Exploring the Relationship Between Online Sentiment and Company Stock Returns

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Abstract

This dissertation explores the relationship between sentiment expressed on social media towards a company, and that company's equity. Five companies will be used that are listed on the London Stock Exchange, and posts will be collected from Twitter, along with search data from Google Trends. ARIMAX regressions show that extreme sentiment has a bearing on company's stock returns, but daily mean sentiment does not. Furthermore, using sentiment as the sole investment strategy yields a smaller loss than a passive FTSE 100 index tracker across the same time period.

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1. Introduction

1.1 Background

Behavioural economics suggests that understanding the psychology of economic actors often accounts for, and can help us understand, their decision making (Federiks, 2015). Whilst economic actors do not account for *all* of the transactions in the stock market (many are pre-programmed trading algorithms – around 90% according to Kolanovi (Cheng, 2018)); it is still reasonable to expect a potential relationship between stock returns and stakeholders' emotions. This may be that some shareholders of a company are anxious about the future due to negative press, and thus decide to sell, decreasing the price of said stock. Furthermore, it could be that customers are increasingly unhappy with the service provided by a company, which may directly or indirectly impact the value of the company. One potential way to monitor these emotions is through gathering the publicly announced emotions from the stakeholders of a business (the shareholders, customers, media etc), and analyse them through a linguistic tokenisation process called sentiment analysis.

Sentiment analysis is a language processing technique, in which one can systematically quantify the emotion and subjectivity of a large amount of data, whether it be sourced from a book, online reviews or social media posts. There are two approaches: a lexicon-based approach, and a Machine Learning based approach (Medhat et al., 2014). The Machine Learning approach usually is entails manually making a long list of tagged sentiment words, from then on supervised learning can take place. This yields high-precision, but relies on a large corpus (Hu and Liu, 2004). The second approach, and the one this study uses, is lexicon-based, from which several words are manually chosen in the positive and negative sentiment categories, and synonyms and antonyms in an automated process to create a large documentation of categorised words. Note that categorisation on its own is not the only method, for example SentiStrenght's lexicon elaborates on this (Thelwall, 2018), as it uses a -5 to 5 value for each word, thus it could have one of ten values that stipulates the degree of positivity/negatively expressed (the word 'love' may suggest a higher numerical value than the word 'nice'). This is perhaps the largest axiom of this approach, where your research from here on becomes predicated on the assumptions your lexicon makes, further discussion of which is in section 3.1.3 and 3.6.

Large pieces of text can then be analysed, by matching up subjective words to the respective word and integer in the lexicon database being used. If done on a large scale, this can allow the researcher to oversee the consensus on a given topic, or product, which can produce some insightful outcomes.

Some research suggests social media activity is an early commercial and economic indicator (Bollen et al, 2011; Luo et al, 2013). In a similar vein, this paper explores the benefits of using the sentiment of public social media posts that reference a company in giving an indication of a company's valuation (share price). This means that every day during the timeframe of this research (between 04/06/2018 to 17/08/2018), there will be a recording of, a cumulative measure of, and a mean of all sentiment expressed by all Twitter users in the tweets directed towards each of the five companies used in this research.

Additionally, Google Trends will be used to further increase the depth of data around stakeholder’s behaviour towards both the economy and company, as both can indicate a change of circumstance in both the macroeconomy (Preis et al., 2013) and a company’s performance in the stock market (Kristoufek, 2013) respectively.

Given that previous literature in this field is predominantly exploring index movements for whole markets (Mittal and Goel, 2012; Das and Chen, 2007; Bollen et al in 2011), this research will focus on the stock returns of individual companies. Considering that there are 250 companies in the FTSE 250, it is self-evident that the relationship between individual stocks may substantially differ to the market index as a whole. There are however a few studies on sentiment affecting equity such as Yu et al. (2013), and for example Luo et al (2013) who conducted a sample spanning around two years on firm equity and its relationship with social and old media. The firms included however where exclusively tech firms (Apple, Sony etc). Furthermore, exploring if customers’ view towards the company may influence the company’s valuation, is significantly different to exploring if the general populations’ emotions on Twitter effect the stock market as a whole (for example Mittal and Goel, 2012).

To further add to the novelty of this research, the companies used will be operating in the London Stock Exchange, as the Dow Jones and S&P almost has a monopoly regarding being the subject of previous literature surrounding the stock market and sentiment analysis (Mittal and Goel, 2012; Gilbert and Karaholios, 2010). This is important because, for example, it may be that the Dow Jones is inherently unique in the way it operates and its companies’ influences, perhaps due to the New York Stock Exchange being the largest exchange in the world, with a capitalisation of around $19 trillion (Markets.ft.com, 2018). The companies used in this research from the FTSE 250 are: Tesco PLC, BP PLC, Marks and Spencer's, ITV PLC and Ryanair.

1.2 Research Aims and Focus

This thesis will use various statistical techniques such as Autoregressive Integrated Moving Average (Wu and Coggeshall, 2012) and Granger causality (Sørensen, 2005) in order to test the relationship, and predictive power, that sentiment directed towards a UK company has on its share price. It is also important to explore the practical benefits in an investment sense (for example, if this technique was used commercially). This will be done by comparing what the profits/loss is across the period from 04/06/2018 to 17/08/2018 if one was to invest £1,500 in each of the 5 companies, and the shares were bought and sold based solely on the change in sentiment. The return on these five investments will then be compared to what the return would have been if one passively invested the same amount on the FTSE 250 index tracker. In other words, when being used as an investment technique, can sentiment analysis help outperform the market.

In such a case, sentiment analysis would offer value as a method of fundamental analysis when investing in a company's stock. An example of a null hypothesis would therefore be if a substantial rise in positive sentiment towards a company was not reflected by an increase in the company's stock price.

Therefore, the objectives of this research are:

1. To test if a positive relationship exists between the sentiment directed towards the chosen companies on social media and the company's share prices.

2. Ensure research is contextualised within current literature and studies, using a literature review and ensuring the research proposed has sufficiently novel and timeliness, and therefore offers something of value. Equally, if findings are proven to be positive on a small scale of 3 months sentiment data, scaling up in future research must be feasible.

3. The research and findings should be presented in a clear and interesting way, accessible to the reader with high attention to detail. Furthermore, unexpected fringe findings will be expressed, as well as the implications of the project's findings.

4. To compare the performance of the model created by this research against a standard passive investment method for context and profitability comparison.

1.3 Value of This Research

1.3.1 Academia

The findings of this research could be used to initiate more research into the field of sentiment analysis in a corporate or financial context. This could inspire further research from academics to further understand the relationships underpinning the public and media sentiment towards companies and their valuation. Furthermore, if the outcomes of this project are overwhelmingly positive, and perhaps published, such investment techniques could have an even greater impact on commercial, individual or Governmental use.

1.3.2 Commercial

If the outcomes of this project are that of a well-presented use of sentiment analysis as an indicator for stock returns, and particularly if it outperforms passive index investment consistently, then there may be some value in this research commercially. For example, investment banks often use, and continually alter and update, their trading algorithms which consist of many inputs, signals and indicators. This may be mere experimentation however, due to the small sample size of this research, it may require another research experiment for a longer duration of trading days.

1.3.3 Retail Investors

Retail investors are individuals that are investing their own money. Stock market investment is a zero-sum game, and retail investors are competing against commercial investors, who have more resources, and arguably more (asymmetric) information. Having publicly available research on how to use publicly available data as an indicator for stock returns, could potentially help restore some of the asymmetry within stock investment, which could help stabilise stock returns and reduce abnormal losses and welfare loss for individual stakeholders.

1.3.4 Government

The potential Governmental use of this research is perhaps vaguer and more indirect. The Government could however find value in bettering their understanding of the stock market in which the largest UK companies operate in. The new information (sentiment analysis) could provide them with a better understanding of the economy, and its potential threats, even if it the technique can only produce potential threats in the very immediate future (under a week). Furthermore, they could perhaps be further inspired to use sentiment analysis as an alternative to opinion polls regarding the understanding of the public consensus on current political events.

1.4 Thesis Structure

This thesis follows a standard research structure, which is: A review of the previous literature on the topic of sentiment analysis (its origins, its commercial use, and finally its use in the stock market). Next there will be a section dedicated to the potential social and economic implications of research in this field. There will then be a methodology section, which will explain the methods of this research, and the some of the philosophy behind it. After this, there will be a results section, with much of the overall and general findings, and then a more in-depth discussion on the results and its limitations. Finally, there will be an investment simulation of using these findings as a core investment technique, comparing them to a passive investment index tracker, and then the conclusions drawn on the research as a whole.

2. Literature Review

This section of the thesis will review the origins, background and previous literature of sentiment analysis, both for corporate uses and its relationship to the stock market. Some literature will be reviewed in helping understand the stock market with some very well documented theories and evidence, to help decide if fundamental analysis (of which sentiment analysis is a part of) is even possible regarding stock market investment. And finally, its potential economic and social impact

2.1 Background and overview Sentiment Analysis

Sentiment analysis has been around for a couple of decades, but only in the last 6 years has it become extremely popular. This arguable was spearheaded by capitalising on consumers' increasing propensity to write online reviews of products and film (Ervelles et al., 2016), thus giving a perfect opportunity for some supervised Machine Learning techniques to build lexicons and gain sentiment insight. Hu and Liu (2004) provide a good starting point when reviewing the historical literature on the use of sentiment analysis. Hu and Liu were examining customer reviews on e-commerce websites, where there can be thousands of reviews for a single popular product. This of course proves difficult for a someone to sort through, particularly a potential customer. Hu and Liu endeavour to mine the opinions expressed towards a given product from all the customer reviews, categorizing each opinionated review as positive or negative. They broke the sentences in the reviews down and identified into “good” and “bad” seed adjectives that they (manually) understand the sentiment of (around 30 words). Synonyms and anonyms were then applied in order to expand the sentiment lexicon of the reviews using Wordnet, where the words from the review could be better matched with the positive and negative opinion words created (around 6800 in total). The paper succeeded in creating a feature-based summary from a large number of customer reviews.

Tong (2001) also heavily contributed to the sentiment analysis literature early on, having created his own sentiment analysis hybrid algorithm that auto-summarised the sentiment for a e-reviews that had many posts (user reviews). This was using only the most relevant sentences and then processed in a Naïve Bayesian classifier (supervised learning using their tags for training data). This model proved to be accurate, and useful in summarising large amounts of user sentiment.

A famous paper in 2008 by Pang and Lee further brought the sentiment analysis into the academic spotlight. Given the usefulness of online reviews, in that they are rich in human opinion and information, they discovered that 32% of the 2000 American adults surveyed had rated a product or service online. Furthermore, the likelihood they wood review a product went from 20% to 90% for a product that was rated 5-star compared to 4 star. This paper demonstrates in many ways that sharing opinions, and discovering others’ opinions, is a core reason for their time spent online. This is related to the term used early on by Dave et al. (2003) called ‘opinion mining’ – a set of search results for a given item that aggregates opinions. A key part of Pang and Lee’s pilot study was to produce help produce the keywords for sentiment classification.

Furthermore, the popularity of sentiment analysis could be reasoned by the rise of social media, which can be viewed as a database containing hundreds of millions of users’ accounts, where they are documenting sentiments that are most often publicly available; a window into the collective mind and thoughts of society. For example, a system called “Coooolll” was created by Tang et al. (2014) which used supervised learning by concatenating the SSWE (sentiment-specific word embedding) features learning from 10,000,000 tweets. This means utilising the “sentiment information of sentences as well as the syntactic context of words”. Hand crafted features can also be included, as they showed, by including some negation, emoticons and (upper-case) capitals, among others. The effectiveness of this system positive/negative classification has been verified, most notably by ranking 2nd in a SemEval 2014 task 9 that included 45 different systems.

Demographic can also be identified within the data on Twitter, not just treating the users of a social media platform as a collective. A study that captures this is Michell et al (2013), where they collect 80 million words that are geo-tagged, gathered on Twitter in 2011, as well as a annual survey of characteristics of all 50 states.

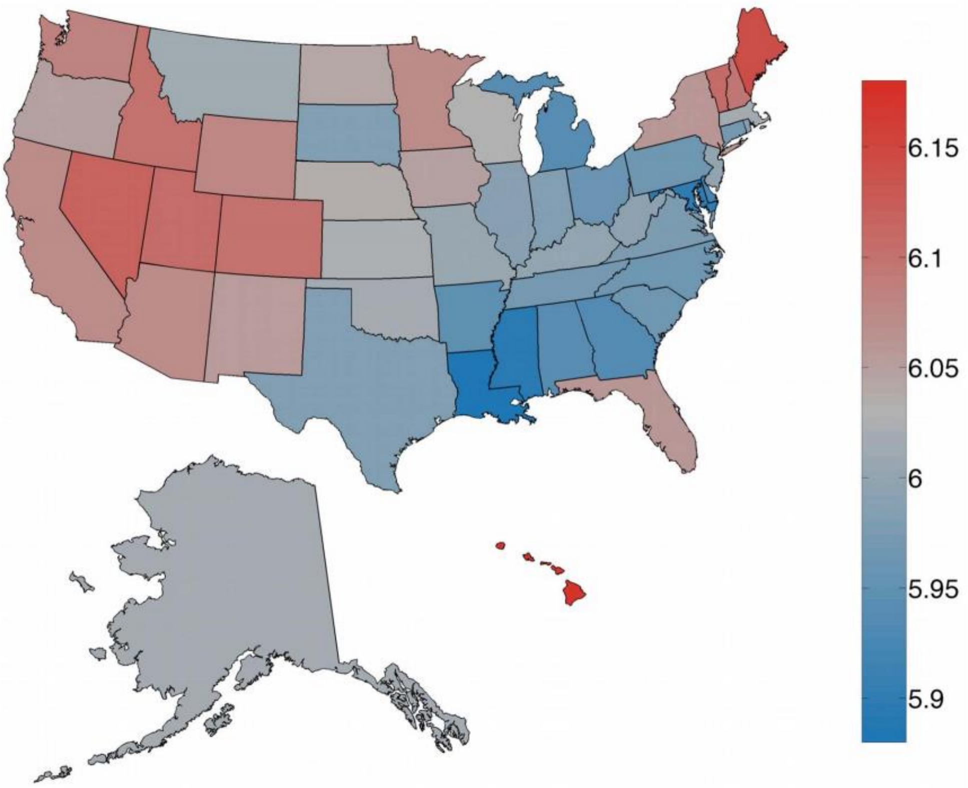

Figure 1 (Mitchell et al., 2013): Average word happiness for geo-tagged tweets in 2011

As eloquently shown on Figure 1, it is not only visible that there are clear differences in the sentiment used in Tweets depending on location, also that there is a clear pattern (sentiment appears similar among clustered neighbouring states, with the West coast clearly Tweeting the most positively)

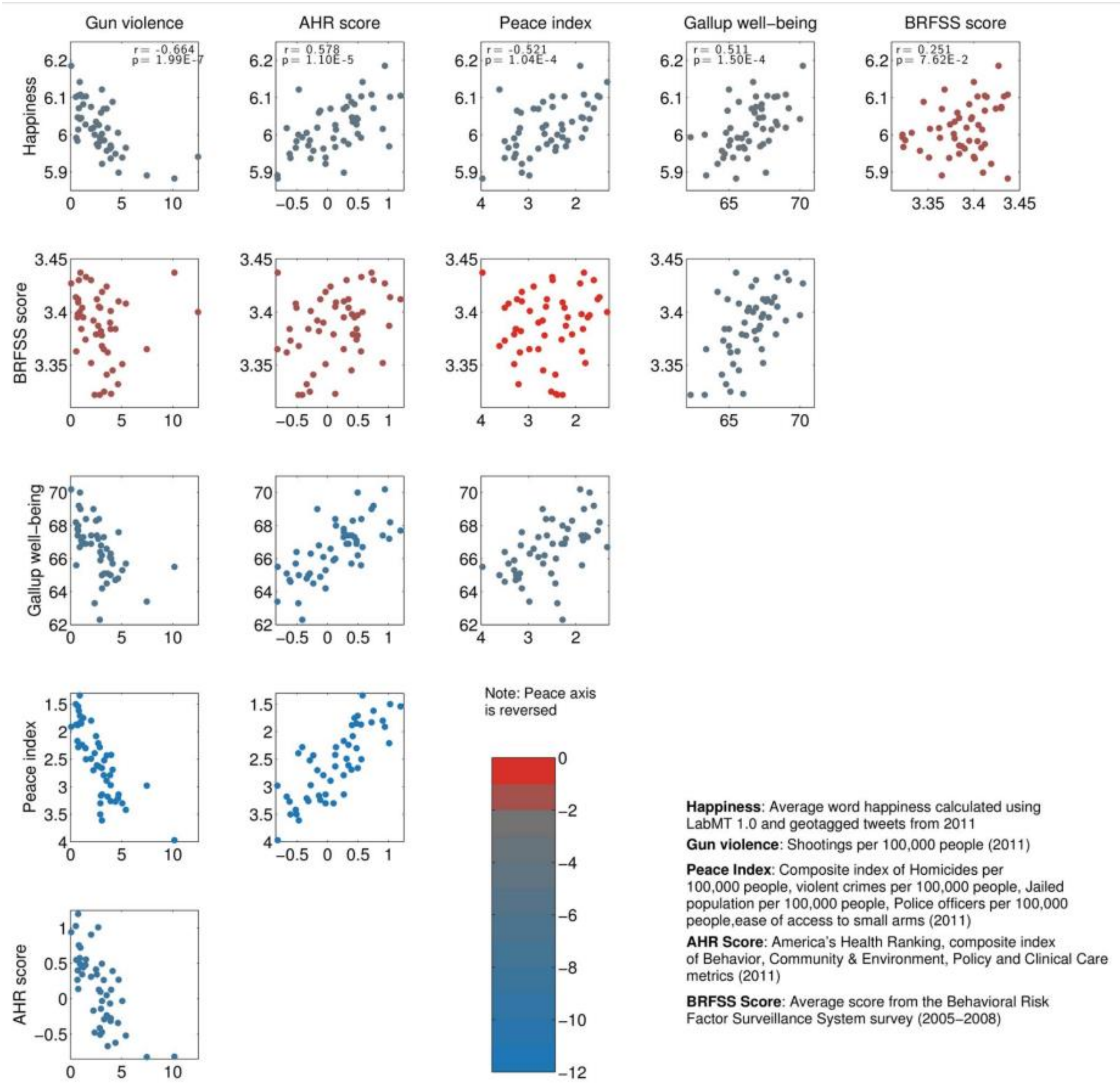

Figure 2 (Mitchell et al., 2013): Scatter plot of different measures of well-being

Sentiment on Twitter is not just a trivial endeavour, as significant relationships with Twitter sentiment and well-being measures are shown to exist, as shown on Figure 2. The finding suggests that perhaps the sentiment expressed on social media can somewhat reflect their well-being, or neighbours' well-being.

2.2 The Role of Sentiment Analysis in Corporate Success

One notable use of sentiment analysis, as reported in the Financial Times (Dempsey, 2013) was from Volkswagan. Volkswagan (Bugatti's parent company) have spent time and money on building a large following on Twitter, but as Dempsey reports, this may not be as much to do with trying to sell their cars to their followers, but rather use their followers' sentiments to gauge the value and current perception of the Bugatti brand. This is perhaps due to the car being a luxury good ($2,000,000+ in price for one unit), meaning that branding is absolutely necessary to drive sales. Furthermore, Dempsey also reports the company Brandwatch (a service to monitor social media for companies) explain that they can achieve 70% accuracy regarding the classification of tweets into positive, negative and neutral sentiment. This service can be hired for a company to gain insight into which direction their new marketing campaign is heading, but Brandwatch explain that human manual interpretation has to take place if a company wants to exceed 70% accuracy.

Market analysis is a very important aspect of business that needs to be considered when operating in - or more pertinently, joining - a market. Market analysis means to understand how big the market is, how fast it is growing, the factors that drive change in the market, the demographic of the market and so on (Chernev, 2007). Sentiment analysis is therefore a fantastic opportunity to add depth to one's market analysis. Recent years has shown consumers to share the consumption-related experiences publicly online, thus, given then increasingly profound ways to analyse Big Data (Machine Learning, for example), marketing departments have a tremendous opportunity to understand market intelligence (Ervelles et al., 2016).

Additionally, Wang and Wang (2014) developed a product weakness detection tool using sentiment analysis. This was done by using both comparative (comparison network) and non-comparative (sentiment analysis score) evaluations of e-reviews. The product weakness finder outperforms other (baseline) methods, as it proves to be more accurate, though interestingly the comparative and non-comparative method are not strongly correlated. These findings could potentially increase social welfare by reducing defects and weak products, as well as improving profits for companies by increasing the value of their stock.

When gaining such personal insight into the public, and the magnitude of the users in size and the predictive power that this can bring, there is also capacity for ethically dubious business to occur. During the 2016 United States presidential election, Cambridge Analytica has been reported to have gathered data on over 50m Facebook users (Kuchler and Garram, 2018; Solon, 2018; The Economist, 2018). This data was allegedly used by Cambridge Analytica to enhance Donald Trump's chances of winning the election to become president, as exposed in an undercover operation by Channel 4 (Kleinman, 2018). Such data could have potentially been used in various ways, such as creating a political profile of users from their historical "likes" and interests, where political advertising could then be bespoke to users' psychology, interests and beliefs, thus maximising their effectiveness. In the aforementioned hypothetical example, it is clearly a breach of ethics, due to the intentional manipulation. The mere gathering of users data to be passed on to a third party however also has ethical considerations on its own, as users potentially are not aware that when they post personal thoughts, it could be used by a third party. Recently, and possibly in light of the recent Cambridge Analytica news, Facebook have applied more and more restrictions on their API (Facebook for Developers, 2018) thus decreasing the amount of user-data available to third parties.

2.3 The Role of Sentiment Analysis in the Stock Market

Gilbert and Karaholios (2010) were very early in reporting of how the emotional state of people (sourced from online social media) can anticipate the future of stock returns. Using over 20 million LiveJournal posts, they identified categorical emotions such as fear and anxiety, and created an Anxiety Index. Using this index, they could anticipate down-swings in the S&P 500 index.

In 2007, Das and Chen used retail investors' (individual investors) comments on stock market message boards (forums) in order to test their relationship with the stock market, using 5 classifier algorithms in combination with a voting scheme. They discover that the aggregated sentiment collected tracked the stock index more strongly than with individual securities. They state their "preliminary evidence" suggests market activity influences (small) investor sentiment on the message boards, which can be described as a confounding variable, and suggest further investigation of their influence from press releases, media outlet news and management announces.

Sentiment analysis was arguably first made popular in the world of investment by Bollen et al in 2011 however, a paper that used 10,000,000 tweets from the year 2008 (excluding January) in order to predict stock returns. They had two methods of estimating the sentiment of the data; using OpionionFinder, and Google-profile of mood states, in order to capture the aggregate mood of the population. OF finder has a large lexicon of nearly 8,000 words (positive/negative classification), while the GPOMS had 6 moods (Alert, Sure, Vital, Kind, Happy and Calm). They found a correlation when they applied the GPOMS to the tweets with the Dow Jones Industrial Average – most notably the 'calm' and 'Happy' mood states.

On the back of this, Mittal and Goel (2012) the following year were seemingly inspired to conduct a similar study using Twitter. They also used Self-Organizing Fuzzy Neural Network (SOFNN) and sentiment analysis to explore stock returns in DJIA. They discovered only calmness and happiness are Granger causative of the Dow Jones index.

Whilst this provides a good basis for using sentiment, Yu et al (2013) took it a step further and compared the sentiment from social media (blogs and twitter) to conventional media (Google News, which reports stories from many reputable sources such as New York Times, Reuters etc.) in how they correlate with a firm's equity. The data used was messages from the public or journalists/editors, and used 56,746 messages from 824 firms, covering six different industries. The findings where that messages on social media has a stronger relationship with a firm's equity than conventional media, despite both having a significant effect. Furthermore, it varied widely within social media (blogs and Twitter had a positive impact, forums had a negative impact). Positive blog posts had a strong effect on stock return, and negative forum posts have a strong negative impact on returns. Yu et al. (2013) do not suggest that sentiment analysis will rectify investors' modest attempts to predict stock returns, but rather merely contribute to our understanding of the impacts of information from stock returns. The most significant recommendation was for firms to utilise the unique leverage of differentiating sources to conduct their marketing strategies on.

Luo et al (2013) also conducted their study on individual firms' equities, and chose large, household-name technology companies. There were many explanatory variables used, such as blog post sentiment, traffic page views, Google search intensity, Google blog posts among several more, and a Vector Autoregressive model was used (VARX), which implied traffic, ratings, blogs and search to be "explained by both past variables of themselves (autoregressive) and past variables of each other (cross effects). The VARX model also attempted to account for feedback loops (a downturn in a firm's equity could cause more future negative blog posts for example). The conclusion of the study was that social-media based metrics are significant indicators of a firm's equity value.

2.4 Google Trends

Google Trends is not conventionally known as a sentiment analysis method but can offer some similar insights. Google Trends is a service offered by Google to view the analytical data surrounding all Google searches (both singular words and phrases) conducted around the world. For example, one can view the amount of times "gold price" is being searched this month compared to the same month a year previous. This is of course a lot of data being gathered, and has some potential surrounding its uses both in business and investment.

It is well researched in the literature of finance that economic actors like react to economic uncertainty due to its effects on the stock market (Boguth and Kuehn, 2013). Lemieux and Peterson (2011) among others discovered that this economic uncertainty drives a pursuit for more information among economic actors, as this is antidote to uncertainty. By this logic, it seems Google Trends is an extremely unique resource, due to Google having a profound global monopoly on internet searches, and is potentially expanding into China where it is currently banned (BBC, 2018).

Preis et al. (2013) analysed 98 search terms surrounding trading, economics, and personal finance (for example, the word "debt"). They discovered that not only does Google Trends help identify the state of the macroeconomy, but it offers insight into the behaviour of the economically active public. They examined the relationship between these search terms and the Dow Jones index, and found the search terms from user based in the US compared to global searches performed better. Lastly, they use the best performing search term ("debt") and used it as the leading indicator for an investment strategy that was simulated from 2004 to 2011. This strategy vastly outperformed the "buy and hold" strategy in comparison, as well as the standard deviation of 10,000 simulations using a random investment formula.

Choi and Varian (2012) also found similar results. Using a seasonal autoregressive model that included Google Trends explanatory variables outperformed more models without these predictors, when forecasting commercial activity with things such as motor vehicles sales, house sales and travel. Vosen and Schmidt (2011) compared Google Trends to survey-based indicators when forecasting consumption. Again, autoregression was accounted for due to the nature of previous consumption being a function of future consumption, and when adding Google Trends data into the model, it outperformed survey-based indicators in almost all experiments conducted.

Kristoufek (2013) arguably discovered one of the most reliably practical uses for Google Trends in the investment industry when using it as a method of diversification. Diversification is paramount to portfolio investment due to it reducing systematic risk. Kristoufek discovered that companies that were high searched correlated with riskiness for that stock (volatility). Popular stocks (according to Google Trends) were thus given a lower weighting to less popular stock in the portfolio. This strategy unequivocally outperformed the homogeneously weighted portfolio and the benchmark index.

Dzielinski (2012) further confirms the value of Google Trends, and does so by only using one search term, "economy". Dzielinski discovers that the measuring the quantity of searches over time for "economy" can be used as an economic indicator, and thus (both theoretically and empirically) can be used as a stock market indicator. Dzielinski uses the search term "economy" to compare with a peer group indicator designed specifically with investors, and outperforms it. The search term backs up the aforementioned theoretical intuition of uncertainty driving the pursuit for more information, as the search query correlated positively with other measure of uncertainty, and correlated negatively with measures of business and consumer confidence.

2.5 Efficient Market Hypothesis

Burton G Malkeil (2003) examines the Efficient Market Hypothesis (EMH), stating "a capital market is said to be efficient if it fully and correctly reflects all relevant information in determining security prices". Here, Malkeil reflects on the Efficient Market Hypothesis, 30 years on from when Eugene Fama and himself wrote the famous paper, "Efficient Capital Market" in 1970. In this dissertation, security prices are stipulated to always reflect available information in an efficient market. This implies that there are abnormal gains or losses to be made in an efficient market, as no under/over-valued stocks exist; if one can predict a stock will rise, it will have already risen. This therefore implies expected profits to equal 0, and for the hypothesis to be accepted, the market must be efficient at all times. Malkeil and Fama (1970) state there are three conditions for the market to be efficient. Firstly, all information (something that may have an effect on a security price) should be available, and free. Secondly, there must be no transaction costs in the market. Lastly, all participants need to be rational, that is, they must react in the same way to new information.

The paper stipulates three kinds of market efficiency: Weak, semi-strong and strong.

Weak form efficiency implies the information set is merely historical prices. In this case fundamental analysis *can* theoretically yield an advantage (using public information to identify under/over-valued stocks), but technical analysis is unviable and thus historical prices bear no meaning to the future price of the stock in question.

Semi-strong efficiency implies only public information is incorporated in the price. Such information is PR stunts, financial statement announcements and published reports; all of these are a factor in reflecting the security's price.

Strong form suggests that all relevant information (private and public) is included in the reflected stock price, thus even (illegal) insider trading cannot even yield an abnormal profiting position. Hence under no grounds is it possible to make excess returns.

The underlying axiomatic claim is one that is the pillar of neoclassical economics; that all economic actors act in a rational way, to make independent decisions on the available information that will maximise their utility (Ackert & Deaves, 2010).

There have been countless criticisms however since these almost-30-year-old stipulations. Strong form efficiency is the boldest claim, but also very difficult to test, as it suggests non-public information is included in the reflective stock price. There are many psychological studies to prove this to be a flawed assumption however. Firstly, people "overreact" to dramatic or unexpected news, as shown in psychological experiments (Bondt and Thaler, 1985). For context, an appropriate reaction has a well-established norm, with Bayes' rule prescribing the standard reaction to new information. This study argues against Bayes' theorem, suggesting recent information is over-weighted compare older information, which becomes less prioritised/weighted. Furthermore, Bondt and Thaler (1985) say this matters at a market level, and is consistent with the overreaction hypothesis, where the "losers" portfolio outperforms the "winners" portfolio. The "losers" portfolio is formed of previous extreme capital losses, and the "winners" have experienced extreme previous capital gains. Thus, by definition, new information appearing about these companies will be digested by economic agents differently, due to differing of expectations. This profoundly threatens the rationality assumption, that economic actors react in the same way conditionally.

EMH is consistent with the random walk hypothesis, which states price changes are random and cannot be predicted; no excess returns can thus be possible. This hypothesis is closely associated with EMH, and is also frequently criticised, most notably by Lo and MacKinlay (1988). Firstly, they observe that autocorrelation exists both with portfolio returns, and individual security returns, which was an interesting early finding that advised further study of stocks to use ‘auto-regression’ in their models. The main finding of this study however was the rejection of the random walk hypothesis. This was predominantly down to the weekly stock market volatility, where a patterned variation (mean-reverting model) in the variance occurred over time (non-stationarity). They suggest this cannot be down to infrequent trading or time-varying volatilities.

This was further backed up by Schwert (1989), where there was an examination of the reasons why volatility in the stock market changes over time, using the Great Depression as the experiment time-period. They suggest aggregate leverage (firms issuing debt in larger proportion than equity for example) is significantly correlated with volatility yet remains only a minor factor in the volatility movements. They also state there is weak evidence to suggest macroeconomic volatility can predict stock volatility. The number of trading days is positively correlated to stock volatility, as well as share trading growth being related to volatility. Furthermore, similar to Lo and MacKinlay, autoregression was accounted for in their study, as an autocorrelation within stock price over time is apparent.

2.6 Social and Economic Impact

Two important things to consider when using sentiment analysis to analyse the stock market is the ethical considerations of where the sentiment is mined from (covered in section 3.6 and 2.2), and how the stock market can affect the economy and society in general. A very well-known event of when the stock market adversely effected the economy was during the 1930s Depression in the United States. 1929 to 1930 can be observed as the catalyst for the great rescission, where stock prices fell almost 20% in the UK, and just over 30% in the US (Mitchel, 1988). When the stock market collapsed, the Federals Reserve reduced interest rates in an attempt to offset this; the Wall Street crash further perpetuated the diminishment of the stock market value (Crafts and Fearon, 2010). This can of course adversely affect dividend payments to stock holders and their personal income, but the relationship between the stock market and the economy in general can be more accurately described as being two-way. The stock market crash is described as *the* iconic characteristic of the Great Depression, although many economists suggest that it was just one of many factors at play (Crafts and Fearnon, 2010).

Some academics argue that stock returns reflect the economy quite accurately. Fisher (1930) defended the extremely high stock prices in 1929 as reflecting the true state of the economy, for example. It is therefore important to consider the more general psychological and sociological stress the public can go under due to the stock market merely signally a downturn, due to it reflecting the economy, or the near-future state of the economy. Any study within this subject thus has to take this into consideration, as well as the issue of privacy, as earlier explained in section 2.2/

3. Research Methodology

3.1 Research Philosophy

3.1.1 Ontology

Ontology is the package of assumptions about what can be known; the nature of existence underpinning a system of ideas (Hubbard et al. 2002). Ontology in the positivist paradigm stipulates that the world exists independently of human knowledge, in contrast to interpretivist ontology where reality is socially constructed and relative. This research paper lies on the assumption that social entities (media, collective tweets etc) should be perceived objectively, and is thus the very nature of quantifying sentiment.

3.1.2 Epistemology

Epistemology is the set of assumptions on how one can understand the world, in other words, how knowledge is arrived at (Hubbard et al. 2002). In this research paper knowledge is assumed to be arrived at through observable, measurable facts using scientific methods. Consequently, if relationships and reliable measurements are observed, predictions can be made rather than mere theoretical abstraction.

3.1.3 Methodology

Methodology is a set of processes which can be used to investigate something, of which is predicated on its epistemological and ontological beliefs. Due to the epistemology and ontology underpinning this research, it can be said to be an investigation within a positivist paradigm. The methods used are typical of a neoclassical paradigm of orthodox economics, where the research is deductive with as large samples as possible and with a range of data that can be compared and analyses. This methodology therefore has an axiom that the researcher is neutral, value-free, and both independent and detached from the research.

Sentiment analysis can often seem like it touches shoulders with interpretivist ideas, due to it being focused on discovering sentiment (a subjective nature of reality). However, it is profoundly imbedded in positivism, due to it being entirely predicated on a lexicon that has been designed a person(s) or in this case Machine Learning (NLTK), to measure – and thus operationalise (objectify) - the subjective emotions of the public and media. A true interpretivist would use ethnographic research in the case of sentiment analysis, by potentially interviewing (open-ended) a small sample of people to truly understand the meaning of each and every participants' linguistic expressions.

This assumption is the biggest threat to sentiment analysis and its standard methodology, that the lexicon used is a "one-size-fits-all" approach to assuming the sentiment behind all observations. It is arguably impossible for a lexicon to be built by someone, or group of people, without their background or biases influencing it. For example, a group of middle-aged middle-class men are unlikely to fully understand the sentiment behind some of the language used by young working-class females, which would influence the construction of the lexicon and its tokenized values, thus compromising the value-free axiom that predicates scientific methodology. This is a serious limitation but is somewhat countered in this research by using a lexicon that is created by supervised Machine Learning techniques, thus being detached from human value and bias. It is however still a large axiom that does not entirely counter the "one-size-fits-all" limitation, because the lexicon is still universally operationalised and applied to all observations.

3.2 Research Strategy

There were 3 main areas of strategy regarding this thesis. Firstly, extensive research was undergone in reading through previous literature on sentiment analysis. In doing this, in an interesting topic was common in recent research; how sentiment analysis may be used to further understand the stock market. Given the elusive nature of the mechanisms that effect the stock market, or variables that can be used to predict it, it is difficult yet important to continue research in this field. Furthermore, it appears much of the research to be geared toward stock market indexes, or merely American markets in general, thus focusing on individual firms within the London Stock Exchange appeared the more vital path.

Secondly, project management was a key focus in order to ensure enough time, and consistency regarding chronology, was there to complete the research piece. A Gantt chat was used in Excel to understand the timeframe and sequential order (or non-linearity) of tasks to be undergone. Additionally, Trello was used in cooperation with the supervisor of this thesis, Marco Palomino, in order to document tasks that had been started, were completed, and were needed to do in the future. This ensured transparency and a place to reference previous completed tasks in the future if needed.

Lastly, skills were necessary to be further developed in order to effectively tackle some of the key tasks of this research piece. Most notably, the programming language R, in the software RStudio was planned to be the dominant software of analysis and data collection. Reading previous literature, exercise books, online forums and online tutorial short-courses were all equally used in developing my skills at the beginning of this thesis endeavour (January 2018 onwards)

3.3 Data Collection

This section will explain the methods, reasoning, sources and objects of what is collected for this piece of research. All data collected and used was between 04/06/2018 to 17/08/2018. This means there are 75 days for the five companies. Saturday and Sunday are not included in the analysis however, as these are non-trading days, where the London Stock Exchange is not open for trading. This removes 20 days, leaving 55 days of data for all five companies' results and analysis.

3.3.1 Tweets

Similar to the Yu et al paper (2013) social media will be used, with Twitter being the source.

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tweets were collected from Twitter users. Tweets were used that contained the company's user handle, usually in the format of "@companyname". This means the tweet written is intended to be read by the company, or just to specifically highlight the company they are talking about to their followers, thus leaving no doubt that the Tweets collected are from stakeholders. This specificity was done to eradicated unwanted tweets; for example if all tweets were used that only contained the company, then tweets using words or mistakes containing "bp" or "itv" would have been used, even if they were not referencing the company.

3.3.2 Sources and Software

TwitteR (a package used in RStudio) will be used to access a Twitter API and retrieve tweets, from the same time frame. Tweets can only be retrieved back 9 days using this API, meaning regular retrieval was necessary. A function which instructs all tweets to be collected (n=200,000) that includes, for example, "@Tesco" in the tweet (the official account representing Tesco PLC).

Worldwide searches on Google can be tracked by using a service they provide called Google Trends. This metric is open for the public to use in order to examine how many searches a specific term or phrase has been executed in a given time period in a given location. Worldwide searches will be used in this research, as FTSE250 consists of worldwide investors, and all other sentiment metrics are worldwide. There is thus a daily index of how many searches each company has received, with 100 being the maximum searches the company has received in the given timeframe. Google Trends will also be used for the search term Economy, reasons explained for in section 3.4.1.

Share price and volume for the companies were sourced from Yahoo Finance (Yahoo Finance, 2018) using the London Stock exchange prices (BP are floated on various markets with differing prices). Closing price was used. Lastly, Gretl (Gretl.sourceforge.net, 2018) software (open source) will be used for the free and effective statistical models, graphs and tests that it provides.

3.3.3 Companies

This project will use the programming language R and Python, along with multiple Rstudio packages to collect, wrangle and interpret the sentiment-driven data at five different companies listed on the London Stock Exchange. Brown and Cliffs' paper (2004) denounces the conventional wisdom that small stocks are most influenced by changes in sentiment, and in this paper all the companies chosen are household names (relatively high amount of mentions) that have a large market capital, as well as a relatively high Beta compared to their competitors.

The companies chosen are: Tesco, Marks and Spencer, ITV, BP and Ryanair.

3.3.4 Variables

All variables used in this study are displayed below in Table 1, and justified in section 3.4.

Close / Share Price	**Daily closing stock price of the company**
S	Daily mean of the Twitter sentiment directed towards the company
VP / Very Pos	A count of how many 'very positive' tweets there are daily towards a company (sentiment scores of 2 or above for each tweet)
VN / Very Neg	A count of how many 'very negative' tweets there are daily towards a company (sentiment scores of -2 or below for each tweet)
GT_S / GT Searches	Google Trend; the quantity of daily searches mentioning the company
GT_E / Economy	Google Trend search term "economy"
FTSE	FTSE 100 index

Table 1 - Variables

3.3.5 Lexicon

The sentiment lexicon used will be the positive and negative word list used by Steven Bird and Edward Loper, who started the Natural Language Toolkit, a project that begun in 2001 (NLTK, 2018). They have produced many, reputable libraries and programs written in Python language, with heavy uses of Machine Learning techniques. This dissertation will be using the Opinion Lexicon they provide cited from Hu and Liu (2004); a list of positive words and negative words. Most are unique words, however there are some misspelled variations of words on purpose, to account for common spelling mistakes of positive/negative words. The list was compiled over many years since 2004 by Hu and Liu, through many different papers (Liu et al., 2005) using various algorithms and Machine Learning techniques, using compiled data from places such as online reviews, and have been cited by 10,000+ journals on Google Scholar alone.

The negative word list contains 4783 words, while the positive word list contains 2006 entries.

3.4 Framework for Data Analysis

3.4.1 Economic Influences

There are many macroeconomic variables than can accumulate to influence the stock market. Unemployment and inflation are the main ones that are used as dependent variables in stock market regressions, as they are proven to be inter-related, often described as being due to the Fisher-effect (Ganzalo and Taamouti, 2017). These macroeconomic indicators are used because they are a factor in the prices of stock stocks that make up the stock market. Finding daily macroeconomic indicators is difficult, and with the short time frame of the observations used in this study, not appropriate. Thus, the FTSE100 index will be included, for various reasons.

Firstly, the companies in this study are not in the FTSE100, they are however in the FTSE 250. This means that there isn't an issue of confounding variables; the independent (variable) is not a factor in the dependent. Rather, the FTSE100 variable will be used to reflect macroeconomic conditions indirectly, but more importantly, will directly reflect the psychology of the (London) stock exchange. Thus, this is an attempt to account for changes in the companies' stock prices that are caused by general changes in the market, perhaps most effectively explained by herd behaviour and investor psychology (Poshakwale and Mandal, 2014).

Kristoufek (2012) and Dzielinski (2012) as explained in the literature review provides sound reasoning for the metric of "Economy" searches on Google Trends to determine behaviour in the stock market. It goes as follows: when an economic actor is worried or losing confidence in the economy (or company in this case), then they immediately treat this worry with seeking more knowledge (particularly given the monetary risk involved). The search term "Economy" will thus be gathered from Google Trends as a daily index for a barometer of the macroeconomy (more specifically, it is the publics' concern for the economy) in the same way Dzielinski (2012) used it.

3.4.2 Seasonality

A Dummy variable is often used to account for seasonality; for example, the Twitter Happiness Index is nonstationary due to people being happier on the weekends (Abdullah, 2015), as well as the January effect. This however is not much of an issue with this research due to stock markets not trading on weekends, and the timeframe of the observations being within a short period of a few months.

3.4.3 Stationarity Tests

In time-series modelling, it is necessary to remove the effects that are caused by variance differing over time or general trends, as this is unaccounted for in our regression model. Stationarity is when the mean and variance of a variable is independent of time, and is thus inconsistent; such non-stationary data can be described as having a Unit Root (Verbeek, 2008). Stock returns are notorious for having a moving average (Campbell and Shiller, 1988), thus often having a trend, and using a model that accounts for a moving average (MA) is important, such as ARIMA.

The ARIMA model will be used for this study on Gretl, as it can deal with non-stationarity in the independent variable by changing d=1 to first difference the y variable in the time series. All the other (dependent) variables however will be unit root tests using the Augmented Dickey-Fuller test on Gretl, which will either reject (or not) the null hypothesis of non-stationarity. If this variable does not have an acceptably low p-value, it will be First Differenced. This is explained further in section 4.1.1.

3.4.4 Stock Return

As shown throughout the literature review, stock return is used rather than the stock price. This is to eliminate any unit root problems that may arise in the time series model. The formula used in this study for stock return is as follows:

$$R_t = \frac{P_t}{P_{t-1}} - 1$$

In the above formula, P is the stock price, t is the day of the stock price (thus P_{t-1} is the previous day's stock price).

3.4.5 Sentiment tokenisation

The list of words from the positive lexicon is stored in a plain text file in the same RStudio directory of the tweets. The tweets, using a function and various packages, are individually examined to 'match' with any of the positive words in the respective plain text file of the lexicon. A Tweet containing the word "love" is then noticed, and a +1 accrues to this Tweet's sentiment. If a negative word is matched, -1 will be deducted from the Tweet's sentiment. Sentiment is thus a whole number, per tweets, and averaged out per day, for each company.

Extreme sentiment (very positive/negative variables) are Tweets where two or more words from the respective lexicon are matched, thus indicating more passion and purposefulness behind the stakeholder's Tweet. This will be separate variables of Very Positive and Very Negative, where 1 denotes that the tweet contains extreme sentiment, and 0 denotes that is doesn't. The daily mean will be calculated across all tweets.

3.5 Models Used

The dependent variable for all analysis will be the daily closing price of the stock. It is evident from the literature reviewed to suspect that there is a link between the stock market and public sentiment.

ARIMA is used for various reasons, one of which is that it accounts for autocorrelation, a the aforementioned problem. Furthermore, ARIMA modelling techniques have been widely used in previous literature (discussed in section 2) in order to analyse the conditional mean.

<u>3.5.1 ARIMAX:</u>

This project will use ARIMA (Autoregressive integrated moving average) to establish a basic stock prediction algorithm (Wu and Coggeshall, 2012), and will also incorporate public mood from social media, a la objective 1. As examined in the literature review, there is a strong argument against the notion that stocks are a Random Walk. With that in mind, and the notion of autoregression, the model needs to account for past price being a function of future price.

$$Y = \beta x_S + \beta x_{GT\_S} + \beta x_{GT\_E} + \beta x_{FTSE} + \phi 1 Y_{t-1} + \phi 2 Y_{t-2} + \ldots + \phi_p Y_{t-p} - \theta_1 \epsilon_{t-1} \ldots - \theta_q \epsilon_{t-q} + \epsilon t$$

p is the number of lagged values of Y (AR nature of model)

q is the number of lagged values of the error term (MA nature of model)

d is the number of times Y has to be differences to produce the stationary Y

There will be two variations of the ARIMAX model used. The first, which is the one denoted above, will have four explanatory variables; the average daily sentiment score from Twitter, from the media, daily Google Trend searches for the company, and finally the FTSE100 index. The second ARIMAX model will use the extreme sentiments (very positive and very negative) as different variables from Twitter instead of the daily sentiment (S), and the remaining three explanatory variables from the previous model will also be used. The degree to which each of these variable has an impact on the stock price is the Betas of each component.

The two models differ because one will show general mean daily sentiment, which is a fair representation of how stakeholders feel towards the business on a given day, and extreme sentiment, which highlights the extreme opinions expressed from stakeholders, whilst filtering out the more tame, diplomatic or general opinions expressed. The FTSE100 index, as explained, will factor in the general stock market psychology that factors into the companies' prices, and Google Trends further adds to both models factoring in the general public's quest to seek more knowledge on the respective company on a given day, as explained by Boguth and Kuehn (2013) in the literature review, can derive from uncertainty.

3.5.3 Investment Simulation

For the investment simulation (comparing the results to passive investment on the FTSE 250 index), sentiment from Twitter will be used as the sole, leading indicator for the purchasing or selling of stock. The sentiment used will be the daily average. A one-day-lag model will be used, to ensure realistic investment practice. The model will be a simple IF statement, that if the sentiment on the current day be greater than it was yesterday, £1,000 should be spent on buying the initial stock. The amount of shares needed to then pay for £1,000 of stock in that given company will be calculated, and this amount of shares will then be used in every future purchasing/selling of stock. If the function result is the same instruction two days in a row ("buy" two days in a row because sentiment has increased over three days) then the investment strategy is to be inactive for that day. The 1-day-lag model will presume itself with knowing the sentiment on that day (before the markets open at 8am, and assumes that this will reflect the sentiment of the day as a whole), with the function concerning itself with if today was more positive or negative than yesterday.

3.6 Limitations of Methods Used

There are several issues that surround the collection of messages on Twitter. Firstly, there is an ethical consideration that has to be made, that these are the tweets from the public that were intended for their followers to read, not necessarily be used by an unknown person for research. The nature of Twitter being very public however, with the option that users can change their tweets to private, is what puts the use of Twitter APIs on the 'right' side of ethical consideration. Furthermore, one cannot be sure that all tweets are authentically the public, as there have been many cases of bots, in particular Russian Tweeting bots which were rife in the 2016 US presidential election (Swaine, 2018), cannot be avoided for the samples used in this research. To elaborate, 66% of shares from popular website tweets that contain a link, are bots, and among news sites 66% of tweeted links are made by bots (Wojcik et al., 2018). Bots however, due to the motivation behind their existence, tend to tweet links, but more importantly so not tend to direct sentiment-laden tweets at a specific company using "@", given the specificity of the tweet, thus this should not discredit this research results to any credible degree. The only credible circumstance in which this becomes an issue – but evidence of this does not exist - would be that companies (and more specifically, the ones related to this thesis) are using bots to tweet fabricated negative experiences of their consumer experience with their competitors.

There is also a potential limitation with the participants of the stock market, and their investment techniques. CNBC reported (2017) Marko Kolanovi's notes to clients (head of derivatives research for JP Morgan) saying "Fundamental discretionary traders" account for roughly 10% of global trading volume. This means that classic fundamental analysis is not as popular as it once was, with passive and quantitative (algorithmic) trading accounts for roughly 60%. Whilst there is no research on this topic for the FTSE specifically, it is a fair assumption that the London Stock Exchange has followed this trend. This poses a threat to the logic of why a company's stock might be influenced by its online sentiment –the price generally reflecting customer experience for example. This logic is somewhat under threat from Kolanovi's statements, however it does not necessarily threaten that there may still be a potential relationship. There are a number of reasons why the relationship between sentiment and stock price may still be present (for example, the algorithms themselves may include sentiment as one of their inputs). The theory is not the purpose of this thesis, rather the exploration of the relationship itself, and a potentially viable investment strategy if further research was conducted.

Another limitation is the large axiom that the lexicon lies on, presuming the sentiment of a large list of words. The problems here are two-fold (both philosophical and practical): firstly, the lexicon used in this thesis, first used by Hu and Liu in 2004 but later developed, had an original list of words manually tagged with a sentiment classification, and then synonyms and antonyms applied to grow the list. This violates the positivist axiom that research is value-free; here, researcher interpretation *is* a part of the methodology, even if only briefly. This axiom violation is even larger in the Machine Learning approach to sentiment analysis however, due to the original list of manually tagged words usually being longer before the supervised learning process is used (Medhat et al., 2014). Furthermore, this list is grown exponentially by synonyms and antonyms, which could exacerbate any initial mis-judgements. Secondly, there is an assumption that all Twitter users have the same interpretation of these words, and apply the same meaning and sentiment behind them that is consistent with the lexicon's interpretation.

Finally, another limitation of this study is that data has been collected over a short period, 63 days. This is not a particularly long period for any time series analysis or testing of a relationship. The observations are however very large (

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tweets). This paper therefore is not to conclude if there is a definite relationship, or if is a technique that can be securely and reliably used for investment purposes, but rather a short exploration to the relationship and potential benefits, from which further research can be conducted on the back of this thesis.

4. Results and Discussion

4.1 Preliminary Tests

4.1.1 Unit Root Test

This was examined in this paper by assessing if the average variance is constant over time, and if there is a clear trend in the data. If a variable is observed, through the Dickey-Fuller test, to be nonstationary, then the First Difference will be taken of this variable. This means to calculate the difference between the successive observations

The null hypothesis is non-stationarity, thus

p-value > significance level = cannot reject the null = non-stationarity

The ADF test is done both with constant, and with constant and trend.

With constant model: $\Delta y_t = \alpha + \gamma\, y_{t-1} + \varepsilon_t$

With constant and trend model: $\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \lambda_t + \varepsilon_t$

β_t represents the time trend coefficient, whilst α represents the constant (Y axis intercept). $\gamma = 0$ is the condition that carries out the test under the null hypothesis.

** and *** represents the 5% and 1% significance level respectively. Results are shown in B of the appendix.

There were 10 variables that had to be differenced among all variables for all companies. A common variable that was nonstationary was Google Trends, which more often than not showed signed of variance change and change in the mean.

All independent variables therefore will be stationary in the ARIMAX models that are run. The dependent variables will be dealt with slightly differently: by making d=1 in the p, d, q.

4.1.2 Descriptive statistics

The trading days of the observations is between 04/06/2018 and 17/08/2018, thus 55 different days of observations. It is clear that Ryanair suffers from the most negative tweets, with a mean of -0.25, the only company that has on average more negative sentiment per day than positive. Furthermore, Ryanair have the most extremely negative tweets (tweets containing 2 or more negative words) as a percentage of all tweets (9.68%). This could be due to recent strikes, which has affected 70,000 customers (Independent, 2018) and issues with their service that have been published in the media (Pearson-Jones,2018).

On the other hand, Marks and Spencer have the most positive sentiment from the tweets gathered, with and average score of 0.44 per tweet, and 17.45% of tweets being ‘very positive’. The company with the most tweets, by far, was ITV with 176055 tweets. This is expected due to the 2018 world cup taking place on ITV TV channels and yields many viewers.

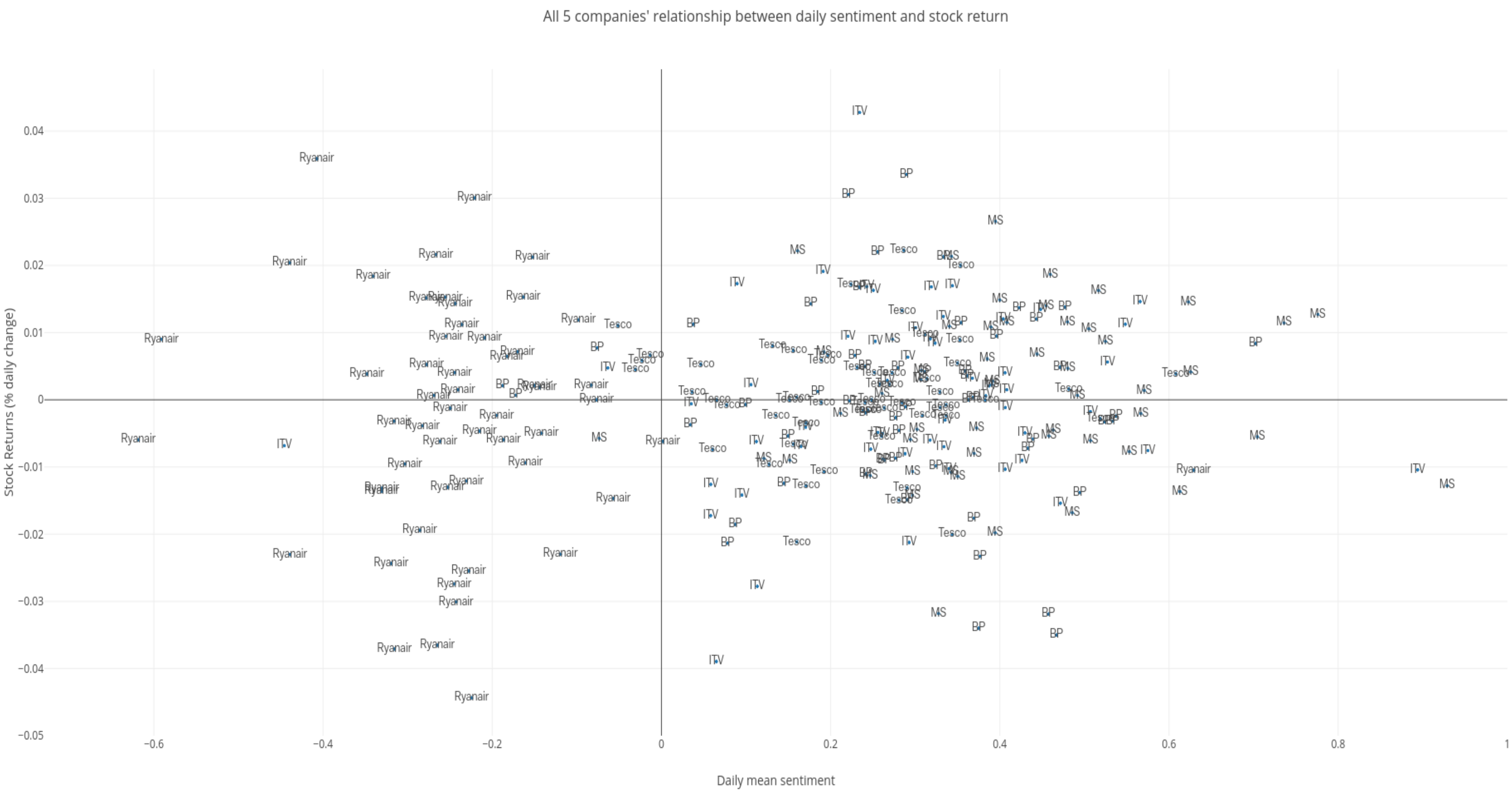

Figure 3: All 5 companies' daily mean sentiment visualised. Approximately 6 extreme outliers were excluded for a more appropriate graph display.

Company	Tweets (n)	No. of Very Negative tweets	% very Negative tweets	No. of Very Positive tweets	% Very Positive tweets	Mean
Marks & Spencer	57642	1366	2.3698	10058	17.449082	0.4438604
BP	11384	329	02.89	779	6.842937	0.2877723
Ryanair	96236	9315	09.6793	4256	4.422461	-0.2505403
Tesco	111507	5064	04.5414	11476	10.291731	0.2073143
ITV	176055	6591	03.7437	21123	11.997955	0.2931527

Table 2 – Descriptive Statistics

4.1.3 Correlation Analysis

The results for the correlations between the 5 companies are in tables 3 to 7. Given that Sentiment positively correlates strongly with Very Positive sentiment, this signals consistency in the methodology. There is a mix of positive and negative correlations regarding stock returns and daily sentiment, as well as Google Trend company searches and sentiment. This signals doubt for a potential relationship, however this is not a significant finding yet, as the ARIMAX model will more tactfully explore any potential relationships, where it can account for many other factors such as lags and autoregression.

4.2 Estimating Parameters

The nature of the ARIMAX models was identical for both, where integration is apparent and so the y variable is differenced (stock returns) with d=1 in the {p,d,q} to make sure to account for nonseasonal differences. {1,1,1} was used for {p,d,q}. This was decided due to account for autocorrelation using the correlograms that produce ACF and PACF results of the analysis (appendix B) which is why a lag for the stationary series was applied, hence p=1. A nonseasonal approach was taken, due to the short time frame of the data.

Exact Maximum Likelihood was used on the time series models.

4.2.1 ARIMA: Extreme Sentiments

Dependent variable: Share price										
	Tesco		**ITV**		**BP**		**Ryanair**		**M&S**	
	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value
Phi_1	−0.143773	0.3038	−0.206587	0.2486	−0.0828821	0.5743	0.338061	0.0118 **	0.116832	0.4768
Theta_1	−1.00000	<0.0001 ***	−0.888421	<0.0001 ***	−1.00000	<0.0001 ***	−1.00000	<0.0001 ***	−0.970045	<0.0001 ***
VP	−0.00188201	0.0025 ***	0.000939843	0.9697	0.0441055	0.0579 *	0.0348102	0.5174	0.00757182	0.6906
VN	0.0993866	0.0468 **	−0.0968525	0.0412 **	−0.0346662	0.1804	0.209511	0.0298 **	0.00379811	0.9798
GT_S	−0.000549953	0.0442 **	8.16188e-05	0.3256	−0.000545927	0.0632 *	−0.000478152	0.0625 *	9.52609e-05	0.6735
FTSE	4.84457e-05	0.0034 ***	0.000118362	0.0003 ***	0.000211477	<0.0001 ***	7.88398e-05	0.0194 **	9.38662e-05	0.0002 ***
GT_E	−0.000158284	0.1726	−5.15422e-05	0.7644	7.96557e-05	0.4939	8.35970e-05	0.6796	5.31596e-05	0.6924
Standard D of innovations	0.007125		0.011910		0.007623		0.016452		0.010172	
Akaike Criterion	−360.4365		−301.2739		−346.3515		−265.6622		−317.3677	

Table 8: Results of the 1st ARIMA regression; significance codes are 0.05 '*', 0.01 '' and 0.001 '***'.**

All regressions run for the 5 companies in the Extreme sentiment model resulted in some significant findings. Firstly, it is interesting to see 4 out of the 5 companies' Very Positive variable being positively correlated with stock returns (the dependent variable). However, despite this only BP has any vague statistical significance among the positively correlated, with a p value of 0.059. The one truly significant finding for Very Positive, was for Tesco, which was the only negative coefficient, and had a very significant p-value of 0.0025. Perversely, Tesco's Very Negative variable is positively correlated with stock returns, with a coefficient of 0.0993 and a p-value of under 0.05. The null hypothesis can thus be rejected in both of these findings for Tesco, which goes directly against the expected results (mentioned in objective 1). Ryanair and ITV however have a more expected positive coefficient for Very Positive tweets, both with p-values under 0.05.

It appears Google Searches for the company has somewhat of a relationship on stock returns for Tesco, BP and Ryanair, but Tesco being the most significant (the coefficient being negative regarding Tesco, however). Finally, it appears the FTSE 100 has the most profound and consistently vital input into the stock price of companies, with a highly significant p-value, and consistently positive coefficient, for all 5 companies.

4.2.2 ARIMA: Average Sentiment - Removing Extreme Sentiment

Dependent variable: Economic Growth										
	Tesco		**ITV**		**BP**		**Ryanair**		**M&S**	
	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value
Phi_1	−0.0828711	0.5760	−0.112510	0.4889	−0.0898763	0.5382	0.321502	0.0152 **	0.147663	0.3542
Theta_1	−0.894197	<0.0001 ***	−0.913500	<0.0001 ***	−1.00000	<0.0001 ***	−1.00000	<0.0001 ***	−1.00000	<0.0001 ***
S	−0.00655597	0.4633	0.00723206	0.3503	0.00380048	0.5466	−0.00310557	0.8413	0.00220750	0.7740
GT_S	−0.000533741	0.0891 *	8.90639e-05	0.2849	−0.000551529	0.0732 *	−0.000488469	0.0696 *	0.000302496	0.2733
FTSE	5.88290e-05	0.0009 ***	9.59081e-05	0.0014 ***	0.000207135	<0.0001 ***	7.94767e-05	0.0230 **	5.23769e-05	0.0621 *
GT_E	−0.000174313	0.1872	−2.94572e-05	0.8641	4.73421e-05	0.6910	0.000109872	0.6047	0.000145188	0.4426
Standard D of innovations	0.007767		0.012236		0.007921		0.017156		0.011003	
Akaike Criterion	−355.6508		−300.3449		−344.2736		−263.1848		−316.0764	

Table 9: Results of the 2nd ARIMA regression; significance codes are 0.05 '*', 0.01 '' and 0.001 '***'**

The sentiment variable appears to have underperformed the extreme sentiment as per the previous ARIMAX regressions, yielding no significant findings. The FTSE 100 index continues to show extreme significance in FTSE 250 firms' equities, and again some interesting relationships with Google Searches for companies, but none that can reject the null hypothesis.

4.3 Further analysis

4.3.1 Predictive power

Despite few significant findings for sentiment and extreme sentiment, it is important still to test the predictive power of the model across all 5 companies. A sub-sample was made from the original dataset in order to understand how accurately the ARIMAX model can predict future stock returns, when the parameters are known. 55 days are included in the analysis, but due to the nature of the autoregression model, only 52 are used. Of this, a sample of 47 is taken, and thus the forecast attempts to predict the final 5 stock return values. The results can be seen in the appendix (F).

Despite Tesco having the most significant findings in the regressions regarding extreme sentiment, BP seemingly has the greatest predictive power in the small sub-sample that was made, with a mean error of 0.0018411. As displayed in appendix E, and below on Figure 5, it forecasts the changes in direction accurately, which is paramount to stock investment.

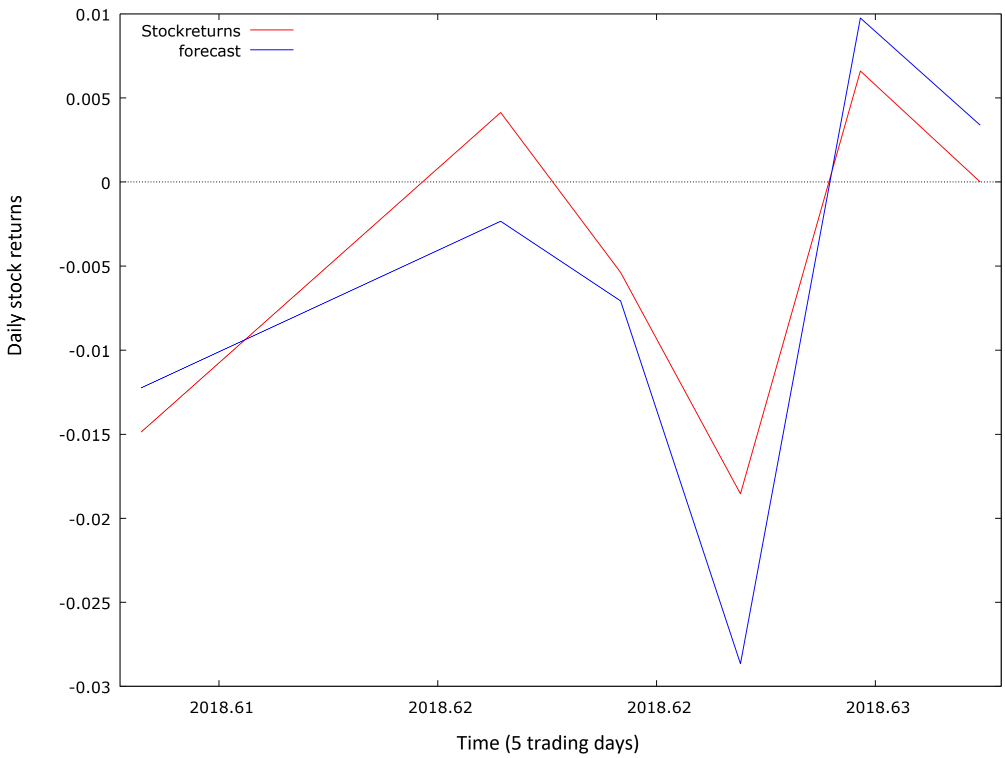

Figure 4: Predicted stock returns using the extreme sentiment ARIMAX model.

4.3.2 Profitability as an Investment Technique

Company	Initial investment	How many shares are bought/sold	Final profit/loss
BP	£1003.98	174	£17.40
Tesco	£1001.16	405	-£92.34
Ryanair	£1002.60	60	-£62.70
Marks and Spencer	£1000.40	347	£97.54
ITV	£1000.87	597	£15.22
Total	**£5009.01**		**-£24.88**
FTSE100 index	£5009		-£109.22

Table 10: Investment simulation

The result shows to be a -0.4967% loss over 55 trading days. Sentiment daily mean doesn't appear an effective investment strategy with no context. Despite three out of the five companies yielding profits, the losses on the two companies Ryanair and Tesco are both very significant, around 6% and 9% losses respectively, which is a large percentage given only 55 trading days. Results would likely have been more accurate if the ARIMAX model was used to dictate investment by using its coefficients, however, this would be unrealistic, as knowing the current FTSE index for example on the day of trading would not be possible. A possible future suggestion is to use the explanatory variables at a long lag, thus having more practical and realistic inputs.

The key finding here however is that it performed significantly better than the FTSE100 index passive investment. The FTSE100 index dropped from 7,741.29 to 7,558.29, and thus the £5009 initial investment (equivalent to the cumulative value of the 5 companies' initial investments) ended up being valued at £4,882 which is a (-2.36%) decrease, far more than the sentiment investment percentage loss. This meets the initial research objective (objective 4) but should definitely be further examined, perhaps with more companies, but most importantly, for a greater amount of trading days).

Given that the FTSE100 is the most considerably the most statistically significant variable in the ARIMAX models, it is no surprise that the sentiment investment technique struggled, both because it is didn't use the FTSE100 variable (due to practicality/realism), and because the 5 companies tended to have a bad 55 days of trading due to the downward turn in the FTSE, which is proven to somewhat reflect the 5 companies' equities.

There was a large assumption in this simulation however, which is that the markets open at 8am. This means sentiment for that day has to be collected and analysed before the market opens. Whilst it is possible to get some data, it may not be a fair representation on the whole day's sentiment towards a company.

4.3.3 Value of the findings

The value of the findings of this dissertation is grounded in building on current knowledge and literature, despite some inconclusive implications of online sentiment. The findings reinforce the importance that knowledge has on stocks, even with the Tesco finding, which is statistically significant but with perverse (opposite of expected, as mentioned in objective 1) coefficients. This reinforces Efficient Market Hypothesis initially, that information reflects prices. However, the investment simulation (outperforming the market) indicates that there could be a time lag, meaning abnormal profits could be possible. This contributes to the growing evidence against EMH's strong and medium form efficiency, which assert stock prices are always immediately reflected by all public information (among other factors). The caveat of this however is the question: is analysing vast amounts of tweets using an API in RStudio publicly attainable? It is in the literal sense, but this assumes that all investors would know that sentiment can affect stock price. This further adds to the value of this research, as it is restoring some asymmetric information between investment corporations and individual investors by publicly publishing information's effects on stocks.

Most importantly, this research is an aid for business success. Businesses spend a lot of money on Research & Development (including market research), and this research contributes to that quantitative research, particularly for investment firms. The value doesn't just end with investors however. Market researchers, product analysts, ad-campaign managers are a few among many departments that can benefit from using sentiment analysis. A/B testing products for example would be one way you could effectively understand public perception, as you could examine their changing opinions towards the company as they bring out new products to market using the same methodology as this dissertation.

5. Conclusion

As examined in the literature review, there has been a standard that has developed in performing sentiment analysis, which is provenly effective in accurately identifying sentiment in text. Hu and Liu (2004) created a well-established norm for lexicon-based sentiment analysis that has profoundly affected this area in academia, this thesis included. This lexicon helped yield some interesting findings that contribute to previous research.

The results of the two novel ARIMAX regressions showed many significant statistical relationships. Firstly, FTSE 100 was profoundly consistent in representing changes in the FTSE 250 companies, and could thus account for herd behaviour and unexpected psychology of the FTSE 250 market. Furthermore, sentiment mean showed no real relationships, but extreme sentiment was shown to have some statistical significance, most notably however, with Tesco which had perverse coefficients. This cannot be explained by the tests done, or the theory covered in the literature review, but it still achieves the 1st research objective (section 1.2). It appears Beta cannot explain this perverse relationship, given that Tesco has very similar (but slightly lower) Beta than Marks and Spencer, which is in the same industry and did not yield the same result.

Google searches for a company showed some vague relationships, however, interestingly the results of the analysis and regression slightly contradicted Dzielinski's (2012) findings, that the term "Economy" can signal changes in the uncertainty in the economy, and thus effecting the stock market. It is likely that having only 5 businesses in this study did not yield a fair representation of the stock market as a whole, and thus making the Google Trend search term for "Economy" somewhat redundant. The FTSE100 index was the variable that had the strongest relationship with the share price, which somewhat signals that there the 5 businesses reflect its neighbouring stock market (the companies used where in the FTSE250, not FTSE100). FTSE 100 index clearly has the most input into the price of the FTSE 250 firms' equities. This is an interesting finding, and a confounding variable can be ruled out due to them being separate markets; i.e. Ryanair's stock price cannot be said to influence the FTSE100 index. Overall, the regressions on the whole were not too significant, but there was many interesting findings within them.

Furthermore, using the mean sentiment of daily tweets directed towards a company as a leading indicator (or regression) to dictate the buying or selling of that stock proved to be an effective investment strategy for 3 out of the 5 companies. Furthermore, for all 5 companies cumulatively, despite it resulting in a loss, it vastly outperformed the FTSE100 tracking index which resulted in a much greater loss. This has some commercial prospects in being integrated into trading strategies for investors due to the ease of this process being automated using an API, particularly with 90% of trades being algorithms (Cheng, 2018). Furthermore, the predictive power shown in section 4.2.3, whilst somewhat underwhelming, still contributes to the prospects of it being a potential trading strategy, due to the refinements and improvements that could be made on top of the techniques and models used in this study.

The investment simulation in conjunction with the (extreme sentiment) ARIMAX regression meets objective 1 and 4 of this research, and can offer genuine value to individual investors by restoring any asymmetric information (or merely unknown to all parties) that may have been present. Though further simulations are recommended, outperforming a stock index is the milestone of any successful investment strategy, not to mention that the simulation could be easily improved by adding some other variables of other successful strategies. These findings also offer value to Government and economic actors in understanding the mechanics of the stock market, which is important for restoring economic uncertainty (and therefore business and consumer confidence). Lastly, the findings of this dissertation can provide great value to market researchers, among other business departments, through understanding the changing public's perception of the company using the methodology used in this research. For example, A/B testing strategy for bringing new products to market could improve the accuracy of the businesses understanding of how well the products are being received. Keywords can even be introduced to provide even more specific insight, for example not only can the company's name be included in retrieving tweets, but also words like "quality" to understand the perception of a products quality of a given company.

Overall, this research met all 4 objectives, despite the various results varying in significance. The research built on top of previous studies and literature due to the amalgamation of different and previously used variables and lexicon (objective 2). However, the methodology was relatively novel in using ARIMAX, as well as companies' equity price within the London Stock Exchange, and also using Tweets directed at company accounts in conjunction with Google Trends. The amalgamation of methods proved the research to be innovative, and the results proved to be valuable. Further research is recommended using a similar methodology; particularly a similar investment simulation but run for more trading days to further confirm the strategy's commercial value.

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Appendices

Appendix A:

BP PLC metadata (daily mean)

Date	Sentiment	Very Pos	Very Neg	GT Searches	FTSE100 Ind	Volume trades	Stock return	GT 'Economy'
04/06/2018	0.5	0	0	77	7,741.29	46152839	0.003815	90
05/06/2018	0.5238095	0.190476	0.009524	75	7,686.80	49637814	-0.00328	79
06/06/2018	0.2222222	0.033333	0.022222	77	7,712.37	40957038	-0.00017	74
07/06/2018	0.2555556	0.111111	0.033333	78	7,704.40	49018704	0.022014	68
08/06/2018	0.3243243	0.135135	0.054054	79	7,681.07	39569180	-0.00984	67
11/06/2018	0.2795699	0.096774	0.032258	79	7,737.43	37748326	0.004796	85
12/06/2018	0.4945055	0.076923	0.010989	80	7,703.81	44792431	-0.01381	69
13/06/2018	0.2635468	0.022167	0.039409	80	7,703.71	39364631	-0.00899	100
14/06/2018	0.3333333	0.04878	0.060976	78	7,765.79	59081596	0.02128	82
15/06/2018	0.467033	0.104396	0.027473	83	7,633.91	86838145	-0.03501	64
18/06/2018	0.443038	0.094937	0	77	7,631.33	31181171	0.012035	77
19/06/2018	0.2413793	0.075862	0.006897	80	7,603.85	40681357	-0.00192	75
20/06/2018	0.2416667	0.0375	0.016667	80	7,627.40	38623201	-0.01104	62
21/06/2018	0.2767296	0.069182	0.006289	81	7,556.44	34319248	-0.00868	66
22/06/2018	0.2209945	0.099448	0.005525	84	7,682.27	45735821	0.030563	58
25/06/2018	0.375	0.0625	0	83	7,509.84	33395773	-0.03399	78
26/06/2018	0.354067	0.086124	0	82	7,537.92	45234687	0.01149	73
27/06/2018	0.2896552	0.089655	0.034483	79	7,621.69	42139998	0.033546	64
28/06/2018	0.3684211	0.080627	0.022396	86	7,615.63	32802922	0.000343	57

29/06/2018	0.4331337	0.055888	0.015968	88	7,636.93	37745377	-0.00721	53
02/07/2018	0.2615385	0.065385	0	80	7,547.85	31472679	-0.00882	62
03/07/2018	0.1764706	0.047059	0.041176	80	7,593.29	43902388	0.014306	66
04/07/2018	0.537234	0.148936	0.037234	82	7,573.09	22333424	-0.00241	64
05/07/2018	0.3589744	0.092308	0.087179	84	7,603.22	26182815	0.00431	61
06/07/2018	0.4390244	0.105691	0.04878	80	7,617.70	28887565	-0.00584	56
09/07/2018	0.3960396	0.118812	0.019802	87	7,687.99	35186880	0.009497	65
10/07/2018	0.7023411	0.026756	0.006689	81	7,692.04	32253320	0.008382	64
11/07/2018	0.4573643	0.062016	0.03876	78	7,591.96	48176864	-0.03189	62
12/07/2018	0.1847134	0.044586	0.089172	86	7,651.33	36722314	0.001227	67
13/07/2018	0.2884615	0.057692	0.038462	89	7,661.87	30987797	-0.00105	67
16/07/2018	0.3764706	0.105882	0.023529	85	7,600.45	32106826	-0.0233	69
17/07/2018	0.4710744	0.123967	0.008264	86	7,626.33	42574302	0.004843	75
18/07/2018	0.3612335	0.07489	0.026432	86	7,676.28	30553725	0.00357	66
19/07/2018	0.4228188	0.120805	0.006711	83	7,683.97	31067188	0.013696	70
20/07/2018	0.2808219	0.061644	0.006849	86	7,678.79	29760504	-0.00456	61
23/07/2018	0.0992366	0.030534	0.022901	86	7,655.79	17220403	-0.00071	69
24/07/2018	-0.18797	0.052632	0.195489	86	7,709.05	27193125	0.002117	65
25/07/2018	0.034188	0.034188	0.145299	83	7,658.26	23645784	-0.0037	69
26/07/2018	0.2767857	0.044643	0.008929	88	7,663.17	24300571	-0.00265	73
27/07/2018	0.2407407	0.098765	0.030864	89	7,701.31	35955255	0.00496	58
30/07/2018	0.5333333	0.008333	0	93	7,700.85	33297688	-0.00317	75
31/07/2018	0.4770318	0.130742	0.021201	100	7,748.76	37588413	0.013793	76
01/08/2018	0.3692308	0.084615	0.023077	90	7,652.91	42795079	-0.01762	63
02/08/2018	0.1447368	0.026316	0.026316	93	7,575.93	37225192	-0.01243	75

03/08/2018	-0.075949	0.012658	0	95	7,659.10	26443493	0.007731	67
06/08/2018	0.0375	0.025	0.0375	97	7,663.78	37294768	0.01124	78
07/08/2018	0.2340426	0.042553	0	94	7,718.48	30243533	0.016761	67
08/08/2018	-0.172414	0	0.068966	100	7,776.65	29589392	0.000694	72
09/08/2018	0.078125	0.015625	0	96	7,741.77	30530058	-0.02133	64
10/08/2018	0.2906977	0.267442	0.186047	98	7,667.01	40006428	-0.01488	69
13/08/2018	0.3111111	0.088889	0.022222	96	7,642.45	36059856	0.004137	79
14/08/2018	0.1496063	0.03937	0.007874	94	7,611.64	36388562	-0.00537	74
15/08/2018	0.0872211	0.028398	0.016227	99	7,497.87	40941196	-0.01855	70
16/08/2018	0.2287582	0.026144	0.019608	100	7,556.38	34292445	0.006605	73
17/08/2018	0.3628319	0.088496	0.026549	96	7,558.59	22117907	0	66

Marks and Spencer’s metadata (daily)

Date	Sentiment	Very Pos	Very Neg	GT Searches	FTSE100 Ind	Volume trades	stock returns	GT 'Economy'
04/06/2018	0.48	0.04	0	60	7,741.29	8860703	0.011595	90
05/06/2018	0.570771	0.135788	0.019563	61	7,686.80	10608989	0.001389	79
06/06/2018	0.622934	0.131198	0.011364	58	7,712.37	9570921	0.014568	74
07/06/2018	0.246792	0.124528	0.033962	63	7,704.40	11774795	-0.01128	68
08/06/2018	0.391451	0.164229	0.028121	59	7,681.07	11998106	0.002766	67
11/06/2018	0.394895	0.129129	0.036036	59	7,737.43	10454778	0.026552	85
12/06/2018	0.161054	0.096032	0.01067	61	7,703.81	16833882	0.02217	69

13/06/2018	0.294333	0.107861	0.02468	60	7,703.71	9741440	-0.00592	100
14/06/2018	0.4	0.132948	0.024277	58	7,765.79	9804856	0.014876	82
15/06/2018	0.350296	0.101775	0.021302	57	7,633.91	13421133	-0.0114	64
18/06/2018	0.485628	0.140696	0.013616	58	7,631.33	9394673	-0.0168	77
19/06/2018	1.185817	0.376122	0.018851	59	7,603.85	10599841	-0.00335	75
20/06/2018	0.928803	0.275081	0.01726	63	7,627.40	10548473	-0.01278	62
21/06/2018	0.566763	0.188679	0.011611	61	7,556.44	9680644	-0.00204	66
22/06/2018	0.454915	0.146223	0.015435	59	7,682.27	6368894	0.013993	58
25/06/2018	0.458052	0.152363	0.02893	59	7,509.84	6161949	-0.00539	78
26/06/2018	0.389499	0.139194	0.020757	59	7,537.92	10690517	0.010829	73
27/06/2018	0.306452	0.111205	0.016978	58	7,621.69	9622545	0.003013	64
28/06/2018	0.296981	0.101266	0.017527	62	7,615.63	8905344	-0.01068	57
29/06/2018	0.302111	0.093668	0.01715	60	7,636.93	8902757	-0.00439	53
02/07/2018	0.408348	0.14882	0.018149	66	7,547.85	16785685	0.011521	62
03/07/2018	0.480366	0.162304	0.027487	74	7,593.29	11451695	0.00469	66
04/07/2018	0.459788	0.14871	0.039454	73	7,573.09	10537459	0.018673	64
05/07/2018	0.736025	0.322981	0.02381	100	7,603.22	16233146	0.011457	61
06/07/2018	0.704442	0.298277	0.016319	75	7,617.70	8218146	-0.0055	56
09/07/2018	0.516807	0.193277	0.021008	70	7,687.99	12194614	0.016271	65
10/07/2018	0.463158	0.163158	0.018421	69	7,692.04	15006020	-0.00448	64
11/07/2018	1.037823	0.473741	0.022313	63	7,591.96	10672358	-0.00129	62
12/07/2018	0.524896	0.204357	0.025934	70	7,651.33	11575307	0.008696	67
13/07/2018	0.625767	0.194785	0.021472	67	7,661.87	9714622	0.004151	67
16/07/2018	0.612903	0.220844	0.019851	68	7,600.45	6755524	-0.01366	69
17/07/2018	0.273148	0.101852	0.020833	63	7,626.33	5769370	0.00901	75

18/07/2018	0.507246	0.181159	0.028986	63	7,676.28	7974029	-0.00607	66
19/07/2018	0.385151	0.136891	0.027842	59	7,683.97	6754942	0.006107	70
20/07/2018	-0.07358	0.089264	0.024125	60	7,678.79	4733999	-0.00575	61
23/07/2018	0.553145	0.13449	0.015184	64	7,655.79	8261748	-0.00771	69
24/07/2018	0.49177	0.141975	0.022634	62	7,709.05	9057510	0.000648	65
25/07/2018	0.372549	0.139434	0.039216	62	7,658.26	6406662	-0.00421	69
26/07/2018	0.44405	0.133215	0.021314	63	7,663.17	4213427	0.006825	73
27/07/2018	0.390476	0.19619	0.024762	60	7,701.31	3338310	0.00226	58
30/07/2018	0.260797	0.106312	0.046512	64	7,700.85	7905387	0.000966	75
31/07/2018	0.151724	0.111494	0.024138	61	7,748.76	10764375	-0.00901	76
01/08/2018	0.32766	0.121986	0.025532	59	7,652.91	10570730	-0.03182	63
02/08/2018	0.394477	0.130178	0.04931	58	7,575.93	10534760	-0.01979	75
03/08/2018	0.340426	0.106383	0.019504	59	7,659.10	5076006	0.010948	67
06/08/2018	0.19214	0.098253	0.019651	64	7,663.78	4664572	0.007107	78
07/08/2018	0.307317	0.078049	0.019512	60	7,718.48	4953976	0.004368	67
08/08/2018	0.775862	0.318966	0.008621	62	7,776.65	6078125	0.012713	72
09/08/2018	0.505245	0.218531	0.04021	59	7,741.77	4972010	0.010571	64
10/08/2018	0.342373	0.122034	0.025424	61	7,667.01	3888627	-0.01079	69
13/08/2018	0.296912	0.149644	0.028504	61	7,642.45	4768456	-0.01421	79
14/08/2018	0.211864	0.107345	0.022599	62	7,611.64	5189815	-0.00201	74
15/08/2018	0.121212	0.110672	0.079051	60	7,497.87	5684875	-0.00873	70
16/08/2018	0.342715	0.120861	0.028146	58	7,556.38	7133783	0.021349	73
17/08/2018	0.369658	0.149573	0.027778	56	7,558.59	5011291	-0.00796	66

Tesco PLC metadata (daily)

Date	Sentiment	Very Pos	Very Neg	GT Searches	FTSE100 Ind	Volume trades	Share price	GT 'Economy'
04/06/2018	0.046512	0.023256	0.069767	75	7,741.29	19946093	247.2	90
05/06/2018	0.151627	0.077663	0.037722	83	7,686.80	20660610	247.2	79
06/06/2018	0.263464	0.099709	0.037846	78	7,712.37	22829564	246.9	74
07/06/2018	0.251759	0.110242	0.040657	75	7,704.40	36949250	247.9	68
08/06/2018	0.248567	0.106017	0.035817	73	7,681.07	43857371	247.9	67
11/06/2018	0.231419	0.09375	0.047297	69	7,737.43	38208949	249.1	85
12/06/2018	0.481547	0.094903	0.031049	67	7,703.81	29619697	249.5	69
13/06/2018	0.51885	0.11246	0.015335	75	7,703.71	23450398	248.8	100
14/06/2018	0.272663	0.108222	0.035137	71	7,765.79	46143447	249.8	82
15/06/2018	0.353639	0.10443	0.029272	69	7,633.91	87905090	254.8	64
18/06/2018	0.189129	0.075949	0.030529	66	7,631.33	25885635	256.3	77
19/06/2018	0.329457	0.099225	0.035659	66	7,603.85	35753106	256	75
20/06/2018	0.284526	0.114809	0.040765	66	7,627.40	35439972	259.4	62
21/06/2018	0.290417	0.138259	0.037308	65	7,556.44	29085684	256	66
22/06/2018	0.286576	0.128205	0.036199	64	7,682.27	29642584	261.7	58
25/06/2018	0.308601	0.101116	0.038739	66	7,509.84	29335705	261.1	78
26/06/2018	0.280801	0.072382	0.030287	65	7,537.92	40553083	257.2	73
27/06/2018	0.23857	0.081463	0.034913	66	7,621.69	31063202	256.8	64

28/06/2018	0.329204	0.107375	0.025959	70	7,615.63	26903323	257.1	57
29/06/2018	0.244173	0.073807	0.024417	73	7,636.93	25962000	256.7	53
02/07/2018	0.135271	0.082169	0.042482	71	7,547.85	44479768	256.1	62
03/07/2018	0.311599	0.152978	0.042006	66	7,593.29	25422787	258.6	66
04/07/2018	0.260283	0.140931	0.044504	71	7,573.09	23931252	257.2	64
05/07/2018	0.352821	0.144103	0.032821	69	7,603.22	25955538	259.5	61
06/07/2018	0.26947	0.134735	0.046345	69	7,617.70	14132956	260.1	56
09/07/2018	0.336513	0.157849	0.039029	72	7,687.99	20724104	259.9	65
10/07/2018	0.34377	0.143131	0.033866	69	7,692.04	54047363	254.7	64
11/07/2018	0.284424	0.112867	0.034612	60	7,591.96	25605316	254.6	62
12/07/2018	0.313931	0.151079	0.040549	64	7,651.33	23820310	255.4	67
13/07/2018	0.382902	0.161638	0.037356	63	7,661.87	18767857	255.4	67
16/07/2018	0.336628	0.141279	0.036628	67	7,600.45	31407349	254.8	69
17/07/2018	-0.01328	0.106918	0.116003	62	7,626.33	38478797	256.5	75
18/07/2018	0.189024	0.141006	0.058689	64	7,676.28	24023402	256.4	66
19/07/2018	0.35	0.144706	0.034118	63	7,683.97	19958799	257.8	70
20/07/2018	0.608117	0.274784	0.026613	62	7,678.79	17842718	258.8	61
23/07/2018	0.170904	0.083333	0.043785	70	7,655.79	13738047	257.9	69
24/07/2018	0.06057	0.064133	0.05285	68	7,709.05	33715352	256	65
25/07/2018	-0.02298	0.055317	0.082587	65	7,658.26	22201812	257.5	69
26/07/2018	0.065517	0.081034	0.06954	69	7,663.17	22956064	257.5	73
27/07/2018	0.159701	0.091703	0.053026	68	7,701.31	20237006	257.6	58
30/07/2018	0.155863	0.117261	0.062637	68	7,700.85	18299547	255.9	75

31/07/2018	0.224124	0.101059	0.04564	64	7,748.76	43146773	260.3	76
01/08/2018	0.127273	0.083636	0.048727	64	7,652.91	28907930	257.8	63
02/08/2018	0.077058	0.075306	0.042907	66	7,575.93	26168982	257.6	75
03/08/2018	0.155855	0.10278	0.053075	67	7,659.10	20530491	259.5	67
06/08/2018	0.240841	0.102102	0.032432	71	7,663.78	36449051	259.4	78
07/08/2018	0.257888	0.087791	0.037037	66	7,718.48	30838529	260	67
08/08/2018	0.131455	0.122066	0.084507	67	7,776.65	29195061	262.1	72
09/08/2018	-0.05135	0.066027	0.121332	66	7,741.77	20013276	265	64
10/08/2018	-0.03072	0.075862	0.09279	65	7,667.01	25247232	266.2	69
13/08/2018	0.171032	0.07473	0.038521	66	7,642.45	21941011	262.8	79
14/08/2018	0.192369	0.09539	0.038156	64	7,611.64	24251588	260	74
15/08/2018	0.160061	0.087652	0.038872	64	7,497.87	39260341	254.5	70
16/08/2018	0.196733	0.097253	0.035635	64	7,556.38	24865400	256.2	73
17/08/2018	0.036245	0.096851	0.096257	61	7,558.59	22908972	256.5	66

Ryanair metadata (daily)

Date	Sentiment	Very Pos	Very Neg	GT Searches	FTSE100 Ind	Volume trades	stock returns	GT 'Economy'
04/06/2018	-0.59091	0	0.318182	72	7,741.29	1783810	0.009004	90
05/06/2018	-0.18662	0.05	0.104225	69	7,686.80	2010411	-0.00595	79
06/06/2018	0.629289	0.345607	0.054393	74	7,712.37	1172793	-0.01047	74

07/06/2018	-0.11929	0.083571	0.099286	74	7,704.40	2739524	-0.02298	68
08/06/2018	-0.26151	0.056037	0.11541	64	7,681.07	4655779	-0.00619	67
11/06/2018	-0.24435	0.036807	0.092239	74	7,737.43	2221253	0.004049	85
12/06/2018	-0.14391	0.035242	0.090308	71	7,703.81	1225924	0.001861	69
13/06/2018	0.001795	0.083483	0.054758	70	7,703.71	1689896	-0.00619	100
14/06/2018	-0.0829	0.029793	0.071244	66	7,765.79	1838069	0.002181	82
15/06/2018	-0.21489	0.037606	0.0967	62	7,633.91	1612200	-0.00466	64
18/06/2018	-0.16063	0.025586	0.076759	73	7,631.33	1563806	-0.00937	77
19/06/2018	-0.25461	0.042627	0.103687	69	7,603.85	1654543	0.009458	75
20/06/2018	-0.15224	0.047761	0.078607	71	7,627.40	2207512	0.021237	62
21/06/2018	-0.16319	0.038194	0.079861	67	7,556.44	2194724	0.015291	66
22/06/2018	-0.0765	0.076503	0.074681	63	7,682.27	1768274	0	58
25/06/2018	-0.24479	0.033545	0.093382	72	7,509.84	2008776	-0.02741	78
26/06/2018	-0.23046	0.024365	0.083249	71	7,537.92	1707254	-0.01208	73
27/06/2018	-0.61819	0.013614	0.034035	66	7,621.69	2095260	-0.00596	64
28/06/2018	-0.43905	0.024793	0.051136	67	7,615.63	4561929	-0.02302	57
29/06/2018	-0.3407	0.036534	0.118946	67	7,636.93	1292072	0.018399	53
02/07/2018	-0.33042	0.024295	0.097182	73	7,547.85	1725220	-0.01363	62
03/07/2018	-0.28238	0.031952	0.090674	76	7,593.29	1900237	-0.00386	66
04/07/2018	-0.18232	0.033728	0.0866	79	7,573.09	1530341	0.006452	64
05/07/2018	-0.31933	0.021723	0.082549	84	7,603.22	2679643	-0.02436	61
06/07/2018	-0.26885	0.033606	0.08356	71	7,617.70	2328538	0.000657	56
09/07/2018	-0.27742	0.029032	0.106452	84	7,687.99	1410030	0.005253	65
10/07/2018	-0.05672	0.02439	0.076007	78	7,692.04	1008828	-0.0147	64
11/07/2018	-0.1947	0.018692	0.076324	75	7,591.96	1061354	-0.00232	62

12/07/2018	-0.40733	0.039511	0.188937	80	7,651.33	2036970	0.03588	67
13/07/2018	-0.34801	0.037997	0.137306	71	7,661.87	2322953	0.003849	67
16/07/2018	-0.27805	0.027529	0.086717	85	7,600.45	1535297	0.015163	69
17/07/2018	-0.25537	0.03775	0.092524	82	7,626.33	1432409	0.015276	75
18/07/2018	-0.25256	0.028772	0.088235	94	7,676.28	2795316	-0.01302	66
19/07/2018	-0.24958	0.031056	0.101637	93	7,683.97	2304712	-0.00126	70
20/07/2018	-0.22771	0.03805	0.090963	79	7,678.79	2316610	-0.02547	61
23/07/2018	-0.28737	0.040593	0.105026	87	7,655.79	5871994	-0.06357	69
24/07/2018	-0.26471	0.040441	0.089706	90	7,709.05	4593980	-0.03653	65
25/07/2018	-0.17003	0.039769	0.075504	100	7,658.26	3629648	0.007153	69
26/07/2018	-0.14989	0.033064	0.07421	83	7,663.17	3217533	0.002131	73
27/07/2018	-0.26642	0.035022	0.103815	72	7,701.31	2128980	0.021616	58
30/07/2018	-0.28557	0.035178	0.102431	87	7,700.85	1174564	-0.01942	75
31/07/2018	-0.31596	0.017683	0.101908	83	7,748.76	1909382	-0.00318	76
01/08/2018	-0.22423	0.042473	0.088695	84	7,652.91	3183195	-0.04436	63
02/08/2018	-0.24264	0.029438	0.082962	74	7,575.93	4780147	-0.03008	75
03/08/2018	-0.14173	0.048819	0.070866	72	7,659.10	3307283	-0.00498	67
06/08/2018	-0.43946	0.027096	0.140559	79	7,663.78	1621738	0.020392	78
07/08/2018	-0.24364	0.043636	0.105455	81	7,718.48	1518259	0.014329	67
08/08/2018	-0.0979	0.090909	0.062937	95	7,776.65	1494548	0.011896	72
09/08/2018	-0.30323	0.025806	0.101935	89	7,741.77	1015611	-0.00955	64
10/08/2018	-0.31544	0.034124	0.117769	96	7,667.01	1690081	-0.03709	69
13/08/2018	-0.22075	0.066981	0.124528	73	7,642.45	1374743	0.030046	79
14/08/2018	-0.24045	0.045262	0.097595	67	7,611.64	1049870	0.001496	74
15/08/2018	-0.23583	0.039816	0.090352	62	7,497.87	1039335	0.011202	70

16/08/2018	-0.20883	0.054329	0.093379	63	7,556.38	880017	0.009232	73
17/08/2018	-0.33039	0.042875	0.131148	65	7,558.59	996340	-0.01317	66

ITV PLC metadata (daily)

Date	Sentiment	Very Pos	Very Neg	GT Searches	FTSE100 Ind	Volume trades	stock returns	GT 'Economy'
04/06/2018	0.548387	0.193548	0.032258	45	7,741.29	8297366	0.011253	90
05/06/2018	0.323568	0.115435	0.022737	45	7,686.80	12031968	0.008421	79
06/06/2018	0.089453	0.104914	0.051353	39	7,712.37	18025213	0.017298	74
07/06/2018	0.387337	0.065549	0.018994	48	7,704.40	49635480	0.002052	68
08/06/2018	0.339775	0.07139	0.033816	33	7,681.07	11477395	-0.01024	67
11/06/2018	0.242769	0.086448	0.024049	32	7,737.43	16965606	0.016849	85
12/06/2018	0.170581	0.098269	0.04759	30	7,703.81	12153738	-0.00407	69
13/06/2018	0.367708	0.14375	0.029688	33	7,703.71	13651962	0.003211	100
14/06/2018	0.250476	0.104433	0.039434	90	7,765.79	31686783	0.016293	82
15/06/2018	0.11334	0.089268	0.027583	64	7,633.91	41751682	-0.02777	64
18/06/2018	0.261236	0.139747	0.044593	63	7,631.33	13534060	-0.00501	77
19/06/2018	0.527449	0.228041	0.024071	53	7,603.85	10932254	0.005623	75
20/06/2018	0.19124	0.081736	0.039499	51	7,627.40	19360803	0.019129	62
21/06/2018	0.267006	0.100764	0.03092	64	7,556.44	20647614	0.002888	66

22/06/2018	0.344103	0.10359	0.038462	58	7,682.27	14570301	0.016988	58
25/06/2018	0.105932	0.050847	0.038741	42	7,509.84	13963070	0.002265	78
26/06/2018	0.112266	0.113306	0.132017	43	7,537.92	10754117	-0.00621	73
27/06/2018	-0.44572	0.102205	0.24894	47	7,621.69	16600541	-0.00682	64
28/06/2018	0.058398	0.049403	0.065772	70	7,615.63	16191485	-0.01259	57
29/06/2018	0.252868	0.051147	0.039197	30	7,636.93	17901921	0.008696	53
02/07/2018	0.058252	0.065851	0.054453	69	7,547.85	16272845	-0.01724	62
03/07/2018	0.03536	0.033796	0.030771	92	7,593.29	15824427	-0.00058	66
04/07/2018	0.448267	0.167318	0.014334	33	7,573.09	7971583	0.013458	64
05/07/2018	0.406479	0.205184	0.032397	28	7,603.22	11893802	-0.00115	61
06/07/2018	0.234429	0.124571	0.0564	65	7,617.70	29474173	0.042775	56
09/07/2018	0.164894	0.06516	0.015293	29	7,687.99	15355420	-0.00693	65
10/07/2018	-0.06332	0.057168	0.014952	33	7,692.04	11755931	0.004745	64
11/07/2018	0.095169	0.075028	0.035437	100	7,591.96	13626085	-0.01417	62
12/07/2018	0.894021	0.342613	0.049351	31	7,651.33	20253907	-0.01043	67
13/07/2018	1.311409	0.467581	0.039277	28	7,661.87	11587612	-0.00285	67
16/07/2018	0.255955	0.095283	0.025222	26	7,600.45	9565993	-0.00485	69
17/07/2018	0.406452	0.143369	0.032258	26	7,626.33	14047880	-0.01033	75
18/07/2018	0.300312	0.118565	0.027301	24	7,676.28	13533813	0.010728	66
19/07/2018	0.288069	0.083059	0.038893	25	7,683.97	18964796	-0.00803	70
20/07/2018	0.429765	0.135915	0.027335	27	7,678.79	7971014	-0.00492	61
23/07/2018	0.574964	0.183406	0.034934	25	7,655.79	14868488	-0.00756	69
24/07/2018	0.507106	0.190568	0.032946	25	7,709.05	17969955	-0.00176	65
25/07/2018	0.317847	0.134956	0.053097	25	7,658.26	22349331	0.009094	69
26/07/2018	0.064922	0.088663	0.057171	24	7,663.17	23411507	-0.03895	73

27/07/2018	0.291343	0.099889	0.048835	24	7,701.31	17345686	0.006352	58
30/07/2018	0.317631	0.087483	0.03432	31	7,700.85	12874161	-0.00601	75
31/07/2018	0.335461	0.116657	0.031921	18	7,748.76	16407899	-0.00302	76
01/08/2018	0.292887	0.109623	0.037657	15	7,652.91	16709567	-0.02123	63
02/08/2018	0.406181	0.111111	0.027226	14	7,575.93	16726024	0.004028	75
03/08/2018	0.404106	0.1261	0.049267	15	7,659.10	11266536	0.012037	67
06/08/2018	0.220624	0.088729	0.079137	16	7,663.78	20920838	0.009454	78
07/08/2018	0.333333	0.114379	0.045752	14	7,718.48	24902931	0.012387	67
08/08/2018	0.565934	0.164835	0.027473	14	7,776.65	11930738	0.014622	72
09/08/2018	0.383405	0.155222	0.033619	14	7,741.77	7943647	0.000588	64
10/08/2018	0.247498	0.080053	0.027352	13	7,667.01	10565586	-0.00735	69
13/08/2018	0.471698	0.131082	0.020854	14	7,642.45	8832008	-0.0154	79
14/08/2018	0.42632	0.115839	0.012608	13	7,611.64	11658379	-0.00902	74
15/08/2018	0.333868	0.108347	0.019262	14	7,497.87	15638666	-0.00698	70
16/08/2018	0.319	0.136	0.023	13	7,556.38	11479232	0.016809	73
17/08/2018	0.408186	0.123894	0.021018	12	7,558.59	10236731	0.001503	66

Appendix B:

BP		ADF test constant	ADF test constant + trend
Sentiment		0.001127***	0.0008843***
	First difference	2.222e-006***	2.969e-005***
Very Pos		0.3791	0.4902
	First difference	1.767e-011***	2.311e-010***
Very Neg		2.964e-006***	2.21e-005***
GT searches		0.9174	0.0003744***
	First difference	1.089e-009***	4.287e-005***
FTSE100 index		0.0045***	0.02306**
	First difference	3.957e-011***	2.98e-010***
GT "Economy"		0.6078	5.135e-006***
GT "Economy"	First difference	3.389e-011***	1.055e-009***
Stock returns		1.723e-012***	2.521e-011***
MS			
Sentiment		0.000309***	0.001091***
	First difference	2.373e-014***	1.236e-013
Very Pos		3.968e-005***	0.0003125***
Very Neg		9.434e-008***	6.418e-008***
GT searches		0.1521	0.4129
	First difference	2.122e-011***	0.0001***
FTSE100 index		0.0045***	0.02306**
	First difference	3.957e-011***	2.98e-010***
GT "Economy"		0.6078	5.135e-006***
GT "Economy"	First difference	3.389e-011***	1.055e-009***
Stock returns		8.583e-007***	0.0002851***
Tesco			
Sentiment		0.8158	2.862e-005***
	First difference	1.513e-006***	2.092e-005***
Very Pos		8.648e-005***	0.0006214***
Very Neg		0.9886	0.0002202

	First difference	1.13e-005***	3.991e-005***
GT searches		0.02199**	0.01676**
	First difference	2.999e-010***	2.286e-009***
FTSE100 index		0.0045***	0.02306***
	First difference	3.957e-011***	2.98e-010***
Stock returns		5.995e-009 ***	3.751e-008***
GT "Economy"		0.6078	5.135e-006***
GT "Economy"	First difference	3.389e-011***	1.055e-009***
Ryanair			
Sentiment		2.973e-006***	5.806e-006***
Very Pos		1.623e-021***	6.77e-006***
Very Neg		1.552e-009***	1.09e-009***
GT searches		0.6215	0.9704
	Frist difference	0.008441***	0.02877**
FTSE100 index		0.0045***	0.02306**
	First difference	3.957e-011***	2.98e-010***
GT "Economy"		0.6078	5.135e-006***
GT "Economy"	First difference	3.389e-011***	1.055e-009***
Share price		3.658e-006***	4.005e-005***
ITV			
Sentiment		1.102e-005***	1.775e-005***
Very Pos		2.46e-006***	2.004e-005***
Very Neg		0.0002293***	0.001277***
GT searches		0.6224	0.1384
	Frist difference	4.248e-022***	3.245e-023***
FTSE100 index		0.0045***	0.02306**
	First difference	3.957e-011***	2.98e-010***
GT "Economy"		0.6078	5.135e-006***
GT "Economy"	First difference	3.389e-011***	1.055e-009***
Share price		1.878e-008 ***	1.354e-007 ***

BP correlation matrix

Appendix C:

BP correlation matrix

Sentiment	VeryPos	VeryNeg	GTSearches	FTSE100Ind	
1.0000	0.4108	-0.3838	-0.3895	-0.0749	Sentiment
	1.0000	0.2458	-0.1472	-0.0529	VeryPos
		1.0000	0.0808	0.1615	VeryNeg
			1.0000	-0.0100	GTSearches
				1.0000	FTSE100Ind
		GTEconomy	Volumetrades	Stockreturns	
		0.0026	0.2643	-0.0768	Sentiment
		-0.1548	0.1834	0.0091	VeryPos
		-0.0841	-0.0935	-0.0330	VeryNeg
		-0.0513	-0.2856	-0.0497	GTSearches
		0.2268	0.0857	0.3276	FTSE100Ind
		1.0000	0.1488	0.0538	GTEconomy
			1.0000	-0.1201	Volumetrades
				1.0000	Stockreturns

Marks and Spencer correlation matrix

Sentiment	VeryPos	VeryNeg	GTSearches	FTSE100Ind	
1.0000	0.8475	-0.2960	0.2808	-0.0849	Sentiment
	1.0000	-0.0932	0.3923	-0.1410	VeryPos
		1.0000	-0.0197	-0.2788	VeryNeg
			1.0000	-0.1375	GTSearches
				1.0000	FTSE100Ind
			GTEconomy	stockreturns	
			-0.1121	0.0425	Sentiment
			-0.2761	-0.0081	VeryPos
			0.0385	-0.1641	VeryNeg
			-0.2771	0.1578	GTSearches
			0.2268	0.2317	FTSE100Ind
			1.0000	0.1139	GTEconomy
				1.0000	stockreturns

Tesco correlation matrix

Sentiment	VeryPos	VeryNeg	GTSearches	FTSE100Ind	
1.0000	0.6810	-0.7785	0.0519	-0.0327	Sentiment
	1.0000	-0.2830	-0.2353	-0.0197	VeryPos
		1.0000	-0.2326	0.1894	VeryNeg
			1.0000	0.3219	GTSearches
				1.0000	FTSE100Ind
			GTEconomy	stockreturns	
			-0.0569	-0.0062	Sentiment
			-0.3014	0.0833	VeryPos
			0.0130	0.2023	VeryNeg

			0.2670	-0.0475	GTSearches
			0.2268	0.3437	FTSE100Ind
			1.0000	-0.0881	GTEconomy
				1.0000	stockreturns

Ryanair correlation matrix

Sentiment	VeryPos	VeryNeg	GTSearches	FTSE100Ind	
1.0000	0.8253	-0.4541	-0.0236	0.1729	Sentiment
	1.0000	-0.2302	-0.0628	0.1911	VeryPos
		1.0000	0.0005	0.1451	VeryNeg
			1.0000	0.3634	GTSearches
				1.0000	FTSE100Ind
			GTEconomy	stockreturns	
			0.1387	-0.0439	Sentiment
			0.1165	-0.0110	VeryPos
			0.2353	0.2242	VeryNeg
			-0.0241	-0.2304	GTSearches
			0.2268	0.0231	FTSE100Ind
			1.0000	0.0830	GTEconomy
				1.0000	stockreturns

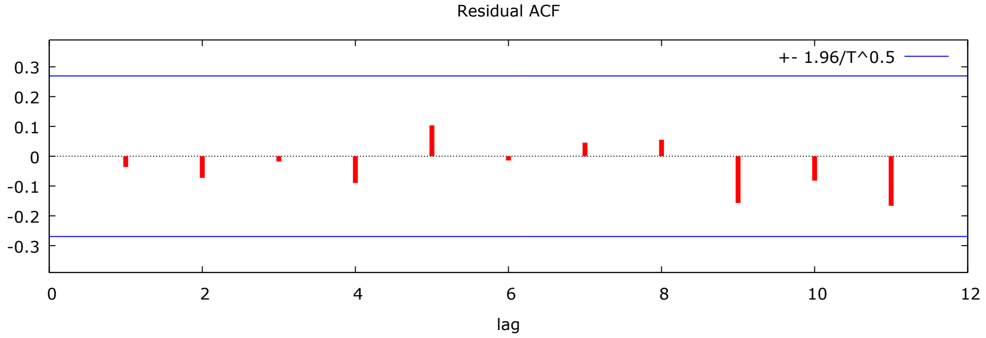
ITV correlation matrix

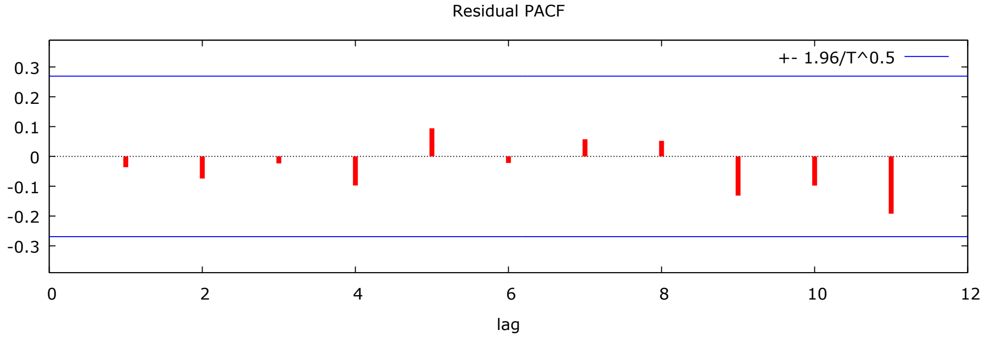
Sentiment	VeryPos	VeryNeg	GTSearches	FTSE100Ind	
1.0000	0.8308	-0.4615	-0.3435	0.1704	Sentiment
	1.0000	-0.0440	-0.2125	0.0917	VeryPos
		1.0000	0.1444	-0.1100	VeryNeg
			1.0000	-0.1529	GTSearches
				1.0000	FTSE100Ind
			GTEconomy	stockreturns	
			0.1345	0.0910	Sentiment
			0.0978	0.0385	VeryPos
			-0.1114	-0.0758	VeryNeg
			-0.1212	0.0420	GTSearches
			0.2268	0.1843	FTSE100Ind
			1.0000	0.0375	GTEconomy
				1.0000	stockreturns

Appendix D:

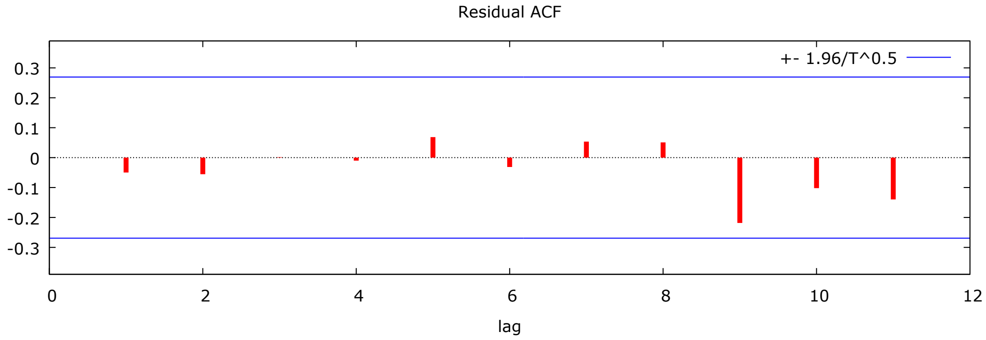
Residual Autocorrelation (correlogram) of the ARIMAX models

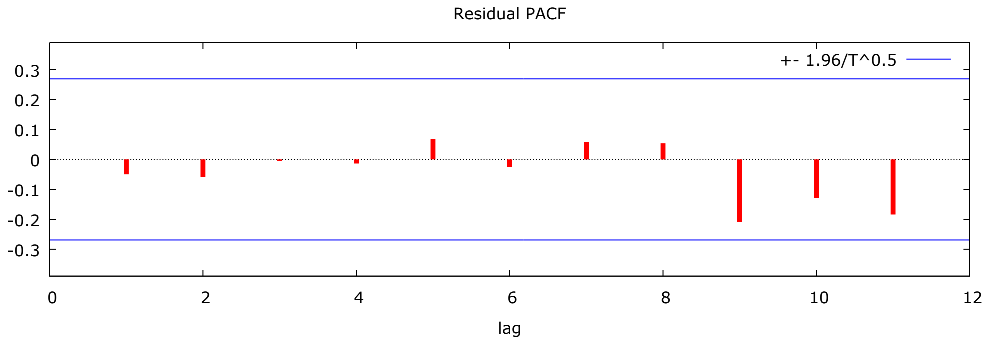
BP Extreme sentiment





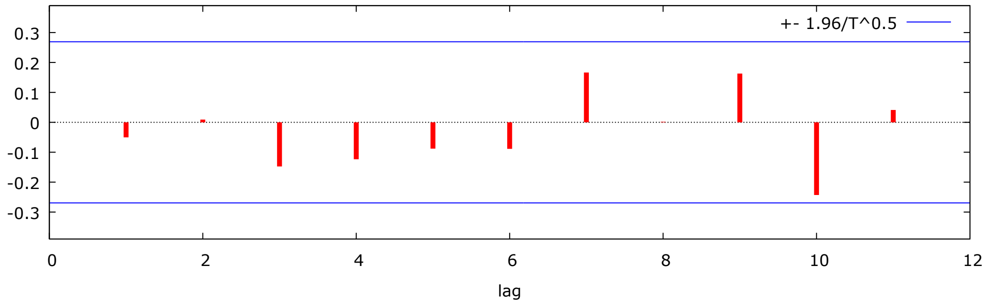
BP mean sentiment



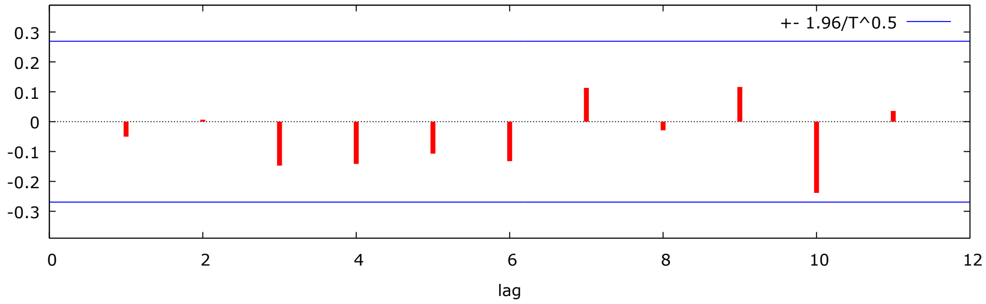


Marks and Spencer Extreme sentiment

Residual ACF

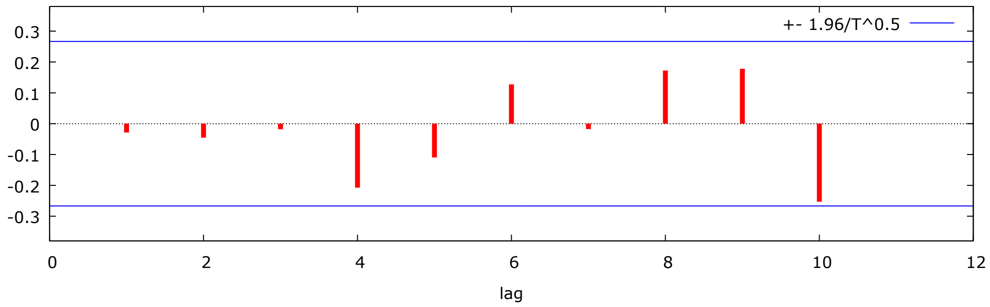


Residual PACF

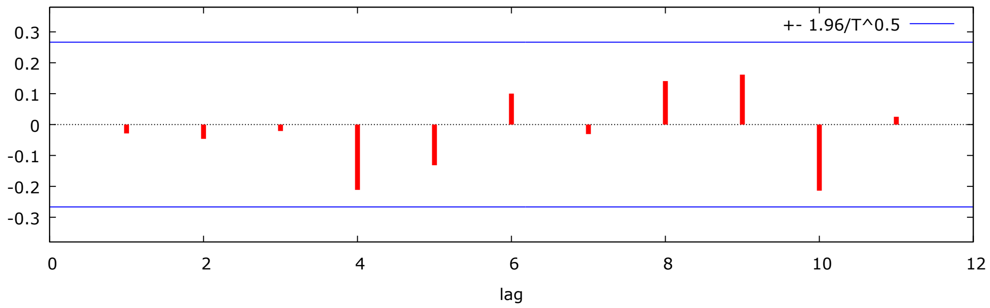


Marks and Spencer Mean Sentiment

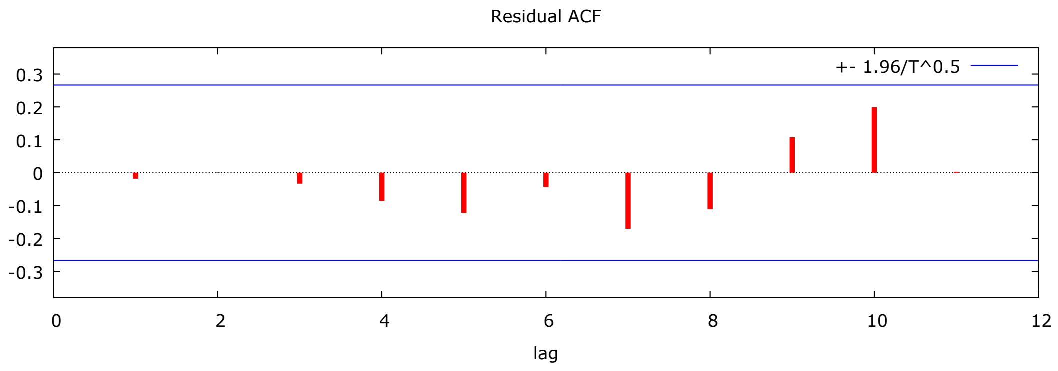
Residual ACF

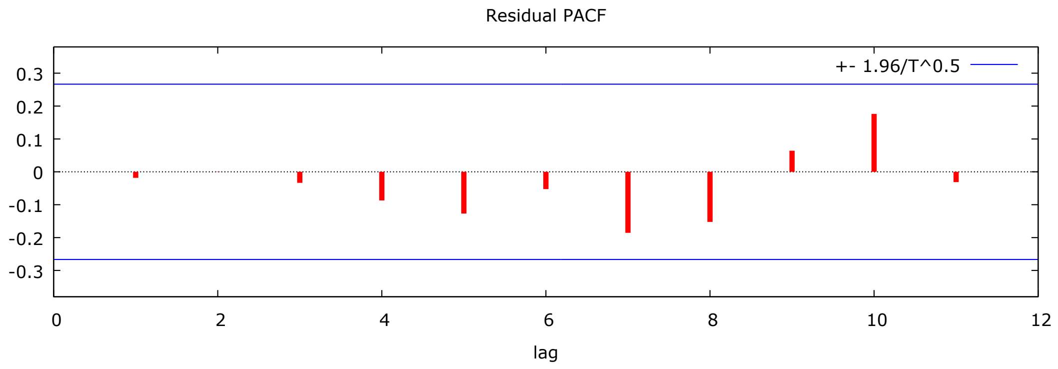


Residual PACF

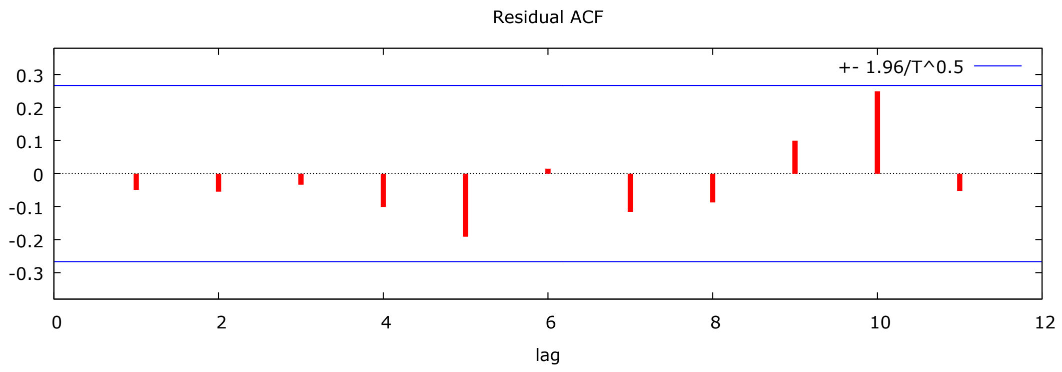


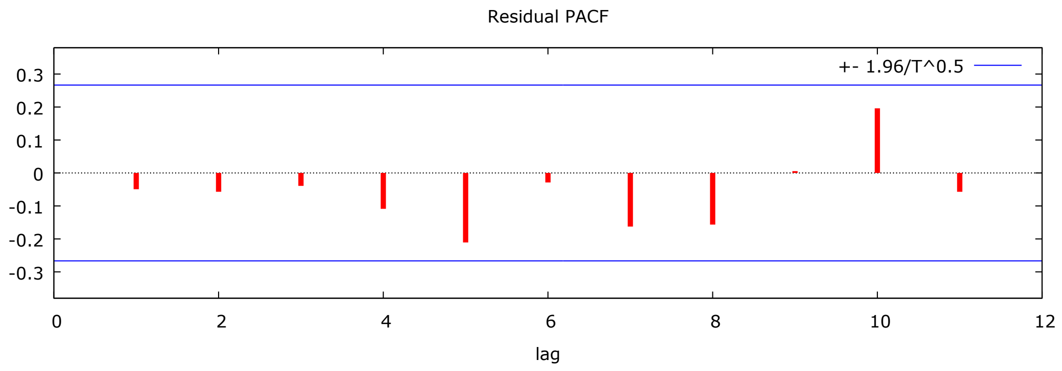
Tesco Extreme Sentiment



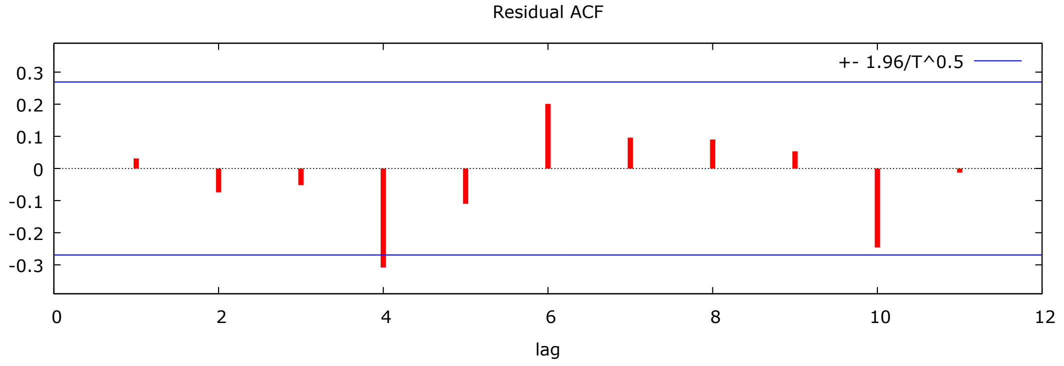


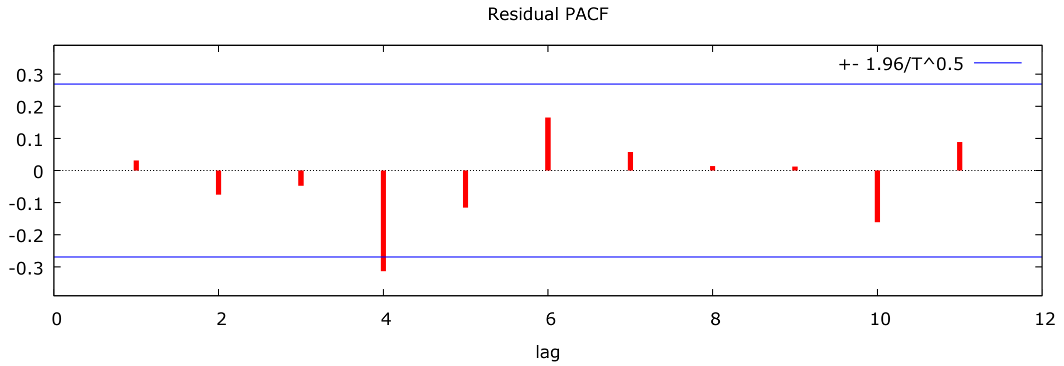
Tesco Mean Sentiment



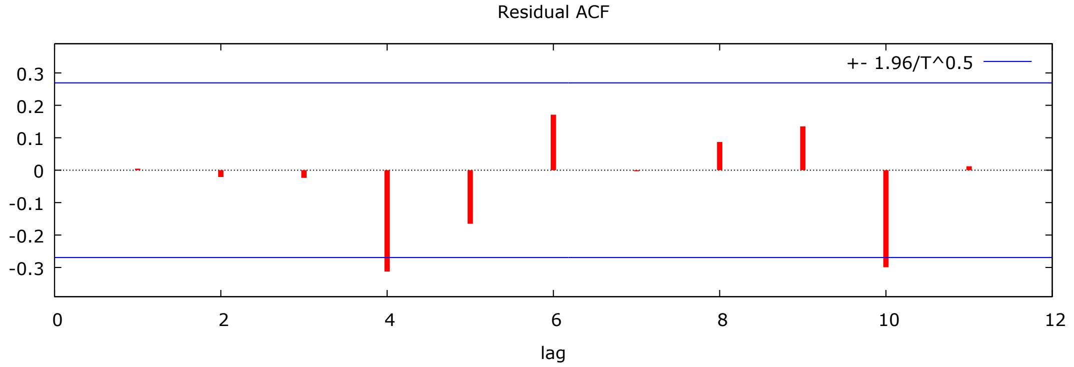


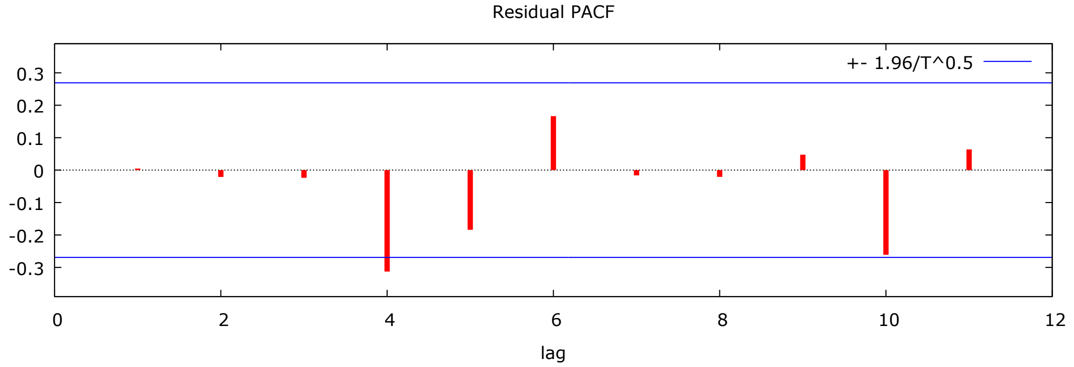
Ryanair Extreme Sentiment



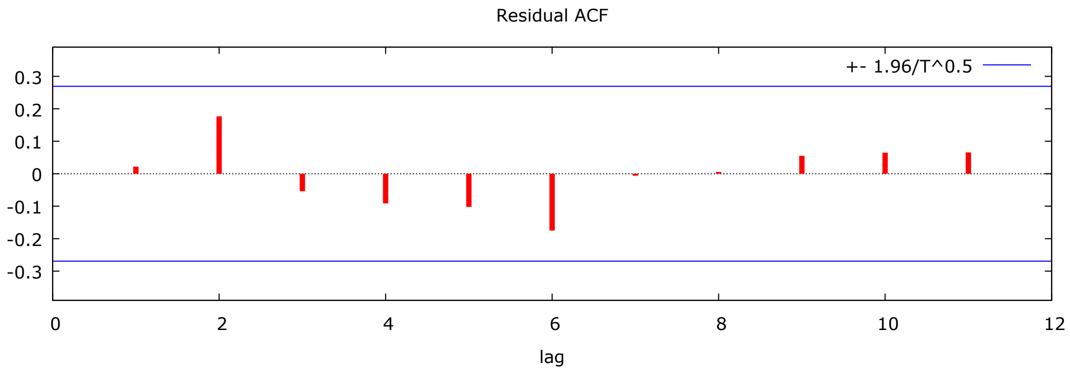


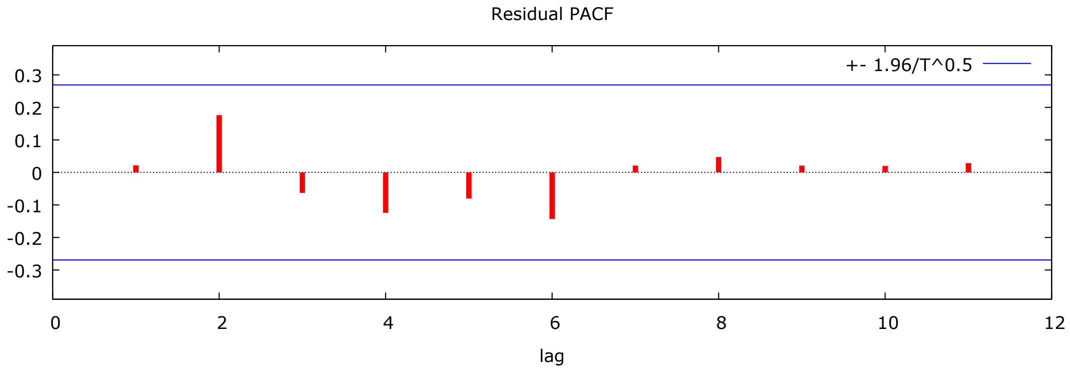
Ryanair Mean Sentiment



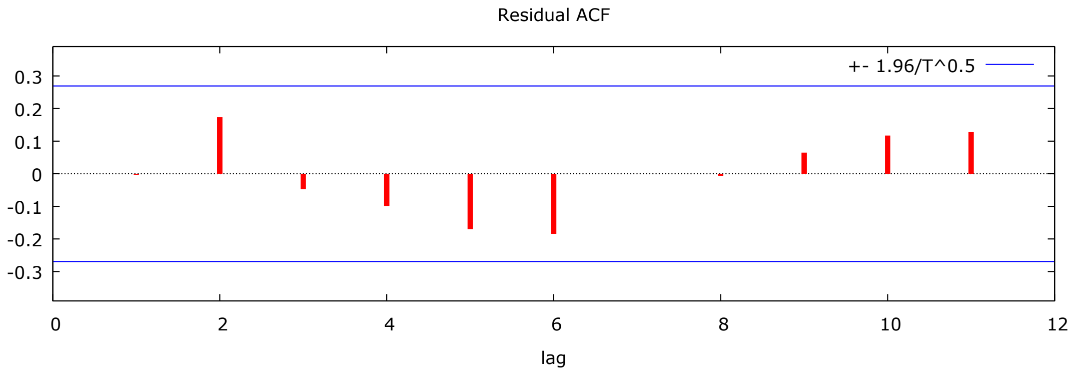


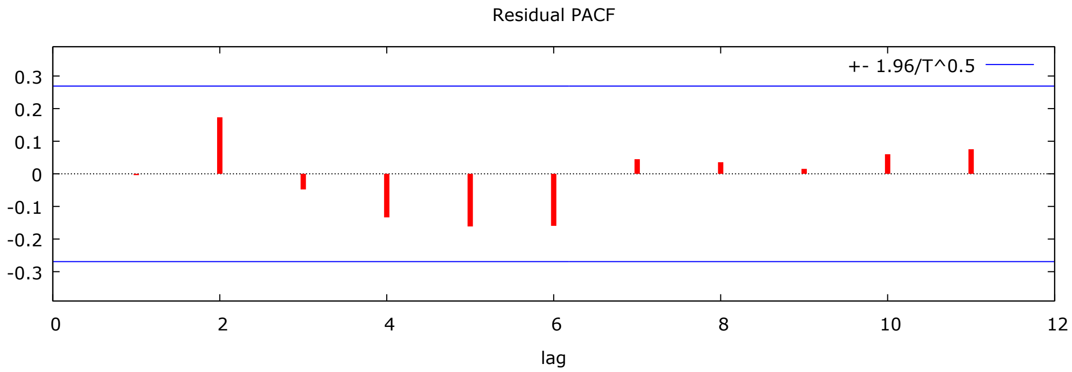
ITV Extreme Sentiment





ITV Mean Sentiment





Appendix E:

BP extreme sentiment

ARMAX, using observations 2018-06-06:2018-08-17 (T = 53)
Dependent variable: (1-L) Stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	−0.0828821	0.147541	−0.5618	0.5743	
theta_1	−1.00000	0.0571915	−17.49	<0.0001	***
VeryPos	0.0441055	0.0232611	1.896	0.0579	*
VeryNeg	−0.0346662	0.0258777	−1.340	0.1804	
d_GTSearches	−0.000545927	0.000293877	−1.858	0.0632	*
d_FTSE100Ind	0.000211477	1.89841e-05	11.14	<0.0001	***
d_GTEconomy	7.96557e-05	0.000116426	0.6842	0.4939	

Mean dependent var	0.000062		S.D. dependent var	0.023111
Mean of innovations	−0.000454		S.D. of innovations	0.007623
Log-likelihood	181.1758		Akaike criterion	−346.3515
Schwarz criterion	−330.5892		Hannan-Quinn	−340.2901

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	-12.0653	0.0000	12.0653	0.5000
MA					
	Root 1	1.0000	0.0000	1.0000	0.0000

BP Mean sentiment

ARMAX, using observations 2018-06-06:2018-08-17 (T = 53)
Dependent variable: (1-L) Stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	−0.0898763	0.146022	−0.6155	0.5382	
theta_1	−1.00000	0.0692294	−14.44	<0.0001	***
Sentiment	0.00380048	0.00630430	0.6028	0.5466	
d_GTSearches	−0.000551529	0.000307875	−1.791	0.0732	*
d_FTSE100Ind	0.000207135	1.97327e-05	10.50	<0.0001	***
d_GTEconomy	4.73421e-05	0.000119114	0.3975	0.6910	

Mean dependent var	0.000062		S.D. dependent var	0.023111
Mean of innovations	−0.001089		S.D. of innovations	0.007921
Log-likelihood	179.1368		Akaike criterion	−344.2736
Schwarz criterion	−330.4816		Hannan-Quinn	−338.9699

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	-11.1264	0.0000	11.1264	0.5000
MA					
	Root 1	1.0000	0.0000	1.0000	0.0000

Marks and Spencer Extreme Sentiment

ARMAX, using observations 2018-06-06:2018-08-17 (T = 53)
Dependent variable: (1-L) stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	0.116832	0.164208	0.7115	0.4768	
theta_1	−0.970045	0.0931622	−10.41	<0.0001	***
VeryPos	0.00757182	0.0190230	0.3980	0.6906	
VeryNeg	0.00379811	0.149813	0.02535	0.9798	
d_GTSearches	9.52609e-05	0.000226049	0.4214	0.6735	
d_FTSE100Ind	9.38662e-05	2.54218e-05	3.692	0.0002	***
d_GTEconomy	5.31596e-05	0.000134393	0.3956	0.6924	

Mean dependent var	−0.000176	S.D. dependent var	0.015703
Mean of innovations	−0.001810	S.D. of innovations	0.010172
Log-likelihood	166.6839	Akaike criterion	−317.3677
Schwarz criterion	−301.6054	Hannan-Quinn	−311.3063

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	8.5593	0.0000	8.5593	0.0000
MA					
	Root 1	1.0309	0.0000	1.0309	0.0000

Marks and Spencer Mean Sentiment

ARMAX, using observations 2018-06-05:2018-08-17 (T = 54)
Dependent variable: (1-L) stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	0.147663	0.159389	0.9264	0.3542	
theta_1	−1.00000	0.120085	−8.327	<0.0001	***
d_Sentiment	0.00220750	0.00768714	0.2872	0.7740	
d_GTSearches	0.000302496	0.000276155	1.095	0.2733	
d_FTSE100Ind	5.23769e-05	2.80764e-05	1.866	0.0621	*
d_GTEconomy	0.000145188	0.000189102	0.7678	0.4426	

Mean dependent var	−0.000362	S.D. dependent var	0.015614
Mean of innovations	−0.001135	S.D. of innovations	0.011003
Log-likelihood	165.0382	Akaike criterion	−316.0764
Schwarz criterion	−302.1535	Hannan-Quinn	−310.7069

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	6.7722	0.0000	6.7722	0.0000
MA					
	Root 1	1.0000	0.0000	1.0000	0.0000

Tesco Extreme Sentiment

ARMAX, using observations 2018-06-05:2018-08-17 (T = 54)
Dependent variable: (1-L) stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	−0.143773	0.139823	−1.028	0.3038	
theta_1	−1.00000	0.0544882	−18.35	<0.0001	***
VeryPos	−0.00188201	0.000622066	−3.025	0.0025	***
d_VeryNeg	0.0993866	0.0499884	1.988	0.0468	**
d_GTSearches	−0.000549953	0.000273295	−2.012	0.0442	**
d_FTSE100Ind	4.84457e-05	1.65348e-05	2.930	0.0034	***
d_GTEconomy	−0.000158284	0.000116044	−1.364	0.1726	

Mean dependent var	−0.000076		S.D. dependent var	0.012669
Mean of innovations	−0.000011		S.D. of innovations	0.007125
Log-likelihood	188.2183		Akaike criterion	−360.4365
Schwarz criterion	−344.5246		Hannan-Quinn	−354.2999

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	-6.9554	0.0000	6.9554	0.5000
MA					
	Root 1	1.0000	0.0000	1.0000	0.0000

Tesco Mean Sentiment

ARMAX, using observations 2018-06-05:2018-08-17 (T = 54)
Dependent variable: (1-L) stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	−0.0828711	0.148171	−0.5593	0.5760	
theta_1	−0.894197	0.0686838	−13.02	<0.0001	***
d_Sentiment	−0.00655597	0.00893913	−0.7334	0.4633	
d_GTSearches	−0.000533741	0.000313962	−1.700	0.0891	*
d_FTSE100Ind	5.88290e-05	1.77603e-05	3.312	0.0009	***
d_GTEconomy	−0.000174313	0.000132164	−1.319	0.1872	

Mean dependent var	−0.000076		S.D. dependent var	0.012669
Mean of innovations	−0.001297		S.D. of innovations	0.007767
Log-likelihood	184.8254		Akaike criterion	−355.6508
Schwarz criterion	−341.7279		Hannan-Quinn	−350.2813

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	-12.0669	0.0000	12.0669	0.5000
MA					
	Root 1	1.1183	0.0000	1.1183	0.0000

Ryanair Extreme Sentiment

ARMAX, using observations 2018-06-06:2018-08-17 (T = 53)
Dependent variable: (1-L) stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	0.338061	0.134177	2.520	0.0118	**
theta_1	−1.00000	0.0577271	−17.32	<0.0001	***
VeryPos	0.0348102	0.0537683	0.6474	0.5174	
VeryNeg	0.209511	0.0964379	2.172	0.0298	**
d_GTSearches	−0.000478152	0.000256648	−1.863	0.0625	*
d_FTSE100Ind	7.88398e-05	3.37216e-05	2.338	0.0194	**
d_GTEconomy	8.35970e-05	0.000202433	0.4130	0.6796	

Mean dependent var	−0.000136		S.D. dependent var	0.023566
Mean of innovations	−0.000262		S.D. of innovations	0.016452
Log-likelihood	140.8311		Akaike criterion	−265.6622
Schwarz criterion	−249.8998		Hannan-Quinn	−259.6007

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	2.9580	0.0000	2.9580	0.0000
MA					
	Root 1	1.0000	0.0000	1.0000	0.0000

Ryanair Mean Sentiment

ARMAX, using observations 2018-06-06:2018-08-17 (T = 53)
Dependent variable: (1-L) stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	0.321502	0.132379	2.429	0.0152	**
theta_1	−1.00000	0.0522814	−19.13	<0.0001	***
Sentiment	−0.00310557	0.0155074	−0.2003	0.8413	
d_GTSearches	−0.000488469	0.000269200	−1.815	0.0696	*
d_FTSE100Ind	7.94767e-05	3.49561e-05	2.274	0.0230	**
d_GTEconomy	0.000109872	0.000212240	0.5177	0.6047	

Mean dependent var	−0.000136		S.D. dependent var	0.023566
Mean of innovations	−0.000212		S.D. of innovations	0.017156
Log-likelihood	138.5924		Akaike criterion	−263.1848
Schwarz criterion	−249.3927		Hannan-Quinn	−257.8810

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	3.1104	0.0000	3.1104	0.0000
MA					
	Root 1	1.0000	0.0000	1.0000	0.0000

ITV Extreme Sentiment

ARMAX, using observations 2018-06-06:2018-08-17 (T = 53)
Dependent variable: (1-L) stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	−0.206587	0.179042	−1.154	0.2486	
theta_1	−0.888421	0.128749	−6.900	<0.0001	***
VeryPos	0.000939843	0.0247357	0.03800	0.9697	
VeryNeg	−0.0968525	0.0474505	−2.041	0.0412	**
d_GTSearches	8.16188e-05	8.30208e-05	0.9831	0.3256	
d_FTSE100Ind	0.000118362	3.28199e-05	3.606	0.0003	***
d_GTEconomy	−5.15422e-05	0.000171994	−0.2997	0.7644	

Mean dependent var	−0.000131		S.D. dependent var	0.019573
Mean of innovations	−0.001520		S.D. of innovations	0.011910
Log-likelihood	158.6369		Akaike criterion	−301.2739
Schwarz criterion	−285.5116		Hannan-Quinn	−295.2125

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	-4.8406	0.0000	4.8406	0.5000
MA					
	Root 1	1.1256	0.0000	1.1256	0.0000

ITV Mean Sentiment

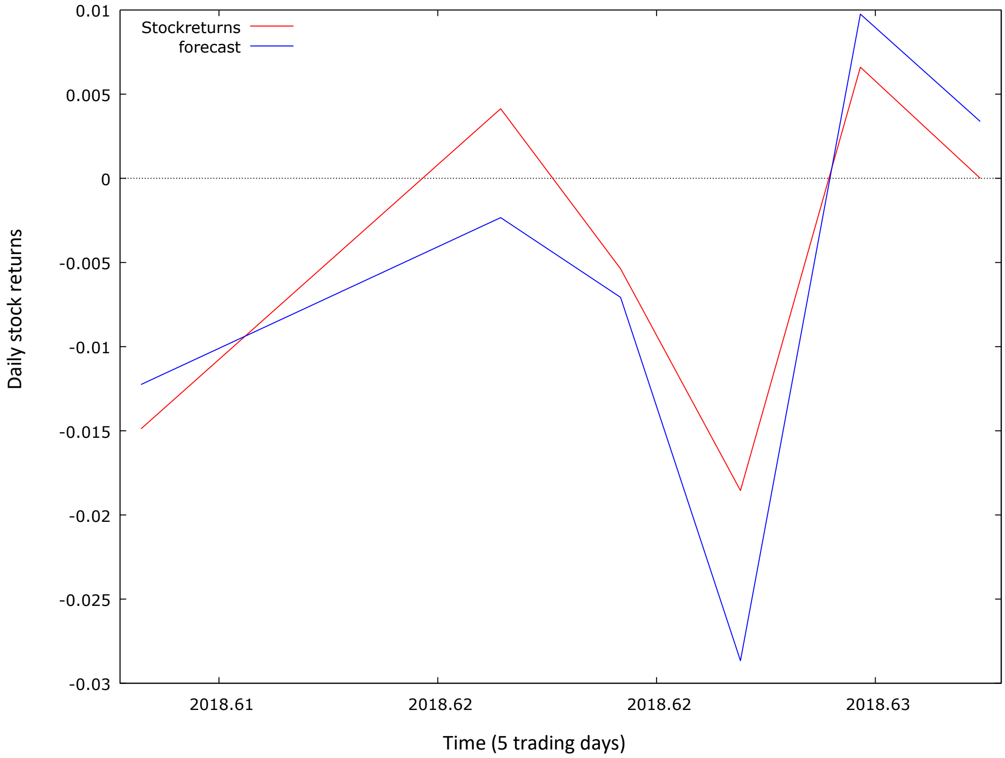
ARMAX, using observations 2018-06-06:2018-08-17 (T = 53)
Dependent variable: (1-L) stockreturns
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
phi_1	−0.112510	0.162560	−0.6921	0.4889	
theta_1	−0.913500	0.104254	−8.762	<0.0001	***
Sentiment	0.00723206	0.00774269	0.9341	0.3503	
d_GTSearches	8.90639e-05	8.32876e-05	1.069	0.2849	
d_FTSE100Ind	9.59081e-05	3.00315e-05	3.194	0.0014	***
d_GTEconomy	−2.94572e-05	0.000172043	−0.1712	0.8641	

Mean dependent var	−0.000131		S.D. dependent var		0.019573
Mean of innovations	−0.001813		S.D. of innovations		0.012236
Log-likelihood	157.1725		Akaike criterion		−300.3449
Schwarz criterion	−286.5529		Hannan-Quinn		−295.0412

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	-8.8881	0.0000	8.8881	0.5000
MA					
	Root 1	1.0947	0.0000	1.0947	0.0000

Appendix F:
BP Extreme Sentiment



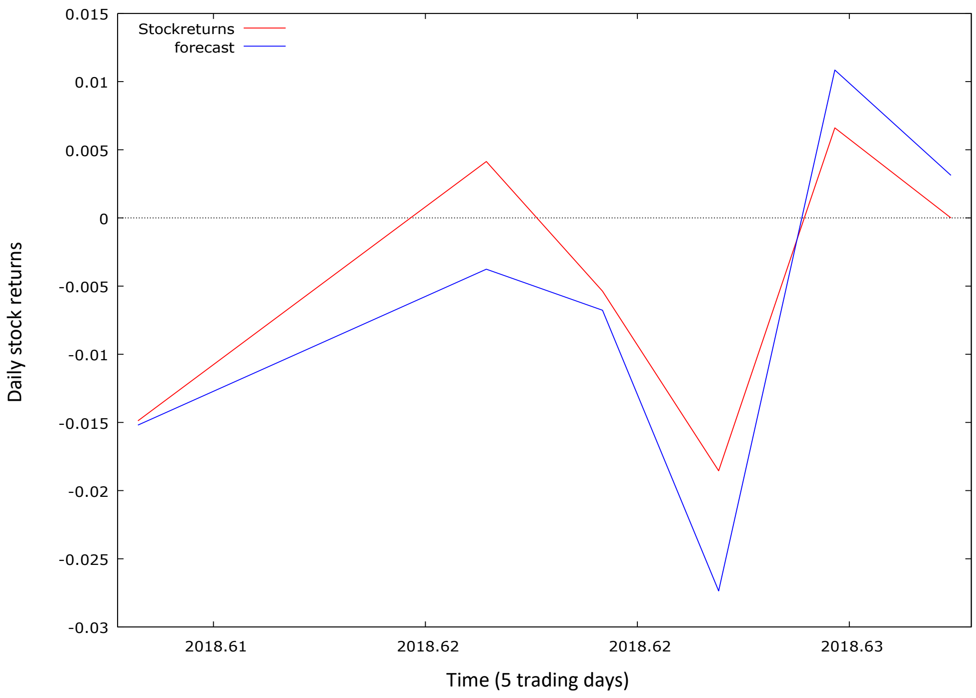
Date	Stockreturns	prediction
2018-08-10	-0.014883	-0.012250
2018-08-13	0.004137	-0.002334
2018-08-14	-0.005373	-0.007072
2018-08-15	-0.018549	-0.028659
2018-08-16	0.006605	0.009758
2018-08-17	0.000000	0.003379

Forecast evaluation statistics

Mean

Error	0.0015192
Root Mean Squared Error	0.0054047
Mean Absolute Error	0.0045741
Bias proportion, UM	0.079011
Regression proportion, UR	0.4616
Disturbance proportion, UD	0.45939

BP Mean Sentiment

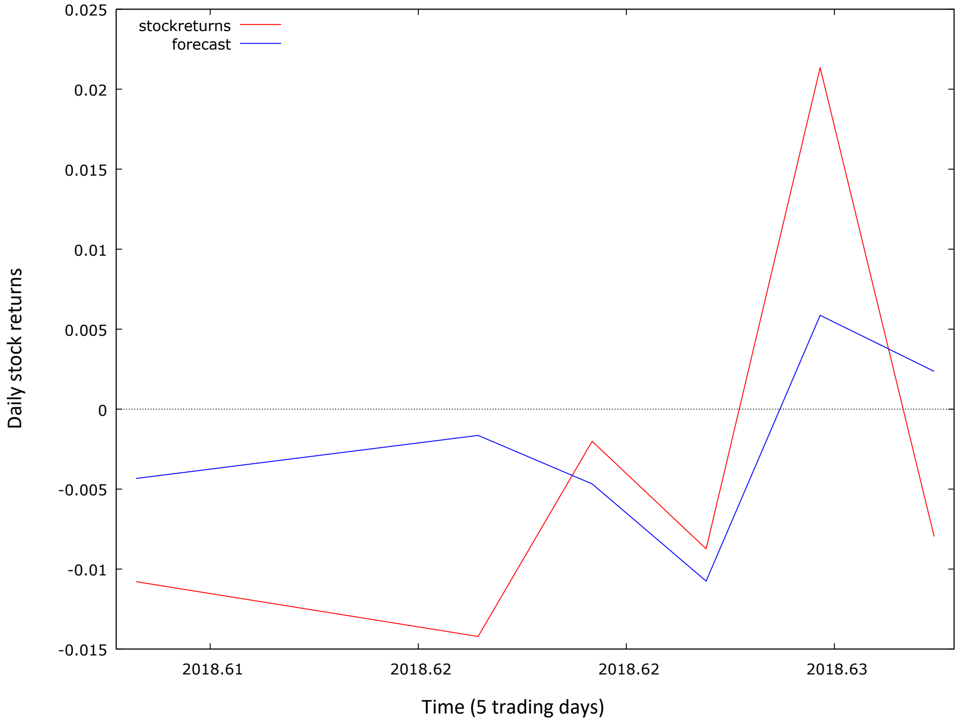


Date	Stockreturns	prediction
2018-08-10	-0.014883	-0.015195
2018-08-13	0.004137	-0.003761
2018-08-14	-0.005373	-0.006770
2018-08-15	-0.018549	-0.027357
2018-08-16	0.006605	0.010849
2018-08-17	0.000000	0.003124

Forecast evaluation statistics

Mean Error	0.0018411
Root Mean Squared Error	0.0053195
Mean Absolute Error	0.004297
Bias proportion, UM	0.11979
Regression proportion, UR	0.46626
Disturbance proportion, UD	0.41395

Marks and Spencer Extreme Sentiment

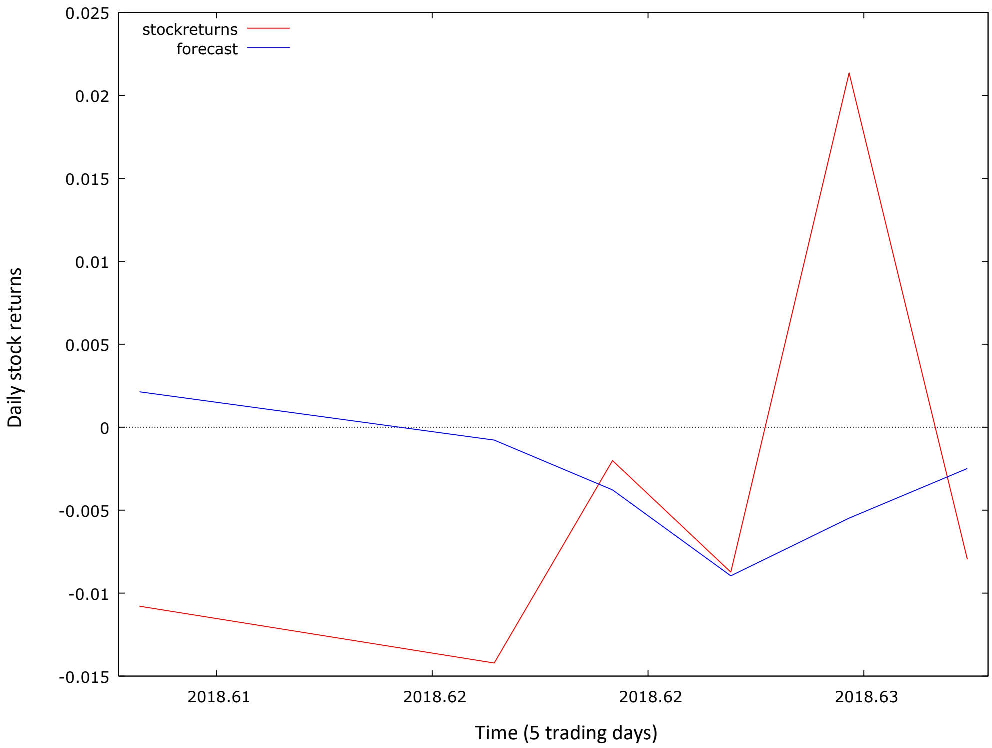


Date	stockreturns	prediction
2018-08-10	-0.010788	-0.004335
2018-08-13	-0.014210	-0.001643
2018-08-14	-0.002011	-0.004674
2018-08-15	-0.008734	-0.010751
2018-08-16	0.021349	0.005866
2018-08-17	-0.007963	0.002363

Forecast evaluation statistics

Mean Error	-0.0015304
Root Mean Squared Error	0.0096356
Mean Absolute Error	0.0082514
Mean Percentage Error	32.495
Mean Absolute Percentage Error	84.322
Theil's U	0.4735
Bias proportion, UM	0.025226
Regression proportion, UR	0.038971
Disturbance proportion, UD	0.9358

Marks and Spencer Mean Sentiment

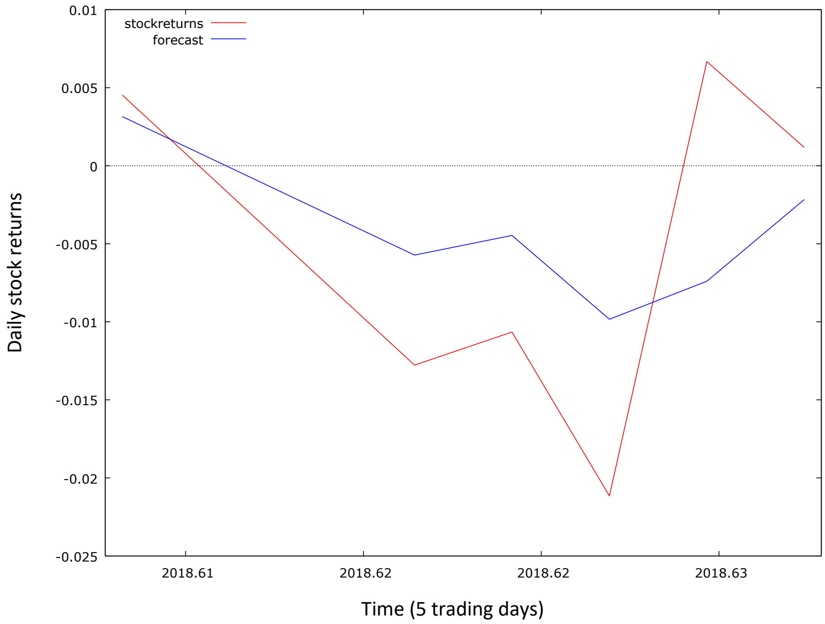


Date	stockreturns	prediction
2018-08-10	-0.010788	0.002133
2018-08-13	-0.014210	-0.000777
2018-08-14	-0.002011	-0.003779
2018-08-15	-0.008734	-0.008960
2018-08-16	0.021349	-0.005480
2018-08-17	-0.007963	-0.002490

Forecast evaluation statistics

Mean Error	-0.00050075
Root Mean Squared Error	0.013542
Mean Absolute Error	0.010108
Mean Percentage Error	53.038
Mean Absolute Percentage Error	83.196
Theil's U	0.65589
Bias proportion, UM	0.0013673
Regression proportion, UR	0.35267
Disturbance proportion, UD	0.64597

Tesco Extreme Sentiment

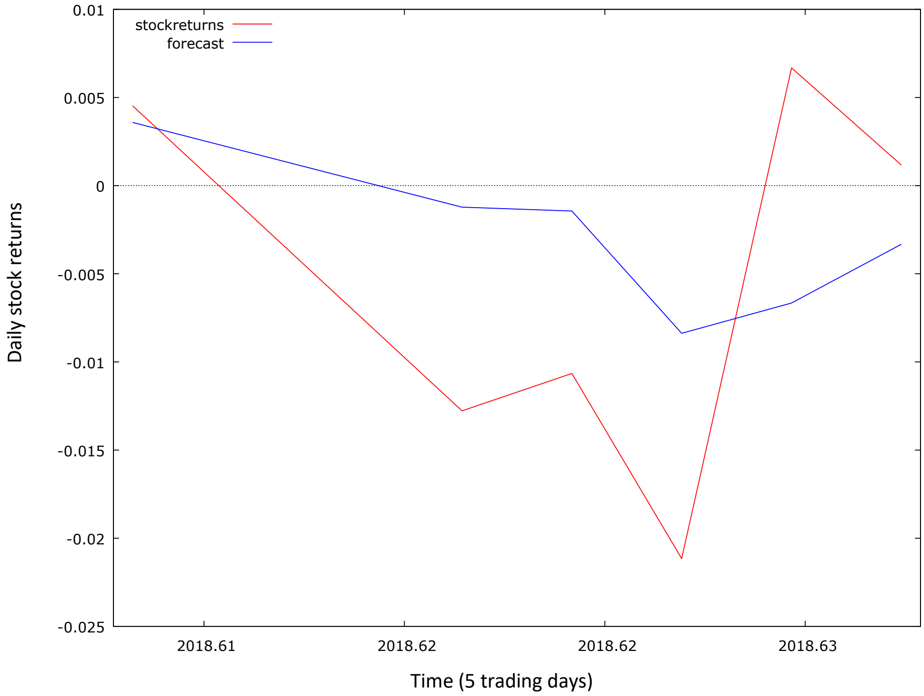


Date	stockreturns	prediction
2018-08-10	0.004528	0.003149
2018-08-13	-0.012772	-0.005725
2018-08-14	-0.010654	-0.004467
2018-08-15	-0.021154	-0.009837
2018-08-16	0.006680	-0.007402
2018-08-17	0.001171	-0.002167

Forecast evaluation statistics

Mean Error	-0.00095888
Root Mean Squared Error	0.0084397
Mean Absolute Error	0.0072253
Mean Percentage Error	115.52
Mean Absolute Percentage Error	115.52
Theil's U	0.49869
Bias proportion, UM	0.012909
Regression proportion, UR	0.050165
Disturbance proportion, UD	0.93693

Tesco Mean Sentiment

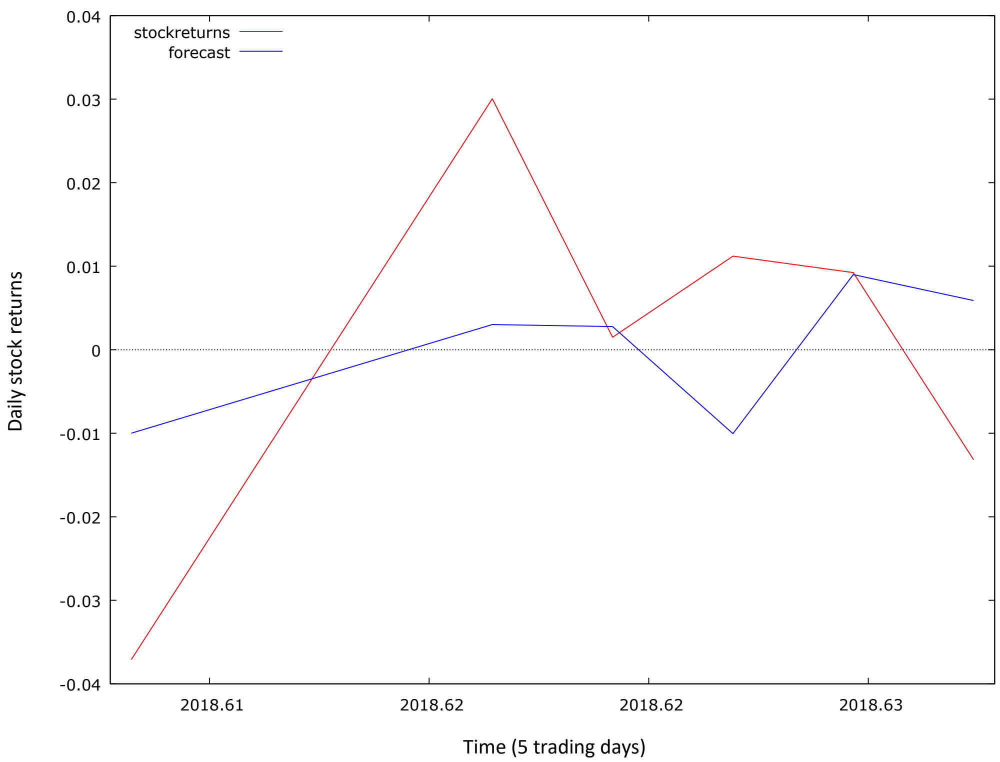


Date	stockreturns	prediction
2018-08-10	0.004528	0.003586
2018-08-13	-0.012772	-0.001221
2018-08-14	-0.010654	-0.001441
2018-08-15	-0.021154	-0.008376
2018-08-16	0.006680	-0.006658
2018-08-17	0.001171	-0.003328

Forecast evaluation statistics

Mean Error	-0.0024606
Root Mean Squared Error	0.0098374
Mean Absolute Error	0.0087205
Mean Percentage Error	140.34
Mean Absolute Percentage Error	140.34
Theil's U	0.71934
Bias proportion, UM	0.062564
Regression proportion, UR	0.0014985
Disturbance proportion, UD	0.93594

Ryanair Extreme Sentiment

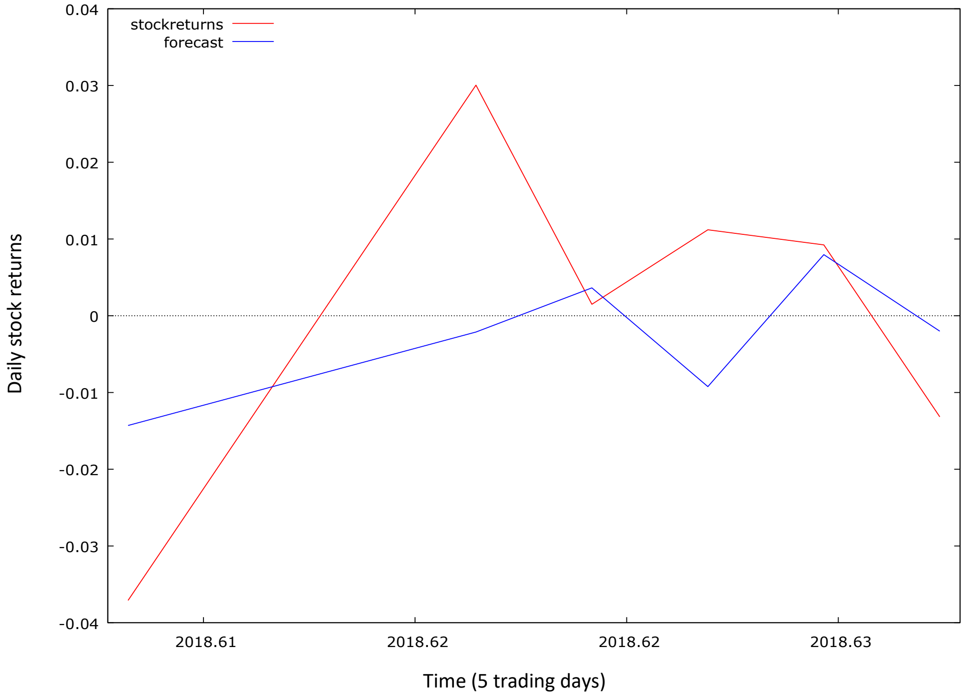


Date	stockreturns	prediction
2018-08-10	-0.037092	-0.009994
2018-08-13	0.030046	0.003011
2018-08-14	0.001496	0.002770
2018-08-15	0.011202	-0.010047
2018-08-16	0.009232	0.008995
2018-08-17	-0.013172	0.005890

Forecast evaluation statistics

Mean Error	0.00018115
Root Mean Squared Error	0.019501
Mean Absolute Error	0.015993
Mean Percentage Error	69.137
Mean Absolute Percentage Error	97.529
Theil's U	1.9893
Bias proportion, UM	8.629e-005
Regression proportion, UR	0.0008198
Disturbance proportion, UD	0.99909

Ryanair Mean Sentiment

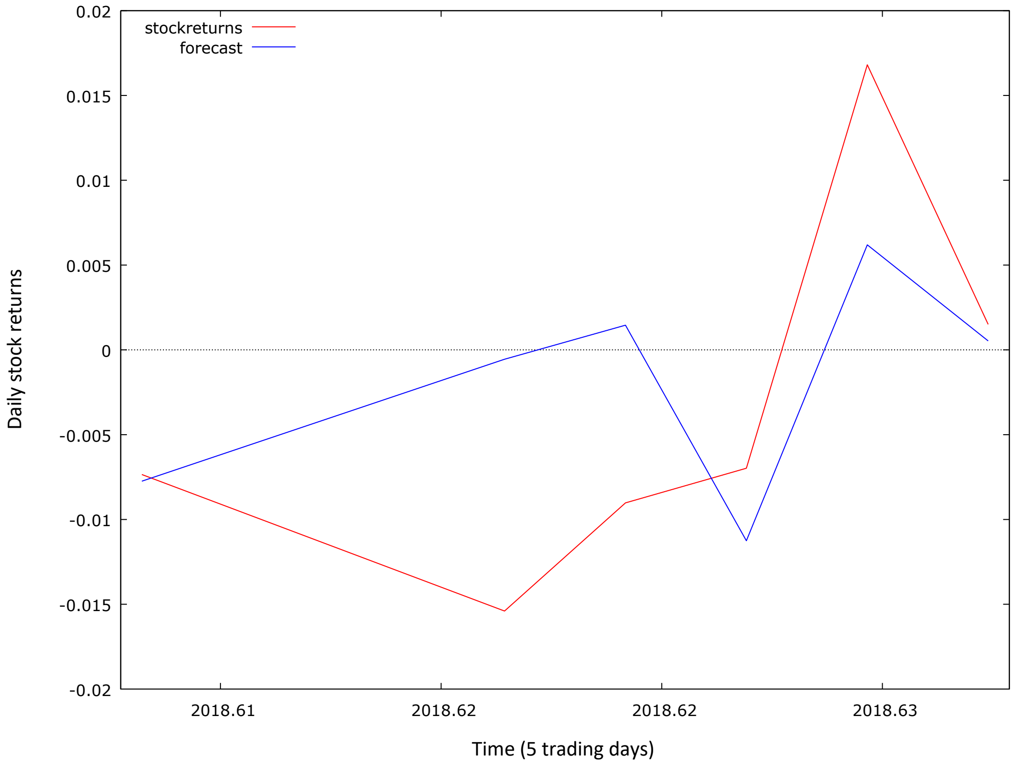


Date	stockreturns	prediction
2018-08-10	-0.037092	-0.014299
2018-08-13	0.030046	-0.002121
2018-08-14	0.001496	0.003632
2018-08-15	0.011202	-0.009235
2018-08-16	0.009232	0.007965
2018-08-17	-0.013172	-0.002010

Forecast evaluation statistics

Mean Error	0.0029633
Root Mean Squared Error	0.01872
Mean Absolute Error	0.014994
Mean Percentage Error	51.105
Mean Absolute Percentage Error	98.701
Theil's U	1.9022
Bias proportion, UM	0.025057
Regression proportion, UR	0.028628
Disturbance proportion, UD	0.94632

ITV Extreme Sentiment

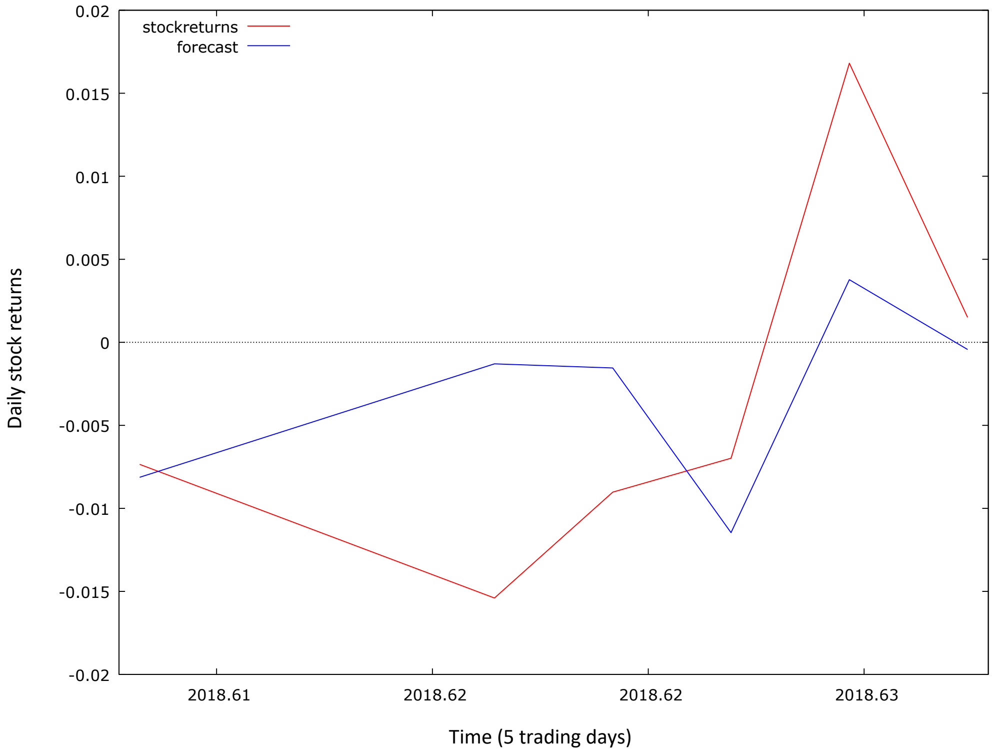


Date	stockreturns	prediction
2018-08-10	-0.007349	-0.007742
2018-08-13	-0.015398	-0.000554
2018-08-14	-0.009023	0.001455
2018-08-15	-0.006980	-0.011255
2018-08-16	0.016809	0.006191
2018-08-17	0.001503	0.000529

Forecast evaluation statistics

Mean Error	-0.0015104
Root Mean Squared Error	0.0087775
Mean Absolute Error	0.0069304
Mean Percentage Error	45.654
Mean Absolute Percentage Error	67.852
Theil's U	0.7148
Bias proportion, UM	0.02961
Regression proportion, UR	0.00087168
Disturbance proportion, UD	0.96952

ITV Mean Sentiment



Date	stockreturns	prediction
2018-08-10	-0.007349	-0.008129
2018-08-13	-0.015398	-0.001295
2018-08-14	-0.009023	-0.001546
2018-08-15	-0.006980	-0.011462
2018-08-16	0.016809	0.003774
2018-08-17	0.001503	-0.000431

Forecast evaluation statistics

Mean Error	-0.00022478
Root Mean Squared Error	0.008652
Mean Absolute Error	0.0069684
Mean Percentage Error	50.981
Mean Absolute Percentage Error	75.919
Theil's U	0.74353
Bias proportion, UM	0.00067499
Regression proportion, UR	0.0037622
Disturbance proportion, UD	0.99556