities, should form part of their integrated marketing strategy. Social media platforms provide a low cost means for companies to involve their consumers in product development activities and it also provides a place for consumers to spread positive word-of-mouth. Moreover, social media platforms also provide marketers with a means to have bi-directional communication with their customers and potential customers and they should use these platforms to encourage open conversations with their customers and also reply on their questions and complaints.

Lastly, management need to take note of the hidden insights contained in social media sites. Sentiment analysis can assist companies to proactively track the moods and opinions of their consumers. The insights gained from social media sentiment analysis could assist management to put proactive interventions in place to turn negative opinions around. Investors can also benefit from social media sentiment analysis by identifying financial-oriented sentiment and its trends as well as customer satisfaction levels. As shown in this study, acting on this information could lead to higher future returns.

7.2.2. Academic recommendations

From this study, various academic implications and recommendations are formed. As is evident from the amount of literature available on social media and social media sentiment's relationships with customer satisfaction and stock price performance, this is still a fairly new study field. The results of previous studies as well as this study, opens the door to many possibilities for future research. One of the interesting findings of this study was that the relationship between social media sentiment and stock price performance does not get stronger over time. This is due to the rapid pace at which social media platform users, as well as the amount of data posted on these platforms, are growing. Combined with this, the demographics and usage patterns of social media users are changing. Academics need to find better ways to filter through the noise contained on these platforms in order to find insights that could be used for decision-making. This will allow academics to add to the existing marketing and financial behaviour body of literature.

Furthermore, academics can also extend the scope of their studies to include different types of social media sentiment, as this study has demonstrated, to identify what type of content have better predictive capability. Academics should also study the relationship of social media sentiment with other variables to understand the role that social media plays in other areas of the business. Moreover it is critical for academics to understand how marketing is associated with financial outcomes and what the relationships between these variables are.

Lastly, academics need to stay abreast of the latest technology and usage trends around social media and proactively include these in their future research. This will allow them to put a foundation in place that can be used by managers to explore the potential benefits social media can offer to their company.

7.3. Suggestions for future research

This research identified a positive relationship between social media sentiment and its ability to predict stock price performance. The study also suggests that financial-oriented social media sentiment can predict stock price performance better than customer-oriented social media sentiment or even global social media sentiment. This study focussed on 79 American listed companies for the period 1 January 2011 – 31 December 2012. Further research suggestions are as follows:

a) This study should be repeated in developing countries like South Africa to identify potential differences between developing countries and developed countries when testing the relationships between customer satisfaction, social media sentiment and stock price performance. This study did not include South African companies because the researcher wanted to do a longitudinal study. South Africa only recently started to publish customer satisfaction scores using a similar method to the ACSI. The South African customer satisfaction index or SACSI started operating in September 2012 and a limited number of industries had data published at the time that this research was conducted. The SACSI can be found at http://www.sacsi.co.za.
b) The ACSI was used to collect customer satisfaction scores. A limitation with the ACSI is that they only publish customer satisfactions scores once a year leading to the researcher having to use extrapolation techniques to calculate daily values. Future research could repeat this study but use a different method to determine customer satisfaction scores. One such database that could be considered is Brandindex and it is available at http://www.brandindex.com.
c) This study was one of the first studies that investigated social media sentiment in its decomposed nature. Global social media sentiment's relationships with customer satisfaction and stock price performance were tested alongside customer-oriented social media sentiment and financial-oriented social media sentiment. Future research could find different types of social media sentiment including company generated social media sentiment or employee-oriented social media sentiment. These types of social media sentiments could then be tested with other variables to identify potential relationships.
d) Previous studies have shown that even though customer satisfaction does not predict stock price performance, higher stock returns can be expected in the future should an investor act on changes in customer satisfaction scores (Aksoy *et al.,* 2008). Further research could shed light on when markets adjust to changes in customer satisfaction. Lags of up to six months can potentially be tested.
e) The researcher did not take the demographics of Twitter users into consideration when she performed the sentiment analysis. Future research could categorise tweets according to different demographic criteria and repeat the study to test if different relationships can be found based on the different demographic categories.
f) This study should be repeated using a different classification of company type. One such classification could be consumer products and non-consumer products.

Another classification could be companies with a comprehensive online social brand versus companies with a smaller online social brand or no online social brand. Future studies could also test companies separately and not in an aggregated manner to understand why certain companies might show different relationships between the variables.

g) A more detailed study should be conducted, but this time with hourly changes in social media sentiment and stock price changes. This will allow academics to identify how fast the market reacts to social media sentiment. Investors and managers could use these insights to put the necessary interventions in place to turn negative sentiment into positive sentiment. The number of posts per hour can also be worked into the study to understand what influence that has on the findings.

h) The study could be repeated using data across different social media platforms and not only Twitter. The insights could be valuable to determine which platforms are the most influential in impacting customer satisfaction and stock price performance.

i) Future studies should also research the impact of brand hijacking on social media platforms. The researcher had to remove numerous spam tweets before accurate analysis could be done. Brand hijacking and the spreading of rumours on social media sites can potentially have a very negative impact on customer satisfaction and electronic word-of-mouth. The potential impact of this is worth investigating.

j) Lastly, the social media sentiment analysis tool can be optimised to use better filters in order to remove noise from tweets. This will result in more accurate and reliable results.

7.4. Concluding statement

Customer satisfaction is important to both marketers and investors. Investors have started to realise the potential of acting on customer satisfaction changes because they can use this information to identify stock with potential higher future returns. Furthermore, companies have started to include their customer satisfaction scores in their integrated financial reports thereby showing commitment to keeping the customer satisfaction levels positive. This study demonstrated the predictive ability of social media sentiment. Hidden insights are contained on social media platforms and once analysed can result in better target marketing strategies and more proactive business decisions. Management and academics can therefore not ignore the door of opportunities that has been opened for them to explore.

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Appendix A: Search terms

"***" indicates that the company is an utility company.

Each search phase was constructed as follows: "Search term" lang:en include:retweets since:2009-12-31 until:2013-01-01 where the "search term" denotes the keywords that were searched for as per the table below; "lang:en" indicates that only English tweets should be included; "include: retweets" instructs the search engine to include tweets that were retweeted in the results and "since:2009-12-31 until:2013-01-01" requested tweets for the period 1 January 2011 – 31 December 2012.

Company name:	Search term:
Aetna	aetna
Ameren ***	ameren
American Air	americanair OR "american air"
American Electric Power ***	"american electric power"
Anheuser-Busch InBev	"anheuser-busch inbev" OR abinbev OR "ab inbev"
Atmos Energy ***	"atmos energy" OR atmosenergy
Campbell Soup	"campbell soup" or cambellsoupco
CenterPoint Energy ***	"centerpoint energy"
CenturyLink	centurylink OR centurylinkent
Charter Communications	"charter communications" OR chartercom
Choice	choicehotels
CMS Energy ***	"cms energy"
ConAgra	conagra OR conagrafoods
Consolidated Edison ***	"consolidated edison"
Costco	costco
Del Monte	"del monte" OR delmonte
Dell	dell
Dial	#dial OR @dial
Dillard's	dillards OR "dillard's" OR dillardsstores
DIRECTV	directv
Dole	"dole" or dolefoods
Dominion Resources ***	"dominion resources" OR @dom OR #dom
Dr Pepper Snapple	"dr pepper snapple" OR "dr pepper" or "snapple" OR drpeppersnapple OR drpepper OR snapple
Duke Energy ***	"duke energy" OR dukeenergy
Edison International ***	"edison international" OR conedison
Electrolux	electrolux
Entergy ***	entergy
Exelon ***	exelon
FedEx	fedex

Company name:	Search term:
FirstEnergy ***	firstenergy
Gap	#gap OR @gap
General Electric	"general electric" OR generalelectric
General Mills	"general mills" OR generalmills
H.J. Heinz	hjheinzcompany OR "H.J. Heinz"
Hanesbrands	hanes OR handesbrands
Hershey	hersheys
Home Depot	"homedepot"
Honda	honda
InterContinental	intercontinental OR interconhotels
J.C. Penney	jcpenney OR "j.c. penney"
Jones Group	"jones group" or jonesgroupinc
Kellog	kellogg or kelloggs or kellogs_us
Kohl's	kohls or "kohl's"
Kroger	kroger
Lowe's	"lowe's" OR lowes
Macy's	"macy's" OR macys
Marriott	marriott or marriottintl
Mazda	mazda or newsfrommazda
Nestle Purina PetCare	"nestle purina petcare" or "purina pet" OR @purinaonedog OR #purinaonedog OR @petcentric OR #petcentric
NextEra Energy ***	"nextera energy"
NiSource ***	nisource
Northeast Utilities ***	"northeast utilities"
Orbitz	orbitz
Overstock	overstock
Pacific Gas and Electric ***	"pacific gas and electric"
Papa John's	"papa johns" or "papa john's"
Pepco Holdings ***	"pepco holdings" OR pepcoholdings
Philip Morris	"philip morris cigarettes" OR "philip morris international" OR "philip morris tobacco"
Priceline	priceline
Progressive	progressive
Reynolds American	rai_news OR "reynolds american"
Samsung Electronics	samsungtweets OR "samsung electronics"
Sempra Energy ***	"sempra energy"
Southern Company ***	"southern company"
Southwest air	southwestair OR "southwest air"
Sprint Nextel	"sprint nextel" OR @sprint OR #sprint
Supervalu	supervalu
TD Ameritrade	"td ameritrade" OR tdameritrade
Tyson	tysonfoods
Unilever	unilever
UnitedHealth	unitedhealth OR uhg_aarp_la
US Airways	"us airways" OR usairways

Company name:	Search term:
Vanity fair	"vanity fair" OR vanityfair
Volkswagen	volkswagen or @vw or #vw
Walgreens	walgreens
Whirlpool	whirlpool
Whole Foods	"whole foods" OR wholefoods
Wyndham	wyndham
Xcel Energy ***	"xcel energy"

Appendix B: Customer-oriented dictionary

adoption	delivery	loyalty
advertisement	demographic	marketer
alternative	design	Marketing
ambience	designing	media
assortment	differentiated	merchandise
Audience	differentiation	multichannel
availability	differentiator	online
awareness	dissatisfaction	personal
B2C	emotion	post sale
banner	end user	product
bargain	enduser	promotion
brand	end-user	relationship
branding	event	retain
campaign	excellence	Satisfaction
capability	expectations	satisfied
catalog	experience	Satisfy
channel	feature	segmentation
Client	free	segments
communicate	goods	servicing
communication	image	shopping
community	innovation	showroom
complaint*	label	targeting
complementary	launch	telemarketing
consumer	lifestyle	variety
convenience	logo	Voice
customer	loyal	word of mouth

Appendix C: Financial-oriented dictionary

$	deflation	indicator	provision
%	depreciation	inflation	rate
accounting	deregulation	initial public offering	ratio
acquisition	derivatives	insurance	recession
analyst	disclosure	interest	regulating
annual	dividend	invest	regulator
assets	dollar	investment	reserves
audit	downsizing	investor	results
balance	downturn	invoice	return on investment
bank	earnings	IPO	Reuters
billing	economic	joint venture	revenue
bonds	economy	lease	risk
borrow	equity	liabilities	ROCE
budget	exchange	liquidity	ROI
buying	expenses	loss	Sarbanes Oxley
capital	finance	losses	save
cash	financial	margins	saving
CFO	forecast	merger	securities
COGS	fraud	metrics	sell-off
company secretary	fund	money	shareowners
compensation	GAAP	NASDAQ	shares
compliance	gearing	net	SOX
control	goodwill	net present value	stake
controls	governance	NPV	standards
corporate	governing	NYSE	statutory
costs	gross	overhead	stocks
CPI	hedge	payment	sustainability
credit	hedging	percent	tax
CSR	IFRS	premiums	trade
currency	income	prescribed officer	traded
debt	index	profit	turnover
			USD