Bachelor Thesis

UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Feeling the Heat of Climate Change -

How Sensitive Could It Be?

Bachelor of Science (B.Sc) in Finance

The University of Gothenburg - School of Business, Economics and Law

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Abstract

This thesis examines if climate sensitivity predicts stock returns and how well this measurement performs. The sample consists of the S&P 500 and the monthly stock return for the period between 1979 to 2019. The method is first to estimate the climate sensitivity for stock returns from temperature anomaly. The data of the temperature anomaly comes from the National Oceanic Atmospheric Administration. The Fama & French three factors and the fourth factor from Carhart controls the results for robustness. Furthermore, five climate sensitivity portfolios were built, based on the estimated effect for each company, within the sample. The results show that there are differences amongst the industries and also the climate sensitivity portfolios. Firstly, two of the industries, Transport & Public Utilities, and Finance & Insurance & Real Estate, were significantly affected by changes in temperature anomaly. Also, the most climate-sensitive portfolio had the highest measurement between its stock returns and changes in the temperature anomaly. This portfolio also showed the highest weighted average monthly return.

Keywords: Climate Sensitivity ⧫ Predictability of Stock Returns ⧫ Temperature Anomaly ⧫ Fama & French Three-Factor Model ⧫ Carhart Four-Factor Model

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1. Introduction

This section of the thesis will at first present the background, followed up with a problem description and the purpose of this thesis. Lastly, the introduction presents limits within the area, and then the structure for the following part is described.

1.1 Background

Corporate Social Responsibility, also known as CSR, is about the effect each company's operations have on the environment and the society. CSR has become a major topic during the past decades as the effects of the changes in the climate becomes more prominent. An attempt to gain a better understanding of this is the ESG-ratio that takes the Environmental, Social and Governance aspects into account. The ratio helps investors to exclude those companies that are not as sustainable as is wanted. Investors could then implement this into stock return predictability based on their preferable ratio of ESG. Stock return predictability with the implementation of sustainability-measurements has, therefore, become an exciting subject in the field of finance.

The subject of stock return predictability has encountered various theories since its commencement in the 1960s. Earlier theorists, such as William F. Sharpe (1964) and John Lintner (1965), created the *CAPM* for predictability which proved to be a useful instrument during its prime time. Nevertheless, eventually its flaws appeared to those examining it. The *CAPM* encountered a backlash from Eugene Fama and Kenneth French in 1993 as they introduced *The Fama & French Three-Factor Model* (FF3M) (Fama & French, 1993). FF3M was a modification of the *CAPM*, and the purpose with it was to cover those anomalies that the *CAPM* missed out on by instead using three factors (Fama & French, 1996). The FF3M quickly rose to fame, and more factors were added, which lead to the *Carhart Four-Factor Model* (FFCM) (1997) and *The Fama & French Five-Factor Model* (2015). These models do provide investors with a comprehensive picture of a stock return, but they still lack a measurement that takes the climate aspect of companies into account.

A significant discussion during the past decade has been about climate, and it has become desirable to make investments that take this aspect into account. So, the question that's asked, is how to implement a measurement, that takes climate into account when predicting a stock return? Investing is, for example, highly dependent on how volatile it could be, what risks are present and more importantly, what the return of the investment will be. When making a stock return prediction, there are different risks necessary to account for, such as a potential financial crisis, trends in the economy and the financial markets, rapid changes in the supply and demand of goods or services. However, what more could affect the predictability of a stock return are the risks that come with changes in the climate. There are several kinds of climate risks that investors need to account for, such as the risk of droughts or fires that makes it difficult for agricultural industries to operate. Other risks come from storms that cause havoc on the seas and in the air, which disrupts transports and communications. Another risk is the effects of floods or earthquakes that destroy communities and businesses. The fluctuations in the climate could come from the changes in the temperature since it affects the climate and the weather conditions.

A recent phenomenon is that the average global temperature anomaly has increased (a global temperature higher than the average) during the past 40 years, according to the National Oceanic and Atmospheric Administration (NOAA, 2020a). The change in temperature anomaly affects the investors in terms of how the company's operations are affected. This change has, therefore, led to an increase in concern in measuring the consequences of these changes. Furthermore, this affection indicates that the risks and effects of changes in the temperature anomaly should be taken into consideration when making investment decisions based on stock return predictability.

Measuring climate risks by measuring a stock's climate sensitivity could function as an additional tool in the process of stock return predictability. Discussions about how to integrate new variables, that accounts for changes in the climate, could be seen in earlier research that has shown that temperature and the stock market return have a negative relationship (Cao & Wei, 2005; Floros, 2008; Kumar, Xin and Zhang, 2019). Based on these studies and the predictability about stock returns, some literature has shown that an additional explanatory variable could be the temperature anomaly. This subject is still in its earlier stage and thus needs some further investigation about whether the climate factor "temperature anomaly" is a valid aspect to take into account. This thesis will, therefore, examine the stock return predictability of the climate sensitivity measurement and why climate sensitivity predicts stock returns.

The findings in this thesis are somewhat consistent with previous research. There are similarities in terms of why climate sensitivity predict stock returns since it shows that there is a relationship between stock returns and the changes in temperature anomaly. When evaluating the industries, the findings in this thesis show that two industries are more sensitive to these changes than the other industries. In comparison with earlier research, the most sensitive portfolio had the highest estimated climate sensitivity but what was different is that the same portfolio showed the highest weighted average monthly stock return.

1.2 Problem Description

This thesis examines the problem of whether climate sensitivity predicts stock returns and how this theory could improve the perception of the predictability of stock returns. Climate sensitivity has several definitions, and it is not yet clear what measurement one should use in practice or what measurement is the best one. It could be by measuring the amount of sunshine in a day, the humidity in the air, the cloudiness in a day, a period of droughts or storms, or the seasonality effect of floods. These are all changes in the climate worth taking into account when predicting the future value of a company, henceforth, the future of its stock value.

In this thesis, climate sensitivity will be measured by how stock returns are affected by changes in temperature anomaly. Some stocks have a positive relationship with the temperature while others have a negative relationship. When expressing this measurement in real terms, it becomes difficult to conclude if a higher value of climate sensitivity is better than a lower value. The climate sensitivity measure will, therefore, be reported in absolute value to simplify the interpretation of this measurement. The decision of reporting absolute values enables the climate sensitivity measurement to capture those companies that are the most volatile and to investigate further if this volatility also tends to generate a lower stock return or not. This decision makes it more transparent to which extent climate sensitivity predict stock returns and what differences there are between the stocks in the sample. Earlier researches have used temperature anomaly, as a variable to predict stock returns, to display how exposed companies are to these changes (Cao & Wei, 2005; Floros, 2008; Kumar et al., 2019).

Testing the theory about “why climate sensitivity predict stock returns” has shown different results around the world. Floros (2008) found that there was a significant negative relationship between stock market returns and temperature for Austria, Belgium, and France but not for Greece and the UK. Pardo & Valour (2003) found no effect on the Spanish stock returns due to the weather conditions of sunshine and humidity. Cao & Wei (2005) found a significant negative relationship between stock markets and the temperature when testing it on the US, Canada, Britain, Germany, Sweden, Australia, Japan and Taiwan. It is, therefore, interesting to investigate whether the relationship is different between the stock returns of the S&P 500 and the changes in the temperature anomaly of North America.

This thesis will also contribute to the understanding of making climate measurements that helps investors gain a complete picture of the predicted stock's return. A similar alternative is the ESG-ratio that takes the Environmental, Social and Governance aspects into account. This ratio helps investors to exclude those companies that are not as sustainable as is wanted for the investor. Hopefully, the climate sensitivity measurement of temperature anomaly could have a function that is on a similar path as the function of the ESG-ratio. Nevertheless, since this is a relatively new way of thinking and that measuring climate sensitivity does not yet have a clear guideline on how to proceed, more research about this topic is, therefore, desirable.

1.3 Purpose

This thesis aims to implement climate sensitivity, as a variable of temperature anomaly, in the process of predicting stock returns. Also, if this measure of climate sensitivity will be a relevant factor to include in the stock return predictability for the sake of showing companies' ability to adapt for changes in the temperature. Moreover, this thesis will further examine if it will be profitable to invest in those stocks that have low climate sensitivity, rather than those stocks that have high climate sensitivity, or if there is another alternative in which one could use this in stock return predictability.

1.4 Limits with the Thesis

An important question that puts restraints on the thesis is whether temperature anomaly, alone, is enough for picking up and show the effect of the change in the climate. There could be other factors necessary to account for in the climate sensitivity measure, such as sunshine and weather for example (Saunders, 1993; Hirshleifer & Shumway 2003; Pardo & Valour, 2003; Hong, Li and Xu, 2019; Huang, Kerstein, and Wang, 2018). Additionally, predicting stock returns with climate sensitivity measures is a relatively new subject, and the theory is, thus, in its earlier stages which put limits on what findings there have been to this point.

1.5 Structure of the Thesis

The rest of the thesis has the following structure: Part 2 presents a discussion about the tested theory and a literature review. Part 3 shows the data of the thesis, and part 4 shows the method of choice.

Part 5 contains the results and part 6 presents a discussion about the results. Lastly, part 7 will conclude the findings of the thesis, and part 9 presents the Appendix of descriptive statistics.

2. Theory and Literature Review

This part presents the theory in this thesis and how it came to be. Furthermore, a presentation of previous research about the topic of climate sensitivity predictability and what the results of these studies have been.

2.1 Why Climate Sensitivity Predicts Returns

There are some contributions to the theory of “why climate sensitivity predicts stock returns” and why this is a factor to take into account. Firstly are the findings of Kumar et al. (2019) and Cao & Wei (2005), where they investigated whether a firm’s exposure to climate change affects stock prices. What was concluded was that those stocks with low climate sensitivity (i.e. less affected by higher temperature) tend to have a better return than those stocks with high climate sensitivity. Similar findings have been found in the works of Floros (2008) and in Cao & Wei (2005) where it shows that there is a significant negative relationship between stock market returns and the temperature. An explanation of this relationship could partly be because climate change affects the temperature, which leads to abnormal and more volatile changes in the temperature. Companies vulnerability are different from changes in the temperature, and their operations should, therefore, influence the profits of these companies.

By measuring the temperature anomaly, Kumar et al. (2019), created a climate sensitivity measure which proved to be a sufficient tool in terms of stock returns predictability. Similar research exists in the study of Cao & Wei (2005) in which they examined how the behaviour of investors are affected by abnormal changes in the temperature. Temperature anomaly, as a tool for climate sensitivity, indicated that temperature increase does not only have an impact on the environment but also people’s moods and feelings. Moreover, they concluded that these changes in temperature anomaly tend to affect the risk-aversion of these individuals. A factor that could explain the theory about “why climate sensitivity predicts stock returns” is *temperature anomaly* and will, therefore, be a sufficient tool for measuring climate sensitivity in this thesis.

Previous research has used the temperature as the variable of interest for predictability within the area of climate sensitivity. Furthermore, Mendelsohn et al. (1994) describe that the temperature changes are a consequence of the increase in greenhouse gas emissions. Also, the IPCC (2018) believes that human activity has created a change in the global average temperature. They further believe the increase in the global average temperature is approximately around 1 degree, and this measurement of global warming could reach 1,5 degrees by 2030 if it follows its current trend. Based on these facts, temperature could function as a measurement that verifies the climate sensitivity of stocks returns due to the effect of climate change. The same conclusion was found in the works of Deschênes & Greenstone (2007) when they implemented the temperature factor in their method. These findings are relevant since the change of the climate causes the temperature to rise.

The change in temperature forces companies to adapt to the new environment to sustain their firm-level performance. Another expectation about the theory of "why climate sensitivity should predict stock returns" are the findings in previous research about the effect of temperature (Dell et al., 2009; Bansal & Ochoa, 2012). These results have shown that there is a negative correlation between temperature and economic achievements. Moreover, there have also been studies about how these temperature changes have affected different industries. Lesk et al. (2016) investigated in the cereal production in which they discussed how weather disasters had affected this production. Furthermore, what temperature also seems to affect is different industry outputs, such as the agriculture industry which have suffered from temperature increase, and also the energy industry which benefits from colder weather (Dell et al., 2014). When evaluating the theory about "why climate sensitivity predicts stock returns", it is necessary to take into consideration how temperature affects these different aspects.

In order to perform an analysis of climate sensitivity, it is essential to distinguish the measure of this sensitivity. To capture different ranks of sensitivity, we intend to use the absolute value of our variable of interest, *Temperature Anomaly*. Because this would show that companies and industries that are vulnerable to temperature changes, either negative or positive, should be considered to have a high sensitivity. In this thesis, we intend to use the temperature for a measure of climate sensitivity and try to see if the temperature anomaly predicts returns, as is stated in theory.

2.2 Literature Review

Climate risk is a subject that has gained more attention since it shows that these risks have financial implications on the investors' firm portfolios (Krueger et al., 2019). Taking climate risks into account has proven to be desirable amongst investors, as is presented in the survey made by Krueger et al. (2019). Thus, it is therefore motivated to investigate more and to distinguish how to account for climate risks. Besides, how one should implement these estimations for predictability in terms of stock returns. So, in order to measure these climate risks, one could do this through the use of climate sensitivity.

Climate sensitivity has many definitions, and one of them is by measuring how stock returns are affected by fluctuations in the temperature. Kumar et al. (2019) found that firms' vulnerability, to temperature anomaly changes, predict stock returns. Also, those stocks considered to have a low climate sensitivity tended to perform better than those stocks with high climate sensitivity. By this knowledge, Kumar et al. (2019) could then create a financial strategy based on a "Long-Short-Strategy". This strategy took use of the return predictability and generated a risk-adjusted yearly return of 3,6%. What more appears from Kumar et al. (2019) study was that those companies with higher climate sensitivity were associated with lower firm profits in the future.

Similar to the results of Kumar et al. (2019), were the results of Floros (2008). This study investigated if there was any relation between stock market returns and temperature. Floros (2008) bases the results of the study on the stock markets of Austria, Belgium, France, Greece, and the UK. The findings of Floros (2008) showed that there was a significant negative relationship between stock market returns and temperature for Austria, Belgium, and France but not for Greece and the UK. These results are partly consistent with the results of Cao & Wei (2005) were they also examined whether stock market returns are related to temperature. However, differently from Floros (2008), these results were instead based on more than 20 international stock indices.

Defining the climate sensitivity measure on the fluctuations of temperature has resulted in other findings, such as Cao & Wei (2005), who found that it affected the risk-aversion of investors. In their conclusion, they suggested that both low and high temperatures cause aggression, but that high temperature also caused hysteria and apathy, which then affects the investors' behaviour. The significant contribution of their findings was that there is an overall negative correlation between temperature and stock market returns. They further hypothesized that low temperature leads to higher stock returns while the high temperature could lead to both low and high stock returns. Based on the findings of Kumar et al. (2019), Floros (2008), and Cao & Wei (2005), the expected results in this thesis is that there is a negative correlation between stock returns and temperature. Similarly to Kumar et al. (2019), this thesis intend to build climate sensitivity portfolios and see whether the same relationship about the stock returns shows in the sample of the S&P 500.

However, previous research has shown that the climate sensitivity measure can take the use of other factors than the temperature. Hong et al. (2019) based their climate sensitivity measure on droughts, which are due to the change in global warming, and then how this affects the performance of food stocks. In their report, they describe that the increase in global temperature tends to exacerbate the risk of droughts. This exacerbation partly explains their findings that the return predictability was consistent with food stocks underreacting to risks of droughts that were due to climate change. Also, another discovery was that there was a 7% annual difference in profits between those stocks that were at most risk of climate change and more vulnerable, than with those stocks that were least affected by the risks of climate change and less vulnerable.

Another research that defined climate sensitivity, in another way, is the study written by Huang et al. (2018) in which they investigated how climate risks affect firm performances. They measured climate sensitivity through extreme weather conditions that are captured by the Global Climate Risk Index. What they discovered was that the likelihood of extreme weather events such as heatwaves, flooding, and storms, due to climate change, was to be associated with lower and more volatile earnings and cash flows. These findings also explain how the change of the firm performance level could affect the rate of those companies' stock returns since the value of the company will be affected.

Huang et al. (2018) furthermore concluded that there are differences in how specific industries are affected by extreme weather which, therefore, makes them more or less vulnerable to climate risk. The results in this thesis expect to be showing that various industries are affected differently, based on the literature review of Huang et al. (2018) and Hong et al. (2019). It is essential to distinguish that climate changes, through the temperature, have caused other effects on different industries than climate risks. Here is a good example where the risk for droughts are underrated and affect food stocks more than the market thinks.

Previous research about interpreting climate sensitivity has also defined the measurement into weather conditions that have found inconsistent results. Pardo & Valour (2003) tested if the climate variables sunshine hours and humidity levels were to influence stock returns in Spain. Their analysis concluded that there is no effect on the Spanish stock returns due to these weather conditions. However, Saunders (1993) found that economic information was not the only factor to affect stock prices in New York City. He also concluded that the weather influenced the mood, and thereby the stock prices, which affects the return.

Similarly, to these findings, are the results from Hirshleifer & Shumway (2003) that showed that sunshine and stock returns are highly correlated which, furthermore, implies that the climate factor "weather" implies the stock market returns. In this thesis, there will be no other measurement than the climate sensitivity of temperature anomaly. Nevertheless, the results from measuring sunshine and humidity (Pardo & Valour, 2003; Saunders, 1993; Hirshleifer & Shumway, 2003) should correlate with the degree of temperature. For example, if there is more sunshine (humidity) in a day, then it should be more likely that the temperature will get higher (lower). Furthermore, concerning measuring climate sensitivity, it is essential to keep in mind that other factors could cause a relationship with the temperature.

When concluding the literature review of this thesis, it follows that the effects of the changes in the climate are, with no doubts, a relevant factor to include in the prediction of stock returns. Adding a climate sensitivity measurement into stock return predictability could provide a better estimate of the return of the stock investment and therefore enhance the chances of making an investment that is more sustainable against the effects of climate change. Maybe, temperature anomaly could be a good indicator to rely on for these predictions.

2.2.1 Evaluation of the Literature Review

Even though the literature review does provide relevant insights and facts about previous research, it still lacks some flaws necessary to be aware of when reading the findings in this thesis. At first, when evaluating whether measuring climate sensitivity is relevant for stock returns predictability or not, Krueger et al. (2019) found that it was relevant. However, these results, based on a survey, make it more challenging to examine whether the participants gave honest answers or not.

Secondly, the results from previous research do not necessarily represent the truth about what the actual casualties are. The findings in the working paper of Kumar et al. (2019) has not yet tested their model on other markets around the world. It is, therefore, too early to state if the results from their study will give similar conclusions if it took place on another market of the world. In comparison, the results of Floros (2008) uses different markets in Europe, and the results are, therefore, more comprehensive than Kumar et al. (2019). Nevertheless, Floros (2008) showed different effects from the temperature, both a significant negative effect and a non-significant positive effect. An explanation to these findings, though not presented by the author, could be that there are spurious correlations or that there is another factor than the temperature that affects the stock market returns in that study. Furthermore, the papers of Hong et al. (2019) and Huang et al. (2018) are studies based on the information from different countries around the world and do provide this thesis with relatively new research about the effects on stock returns due to the change in the climate and that industries are affected differently.

Thirdly, defining climate sensitivity could be done in various ways, and this thesis defines it through the use of *temperature anomaly* since the temperature has proven to be a good indicator of measuring the risk of climate change (Cao & Wei, 2005; Kumar et al., 2019; Hong et al., 2019; Huang et al., 2018; Floros, 2008). However, one still needs to be aware of the fact that other factors could explain the changes in the stock returns, due to the change in the climate (Pardo & Valour, 2003; Saunders, 1993; Hirshleifer & Shumway, 2003).

Lastly, when comparing the results of our thesis, to the ones mentioned in the literature, the following differences are shown. In terms of why climate sensitivity predicts stock returns the results from our thesis indicate that all industries seem to be affected by the temperature anomaly, but all estimates are not significant. There are only two industries, out of nine from the S&P 500, that are significantly affected by temperature anomaly. Also, the theory seems to be decently consistent with the results of our thesis since those industries with higher climate sensitivity also tend to show a lower weighted average monthly return than those industries with lower climate sensitivity. These results are partly consistent with the findings of Kumar et al. (2019) and Cao & Wei (2005). However, this thesis shows that the monthly return is much higher in terms of magnitude. This difference could be due to different weights used in the calculations or the period used for measurement, for instance.

What more appears from the results is that various industries have a different magnitude of climate sensitivity. This difference makes the industries more or less vulnerable to these changes, which are partly consistent with the findings of Hong et al. (2019) and Huang et al. (2018). Furthermore, the climate sensitivity portfolios created in our thesis show that the portfolio with the highest climate sensitivity measurement also has the highest weighted average monthly return of 2,099% which is inconsistent with previous findings of the literature (Kumar et al., 2019; Floros, 2008; Cao & Wei, 2005). The results of this thesis, therefore, contributes to the debate of the theory about "why climate sensitivity predict stock returns".

3. Data

In order to evaluate the purpose in this thesis, the used data are from different online sources such as the National Oceanic and Atmospheric Administration, Wharton Research Data Service and the Kenneth French website. This section offers a description of the data in terms of the variables selected and how they are defined.

3.1 National Oceanic and Atmospheric Administration

The collected data for measuring the factor of climate sensitivity, in this thesis, has been downloaded from the National Oceanic and Atmospheric Administration (NOAA, 2020a). This database provides measurements of the temperature anomaly, for North America, between 1900 to 2019. The database provides monthly observations of the temperature anomaly that describes to be showing if the temperature is either increasing or decreasing. The value of temperature anomaly shows if there is a deviation between temperature in one month and the historical average temperature for this particular month. As explained through NOAA's website, a positive (negative) temperature anomaly shows that the temperature has been warmer (colder) than the historical mean. Also, these measurements will help to create the variable of interest named *TemperatureAnomaly,* which shows the temperature anomaly, in each month. Table A in the Appendix shows a graph that represents the trend in temperature anomaly. Changes in the temperature anomaly between 1979 - 2019 are in the range of 1 and (-1). This range starts to fluctuate with more substantial changes around the year 2000. Values above 1 for the temperature anomaly shows that the temperature has increased by the same amount, of degree celsius, which means that the temperature in this month has been 1 degree warmer than average for that period. Also, there are descriptive statistics about the temperature anomaly in the Appendix, in Table B.

3.2 Wharton Research Data Service

The sample includes companies from the S&P 500, listed through the period between January 1979 to December 2019. The first number of observations was 1501 companies and the time that these companies had been active differed. A first selection to get a manageable amount of companies was to choose the companies that have been active for the whole period. The second selection was to sort companies that remain active throughout December 2019 and have been active for at least five years. The sample resulted in 371 companies over 41 years. The monthly stock return and the SIC industry code, from WRDS, are used in this sample for each company. According to WRDS (2020), the monthly stock returns are calculated as a monthly price difference, adding reinvestment of dividends and cash equivalents. Furthermore, this sample contains companies with different types of shares. However, this thesis uses the shares with the IID-number 01, which eliminates the possibility of having more than one stock return for one company within one month. The IID-number 01, according to WRDS, is the shares with the highest rank. This type of share should also be the share that has existed the longest in the company.

3.3 Kenneth French Database

The database of Kenneth French (2020a) provides additional control variables that offer a better understanding of how the temperature anomaly affects the returns of the stocks. A first effect to take into consideration is the effect on the stock's returns concerning the risk-free rate. Kenneth French's (2020a) website provides the Fama & French Factors for different industries and portfolios in the United States. Variables, such as the return on the market, and the risk-free rate for the US-market, were downloaded from here. These variables make it possible to show the return for each stock by removing the risk-free rate that is the one-month treasury bill rate. The market factor is calculated from an excess return, from the database CRSP, for listed firms at the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the National Association of Securities Dealers Automated Quotations (NASDAQ).

The Kenneth French (2020a) database further provides the thesis with the variables from the Fama & French three-factor model and the four-factor by Carhart. Those variables where Small Minus Big (SMB), High Minus Low (HML) and the Momentum factor (MOM). Kenneth French (2020a) built these factors from the portfolios presented on his website. There are two portfolios by size (market equity), and three portfolios of the ratio between the book equity and market equity. A division of these portfolios generated a small and a big portfolio with a subcategory of "value, neutral and growth". From these portfolios, French (2020a) built the SMB by taking the average return for the small portfolio and subtracting the average return of the big portfolio. By taking the average return of the value portfolios and subtracting the growth portfolios, which generated the variable HML. Lastly, the MOM factor is built from the average return in the portfolio with high prior subtracted with the portfolio with low prior. French (2020a) describes prior to being the cumulative return for the past 11 months.

3.4 Evaluation of Databases

The National Oceanic and Atmospheric Administration is a part of the US Department of Commerce to produce reports of the weather and the climate (US Department of Commerce, 2020). Also, as NOAA (2020b) states, science is a big part of their administration which indicates that the measurement of temperature anomaly should be a reliant source for temperature data. Also, another indication that this source is useful is that earlier research such as Kumar et al. (2019) and Cao & Wei (2005) have used the temperature data. WRDS (2020) is a public database that is providing data in many areas such as finance and economics, for example. It collects many databases together to provide the user with a helpful tool to collect data (WRDS, 2020b). This database is a helpful tool due to the availability of data from different sources gathered in one place. Lastly, the website of Kenneth French (2020b) provides data from his earlier research together with Eugene Fama about their findings. This database provides precalculated datasets for the three- and four-factor model for different industries and countries. French is a well-known scientist in the field of finance, so the data collected from this source certainly provides reliable data.

4. Method

This part presents a detailed description of the modifications and the processing of the data. There will also be explanations of the calculations together with a description of the regressions. From this stage in the report, climate sensitivity is now the estimated effect on the company's stock returns due to changes in the temperature anomaly.

4.1 Time Frame

This analysis is from January 1979 to December 2019, and the specified period is chosen accordingly to the change of the temperature anomaly. NOAA (2020a) displays the temperature anomaly for the whole 20th-century, and when looking at the data one can see a trend of an increasing temperature anomaly. This increase built an assumption that a reasonable time frame to measure climate sensitivity is for the period that the temperature anomaly started to increase. According to the graph, in Appendix Table A, the temperature anomaly started to increase from 1979 and as the graph presents, the temperature anomaly becomes more positive after this year. Earlier research within the area about predicting stock returns with climate sensitivity has used similar time frames (Cao & Wei, 2005; Floros, 2008; Kumar et al., 2019).

4.2 Climate Sensitivity for Industries

The first analysis of climate sensitivity examined whether different industries, within the S&P 500, experience temperature anomaly change differently. The choice of sample is because the availability of data and the lack of research, within this market. What more is that these companies are well-performing, and many of the companies have lasted for a long time.

At first, sectioning for the sample was done accordingly to the standard industry classification code (SIC) for each company. Each company got sorted into different industry portfolios according to their SIC code that the US Securities and Exchange Commission (2020) have specified, (see descriptive statistics for industries in Table C in the Appendix). Accordingly, to the descriptive statistics and necessary to be aware of, is that there are an unequal amount of companies in each industry. After this sectioning, three regressions estimated the effect of the temperature anomaly on the stock returns in each industry, see regression (1-3):

$$r_{P,t} - r_{f,t} = \beta_0 + \beta_1 TemperatureAnomaly_t + \beta_2(r_{mkt,t} - r_{f,t}) + \varepsilon_t \tag{1}$$

$$r_{P,t} - r_{f,t} = \beta_0 + \beta_1 TemperatureAnomaly_t + \beta_2(r_{mkt,t} - r_{f,t}) + \beta_3 SMB + \beta_4 HML + \varepsilon_t \tag{2}$$

$$r_{P,t} - r_{f,t} = \beta_0 + \beta_1 TemperatureAnomaly_t + \beta_2(r_{mkt,t} - r_{f,t}) + \beta_3 SMB + \beta_4 HML + \beta_4 MOM + \varepsilon_t \quad (3)$$

$r_{P,t}$= The return within portfolio P at time t.

$r_{f,t}$ = The risk-free rate, out from a one-month T-bill, in each time t.

$r_{mkt,t}$= The return on the market in time t.

$TemperatureAnomaly_t$= Climate sensitivity measure from NOAA (2020) which contains temperature anomaly in each time t.

SMB= The Small Minus Big variable contains the average return, out from Kenneth French (2020a) website, from three portfolios that have lowest market capitalization subtracted with three portfolios that have the highest market capitalization.

HML= The High Minus Low variable have the average return of two value portfolios subtracted with two growth portfolios (French, 2020a).

MOM= The Momentum variable contains the difference between the cumulative return for two high portfolios subtracted with the two low portfolios (French, 2020a).

The model of interest is regression (1) where the estimated variable of interest is *TemperatureAnomaly*. Furthermore, the Fama & French three-factor model (FF3M) which refers to regression (2) and the fourth-factor model of Fama, French & Carhart (FFCM) in regression (3) are robustness tests for the estimated effected of climate sensitivity in regression (1). These estimates are regressed to evaluate the null hypothesis (X1) that the temperature anomaly variable does not contribute with any explanation to the model.

$$H_0: \beta_1 = 0 \quad (X1)$$ [1]

The output of the estimations from regressions (1-3) are in absolute terms of the coefficient for the climate sensitivity. The reason for this is that the coefficient could either have a positive or negative fluctuation which makes the estimations easier to compare when expressed in absolute terms. Within the panel data, all regressions are using Newey West standard errors to correct for autocorrelation.

[1] This null hypothesis refers to equation (1-3), which test the hypothesis that the explanatory variable temperature does not contribute with the understanding of the return of portfolio P at time period *t*.

Furthermore, the weighted return for each portfolio is calculated accordingly to equation (4):

$$Weighted\ Return = \frac{1}{N_t} \Sigma\, r_{i,t} \tag{4}$$

$r_{i,t}$= Return in portfolio i at time period t.

N_t= The number of companies in the time period t.

The thesis uses Newey West standard errors to calculate t-statistics that produce a significance level. Also, to show the reliability of the return within the portfolios, as regression (2-3), use additional variables for robustness tests.

4.3 Climate Sensitivity Portfolios

The second analysis is to evaluate the climate sensitivity once more built upon temperature anomaly, for the sample within the S&P 500. In order to build five new portfolios that represent high to low climate sensitivity, the temperature anomaly effect was estimated for each company in the sample through regression (1). This regression gives an estimated output of 371 temperature anomaly coefficients, used for sorting the 371 companies by their sensitivity into different portfolios. This sectioning used the absolute value of the estimated effect where a high (low) estimated coefficient represents high (low) sensitivity. From these absolute values, the most (least) sensitive companies were sorted into portfolio High (Low) depending on their sensitivity. Furthermore, dividing the rest of the companies by their sensitivity into portfolio 4, 3 or 2. This sectioning was done by dividing the sample into five groups by using percentiles for absolute values. Each of the five portfolios contains 74 companies except for the High portfolio that contains 75 companies.

The estimated coefficient of this climate sensitivity measurement is assumed to best capture the sensitivity by observing the data in absolute values. As explained in earlier parts, this is most suitable because the sensitivity measurement could either be positive or negative. With sectioning based on the absolute value, the High portfolio contains the companies that are most sensitive, not only negative but also positive, which makes the measurement easier to interpret.

Furthermore, portfolio High, 4, 3, 2 and Low are regressed as regression (1-3) to express the estimated climate sensitivity for each of the portfolios in absolute values. Also, as stated earlier, regression (2-3) is to control if the results in regression (1) is reliable. The presentation of the estimated coefficients is to, again, show how sensitive the stock returns, of the climate sensitivity portfolios, are to changes in the temperature anomaly. For these portfolios, the weighted average return, as equation (4) above, has been calculated. Also, the Newey West standard errors were calculated in order to show the t-statistics and to show the significance level. Finally, these tests evaluate whether the temperature coefficient rejects the null hypothesis (X1). In other words, that temperature anomaly does not have any effect on the stock returns within each of the portfolios.

4.5 Evaluating the Model

This section tests the regression models for their validity and correctness. Firstly, an out of sample test validate the proposed method. Secondly, this part presents descriptions of the OLS assumptions to test the correctness of the estimations. Presented lastly is a discussion about robustness tests.

4.5.1 Out of Sample Test

The estimation in section 4.3, where the climate sensitivity portfolios take form, do not express how well this method is performing in terms of predictability. An out of sample test is, therefore, implemented to validate the predictability of the results from the above sections. The same procedure as the one used in section 4.3 is used here but only for half of the sample. Firstly, a division of the sample, split into two groups where the first group is the “training data set” (1979 January – 1999 December) and the second group is the “test data set” (2000 January – 2019 December). The training data set is to fit a model and see how this model works in a new environment, i.e. the test data set.

The first step is to build five new portfolios based on regression (1), but instead using the training data for measuring climate sensitivity. This estimation, was again, sorted by the absolute value of the temperature anomaly coefficient and sorted into High, 4, 3, 2 and Low portfolio, based on a percentile calculation. Because all companies have not been active during the whole sample period, these portfolios now contain 64 companies each. Furthermore, these new climate sensitivity portfolios, regressed according to regression (1-3), with one exception, i.e. only using the training data set to examine the predictability of using the temperature anomaly. This estimation is also presented in absolute terms, as discussed earlier.

Also, using the portfolios built upon the training data set (1979 January - 1999 December), the weighted average return was calculated for these portfolios for the out of sample period (2000

January - 2019 December). Also, this out of sample period examines the difference between the Low portfolio and the High portfolio. For these results, the regressions used Newey West standard errors to validate the t-statistics, hence, the significance level.

4.5.2 OLS Assumptions

When estimating Ordinary Least Squares (OLS), Peter Kennedy (2008) describes that there are assumptions necessary to fulfil. Firstly, when estimating a linear model, it is essential to distinguish that the relationship does take a linear shape and that the chosen explanatory variables are most suitable. This relationship is examined throughout this thesis by first plotting the data and adding more explanatory variables as regression (1-3), which shows a linear relationship. The second assumption for OLS-models is about exogeneity, which implies that the independent variables do not have any relationship with the error term. By looking at the covariance, between the independent variables and the error term, one can control for the second assumption. The models in this thesis show no covariance between the chosen variables and the error term.

Thirdly, Kennedy (2008) describe that the model should not contain heteroscedasticity, and in terms of time series regression autocorrelation could be an issue. The Wooldridge test is testing the possibility of autocorrelation within the panel, for the models, which is a substitute for the Durbin Watson tests in Stata. This test showed signs of autocorrelation for some of the estimations. This thesis uses Newey West standard errors in order to correct for possible autocorrelation within the panel. Lastly, when estimating an OLS model, multicollinearity between independent variables could be the case, and each model is, therefore, tested through VIF tests. The VIF test examines possible multicollinearity and gives the variables a number and what is desirable is an output lower than five. When looking at the VIF test, all variables got a VIF under five, which indicates that there is no problem of multicollinearity.

Out from these tests, one could conclude that the models, and more especially the estimated climate sensitivity, becomes more reliable. The results are more trustworthy because there is no real problem with the sample in terms of OLS regression.

4.5.3 Robustness Test

A correction of the model’s validity, described in the method, is necessary at this stage. This section of the thesis aims to describe the method of how to examine the model’s validity even more. The decision of regression (1), mentioned in part 4.2 in the method, comes from the first robustness test, where the first test was performed accordingly to regression (5):

$$r_{P,t} - r_{f,t} = \beta_0 + \beta_1 TemperatureAnomaly + \varepsilon_t \tag{5}$$

Regression (5) is the same as regression (1), with one exception, i.e. excluding the market factor. After this regression stage, regression (1) was performed, which, to our notice, gave more accurate results because much of the significance of the estimated effect of the temperature coefficient disappeared. These results indicated that the market factor was needed to provide better estimates.

Furthermore, to validate regression (1) even more, additional control variables are needed to give a better estimation. This thesis will make use of the FF3M and the FFCM since these models have been used to show the relationship on the market and should, therefore, be appropriate control variables.

5. Results

This part of the thesis will present the results of the methodology described in section 4. Firstly, part 5 shows a presentation of the results for the industry analysis. This part will further present results from the climate sensitivity portfolios tests and lastly the evaluation of the model proposed.

Table 1A- Climate Sensitivity for Industries

Industry	Regression (1)	FF3M	FFCM
Manufacturing	0,013	0,033	0,043
Retail & Trade	0,035	0,019	0,01
Public Administration	0,055	0,127	0,118
Wholesale & Trade	0,068	0,057	0,059
Construction	0,070	0,091	0,086
Mining	0,071	0,054	0,053
Services	0,154	0,089	0,082
Transport & Public Utilities	0,188***	0,139**	0,140**
Finance & Insurance & Real Estate	0,235***	0,182***	0,192***

*Table 1A shows the estimated effect of climate sensitivity on each of the industry stock returns between the years of 1979 to 2019. The coefficient is presented in absolute values. What more is reported is how this effect changes when controlling for the Fama & French-, and Carhart- factors. The significance level is ranked in the following way: *0,05, **0,01, ***0,001.*

An economic interpretation of the climate sensitivity measurement, in Table 1A, shows that a change in the temperature anomaly by one unit will cause the stock return for companies within an industry to change by the percentual value, presented in table 1A. For example, when interpreting the results of the industry Transport & Public Utilities from Regression 1, it shows that a change in the temperature anomaly by one unit will cause the rate of the monthly return to change by 0,188 percentual units. Table 1A further shows that the magnitude of this effect changes when comparing Regression 1 with the FF3M and FFCM.

The results indicate that all industries seem to be affected by the temperature anomaly, but all estimates are not significant. There are only two industries that are significantly affected by a change in temperature anomaly; Transport & Public Utilities, and Finance & Insurance & Real

Estate. Worth to mention is that the results of Transport & Public Utilities in the FFCM-regression is significant at a Type-1 error of 0,01%. Comparably to the Finance & Insurance & Real Estate which is significant at a Type-1 error of 0,001%. This level of significance makes the predicted results of Transport & Public Utilities less significant than the results of Finance & Insurance & Real Estate in FFCM. Furthermore, Finance & Insurance & Real Estate is the most sensitive since it has a higher value of the climate sensitivity measurement in all of the regression models. However, what separates the results of these two industries is how the magnitude of the effect changes when controlling for more variables. These effects become smaller for Transport & Public Utilities and Finance & Insurance & Real Estate. At first, the magnitude of the effect becomes smaller when going from Regression 1 to FF3M, and then the magnitude of the effect becomes larger when moving from FF3M to FFCM. However, this change is more substantial for Finance & Insurance & Real Estate, than Transport & Public Utilities, when moving from FF3M to FFCM.

The results of Table 1A indicates that some industries are more affected than others due to changes in temperature anomaly. A factor that, of course, affects the significance of these results is the number of companies included in each industry portfolio and for a more comprehensive interpretation of this, see Table C in the Appendix. According to Table C in the Appendix, the industries Construction, Public Administration and Wholesale & Trade have less than ten companies. In order to give a more comprehensive picture, one could need more balanced data with an equal amount of companies within each industry. To summarize these results, it would be interesting to examine whether the industry that is affected more by climate sensitivity also tend to have a lower return or not.

Table 1B - Weighted Average Return for Industries

Industry	Regression (1)	FF3M	FFCM
Manufacturing	1,620***	0,872***	0,938***
Retail & Trade	2,078***	1,316***	1,384***
Public Administration	1,386***	0,578***	0,625***
Wholesale & Trade	1,571***	0,963***	0,974***
Construction	2,006***	0,928**	0,905**
Mining	1,251***	0,472	0,450
Services	2,138***	1,453***	1,545***
Transport & Public Utilities	1,323***	0,743***	0,747***
Finance & Insurance & Real Estate	1,659***	0,750***	0,835***

*Table 1B shows the Weighted Average Monthly Return of each industry and all units are in percentage. These results are based on the period between the years of 1979 to 2019. The significance level is ranked in the following way: *0,05, **0,01, ***0,001*

Table 1B presents the value of 1,62 for the Manufacturing industry, which is equal to the weighted average monthly return in percentual units (1,62%), for this industry, within the period of measurement. Furthermore, Table 1B displays that the industry that has the highest weighted average return each month is Services at 2,138%. Also, the industry that has the lowest weighted average return in each month is the industry of Mining that has a value of 1,251%. A t-statistic evaluated the weighted average monthly return, which showed a level of significance of 0,001 and further validated the credibility in these results.

Table 1B show that the industry of Transport & Public Utilities, which have the second-highest estimate of climate sensitivity, also have a weighted average monthly return that is lower than six of the industries that possess a lower climate sensitivity. However, the results also show that the industry with the highest climate sensitivity, Finance & Insurance & Real Estate, do have a weighted average monthly return that is lower than three industries (with Transport & Public Utilities excluded). Table 1B also shows that the industry of Services has the third highest climate sensitivity and the highest weighted average monthly return. Also, in comparison with Services are the results of Construction and Retail & Trade that have a similar weighted average monthly return but a much lower value of the climate sensitivity measure. Further discussions about these results will occur in part 6.

Table 2A - Climate Sensitivity Portfolios

Portfolio	Regression (1)	FF3M	FFCM
High	0,244**	0,278***	0,289***
4	0,183***	0,175***	0,182***
3	0,026	0,023	0,029
2	0,017	0,031	0,023
Low	0,059	0,072	0,061

*Table 2A shows the estimated effect of climate sensitivity on each of the climate sensitivity portfolio returns between the years of 1979 to 2019 and is presented in absolute values. What more is reported is how this effect changes when controlling for the Fama & French-, and Carhart-factors. The significance level is ranked in the following way: *0,05, **0,01, ***0,001.*

Table 2A presents an evaluation of the climate sensitivity measure in three different models, which are Regression (1), FF3M and FFCM. The first column, "Portfolio", displays the different climate sensitivity portfolios described in the method, in part 4.3. The findings show that the two portfolios that are the most sensitive to the climate, according to our estimation, is portfolio High and 4, according to regression (1). The economic interpretation for this measure is that if there is a change in temperature anomaly, then the return of these portfolios are the most affected through this change. For example, if the temperature anomaly experiences a change by one unit, the monthly return for the High portfolio would change by approximately 0,244 percentual units according to regression (1).

The results in regression (1) are controlled by adding the FF3M and the FFCM factors to see whether the relationship remains. The results vary for the different portfolios. For portfolio High, the estimated climate sensitivity remains significant and the magnitude of the coefficient increases. For portfolio 4, the estimated effect decreases when moving from Regression (1) to FF3M and then increases when moving from FF3M to FFCM. What more is that the results of portfolio 4 remain statistically significant throughout the regressions. Portfolio 3, 2 and Low show an insignificant effect on the stock returns due to a change in the temperature anomaly.

The results from table 2A show that those portfolios that are more climate-sensitive also have a higher effect on the stock return in those portfolios. It, therefore, becomes interesting to investigate whether this relationship could be seen in the weighted average monthly return of the portfolios, as will be examined in table 2B.

Table 2B - Weighted Average Return

Portfolio	Weighted Return	FF3M	FFCM
High	2,100***	1,251***	1,309***
4	1,645***	0,932***	0,989***
3	1,590***	0,860***	0,897***
2	1,588***	0,865***	0,922***
Low	1,506***	0,709***	0,773***
Low-High	-0,594***	-0,541***	-0,536***

*Table 2B presents the weighted average monthly return for climate sensitivity portfolios, and all units are in percentage. Also, the difference portfolio Low-High is shown where the returns in portfolio High are subtracted from portfolio Low. The weighted returns in regression (1) are then controlled for the Fama & French 3-factor and the 4-factor model by Carhart. The significance level is ranked in the following way: *0,05, **0,01, ***0,001.*

Table 2B presents the weighted average monthly return for each of the climate sensitivity portfolios and also the difference between the weighted return in portfolio Low and portfolio High. The table further presents the weighted average monthly return, for each portfolio, through a t-test where all portfolios present a significant weighted average monthly return. Also, the difference return between Low and High show significant results. What this means is that the High portfolio has a significantly higher return than the Low portfolio during the time frame.

Including additional factors in the calculation of the weighted average monthly return was necessary to validate these results to see if the relationship remains. When looking at Table 2B, the numbers show that the portfolios weighted average monthly returns remain statistically significant throughout all models and tests. These results indicate that even when controlling for the Four-factor model, the difference between the Low minus High remains significant. Furthermore, the difference in the weighted average return between the Low and High portfolios becomes smaller. It is also mentionable that the magnitude of the weighted average monthly return diminishes, which could partly be explained by the additional control-variables used in the regression.

Table 3A - Estimation of Climate Sensitivity In Sample

Portfolio	Regression (1)	FF3M	FFCM
High	0,063	0,009	0,062**
4	0,233**	0,251**	0,049
3	0,034	0,039	0,081**
2	0,038	0,034	0,058*
Low	0,007	0,002	0,081**

*Table 3A presents the estimated effect of temperature anomaly, in absolute terms, for the in-sample predictions in the period of 1979 to 1999. The portfolios are built on the training data set and predictions on the training data set. The estimations of regression (1), are then controlled for the Fama & French 3-factor and the 4-factor model by Carhart. The significance level is ranked in the following way: *0,05, **0,01, ***0,001.*

The results from the in-sample test, of the five climate sensitivity portfolios, are presented in Table 3A. Built upon the "training data", this table presents the estimated temperature anomaly coefficient for the climate sensitivity portfolios. As seen in the table above, only portfolio 4 has a significant estimated temperature anomaly effect, both in regression (1) and in the FF3M. Portfolio 4 is also the most sensitive one in these two regressions. Regression (1) and the FF3M show that portfolio High is more sensitive than portfolio Low. Interesting to mention is that the estimated climate sensitivity for all portfolios, except for portfolio 4, becomes significant in the FFCM model. Differently from regression (1) and the FF3M, the magnitude of the estimated effect in FFCM show that portfolio Low is more sensitive than portfolio High. Table 3A further shows that the effect becomes larger for portfolio Low, 2 and 3 when moving from regression (1) to FF3M. The same does not apply for portfolio High and portfolio 4.

So, the overall results indicate that the in-sample predictions encounter a similar relationship as the one described in Table 2A, for regression (1) and FF3M. There is a pattern which shows that the high climate sensitivity portfolios (High and 4) are more affected by temperature anomaly changes than the low sensitive portfolios (Low and 2). However, portfolio 4 has the significantly highest estimate of the temperature anomaly coefficient. In comparison with Table 2A, when controlling for the additional factor in the FFCM, the results become the opposite. Portfolio Low and portfolio 3 has the highest climate sensitivity, according to if temperature anomaly changes. In Table 2A, the magnitude of the sensitivity becomes greater for the high sensitive portfolios (High and 4) when controlling for more explanatory variables. The relationship shown in Table 2A does not seem to appear in Table 3A since the opposite happens.

Table 3B - Out of Sample Calculation of the Weighted Average Return

Portfolio	Weighted Return	FF3M	FFCM
High	1,427***	0,860***	0,911***
4	1,199***	0,692***	0,730***
3	1,157***	0,640***	0,664***
2	1,017***	0,553***	0,566***
Low	1,132***	0,582***	0,626***
Low-High	-0,296	-0,279*	-0,285*

*Table 3B presents the weighted average monthly return for the out of sample, in the period 2000 to 2019. The portfolios are built on the training data set and calculations on the test data set. Also, the difference portfolio Low-High is shown where the returns in portfolio High are subtracted from the returns in portfolio Low. The weighted average returns in regression (1) are then controlled for the Fama & French 3-factor and the 4-factor model by Carhart. The significance level is ranked in the following way: *0,05, **0,01, ***0,001.*

Table 3B shows the results of calculating the weighted average monthly return, from the formation of the climate sensitivity portfolios based on the training data. Controlling these returns through the use of FF3M and FFCM enables the thesis to validate the returns. Similar to Table 2B, is that portfolio High has a higher return than portfolio Low. In comparison to the results of Table 2B is that the difference portfolio Low-High are not significant. However, this becomes significantly negative in the two control models. Furthermore, the return decreases when controlling for the FF3M and when adding the momentum factor in FFCM. Compared to FF3M, the returns increases for the portfolios High to Low. For the difference portfolio, Low-High, the weighted return follows the pattern that the return in portfolio High is higher than portfolio Low. Nevertheless, the difference first becomes smaller and then it increases in the FFCM compared to FF3M. From the out of sample test, similar patterns to Table 2B appears, but unfortunately, the difference portfolio is not significant in regression (1) which makes the investment strategy weaker.

More importantly, is that the relationship remains where the High portfolio does perform a better weighted average monthly return for the out of sample period. Table 2B shows the same relation between the two climate sensitivity portfolios, and this relationship remains when splitting the sample in half, as is displayed in Table 3B. Based on these results, we conclude that the out of sample prediction indicates that it is more profitable, within this sample, to make an investment in the High portfolio rather than in the Low portfolio.

6. Discussion

This part of the thesis presents a discussion about the results from part 5. The discussion mention reasons behind why the results have become as they are and how these results are in comparison with previous findings of why climate sensitivity predict stock returns. Also, another discussion is how one could put these findings into practical use, based on the theory.

The results from testing the theory about “why climate sensitivity predicts stock returns” contributes to a more comprehensive picture of this theory. Table 1A compared nine industries and only two of them, Transport & Public Utilities, and Finance & Insurance & Real Estate, showed that they are significantly affected by temperature anomaly. These results are similar to the findings of Kumar et al. (2019) and Cao & Wei (2005), which is that different industries are differently affected. Why this may be the case could be because companies have different exposures to climate change which makes them more or less vulnerable to the changes in the temperature anomaly. Companies in the sector of Transports & Public Utilities and the sector of Finance & Insurance & Real Estate, have a higher estimated climate sensitivity. The consequence of a higher estimation is that these industries are more exposed to fluctuations in the temperature anomaly and, therefore, riskier in that aspect. Furthermore, when the temperature anomaly changes, then the stock return within these industries will be affected more than the other industries that did not show this relation.

For instance, companies in the sector of Transport & Public Utilities may encounter weather problems that put restraints on their operations and thus affects these companies’ profits. These weather conditions lower the profits and may cause a higher climate sensitivity to appear. Also, Finance & Insurance & Real Estate may be sensitive to the changes in the temperature anomaly due to the difficulty of making correct predictions, and underestimating the effect of the changes in the temperature anomaly, when determining the value or price of an asset. Another aspect of the temperature anomaly changes, for the Finance & Insurance & Real Estate industry, is that they have experienced more volatile weather such as storms, which caused damage to customers properties. This speculation has some support from the conclusions of Huang et al. (2018) and Hong et al. (2019) that climate changes affect the economic performances of firms. It would, therefore, be interesting to examine how likely it is that the temperature anomaly will change with a higher/lower magnitude when making predictions about the stock return of these type of stocks. This strategy could enable investors to implement a better investment strategy when dealing with these stocks.

The expectation of the results in Table 1B was that those industries that had shown a higher climate sensitivity should also show a lower weighted average monthly stock return. This expectation comes from the results in Table 1A and the previous conclusions of Kumar et al. (2019), and Cao & Wei (2005). However, the results from Table 1B show that industries that are less sensitive to temperature anomaly, such as Services, Construction, Wholesale & Trade, Public Administration, Retail & Trade, and Manufacturing, do have a higher weighted average monthly stock return than Transport & Public Utilities, which is more sensitive to temperature anomaly changes. Besides with this is that the industry of Finance & Insurance & Real Estate had a weighted average monthly return that was lower than three industries, and Services showed an inconsistent result with the theory of "why climate sensitivity predict stock returns".

Why this may be the case is because Services appears both indoors and outdoors. This industry operates within areas such as telecommunication, accounting, programming, medical treatments and then into other areas that are temperature sensitive such as facility management or car leasing, for example. The sample-division of these two methods of services, tested in this thesis, do affect how sensitive this industry appears to be. For example, those companies that provide services indoors should be less exposed to changes in the temperature anomaly, hence, have a lower climate sensitivity. The opposite relation should then apply for those companies that offer services on the outdoors. So, why Services have a higher climate sensitivity measure and a higher weighted average monthly return may be because they have a larger portion of outdoor-companies, that are more sensitive to changes in the temperature anomaly. For further studies, this could be a reason to have more subcategories when examining the climate sensitivity within different industries.

Furthermore, it would be desirable to examine if the differences amongst the industries are similar in other markets in the US or if these results are consistent in other countries. All in all, the results from Table 1B are decently coherent with the theory that those stocks that are less sensitive to temperature anomaly also show a higher return than those stocks that are more sensitive. Similar findings occur in the reports of Cao & Wei (2005) and Floros (2008).

Accordingly to the purpose, the most sensitive companies should experience a decreasing return when the climate changes, which one could say through Table 2A. The estimated effect of temperature anomaly is larger for the portfolios that are more sensitive to the climate by a change in the temperature anomaly. Thus, according to Table 2B, the companies that are the most sensitive perform a better weighted average monthly return than the companies that have low sensitivity, according to this climate sensitivity measurement.

Comparably to earlier research, Kumar et al. (2019) and Cao & Wei (2005) found similar results in which the most sensitive portfolios have a larger estimated climate sensitivity. These estimates indicate that a company that is more climate-sensitive also would experience a larger change, in the stock return, when the temperature anomaly changes. Differently, Kumar et al. (2019) found that the most sensitive portfolios did perform worse when looking at the weighted return and more specific, when subtracting the Low portfolio return with the High portfolio return. What they found in the difference portfolio was that the weighted average monthly return was positive. A reason for this could be the fact that the sensitivity portfolio High contains companies with a historically higher stock return than the Low portfolio. This difference has started to flatten out during the recent years, and this partly explains the relationship between the temperature anomaly and the monthly stock returns, for the High portfolio. Another explanation for this difference in the results is the different samples used for estimating.

Another reason for the difference between portfolio Low and portfolio High, mentioned in the section above, could be the calculation of the weighted average monthly return. When evaluating the weighted average monthly return, the portfolio that is the most sensitive is performing better. Also, this relationship still holds when controlling for the Three- and Four-factor models from Fama & French, and Carhart. Table 2B shows that the High portfolio has a significantly higher return than the Low portfolio. Nevertheless, the magnitude is not as large as when looking at the weighted average monthly return without the control variables. One reason for this could be the inclusion of more variables which could diminish the estimated effect for the variables used from the start, as in this case.

The evaluation of the model proposed, that climate sensitivity predicts stock returns through the use of temperature anomaly, show insignificant results when examining Table 3A and Table 3B. Firstly, when comparing Table 2A and Table 3A, there is a difference in both the significance level and the magnitude of the estimated effect. For example, portfolio High in the in-sample tests, apart from the significance level, show a higher climate sensitivity than the Low portfolio. Furthermore, portfolio 4 is the only portfolio that has a significant estimate of the climate sensitivity measure, in Table 2A and 3A, when examining the results of Regression (1) and the FF3M. On the other hand, in the control model FFCM, portfolio Low and portfolio 3 becomes significant with the highest sensitivity, which is different from the results in Table 2A. So, by examining Table 3A compared to Table 2A, the results differ in terms of significance level and size of the estimated climate sensitivity.

Why these differences may appear is because Table 2A consists of the whole sample compared with Table 3A, which is not. Worth mentioning, in Regression (1) the relationship does show that the High portfolio is more affected by the temperature anomaly changes than the Low portfolio. If the choice of the out of sampling period was different, the predictability might improve to the better. An example could be to try a five-year period that estimates the consecutive five years for the out of sample test.

When comparing Table 2B and Table 3B, some aspects are interesting to discuss. Firstly, the weighted average monthly return for the portfolios High, 4, 3, 2 and Low are all significant. The magnitude of the returns are smaller, for example, the High portfolio has a weighted average monthly return that is 2,1% for the whole sample period while the out of sample test only has a return of 1,4%. In comparison, the difference portfolio (Low-High) has a different result between the two tests. In the out of sample test, the difference portfolio Low-High does not have significantly different results, between the Low and High portfolio, which appears in Table 2B. Nevertheless, when controlling for the FF3M and FFCM in Table 3B, the difference becomes significant. This appearance of the significance level, when controlling for more explanatory factors, could be because the explanatory variables, in the FF3M and FFCM, have more explanatory power than the constant in the weighted average monthly return.

Another relation between Table 2B and 3B is that the difference between portfolio High and Low diminishes. Unfortunately, this indicates that more evaluation of the model is needed when doing the out of sample tests. Based on these results, one could form an investment strategy that goes long in the High portfolio and short in the Low portfolio. Implementing this strategy with the climate sensitivity portfolios, based on the first 20 years of the sample, would generate a monthly excess return of 0,29% between the years of 2000 to 2019. As mentioned in the result section, it is essential to highlight that the High portfolio does have a higher weighted average monthly return than the Low portfolio. These results are important to pinpoint, which is that the relationship in Table 2B still holds in the out of sample test, as was seen in Table 3A. This relation indicates that it is more profitable to invest, within this sample of the S&P 500, in the portfolio with the highest climate sensitivity estimate. These findings are inconclusive with the findings found in earlier research (Kumar et al., 2019; Cao & Wei, 2005).

7. Conclusion

In summary, this thesis examines the problem of whether climate sensitivity predicts stock returns and how this theory could improve the perception of the predictability of stock returns. The result section shows that temperature anomaly has an effect on the stock return, but the effect is not significant for all measures. What was first found was that some industries, such as Transport & Public Utilities and Finance & Insurance & Real Estate, are more affected by temperature anomaly than other industries. The theory about "why climate sensitivity predict stock returns" seems to be decently coherent with the results, about the industries, as those industries with a higher climate sensitivity measure also seem to have a lower weighted average monthly return.

Based on how sensitive companies are to temperature anomaly changes, a comparison between the climate sensitivity portfolios showed differences. The results from these estimates showed that the most sensitive portfolio would experience a bigger change in the weighted average monthly return if the temperature anomaly should change. Furthermore, the portfolio that was the most sensitive had a significantly higher stock return than the portfolio with the lowest sensitivity.

In the out of sample test, we first estimated the climate sensitivity for the training data (year 1979 to 1999) that did not perform so well when examining the estimated temperature anomaly. Thus, the weighted average monthly return, for these portfolios out of sample (year 2000 to 2019), follows the same pattern as the results for the whole sample. What that means is that the High portfolio has a higher return than the Low portfolio. In conclusion, more evaluation of the model is needed, such as more tests in order to better capture the findings of the whole sample period.

This thesis contributes to the debate of "why climate sensitivity predicts stock returns" and the difference, from earlier research, is that the portfolio with the highest estimate of climate sensitivity also showed the highest weighted average monthly stock return. In which, the High portfolio is more profitable to invest in compared to the Low portfolio, for this sample. What was shown is that temperature anomaly does show a relationship with the stock returns within the S&P 500, from 1979 to 2019, and these results are, thus, somewhat consistent with previous studies (Cao & Wei, 2005; Floros, 2008; Kumar et al., 2019).

Lastly, further research within this area should consider whether the temperature anomaly, as a measurement of climate sensitivity alone, is enough to capture how sensitive companies are to changes in the climate. Inclusion of more variables, such as sunshine, rain, carbon dioxide and other climate variables, in the sensitivity measure may capture the relationship on the S&P 500 more clearly. Another option is to add more variables in the process of formatting the climate sensitivity portfolios. For example, this could be the Fama & French factors and maybe other factors that explain stock returns. However, it would be interesting to investigate further how sensitive, each subcategory within each industry, are to changes in the temperature anomaly, based on the results of the industry Services. Also, regarding the out of sample predictability, one could use a shorter in-sample period, perform a rolling estimation type and re-estimate the portfolios every five years, for example. This estimation may give a better chance to evaluate the predictability of a financial strategy, based on the climate sensitivity measure.

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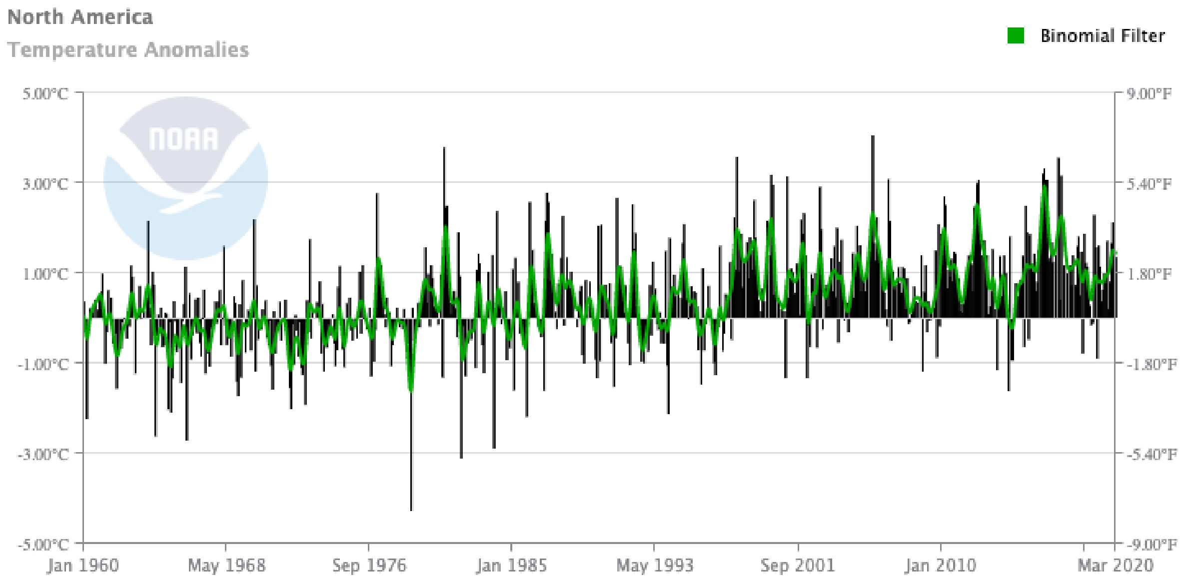
9. Appendix

Table A

Table A shows a time series plot, from NOAA (2020), of the temperature anomaly and how fluctuates over the time frame specified in the method part.



Source: NOAA National Centers for Environmental information, Climate at a Glance: Global Time Series, published April 2020, retrieved on April 22, 2020, from https://www.ncdc.noaa.gov/cag/

Table B

This table shows the mean, variance, standard deviation, minimum and maximum value for the temperature anomaly during three time periods. Firstly, the period 1900-2019, secondly, for the period up to the time frame used in this thesis and thirdly, the time frame in the thesis. This table shows the temperature anomaly in a different period to get an understanding of how it differs.

	mean	Var	sd	min	max
Temperature Anomaly (1900-2019)	0,173	1,125	1,061	-5,170	4,060
Temperature Anomaly (1900-1978)	-0,121	0,884	0,940	-5,170	3,440
Temperature Anomaly (1979-2019)	0,667	1,143	1,069	-4,290	4,060

Table C

Table C displays each industry and the number of companies within all industries and their SIC code. This table aims to show the distribution of the sample in this thesis.

Industry	Number of companies	SIC code
Finance & Insurance & Real Estate	72	6000-6999
Transport & Public Utilities	50	4000-4999
Services	42	7000-9099
Mining	16	1000-1499
Construction	5	1500-1999
Wholesale & Trade	7	5000-5199
Public Administration	3	9000-9999
Retail & Trade	28	5200-5999
Manufacturing	148	2000-3999