MAST90106 Capstone Project:
Relationship between Climate Events and Financial Performance

The University of Melbourne

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Group 22

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1 Introduction

Climate changes and events affect financial markets in many ways, for example Typhoons destroy buildings, they affect the normal business of companies and governments, bushfire block roads and because of the damage they cause there may be an interruption to company supply chains. Handling these random natural events help investors, companies, and governments to build a more comprehensive picture of the financial markets, which leads them to make more rational investment decisions. Understanding this relationship promotes the capability to tolerate climate risks. Therefore, identifying the relationship between climate change and financial performance is critical.

Our project aims to assess the relationship between climate and corporate financial performance. The overarching endpoint of this work is to better comprehend how businesses are currently impacted by their climate, with the directive that this work may inform analysis of how climate change will impact corporate financial performance.

The project utilizes climate data and financial data to investigate the relationship between the two. Quantification of climate events is a challenge, since climate events pose direct and indirect effects to financial markets, and these effects will not fade away for some time period, which depends on the type and severity of the event. Meanwhile, it is difficult to enumerate the effects of climate events. In terms of financial markets, though there are a batch of corporate financial performance (CFP) measures, selecting the best indicators to be used in an analysis may not be straightforward. Besides the feature selection and quantification, determining the appropriate research scope is also a challenge. Typically, researchers model financial markets in three level, company level, industry (index) level, and macroeconomics level, and recent research tends to combine some of them [13]. In terms of the data, climate data is full of noise and periodic changes, such as temperature, which needs deliberated preprocessing methods to normalise the data. Financial data is similar to the climate data but with random fluctuation and it is affected by multiple factors and multiple systems both in and out of the markets. For the above reasons, this research stream is out of favour [8] and it is difficult to find related works.

To achieve our research goal we decided to assess the impacts of temperature and bushfires on corporate financial performance, given that their links to climate change are well-grounded at this preliminary stage.

2 Related Work

2.1 Previous Literature Category

Despite the sparsity of climate-finance literature [12], previous literature in the climate-finance area can be broadly categorised by the climate factors focused upon and the level of financial impact being assessed. Climate factors may be climate variables (such as temperature, precipitation, air pressure, cloud cover, El Nino-Southern Oscillation phase, etc) which are present everyday and may be thought of as continuous variables [14][15]. Climate factors may otherwise be climate events (such as bushfires, flash flooding events, cyclones, earthquakes, etc) which are isolated incidents whose damages may become more impactful [16]. Financial impacts considered are typically on the level of company, industry, or index level impacts. Additionally, financial impacts considered are returns-based, risk-based, or both. Our work fits into this segmentation as work that considers one climate variable, one climate event and focuses on company-level impacts to financial returns.

2.2 CFP Measurement

Before we are able to assess these relationships we must first decide on how to measure corporate financial performance. CFP measures may be accounting-based (Net Income, Return on Assets (ROA), Zmijewski score), market-based (stock returns, market value of a company), or composite measures [9]. In this project we have data for and plan to use multiple accounting-based measures. These data are available for all companies (not just publicly listed firms) and these measures can be used for reliable comparisons between companies of different sizes within the same industry. The drawback of accounting-based measures is that they are typically only available on a yearly basis while some market-based measures are available on a daily basis. Yearly data appear to be sufficient as climate change is a phenomenon observed on the time-scale of decades, however, it has been argued that higher frequency data produces more reliable results [11]. The argument for this is that periods of hot and cold temperatures will not appear in the yearly mean value. While this is a limitation to the data we currently have, it is not a limitation inherent to yearly data — we could also use the standard deviation of temperature for each year or another distribution-based statistic to describe this phenomenon. Moreover, this tradeoff — reliable financial data vs reliable temperature data — is not an issue for bushfire and natural disaster data as there are no opposite effects from which misleading data may arise. To ensure a comprehensive analysis, the use of both accounting-based measures and stock prices are included in this study, with an awareness of how averaging daily data may be influencing any results.

2.3 Relationship Assessment

After having decided upon CFP operationalisations used we next considered how to assess the relationship between two variables. This was broken down into correlation analysis and data modelling with statistical testing. Correlation analysis methods available to us were correlation measures (Pearson, Spearman, Kendall, mutual information, cross-entropy, coefficient of upper/lower tail dependence) and correlation structures (copulas). It is anticipated that if there is a relationship that it will be monotonic but not necessarily linear, in which case the Spearman and Kendall correlation measures are well-suited to our analysis. However, some studies have reported relevant non-monotonic relationships suggesting that the use of non-linear correlation measures (mutual information, cross-entropy) will ensure a comprehensive correlation analysis [6][11]. Modelling analysis methods available to us include GARCH [3][6][7], linear modelling, quantile regression [11], ARMA[1], and other time-series based methods [5]. These two analysis approaches are intended to be complimentary in providing a robust analysis of any observed relationship.

Previous studies assessing the relationship between temperature and financial performance justify quantile regression as an appropriate modelling approach as it may improve analysis when some companies, but not all companies, are impacted by temperature fluctuations or a climate event [11]. Previous studies assessing the relationship between natural disasters and financial performance justified GARCH modelling due to the heteroskedasticity and non-normality of financial performance data while using market-based measures with daily observations [3][6][7]. While GARCH modelling allows for a more accurate representation of our data, previous implementations appear to suffer from an uncritical use of this method. Our particular concern is the modelling of error variance $h(t)$ which is optimised via maximum likelihood methods where there is a perverse incentive to have large $h(t)$. As such, this may lead one to obtain a model which fails to accurately model the data. Our takeaways from these are that quantile regression may allow for a more realistic analysis, while GARCH modelling may be well-suited to this task if we can ensure $h(t)$ remains representative of our data.

2.4 Natural Disaster Data Utilization

Previous use of natural disaster data has largely relied on representing daily data as binary data where 0 are days without a natural disaster and 1 are days with a natural disaster [1][3][6]. The drawback of this approach is that there is no distinction in the scale of impact of a natural disaster event.

Moreover, this appears insufficient when considering yearly data (which we are), as there are bushfires every year the difference is in how many occurred and the extent of total damage suffered. As we have data for both the frequency and impact extent, these will be used in our study.

When considering the impacts of natural disasters on financial performance, we may distinguish between direct and indirect impacts. Direct impacts are those which the company suffers from the natural disaster event, while indirect impacts include those which other companies (which the original company is connected to e.g. via supply chains) suffer. Previous studies have assessed the prolonged influence of climate events by including historical dependence in their models [6]. However, to the best of our knowledge there are no such models which distinguish between direct and indirect influences which, in our view, impact companies on different time-scales. While direct impacts have immediate effects, indirect impacts may only be evident after days, weeks, or possibly months. Additionally, the use of historical dependence in these models obfuscates that actual prolonged impacts of natural disaster events on CFP by including implicit impact chains in the model. For example, if a company's stock price is predicted by its previous day's stock price and the 1-5 day impact delay of a bushfire — if a bushfire occurs on a Monday then Tuesday's stock price is predicted by Monday's stock price and the 1-day impact of the bushfires, but Wednesday's stock price is predicted by Tuesday's stock price and the 2-day impact of bushfires. In this situation the bushfires impact Wednesday's stock price in two ways with only one being explicitly interpreted as a result. As such, this type of model formulation may be a better representation of the underlying data, however regression parameters alone may lead to inaccurate model interpretation. On the one hand this is an undocumented limitation of previous work, on the other hand this serves to inform our results interpretation.

3 Dataset

3.1 Climate Data

According to the results of previous studies, we chose to use data on the land average temperature and annual wildfires in the United States to study the relationship between climate change and financial performance.

3.1.1 General Information of Climate Datasets

The dataset including the land average temperature in the U.S. is provided by the person in charge of the Lensell, and the dataset is published on the Kaggle[1] website. Kaggle repackaged the original data that is from the latest compilation compiled by Berkeley Earth, a subsidiary of Lawrence Berkeley National Laboratory. It contains 5 sub-files: `GlobalTemperatures.csv`, `GlobalLandTemperaturesByCountry.csv`, `GlobalLandTemperaturesByState.csv`, `GlobalLandTemperaturesByMajorCity.csv` and

[1]The source is https://www.kaggle.com/berkeleyearth/climate-change-earth-surface-temperature-data

`GlobalLandTemperaturesByCity.csv`. We use `GlobalLandTemperaturesByState`because we have the geographic location of the listed agricultural companies. To do this we rely on the assumption that a company's listed address on Yahoo Finance is representative of where its operations are located. The reason may be that the United States is a country with a large area, and the temperature situation in different states will be different. Furthermore, forests, bushes, and grasslands account for more than half of the land area in the United States. These ecosystems are important resources in terms of environment and economy. According to the description of related reports, climate change may affect the occurrence of climate events. As well as several studies have found that climate change has led to an increase in the frequency and burning area of wildfires. Increasing the frequency of fires due to increased temperature and drought. Furthermore, the occurrence of wildfires are likely to have an important economic impact. National Ocean and Atmospheric Administration indicates that there were 18 wildfire incidents in the United States causing more than $1 billion in damages between 1980 and 2020. Thus, it is worth studying these climate events and take them into account in the model. The dataset of wildfire frequency and burned acreage data comes from the National Interagency Fire Center [2], which compiles wildfire reports sent from local, state, and federal entities that are involved in fighting fires.

3.1.2 Data Cleaning and Pre-processing

(a) Attributes:
In the monthly average temperature dataset of each state, the attributes are included `Date`, `Average Temperature`, `Average Temperature Uncertainty` (95% confidence interval around the average), `State`, and `Country`.

The attributes of United States wildfire dataset summarizes as year, the total number of wildfires per year and annual wildfire-burned area (in millions of acres) .

(b) Data Cleaning:
The object of data cleaning is to ensure that the data is correct, consistent and usable. After cleaning, there are no missing values, duplicate data and obvious outliers in both datasets. However, in the land average temperature data, there are only 9 months of data in 2013 (2013/01-2013/09), and other years includes full 12 months.

(c) Data Pre-processing:
In order to analyze on nation scale, we need to preprocess temperature dataset to achieve the yearly and monthly average land temperatures of the USA. According to the Country attribute, we filter out the data in the United States. In addition, we not only calculate the annual average temperature

[2] The source is https://www.nifc.gov/.

for each state but also the monthly average temperature of all states as the average temperature of the corresponding month in the United States. Based on monthly data, the average temperature in the United States each year is achieved as well. Moreover, in order to show the change trend of temperature, we build yearly and monthly temperature difference datasets. Take the monthly one as example, the average temperature in January 2002 minus the value in January 2001.

(d) Choice of Bushfire indicators:

The bushfire dataset contains the total number of wildfires per year and annual wildfire-burned area. We prefer to use the annual wildfire-burned area as the bushfire indicator.

According to Figure 1, the trend between the number of fires and the burning area is not the same. Although the total number of bushfires is relatively high, the total burning area is not necessarily large. In addition, the burned area is more capable of reflecting the impact of fire. For instance, the number of fires is high in 1985, but the burned-area is relatively lower than most other period. The similar example is in 2020 as well. Therefore, in the current stage, we will first use burned area as the variable to indicate the climate events.

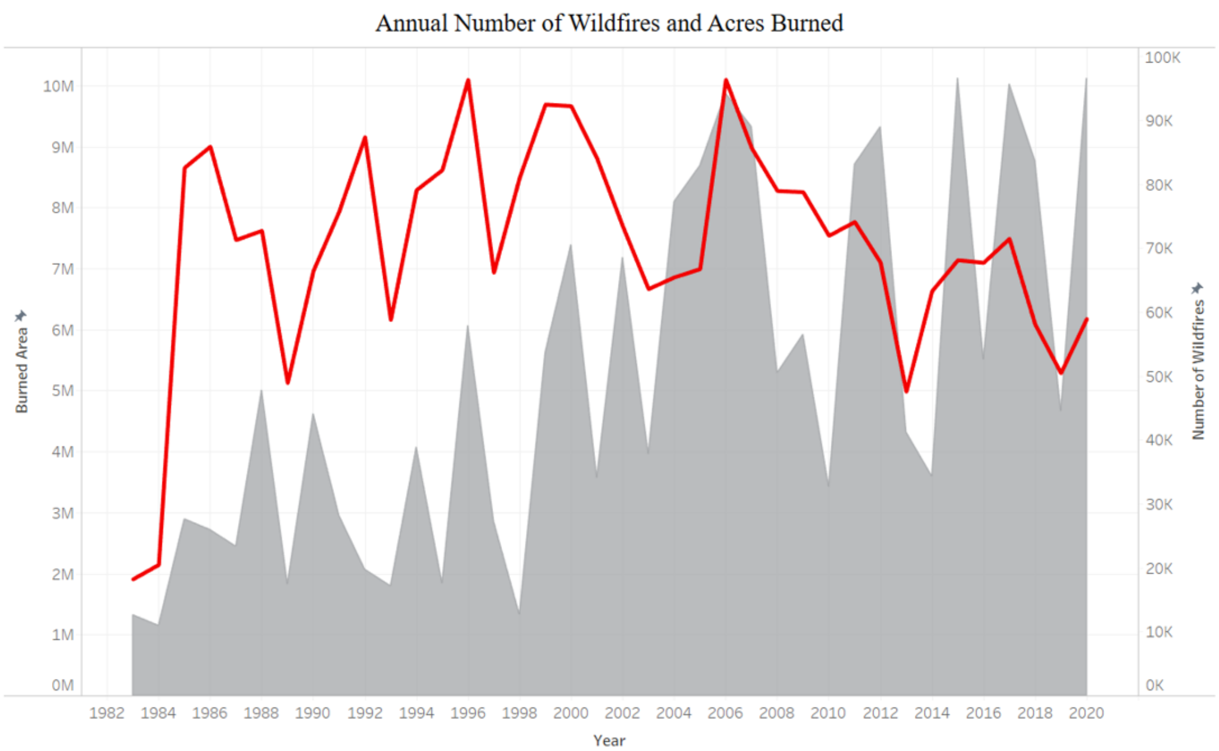

Figure 1: Annual Number of Wildfires and Wildfire-burned Area

3.1.3 Summary of Climate Datasets

Since we are currently based on the national scale and annual scale, the summary of all the climate-related datasets we use in the correlation analysis are shown in the Figure 2. The monthly data set is the average monthly temperature of the United States and the monthly average temperature of each state, and their time range is from January 1980 to September 2013. Similarly, the annual data set contains the annual average temperature of the United States and the annual average temperature of each state, and their time range is from 1980 to 2013. In addition, the wildfire data records 38 burning area data from 1983 to 2020. The maximum burnt area is 96385 in millions of acres and the minimum is 18229 in millions of acres.

Datasets	Size	Max Value	Min Value	Time Interval
Monthly Average Temperature in U.S.	405	24.87759	-4.07057	1980/01–2013/09
Yearly Average Temperature in U.S.	34	13.06522	10.74338	1980 - 2013
Yearly Difference of Temperature in adjacent year	33	1.355658	-0.74972	1981 - 2013
Bushfire	38	10,125,149	1,148,409	1983 - 2020

Figure 2: Summary of Annual Climate Dataset

3.2 Financial Data

The basic idea of cleaning and processing on financial data in this project as follow:

(a) using `read_csv` function of `pandas` library [3] in python to read each company data file;

(b) assign *#DIV/0!* value as `NaN`;

(c) remove `NaN` value from data frame;

(d) remove the year of data if it is incomplete;

(e) remove the company from industry list if the available period is less than 8 years;

(f) remove abnormal data;

(h) generate financial figures for each company on monthly and yearly base;

(i) generate industry financial figures on monthly and yearly base.

3.2.1 Share Price

(a) Cleaning

For share price of each company, there is no missing value needs to be removed. There are three companies, CTV-PA, CTV-PB, and CTVA, only have four years available data, so those three companies

[3] The official document is https://pandas.pydata.org/docs/reference/api/pandas.read_csv.html?highlight=read_csv#pandas.read_csv.

will be removed from Agriculture company list. The reason is that when we do yearly base correlation analysis, there is no sufficient data to support further analysis.

When evaluating the data, the share price of company YTEN is abnormal, shown in Figure 3. More specifically, the share price decreased from $40,000 to $6 within 20 years. By reviewing the financial statements of YTEN, we found that YTEN was issuing shares during the past 20 years. Originally, there are 8,000 shares, while this amount rapidly increases to over 3,000,000 in 2020. We removed this company from Agriculture industry company list, as this price fluctuation is mainly because of financial operations. However, the other financial ratios of YTEN other than share price and number of shareholders could still be available for analysis.

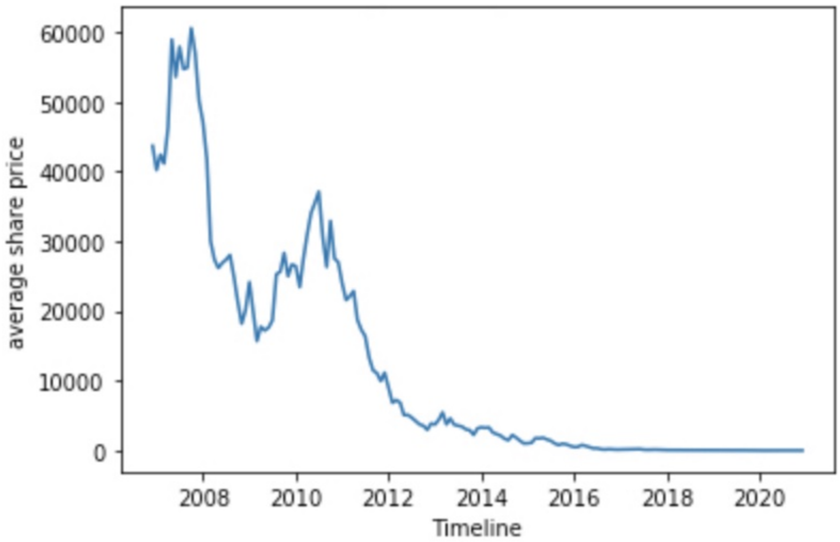

Figure 3: The Average Share Price of YTEN from 2006 to 2020 (in USD)

(b) Processing:
For share price, all the daily data will be converted into monthly and yearly base as we only acquired climate data in monthly. To be more special, data of a month is calculated by average daily data and yearly data is an average value of month data in the year. Moreover, we will generate those data of each company. Then we will create "industry index" which is an average value of total valid companies in the industry.

We will generate share price date set which is basic data, then based on the share price data the return of share price will be generated. Share price data is the most direct indicator of financial performance valuation, while the weakness of share price is that some companies with large absolute values will have significant impact on the performance of data on industry level. Therefore, return of share price will be applied in the project. Return of share price is a percentage despite the impact of absolute values of share prices. In another way, return of share price is the normalization of share prices.

After cleaning and processing for share price data, we got following data sets:

(1) monthly share price of each agriculture company (14 companies);

(2) yearly share price of each agriculture company (14 companies);

(3) monthly agriculture share price index;

(4) yearly agriculture share price index;

(5) monthly return of share price for each agriculture company (14 companies);

(6) yearly return of share price for each agriculture company (14 companies);

(7) monthly agriculture share price return index;

(8) yearly agriculture share price return index.

3.2.2 ROA

ROA is a financial ratio which can reflects the profitability of a company. The equation as follow:

$$ROA = \frac{Net\ Income_t}{Total\ Asset_t},$$

where $NetIncome_t$ comes from income statement for the end of year t and $TotalAsset_t$ comes from balance sheet as at the end of year t. This ratio, a percentage number, indicates how much a company can earn by using 1 dollar asset. However, there is a limitation of the simple ROA we just introduced, because net income evaluates the performance of a company for the whole financial year, while total assets only reflects the financial position of a company at the specific point in time. To be more objective, there is another method to calculate ROA, shown as follow:

$$ROA = \frac{Net\ Income_t}{average(Total\ Asset_t, Total\ Asset_{t-1})},$$

where the denominator is the average value of total asset at the end of this year and total assets at the end of last year. The second method may better reflect the real situation of the company's performance over the course of the entire year. For simplicity, this report will call the ROA calculated by first method as ROA1 and the second as ROA2. In addition, ROA1 and ROA2 have been cleaned and processed in the same way in this project.

(a) Cleaning:

Firstly, `NaN` values and invalid values have been removed during the data reading process. Then by reviewing `csv` data of financial statement of each company, we remove the incomplete data of the year. This is because net income is the difference between revenue and expense in income statement, and total asset is the sum of current asset and non-current asset in balance sheet. If there is a incomplete financial statement, the calculated ROA could be extremely large or small, which could be an outlier in the data set. After that, to select data over a sufficient time period, CTV-PA, CTV-PB, CTVA are removed from the company list as the valid data is not enough, while the other companies all have valid data from the previous 9-35 years. By plotting the data for ROA of each company, there are three companies which may be outliers of the data set, as some of their ROA values are lower than -1.0. The Figure 4 and Figure 5 show ROA1 and ROA2 of these three companies. We will keep these companies in the data set at this stage, and if the result of any hypothesis test is not optimal, then we will try it again without those three companies.

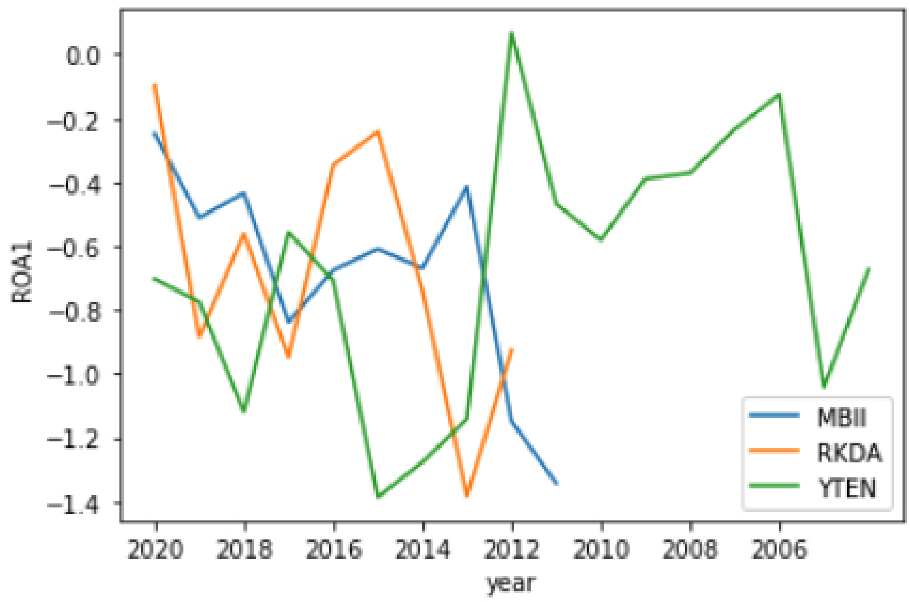

Figure 4: ROA1 Value of YTEN, RKDA, MBII in Different Year

Figure 5: ROA2 Value of YTEN, RKDA, MBII in Different Year

(b) Processing:

As financial ratios are calculated from yearly financial statements all the financial ratios in our data set will be on yearly basis. The basic data set of financial ratios are the ratio itself for each company. Further, we will generate the changes in ROA, because we will focus on temperature changes as our predictor, as mentioned above. For generating the industry index, it is similar with share price. it will be calculated as a average value of ROA of companies within the industry and then based on this data set, change of ROA will be calculated.

After cleaning and processing for ROA, we got the following data sets:
(1) ROA1 of each agriculture company (15 companies);
(2) ROA2 of each agriculture company (15 companies);
(3) changes of ROA1 of each agriculture company (15 companies);
(4) changes of ROA2 of each agriculture company (15 companies);
(5) Agriculture ROA1 index;
(6) Agriculture ROA2 index;
(7) Agriculture changes ROA1 index;
(8) Agriculture changes ROA2 index.

ROA is the financial ratios we have applied on the project at this stage and more financial ratios will be introduced at the following part.

3.2.3 Other Financial Ratios

There are some financial ratios other than ROA which can reflect the financial performance of a company. This part will introduce those ratios which have been acquired and calculated, but have not been cleaned and processed.

Ratios evaluating profitability, which directly reflect the financial performance of a company,
(a) Return on Capital (ROC):
ROC indicates how much a company can earn by using \$1 capital.

$$ROC = \frac{Net\ Income}{Debt\ +\ Equity},$$

where Net Income comes from income statement for the end of year and Debt and Equity come from balance sheet as at the end of year.

(b) Return on Equity (ROE):
ROE indicates how much a company can earn by using \$1 equity.

$$ROE = \frac{Net\ Income}{Total\ Equity},$$

where Net Income comes from income statement for the end of year and total Equity come from balance sheet as at the end of year.

(c) Net Margin:
Net Margin indicates the proportion of Net Income in Total Revenue.

$$Net\ Margin = \frac{Net\ Income}{Total\ Revenue},$$

where Net Income and Total Revenue come from income statement for the end of year.

(d) Operating Margin:

Operating Margin indicates the proportion of Operating activity Income in Total Revenue.

$$Operating\ Margin = \frac{Operating\ Income}{Total\ Revenue},$$

where Operating Income and Total Revenue come from income statement for the end of year.

(e) Earning Per Share (EPS):

EPS indicates how much a company can earn for per share.

$$EPS = \frac{Net\ Income}{Number\ of\ Issued\ Shares},$$

where Net Income comes from income statement for the end of year, and Number of Issued Shares comes from balance sheet as at the end of year.

Ratios evaluating liquidity, which shows the financial situation of a company,

(f) Current Ratio:

Current ratio measures weather a company have enough assets to cover short-term obligations, however, it can only compare within the same industry as different industries have different situations.

$$Current\ Ratio = \frac{Current\ Asset}{Current\ Liability},$$

where Current Asset and Current Liability come from balance sheet as at the end of year.

(g) Quick Ratio:

Quick ratio measures weather a company have enough cash equivalent assets to cover short-term obligations, same with current ratio, it can only compare within the same industry.

$$Quick\ Ratio = \frac{Current\ Asset - Inventory}{Current\ Liability},$$

where Current Asset, Inventory and Current Liability come from balance sheet as at the end of year.

(h) Debt to Equity Ratio (D/E ratio):

D/E ratio measure the leverage of a company.

$$D/E\ Ratio = \frac{Debt}{Total\ Equity},$$

where Debt and Total Equity come from balance sheet as at the end of year.

The following section will introduce the correlation analysis based on the climate data and financial data we processed.

4 Correlation Analysis

This project aims to investigate the relationship between financial performance, climate change and climate events. Correlation is an important and foundational statistical relationship between two variables, which measures the strength and direction of the association between two variables. Beginning with an investigation of the correlation between climate events and financial performance can help us intuitively understand the linear or monotonic relationship between variables and lay the foundation for subsequent non-linear, time series, and regression modelling analyses.

The direction of the correlation is implied by the sign of its coefficient, a + sign indicates a positive relationship, that is the two variables vary in the same direction; otherwise a − sign indicates a negative relationship. As for the strength of the relationship, the values range from -1 to $+1$, a -1 or $+1$ indicates the two variables has a impeccable degree of association in the same or the opposite direction. The closer the coefficient value is to 0, the weaker the correlation is.

This analysis employs Pearson correlation coefficient, Spearman rank correlation coefficient, and Kendall rank correlation coefficient to test correlation, and p-value to determine the the significance of the test results. Typically, if the p-values of three correlation coefficients are smaller than 0.05, we accept that there is a correlation between climate variable and financial indicator. Since climate data and financial data are both continuous data, the three correlation coefficients are available. Pearson correlation is a parametric and linear correlation, while Spearman correlation and Kendall correlation are non-parametric and monotonic correlation. Parametric correlation contains more information than non-parametric correlation, such as the mean and deviation of the data, thus Pearson correlation is more powerful but as we do not know if the relationship is truly linear, it may not be suitable for our data analysis.

In this preliminary stage, we focus on agriculture companies in the United States of America (USA), since the performance of agriculture companies is highly related to the climate [2] and both the financial data and climate data are available in USA. ROA serves as the measurement of the financial performance, because ROA is a comprehensive indicator for evaluating a company's financial performance, a higher ROA equates to more effective asset utilization, stronger profitability, and better financial performance [13, 4]. Further, we use two methods to compute the ROA, and the second one uses the average of the current year and past year total assets, while the first focuses on the current year data. Temperature serves as the measurement of the global warning, and bushfire burnt area serves as the measurement of bushfire, which is more objective to reflect the severity of wildfires than the burnt frequency.

The analysis scenarios consists of the correlation between ROA and temperature difference, the correlation between ROA difference and temperature difference, and the correlation between ROA and bushfire areas. Due to the time frame, the correlation between ROA difference and bushfire brunt areas difference is not yet completed. The difference of ROA, temperature and bushfire brunt areas has three levels, the first one is the current year's data minus the past year's data; the second is the current year's data minus the average past two year's data; the third is the current year's data minus the average past three year's data. Compared to the data without difference, the difference data include the changing trend directly and the average of the past n year(s) reduces the influence of the noises and the outliers in a certain year. A 3-year moving average drought climate index [10] shares the similar idea with the difference. Therefore, we can use differences as our variables. There are only 10 companies have sufficient data to support the above analysis scenarios, which are YTEN, AVD, IPI, MGPI, SMG, FMC, MBII, UAN, CF, MOS [4].

4.1 ROA and Temperature Difference

The full results of the correlation analysis between ROA and temperature difference is shown in Table 2. According to this table, IPI has a significant correlation, and YTEN shows a strong correlation, the rest companies don't display the association between temperature difference. Figure 6, 7, 8, 9 illustrate the IPI and YTEN both have a negative correlation, that is, with the ROA growing, the temperature difference becomes smaller. In Table 2, though ROA1 coefficients are larger than ROA2 coefficients in 63%, the ratio of both ROA1 p-values and coefficients are greater than ROA2's is 47%. This phenomenon implies larger coefficients don not promise a larger p-value. As for the insignificant companies, FMC has a cluster exclude the outlier in Figure 10, and SMG data is scattered in various places and it is difficult to capture the pattern in Figure 11.

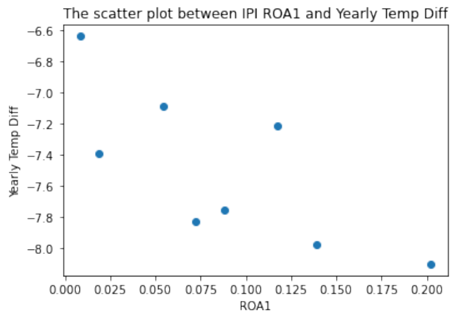

Figure 6: IPI ROA1

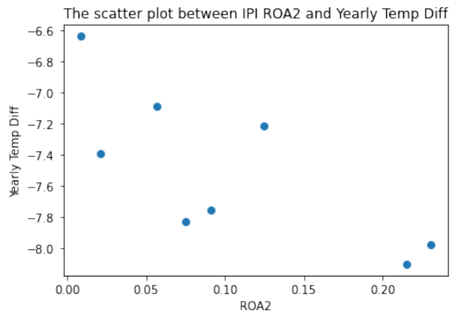

Figure 7: IPI ROA2

4.2 ROA Difference and Temperature Difference

The results of 1 year ROA difference and temperature difference are shown in Table 3, Table 4 displays the results 2 year ROA difference and temperature difference, and Table 5. Similar to the results of ROA and temperature difference, these three tables did not show a significant correlation

[4]These are the abbreviations of the company names, the details of the companies are shown in Table 1.

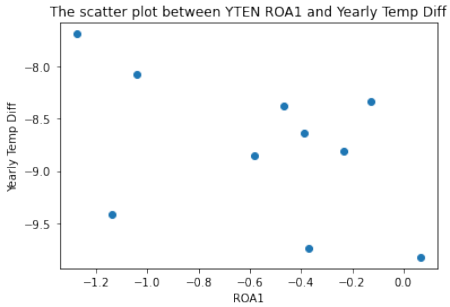

Figure 8: YTEN ROA1

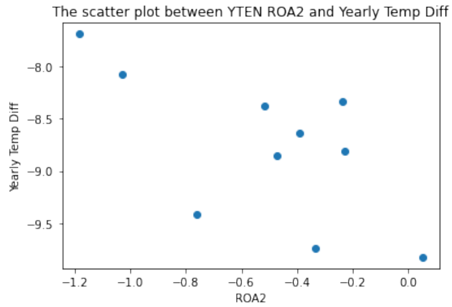

Figure 9: YTEN ROA2

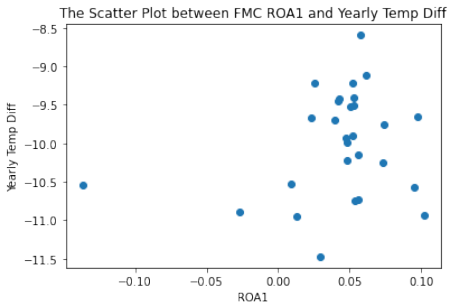

Figure 10: FMC ROA1

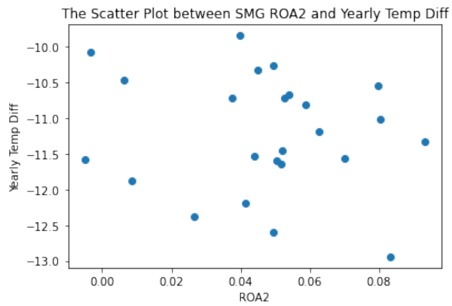

Figure 11: SMG ROA2

in the industry scope, only some companies showed a significant correlation. Since MBII doesn't have enough data, this scenario excludes it.

As for Table 3, CF has a strong correlation between ROA1 (Figure 12) and 1 year temperature difference while ROA2 (Figure 13) does not. And the proportion of ROA1 coefficients are larger than ROA2 coefficients is 49%, while the ratio of both ROA1 p-values and coefficients are greater than ROA2's is 35%.

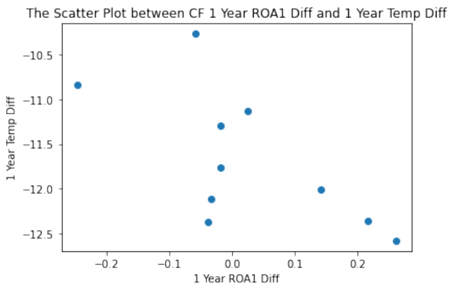

Figure 12: CF 1-year ROA1

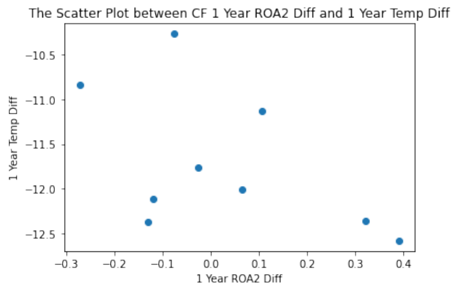

Figure 13: CF 1-year ROA2

In terms of Table 4, CF has a significant correlation between 2 year ROA1/ROA2 difference and 1 year temperature difference, which is shown in Figure 14 and Figure 15. And the proportion of ROA1 coefficients that are larger than ROA2 coefficients is 41%, while the ratio of both ROA1 p-values and coefficients are greater than ROA2's is 35%.

For Table 5, CF shows a significant correlation between 3 year ROA1 difference and 1 year temperature difference in Figure 16 and a strong correlation between 3 year ROA2 difference and 1 year temperature

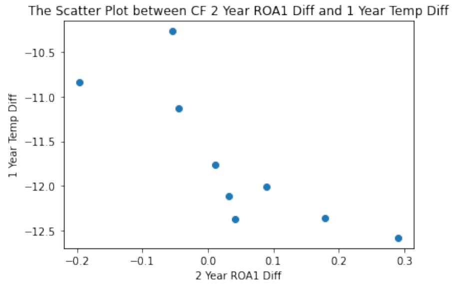

Figure 14: CF 2-year ROA1

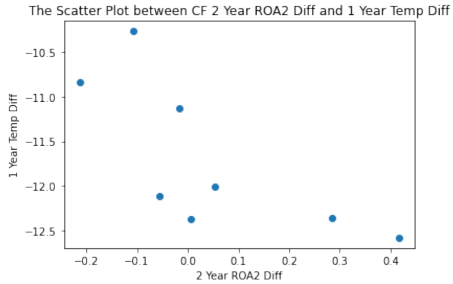

Figure 15: CF 2-year ROA2

difference in Figure 17. The reason why UAN has a significant Spearman correlation over the 3 temperature levels is UAN only has three points which are easy to obtain a perfect rank shown in Figure 18, and IPI is the same as UAN shown in Figure 19. The proportion of ROA1 coefficients that are larger than ROA2 coefficients is 49%, while the ratio of both ROA1 p-values and coefficients are greater than ROA2's is 22%.

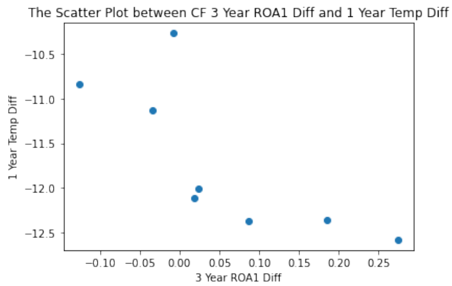

Figure 16: CF 3-year ROA1

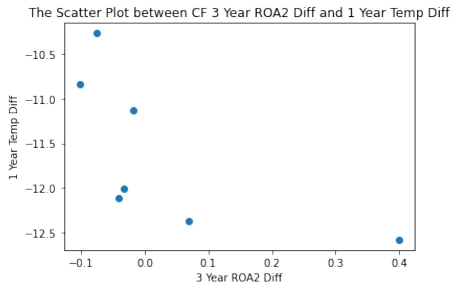

Figure 17: CF 3-year ROA2

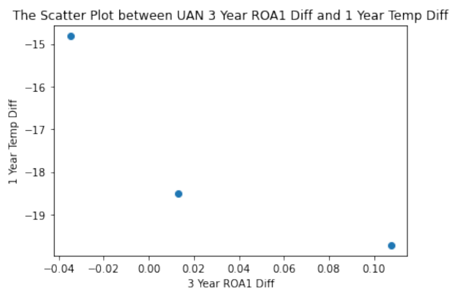

Figure 18: UAN 3-year ROA1

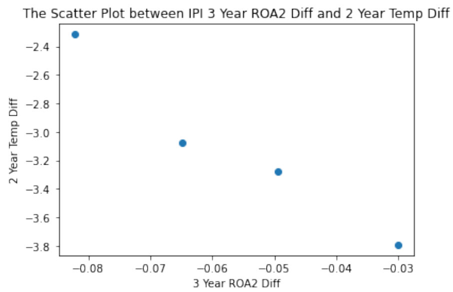

Figure 19: IPI 3-year ROA2

In this scenario, we can conclude that CF has a correlation between ROA1 difference and 1-year temperature difference, and Spearman correlation is more general than Pearson and Kendall, since it captures the monotonic directly.

4.3 ROA and Bushfire Bruned-areas

According to Table 6, FMC shows a strong relationship between ROA1/ROA2 value and brunt areas shown in Figure 20 and Figure 21, which indicates the bushfire pose a positive influence over FMC finical performance. The reason for this event may be that bushfire has led to a decrease in local food reserves, and the increase in demand for food has brought about a rise in food prices and bullish agricultural enterprises. In a nutshell, the correlation between agriculture and bushfire needs more research.

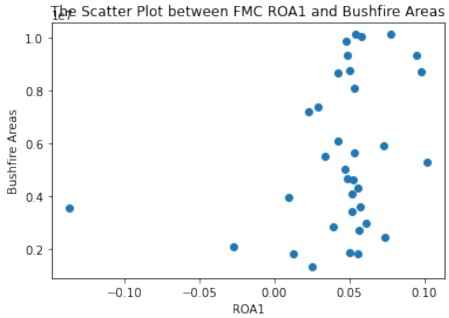

Figure 20: FMC ROA1

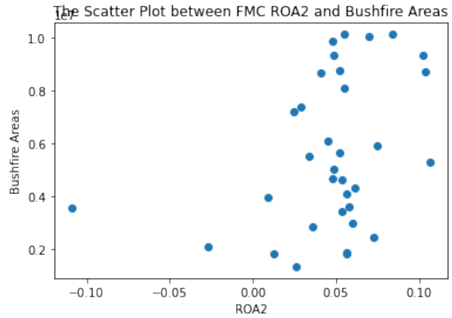

Figure 21: FMC ROA2

5 Proposal for Semester 2

For Semester 2, we propose to address our client's research question by extending our correlation analysis, constructing multiple types time-series models for relationship analysis, and assessing whether company-level results may be extended to the industry level.

The proposal will involve reproducing our above correlation analysis for multiple other CFP measures, extending it to use other correlation measures mentioned in Section 2.3, obtaining daily temperature data to account for the hot-cold issue mentioned in Section 2.2, and conducting correlation analyses with these data.

Once we have a detailed correlation analysis completed, we will implement numerous models and compare their performances: these models will include linear regression, quantile regression, GARCH, and ARMA models. The quantile regression aims to model the different severity degree in the same climate change and event, and segmented regression tends to model the before and after at the climate event flash-points. Then GARCH and ARMA model serve to handle the historical information, such as the past 7-day data, and the wait time distribution which measures the delay time of the effects of the climate events.

Finally, the achievable results in this project is to reach a time-series model in company level, and once results for the company-level impacts are finalised, we will assess whether any found relationship may be interpreted as occurring on an industry level. This may involve analysis on all company data together, or it may involve a binomial test to assess whether significant p-values are plausibly explained by data randomness.

If there is enough time, we would like to also explore several model extensions: including the impact of temperature on risk-based returns measures which in turn impacts actual returns, including geographic details of company location for greater modelling precision, and using differential equation-based models, such as training neural network models to see how machine learning methods finding the relationship without much explanation.

6 Timeline

Timeline is shown in Figure 22.

7 Conclusion

With the increased presence of climate change discussions in everyday life, it has become apparent that climate events also impact the financial markets. Each company is exposed to a sort of risks due to climate change, such as supply chain risks, operational risks, or market risks. Some companies give an overview of the risks they face in their annual reports and discuss the impact on their business. However, the number of comprehensive discussions is limited. Moreover, the academic research on the relationship between climate events and stock performance is also extremely limited.

This project proposes to investigate the relationship between climate events and companies' financial performance. Based on the literature review and the expected results after the completion of the project, we currently covered companies of the agricultural industry in the United States. The temperature difference and the burned-area of wildfires are as independent variables reflecting climate events. In addition, we calculated a variety of financial indicators according to the host organization's requirements and then selected ROA1 and ROA2, calculated under different formulas, response variable reflecting the company's financial performance. According to the main topic of the project, this report uses three correlation analysis methods (Spearman, Pearson and Kendall coefficient) to analyze the relationship between ROA and Temperature Difference, ROA Difference and Temperature Difference, ROA and Bushfire burned-areas. The final result shows that the ROA of individual companies has a significant negative correlation with temperature changes, which means that as the temperature difference rises, the ROA will decline. In addition, the analysis results show that there is a strong positive relationship between the ROA1/ROA2 value of several agricultural companies and the bushfire burned-area.

In addition, to summarize the research and analysis of this semester, we also made a detailed plan for the second semester in terms of modeling and data. For example, we will add more climate data and companies financial data from other industries. And we are going to mostly focus on using the time series model to analyze at the company and industry levels to get the comprehensive conclusion that fits the object of the project.

8 Appendix

8.1 Company List

Abbreviation	Full Name	Website
YTEN	Yield10 Bioscience, Inc.	http://www.yield10bio.com
AVD	American Vanguard Corporation	http://www.american-vanguard.com
IPI	Intrepid Potash, Inc.	http://www.intrepidpotash.com
MGPI	MGP Ingredients, Inc.	http://www.mgpingredients.com
SMG	The Scotts Miracle-Gro Company	http://www.scottsmiraclegro.com
FMC	FMC Corporation	http://www.fmc.com
MBII	Marrone Bio Innovations, Inc.	http://www.marronebio.com
UAN	CVR Partners, LP	http://www.cvrpartners.com
CF	CF Industries Holdings, Inc.	http://www.cfindustries.com
MOS	The Mosaic Company	http://www.mosaicco.com

Table 1: The Selected Companies in Correlation Analysis

8.2 Correlation Analysis Results

Company	ROA	Pearson			Spearman			Kendall		
		1 year	2 year	3year	1 year	2 year	3 year	1 year	2 year	3 year
YTEN	ROA1	-0.467(0.173)	-0.366(0.298)	-0.261(0.466)	-0.442(0.200)	-0.309(0.385)	-0.139(0.701)	-0.333(0.216)	-0.244(0.381)	-0.067(0.862)
	ROA2	-0.652(**0.041**)	-0.371(0.291)	-0.239(0.507)	-0.588(0.074)	-0.309(0.385)	-0.067(0.855)	-0.467(0.073)	-0.200(0.484)	-0.022(1.000)
AVD	ROA1	-0.120(0.542)	-0.678(0.065)	-0.103(0.603)	0.109(0.579)	-0.524(0.183)	0.063(0.748)	0.079(0.570)	-0.429(0.179)	0.048(0.739)
	ROA2	-0.134(0.496)	-0.609(0.109)	-0.090(0.647)	0.109(0.581)	-0.476(0.233)	0.084(0.670)	0.085(0.544)	-0.357(0.275)	0.063(0.652)
IPI	ROA1	-0.749(**0.033**)	-0.678(0.065)	-0.609(0.109)	-0.786(**0.021**)	-0.524(0.183)	-0.357(0.385)	-0.643(**0.031**)	-0.429(0.179)	-0.286(0.399)
	ROA2	-0.752(**0.031**)	-0.609(0.109)	-0.549(0.158)	-0.762(**0.028**)	-0.476(0.233)	-0.310(0.456)	-0.571(0.061)	-0.357(0.275)	-0.214(0.548)
MGPI	ROA1	0.092(0.656)	0.130(0.528)	0.232(0.255)	0.026(0.901)	0.032(0.877)	0.197(0.336)	0.022(0.896)	0.015(0.930)	0.138(0.336)
	ROA2	0.087(0.674)	0.124(0.548)	0.231(0.257)	0.024(0.909)	0.022(0.917)	0.186(0.362)	0.022(0.896)	0.003(1.000)	0.126(0.382)
SMG	ROA1	-0.172(0.423)	-0.135(0.529)	-0.159(0.457)	-0.126(0.557)	-0.105(0.625)	-0.088(0.683)	-0.101(0.507)	-0.080(0.606)	-0.072(0.641)
	ROA2	-0.145(0.501)	-0.144(0.502)	-0.183(0.393)	-0.101(0.639)	-0.117(0.588)	-0.094(0.662)	-0.065(0.677)	-0.087(0.572)	-0.065(0.677)
FMC	ROA1	0.217(0.267)	0.106(0.592)	0.042(0.833)	0.134(0.498)	0.112(0.570)	0.123(0.532)	0.085(0.544)	0.079(0.570)	0.090(0.518)
	ROA2	0.207(0.290)	0.091(0.647)	0.033(0.868)	0.131(0.507)	0.054(0.784)	0.070(0.725)	0.079(0.570)	0.042(0.769)	0.032(0.830)
MBII	ROA1	0.211(0.865)	0.356(0.768)	0.419(0.725)	0.500(0.667)	0.500(0.667)	0.500(0.667)	0.333(1.000)	0.333(1.000)	0.333(1.000)
	ROA2	0.433(0.715)	0.564(0.618)	0.619(0.575)	0.500(0.667)	0.500(0.667)	0.500(0.667)	0.333(1.000)	0.333(1.000)	0.333(1.000)
UAN	ROA1	-0.285(0.584)	-0.056(0.916)	-0.082(0.878)	-0.600(0.208)	-0.086(0.872)	0.029(0.957)	-0.467(0.272)	-0.200(0.719)	-0.067(1.000)
	ROA2	-0.287(0.582)	-0.049(0.926)	-0.075(0.887)	-0.543(0.266)	0.029(0.957)	0.200(0.704)	-0.333(0.469)	-0.067(1.000)	0.067(1.000)
CF	ROA1	-0.438(0.178)	0.123(0.719)	0.243(0.472)	-0.582(0.060)	0.191(0.574)	0.345(0.298)	-0.455(0.060)	0.055(0.879)	0.236(0.359)
	ROA2	-0.359(0.278)	0.031(0.928)	0.180(0.596)	-0.518(0.102)	0.109(0.750)	0.255(0.450)	-0.418(0.087)	0.018(1.000)	0.127(0.648)
MOS	ROA1	0.084(0.678)	0.071(0.726)	0.053(0.793)	0.095(0.639)	0.018(0.928)	0.021(0.916)	0.071(0.620)	0.009(0.967)	0.043(0.773)
	ROA2	0.069(0.731)	0.059(0.769)	0.044(0.829)	0.062(0.758)	0.002(0.990)	0.007(0.973)	0.048(0.741)	0.009(0.967)	0.020(0.901)

Table 2: Correlation Analysis Results of ROA Value and Temp. Diff.

Company	ROA	Pearson			Spearman			Kendall		
		1 year	2 year	3year	1 year	2 year	3 year	1 year	2 year	3 year
YTEN	ROA1	-0.355(0.349)	-0.073(0.851)	-0.082(0.835)	-0.117(0.765)	0.167(0.668)	0.167(0.668)	0.000(1.000)	0.111(0.761)	0.111(0.761)
	ROA2	-0.607(0.111)	-0.256(0.541)	-0.068(0.873)	-0.476(0.233)	-0.095(0.823)	0.048(0.911)	-0.357(0.275)	-0.071(0.905)	0.000(1.000)
AVD	ROA1	-0.132(0.513)	-0.191(0.339)	-0.249(0.211)	0.267(0.179)	0.030(0.882)	-0.063(0.753)	0.168(0.229)	0.026(0.869)	-0.026(0.869)
	ROA2	-0.142(0.488)	-0.188(0.357)	-0.237(0.244)	0.186(0.362)	-0.015(0.943)	-0.072(0.726)	0.108(0.457)	-0.009(0.965)	-0.052(0.727)
IPI	ROA1	0.179(0.701)	0.236(0.610)	0.144(0.758)	0.607(0.148)	0.571(0.180)	0.464(0.294)	0.524(0.136)	0.429(0.239)	0.333(0.381)
	ROA2	-0.138(0.794)	0.194(0.713)	0.190(0.719)	0.029(0.957)	0.486(0.329)	0.486(0.329)	0.067(1.000)	0.333(0.469)	0.333(0.469)
MGPI	ROA1	0.092(0.663)	0.159(0.449)	0.131(0.532)	-0.019(0.927)	0.164(0.434)	0.247(0.234)	-0.027(0.872)	0.100(0.502)	0.173(0.236)
	ROA2	0.094(0.663)	0.163(0.445)	0.143(0.504)	0.020(0.926)	0.197(0.357)	0.314(0.135)	0.029(0.864)	0.116(0.446)	0.210(0.159)
SMG	ROA1	0.006(0.980)	0.009(0.969)	-0.058(0.793)	-0.007(0.975)	-0.030(0.893)	-0.129(0.556)	-0.036(0.835)	-0.020(0.917)	-0.067(0.676)
	ROA2	-0.034(0.881)	-0.165(0.462)	-0.264(0.236)	-0.069(0.759)	-0.207(0.355)	-0.315(0.154)	-0.108(0.503)	-0.152(0.342)	-0.195(0.217)
FMC	ROA1	0.102(0.614)	0.221(0.268)	0.052(0.796)	0.117(0.562)	0.063(0.755)	-0.009(0.964)	0.066(0.650)	0.048(0.741)	0.003(1.000)
	ROA2	0.095(0.646)	0.186(0.362)	0.018(0.930)	0.089(0.665)	0.017(0.935)	-0.026(0.901)	0.046(0.760)	0.009(0.965)	-0.028(0.861)
UAN	ROA1	-0.054(0.931)	-0.057(0.927)	0.151(0.809)	-0.100(0.873)	-0.200(0.747)	0.300(0.624)	0.000(1.000)	-0.200(0.817)	0.200(0.817)
	ROA2	-0.385(0.615)	-0.590(0.410)	-0.648(0.352)	-0.400(0.600)	-0.800(0.200)	-0.800(0.200)	-0.333(0.750)	-0.667(0.333)	-0.667(0.333)
CF	ROA1	-0.660(**0.038**)	-0.074(0.839)	0.223(0.536)	-0.576(0.082)	-0.079(0.829)	0.176(0.627)	-0.422(0.108)	-0.111(0.727)	0.156(0.601)
	ROA2	-0.517(0.154)	-0.027(0.944)	0.179(0.646)	-0.383(0.308)	0.050(0.898)	0.167(0.668)	-0.278(0.358)	-0.056(0.919)	0.000(1.000)
MOS	ROA1	0.178(0.386)	0.092(0.655)	-0.035(0.865)	0.223(0.273)	0.236(0.245)	0.166(0.416)	0.095(0.512)	0.169(0.237)	0.120(0.406)
	ROA2	0.139(0.498)	0.073(0.722)	-0.038(0.854)	0.197(0.336)	0.210(0.304)	0.144(0.483)	0.089(0.541)	0.151(0.293)	0.114(0.431)

Table 3: Correlation Analysis Results of 1 year ROA Diff. and Temp. Diff.

Company	ROA	Pearson			Spearman			Kendall		
		1 year	2 year	3year	1 year	2 year	3 year	1 year	2 year	3 year
YTEN	ROA1	-0.603(0.113)	-0.073(0.851)	-0.127(0.764)	-0.429(0.289)	0.167(0.668)	0.095(0.823)	-0.286(0.399)	0.111(0.761)	0.071(0.905)
	ROA2	-0.879(**0.009**)	-0.256(0.541)	-0.514(0.238)	-0.643(0.119)	-0.095(0.823)	-0.357(0.432)	-0.429(0.239)	-0.071(0.905)	-0.238(0.562)
AVD	ROA1	-0.080(0.699)	-0.191(0.339)	-0.151(0.462)	0.224(0.271)	0.030(0.882)	0.010(0.962)	0.132(0.358)	0.026(0.869)	0.022(0.896)
	ROA2	-0.096(0.649)	-0.188(0.357)	-0.132(0.530)	0.187(0.371)	-0.015(0.943)	0.064(0.762)	0.113(0.445)	-0.009(0.965)	0.060(0.694)
IPI	ROA1	-0.064(0.904)	0.236(0.610)	0.261(0.617)	-0.029(0.957)	0.571(0.180)	0.429(0.397)	-0.067(1.000)	0.429(0.239)	0.200(0.719)
	ROA2	-0.682(0.205)	0.194(0.713)	0.000(1.000)	-0.800(0.104)	0.486(0.329)	0.000(1.000)	-0.600(0.233)	0.333(0.469)	-0.200(0.817)
MGPI	ROA1	0.168(0.434)	0.159(0.449)	0.249(0.240)	0.075(0.728)	0.164(0.434)	0.302(0.152)	0.043(0.787)	0.100(0.502)	0.210(0.159)
	ROA2	0.174(0.426)	0.163(0.445)	0.262(0.228)	0.071(0.747)	0.197(0.357)	0.316(0.142)	0.075(0.638)	0.116(0.446)	0.217(0.155)
SMG	ROA1	-0.011(0.962)	0.009(0.969)	-0.214(0.339)	0.003(0.990)	-0.030(0.893)	-0.235(0.291)	0.004(1.000)	-0.020(0.917)	-0.169(0.288)
	ROA2	0.082(0.725)	-0.165(0.462)	-0.187(0.417)	0.205(0.372)	-0.207(0.355)	-0.142(0.540)	0.143(0.386)	-0.152(0.342)	-0.114(0.492)
FMC	ROA1	0.050(0.810)	0.221(0.268)	-0.020(0.922)	0.041(0.841)	0.063(0.755)	-0.069(0.736)	0.009(0.965)	0.048(0.741)	-0.052(0.727)
	ROA2	0.032(0.881)	0.186(0.362)	-0.063(0.766)	-0.006(0.977)	0.017(0.935)	-0.145(0.490)	-0.027(0.872)	0.009(0.965)	-0.120(0.418)
UAN	ROA1	-0.857(0.143)	-0.057(0.927)	-0.635(0.365)	-0.400(0.600)	-0.200(0.747)	-0.200(0.800)	-0.333(0.750)	-0.200(0.817)	0.000(1.000)
	ROA2	-0.875(0.322)	-0.590(0.410)	-0.932(0.237)	-0.500(0.667)	-0.800(0.200)	-0.500(0.667)	-0.333(1.000)	-0.667(0.333)	-0.333(1.000)
CF	ROA1	-0.796(**0.010**)	-0.074(0.839)	0.066(0.866)	-0.900(**0.001**)	-0.079(0.829)	-0.017(0.966)	-0.778(**0.002**)	-0.111(0.727)	-0.056(0.919)
	ROA2	-0.727(**0.041**)	-0.027(0.944)	-0.015(0.972)	-0.810(**0.015**)	0.050(0.898)	-0.143(0.736)	-0.643(**0.031**)	-0.056(0.919)	-0.143(0.720)
MOS	ROA1	0.225(0.281)	0.092(0.655)	0.014(0.947)	0.185(0.377)	0.236(0.245)	0.225(0.280)	0.073(0.627)	0.169(0.237)	0.180(0.218)
	ROA2	0.187(0.371)	0.073(0.722)	0.008(0.971)	0.210(0.314)	0.210(0.304)	0.242(0.245)	0.093(0.532)	0.151(0.293)	0.173(0.236)

Table 4: Correlation Analysis Results of 2 year ROA Diff. and Temp. Diff.

Company	ROA	Pearson	Pearson	Pearson	Spearman	Spearman	Spearman	Kendall	Kendall	Kendall
		1 year	2 year	3year	1 year	2 year	3 year	1 year	2 year	3 year
YTEN	ROA1	-0.667(0.102)	-0.596(0.158)	-0.515(0.237)	-0.679(0.094)	-0.464(0.294)	-0.464(0.294)	-0.524(0.136)	-0.429(0.239)	-0.333(0.381)
	ROA2	-0.779(0.068)	-0.701(0.121)	-0.701(0.121)	-0.486(0.329)	-0.371(0.468)	-0.371(0.468)	-0.333(0.469)	-0.333(0.469)	-0.333(0.469)
AVD	ROA1	-0.053(0.802)	-0.060(0.775)	-0.065(0.758)	0.260(0.209)	0.164(0.434)	0.198(0.344)	0.153(0.297)	0.147(0.319)	0.180(0.218)
	ROA2	-0.127(0.555)	-0.127(0.555)	-0.127(0.555)	0.206(0.334)	0.115(0.593)	0.115(0.593)	0.109(0.476)	0.101(0.507)	0.101(0.507)
IPI	ROA1	-0.561(0.325)	0.030(0.962)	0.129(0.836)	-0.800(0.104)	0.000(1.000)	0.000(1.000)	-0.600(0.233)	-0.200(0.817)	-0.200(0.817)
	ROA2	-0.893(0.107)	-0.978(**0.022**)	-0.978(**0.022**)	-0.800(0.200)	-1.000(**0.000**)	-1.000(**0.000**)	-0.667(0.333)	-1.000(0.083)	-1.000(0.083)
MGPI	ROA1	-0.060(0.785)	0.132(0.547)	0.217(0.319)	-0.082(0.710)	0.077(0.727)	0.130(0.553)	-0.075(0.638)	0.051(0.754)	0.099(0.530)
	ROA2	-0.055(0.807)	0.136(0.545)	0.136(0.545)	-0.080(0.725)	0.083(0.713)	0.083(0.713)	-0.082(0.616)	0.048(0.781)	0.048(0.781)
SMG	ROA1	0.056(0.810)	-0.091(0.696)	-0.206(0.370)	0.183(0.427)	-0.155(0.504)	-0.203(0.378)	0.143(0.386)	-0.133(0.420)	-0.171(0.294)
	ROA2	0.025(0.916)	-0.024(0.920)	-0.024(0.920)	0.192(0.416)	-0.006(0.980)	-0.006(0.980)	0.137(0.422)	-0.021(0.924)	-0.021(0.924)
FMC	ROA1	0.154(0.461)	0.174(0.405)	0.006(0.978)	0.064(0.762)	-0.006(0.977)	-0.127(0.545)	0.020(0.908)	-0.027(0.872)	-0.100(0.502)
	ROA2	0.146(0.495)	0.133(0.536)	0.133(0.536)	0.103(0.633)	-0.057(0.790)	-0.057(0.790)	0.051(0.750)	-0.065(0.677)	-0.065(0.677)
UAN	ROA1	-0.892(0.299)	-0.848(0.356)	-0.824(0.384)	-1.000(**0.000**)	-1.000(**0.000**)	-1.000(**0.000**)	-1.000(0.333)	-1.000(0.333)	-1.000(0.333)
	ROA2	Nan	Nan	Nan	Nan	Nan	Nan	Nan	Nan	Nan
CF	ROA1	-0.759(**0.029**)	-0.395(0.333)	-0.074(0.862)	-0.881(**0.004**)	-0.524(0.183)	-0.095(0.823)	-0.714(**0.014**)	-0.429(0.179)	-0.071(0.905)
	ROA2	-0.659(0.107)	-0.476(0.280)	-0.476(0.280)	-0.821(**0.023**)	-0.500(0.253)	-0.500(0.253)	-0.619(0.069)	-0.333(0.381)	-0.333(0.381)
MOS	ROA1	0.212(0.320)	0.105(0.626)	0.002(0.994)	0.126(0.557)	0.230(0.281)	0.230(0.279)	0.036(0.825)	0.145(0.337)	0.167(0.268)
	ROA2	0.171(0.423)	0.080(0.711)	0.080(0.711)	0.136(0.527)	0.236(0.268)	0.236(0.268)	0.043(0.787)	0.152(0.313)	0.152(0.313)

Table 5: Correlation Analysis Results of 3 year ROA Diff. and Temp. Diff.

Company	ROA	Pearson	Spearman	Kendall
YTEN	ROA1	0.230(0.375)	0.213(0.411)	0.147(0.440)
	ROA2	0.199(0.459)	0.168(0.535)	0.117(0.564)
AVD	ROA1	-0.017(0.923)	-0.064(0.713)	-0.055(0.639)
	ROA2	0.035(0.845)	-0.011(0.949)	-0.023(0.847)
IPI	ROA1	-0.175(0.532)	-0.114(0.685)	-0.029(0.923)
	ROA2	-0.272(0.347)	-0.235(0.418)	-0.143(0.518)
MGPI	ROA1	0.046(0.801)	0.106(0.559)	0.076(0.549)
	ROA2	0.057(0.757)	0.114(0.536)	0.077(0.551)
SMG	ROA1	0.210(0.256)	0.276(0.133)	0.209(0.103)
	ROA2	0.185(0.327)	0.228(0.225)	0.168(0.201)
FMC	ROA1	0.305(0.075)	0.266(0.123)	0.170(0.151)
	ROA2	0.353(**0.041**)	0.264(0.131)	0.169(0.159)
MBII	ROA1	-0.222(0.538)	-0.018(0.960)	-0.022(1.000)
	ROA2	-0.142(0.716)	0.117(0.765)	0.167(0.612)
UAN	ROA1	-0.321(0.284)	-0.330(0.271)	-0.231(0.306)
	ROA2	-0.184(0.568)	-0.294(0.354)	-0.212(0.381)
CF	ROA1	-0.083(0.743)	-0.013(0.958)	0.046(0.823)
	ROA2	-0.202(0.436)	-0.203(0.434)	-0.088(0.655)
MOS	ROA1	0.118(0.512)	0.099(0.583)	0.082(0.505)
	ROA2	0.130(0.472)	0.084(0.641)	0.063(0.609)

Table 6: Correlation Analysis Results of ROA Value and Bushfire Brunt Areas

8.3 Timeline Table

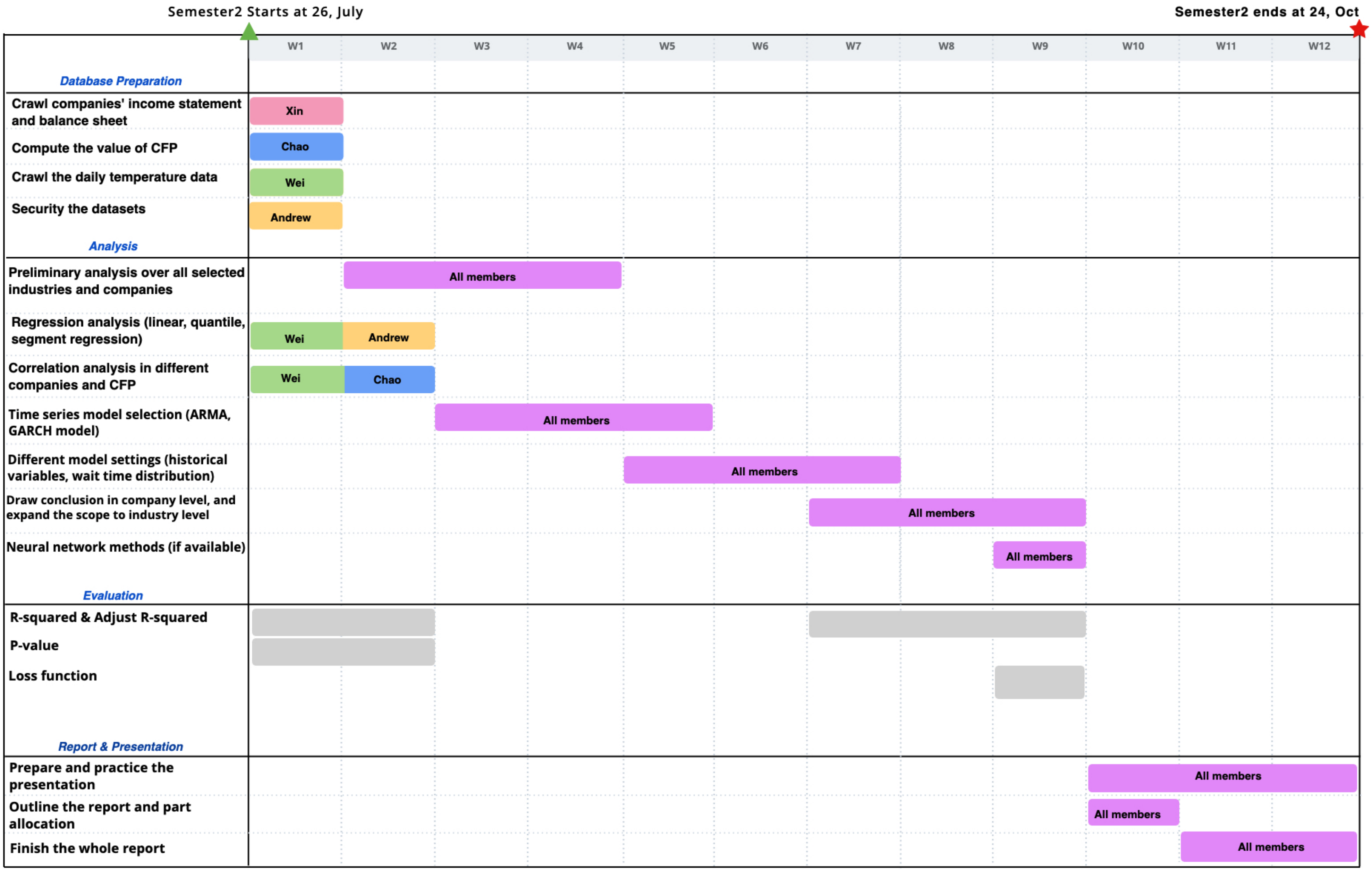

Figure 22: The Timeline of Semester 2

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