Essays in Climate Finance

by

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Abstract

Climate risk has been a topic of growing relevance in the recent years. With tightening regulations and increasing attention by the public and the media it is becoming more apparent that investors want to construct portfolios that take into account the climate risk perspective. If the aspect of climate risk has to be considered into investment decisions then it is to be expected that like other risk factors climate risk influence the price of trade-able assets. In the academic research area some seminal work has been done to study the effect of climate related news on trade-able assets like stocks, Engle et al. (2020). It can also be noted that the investment decisions might get affected by ESG or climate news inconsistently across different regions in the world. Hence this paper aims to study two topical research questions on climate finance.

First, I use Natural language processing (NLP) techniques to extract the embedded sentiment on climate related news.Then depending on the observed sentiment (whether positive or negative) I check the effect on daily movement of stock prices.To measure the effect I consider two event study methods, *the Constant mean method and the Market model method*. Subsequently, I estimate the efficiency of the sentiment analyzer in predicting the shocks of the daily stock returns generated. As a result, I found that the daily sentiment analyzer has an accuracy rate of 50%. The findings show that on a particular day if a positive climate news is published for a company then the price movement exhibited a positive shock. While if there is a negative news published then the particular stock also exhibits a negative shock on its prices. In the paper I also measure the evolution of this premium over the years and the contribution across industries to the overall premium over the study period.

Second, I study the adoption of approaches to incorporate climate-related consideration in investment operations by the global signatories of UN Principles for Responsible Investment *UNPRI*. It spans across 6 regions and comprises around 50 economies of the world. There are 14 approaches in total that has been considered for this analysis. For developed market regions inferences can be drawn in the study. For example, it can be inferred that European asset managers have more active interest on these climate related approaches. One interesting find of the study is that approaches related to physical climate risk like scenario testing is particularly significant for countries and regions (like Oceania) that are more prone to experience severe physical risk events. I found that institutional investors prefer approaches like carbon footprint and they rely on approaches like monitoring emissions data in the portfolio choices. In the study I found that generally larger investors adhere to these approaches in their investment portfolio. There are some possible policy implications that can be drawn from my findings.

Paper 1: Study on the effect of climate-related news sentiments on stock prices

1 Study the effect of climate related news sentiments on stock prices

1.1 Abstract

This paper develops a method to study the impact of climate related news sentiments on daily stock prices. First the paper uses two natural language processing algorithms, namely the *VADER and TextBlob* lexicons. With the proper implementation of the lexicons the sentiments from the news articles are extracted. The polarity scores generated as an output quantify the sentiments to be either positive or neutral or negative. The sentiment analysis is done on daily climate related news for the *FTSE 100* stocks. The study period considered for this paper is from 2006 to 2020. It should also be noted that since climate related news might not be published daily so in this paper I only consider those days when the news was published.

After the first step, the paper analyzes the stock return movements on the relevant dates for the respective stock names that had climate related news published. To study the stock return movement the paper bifurcates a return on a particular day into two types, expected normal return and excess over normal or shock component. To do this the paper utilizes two models, *the Constant mean model and the Market model*. Further the paper approaches the method of calculation the normal and shock returns from two time windows, one been short term 5 days window and the other been a bit longer 22 days window. The study analyzes the relation between the sentiment obtained from the news articles and the stock return behavior for the relevant days. It also studies the evolution of the shock return over the study period for the *FTSE 100* stocks. Further it analyzes the contribution of the different industries year wise to the overall positive or negative shocks.

I find that the technique based on the lexicons to extract the sentiments and then relate it to the historical stock returns show around 50% accuracy. The study been a simple setup hence the accuracy could be improved by analyzing the sensitivity of the different parameters and that remains a further area of research. It also shows that over the study period particularly during the significant *COP* events like 2009, 2015-2016, etc. the positive or negative premium of the stock returns increase and then fades away as the event ends and time progresses. And that primarily the industries that have exposure to climate risk related events like Banks, Mining, Oil & Gas are the ones whose companies are more responsive when there are positive or negative climate related news.

[1]

[1] *Keywords*: sentiment analysis, climate risk, news articles, lexicons, positive/negative shocks

1.2 Introduction

The impact of climate change is directly observable now throughout the globe. There has been a substantial increase in super cyclones, hurricanes, intense rainfall, heat waves, etc. While I are aware of the adverse effects of the climate change, there is still uncertainty on the trajectory of the climate change. The expected economical cost in the future is substantial. For obvious reasons the financial industry in particular asset managers need to be ready to cope with the return variation arising from the uncertainty of this economic cost.

Throughout the world most nations have emphasized the steps to control the climate risk impact. Alongside there is a growing interest on Climate Investment Funds(CIF), Green Climate Fund(GCF), Climate Finance Partnership(CPF), Environmental Social and Governance(ESG) investment both from a CSR perspective and from a pure investment perspective as well. Currently some studies (Bloomberg Intelligence) estimate that the Assets Under Management (AUM) on the ESG investment would cross USD 50 trillion. Climate risk being a primary component on this type of investment, it is interesting to study the impact of this risk factor on the stock returns.

Though it is non financial in nature but climate risk has been identified as a "new" source of financial risk in recent times Chenet (2021). Research has identified two types of climate risk factors: - i) Physical risk and ii) Transition risk

There has been studies on how physical and transitional risk affect the stock returns over a time period Bua et al. (2022), Alekseev et al. (2021). Due to the increase in Greenhouse gases (GHGs) the radiation mechanism is getting disturbed. This phenomenon in turn is increasing the earth's surface temperature. The global warming phenomenon intensifies heat waves and droughts. With rise in sea level temperature, cyclones and floods are becoming more severe.Hence global warming is likely to effect climate adversely. These activities destroy/hamper physical assets, human lives, availability of raw materials/resources and many more things. Therefore, due to weather related events the cash flow of firms/individuals gets impacted, collateral value gets reduced or written off. This type of exposure is referred to as physical risk.

Global leaders agreed in the Paris conference (December 2015) to implement stringent policies (like carbon pricing mechanisms) with the objective of net zero off carbon footprints across the globe. There has been a push for companies to transit into a low carbon economy. Changes in policy, technology or sentiment are having significant impact in the credit quality and future of a company. For

example, a company whose business model is not aligned with transition to a low carbon economy would get significantly impacted in terms of cash flow generation and sustainability. Also sudden change in policy and technology would provide banks more opportunity to grow in green sectors. This aspect accounts for the transition risk.
Physical risk has direct and mostly tangible impact that affects human capital, physical resources, assets like building, etc. Any negative impact on these items will bring immediate negative changes in cash flow or decrease in marked collateral value. Hence this might be looked into some kind of default risk and the riskiness can be captured in the probability of default (PD) and loss given default (LGD). The paper Gostlow (2019) show that physical risk factors are geography dependent. For instance, North American stocks are more exposed to extreme rainfall, while European and Japanese stocks are more exposed to extreme rainfall, heat stress, etc.

Transition risk as the name itself suggests does materialize over time as new policies are implemented to steer companies towards a low carbon economy configuration. In literature, transition risk factor pricing is mostly proxied by the price risk of carbon emission (Daniel et al. (2016), Gostlow (2019)). The transition can be smooth affecting firm cash flow gradually or abrupt as a consequence of an unexpected shock for example in terms of regulation. Also there can be firms that might not be able to transit due to technological non preparedness. Several empirical works attempted on to construct a Physical risk index and Transition risk index (Apel et al. (2021), Bua et al. (2022)) and to detect their respective effects on the stock returns. Asset pricing scholars are exploring this further.

Several aspects of climate risk economics are relevant to the asset management industry. These include how the climate risk is priced and hedged, how it affects the investment decisions, how much are investors aware of it, and how they incorporate its quantification in their decision making process. As mentioned, scholars are conducting advanced empirical works in this area. This field of study is referred to as ”Climate Finance”. One relevant area where research has been conducted is the empirical investigation of the effect of climate related news on stock prices/returns (Engle et al. (2020), Khedr et al. (2017), Ardia et al. (2020)). In these papers the general approach is to build a news index based on climate risk idioms/terms, if there is a climate related news published on a particular day then that is considered as negative news and scholars measure the impact of the shock. The approach implies that “no news is good news” when it comes to climate risk.

As mentioned, the effect of physical or transition risk on stock prices would vary as per their very nature. For example, stock A could announce today that it will become carbon neutral in 20 years. This news could have an immediate impact on its stock prices over the subsequent one or two trading days. However the true materiality on stock prices could eventually be observed as the firm A gradually reaches its target over the years. Further research could be done in this area. With the advancement of technology and availability of different tools one can also research the accuracy of sentiment analyzers in predicting stock returns. In this paper I use two ML sentiment analyzer lexicon named - VADER (Valence Aware Dictionary for Sentiment Reasoning) and TextBlob. I apply VADER and TextBlob on the news articles to estimate whether a specific news article convey positive/negative/neutral sentiment. Then I measure how stock returns on the relevant news publication dates behave as a response to the shock induced from the climate related news. I use two event study methods – Rolling Constant mean and rolling market model to calculate the excess return/shock generated during the news dates.

Literature Review

In this section i present different strands of the literature on the asset pricing implications of climate risks exposures. I first discuss how researchers address the topic on pricing climate risk. Then I focus on the latest papers featuring language processing/topic modeling algorithms related to climate risk and study its effect in the stock market. I also discuss studies on the relationship between news sentiment analysis in general and stock market movements.

The paper by Chen and Silva Gao (2012) focuses in a single industry (namely the Electrical utilities). The authors use carbon emission rates obtained from EPA to measure the environmental impact of each companies. They then estimate the implied cost of equity and cost of debt of the in sample companies. As this paper focus on one industry, hence it remains an interesting area to study on what is the effect of climate risk on other industries.

Next, Daniel et al. (2016) applies asset pricing theory to price climate risk. They develop a Epstein Zen (EZ) preference climate model. It decomposes the optimal carbon price in to two components: expected discounted damages and risk premium. To calculate the optimal price of CO2 the paper employs a discrete time binomial model. This paper employs sophisticated asset pricing techniques and equations. There remains a scope on how stock prices are affected on a granular level (daily/region-wise/industry-wise, etc.). After this I investigate research work conducted on categorizing the climate risk factors in Physical risk and Transition risk.

Chenet (2021) analyze the physical and transitional risk factors investigating whether climate risk is correctly priced, to which he finds that due to the unconventional nature of the climate risk properties it might not be possible to replicate efficient market hypothesis and so currently the market price might not be a true reflection. BOE and PRA in 2018 came up with a descriptive note that illustrates the significance of climate risk in finance and why regulators are preparing for it. The author proposes a formal definition of physical and transition risks and explains how transition risk can be characterized. To this effect it remains an interesting area to study how market's perception about impact of climate risk on stocks have evolved over the years.

S&P (2019) discuss on the interplay between physical and transition risk factors.[2] Gostlow (2019) identifies the risk factors characterizing the physical risks and that can explain the variation in global stock returns. It divides the physical risk factors based on geography, like North American stocks are exposed to extreme rainfall factor. For transition risk they use carbon dioxide as a risk factor. It then compares the market pricing with the physical risk scores of a third party data provider Four Twenty Seven. This paper focuses on risk factors globally although only the ones that are related to physical risk. The scope of this paper is not to capture the climate risk as a whole. for example, it remains open irrespective of the risk factor type what is the affect of climate risk on stock market at a granular level.

Engle et al. (2020) proposes to build a dynamic portfolio based on climate change news. The authors develop a machine learning tool based on the approach of text as data. They then develop a model to capture the climate risk premium of a stock along with the other factors. Now based on the indication of the ML model the authors build a Long Short portfolio to hedge the innovations or shocks due to climate risk. As they conclude the hedge portfolio delivers its purpose and exhibits positive results when compared with its peer indices. The authors also use two external ESG data sources, namely MSCI and Sustainalytics to benchmark the portfolio performance. My research paper tends to contribute to some of the open questions that were discussed in this particular paper. In this paper any news on climate risk is considered as negative news.

In one paper Google search volume data was used as a proxy measure of people's attention to climate change Choi et al. (2020). There is one recent paper where authors construct the physical risk index and transition risk index and researches that if news on physical risk and transition risk carry relevant information that is reflected in asset prices Bua et al. (2022). There has been also some study on how climate events affect investment decisions. Like Alekseev et al. (2021) show that local extreme heat events has an impact on mutual fund holdings and investors would reallocate their capital when climate news shock occur thus affecting equilibrium prices. And there has been study on the performance of green vs brown stocks.All these papers have an open scope which is needed to be studied. For ex-

[2] In the discussion paper, authors have made four quadrants each representing how much assets are impacted by physical and transition risks. They have taken S&P 500 and S&P 1200 as their database. For transition risk they have proxied rise of carbon pricing effect on a firm. And to do that they have used Trucost analytics data.

ample, the effect of positive or negative climate related news separately on stocks. And at a granular level how the shocks experienced in stock prices as an effect of positive or negative news behave.
Ardia et al. (2020) construct a media climate change concerns index based on climate change news from major US dailies and find that with unexpected increase in climate change concerns green stocks tend to outperform brown stocks. This paper also extends to topic modeling and finds that the effect on green and brown stocks hold true for both physical and transition risk related concerns. As part of this review, an important point that would be interesting to study is the effect of climate related news on stocks (both green and brown) over the years. And it would be important to understand the effect of both good and negative news on the green and brown stocks.
One other relevant paper by Apel et al. (2021) is based on this growing area of literature and analysis. In this paper the authors build a transition index to approximate changes from climate related news. While developing the methodology to analyze the text the authors relax the assumption that *no news is good news on climate*. The paper goes on to evaluate the performance of Green minus Brown stocks portfolio based on investor's climate objectives. The paper involves Machine learning techniques of language processing, topic modeling, etc. Overall the paper finds that stock returns get affected by transition news in the short term. But long term concerns like emissions or future course of adaption might not affect the stock returns.

This research paper extensively uses the technique of analyzing the sentiment from text or news articles and relate it to the stock price movements. To this aspect a number of papers have been published that study the effect of sentiment analysis and stock price movements. In the paper by Khedr et al. (2017), they use sentiment analysis on financial news and historical stock market prices. In this study, first the *naive Bayes* algorithm is used to get the polarity scores after analyzing the sentiment from stock prices. After that using the polarity scores and historical stock prices the future stock price of the companies are predicted. The study claims this approach had around 89% accuracy.
Pagolu et al. (2016) stock market prediction bases on sentiments analysis from Twitter texts were done. The paper implements two textual representations namely, *Word2vec and N-gram*, for analyzing the public sentiments in the tweets. With the help of supervised machine learning algorithm the paper analyzed the correlation between the stock market movements of a company and the sentiment observed in the tweets.
In the same stream of research, the paper by Smailović et al. (2013) studies whether public opinion expressed in Twitter about products or companies are a suitable data source for forecasting stock prices. The study uses a Granger causality test to show that sentiment (positive and negative) can indicate stock price

movements. The paper also employs Support Vector Machine classification mechanism to categorize the sentiments from the tweets and finds that the prediction power improves.
The paper by Souma et al. (2019) studies how historical news sentiments can be used to forecast financial news sentiments. This paper uses high frequency data using stock returns averaged over one minute from a news article is published. If the stock exhibit positive return then the news published is categorized as positive news and vice versa for negative news. The authors create a word vector to be used as inputs using *TensorFlow* network deep learning. The paper finds that using the deep learning methodologies of recurrent neural network there is forecasting accuracy on the training data set.
Li et al. (2014) studies the impact of sentiment analysis on stock prices. In the paper they use six different approached to analyze the sentiments and plugs those techniques into the stock price prediction framework. The study uses Hong Kong stock exchange prices and news articles for a five year time period. The study comes up with several results but at a broader level it can be seen that also at individual stock, sector or index level sentiment analysis outperforms in both validation and training data set.
From this literature review it can be inferred that sentiment analysis of news articles can provide insights into stock price movements. It is also obvious from the studies that the model and code set up should be prudent enough to capture the respective sentiment polarities through lexicons or machine learning techniques on text reading. And recently there has been a good amount of work on these lines that analyzes the sentiment of climate risk news articles and observes its relation to the stock returns movements. However there remains some open hypotheses and in this paper I would study if some of those hypotheses as mentioned above is valid or not.

1.2.1 Contribution to the literature

The literature review shows that there has been an increasing interest in applying Machine learning or NLP techniques to study the effect of climate related news on assets(particular stocks). These papers direct to various future research areas. And after going through them I can observe that there could be more studies done in these areas. In this paper I particularly focus on enhancing the usage sentiment analyzer on news articles and study its effect on daily stock price data. To move forward with the study I would formulate three hypothesis and then based on the research model outputs study the results and check if these hypothesis holds true.

There has been work done on how the climate risk news would affect asset markets. Particularly,Engle et al. (2020) implemented a portfolio including the

climate risk factor with a factor model portfolio. And used the extracted news sentiment to understand if that has any impact on the stock returns. The paper does not segregate positive and negative news using rule based sentiment analyzers like VADER or TextBlob. It assumes that no climate related news on a stock is considered to be good news and if there is some climate related news then it is considered as negative news. The paper also does not capture the effect of the news sentiments on daily stock returns.
In the other relevant extension paper by Bua et al. (2022) the effect of physical and transition risk related news is studied on stock prices. The authors build a physical risk index and a transition risk index through different approaches including topic modeling and study its impact on stock prices. The other relevant paper by Ardia et al. (2020) checks the performance of green vs brown stocks. They do so by using a text based approach of capturing media coverage on climate change concerns. If there is an unexpected increase in climate change concern then green firm stocks tend to increase in price while brown firm stocks tend to decrease in price. They also use topic modeling approach and concludes that it holds true for both physical and transition risk concerns. However studying the impact of positive and negative news separately and at a granular level were not in scope of these papers. Also an interesting point that comes up from these papers is the evolving premium observed in the stock market over the years due to climate related news.

In this paper, my first hypothesis $H_0 1$ = study the effect of using sentiment analyzers on news articles and then use two different event study methods to measure the shock induced by the sentiments on daily stock prices. In turn in the results the hypothesis measures if the sentiment analysis outcomes do have any relative accuracy with the shock exhibited by respective stock returns.
To perform the first hypothesis testing I explore the arena of segregating and treating positive and negative sentiments conveyed directly from the news articles. This would relax the assumption prevalent in the papers that no news is good news or any climate related news is bad news. Also I implement the algorithm to daily stock data on a particular region making it more granular. Details of the test can be referred to in section 1.5
The second hypothesis $H_0 2$ = capture overtime how the excess returns observed on climate risk related news shocks dates have evolved for the daily stock returns. For example, are the magnitude of cumulative excess returns more now with respect to what it used to be earlier like in 2007-2008 period. Or do I see sudden spikes in specific years where some specific global events like 'COP' has happened. More details can be found in the section 1.6.
The third hypothesis to be checked as part of this paper is $H_0 3$ = the relative contribution of the different industries to the overall premium over the study period. This particular analysis contributes to the growing literature on studying the effect

of news/media coverage on green and brown stocks. As part of this hypothesis test I would check if industries that are sensitive to climate related news exhibits more impact due to the positive or negative shocks. The relevant details can be found in section 1.7.
All these results are studied for the UK region since *FTSE 100* stocks are used in the study.

1.3 Construction approach used to build the study model

The term climate change news has a very broad scope and it encompasses future economic activity uncertainty, recent effect like heat waves/snowstorms, future events of climate evolution, sudden regulatory guideline changes/introduction, etc. To study the effect of climate change news I must first select a reliable source of information. In order to do that I consider newspaper as a source of information that has a wider reach. Now it is true that climate change is a global phenomenon. And be it at the DAVOS conferences or the COP conferences I see that world leaders are announcing different steps to tackle climate change effects. But it is also true that instantaneous or short term or specific climate change related news affect locally or can at best affect a specific region. It is seldom true that a particular climate change related news would affect cross boundaries. Then it becomes evident that the risk generated through climate change would only affect that particular region and economically the effect would be more felt locally/region specific. Hence to account for this aspect I consider one specific region and then observe the news published in that specific region only.

In this section I would describe the data sources and preparation. First I would elaborate about the data used in this paper then go on to detail the methodological steps. Due to the constraint of data availability and accessibility I restrict the study to one particular region. But the study can be extended to cover other regions given data becomes accessible. Also for this study the code base I develop can be used for result replication or extending the study. Off course some minor modifications can be done in the code to keep it relevant to the nature of the data used.

1.3.1 Input data used in the study

As has been highlighted in the previous sections the main input data are the news related to climate change. Now there could be many sources of news - online articles feed to third party search engines like Google or online newspaper. Even there are multiple newspapers published in a specific region or country. So the primary selection was to not fall in the data mining issues and select a proper representative region and a renowned or widely used newspaper from that region.

Although now financial regulatory bodies across the globe are coming up with policies related to climate risk but Bank of England and the Prudential Regulation Authority(PRA) fall among those regulatory bodies who first initiated this change of stance. In one of their publication in 2018 which can be read here they discussed how financial institutions should manage financial risks arising from climate risk.

Accordingly I select United Kingdom as the region for this study.

Now I had to select the period of study. For this paper I use the time period from 1st Feb 2006 to 30th December 2020. Although as I would see in the later sections that the results are shown from 1st Feb 2006 but the month of January 2006 was also considered. This is because I use a rolling window in the methodology to generate the statistics and hence the first 22 days of the year was used to generate the first statistical result. Then I include the Covid period of 2020 in the study. This is because Covid was one in a century event and although it was not directly linked to climate change but it would be interesting to study the effects observed in stock prices during that period.

I select a newspaper source for the UK region that has a good coverage of financial events as well. The access to a streamlined news source for the long study period is costly and hence I rely on data available for academic purposes. Here I would like to again thank my advisor and EDHEC institute as they helped me to get access to the FACTIVA platform. The platform is a store house of news where one can customize the search criteria and get news articles as per the requirement. In the following I provide a snapshot of the search criteria that I use. It can be noted here that for the study I filter using key words as can be seen in the search criteria in Table 1.The choice of keywords are made such that they resemble words that would be used in climate related news.

Since the region of study is United Kingdom so for this paper it becomes a natural choice to consider the stock names that are present in the FTSE 100 index. A detailed descriptive stats of the stocks like their names, industry and market capitalization has been provided in *Appendix* in a tabular format Table 26.

Hence to summarize I consider all the stock names present in FTSE 100 as of March 2022. And have considered climate related news articles published in *The Guardian* newspaper for the study period. As can be inferred the market index for this paper is FTSE 100 index. And the daily FTSE 100 and individual stock price data was downloaded from *Yahoo Finance*. It should be mentioned here that python has already established codes/libraries to connect with Yahoo Finance and it becomes easier to source the data this way.

Search Summary	
Text	3i or Abrdn or Admiral Group or Anglo American plc or Antofagasta or Ashtead Group or Associated British Foods or AstraZeneca or Auto Trader Group or Avast or Aveva or Aviva or B&M or BAE Systems or Barclays or Barratt Developments or Berkeley Group Holdings or BHP or BP or British American Tobacco or British Land or BT Group or Bunzl or Burberry or Coca-Cola HBC or Compass Group or CRH plc or Croda International or DCC plc or Diageo or Entain or Evraz or Experian or Ferguson plc or Flutter Entertainment or Fresnillo or GlaxoSmithKline or Glencore or Halma or Hargreaves Lansdown or Hikma Pharmaceuticals or HSBC or IHG Hotels & Resorts or Imperial Brands or Informa or Intermediate Capital Group or International Airlines Group or Intertek or ITV plc or JD Sports or Johnson Matthey or Just Eat Takeaway or Kingfisher or Land Securities or Legal & General or Lloyds Banking Group or London Stock Exchange Group or M&G or Melrose Industries or Mondi or National Grid plc or NatWest Group or Next plc or Ocado Group or Pearson plc or Pershing Square Holdings or Persimmon plc or Phoenix Group or Polymetal International or Prudential plc or Reckitt or RELX or Rentokil Initial or Rightmove or Rio Tinto or Rolls-Royce Holdings or Royal Dutch Shell or Royal Mail or Sage Group or ”Sainsbury s” or Schroders or Scottish Mortgage Investment Trust or Segro or Severn Trent or DS Smith or Smiths Group or Smith & Nephew or Smurfit Kappa or Spirax-Sarco Engineering or SSE plc or Standard Chartered or ”St. James s Place plc” or Taylor Wimpey or Tesco or Unilever or United Utilities or Vodafone Group or Weir Group or Whitbread or WPP plc
Date	01/01/2006 to 31/12/2020
Source	The Guardian (U.K)
Author	All Authors
Company	All Companies
Subject	Carbon Sequestration Or Climate Change Or Natural Environment Or Natural Gas Markets Or Natural Disasters/-Catastrophes Or Natural Reserves/Resources Discovery Or Natural Resource Scarcity Or Environment Department Or Emission Markets Or Emissions Or Air Pollution Or Environmental Crime
Industry	All Industries
Region	United Kingdom
Language	English
Results Found	2005

Table 1: Factiva news search inputs

1.3.2 Methodology

In this section I would describe the steps that I follow to build the model. The steps would be described at a semi granular level meaning the reader would understand on what has been the modeling choice and methodology followed. But simultaneously it would also be not too detailed to include micro parts like code library details, etc. More details about the coding and libraries used are discussed in the Appendix of this paper. I have provided the code base used in this paper in Appendix.

With the growing importance of climate risk impact there are a number of studies in different fields of finance on how to capture the climate risk premium. Going by the trend there is a large scope of research in the future that would help industry to properly address the impact.

1. To capture the physical risk events, past data is not a good predictor of future. Unlike in other areas of risk factor performance, for physical climate risk the past patterns or data does not predict anything about future. For example, it is not necessary that a cyclone would affect the same region in a similar time frame every year. So the auto-correlation technique or Markov modeling choices might not be an optimal tool to use. For the transitional risk events I do not have a rich store of historical data or events to capture the cause and effects. Hence to study the climate risk related phenomenon I rely on real time data analysis and how it has evolved over the years.
   To mitigate this fact in the paper I use the NLTK library based sentiment analyzers. More precisely I work with the VADER and TextBlob sentiment analyzers. Briefly, the VADER library provides the score of how much an article or piece of text is either positive or negative or neutral. And then normalizes the three sentiments and provides a compound score where more towards +1 is highly positive and more towards -1 is highly negative. Similarly, the TextBlob library provides a score of Polarity and Subjectivity for each news article. Polarity ranges from -1 to +1 where it can be inferred that the more the score is towards -1 the stronger is the negative sensitivity conveyed and vice versa when it moves towards +1. The advantage of using these rule based lexicons is that I do not need to have a train and test data set. With proper setup and library calls if these lexicons are applied on any article or text it does a fair enough job to estimate the sentiment conveyed from that piece of information.
   From the FACTIVA search criteria I had around 2000 news articles for the study period. Then I had to do some data cleaning. This is because not

all the downloaded news articles had news information in their body;some were blank. Also not all the news articles were relevant for the study as there were some articles which were like quotes of stock prices which some how got flagged in the search exercise. After performing the data cleaning I had around 1750 news articles. Now from the scores of particular publication dates I can get an understanding of the embedded sentiment in the news article. When the score is between -1 and zero I treat them as Negative news, when it is equal to zero I mark them as Neutral and from zero to 1 I treat them as Positive news sentiment.
The broad level of thresholds mentioned above would help to make the classification simpler. One can vary the classification thresholds and it can be very well studied further on the relationship between the stock returns and the intensity of the sentiment scores with the varying thresholds.

2. As a next step I develop the code and applied the sentiment analyzers to each news articles. Hence now the study setup has the sentiment analyzer scores with *VADER* and *TextBlob* analysis for each news article. For clarification purposes, it can be noted that each news article is mapped to the news publication date. Also through the *Python* code I was able to extract the names of the stocks present in the news articles. For this study I am using all the stock names present in *FTSE 100* as mentioned in the above section.
For data related accessibility issues, as highlighted previously I consider only those news articles that are flagged as climate related news.
The purpose of the paper is to study the stock returns on the days with positive/negative climate sentiment news publication dates. Once I studied the news articles I found that in a single news article there could be the mention of multiple stock names from the FTSE 100 series. This is also meaningful because for example if there is a regulatory(transition risk) news that affects oil companies then all the oil stocks present in the FTSE 100 series would show the event effect with varying effects in the stock price. Hence I check in each article if there is a mention of one or more (up to 4) stock names from the particular market index (*FTSE 100 index*). Also I did not segregate between green and brown stocks in this paper but based on the results and the datasets it can be conveniently extended to measure the behavior of green and brown stocks with respect to the sentiment conveyed in the news articles. The research work done by Ardia et al. (2020) would be a good reference point to conduct the study.
For the full historical study period I convert the daily prices of the individual stocks into returns and then map the returns of the respective stock names

on particular dates. Similarly I also convert the daily price data of *FTSE 100* index into daily returns. The idea of using returns is to calculate the exact positive or negative shock in the stock prices.
At this stage in the study model for each climate news article I have - the publication dates, the sentiment analyzer scores calculated by the lexicons, the stock names from the respective news articles, the individual stock returns and index returns for the particular publication dates.

3. As for the next step I calculate the normal and excess returns of the stocks on the relevant dates. The methodology I followed can be referred to *The Constant mean model*and *The Market model* by MacKinlay (1997).
In this step as mentioned I use the two models. Both this models are well established. The *Constant mean model* estimates the normal return of an asset based on its historical mean (assuming it to be constant over the event window). As it implies this model is one of the simplest models but Brown and Warner (1985) and Brown and Warner (1980) show that the results from this model are very similar to the ones obtained from sophisticated models. The model can be shown as follows in the form of an equation:

$$\mathrm{R}_{it} = \mu_i + \Psi_{it}$$

where R $\rightarrow$ represents the stock(i)'s return on a particular date t,
μ $\rightarrow$ represents the constant mean of the stock exhibited over a fixed interval of event study period
Ψ $\rightarrow$ is the shock or noise observed over the constant normal mean return on a particular date t

For the purpose of this study I select a sufficiently longer period starting from 2006 to 2020. The study period would have many economic cycles therefore keeping a constant mean over the study period would not be relevant. Hence, I take two approaches i) use a rolling 22 days time period as event period. This is because in general a month has close to 22 trading days and by having a rolling window the model can capture the evolution of the stock returns over a longer time period. And ii) use another rolling 5 days time period as event study window. As 5 days provides a view on the stock return for a smaller 1 week horizon. So in the first case μ is the mean of 22 days and rolled consecutively for the entire study period. And in the second case it is the mean of 5 days and similarly rolled for the entire study period.

On the other hand *the Market model* is a statistical method and estimates the normal return of an asset to be a linear function of the market (or its index) calculated over the event window time period. The linear specification of the model follows from the assumed joint normality of the asset returns. In the paper by MacKinlay (1997) mentions that the Market model is a potential improvement over the Constant mean model. Because since it removes the portion of the return that is related to variation in the market's return the variance in the abnormal return is reduced. The *Market model* can be represented in the following equation format:

$$\mathrm{R}_{it} = \alpha_i + \beta_i \mathrm{R}_{mt} + \varepsilon_{it}$$

where R $\rightarrow$ represents the stock(i)'s return on a particular date t,
$\alpha \rightarrow$ represents the constant term from the regression
$\beta \rightarrow$ represents the sensitivity to market for stock i
$\varepsilon \rightarrow$ shock or noise observed over the normal return on a particular date t

Similarly as above for the purpose of this study I follow two approaches i) use a rolling 22 days time period as event period. This is because in general a month has close to 22 trading days and by having a rolling window the model can capture the evolution of the stock returns over a longer time period. And ii) use another rolling 5 days time period as event study window. As 5 days provides a view on the stock return for a smaller 1 week horizon. So in the first case the market return and the stock return has 22 days of overlapping period for which the regression is performed and then rolled consecutively for the entire study period. And in the second case it has 5 days of overlapping period and similarly rolled for the entire study period. To perform the regression I use the *Rolling OLS*method. Details of the code is available in the Appendix.
It can be noted here that *the Constant mean and the Market model* is run for the entire study period. Hence for the purpose of the study I can choose and pick up the relevant model outputs for the relevant news publication dates.

4. The final step is to calculate the shock or excess return for the specific dates. This can be done now easily by using simple mathematical operation.
   From step #2 above I get the actual returns of the respective stocks calculated from the adjusted close price. I map the stock names and the respective daily returns in the previous steps.
   From step #3 mentioned above I get the model implied returns based on

the rolling event study window. By this I refer to the outputs generated by the *Constant mean and Market model*. Since these returns are based on the stocks historical rolling values so technically it represents the normal return that the stock would have on that particular date. Hence on a given news publication date I have the stock names that appear in the news, the sentiment scores from the sentiment analyzers, the corresponding daily returns on the considered day and the normal return on the particular day of the respective stocks calculated by the two event study models.

Now the observed effect on the climate news publication date is the difference in returns from step #2 and the returns from step #3. This spread would be the positive or (negative) excess return observed in the stock.

Then I mapped the sentiment scores on the respective publication dates to the excess returns for the whole study period. And study the appropriateness of the estimation. Further I also study how the stock returns behave on the positive/negative sentiment news dates.

It can be related that physical risk is something that is more observable in nature. For physical risk, there are already identified risk events in literature like severe cyclones, heat waves, heavy rainfall, etc. There is already some work done in terms of studying which countries/regions suffers the most due to extreme weather events. It can be found here Global Climate Risk Index 2020. The following figure developed by *S&P and Trucost* provides a good representation of the heat wave that is expected by 2050.

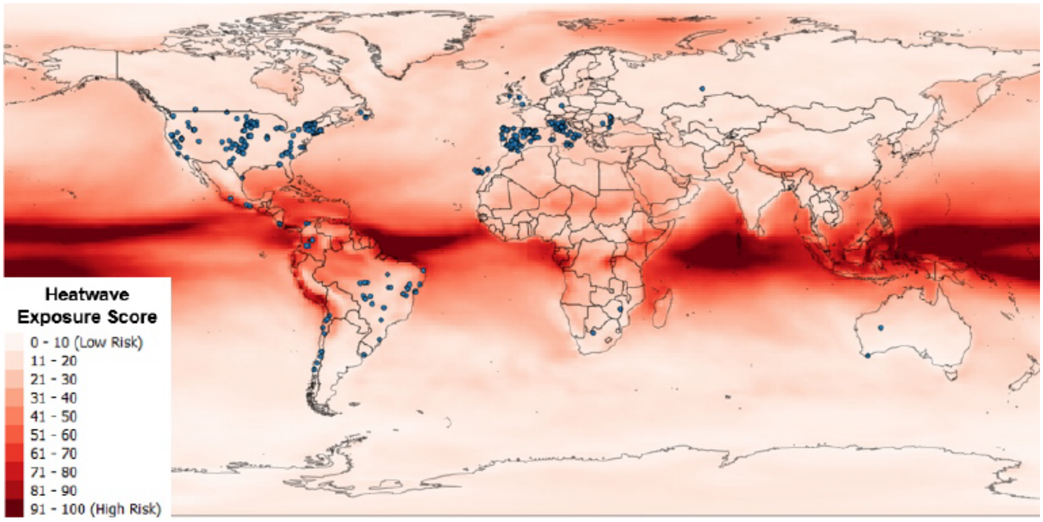

Figure 1: Hazard map for heat wave in 2050 for illustrative purposes only

1.3.3 Key assumptions for this study

As with all models that are used in research work and in practice, this study model also has some key assumptions. They are *key* because when these assumptions are changed the output of the model would also be affected. The following paragraph provides the details of these assumptions.

First, for dates where news was published but there were no stock prices information available from the data source, I first check the previous available day else the next available day price data and use that information. Secondly, in both the event window models (*the Market and the Constant mean model*) the error or shock term is assumed to be homoscedastic with a mean = 0. Hence it satisfies the condition to be model-able. Thirdly, in this study I assume that the (positive/negative) excess return observed or calculated on any particular news publication date in the study is only affected by the sentiment of the news. The measure and accuracy of this effect is illustrated in the *Results* section. And lastly, where there are multiple firm names present in a particular day of the news article, I consider up to 4 firm names. And for the purpose of measuring excess return I take the particular highest/lowest stock return that corresponds with the positive/negative sentiment score on the particular news publication day.

1.4 Hypotheses tests and Results

In the following sections I would test the different hypotheses that were constructed as part of the study on the model and their corresponding results.
In terms of naming convention and representation I would first describe the study method that is been used, then put the results in tabular format and at the end I would discuss about the conclusion that can be drawn from the hypothesis test results. This same nomenclature would be followed for all the study items. It is worthwhile here to mention that after obtaining the sentiment scores across news articles I did another round of data cleaning. In this round I removed those news articles
a) that had more than 4 stock names,
b) had sentiment scores equal to zero as they are not in scope of this paper and
The final number of news articles considered for each of the methods has been mentioned in the respective tables of results of section 1.5.

1.5 Description and results of Hypothesis $H_0 1$

1.5.1 Description

As part of the analysis in this paper I calculate the event study windows based on the already discussed two approaches, *the Constant mean approach and the Market model approach*. For the Constant mean approach, I use two choices where in one I calculate the mean over a 5 D rolling window and in the second I calculate the mean over a 22 day rolling window. Similarly for the Market model approach, I use rolling regression method where I had made two choices one with 5D rolling window and in the second with 22D rolling window. The detailed description of the choices are mentioned in section 1.3.2.

Now I know that for a particular publication date the excess return on a security $=$ Return of the particular stock on that day $-$ the normal return calculate through the event study windows

For this paper I use the two rule based sentiment analyzer lexicons. Since these are rule based so it is not necessary to train the data-set. I discuss on the lexicons in section 1.3.2. The VADER and TextBlob are the two popular sentiment analyzer available within the NLTK library of Python. The basic code base on how to use the sentiment analyzers can be found in open source platforms like *Github*. Also the code that I use in the study has also been provided in section 3.

1.5.2 Results

The following are the tabular format presentation of excess return using the different approaches and sentiment analyzers. The naming convention of the tables are kept self explanatory, however the details are discussed right after it in the *conclusion* section.

Total news articles considered after data cleansing		1454
Sentiment	**Excess Return with 5D rolling Constant Average model**	**Accuracy in %**
Positive	Positive return	51.7%
	No Excess return	1.8%
	Negative return	46.5%
Negative	Negative return	52.3%
	No Excess return	1.7%
	Positive return	46.1%

Table 2: Calculated using VADER and 5D rolling *Constant mean* method

Total news articles considered after data cleansing		1454
Sentiment	**Excess Return with 5D rolling Market model**	**Accuracy in %**
Positive	Positive return	53.6%
	No Excess return	1.2%
	Negative return	45.1%
Negative	Negative return	51.6%
	No Excess return	0.7%
	Positive return	47.7%

Table 3: Calculated using VADER and 5D rolling *Market model* method

Total news articles considered after data cleansing		1454
Sentiment	**Excess Return with 22D rolling Constant Average model**	**Accuracy in %**
Positive	Positive return No Excess return Negative return	52.8% 1.8% 45.4%
Negative	Negative return No Excess return Positive return	52.3% 1.8% 45.9%

Table 4: Calculate using VADER and 22D rolling *Constant mean* method

Total news articles considered after data cleansing		1454
Sentiment	**Excess Return with 22D rolling Market model**	**Accuracy in %**
Positive	Positive return No Excess return Negative return	52.5% 1.2% 46.2%
Negative	Negative return No Excess return Positive return	50.9% 0.7% 48.4%

Table 5: Calculated using VADER and 22D rolling *Market mean* method

Now the same methodology was run on the data set using *TextBlob* sentiment analyzer and the results are presented in the following tabular format.

Total news articles considered after data cleansing		1411
Sentiment	**Excess Return with 5D rolling Constant Average model**	**Accuracy in %**
Positive	Positive return No Excess return Negative return	52.1% 1.9% 45.9%
Negative	Negative return No Excess return Positive return	52.7% 1.4% 45.9%

Table 6: Calculated using TextBlob and 5D rolling *Constant mean* method

Total news articles considered after data cleansing		1411
Sentiment	**Excess Return with 5D rolling Market model**	**Accuracy in %**
Positive	Positive return No Excess return Negative return	54.5% 1.1% 44.4%
Negative	Negative return No Excess return Positive return	49.9% 0.7% 49.4%

Table 7: Calculated using TextBlob and 5D rolling *Market model* method

Total news articles considered after data cleansing		1411
Sentiment	**Excess Return with 22D rolling Constant Average model**	**Accuracy in %**
Positive	Positive return No Excess return Negative return	52.1% 1.9% 45.9%
Negative	Negative return No Excess return Positive return	53.1% 1.4% 45.5%

Table 8: Calculate using TextBlob and 22D rolling *Constant mean* method

Total news articles considered after data cleansing		1454
Sentiment	**Excess Return with 22D rolling Market model**	**Accuracy in %**
Positive	Positive return No Excess return Negative return	53.7% 1.1% 45.2%
Negative	Negative return No Excess return Positive return	55.9% 0.7% 43.4%

Table 9: Calculated using TextBlob and 22D rolling *Market mean* method

In the above tables I show the results separately using VADER and TextBlob sentiment analyzer. The convention of the tables remain self explanatory. For example, when the news article sentiment is positive then I calculate three parameters
a) what is the total % of news articles that exhibit positive excess return (meaning provide a premium for the positive news to that particular stock),
b) what % of news articles showed no excess return and
c) what % of articles provided negative excess return (meaning the positive sentiment had no affect and due to some reason the particular stock had less return than the normal return calculated using the event study windows).

Similarly, when sentiment of the articles is negative then I calculated three parameters;
a) % of articles exhibiting negative excess return thereby showing the stock price reduced on the negative new publication date,
b) % of articles showing no excess return and
c) % of articles that somehow showed opposite effect.

1.5.3 Hypothesis test Conclusion

After looking into the methodology and the results I can conclude the following presentations.
First – Whether I use VADER or TextBlob sentiment analyzer as the choice the results show that around 52% cases the extracted sentiment and the stock return exhibit a similar sign of the shock. This means that on a particular date when positive climate related news was published for a company then the particular company stock provided a premium while on days when there was negative climate related news the stock prices went down. I can say that for around more than half of the cases individual stocks show a similar relation with the shock induced by the sentiment of the climate related news article. Also it is similarly true that asper the present design and modeling choice the accuracy is not more than 46% when granularity at individual stock levels are considered. The recent papers that do sentiment analysis have not considered the sentiment at such granular level separately on a daily data.
Hence, at a granular (individual stock) level with daily price data the effect of climate related news might not always get captured as the horizon of materializing any climate related news (both positive and negative) have a longer time to mature. But there is off course an instantaneous effect that drives the daily price movement of the stocks.

Second – VADER performs marginally better than TextBlob in predicting the sentiment analysis induced by the news articles. Although this is a broad con-

clusion as the efficiency of the lexicons can always be increased by the way of optimization. However for this paper's setup the conclusion holds true.
Overall it can be concluded that the hypothesis holds true.

1.6 Description and results of Hypothesis $H_0 2$

1.6.1 Description

In this part I compare the over time evolution of the aggregated excess return calculated using the 5D and 22D rolling event study windows. The aim is to study on how from 2006-2020 has the aggregated positive and negative premium evolved.

I present the comparison in a chart format. And in this section I incorporate one chart that shows on how the 5D and 22D rolling window using *Constant mean* model evolve over the study period. The sentiment analyzer in this case is VADER. Each line graph shows the total excess return over a particular period. To capture the accuracy total excess return is considered for those stocks whose sign of shock relate to the sentiment observed from the particular news article. So by *Positive-Positive 5D* line the chart shows for a particular year the total positive excess return for those stocks whose news article also predicted a positive sentiment on the corresponding dates. The similar other consecutive charts for the study conveying the same idea of using 5D and 22D rolling window *Constant mean and the Market regression model* are provided in the Appendix section 3.1. And they cover both VADER and TextBlob sentiment analyzer for each event study process.

1.6.2 Results

The chart headings remain self explanatory of the method covered. When the charts are looked in isolation it might not be conclusive and just portray a partial picture. This is because for each year the number of stocks contributing to the aggregate excess return can be very different. Hence it is also necessary to represent the number of stocks considered in the calculation for each year. I include the corresponding table to show the number of stocks that contributed each year. It can be noted here that the number of stocks is not a unique count because it is very well possible that in a given year one stock can be impacted by climate related news multiple times. Also it is worthwhile to mention that it is not necessary that all the stocks would have similar level of excess return hence calculating excess return per stock would not be meaningful. However the number of stocks should relate to the difference in excess returns observed over the years.This means that if the aggregate excess return is comparatively high in any given year then that year should have more number of stocks contributing to it and vice versa for less aggregate return level. For example,in year 2015 the chart shows a big spike and from the count of stocks I can see that it is comparatively higher around 100.This would make sense economically and also tend to point to the fact that there are less chances of some outliers contributing significantly to the total.

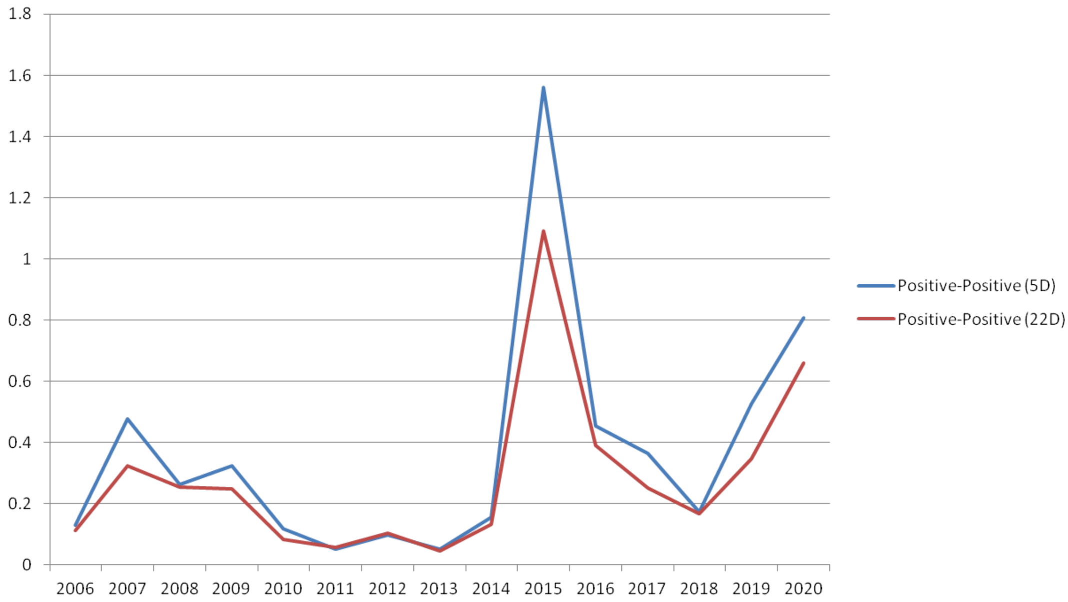

Figure 2: Compare positive excess returns using Constant mean and VADER

Year	Count for 5D	Count for 22D
2006	28	30
2007	41	34
2008	17	17
2009	19	16
2010	6	6
2011	7	7
2012	10	8
2013	6	7
2014	10	12
2015	94	100
2016	31	28
2017	27	29
2018	21	26
2019	26	29
2020	34	36

Table 10: Count of stocks for Positive-Positive using Constant mean and VADER

1.6.3 Hypothesis Conclusion

As the charts show the positive or negative premium has been sensitive with the sentiment in certain years and so it has occasional spikes over the study window. It is interesting to see that in the recent years the positive premium or negative premium movement has increased in magnitude thereby showing the stock prices have become more sensitive on the days when positive/negative climate related news are published.
There has been a particular spike around year 2015-2016 it can be correlated to the effect of Paris Climate Summit in that period. Similar spikes are observed around late 2006 and 2007 and around 2009. These are also the years where in the *COP* some significant decisions were made. The effect seems to peak on 2021 as there would be another *COP* on that period after the *COVID* hiatus. From the evolution of the chart it can be inferred that the premium peaks around the time when there is a *COP* and then the impact goes down. And as companies are adapting to the new normal after *COVID* the sensitivity of the stock movements with climate risk related news seems to show an increasing trend. This makes sense economically because the world after *COVID* would naturally be more concerned on climate change related topics.

Some other related analysis would be that VADER shows marginally better performance level than TextBlob if I consider the spread between 22D and 5D

excess return in each of the cases/charts.
Hence the hypothesis holds true to the extent of the scope of this paper. The 5D excess return is higher than the 22D excess return, thereby inferring that the shock effect is higher when measured in a shorter time period window. From this point it can be inferred that any effect on the climate related news is instantaneous. However there could be more research done on this area to check if this statement holds true.

1.7 Description and result of Hypothesis $H_0$3

1.7.1 Description

In this section of the paper I study the contribution of different industries over the years. The previous sections shows on how the stocks are independently getting affected by the climate related news and exhibit positive or negative excess returns in line with the sentiment observed from the published news. It also shows on how the aggregate excess return across stocks look like and the evolution of the premium over the years.
It would be also interesting to see the contribution of different industries in the aggregate excess return and how it compares over the years of study. I divide the stocks based on their industry classification as per *FTSE 100* information. For the purpose of the study I consider Banks, Food and Drug retailers, Oil & Gas producers, Mining and clubbed everything else as Others.
In the following Results section I am only providing as reference the chart for the 5D event study window that uses the *Constant mean model* and VADER sentiment analyzer. The chart names are self explanatory where one shows the aggregate positive excess return considering the dates when climate news sentiment was also positive. And aggregate negative excess return considering the dates when climate news sentiment was negative. Similar charts for the other event study model and sentiment analyzer combinations are provided in Appendix Section 3.2.

1.7.2 Results

The following charts show the classification of industries contributing to the aggregate premium.

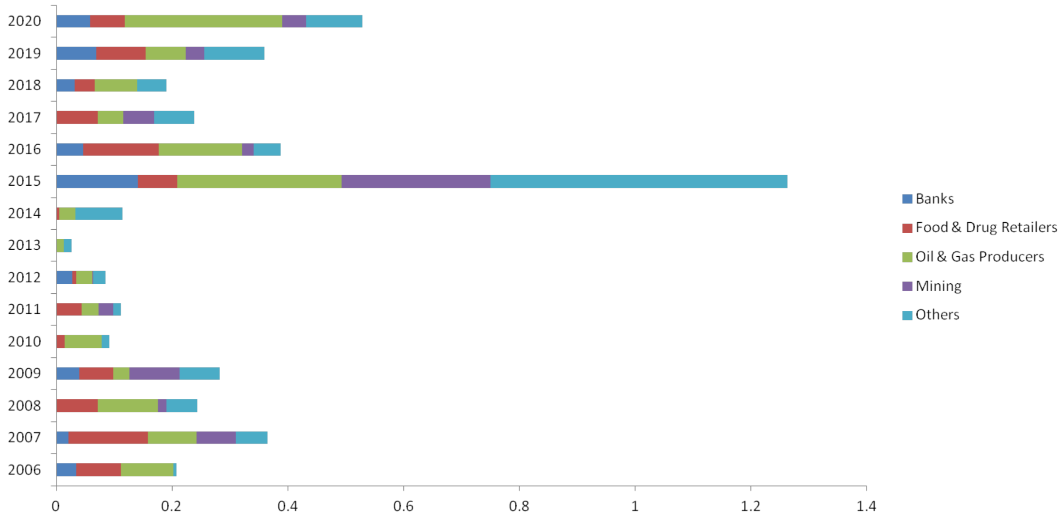

Figure 3: Industry wise contribution using the 5D Constant mean window and VADER analyzer (Stocks with positive returns exhibited for positive sentiments)

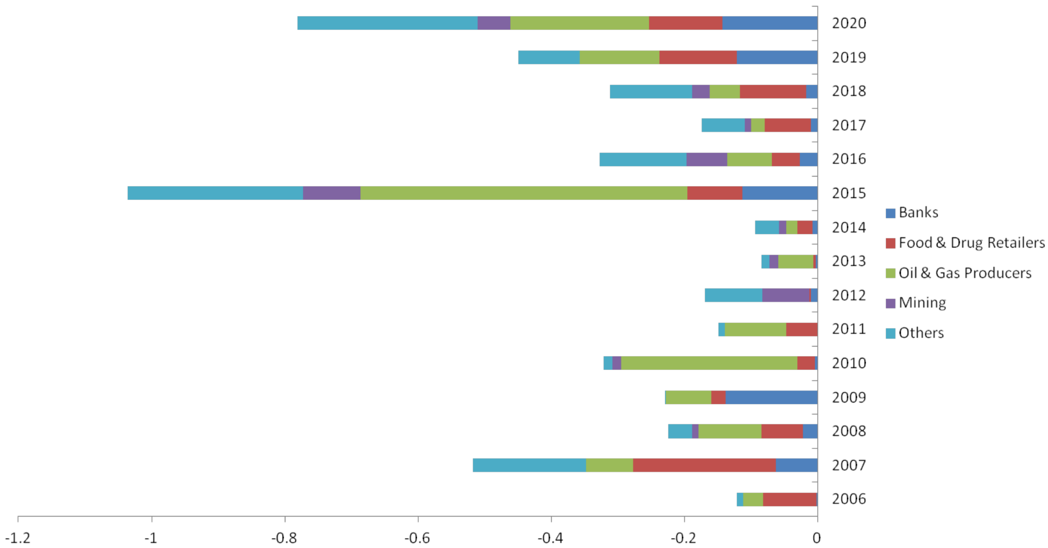

Figure 4: Industry wise contribution using the 5D Constant mean window and VADER analyzer (Stocks with negative returns exhibited for negative sentiments)

1.7.3 Hypothesis conclusion

As can be seen from the charts over the years Banks, Oil & Gas producers and Mining are the industries that contributed the most.As per the study setup it can be inferred that these industries were most sensitive to the sentiment observed in climate related news. It also makes sense economically because if there is a regulation change or transition risk related guideline then it would affect instantaneously the *Brown* stocks. Similarly, Banks would also get effected for their commitment to finance projects/companies that are either pro climate or pro emission related. On the other hand it is also clear that if Banks commit pro climate guidelines like *Net zero carbon* then the effect on their stock price would also be observed in the daily trading. And this remains same for traditional *Brown stocks* in industries like Oil & gas producers. Further research can be done to deep dive and study the effect on the industries. In the context of this paper and the scope the hypothesis holds true.

1.8 Conclusion

This paper is an incremental contribution to the growing area of research that focuses on how investors could build their portfolio and hedge their risk as far as climate risks are concerned. The three hypothesis that were constructed as part of the paper's contribution to this growing field of research holds true in all the cases. It can be noted that the conclusions are inferred on the context and scope of this paper's study set up.

I use a model setup in this paper to study the relation of climate related news sentiments on daily stock prices for the UK region. From the results it can be observed that positive sentiment in climate related news tends to induce positive shock in daily stock prices and negative sentiment can be related to negative shock in the daily prices. Off course the model has its own key assumptions and the output can vary once the assumptions are varied. But for this study with the current assumption parameters and event window parameters, the accuracy is around 50%, for example, a positive sentiment is followed by a positive shock in price is true for at least 50% of the cases. This finding contributes to the existing literature work and expands to the fact that climate news sentiment analysis if tuned properly can also predict the stock return premium at least to some extent. Then it could also be observed on how the premiums have evolved over the years and how the industries contribute over the years to the overall positive/negative premium. The respective results make sense economically as well. For example, during important *COP* events the premium increases and then as the year progresses after the event it dies down. Theoretically this can be inferred as investors in general becomes more sensitive to climate risk related news during global events and once the event is over gradually the sensitivity goes down. Although climate risk related events are a long time period phenomenon, for example, stress testing on climate risk scenarios have a time frame of 30 years. But short term spikes can be observable in the asset price behavior. Also industries that are more sensitive to climate risk related news like Banks, Mining and Oil & Gas show a greater contribution to the aggregate premium over the study period. In fact it is highly likely that regulatory news transition risk will have a greater impact on the brown firms. Similarly Banks would be influenced by their decision on lending (affecting the environment) to new or existing clients or to achieve net zero Carbon phase. Throughout the paper I highlight areas where further research or deep dive could be conducted and I can study the relationship more concretely.

Paper 2: Study on the approaches adopted by responsible investors to incorporate climate considerations in their operations

2 Study on the approaches adopted by responsible investors to incorporate climate considerations in their operations

2.1 Abstract

This paper studies the adoption of approaches to incorporate climate-related consideration in investment decisions by the global signatories of UN Principles for Responsible Investment *(UNPRI)*. The study uses a unique data-set from the *(UNPRI)* database reported in the year 2018. It provides the magnitude of Assets under Management of 50 largest economies, associated to the adoption of various climate-related metrics and tools, by the different asset managers/signatories reported. The 14 approaches that were reported in the database could be divided into two categories - Activities undertaken by investors to respond to climate change risks and tools used by the investors to manage emission risk. As part of the analysis in this paper I study the relationship between the approaches and the responsible investment for each region. And then do an inter region comparison of the results. In this paper I also study the concentration of responsible investment across the different approaches.

From the study I find that across the regions the approaches are significant to responsible investment. For example, Europe region show sensitivity on activities that seek changes from policy makers related to address climate risk. Investors use tools to manage risk like adopting formal contracts to integrate climate risk in external investment and fund managers actively monitoring the risk related to investments in entities that contribute to emissions. One interesting find of the study is that approaches related to physical climate risk like scenario testing is particularly significant for Oceania countries that are more prone to experience severe physical risk events like sea level rising, cyclones, etc. I also found that overall investments are more sensitive to use tools like carbon foot printing and encourage the investors to monitoring emissions related risks in their portfolio choice, etc. In terms of activities undertaken for climate risk, I found that investors across regions are more prone to use emissions data analysis in their portfolio decisions or seek that climate change related risks should be integrated into the decision making process of the companies. As part of the study I observe that larger investors tend to adhere to these climate related approaches.

[3]

[3]*Keywords*: *UNPRI* signatories, climate risk factors, physical climate risk, relationship between size of investments and 14 approaches

2.2 Introduction

With the growing limelight on climate related risks there has been a considerable shift on investment patterns that take into account the aspect of climate finance. *Responsible investment* is one of the way that asset managers across the world has started to focus on. It is a new way of investing which is based on not only the expected financial return but also on non financial criteria. The financial criteria for any asset manager is to maximize the expected return from the investment. But with responsible investing the aspect of non financial criteria is taken into account and that relates to ESG factors (Environment, Social and Governance). Hence while investing the asset manager bundles up the decision based on ESG factors and long term return maximization.

In this study I use the data of responsible investment from the database of *UNPRI*, United Nations Principles for Responsible Investments. The *UNPRI* has a substantial database of responsible investment initiatives in recent times. As per its website, responsible investments is "a strategy and practice to incorporate environmental, social, and governance (ESG) factors in investment decisions and active ownership."

In the paper by Amel-Zadeh and Serafeim (2018) it is shown that why and how investors use the reported ESG information. It also states that the lack of reporting standards hampers the use of ESG information for investing purposes. Hence it can be said that investors from different countries/regions across the globe react to the ESG information in different ways and based on that it remains a challenge to compare the performance of the responsible investment of these investors. The various interpretation of these policies and usage of this framework in responsible investing has been inconclusive. The OECD report on, "Investment Governance and the Integration of Environmental, Social and Governance Factors" (2017) clearly states that: “This means that data is incomplete and not directly comparable across companies, sectors and countries.”

I use the total assets under management (AUM) from the UNPRI database across six regions. The selected regions broadly covers the different parts of the world. Then I use 14 climate related approaches that are reported. The approaches can be broken down into two broad categories - Activities undertaken by investors to respond to tools used by investors to manage emissions related risk. I have performed a regression method on those approaches and analyzed their sensitivity on the responsible investment size across regions. Since the data level of the dependent and independent variables are different hence I used the pooled regression technique.

I use the reported AUM of the signatories of *UNPRI* as dependent variable since

it is classified under responsible investment. It is evident that all the signatories reported in the database are responsible investors. The data-set from where the data is obtained is UNPRI Collaboration Platform and the data is from 2018 period. The dependent variable had AUMs of individual asset managers/investment companies across countries and regions. The AUM of the asset managers are assigned to countries based on the location of their respective corporate headquarters. For the purpose of this study I aggregate the AUM of asset managers across each region to get the aggregate AUM reported for a particular region. Since the regression is run with the top level aggregation data hence it is very unlikely that the relationship between the responsible investment and climate related approach of a particular region would undergo a material change in the short to mid term period.
The approaches reported in the database are mapped to dummy variables (0 and 1). Where '0' is assigned to a asset manager if it does not comply with the particular approach and '1' is assigned if it complies. The UNPRI database has provided the details for 50 largest countries around the world. The choice of the 14 approaches are purposefully kept climate related so that the study can analyze only the climate related effect on activities and tools used. The details about the approaches are provided in the later sections.

From the output analysis of the study it becomes evident that for each region some of the approaches are statistically significant. Thereby I can infer that those particular approaches affect the responsible investment pattern of the asset manager in that region. I have considered the regression runs that are explanatory (for example, considerable R-square values) and regressors that are statistically significant (p-values of coefficients). As detailed in the *Hypothesis test* sections the impact of the approaches can be observed and it can be concluded that in some regions the climate related approaches have positive and significant impact on responsible investments. While in some other regions either due to lack of data or in actual the climate risk related approaches do not play any statistically significant role in the overall responsible investments. Also the results show that more focus across regions are in activities like using emissions data in investment decisions and integration of climate change related risks in company decisions. Similarly, are more prone to use tools like carbon footprint measure or encouragement is provided to portfolio managers to monitor emissions related risks in their portfolio.

Literature review

In this part I would do a brief literature review to focus on some of the relevant papers/work done. The paper by Amel-Zadeh and Serafeim (2018) deploy a technique of survey based methodology. They show that from the survey based information it can be inferred that due to the lack of a standard framework of reporting asset managers think that it retards the consistency of sustainable investments and hence affects consumer trust.The different standards of sustainable investments also makes it difficult to compare the relative performance against its peers. As a result, several regulatory bodies are recognizing the advantages of identifying and reporting the responsible/sustainable finance. In their paper Hong and Kacperczyk (2009) show that "sin" stocks have higher expected return than otherwise comparable green stocks.They also find that sin stocks are less held by institutions such as pension plans as compared to mutual or hedge funds that are natural arbitrageurs.

I look into the paper by Barnett and Salomon (2012) where they show that as the number of social screening increase the financial return decrease first. But then rebounds as the number of screens reach maximum. Further they also find that financial performance varies with the type of screening used. For example, with community relation screening the financial performance increase but with environment and labor relations screening it decreases. In similar lines,in the paper by Renneboog et al. (2007) show that the risk adjusted return of SRI funds in UK or US are not significantly different from the conventional funds. However, in Continental Europe and Asia-Pacific the SRI funds under perform the benchmark portfolios.

In the paper by Hartzmark and Sussman (2019) the authors show that investors value sustainability.They performed their study for the US mutual fund market. From the paper it can be inferred that investors allocate more towards high sustainable funds.However it was not evidenced whether high sustainable funds outperform their low sustainable peers. In a paper by Hoepner et al. (2018) it is shown that with engagement to ESG issues the shareholder's can benefit as it reduced firms' downside risk. They find evidence that successful ESG engagements, primarily on climate risk, reduces the firm's exposure to downside risk factors. There has also been some work showing the importance of climate risk for institutional investors. In the paper by Krueger et al. (2020) they show that institutional investors believe climate risk has financial implications. Further the paper shows that the large investors or ESG based investors consider risk management and engagement rather than divestment to address climate risk. The paper uses a survey based technique to arrive at the conclusions.

The paper by Dimson et al. (2015) show that successful ESG engagements are followed by positive abnormal returns for firms' while unsuccessful engagements are followed by zero return. In the paper by Pástor et al. (2021) they show that green assets have lower expected return. But it outperforms when positive shock hits the ESG factor. The paper also comments that sustainable investing produces positive social impact by making firms greener and by shifting real investment toward green firms. The paper by Gibson Brandon et al. (2021) show that stock

returns are positively related to ESG rating disagreements.This suggests that for firms with higher ESG rating disagreement the risk premium would be higher. They also state the the relationship is mainly due to the disagreement on the environmental dimension.
Liang and Renneboog (2017) in their paper show that a firms' CSR rating and its legal origin (headquarters) are strongly correlated. They find that the legal origin is a stronger explanation than "doing good by doing well" factors or firm and country characteristics (ownership concentration, political institutions, and globalization): firms from common law countries have lower CSR than companies from civil law countries, with Scandinavian civil law firms having the highest CSR ratings. Alongside in the paper by Mc Cahery et al. (2019) it is shown that there is a strong relationship between ESG disclosure and the quality of firm's disclosure. They found that ESG is correlated to downside risk.And then the paper infers that firms that have good ESG scores might be disclosing more information.They also show that the ESG scores have insignificant impact on risk adjusted financial performance.

2.2.1 Contribution to the literature

From the literature review it becomes evident that climate risk factors are something "must have". But the extent to which global institutional investors deploy different approaches to incorporate climate risks considerations in their decisions is still under-studied. In this paper I study the relationship of different climate risk related approaches with the aggregate investments/AUMs of responsible investing. From the results I can analyze if there are any dominant approach that affect a particular region or regions. I check if AUM size of investors have any relation with their adherence to any of the approaches in responsible investing. In the paper I also study the relative concentration of tools/approaches that the institutional investors have considered in their portfolio selection to account for responsible investing. The outcome of the test results show the effect of approaches on the investments across regions.
There could be further research work at a granular level to study the effect of the approaches on responsible investment and work can be done to come up with a novel framework relevant across regions that defines responsible investment or sustainable investment based on ESG related tools.

2.3 Construction approach used to build the study model

In the following section I would discuss about how the study model has been constructed. In the previous sections it has been widely discussed on the climate risk related approaches. The main aim of this study is to explore the relationship between the responsible investment across the regions and the climate related approaches. The approaches are defined as part of reporting and were in line with the information obtained *UNPRI*. To gauge the relationship I use the well established methodology of *regression*. This is because the output can then be judged based on their significance and if they make sense statistically and economically as well.

2.3.1 Input data used in the study

From the previous explanations by now it is evident to the reader about the input data used in the study. To add more details I would explain the data in this section. The dependent variable is the size of responsible investment.The data is obtained from the survey results of *UNPRI*. From the survey I get the country wise AUM data of asset managers. And the country name mentioned is the country of headquarters of that asset manager. Overall for each asset manager I get their respective AUM, the country of headquarters and the relevant region. The region reflects in which part of the world the country is situated. In total the data has been segregated into six broad regions. These are Europe, Africa & Middle East, North America, Oceania, Asia and Latin America.

Now as mentioned earlier I have considered 14 independent approaches. The theme of these approaches/variables are related to climate risk. The independent approaches that relate to Activities undertaken by investors to respond to climate change risk are - Setting carbon reduction targets for portfolio, Established climate change sensitive asset allocation strategy, Targeted low carbon/climate resilient investments, Reduce portfolio exposure to emissions intensive holdings, Used emissions data or analysis to inform investment decisions, Sought climate change integration by companies, Sought climate policy change with policymakers.The approaches that relate to tools used by investors to manage emissions risk are - Carbon foot printing, Scenario testing, Disclosure on emission risk, Target setting for emission risk reduction, Encourage internal/external portfolio managers to monitor emission risks, Formal contracts to integrate climate in external invest and Emissions risks monitoring/reporting are formalized into contracts when appointing managers. As can be observed the names of these independent approaches are self explanatory.

Across each asset manager the independent approaches in the study has been assigned dummy indicator variable. The dummy indicators are 0 and 1, where 0 is assigned if the approach does not exist for that respective asset manager and 1 is assigned if otherwise.

2.3.2 Methodology

The first hypothesis study uses the regression model. In the previous section I have provided the details about the dependent and the independent variables. Since the level of the dependent and independent variables data is different hence I have to scale the data for proper representation. Then applied the regression technique on the data. The model been with a simpler setup can be run in a *Python script* or in *Excel tool*. I have checked and the results are not different in any of the platforms that was used.
The regressions are conducted region wise. Meaning that for the purpose of the study I segregate all the asset managers under the specific regions. The reason for doing so is that it would now be possible to study the effect of the approaches for different regions separately. Also the GDP varies across countries and hence it would not make sense to combine a Developed country and an Emerging country in the same regression pool. As a result of the segregation there are six different outputs of the model specific to each region. For example countries with region as North America are clubbed together and the regression model was run on them. The equation can be expressed as follows -

$$\text{AUM}_i = \alpha + \beta_j * \text{ Approach}_j + \varepsilon$$

where, β_j is the coefficient for each approach j

AUM_i is the asset under management for each signatory i

α and ε are respectively the intercept and the error term

2.3.3 Key assumptions for this study

For the purpose of this study I have made some key assumptions in the methodology. Since the independent approaches have dummy indicators of 0 and 1 so I assume that either the tool/approach exists or does not exist. There is no consideration made on partial existence. For the asset managers only the country of their headquarter is considered. I use the regression methodology in this model hence its relevant assumptions could be extended here. Also as the signatories are part of *UNPRI* database hence it can be inferred that they follow responsible investment approaches.

2.4 Hypotheses tests and Results

2.4.1 Description

In this paper I formulate two hypotheses tests and study their relevance. As mentioned earlier in one of the tests I use the regression model to analyze the relationship between the independent variables (the 14 approaches) and the dependent variable (AUM of the signatories). The setup of the model has been discussed in detail in section 2.3.2. There are other techniques followed to conclude on the hypothesis tests which are detailed in the following sections. For a informative conclusion I would first show the output of the test and then infer or analyze from them.

2.5 Description and results of Hypothesis $H_0 1$

2.5.1 Description

To understand the impact of the climate risk related approaches I need to first estimate their significance over the responsible investment AUMs. I have segregated the AUMs at regional level and then performed the OLS regression. The regional level segregation provides a consolidated view and is also free from any geographical biases. The regression results show the relationship of the approaches with respect to responsible investment size. It also provides an understanding of the approaches that are statistically significant/relevant for the respective regions. Additionally I analyze the average size of asset managers that have adhered to one or more approaches versus asset managers that do not adhere to any of the approaches.

2.5.2 Results

The following table 11 is the output of the regression model for *Europe* and *North America* region. It can be noted that the AUM numbers are scaled to USD billions. The outputs of the other regions are shared in Appendix 3.4. After the regression output results of *Europe* and *North America* region I show the list of significant approaches of all six regions in a consolidated table 12. The mapping of the regressor names presented in the output tables with their corresponding full names can be found in table 25. Their sequence in the list remains the same and can be referred to in section 2.3.1.

	Europe	North America
Constant	29.894**	80.106**
	(0.000)	(0.003)
Carbon reduction	25.120	774.914**
	(0.407)	(0.028)
Climate sensitive allocation	−6.942	−1108.841**
	(0.836)	(0.000)
Targeted low carbon/climate	4.133	−168.812
	(0.890)	(0.316)
Reduce exposure to emissions	50.333	−79.070
	(0.112)	(0.626)
Analyse emission data for investment	35.856	519.826**
	(0.307)	(0.001)
Climate change integration by Comp	−40.614	816.029**
	(0.253)	(0.000)
Climate policy change	110.574**	−716.806**
	(0.001)	(0.000)
Carbon footprint	−27.306	−272.722
	(0.367)	(0.102)
Scenario testing	47.794	−637.885**
	(0.175)	(0.001)
Disclosure on emission risk	23.041	−152.053
	(0.485)	(0.382)
Set target for emission	−7.850	1593.191**
	(0.831)	(0.000)
Monitor emission risks	−29.630	−83.055
	(0.350)	(0.496)
Contract to integrate climate	254.875**	−2193.875**
	(0.000)	(0.000)
Formal contract on emissions risk	−74.346**	32.936
	(0.035)	(0.815)
R-Square	0.169	0.290
Multiple R	0.411	0.538
N	667	263

Nota: ** $p < 0.05$

Table 11: Regression result for Europe and North America region

	Europe	**Africa & Middle East**	**North America**	**Oceania**	**Asia**	**Latin America**
Setting carbon reduction targets for portfolio	-	-	Significant	-	-	-
Established climate change sensitive asset allocation strategy	-	-	Significant	-	-	-
Targeted low carbon/climate resilient investments	-	Significant	-	-	-	-
Reduce portfolio exposure to emissions intensive holdings	-	-	-	-	-	-
Used emissions data or analysis to inform investment decisions	-	-	Significant	-	-	-
Sought climate change integration by companies	-	-	Significant	-	-	-
Sought climate policy change with policymakers	Significant	-	Significant	-	-	-
Carbon foot-printing	-	-	-	-	-	-
Scenario testing	-	-	Significant	Significant	-	-
Disclosure on emission risk	-	-	-	-	-	-
Target setting for emission risk reduction	-	-	Significant	-	-	-
Encourage internal/external portfolio managers to monitor emission risks	-	Significant	-	-	-	-
Formal contracts to integrate climate in external invest	Significant	-	Significant	-	-	-
Emissions risks monitoring/reporting are formalized into contracts when appointing managers	Significant	-	-	-	-	-
R square	0.17	0.27	0.29	0.18	0.003	0.08
No.of obs	667	45	263	113	56	38

Table 12: Consolidated summary for all the six regions

To test the other part of the hypothesis, I found that out of 1182 participants only 174 asset managers responded positively to one or more of the approaches. The average AUM size who adhere to one or more of the approaches is around USD 160 billion versus the overall average individual AUM size of around USD 60 billion.

2.5.3 Hypothesis test Conclusion

From the results it becomes evident that not all the approaches are significant when compared across the regions. As part of the regression output I get a coefficient of 0 for some regressors. This is because for these approaches the dummy value was 0 for all the signatories in that particular region. Hence by construction those regressors/approaches do not have any explanatory power and do not go into the regression model. This phenomenon is seen for regions like Asia, Latin America and Africa where the overall number of observations are comparatively less. In this test I have ignored the values that do not contribute to the regression model. Overall, the test result show conclusive results for the other regions and after analyzing the output I can infer the approaches that influence the activities and tools that are undertaken for a particular region. The conclusive results are detailed in the following paragraph.

For the regions apart from Asia and LatAm the multiple R value is around 40% showing a tendency towards positive correlation between the dependent and independent approach (that are statistically significant). While the R-square is around 20% to 30%. The value of R-square is justified because all these regions have a significantly high value coefficient of the constant term. It points to the fact that there could be some other activity or tool that influence the AUM but it is not in my current scope of study. The high value of the constant term can be mainly attributed to the data level of the dependent AUM values. But since they are statistically significant hence the explanation power of the model could be improved after introducing more approaches.

Regions like Europe, North America and Oceania have relatively large number of observations in the UN PRI database. Particularly Europe has a significant number of observations (56%of the total). It can be inferred that number of signatories are relatively more in UNPRI from Europe for the study period (2018). Hence it can be said that climate risk is more of an active interest for European asset managers. The countries in these regions are mostly considered as developed economies. It can be inferred that the adaption of responsible investing/SRI is more in asset managers in the developed economies. In case of North America region, activities and 3 tools show show sensitivity. I can conclude that investors

have undertaken activities like setting targets to reduce carbon footprints in their portfolio or establish the asset allocation strategy such that it is sensitive to climate change, etc.Similarly to achieve that the tools or methods in focus are encouraging the portfolio managers to monitor the emissions risk in their portfolio, formalize contracts to integrate climate risk in the investment style, etc. The Oceania region is significantly influenced by the approach *scenario testing*. As the countries in this region like Australia, New Zealand are surrounded by sea it makes sense for the investors to incorporate different scenarios while making investment decisions. This tends to indicate emphasis on the physical climate risk. It shows how the physical risk scenarios which although might not have been observed in the past and there is no 100% guarantee that it would occur in future drives the decision making in responsible/ investments. In Africa and Middle East,investors have undertaken activities like to setup investments that target low carbon footprint or are resilient to climate risk. And in order to do that portfolio managers are encouraged to monitor emissions related risk. At individual approach level there is one other interesting find that can be inferred from the statistical results. For example, *sought climate policy change by policy makers* might be significant in a particular region but have negative coefficient inferring that regulatory policy on climate risk might not have a positive impact in the size of responsible investment. Some of the declaration/regulation could be a disincentive for the investment decisions. This can be related to the idea of how transition climate risk effects the stock values in portfolios. To control overall portfolio emissions managers invest in *green stocks* and its performance can affect the overall AUM. In the literature review I discuss about papers showing performance of *green stocks* not very encouraging at least in the short term. On the other side some approaches like *setting carbon reduction targets for portfolios* seems to be significant and has a very high coefficient value inferring at individual investment firm level climate risk is a major driver in investment decision making.
As part of the other analysis in the hypothesis I found that on average larger investors adhere to one or more of the approaches in their responsible investing pattern. I can infer that relatively larger asset managers have more resources in terms of money, man power, etc. and could be better equipped to adhere to responsible investing.

2.6 Description and results of Hypothesis $H_0 2$

2.6.1 Description

From the above analysis I get a clear idea on the region wise implication of the approaches. It would be also interesting to see how this climate risk related approaches interplay at the country level where these investment firms are headquartered. To this extent I formulate two hypothesis tests -

- Compare the % concentration of AUM across countries over the total AUM on each of these 14 approaches
- Across countries reported in the survey I will study the number of cases when the investors comply with one or more of the climate risk approaches

2.6.2 Results

In the following table 13 and table 14 I show the outcome of the first test which estimates the AUM concentration on the climate risk related tools or approaches

Setting carbon reduction targets for portfolio	Established climate change sensitive asset allocation strategy	Targeted low carbon/climate resilient investments	Reduce portfolio exposure to emissions intensive holdings	Used emissions data or analysis to inform investment decisions	Sought climate change integration by companies	Sought climate policy change with policy-makers
7.14%	10.00%	27.14%	26.00%	35.29%	35.29%	21.78%

Table 13: Activities undertaken by investors to respond to climate change risk

Carbon foot-printing	Scenario testing	Disclosure on emission risk	Target setting for emission risk reduction	Encourage internal/external portfolio managers to monitor emission risks	Formal contracts to integrate climate in external invest	Emissions risks monitoring/reporting are formalized into contracts when appointing managers
28.43%	10.43%	13.36%	17.14%	26.43%	7.14%	9.96%

Table 14: Tools used by investors to manage emissions risk

Now in the following table I categorize the number of instances where the investors under each country were influenced by one or more of any of the 14 approaches. The results are shown at the aggregated country level and for the purpose of the readability of the results I ignore some of the countries who had very negligible contribution to the overall AUM.

Country	Adherence to one or more approach
Australia	103
Austria	0
Belgium	0
Botswana	0
Brazil	11
Canada	54
Cayman Islands	0
China	0
Denmark	13
Finland	30
France	185
Germany	13
Hong Kong	0
India	0
Indonesia	0
Ireland	0
Italy	1
Japan	5
Korea, Republic of	0
Luxembourg	15
Malaysia	0
Mauritius	0
Netherlands	69
New Zealand	9
Norway	19
Portugal	0
Puerto Rico	0
Russian Federation	0
Saudi Arabia	2
Singapore	1
South Africa	15
Spain	0
Sweden	71
Switzerland	26
Turkey	0
United Arab Emirates	0
United Kingdom	189
United States	189

Table 15: Country-wise breakdown of adherence to one or more climate risk related approaches

2.6.3 Hypothesis test Conclusion

From the table 13 I can see that comparatively more focus or concentration is on using emissions data or analyzing the it to make an informed decision in the investment.Similarly investors seem to increasing seek that companies integrate climate change related information/risks in their decisions. These approaches are undertaken by investors as activities to respond to climate change related risks. Some other activities that comes out from the results are reducing exposure to emissions intensive holdings or target to setup a low carbon portfolio that remains resilient to climate change related risks. To that extent in order to respond to the scope of transition to a low carbon economy they seem to embed the emission level information of the target or invested companies. Furthermore from table 14 I can infer that managing the carbon foot-printing is the tool that investors focus more to manage emissions/climate risk. Also the portfolio managers are encouraged to monitor the emissions risk in their investment portfolio and act accordingly. Depending on the country and region the institutional investors have vested their focus through different means to manage the emissions risk. As the table shows that either the contracts are set accordingly with portfolio managers so that they monitor/report the emissions risk or the portfolio re-balancing technique includes a target on emissions reduction. These aspects show that although different tools are used but institutional investors but overall they have started to react or respond to climate risk through their portfolio choice.

In table 15 I see across countries the count of the approaches where the individual asset managers have responded positively. The idea behind analyzing this data is it would give an idea about the level of involvement of the investors in managing climate risk. This means for a particular country if the count is relatively more then they are better prepared in managing the climate related risks as the investors undertake more activities and/or use more tools to tackle emissions/climate risk. I found that there is a heavy concentration on some of the selected countries of the developed world. For example, Australian portfolio managers have responded positively on many of the climate risk approaches. This can be attributed to the fact that Australia is a comparatively larger economy with a strong mining industry and being water locked by all sides severe flood and cyclone scenarios would have a greater impact in the well being of future. Hence the investors manage to the transition of a low carbon economy through different channels of the activities and tools. Similarly in the European region, for example asset managers of France have responded positively in many occasions and I can relate it to the recent Paris agreement and its after effect that French asset managers have chosen to embed climate risk related tools and activities into their portfolio decisions. Also in UK there is regulatory focus on climate risk and it reflects as well in their aggregate count of approaches chosen. For USA as well investors have responded positively in the survey for many of the approaches. One part that stands out from the results is that in cases of most of the developing countries and for some developed countries as well the focus on aligning institutional investment with climate/emissions risk does not seem to be active. Keeping this aspect in mind more focus in terms of policy design and its implementation should be done in these countries.

2.7 Conclusion

The previous sections on the Hypothesis tests mostly analyze the output of the model and concludes accordingly for the respective tests. From this study it is evident that the climate risk related approaches considered in the study have impact on the signatories of the *UNPRI* survey. And I also show the focus of the regions or countries on the activities and tools that are undertaken to manage climate related risks. There could be further research work done to broaden the scope and study the relationship. It can then be substantiated that as argued previously whether there is a need of a common regulatory framework on the guidelines or the regulators/agencies can come up with more granular region/country specific guidelines. Without repeating the conclusions of the hypothesis tests, based on the outputs of the test results, in the following paragraph I discuss possible implications at policy level.

The results for developing regions like Asia, Africa and Latin America remain inconclusive as part of this study. This is due to lack of data from the signatories. At the country level the test results show that asset managers in the developing countries of the Asian and Latin American region have close to zero positive response in the survey. Thereby at the granular level it seems that the incorporation activities and tools related to climate risk aspects is yet to take off. Hence *UNPRI* should focus more on these regions/countries and work on increasing the awareness and contribution of the institutional investors so that their portfolio choice reflect the response of transiting to a low carbon economy or at the least focus on building climate risk resilient portfolios. Further for all the signatories should consider to take into account the perspective of reducing portfolio exposure to emission intensive holdings. Currently this approach does not appear to be uniformly significant at the regional level results. Hence local regulators and global bodies could design the investment policy accordingly. There should be also be focus on building guidelines that impacts portfolio holdings depending on their Carbon foot print or disclosure to emission risk. The results from $H_0 2$ shows that these are very effective tools that some investors have already undertaken. Global bodies like *UNPRI* in consultation with local governments could enact policy guidelines accordingly. Additionally it could also be inferred from the results and conclusions that the regions are not uniformly sensitive to all the approaches. Hence there could be some policy guidelines that are common globally but a flexibility should also exist to design policies based on region specific relevance.

In individual countries under North America region, except USA, it was found that none of the approaches were significant. For USA I see that the responses are positive across many of the approaches and the other North American countries in scope do not show much adherence. This can be inferred as that some institutional investors have incorporated climate risk related investment choice while a larger number of investors in a particular region are still remaining to do so. Hence *UNPRI* can guide the remaining players or the industry as a whole to have a holistic adherence to climate risk specific portfolio choice and ensure a smooth transition to a low carbon economy. I also find that for the Oceania region Scenario testing is a sensitive choice. Since this region is exposed to sea and their would be consequences of physical risk events like cyclones, rising sea level, etc. Policy guidelines in this region should focus on considering and enriching policy guidelines regarding physical risk scenarios.

From the analysis done in this paper I see that investors with larger AUMs tend to undertake the activities and tools to manage their responsible investments. At more granular level it can be a scenario that some asset managers undertake green-washing but at a broader generalized level this does not seem to be the case. Bigger asset managers have more resources to comply with or adhere to the norms and take into account climate risk into their portfolio investment.

3 Appendix

3.1 Charts and tables relevant to test of Hypothesis 2 of paper 1

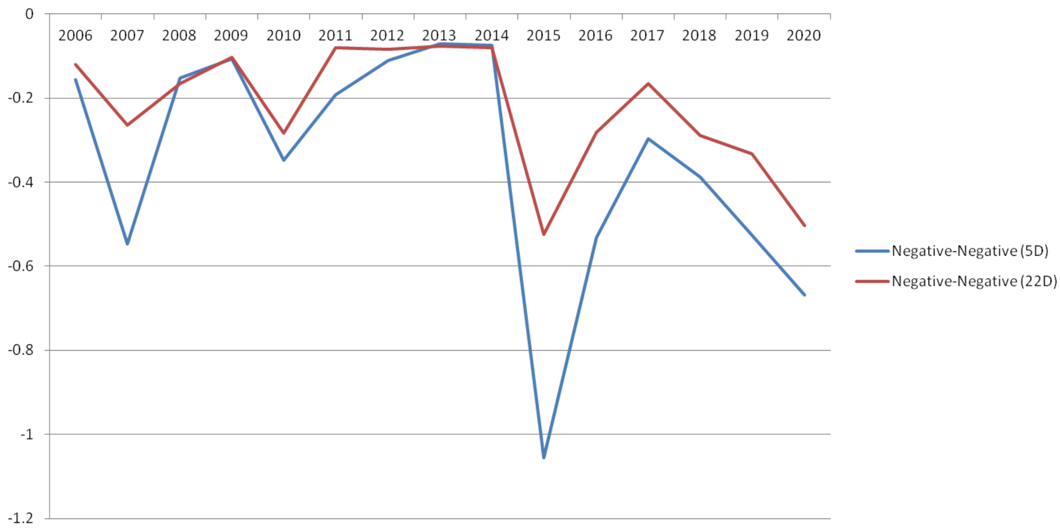

Figure 5: Compare negative excess returns using Constant mean and VADER

Year	Count for 5D	Count for 22D
2006	16	17
2007	44	45
2008	15	17
2009	14	14
2010	19	17
2011	9	8
2012	9	8
2013	8	10
2014	9	10
2015	80	74
2016	27	26
2017	15	16
2018	27	28
2019	42	42
2020	45	47

Table 16: Count of stocks for Negative-Negative using Constant mean and VADER

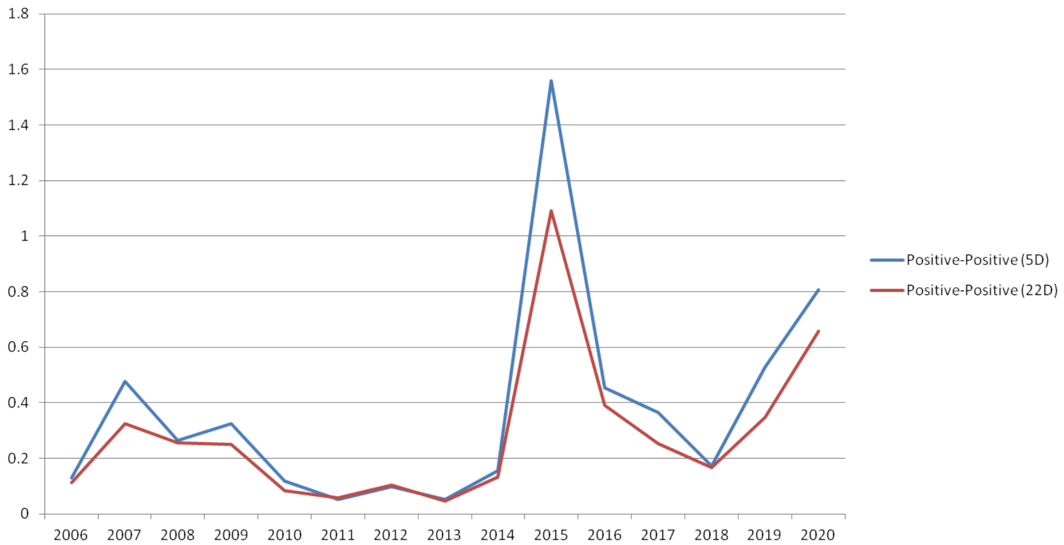

Figure 6: Compare positive excess returns using Market model and VADER

Year	Count for 5D	Count for 22D
2006	21	18
2007	46	36
2008	16	15
2009	19	17
2010	8	8
2011	6	8
2012	9	8
2013	9	12
2014	10	9
2015	103	96
2016	29	35
2017	26	27
2018	22	23
2019	29	32
2020	38	39

Table 17: Count of stocks for Positive-Positive using Market model and VADER

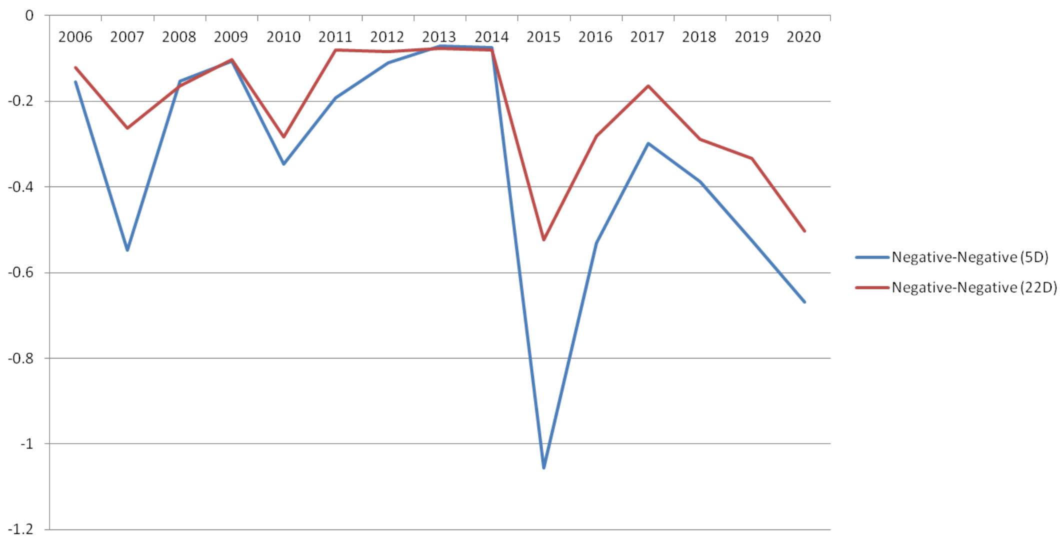

Figure 7: Compare negative excess returns using Market model and VADER

Year	Count for 5D	Count for 22D
2006	16	20
2007	40	36
2008	10	13
2009	9	11
2010	16	17
2011	11	9
2012	9	8
2013	6	8
2014	7	8
2015	78	74
2016	30	29
2017	19	16
2018	31	31
2019	40	39
2020	45	43

Table 18: Count of stocks for Negative-Negative using Market model and VADER

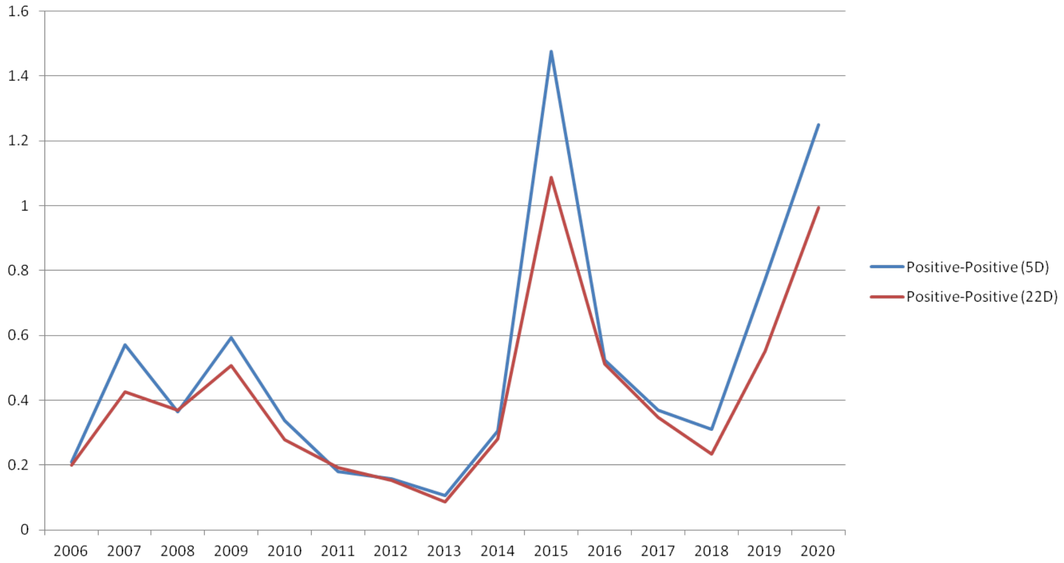

Figure 8: Compare positive excess returns using Constant mean and TextBlob

Year	**Count for 5D**	**Count for 22D**
2006	31	32
2007	55	41
2008	22	22
2009	23	22
2010	18	18
2011	15	15
2012	12	12
2013	12	12
2014	17	18
2015	94	103
2016	41	38
2017	30	31
2018	29	33
2019	57	60
2020	56	55

Table 19: Count of stocks for Positive-Positive using Constant mean and TextBlob

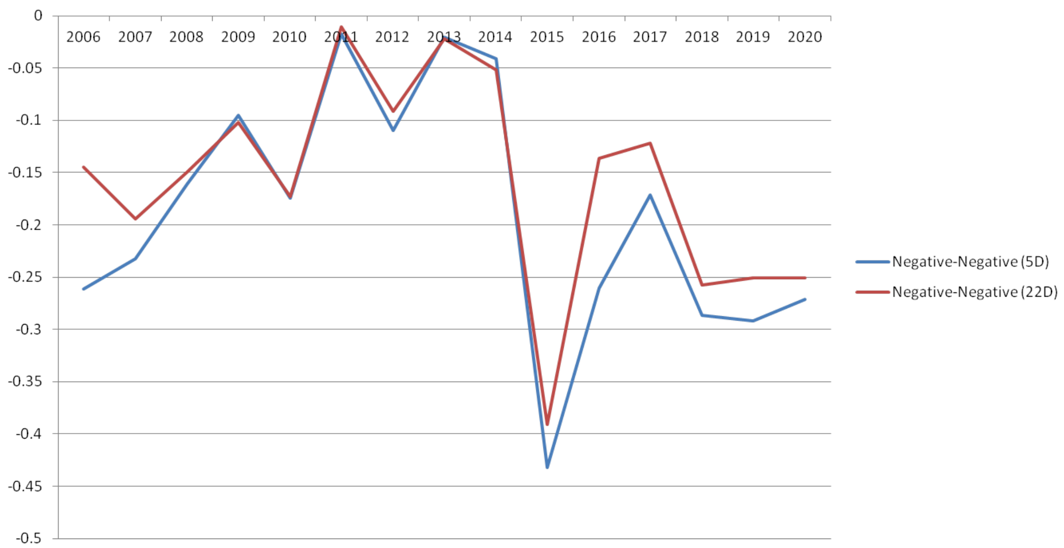

Figure 9: Compare negative excess returns using Constant mean and TextBlob

Year	Count for 5D	Count for 22D
2006	12	12
2007	23	22
2008	10	13
2009	9	11
2010	12	9
2011	2	1
2012	6	7
2013	5	7
2014	5	5
2015	53	51
2016	13	13
2017	10	8
2018	18	19
2019	23	27
2020	25	23

Table 20: Count of stocks for Negative-Negative using Constant mean and TextBlob

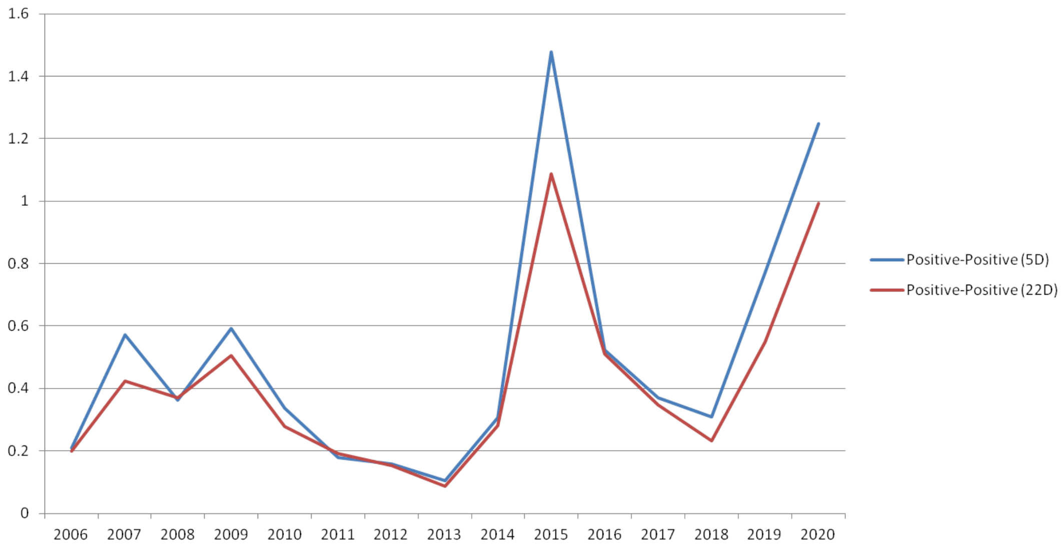

Figure 10: Compare positive excess returns using Market model and TextBlob

Year	Count for 5D	Count for 22D
2006	30	26
2007	58	54
2008	23	21
2009	26	22
2010	20	22
2011	13	16
2012	11	10
2013	14	15
2014	18	17
2015	102	100
2016	43	43
2017	31	33
2018	29	28
2019	59	60
2020	58	60

Table 21: Count of stocks for Positive-Positive using Market model and TextBlob

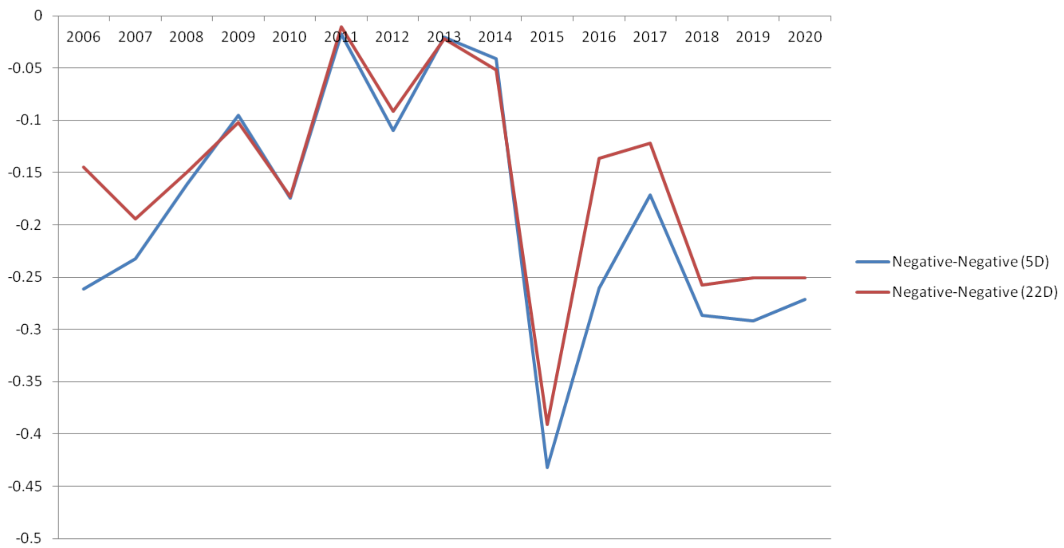

Figure 11: Compare negative excess returns using Market model and TextBlob

Year	Count for 5D	Count for 22D
2006	16	18
2007	23	23
2008	6	10
2009	6	8
2010	9	12
2011	2	3
2012	6	7
2013	3	4
2014	4	6
2015	45	50
2016	18	15
2017	14	14
2018	20	20
2019	19	23
2020	20	24

Table 22: Count of stocks for Negative-Negative using Market model and TextBlob

3.2 Charts relevant to testing of Hypothesis 3 for paper 1

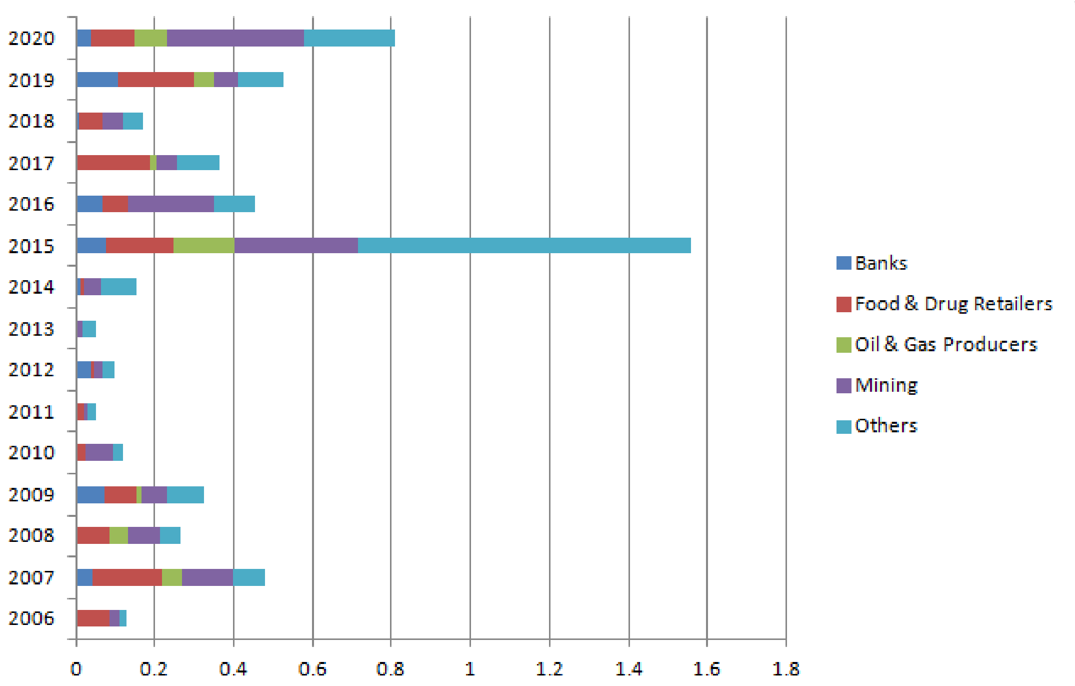

Figure 12: Industry wise contribution using the 5D window Market model and VADER analyzer (Stocks with positive returns exhibited for positive sentiments)

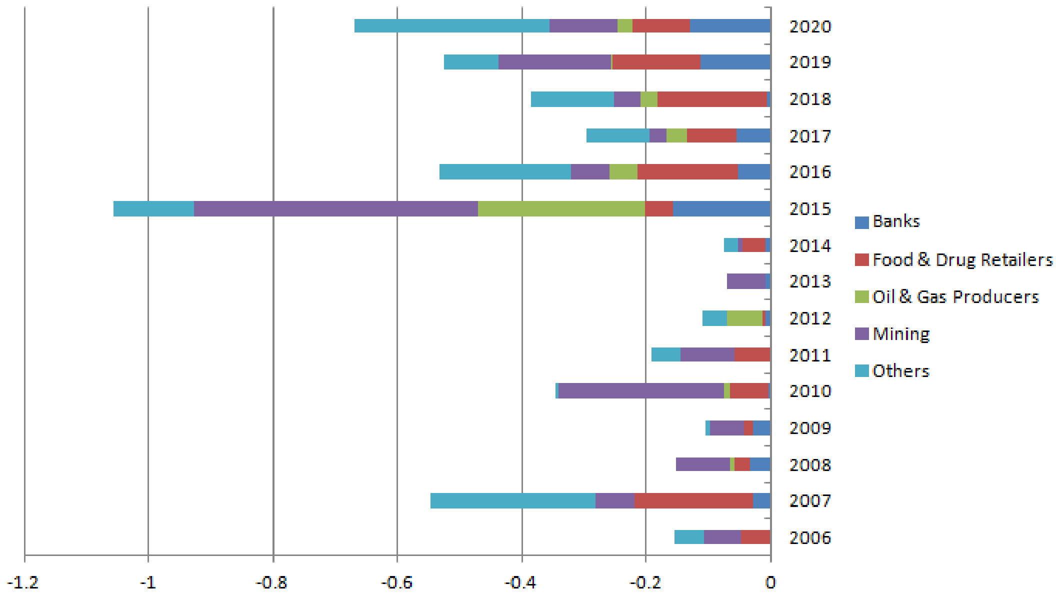

Figure 13: Industry wise contribution using the 5D window Market model and VADER analyzer (Stocks with negative returns exhibited for negative sentiments)

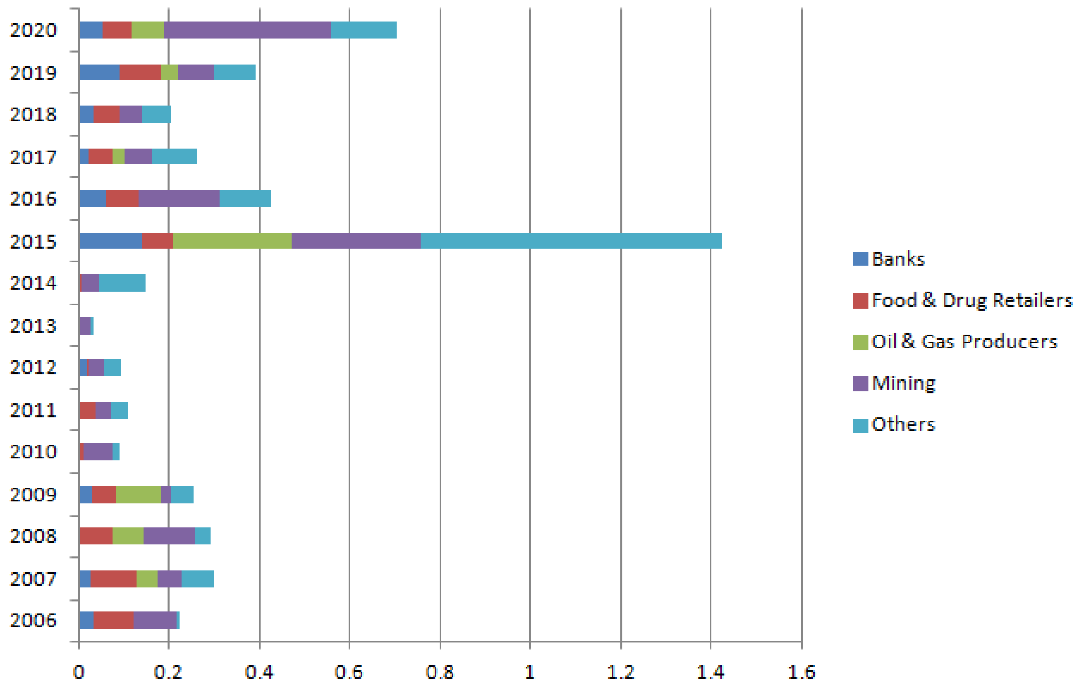

Figure 14: Industry wise contribution using the 22D Constant mean window and VADER analyzer (Stocks with positive returns exhibited for positive sentiments)

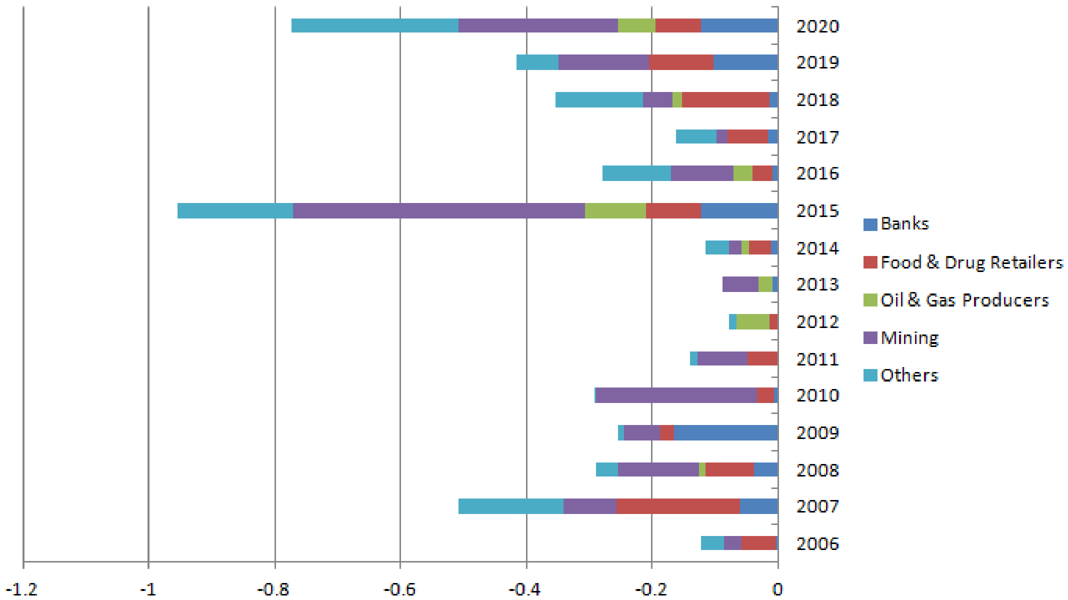

Figure 15: Industry wise contribution using the 22D Constant mean window and VADER analyzer (Stocks with negative returns exhibited for negative sentiments)

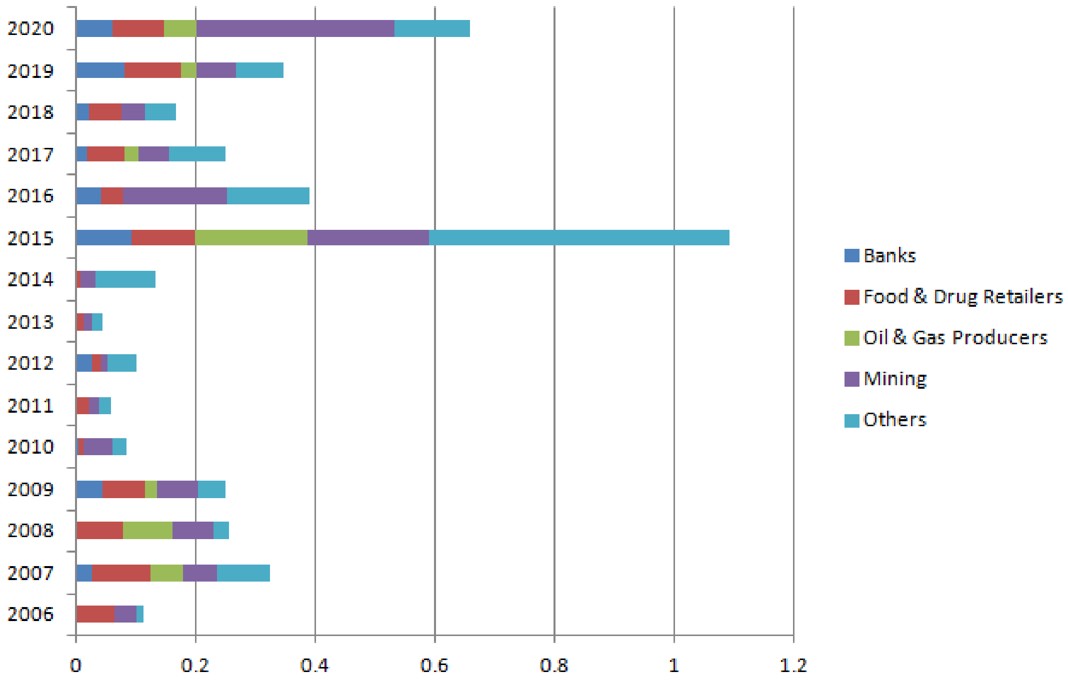

Figure 16: Industry wise contribution using the 22D window Market model and VADER analyzer (Stocks with positive returns exhibited for positive sentiments)

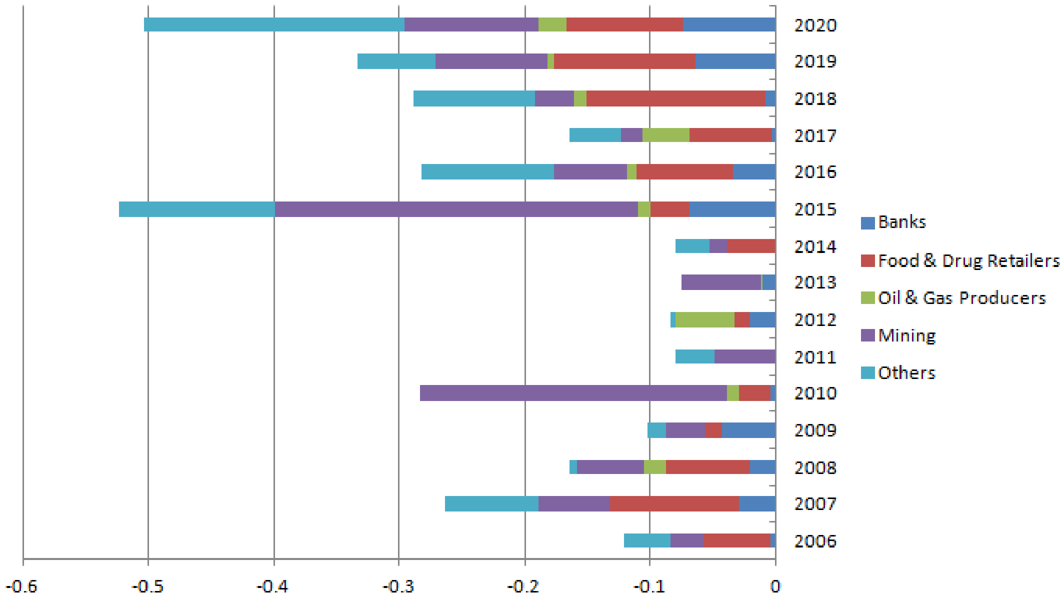

Figure 17: Industry wise contribution using the 22D window Market model and VADER analyzer (Stocks with negative returns exhibited for negative sentiments)

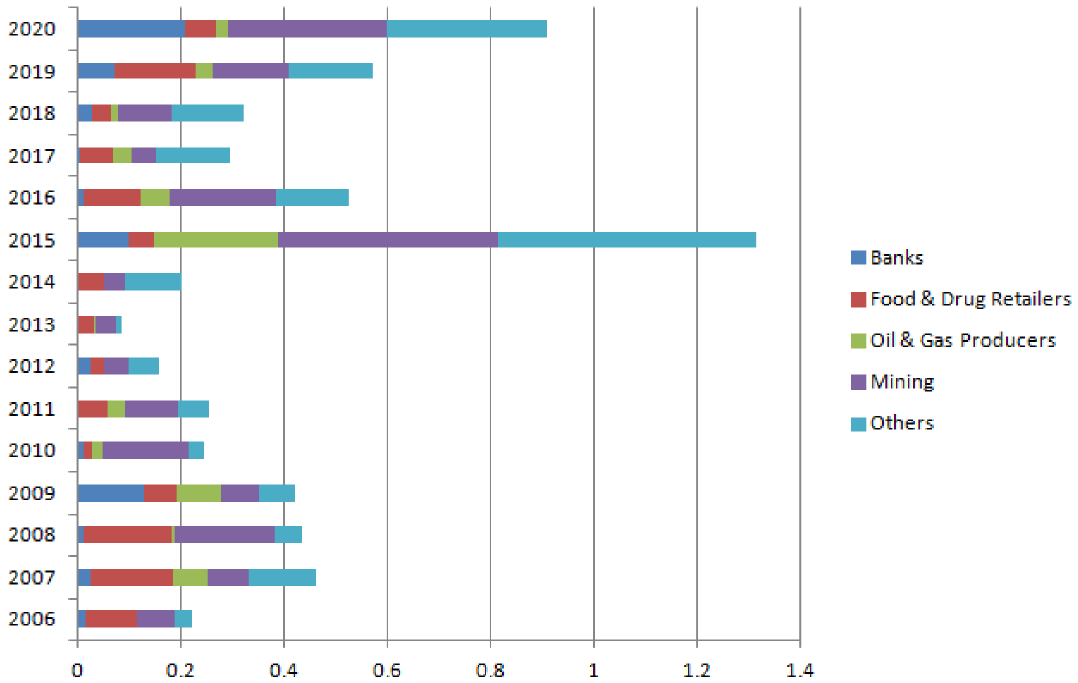

Figure 18: Industry wise contribution using the 5D Constant mean window and TextBlob analyzer (Stocks with positive returns exhibited for positive sentiments)

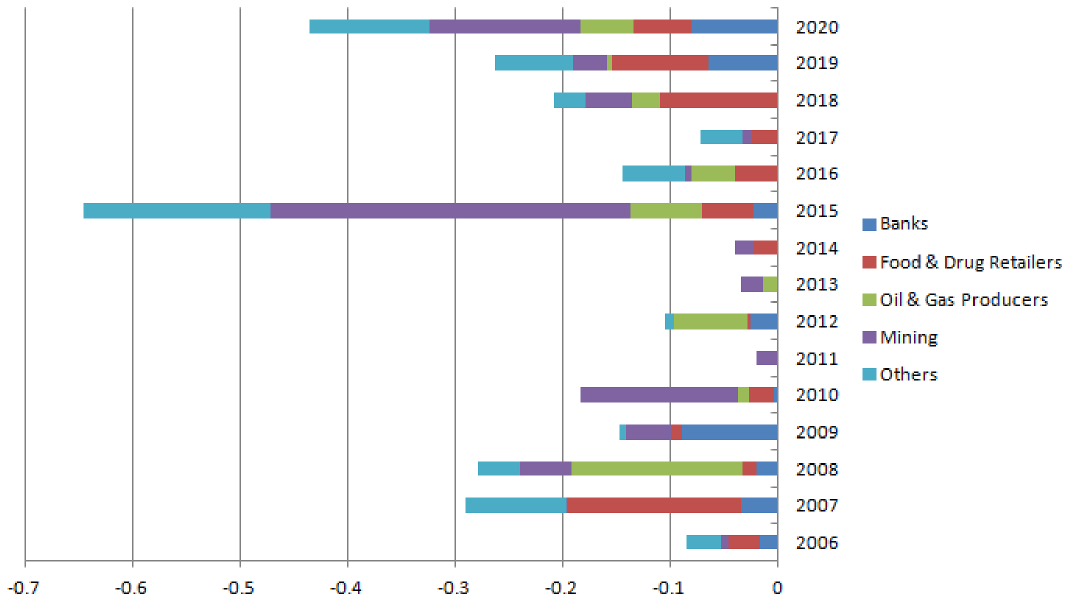

Figure 19: Industry wise contribution using the 5D Constant mean window and TextBlob analyzer (Stocks with negative returns exhibited for negative sentiments)

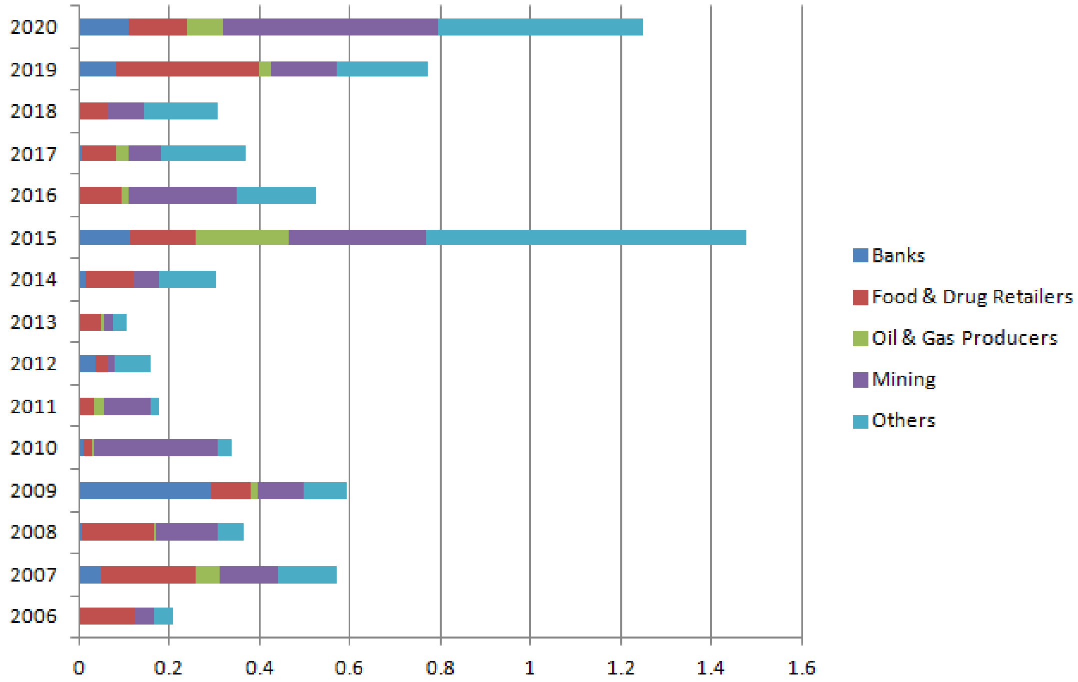

Figure 20: Industry wise contribution using the 5D window Market model and TextBlob analyzer (Stocks with positive returns exhibited for positive sentiments)

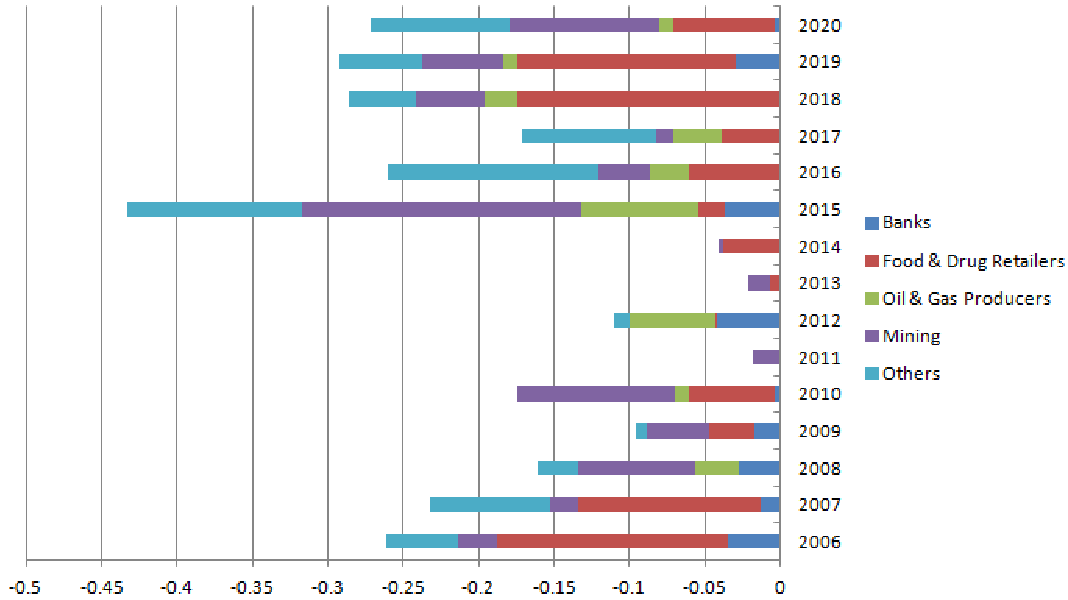

Figure 21: Industry wise contribution using the 5D window Market model and TextBlob analyzer (Stocks with negative returns exhibited for negative sentiments)

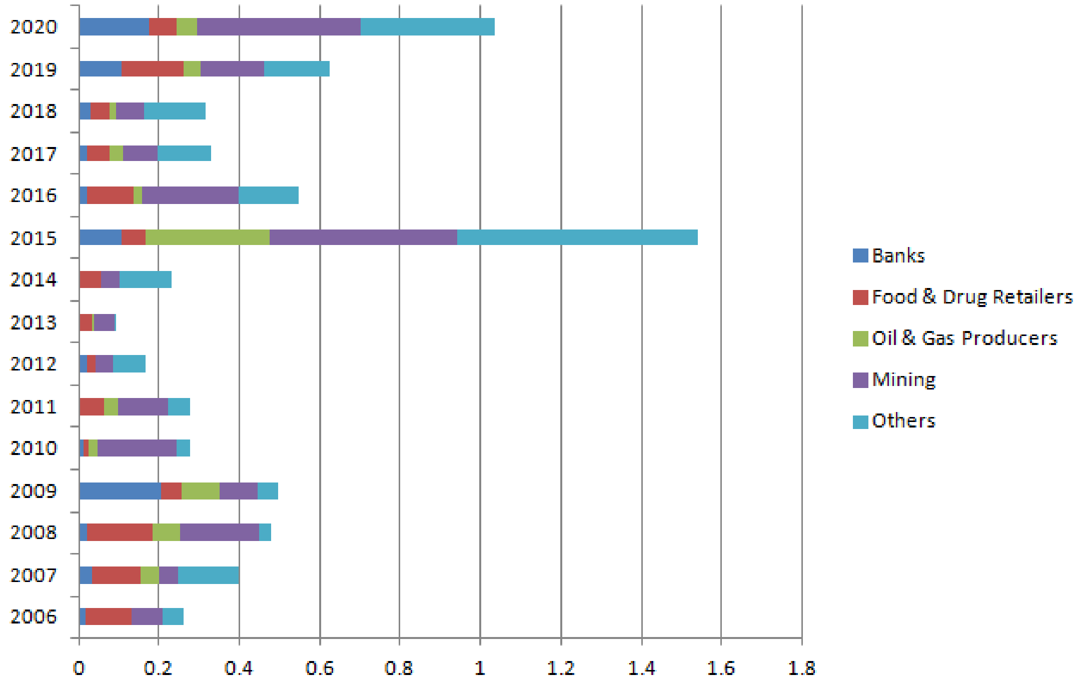

Figure 22: Industry wise contribution using the 22D Constant mean window and TextBlob analyzer (Stocks with positive returns exhibited for positive sentiments)

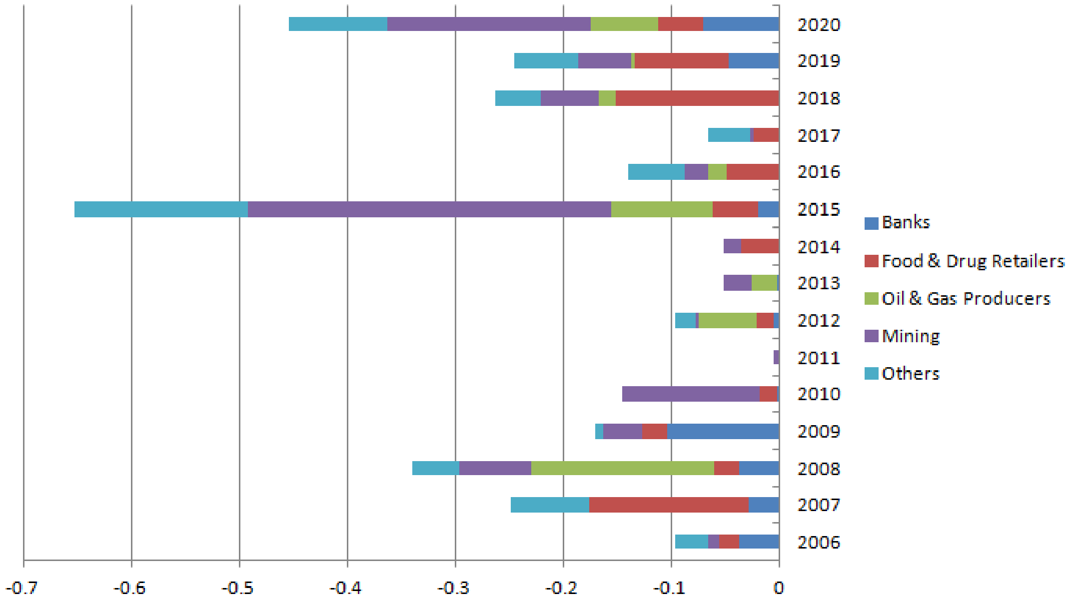

Figure 23: Industry wise contribution using the 22D Constant mean window and TextBlob analyzer (Stocks with negative returns exhibited for negative sentiments)

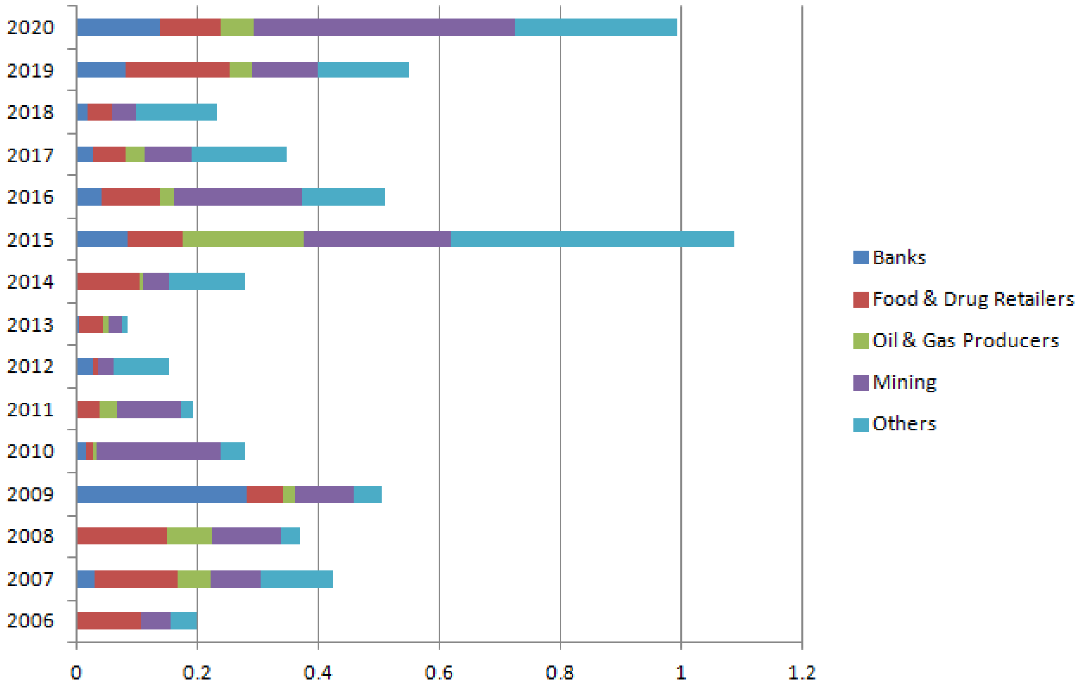

Figure 24: Industry wise contribution using the 22D window Market model and TextBlob analyzer (Stocks with positive returns exhibited for positive sentiments)

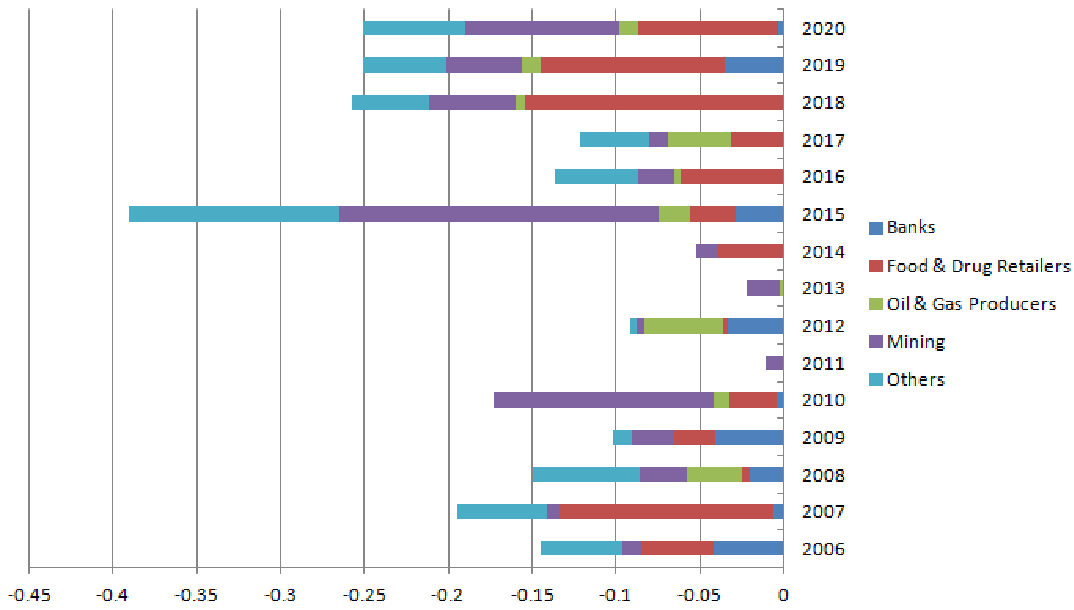

Figure 25: Industry wise contribution using the 22D window Market model and TextBlob analyzer (Stocks with negative returns exhibited for negative sentiments)

3.3 Python code of the model

The code used in building the model is provided here.

Listing 1: Main code body

```
#Code to read the news files, clean the raw data, perform the sentiment analysis using VADER and
    then populate the dataframe as desired

import glob
import pandas as pd
import os
import nltk
import re
import string
nltk.download('vader_lexicon')
from nltk.sentiment.vader import SentimentIntensityAnalyzer
import numpy as np


files = glob.glob(r'G:\EdhecPHD\Thesis■works\Ftse_100_data\*.html', recursive = True)
empty_list = []
for file in files:
        data = pd.read_html(file, index_col = 0)
        empty_list.extend(data)

frames = pd.concat([l for l in empty_list if 'HD' in l.index.values], axis=1, sort=True).T

frames.drop(columns=['SC', 'CY', 'RE', 'PUB', 'NS','IN','LA', 'CO', 'AN', 'SE','SN','ET','BY','IPC
    ','PG'], inplace = True)
frames.rename(columns = {'HD': 'Headline','WC':'Word_Count', 'PD': 'Publication_Date','LP': 'Lead'
    , 'TD': 'Body',}, inplace=True)
frames['Publication_Date'] = pd.to_datetime(frames['Publication_Date'])
frames.sort_values(by='Publication_Date', inplace=True)

frames['Body'] = frames['Body'].fillna(frames['Lead'])
frames['Body'] = frames['Body'].fillna(frames['Headline'])
```

```
import re
import string
from datetime import timedelta

count=0
frames['Lead'] = frames['Lead'].fillna(frames['Headline'])
frames['merged'] = frames ['Body'] + frames['Lead']

analyzer = SentimentIntensityAnalyzer()

frames['scores'] = frames['Lead'].apply(lambda Lead: analyzer.polarity_scores(Lead))
frames['compound'] = frames['scores'].apply(lambda score_dict: score_dict['compound'])


stock_price = pd.read_csv('G:\EdhecPHD\Thesis■works\Ftse_100_data\Ftse_100_stocks_data_return_v2
    .0.csv',usecols= ['Date','Anglo■American■plc','Abrdn','Associated■British■Foods','Admiral■Group
    ','Ashtead■Group','Antofagasta','Auto■Trader■Group','Aviva','Avast','Aveva','AstraZeneca','BAE■
    Systems','Barclays','British■American■Tobacco','Barratt■Developments','BHP','Berkeley■Group■
    Holdings','British■Land','B&M','Bunzl','BP','Burberry','BT■Group','Coca-Cola■HBC','Compass■
    Group','Croda■International','CRH■plc','DCC■plc','Diageo','Entain','Evraz','Experian','Ferguson
    ■plc',      Flutter Entertainment','Fresnillo','Glencore','GlaxoSmithKline','Hikma
    Pharmaceuticals','Hargreaves Lansdown','Halma','HSBC','International Airlines Group','
    Intermediate Capital Group','IHG Hotels & Resorts','3i','Imperial Brands','Informa','Intertek',
    'ITV plc','JD Sports','Just Eat Takeaway','Johnson Matthey','Kingfisher','Land Securities','
    Legal & General','Lloyds Banking Group','London Stock Exchange Group','Mondi','M&G','Melrose
    Industries','National Grid plc','NatWest Group','Next plc','Ocado Group','Phoenix Group','
    Polymetal International','Prudential plc','Pershing Square Holdings','Persimmon plc','Pearson
    plc','Royal Dutch Shell','RELX','Rio Tinto','Reckitt','Royal Mail','Rightmove','Rolls-Royce
```

```
Holdings','Rentokil Initial',"Sainsbury's",'Schroders','Sage■Group','Segro','Smurfit■Kappa','DS
■Smith','Smiths■Group','Scottish■Mortgage■Investment■Trust','Smith■&■Nephew','Spirax-Sarco■
Engineering','SSE■plc','Standard■Chartered',"St. James's■Place■plc",■Severn■Trent','Tesco','
Taylor■Wimpey','Unilever','United■Utilities','Vodafone■Group','Weir■Group','WPP■plc','Whitbread
'])


def find_cc_wds(content, cc_wds=['3i','Abrdn','Admiral■Group','Anglo■American■plc','Antofagasta','
    Ashtead■Group','Associated■British■Foods','AstraZeneca','Auto■Trader■Group',
                                        'Avast','Aveva','Aviva','B&M','
                                          BAE■Systems','Barclays','
                                          Barratt■Developments','
                                          Berkeley■Group■Holdings','BHP'
                                          ,'BP','British■American■
                                          Tobacco',
                                        'British■Land','BT■Group','Bunzl'
                                          ,'Burberry','Coca-Cola■HBC','
                                          Compass■Group','CRH■plc','
                                          Croda■International','DCC■plc'
                                          ,'Diageo','Entain',
                                        'Evraz','Experian','Ferguson■plc'
                                          ,'Flutter■Entertainment','
                                          Fresnillo','GlaxoSmithKline','
                                          Glencore','Halma','Hargreaves■
                                          Lansdown',
                                        'Hikma■Pharmaceuticals','HSBC','
                                          IHG■Hotels■&■Resorts','
                                          Imperial■Brands','Informa','
                                          Intermediate■Capital■Group','
                                          International■Airlines■Group',
                                        'Intertek','ITV■plc','JD■Sports',
                                          'Johnson■Matthey','Just■Eat■
```

```
    Takeaway','Kingfisher','Land■
    Securities','Legal■&■General',
    'Lloyds■Banking■Group',
'London■Stock■Exchange■Group','M&
    G','Melrose■Industries','Mondi
    ','National■Grid■plc','NatWest
    ■Group','Next■plc','Ocado■
    Group','Pearson■plc',
'Pershing■Square■Holdings','
    Persimmon■plc','Phoenix■Group'
    ,'Polymetal■International','
    Prudential■plc','Reckitt','
    RELX','Rentokil■Initial',
'Rightmove','Rio■Tinto','Rolls-
    Royce■Holdings','Royal■Dutch■
    Shell','Royal■Mail','Sage■
    Group',"Sainsbury's",'
    Schroders',
'Scottish■Mortgage■Investment■
    Trust','Segro','Severn■Trent',
    'DS■Smith','Smiths■Group','
    Smith■&■Nephew',
'Smurfit■Kappa','Spirax-Sarco■
    Engineering','SSE■plc','
    Standard■Chartered',"St.■James
    's■Place■plc",'Taylor■Wimpey',
    'Tesco','Unilever',
'United■Utilities','Vodafone■
    Group','Weir■Group','Whitbread
    ','WPP■plc']
):
        found = False
```

```
name_ocurances=0
stock_name=""
price=0
price1=0
global count
count= count +1
counter =0
now = frames.iloc[count-1][2]
now = now - timedelta(1)
now1 = now.strftime("%d-%m-%Y")


for w in cc_wds:

    if w in content:
        #found = True
        try:
            price = (stock_price.loc[stock_price["Date"] == now1 ,w]).iloc[0]
        except:
            try:
                now_prev = now - timedelta(1)
                now1 = now_prev.strftime("%d-%m-%Y")
                price = (stock_price.loc[stock_price["Date"] == now1 ,w]).
                    iloc[0]
            except:
                try:
                    now_tom = now + timedelta(1)
                    now1 = now_tom.strftime("%d-%m-%Y")
                    price = (stock_price.loc[stock_price["Date"] ==
                        now1 ,w]).iloc[0]
```

```
                        except:
                                price = 111

                price1 = price1 + price
                name_ocurances = name_ocurances + 1
                stock_name += str(w)+","

                #break
        return (stock_name,name_ocurances,price1)


frames['Stock■name'], frames['cc_wds'], frames ['Stock■Return'] = zip(*map(find_cc_wds, frames['
    merged']))
#frames['Stock name']= frames['merged'].apply(find_cc_wds)


frames.to_csv('G:\\EdhecPHD\\Thesis■works\\Ftse_100_data\\results_vader\\
    Ftse_100_news_senti_new_v2.1.csv')
frames.drop(columns=['Headline', 'Lead', 'Body', 'Word_Count', 'merged'], inplace = True)
frames = frames.loc[frames["cc_wds"] != 0]
frames.to_csv('G:\\EdhecPHD\\Thesis■works\\Ftse_100_data\\results_vader\\
    Ftse_100_news_senti_updated_v3.1.csv')
-----------------------------------------------------------------------------------------------------

#code to calculate Constant mean model with Rolling 5D/22D
import pandas as pd
import numpy as np

moving_avg = pd.read_csv('G:\EdhecPHD\Thesis■works\Ftse_100_data\Ftse_100_stocks_data_return_v2.0.
    csv', usecols = ['Date',       'Anglo■American■plc',    'Abrdn',          'Associated■British■Foods
    ',      'Admiral■Group',         'Ashtead■Group',          'Antofagasta',   'Auto■Trader■Group',
    'Aviva',         'Avast',         'Aveva',          'AstraZeneca',   'BAE■Systems',   'Barclays',
```

```
    'British■American■Tobacco',    'Barratt■Developments', 'BHP',   'Berkeley■Group■Holdings',
     'British■Land', 'B&M',  'Bunzl',      'BP',   'Burberry',    'BT■Group',    'Coca-
Cola■HBC',       'Compass■Group',       'Croda■International', 'CRH■plc',     'DCC■plc',
     'Diageo',      'Entain',      'Evraz',       'Experian',    'Ferguson■plc', 'Flutter■
Entertainment',      'Fresnillo',    'Glencore',    'GlaxoSmithKline',     'Hikma■
Pharmaceuticals',       'Hargreaves■Lansdown',  'Halma',       'HSBC', 'International■
Airlines■Group', 'Intermediate■Capital■Group',   'IHG■Hotels■&■Resorts', '3i',   'Imperial■
Brands',      'Informa',      'Intertek',    'ITV■plc',      'JD■Sports',    'Just■Eat■
Takeaway',    'Johnson■Matthey',      'Kingfisher',   'Land■Securities',      'Legal■&■General'
,      'Lloyds■Banking■Group', 'London■Stock■Exchange■Group',  'Mondi',       'M&G',   'Melrose
■Industries',   'National■Grid■plc',    'NatWest■Group',       'Next■plc',     'Ocado■Group',
  'Phoenix■Group',       'Polymetal■International',     'Prudential■plc',      'Pershing■
Square■Holdings',     'Persimmon■plc',       'Pearson■plc',  'Royal■Dutch■Shell',    'RELX', '
Rio■Tinto',    'Reckitt',      'Royal■Mail',   'Rightmove',    'Rolls-Royce■Holdings', '
Rentokil■Initial',     "Sainsbury's", 'Schroders',    'Sage■Group',   'Segro',       'Smurfit
■Kappa',       'DS■Smith',     'Smiths■Group', 'Scottish■Mortgage■Investment■Trust',   'Smith■
&■Nephew',      'Spirax-Sarco■Engineering',     'SSE■plc',      'Standard■Chartered',   "St.■
James's■Place■plc",      'Severn■Trent', 'Tesco',       'Taylor■Wimpey',       'Unilever',
     'United■Utilities',     'Vodafone■Group',      'Weir■Group',   'WPP■plc',      'Whitbread
'])

#moving_avg['Date']= pd.to_datetime(moving_avg['Date'])
for indix,column in enumerate(moving_avg.columns[1:]):
        #print(moving_avg[column])
        moving_avg[str(column)+"■Avg"] = moving_avg[column].rolling(5).mean()

#moving_avg.dropna(inplace=true)
moving_avg.to_csv('G:\EdhecPHD\Thesis■works\Ftse_100_data\Ftse_100_MA_5.csv')
```

```
#code to calculate Constant mean model with Rolling 5D/22D
```

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.regression.rolling import RollingOLS

stock = pd.read_csv('G:\EdhecPHD\Thesis■works\Ftse_100_data\Ftse_100_stocks_data_return_v2.0.csv',
    usecols = ['Date', 'Anglo■American■plc', 'Abrdn', 'Associated■British■Foods', '
   Admiral■Group', 'Ashtead■Group', 'Antofagasta', 'Auto■Trader■Group', 'Aviva',
        'Avast', 'Aveva', 'AstraZeneca', 'BAE■Systems', 'Barclays', '
   British■American■Tobacco', 'Barratt■Developments', 'BHP', 'Berkeley■Group■Holdings',
   'British■Land', 'B&M', 'Bunzl', 'BP', 'Burberry', 'BT■Group', 'Coca-Cola■HBC'
   , 'Compass■Group', 'Croda■International', 'CRH■plc', 'DCC■plc', '
   Diageo', 'Entain', 'Evraz', 'Experian', 'Ferguson■plc', 'Flutter■
   Entertainment', 'Fresnillo', 'Glencore', 'GlaxoSmithKline', 'Hikma■
   Pharmaceuticals', 'Hargreaves■Lansdown', 'Halma', 'HSBC', 'International■
   Airlines■Group', 'Intermediate■Capital■Group', 'IHG■Hotels■&■Resorts', '3i', 'Imperial■
   Brands', 'Informa', 'Intertek', 'ITV■plc', 'JD■Sports', 'Just■Eat■
   Takeaway', 'Johnson■Matthey', 'Kingfisher', 'Land■Securities', 'Legal■&■General'
   , 'Lloyds■Banking■Group', 'London■Stock■Exchange■Group', 'Mondi', 'M&G', 'Melrose
   ■Industries', 'National■Grid■plc', 'NatWest■Group', 'Next■plc', 'Ocado■Group',
     'Phoenix■Group', 'Polymetal■International', 'Prudential■plc', 'Pershing■
   Square■Holdings', 'Persimmon■plc', 'Pearson■plc', 'Royal■Dutch■Shell', 'RELX', '
   Rio■Tinto', 'Reckitt', 'Royal■Mail', 'Rightmove', 'Rolls-Royce■Holdings', '
   Rentokil■Initial', "Sainsbury's", 'Schroders', 'Sage■Group', 'Segro', 'Smurfit
   ■Kappa', 'DS■Smith', 'Smiths■Group', 'Scottish■Mortgage■Investment■Trust', 'Smith■
   &■Nephew', 'Spirax-Sarco■Engineering', 'SSE■plc', 'Standard■Chartered', "St.■
   James's■Place■plc", 'Severn■Trent', 'Tesco', 'Taylor■Wimpey', 'Unilever',
      'United■Utilities', 'Vodafone■Group', 'Weir■Group', 'WPP■plc', 'Whitbread
   '])
ftse_100 = pd.read_csv('G:\EdhecPHD\Thesis■works\Ftse_100_data\Ftse_100.csv', usecols = ['Date','
   Adj■Close','Log■Return'])
```

```
#stock['Date']= pd.to_datetime(stock['Date'])
#ftse_100['Date']= pd.to_datetime(ftse_100['Date'])

for indix, column in enumerate(stock.columns[1:]):
        endog = stock[column].values
        exog = sm.add_constant(ftse_100['Log■Return'])
        rols = RollingOLS(endog, exog, window=5)
        rres = rols.fit()
        params = rres.params.copy()
        params.index = np.arange(1, params.shape[0] + 1)
        ftse_100[str(column)+"■const"] = params['const']
        ftse_100[str(column)+"■beta"] = params['Log■Return']

ftse_100.to_csv('G:\EdhecPHD\Thesis■works\Ftse_100_data\Ftse_100_Regress_5.csv')

--------------------------------------------------------------------------------
# Calculating the excess returns from the daily stock data and the regression based Market event
    study model
import pandas as pd
import string
from datetime import timedelta

regress = pd.read_csv('G:\EdhecPHD\Thesis■works\Ftse_100_data\Ftse_100_Regress_5.csv', usecols =['
    Date',          'Adj■Close',      'Log■Return',      'Anglo■American■plc■const',       'Anglo■American■
    plc■beta',        'Abrdn■const',   'Abrdn■beta',     'Associated■British■Foods■const',          '
    Associated■British■Foods■beta',            'Admiral■Group■const',  'Admiral■Group■beta',    'Ashtead
    ■Group■const',  'Ashtead■Group■beta',    'Antofagasta■const',     'Antofagasta■beta',      'Auto■
    Trader■Group■const',         'Auto■Trader■Group■beta',         'Aviva■const',  'Aviva■beta',    '
    Avast■const',  'Avast■beta',    'Aveva■const',  'Aveva■beta',    'AstraZeneca■const',     '
    AstraZeneca■beta',       'BAE■Systems■const',     'BAE■Systems■beta',       'Barclays■const',
    'Barclays■beta',          'British■American■Tobacco■const',         'British■American■Tobacco■beta'
    ,         'Barratt■Developments■const',    'Barratt■Developments■beta',     'BHP■const',     'BHP■
```

```
    beta',    'Berkeley■Group■Holdings■const',    'Berkeley■Group■Holdings■beta', 'British■
    Land■const',   'British■Land■beta',   'B&M■const',   'B&M■beta',   'Bunzl■const',  'Bunzl■
    beta',  'BP■const',   'BP■beta',   'Burberry■const',    'Burberry■beta',    'BT■
    Group■const',    'BT■Group■beta', ....])

excess_ret_MA = pd.read_csv('G:\\EdhecPHD\\Thesis■works\\Ftse_100_data\\results_vader\\
    Ftse_100_news_senti_allstocks_v4.1.csv', usecols = ['Publication_Date',  'scores',     '
    compound',    'Stock■name1',  'Stock■name2',  'Stock■name3',  'Stock■name4',  'cc_wds',
    'Stock■Return1','Stock■Return2','Stock■Return3','Stock■Return4','Excess_MA_stock1','
    Excess_MA_stock2', 'Excess_MA_stock3', 'Excess_MA_stock4'])

excess_ret_MA['Publication_Date'] = pd.to_datetime(excess_ret_MA['Publication_Date'],format = '%d
    -%m-%Y')


for j in range(excess_ret_MA.shape[0]):
        pub_date = excess_ret_MA.iloc[j][0]
        pub_date = pub_date - timedelta(1)
        pub_date1 = pub_date.strftime("%d-%m-%Y")


        name1 = excess_ret_MA.iloc[j][3] + "■const"
        name2 = excess_ret_MA.iloc[j][3] + "■beta"

        try:
                const = (regress.loc[regress["Date"] == pub_date1  ,name1]).iloc[0]
                beta = (regress.loc[regress["Date"] == pub_date1  ,name2]).iloc[0]
                ret = regress.loc[regress[regress["Date"] == pub_date1].index[0],'Log■Return']
        except:
                try:

                        pub_date_prev = pub_date + timedelta(1)
```

```
                pub_date1 = pub_date_prev.strftime("%d-%m-%Y")
                const = (regress.loc[regress["Date"] == pub_date1 ,name1]).iloc[0]
                beta = (regress.loc[regress["Date"] == pub_date1 ,name2]).iloc[0]
                ret = regress.loc[regress[regress["Date"] == pub_date1].index[0],'Log■
                    Return']
        except:
                try:
                                pub_date_tom = pub_date - timedelta(1)
                                pub_date1 = pub_date_tom.strftime("%d-%m-%Y")
                                const = (regress.loc[regress["Date"] == pub_date1 ,name1])
                                    .iloc[0]
                                beta = (regress.loc[regress["Date"] == pub_date1 ,name2]).
                                    iloc[0]
                                ret = regress.loc[regress[regress["Date"] == pub_date1].
                                    index[0],'Log■Return']
                except:
                        const = 1000
                        beta = 111
                        ret = 111

excess_ret_MA.loc[j,'Excess_MA_stock1'] = excess_ret_MA.iloc[j][8] - const - (ret*beta)

if pd.notna(excess_ret_MA.iloc[j][4]):

        name3 = excess_ret_MA.iloc[j][4] + "■const"
        name4 = excess_ret_MA.iloc[j][4] + "■beta"

        try:
                const1 = (regress.loc[regress["Date"] == pub_date1 ,name3]).iloc[0]
                beta1 = (regress.loc[regress["Date"] == pub_date1 ,name4]).iloc[0]

        except:
```

```
            try:
                pub_date_prev = pub_date + timedelta(1)
                pub_date1 = pub_date_prev.strftime("%d-%m-%Y")
                const1 = (regress.loc[regress["Date"] == pub_date1 ,name3]).iloc
                    [0]
                beta1 = (regress.loc[regress["Date"] == pub_date1 ,name4]).iloc[0]
            except:
                try:
                    pub_date_tom = pub_date - timedelta(1)
                    pub_date1 = pub_date_tom.strftime("%d-%m-%Y")
                    const1 = (regress.loc[regress["Date"] == pub_date1 ,name3
                        ]).iloc[0]
                    beta1 = (regress.loc[regress["Date"] == pub_date1 ,name4])
                        .iloc[0]
                except:
                    const1 = 1000
                    beta1 = 111

        excess_ret_MA.loc[j,'Excess_MA_stock2'] = excess_ret_MA.iloc[j][9] - const1 - (ret
            *beta1)

    if pd.notna(excess_ret_MA.iloc[j][5]):

        name5 = excess_ret_MA.iloc[j][5] + "■const"
        name6 = excess_ret_MA.iloc[j][5] + "■beta"

        try:
            const2 = (regress.loc[regress["Date"] == pub_date1 ,name5]).iloc[0]
            beta2 = (regress.loc[regress["Date"] == pub_date1 ,name6]).iloc[0]
        except:
            try:
                pub_date_prev = pub_date + timedelta(1)
```

```
                pub_date1 = pub_date_prev.strftime("%d-%m-%Y")
                const2 = (regress.loc[regress["Date"] == pub_date1 ,name5]).iloc
                    [0]
                beta2 = (regress.loc[regress["Date"] == pub_date1 ,name6]).iloc[0]
            except:
                try:
                    pub_date_tom = pub_date - timedelta(1)
                    pub_date1 = pub_date_tom.strftime("%d-%m-%Y")
                    const2 = (regress.loc[regress["Date"] == pub_date1 ,name5
                        ]).iloc[0]
                    beta2 = (regress.loc[regress["Date"] == pub_date1 ,name6])
                        .iloc[0]
                except:
                    const2 = 1000
                    beta2 = 111

        excess_ret_MA.loc[j,'Excess_MA_stock3'] = excess_ret_MA.iloc[j][10] - const2 - (
            ret*beta2)

    if pd.notna(excess_ret_MA.iloc[j][6]):

        name7 = excess_ret_MA.iloc[j][6] + "■const"
        name8 = excess_ret_MA.iloc[j][6] + "■beta"

        try:
            const3 = (regress.loc[regress["Date"] == pub_date1 ,name7]).iloc[0]
            beta3 = (regress.loc[regress["Date"] == pub_date1 ,name8]).iloc[0]
        except:
            try:
                pub_date_prev = pub_date + timedelta(1)
                pub_date1 = pub_date_prev.strftime("%d-%m-%Y")
                const3 = (regress.loc[regress["Date"] == pub_date1 ,name7]).iloc
```

```
                [0]
            beta3 = (regress.loc[regress["Date"] == pub_date1 ,name8]).iloc[0]
        except:
            try:
                pub_date_tom = pub_date - timedelta(1)
                pub_date1 = pub_date_tom.strftime("%d-%m-%Y")
                const3 = (regress.loc[regress["Date"] == pub_date1 ,name7
                    ]).iloc[0]
                beta3 = (regress.loc[regress["Date"] == pub_date1 ,name8])
                    .iloc[0]
            except:
                const3 = 1000
                beta3 = 111

    excess_ret_MA.loc[j,'Excess_MA_stock4'] = excess_ret_MA.iloc[j][11] - const3 - (
        ret*beta3)

excess_ret_MA.to_csv('G:\\EdhecPHD\\Thesis■works\\Ftse_100_data\\results_vader\\
    Ftse_100_stocks_regress_excess_ret_5.csv')
```

3.4 Regression outputs for paper 2

The regression results for Oceania and Latin America is in table 23, for North America it is in table 11, for Asia and Africa& Middle East it is in table 24. I have already provided the regression output results of Europe region above in table 11.

	Oceania	Latin America
Constant	12.691**	20.569**
	(0.002)	(0.026)
Carbon reduction	−17.704	
	(0.602)	
Climate sensitive allocation	38.657	
	(0.342)	
Targeted low carbon/climate	97.281	
	(0.166)	
Reduce exposure to emissions	11.579	
	(0.701)	
Analyse emission data for investment	−40.908	65.088
	(0.470)	(0.097)
Climate change integration by Comp	1.261	
	(0.965)	
Climate policy change	−50.014	
	(0.474)	
Carbon footprint	−41.235	
	(0.164)	
Scenario testing	74.802**	
	(0.029)	
Disclosure on emission risk	−52.808	
	(0.067)	
Set target for emission	−34.200	
	(0.455)	
Monitor emission risks	50.786	−84.781
	(0.424)	(0.196)
Contract to integrate climate	33.648	
	(0.632)	
Formal contract on emissions risk	−17.631	
	(0.550)	
R-Square	0.180	0.081
Multiple R	0.425	0.285
N	113	38

Nota: $^{**}p < 0.05$

Table 23: Regression result for Oceania and Latin America region

	Africa & Middle East	Asia
Constant	13.855**	94.990**
	(0.004)	(0.002)
Carbon reduction		−91.190
		(0.670)
Targeted low carbon/climate	105.145**	
	(0.001)	
Reduce exposure to emissions	10.639	
	(0.794)	
Analyse emission data for investment	1.529	
	(0.957)	
Climate change integration by Comp		−2.650
		(0.990)
Carbon footprint	−15.298	
	(0.599)	
Monitor emission risks	−114.138**	
	(0.007)	
Formal contract on emissions risk	−4.480	
	(0.877)	
R-Square	0.271	0.003
Multiple R	0.521	0.059
N	45	56

Nota: ** $p < 0.05$

Table 24: Regression result for Africa & Middle East and Asia region

Abbreviated names	**Original names**
Constant	Intercept
Carbon reduction	Setting carbon reduction targets for portfolio
Climate sensitive allocation	Established climate change sensitive asset allocation strategy
Targeted low carbon / climate	Targeted low carbon /climate resilient investments
Reduce exposure to emissions	Reduce portfolio exposure to emissions intensive holdings
Analyse emission data for investment	Used emissions data or analysis to inform investment decisions
Climate change integration by comp	Sought climate change integration by companies
Climate policy change	Sought climate policy change with policymakers
Carbon footprint	Carbon footprinting
Scenario testing	Scenario testing
Disclosure on emission risk	Disclosure on emission risk
Set target for emission	Target setting for emission risk reduction
Monitor emission risks	Encourage internal/external portfolio managers to monitor emission risks
Contract to integrate climate	Formal contracts to integrate climate in external invest
Formal contract on emissions risk	Emissions risks monitoring /reporting are formalized into contracts when appointing managers

Table 25: Mapping of abbreviated Regressor names with original ones

3.5 Descriptive Stats of *FTSE 100* stocks

Company name	Market Cap in GBP	Industry
Anglo American plc	3090004844	Mining
Abrdn	759411597.2	Financial Services
Associated British Foods	1394239644	Food Producers
Admiral Group	607681892	Nonlife Insurance
Ashtead Group	2378858025	Support Services
Antofagasta	917081309	Mining
Auto Trader Group	907443768.9	Media
Aviva	1181751502	Life Insurance
Avast	408201274.5	Software and Computer Services
Aveva	720174366	Software and Computer Services
AstraZeneca	17339433220	Pharmaceuticals and Biotechnology
BAE Systems	1962115058	Aerospace and Defence
Barclays	3437814232	Banks
British American Tobacco	6926942327	Tobacco
Barratt Developments	964959580	Household Goods and Home Construction
BHP	4129897457	Mining
Berkeley Group Holdings	1335908172	Household Goods and Home Construction
British Land	723237068.7	Real Estate Investment Trusts
B&M	777872314.7	Retailers
Bunzl	825490000	Support Services
BP	5454873692	Oil and Gas Producers
Burberry	617316512	Personal Goods
BT Group	1378370031	Fixed Line Telecommunications
Coca-Cola HBC	1073301840	Beverages
Compass Group	2164950364	Support Services
Croda International	1046818356	Chemicals

CRH plc	1831495206	Construction and Materials
DCC plc	552536380	Support Services
Diageo	4617781056	Beverages
Entain	842174858	Travel and Leisure
Evraz	495066513	Industrial Metals and Mining
Experian	2180537850	Support Services
Ferguson plc	1747398576	Support Services
Flutter Entertainment	2185012375	Travel and Leisure
Fresnillo	866412764	Mining
Glencore	2702514689	Mining
GlaxoSmithKline	6586305546	Pharmaceuticals and Biotechnology
Hikma Pharmaceuticals	379573264	Pharmaceuticals and Biotechnology
Hargreaves Lansdown	816986129	Financial Services
Halma	1025241175	Electronic and Electrical Equipment
HSBC	5056242394	Banks
International Airlines Group	4072463280	Travel and Leisure
Intermediate Capital Group	757780594	Investment Services
IHG Hotels & Resorts	887616576	Travel and Leisure
3i	826258069	Financial Services
Imperial Brands	1707366842	Tobacco
Informa	843104379.6	Media
Intertek	1170539076	Support Services
ITV plc	704304102	Media
JD Sports	505413617	General Retailers
Just Eat Takeaway	801083392	Software and Computer Services
Johnson Matthey	753807964	Chemicals
Kingfisher	876077200.3	Retailers
Land Securities	483990845.8	Real Estate Investment Trusts
Legal & General	3470840571	Life Insurance
Lloyds Banking Group	5277328422	Banks

London Stock Exchange Group	2638817706	Financial Services
Mondi	1290365805	Forestry and Paper
M&G	761339750.7	Asset Managers
Melrose Industries	1398434829	Automobiles and Parts
National Grid plc	2759192905	Gas, Water and Multi-utilities
NatWest Group	1747451556	Banks
Next plc	1806362428	General Retailers
Ocado Group	1523219588	Food and Drug Retailers
Phoenix Group	518261619.1	Life Insurance
Polymetal International	2540443973	Precious Metals and Mining
Prudential plc	2511195728	Life Insurance
Pershing Square Holdings	462145710	Financial Services
Persimmon plc	893114680	Household Goods and Home Construction
Pearson plc	635683113	Media
Shell plc	3171568817	Oil and Gas Producers
RELX	2130464325	Media
Rio Tinto	5911755332	Mining
Reckitt	3935616586	Household Goods and Home Construction
Royal Mail	1003776903	Industrial Transportation
Rightmove	725191870.8	Media
Rolls-Royce Holdings	2435863369	Aerospace and Defence
Rentokil Initial	728963540.4	Support Services
Sainsbury's	979844599.6	Food and Drug Retailers
Schroders	722558799	Financial Services
Sage Group	718271467.2	Software and Computer Services
Segro	1280329924	Real Estate Investment Trusts
Smurfit Kappa	723477030	General Industrials
DS Smith	791165474.8	General Industrials
Smiths Group	484462081	General Industrials

Scottish Mortgage Investment Trust	2639125526	Equity Investment Instruments
Smith & Nephew	1350381172	Health Care Equipment and Services
Spirax-Sarco Engineering	487932550	Industrial Engineering
SSE plc	2195339685	Electricity
Standard Chartered	1363860719	Banks
St. James's Place plc	729733617	Financial Services
Severn Trent	784619325	Gas, Water and Multi-utilities
Tesco	1766377835	Food and Drug Retailers
Taylor Wimpey	1189578885	Household Goods and Home Construction
Unilever	11799559512	Personal Goods
United Utilities	731704720.7	Gas, Water and Multi-utilities
Vodafone Group	3002117582	Mobile Telecommunications
Weir Group	836475480	Industrial Goods and Services
WPP plc	1667607553	Media
Whitbread	1423098690	Retail hospitality

Table 26: FTSE 100 descriptive data stats as of December 2020

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