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Have climate changes led to a significant change in the risk premium in weather derivatives?

Does climate changes become a more systematic source of risk?

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Abstract

The purpose of the thesis is to investigate whether the climate changes up until now have had a significant effect on the risk premium in weather derivatives. Weather futures are futures built on weather indices. In this paper I will focus on weather futures built on the HDD weather index. The total risk of an asset is split into firm-specific risk and systematic risk. If higher return is required by investors in order to be compensated for changes in the sensitivity of the weather futures to systematic risk, either changes in the sensitivity to general economic factors or changes in the sensitivity to risk factors related to climate, it should be captured by the assets beta. In the analysis I will look for changes in beta due to climate changes which would indicate a change in the risk premium tied to climate changes.

In order to investigate the thesis and perform the analysis I have gathered data on climate, prices of weather futures on HDD on Chicago and New York, and some data on general economic factors. I use both the capital asset pricing model and the arbitrage pricing theory to build linear regression models to test the thesis. This is in order to see which of the models better explain the return on the weather futures and gives the most reliable results. To tie changes in systematic risk to climate changes I make interaction terms between the climate variables chosen and the risk factors included in the asset pricing models. I also perform a Chow test to look for breaks in the data that could indicate a change in the systematic risk. In addition I run a linear regression in which I make an interaction term between the risk factors in the asset pricing models and the dummy variable year to look for changes in the systematic risk after 2011 in case the climate variables chosen does not capture climate changes properly or how weather futures are affected by climate changes.

The expectation is that the arbitrage pricing theory will be a better model for explaining the return on weather futures than the capital asset pricing model. In the regression results, there are evidences of significant changes in the systematic risk due to climate changes for weather futures on Chicago when using the arbitrage pricing theory. For New York weather futures it is hard to find evidence of significant changes in the systematic risk tied to climate changes.

Preface

This paper is the final step in order to fulfill my master degree within business and administration with a specialization in finance. Working with the paper have been challenging and exciting. In the process of working with the paper I have learned more about research within finance and gone deeper into financial theory, and thereby also learned a lot about derivatives built on commodities. In addition I have learned more about finance related to climate, which I find very interesting, by looking at both theory and empirical studies. The learning outcomes from working with this paper will be valuable in order to have more knowledge about how climate changes affect the behaviour of investors and the returns required in financial markets. As the climate changes are expected to affect life on earth even more in the time to come this will be important knowledge to bear in mind.

I want to thank my thesis advisor, associate professor Johann Reindl, for help with developing my thesis, for helpful advices during my work with the paper and for all the valuable help provided.

Gyda Alexandria Jensen Oslo, 24.05.2020

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Explanation of abbreviations

HDDChicago	The monthly continuous settlement price on HDD futures on Chicago
HDDNY	The monthly continuous settlement price on HDD futures on New York
LogrChicago	The monthly log return of the continuous settlement price on HDD futures on Chicago
LogrNY	The monthly log return of the continuous settlement price on HDD futures on New York
SandP500	Monthly return on the Standard and Poor 500 index
MRpremium	The monthly market risk premium
IPgrowth	Monthly percentage change in the industrial production index
Precipitation	Amount of precipitation in the US in millimeters per month
3MTBILL	Annualized 3-month Treasury bill rate
Monthly3MTBILL	Monthly Treasury bill rate, the measure of the risk-free rate
NotWork	Amount not at work due to bad weather monthly
CDD	Amount of monthly CDD days in the US
CO2	Monthly emissions of carbon dioxide in tons in the US
IP	Monthly value of the industrial production index
TF	Monthly US temperature in Fahrenheit
FinCrisis	Dummy variable indicating whether it is a financial crisis or not
Temptonormal	Dummy variable indicating if temperature has been higher than normal
Year	Dummy variable equal to 1 if the year is after 2011 and 0 otherwise.
MRPyear	Interaction term between market risk premium and the variable year
IPGyear	Interaction term between IPgrowth and the variable year
MRPprec	Interaction term between the market risk premium and precipitation

MRPnwork	Interaction term between the market risk premium and the variable number not at work due to bad weather
MRPCDD	Interaction term between the market risk premium and the amount of CDD days
MRPCO2	Interaction term between the market risk premium and CO2 emission for the US
MRPTemp	Interaction term between the market risk premium and the temperature in the US
MRPtempton	Interaction term between the market risk premium and the variable Temptonormal
IPGPrec	Interaction term between the growth in the industrial production index and precipitation
IPGnwork	Interaction term between the growth in the industrial production index and the variable NotWork
IPGCDD	Interaction term between the growth in the industrial production index and the amount of CDD days
IPGCO2	Interaction term between the growth in the industrial production index and the variable CO2
IPGTemp	Interaction term between the growth in the industrial production index and the temperature variable
IPGTempton	Interaction term between the growth in the industrial production index and the variable Temptonormal

Chapter 1

Introduction

1.1 Background and the choice of research question

Through history as people have become richer they have increased their consumption. In order to meet the increasing demand firms have scaled up their production of physical products or they have started offering more services. As the total consumption and production have increased through history, so have the pollution and the emissions of carbon dioxide (CO2). Firms often emphasize production processes with low cost and consumers care about the lowest price, both usually involving high pollution. The lack of focus on environmental friendly production processes, consumption goods or services, and raw materials have led to high emissions and negative impacts on our climate. The emissions come with dramatic consequences.

The last few summers there have been extreme heatwaves many places around the world which have led to deaths, forests burning, droughts, and tons of food and resources destroyed. Winters are often warmer as well and lack snow. Some cities have experienced floods and the ice in the arctic is melting. Despite the changes we have already experienced, the changes in the climate due to pollution is expected to get worse. Researchers predict more diseases, less ice in the arctic, higher levels of water in the ocean and lack of snow certain places in addition to poor living conditions for animals living under water as well as above. The list of consequences is extensive and despite already seeing some of these changes, the climate changes are expected to become even rougher in the future.

Climate changes affect the economy, firms and the behavior of investors. During the financial crisis in 2008 one could see how entangled the financial markets are, and during the outbreak of the coronavirus on could also see how nations depend on each other and some of the consequences of globalization bringing everyone closer together. In both cases one could see how adversely a lot of firms and nations are affected by global incidents. In finance there are theories about financial assets and how investors behave when trading these assets. As climate changes are expected to get rougher, investors might change their behaviour. For example when trading shares or derivatives in which the payoffs are significantly affected by the consequences of climate changes it would be expected that the investors require higher compensation for bearing higher risk. In addition, climate changes leads to a market for hedging instruments that can protect against adverse climate events.

In addition to considering how climate changes will develop in the future, it would also be interesting to find out how climate changes up until now have affected derivatives that protects against climate changes. Therefore my thesis is to investigate if climate changes have significantly affected the risk premium in weather derivatives. In other words, have the climate changes become a more systematic source of risk? Looking into the past to look for changes in the risk premium due to climate changes could provide important insights to bear in mind for the time to come.

1.2 Contributions

I hope this paper can contribute to the explanation about how climate changes affect the behaviour of market participants and the compensation they require. In addition I hope the paper can contribute to a better understanding about how climate changes affect the risk premium in derivatives built on weather. I will in this paper focus on weather futures contracts due to the availability of data, but even though I am only investigating weather futures I hope the results to some extent can be used when looking at other types of derivatives that are also affected by climate changes and weather, for example derivatives built on snow, rain or electricity, and other types of derivatives built on temperature, for example options. In addition I look at weather futures in the US but I hope that the results to some extent can be generalized to other countries that trade derivatives and futures contracts on climate and weather.

1.3 Limitations

There are some limitations to this study. For example I study only the impact of changes in climate on the risk premium in weather derivatives, in specific weather futures as mentioned in section 1.2, while the climate changes can have affected derivatives built on other variables related to climate or other types of derivatives built on weather. In addition I focus on the US due to the availability of data. The data that I found for both New York and Chicago was for a time period of several years while the data for example from Europe was only available for a short time period. It is easier to compare results across geographical places when there is a large sample of data available for the same time period in all the geographical places. As I mentioned in contributions, despite just looking at the US I hope some of the conclusions to some extent can be generalized or used when looking at other markets or derivatives built on other variables related to climate.

Chapter 2

Theoretical review

In this chapter I will review some of the theory related to my thesis. I will start with defining and explaining some basic financial relations and some methods for pricing risk. I will then define weather derivatives, in which I will define weather futures more in general, explain how weather derivatives are valued and define the different purposes for using weather derivatives. Finally I will discuss the measure of the risk premium in futures contracts built on weather that will be used when doing the analysis.

2.1 Financial markets

2.1.1 Types of risk

In financial markets we distinguish between two types of risk, systematic and unsystematic risk. Systematic risk is the risk that is due to factors in the economy that affect everyone and is the source of risk that is impossible to eliminate through diversification (Brealey, Myers and Allen 2017, 176). The unsystematic risk on the other hand, is the part of the risk that we can eliminate through diversification by spreading the risk (Brealey, Myers and Allen 2017. 176). According to Bodie, Kane and Marcus (2018, 247) the unsystematic risk is unaffected by changes in risk factors that affect the economy. When having a larger portfolio of shares, the unsystematic risk can be eliminated such that the portfolio risk equals the market risk (Brealey, Myers and Allen 2017 176).

2.1.2 The risk-return tradeoff and the capital asset pricing model

Beta (β) can be defined as the covariance between the return of an asset and the return of the market relative to the variance of the market return, and it measures an individual security's sensitivity to market movements (Brealey, Myers and Allen 2017, 182-183). In other words, beta is a measure of the systematic risk, and a postive beta means that the asset tends «to move in the same direction as the market» (Brealey, Myers and Allen 2017, 181).

The market return above the risk-free interest rate is referred to as the market risk premium (Brealey, Myers and Allen 2017, 199). In the 1960s, economists produced the capital asset pricing model (CAPM) that can be written as (Brealey, Myers and Allen 2017, 200)

Expected risk premium on asset i = beta * expected market risk premium

$$(1) \qquad r_i - r_f \quad = \quad \beta \quad * \quad (r_m - r_f)$$

The CAPM calculates the expected return of an investment (Hull 2018 b, 8). According to Hull (2018 b, 9), an investor should only care about the systematic risk because it is the source of risk that can not be eliminated by diversifying and therefore the investor can only expect to be compensated for bearing systematic risk, which is reflected by the capital asset pricing model.

The CAPM is built on several assumptions. For example the assumption that investors can borrow and lend at the same interest rate, which is often not true in practice as banks often charge higher rates when lending out money to be compensated for the risk involved (Brealey, Myers and Allen 2017, 206). According to Brealey, Myers and Allen (2017, 206), CAPM models investors as only being concerned with their future wealth and their uncertainty about it. In addition investors are required to find the optimal relationship between expected return and risk (Bodie, Kane and Marcus 2018, 162 and 320). Since not all of the assumptions are considered to be fulfilled in the real world alternative theories have developed (Brealey, Myers and Allen 2017, 206).

2.1.3 The Arbitrage Pricing Theory

Bodie, Kane and Marcus (2018, 313) defines an arbitrage opportunity as an opportunity to earn a profit that is risk-free without a net investment. According to Bodie, Kane and Marcus(2018, 312), the arbitrage pricing theory (APT) assumes that there are enough securities so that the nonsystematic risk can be eliminated through diversification, that markets are well-functioning so that arbitrage opportunities can not persist and that a factor model can be used to describe security returns.

According to Bodie, Kane and Marcus (2018, 319), the APT distinguishes between nondiversifiable risk, also referred to as factor risk and is the source of risk that requires a risk premium, and diversifiable risk. The APT is not built on an unobservable market portfolio consisting of all assets, like in the CAPM, and if arbitrage opportunities exist it is highly likely that these will be eliminated by investors trying to make profits and thereby restoring equilibrium prices (Bodie, Kane and Marcus 2018, 319). With the APT only a small number of mean-variance optimizers looking for arbitrage opportunities is enough (Bodie, Kane and Marcus 2018, 320).

The APT for determining the excess return can be expressed as (Bodie, Kane and Marcus 2018, 310 and 321)

$$R_i = E(R_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + e_i \tag{2}$$

The model uses several factors to determine the expected risk premium (Bodie, Kane and Marcus 2018, 321). In the APT, e_i represents the firm-specific part of the return while F_1 and F_2 represents risk factors that affect the risk premium on the security (Bodie, Kane and Marcus 2018, 321-322). β_i represents the sensitivity of the excess return to the risk factor F (Bodie, Kane and Marcus 2018, 310).

According to Bodie, Kane and Marcus (2018, 322), the total risk premium is the sum of beta times the risk premium on the systematic risk factor for all the factors included in the model. Equation (2) can be rewritten as (Bodie, Kane and Marcus 2018, 322)

(3)

$$E(r_i) - r_f = \beta_{i1}(\mathrm{E}(r_1) - r_f) + \beta_{i2}(\mathrm{E}(r_2) - r_f) + e_i$$
$$E(r_i) = r_f + \beta_{i1}(\mathrm{E}(r_1) - r_f) + \beta_{i2}(\mathrm{E}(r_2) - r_f) + e_i$$

When two portfolios have the same beta exposures to the same risk factors they must have the same risk premium to avoid arbitrage opportunities (Bodie, Kane and Marcus 2018, 322-323).

2.2 Weather derivatives

2.2.1 Weather derivatives and the market for weather derivatives

Weather derivatives are defined by Stephen Jewson and Anders Brix (2005, 1) as derivatives such that firms or organizations can be insured against weather fluctuations. Some firms and organizations are more exposed to weather as a source of risk than others (Jewson and Brix 2005, 3). For example firms selling ice cream might insure themselves against cold summers with a lot of rain leading to low demand as consumers eat more ice cream when the temperatures are warm.

Weather can impact firms in several ways, for example weather can lead to a reduction in revenues or it can cause a disaster (Jewson and Brix 2005, 2). According to Jewson and Brix (2005, 2) we distinguish between catastrophic and non-catastrophic weather events in which catastrophic weather events are for example rain storms or other events that often cause deaths and extreme damages. Non-catastrophic weather events on the other hand are for example especially warm summers or especially cold winters, which can happen relatively often and which can significantly affect the profits of firms (Jewson and Brix 2005, 2-3).

Jewson and Brix (2005, 2-3) emphasize that when it comes to non-catastrophic weather events derivatives insure the firm and reduces the volatility of a firm's profits, which might provide further positive effects for the firm through for example lower cost of borrowing, higher firm value and lower risk of bankruptcy. According to Jewson and Brix (2005, 3) firms will on average lose money on the hedge, but they state that a hedge can still be beneficial as the usage of weather derivatives as hedging instruments can lead to positive effects for the firm seeking to reduce its risk. Hull (2018 a, 75) states that hedging sometimes leads to a result worse than a situation without hedging. But, Hull (2018 a, 74-76) also emphasizes that the reason why firms hedge is to reduce risk and to avoid large fluctuations in the firm's profits, which should be taken into account when evaluating the hedge.

2.2.2 Futures contracts

Hull (2018 a, 28 and 30) defines futures and forward contracts as agreements to buy or sell an underlying asset for a specified price at the settlement date. The relationship between the futures price and the market price is determined by the trading activities of the key market participants and the arbitrage opportunities they face (Hull 2018 a, 128). Hull (2018 a, 128) makes certain assumptions for a few key market participants, for example no transaction costs when trading, equal tax rate on trading profits, that borrowing and lending occur at the same risk-free interest rate and that they can take advantage of arbitrage opportunities. According to Hull (2018 a, 130-131) the futures and forward price is set so that there are no arbitrage opportunities.

Based on Hull (2018 a) the price that will be paid on the delivery date for the asset underlying a forward contract is, by using continuous compounding (Hull 2018 a, 129)

$$F = S_0 * e^{r_f T} \tag{4}$$

The formula assumes that the underlying asset does not provide income and S_0 is the price of the asset underlying the contract (Hull 2018 a, 129). According to Hull (2018 a, 129), r_f is the risk-free interest rate and is the rate at which money can be borrowed or lent when the credit risk is zero. T in the formula represents time until maturity (Hull 2018 a, 129). According to Bodie, Kane and Marcus (2018, 764) the formula reflects the return given up by buying an asset now instead of buying the asset at the maturity of the contract, which is the risk-free interest rate.

The value of a long forward contract is according to Hull (2018 a, 135) the difference between the spot price in the market and the present value of the delivery price stated in the forward contract, because the investor can buy the asset at the forward price and then immediately resell it at the spot price in the market and profit if the spot price is larger than the forward price. According to Jewson and Brix (2005, 4), the payoff of a weather derivative depends on a weather index that is chosen to represent the weather the hedger is exposed to. The forward price is set such that the value of the forward contract is zero when the contract is entered into (Hull 2018 a, 135). According to Hull (2018 a, 30) deviations from the appropriate forward price leads to profits or losses being made by entering a forward contract.

2.2.3 The differences between futures and forward contracts

While the futures and forward contracts are equal in many ways, they also differ in some aspects. The first difference is for example that while the futures contract is traded on exchanges and standardized, forward contracts are traded in over-the-counter markets and can be tailored to the needs of the individual investors (Hull 2018 a, 65). As futures are traded on exchanges they are also standardized which can give rise to basis risk, which arises due to the problems of not finding a futures contract on the asset we want to hedge or for example due to uncertainty regarding the settlement date (Hull 2018 a, 76-77).

Another difference is that futures contracts are settled daily as they are exchange traded (Hull 2018 a, 65). According to Hull (2018 a, 51), in the trading of futures contracts the brokers requires the traders to deposit an initial margin on a margin account in order to eliminate credit risk. As the futures price in the market fluctuates and affects the value of the contract, gains are added and losses are subtracted from the margin account (Hull 2018 a, 51-52). The margin account pays interest and it is therefore not a cost to the investor as long as the interest rate is not too low compared to similar interest rates in the market (Hull 2018 a, 53).

According to Hull (2018 a, 136-137), forward and futures prices with the same delivery date are theoretically the same if the short-maturity risk-free interest rate is constant or do not vary in an unpredictable way. It is found that the theoretical price difference is small enough to be ignored for short maturity contracts (Hull 2018 a, 137). In this study I will therefore focus on weather futures. The pricing models I will use will be built on the methods for finding the forward price, as in equation (4) above, since the difference in the prices is sufficiently small to be ignored (Hull 2018, 137).

2.2.4 The weather indices

Previously I explained that the payoff of a weather derivative depends on a weather index (Jewson and Brix 2005, 4). These indices are called heating degree days (HDD) and cooling degree days (CDD) (Hull 2018 b, 114). We also have another index referred to as cumulative average temperature (CAT) (CME Group, 2020 b), but I will here focus on HDD and CDD. For the definition of the indices, 65 fahrenheit is 18 degrees celsius (CME Group 2020 b). According to Benth and Benth (2012, 4-5), the CDD index is defined mathematically as the sum of positive differences between the average temperature on a given day and 18 degrees celsius, and the formula for calculating the value of the CDD is

$$(5) \qquad CDD(t_1, t_2) = \sum_{t=t_1}^{t_2} max\,(T(t) - 18, 0)$$

Benth and Benth (2012, 5) also defines the index as measuring the demand for cooling. For example from the perspective of energy producers, the higher CDD means that there are more days with temperatures above 18 degrees celsius and thus higher demand for electricity to use air-conditioning to get cooling (Benth and Benth 2012, 5). T(t) is the average of the highest and lowest temperature during a day and the CDD index on a given day has a value of zero if the average temperature during that day is lower than 18 (Benth and Benth 2012, 4). When calculating the value of the CDD index over a period of time, t_1 is the start of the period and t_2 is the last day in the period (Benth and Benth 2012, 5).

Opposite, Benth and Benth (2012, 5) states that the heating day degree index measures the demand for heating. HDD is defined as the sum of days with temperatures below 18 degrees celsius, or 65 fahrenheit (Benth and Benth 2012, 5). When the weather is cold and the temperatures are low the more people want to turn on the heat and therefore they increase the demand for heating, and the formula for calculating the value of HDD is (Benth and Benth 2012, 5)

$$(6) \qquad HDD(t_1, t_2) = \sum_{t=t_1}^{t_2} max\,(18 - T(t), 0)$$

T(t) is as before the daily average of the highest and lowest temperature, and if the average of the highest and lowest temperature in a day is above 18 degrees celsius, the HDD for that day is zero (Benth and Benth 2012, 4-5). Hull (2018 b, 115) explains that weather futures are settled in cash when the HDD and CDD values are known. Since the payoff of a weather derivative is related to a weather index, the probability that the pay-off is exactly equal to the amount of money lost, because of an event related to bad weather, is low (Jewson and Brix 2005, 5).

2.2.5 The traders of weather derivatives

In general we can according to John C. Hull (2018 a, 33) separate between three main types of usages of derivatives and hence three types of investors. The first type of user is the hedger who uses derivatives in order to reduce risk (Hull 2018 a, 33). The second is the speculator, that uses derivatives in order to bet on the direction of and the size of a movement, for example in the price of the underlying asset (Hull 2018 a, 36). The third type is the arbitrageur that enter transactions in different markets in order to make a risk-free profit (Hull 2018 a, 38).

According to Jewson and Brix (2005, 6), those trading weather derivatives are hedgers, who want to reduce their exposure to weather risk, or speculators, that try to profit from writing derivatives built on weather. The payoff from weather derivatives are often uncorrelated with other investments, therefore the speculator can add weather derivatives to a portfolio and the total risk of the portfolio will increase by less than the risk of the weather derivative added (Jewson and Brix 2005, 6-7). In ideal markets, firms seek insurance that is exactly equal to and opposite of each other such that in total the speculator works as an intermediary that transfer weather risk between hedgers involving no or low risk premium (Jewson and Brix 2005, 7).

2.2.6 Valuation of single contracts

According to Jewson and Brix (2005, 59), it is common to price weather derivatives based on methods that assesses the probabilities of the financial outcomes that can occur. Three ways to value weather derivatives is by using by using burn analysis, by using index modelling or by using daily modelling (Jewson and Brix, 2005).

2.2.6.1 Valuation of single contracts using burn analysis

According to Jewson and Brix (2005, 59), burn analysis is a method in which we evaluate how a contract performed in previous years. According to Benth and Benth (2012, 110), the burn analysis is a valuation method in which the historic distribution of the weather index that is underlying the derivative is used. The method starts by finding the historical values of the weather index in order to find the historical payoffs and the price of the derivative is found by averaging the generated historical payoffs (Benth and Benth 2012, 110). Before doing a burn analysis, one must clean and detrend the data such that the assumption that the time series is stationary and that it is consistent with the climate that is expected to occur during the period of the contract can be made (Jewson and Brix 2005, 63). In addition the assumption that the data gathered from different years are identically and independently distributed is made (Jewson and Brix 2005, 63).

2.2.6.2 Valuation of single contracts using index modelling

Jewson and Brix (2005, 73) mentions the valuation of single contracts using index modelling as an alternative approach to the burn analysis for valuation of weather derivatives. When using index modelling for valuation, the first step is the choice of a distribution that is believed to, with high probability, accurately represent the real and unknown distribution of the index such that the parameters can be estimated (Jewson and Brix 2005, 75). With the distribution one can test the hypothesis that the observations come from the chosen distribution so that the distribution can represent the unknown distribution of the index (Jewson and Brix 2005, 75).

2.2.6.3 Valuation of single contracts using daily modelling

A third method for valuing a single contract is according to Jewson and Brix (2005, 121) by using daily modelling. Daily modelling is about modelling the value of the temperature through statistical methods (Jewson and Brix 2005, 121).

2.3 Measuring the risk premium

As previously mentioned, I decided to use weather futures in my analysis. In order to test whether climate changes have led to a significant change in the risk premium in weather futures I need to find a measure of the risk premium in weather futures. As temperature is not a tradeable asset, the measure of the risk premium must be adjusted compared to tradeable assets.

From Hull (2018 a, 135), as defined previously, the futures price is set so that the present value (PV) of the difference between the future spot price and the futures price is zero

$$PV(S_T - F) = 0 \quad (7)$$

The calculation of the present value of the futures payoff consist of two components. The first component of equation (7), $PV(S_T)$, is the present value of the underlying which is today's expectation about the underlying at maturity. As weather is not a tradeable asset the valuation of the underlying differ from traditional tradeable assets and the present value of the underlying is defined by Markert and Zimmermann (2008, 118-119) by using what they refer to as the risk premium model to value futures on commodities, for example futures built on weather. Markert and Zimmermann (2008, 119) defines the quasi-asset value of a commodity as the present value of the expected market price of the commodity at settlement adjusted for risk through continuous compounding

$$S_t^A = e^{-(r_f + r_p)(T - t)} * E_t(S_T) \tag{8}$$

Where T is the settlement date, t is the current time period, r_p is the risk premium and r_f is the risk-free interest rate (Markert and Zimmermann 2008, 119). S_t^A is the market price of the asset at maturity (Markert and Zimmermann 2008, 119). The other component in the present value calculation in equation (7) is the present value of the futures price, $PV(\mathrm{F})$. Markert and Zimmermann (2008, 121) defines the futures price of the commodity as the expected market price at maturity discounted with the risk premium appropriate.The formula for calculating the futures price (F) is presented in equation (4).

According to Gorton and Rouwenhorst (2019, 48) no money changes hands when a futures contract is entered into. If investors expect that the value of the underlying on the settlement date will be higher than the current market price, the futures price set now will be higher than the current spot price (Gorton and Rouwenhorst 2019, 48). According to Gorton and Rouwenhorst (2019, 48) deviations from the expected future spot price that are unexpected are unpredictable for an investor and the deviations should have an average value of zero over time unless the investor can outsmart the market. If investors are not able to outsmart the market and if they are unable to profit from expected spot price movements they can expect to earn the risk premium, which is the expected payoff in the futures contract (Gorton and Rouwenhorst 2019, 48). According to Gorton and Rouwenhorst (2019, 48) the risk premium is positive if the futures price is above the expected spot price.

From Markert and Zimmermann (2008, 129), the return on the weather futures is the change in the expectation about the amount of heating degree days (expressed as S_T) plus the risk premium (r_p). The return over one month, from t to t + 1, with n periods during a year can be expressed as (Markert and Zimmermann 2008, 128)

(9)

$$r_{t,t+1} = lnF_{t+1,T} - lnF_{t,T}$$

$$r_{t,t+1} = lnE_{t+1}(S_T) + lne^{-r_p\frac{(T-(t+1))}{n}} - \left[lnE_t(S_T) + lne^{-r_p\frac{(T-t)}{n}}\right]$$

$$r_{t,t+1} = lnE_{t+1}(S_T) - lnE_t(S_T) + r_p * \frac{1}{n}$$

From the formula the return is the difference in expectations about the temperature plus the one-period risk premium (Markert and Zimmermann 2008, 129). From above, Markert and Zimmermann (2008, 121) defines the futures price as the expected value of the underlying discounted with the risk premium. As Gorton and Rouwenhorst (2019, 48) defined, if the difference between the futures price and the expected spot price, in other words the payoff at maturity, is different from zero the risk premium is nonzero. Gorton and Rouwenhorst (2019, 48) stated that deviations from the expected spot price that are unpredictable have an average of zero unless the investor can predict the deviations and beat the market. If the investor can not beat the market, the expected return earned is the risk premium (Gorton and Rouwenhorst 2019, 48). Therefore, the investor can expect to earn the risk premium if it is not possible to outsmart the market and the expected return from t to t+1 will be the one-period risk premium (Gorton and Rouwenhorst 2019, 48)

(10) $$E(r_{t,t+1}) = r_p * \frac{1}{n}$$

In order to find an estimate of the risk premium, $\widehat{r_p}$, one can use an asset pricing model, for example the standard CAPM. Another asset pricing model is the APT in which a multifactor APT can be used that include other variables that might affect the return on weather futures, for example growth in total production (Bodie, Kane and Marcus 2018, 321). When it comes to the choice between the two models for estimating the risk premium, Bodie, Kane and Marcus (2018, 320) states that the APT only requires a few investors to be mean-variance optimizers and actively searching for arbitrage opportunities while CAPM requires all investors to be mean-variance optimizers. According to this assumption, the APT appears to be a better fit due to the fact mentioned previously that not all uses weather derivatives for speculation as some uses weather derivatives for hedging purposes. Another important assumption in the APT is the requirement that the market must have enough securities in order to be well diversified (Bodie, Kane and Marcus 2018, 312). In addition, the multifactor APT gives the opportunity to include other variables that could better estimate the expected return (Bodie, Kane and Marcus 2018, 321). For example by including a measure for total production the estimate of the risk premium in weather futures, and the expected return, might be better.

Chapter 3

Empirical review

In this chapter I will look at some previous research on the risk premium in futures built on electricity prices and regarding how to quantify the economic damages coming from climate changes. In addition I will review an article regarding the valuation of weather derivatives.

3.1 Lucia and Torró - "On the risk premium in Nordic electricity futures prices"

In their article Lucia and Torró (2011, 750) investigated the relationship between the futures prices and spot prices on electricity. Lucia and Torró (2011, 750) chose to define the futures premium as the difference between the futures price and the expected spot price on the delivery date. Therefore, the futures price is split into the expected spot price on the maturity date and the futures premium (P(t,T)) (Lucia and Torró 2011, 751). Lucia and Torró (2011, 752) refers to the futures premium as the expected premium while they define the realized premium as the difference between the futures price and the maturity spot price. According to Lucia and Torró (2011, 751-752) the risk premiums can be calculated as

(11)

$$\text{Expected risk premium}: P(t,T) = F(t,T) - E_t(S(T))$$

$$\text{Realized risk premium}: F(t,T) - S(T)$$

$$F(t,T) - S(T) = P(t,T) + E_t(S(T)) - S(T)$$

In which P(t, T) is the risk premium (Lucia and Torró 2011, 751). According to Lucia and Torró (2011, 752), the sum of the expected risk premium and unexpected deviations from the future spot price expected constitute the realized premium. Lucia and Torró (2011, 752) also defines this as the basis (B(t, T)), which is the difference between the futures price and the future spot price.

Lucia and Torró (2011, 752) elaborates on the two approaches for doing the research. The first method is by estimating the realized risk premium, but the drawback is the difficulty of obtaining reliable estimates of the expected spot price (Lucia and Torró 2011, 752). The second method is built on the assumption that the realized risk premium is the expected risk premium plus some random noise that is uncorrelated with the information at time t (Lucia and Torró 2011, 752).

3.2 Auffhammer - "Quantifying economic damages from climate change"

Auffhammer (2018, 37) explains that weather is what we see outside and that the different types of weather are coming from an underlying distribution where the moments of the distribution is climate. Auffhammer (2018, 37) also points to the general definition of climate which is the definition of climate as a long run average of the temperature. According to Auffhammer (2018, 37), climate changes is a shift in the distribution of weather outcomes.

Auffhammer (2018, 38) also states that in order to find how the climate changes affect the economy one must consider the response of economic actors. In order to do so, damage response functions are created that takes into account reactions due to climate changes (Auffhammer 2018, 38). For example Auffhammer (2018, 38) illustrates with the example that higher temperatures during the summer might increase the sale of air conditioners which also might lead to higher consumption of electricity. According to Auffhammer (2018, 33-34), the estimation of the costs due to emissions is difficult due to the fact that emissions locally lead to damages globally and due to the reason that the pollution today will affect the life on our planet many years from now.

3.3 Cao and Wei - "Weather derivatives valuation and market price of weather risk"

According to Cao and Wei (2004, 1066) there has been a huge growth in the market for weather derivatives. But there is no effective pricing method yet and there are many issues regarding the valuation of weather derivatives (Cao and Wei 2004, 1066). Cao and Wei

(2004, 1067) claims empirical evidence shows signs that the risk premium constitute a significant part of the price of a derivative with temperature as the underlying variable.

Cao and Wei (2004, 1069) explains how the fact that temperature not being a tradeable asset means that the traditional valuation methods for derivatives using the no-arbitrage argument cannot be used to value derivatives whose underlying asset is temperature. In order to study the risk premium in the temperature variable, Cao and Wei (2004, 1067-1069) employs Lucas' (1978) pure-exchange economy model in which the economic uncertainties are driven by total dividends and the temperature. At time t the price, X(t, T), of a derivative that has a payoff of q_t at the future time T is (Cao and Wei 2004, 1069)

(12) $$X(t, T) = \frac{1}{U_c(\delta_t, t)} * E_t(U_c(\delta_T, T)) * q_T,$$

$U_c(\delta_T, T)$ is the first order derivative, in other words the marginal utility, with respect to consumption and where δ_T is defined as the aggregate dividend (Cao and Wei 2004, 1069).

Cao and Wei (2004, 1072) assumes that there is an average investor with constant risk aversion and that the investor's utility for a period is given by

(13) $$U(c_i\, , t) = e^{-pt} * \frac{c_i^{\gamma + 1}}{\gamma + 1}$$

where p is the time preference and γ is the risk parameter (Cao and Wei 2004, 1072).

Cao and Wei (2004, 1074) uses an example to demonstrate the valuation method with a delivery price of K and $1 tied to each HDD. HDD$(T_1, T_2)$ is the total number of heating degree days in the time period between $T_1$and T_2 (Cao and Wei 2004, 1074). Cao and Wei (2004, 1074) then applies equation (12) and the expression for risk preferences above to calculate the value of a HDD forward contract at time t in equation (14)

(14) $$f_{HDD}(t, T_1, T_2) = E_t(\frac{U_c(\delta_{T_2}, T_2)}{U_c(\delta_t, t)} * (HDD(T_1, T_2) - K))$$

Cao and Wei (2004, 1074) then plug in the utility function from equation (13) above to get

(15) $$f_{HDD}(t, T_1, T_2) \ = \ e^{-p(T_2 - t)} \ * \ E_t(\frac{\delta_{T_2}^{\gamma}}{\delta_t^{\gamma}} \ * \ (HDD(T_1, T_2) \ - \ K))$$

As mentioned in the theoretical review, Hull (2018 a, 135) writes that the forward price is set so that the value of the forward contract is zero when entered into. With this in mind, Cao and Wei (2004, 1074) get the following expression for the forward price

(16) $$F_{HDD}(t, T_1, T_2) \ = \ \frac{E_t(\delta_{T_2}^{\delta} * HDD(T_1, T_2))}{E_t(\delta_{T_2}^{\gamma})}$$

According to Cao and Wei (2004, 1074), the risk premium for the temperature variable is a result of the difficulty of hedging the risk coming from temperature. Cao and Wei (2004, 1075) explains that the correlation between temperature and the total sum of dividends is important when finding the risk premium in a derivative built on temperature. From the valuation formulas, Cao and Wei (2004, 1075) derives that the market price of risk would be zero if the temperature and total dividends were zero, and the two factors were uncorrelated, and in such a case the derivative could be valued by using the risk-free rate to discount the payoff. According to Cao and Wei (2004, 1075), the same valuation formulas apply for valuing a forward contract built on the CDD index.

Cao and Wei (2004, 1075) rewrites the forward price as

(17)

$$F_{HDD}(t, T_1, T_2) \ = \ \frac{E_t(\delta_{T_2}^{\gamma} \ * HDD(T_1, T_2))}{E_t(\delta_{T_2}^{\gamma})}$$

$$F_{HDD}(t, T_1, T_2) \ = \ E_t(HDD(T_1, T_2)) \ + \ \frac{cov(\delta_{T_2}^{\gamma}, HDD(T_1, T_2))}{E_t(\delta_{T_2}^{\gamma})}$$

The first part of the equation is the expected future value of HDD and the last part constitute the forward premium, in other words the risk premium (Cao and Wei 2004, 1075). Cao and Wei (2004, 1087) finds that the risk premium is significant for the temperature variable and concludes that the risk premium can constitute a significant part of the price of the derivative based on the level of risk aversion among the investors and the total sum of dividends.

Chapter 4

Review of methodology

In this chapter I will review methodology and how I plan to estimate the asset pricing models that will be used when conducting the regression analyses in chapter 6. Finally, I will review the Chow Break test and how I plan to use it in chapter 6.

4.1 Estimation of the asset pricing models

In order to test whether climate changes significantly have affected the risk premium in weather futures I plan to use linear regression to estimate the asset pricing models that I will use in the analysis, the CAPM and the APT. In the theoretical review I reviewed the theoretical models for the CAPM and the APT. In the analysis I plan to perform I plan to run regressions in which I will use the CAPM and the market risk premium as an explanatory variable, and the APT in which I will include both the market risk premium and the growth in the industrial production index as explanatory variables.

Bodie, Kane and Marcus (2018, 287-288) defines the CAPM using the market risk premium as an explanatory variable in the following way

$$E(R_i) = \alpha_i + \beta_i * E(R_m) + e_i(t) \tag{18}$$

In which E(R_i) represents the expected risk premium on asset i, $E(R_m)$ represents the expected market risk premium, $e_i(t)$ is an estimate of the firm-specific risk and α_i is the intercept (Bodie, Kane and Marcus 2018, 249). According to Bodie, Kane and Marcus (2018, 288), a nonzero intercept, α_i, would indicate return without bearing risk and the intercept should be zero, so that the asset provides a reward above the risk-free rate of return for bearing systematic risk, in order for the CAPM to hold. Nonzero alphas would involve investors rebalancing their portfolios which would make the intercept zero (Bodie, Kane and Marcus 2018, 288).

When it comes to using the APT, according to Bodie, Kane and Marcus (2018, 324) the first step is to regress the return of the weather futures on the risk factors to be included in the model in order to explain the risk premium, in this case the market risk factor (M) and the growth in total production (TP). When the betas is found through the regression, the risk premium for each time period is estimated using the regression results (Bodie, Kane and Marcus 2018, 324). The APT by using the market risk factor (M) and total production (TP) to explain the risk premium (r_p) in weather futures could be expressed as (Bodie, Kane and Marcus 2018, 317 and 321)

$$r_p = \alpha + \beta_M * R_M + \beta_{TP} * F_{TP} + e_i \tag{19}$$

In the regression, alpha is the intercept and the expected risk premium if the risk factors are zero, F_{TP} and R_M are the risk factors used to explain the risk premium, and beta is the sensitivity of the asset's risk premium to each of the risk factors (Bodie, Kane and Marcus 2018, 311).

4.2 Interaction between variables

In section 2.1.2 I mentioned that alternative asset pricing theories have developed (Brealey, Meyers and Allen 2017, 206). Ferson and Harvey (1999, 1325) also provide some empirical criticism of the CAPM and uses another version of the asset pricing model. The purpose of Ferson and Harvey's (1999, 1328) research is to test Fama and French's three-factor model and they assume that the beta explaining the linear relationship between the expected return next period and the expected risk premium consist of an intercept and an interaction term

(20)

$$E_t(r_{i,t+1}) = \alpha_{it} + \beta_{it} * E_t(r_{p,t+1})$$
$$\beta_{it} = b_{0i} + b_{1i} * Z_t$$
$$\alpha_{it} = \alpha_{0i} + \alpha_{1t} * Z_t$$

Where Z is a variable that affects the expected return through beta and is included as an interaction term with β_{it} (Ferson and Harvey 1999, 1328).

According to Stock and Watson (2015, 820), an interaction term is defined as a variable that is the product of two individual variables. An example of a regression function with an interaction term could be (Stock and Watson 2015, 328)

$$(21) \quad Y_i = \beta_0 + \beta_1 * X_i + \beta_2 * D_i + \beta_3 * (X_i * D_i) + u_i$$

In the regression function, β_3 is the regression coefficient for the interaction term that is the product of the continuous variable X_i and the binary variable D_i (Stock and Watson 2015, 328-329). β_3 is defined by Stock and Watson (2015, 329) as the difference in the effect on Y_i of increasing X_i by one unit when D_i has a value of one compared to the situation in which it has a value of zero.

I will therfore use the results from Ferson and Harvey (1999) to build regressions with interaction terms. The interaction terms in the linear regression models will be between the climate variables chosen and the risk factors used to explain the risk premium in the asset pricing models in order to look for changes in the sensitivity to systematic risk factors, that would indicate a change in the risk premium in weather futures, due to climate changes. The insight from Ferson and Harvey (1999) allows the changes in the systematic risk to be directly tied to climate changes through the interaction terms.

4.3 Breaks in the data

Another method I will use to look for changes in the systematic risk in weather futures is by testing for breaks. If the date of the hypothesized break is known Stock and Watson (2015, 609) claims that we can use a binary variable with interaction and test a null hypothesis of no break against an alternative hypothesis that there is a break. According to Stock and Watson (2015, 609) this is known as a Chow test for breaks when the break date is known. The null hypothesis is that the coefficient on the dummy variable indicating the year, and that the coefficient on the interaction term between the dummy variable year and the independent variable is zero, and it is tested against the alternative of a nonzero coefficient (Stock and Watson 2015, 609). In other words, the null hypothesis of no break is tested against the alternative hypothesis that there is a break (Stock and Watson 2015, 609).

I will test for a break in my data of returns in 2011 by using the Chow test. My dummy variable for indicating the year will be created so that it has a value of zero before the break date and a value of one after the break date as Stock and Watson (2015, 609) suggests, therefore it will have the value of zero from 2000 including 2010 and the value of 1 after 2011. With the dummy variable D_t indicating if the year is before or after 2011 and the independent variable X_t, the regression would look like the following (Stock and Watson 2015, 609)

$$(22) \quad Y_t = \beta_0 + \beta_1 * X_t + \gamma_0 * D_t + \gamma_1 * (D_t * X_t) + e_t$$

The null hypothesis will test whether the coefficient on the dummy variable, and the coefficient on the interaction term between the independent variable and the dummy variable (γ_0 and γ_1) are zero (Stock and Watson 2015, 609). When testing the hypothesis one has to use the F-statistic since the hypothesis involves several restrictions (Stock and Watson 2015, 609).

Chapter 5

Data and the choice of variables

In this chapter I will explain the reasoning behind the choice of variables and the data included in the regression models I will run in chapter 6. I will start with reviewing general contract specifications on the CME Group for weather futures, I will then review the weather futures prices I have gathered and how I calculate the risk premium. Finally I will review the economic variables and the climate variables chosen to be included in the analysis.

5.1 Contract specifications

When it comes to weather futures, the Chicago Mercantile Exchange (CME) has defined general contract specifications on their homepage for their monthly European and American weather futures contracts. The specifications are similar in many ways but differ in some aspects between the two types of contracts. The contract units on American contracts are $20 times the heating degree day index on the CME (CME Group 2020 c). The contract units on European contracts are either £20 times the CME heating degree day index on London Heathrow or €20 times the CME heating degree day index on a location (CME Group 2020 a). In general, the weather futures contracts are settled in cash (CME Group 2020 a and c). In this paper I will focus on American weather futures contracts due to the availability of data.

5.2 Quoted contracts and prices

To investigate this thesis I have used prices for weather futures quoted on the Chicago Mercantile Exchange and I found the data from Thomson Reuters Eikon's application Datastream (Datastream)[1]. As previously mentioned I chose to focus on looking for changes in the risk premium due to climate changes in weather futures. In Datastream I found weather futures prices. I chose to download different futures prices and focused on making sure that

[1] The application Datastream in the program Thomson Reuters Eikon

the prices were comparable. I chose to gather data from year 2000 and forward. In Datastream I found two continuous weather futures prices on HDD for both New York and Chicago.

A continuous contract can be defined as a contract without a fixed settlement date that will be continued until one party wants to get out of the contract by fulfilling its terms (Kagan 2018). According to Thomson Reuters (2010, 3) the continuous series of futures prices available in Datastream are calculated by Thomson Reuters. Thomson Reuters (2010, 3) states that the continuous series of futures prices are derived from individual futures contracts. Thomson Reuters (2010, 3) explains that the first available contract month that is closest in time is the first value of the continuous series. From data gathered on individual contracts in Datastream the continuous futures series I have gathered appears to be calculated as a type 1 standard, which according to Thomson Reuters (2010, 4) means that the start of the series is the contract month closest to the beginning of the serie and when the closest maturity futures contract expires the continuous series uses the next available futures contract.

By choosing the continuous series for weather futures the data set contains a series of data on futures prices back to 2000. The prices on individual contracts would have made it difficult to collect data for the same time period across geographical locations as only certain contracts were available through Datastream. Most of the individual futures contracts had expired and on some geographical places the prices on the expired futures contracts were only available for a couple of months or for a period of two to three of years. The difficulty of obtaining data for several geographical places, for a long period of time and for the same period of time, would have made it difficult to compare results across geographical places.

There is not a large variation in prices from one day to the next and since most of my other data is collected at a monthly frequency I decided to use a monthly frequency for the weather futures prices. I will use data on the futures prices as close to the end of the month as possible as a lot of my other data is quoted at the end of the month. Therefore, I picked the prices on the 30th each month and if the 30th was a non-trading day, or if the month did not have 30 days, I found the available price closest to the 30th.

5.3 Futures return and the market risk premium

As already described under the theoretical review in section 2.3, I need to find a measure of the risk premium for the weather futures from the price series I have gathered. As I concluded in section 2.3 and as stated in equation (10), the one-period risk premium equals the expected return for the same time period, due to the discussions of Gorton and Rouwenhorst (2019, 48). Lucia and Torró (2011) also provided insight on the measure of the risk premium when looking at the risk premium in futures prices on electricity. One of the conclusions Lucia and Torró (2011) made about how to measure the risk premium is quite similar to Gorton and Rouwenhorst's (2019,48) conclusion that the investor earns the risk premium if the investor can not outsmart the market. I mentioned earlier that Lucia and Torró (2011, 752) defined the realized risk premium as the expected risk premium plus some random noise. The change in temperature is random and according to Gorton and Rouwenhorst (2019,48) the unexpected deviations from the expected spot value of the underlying has an average value of zero. Therefore I decided to use the return as a measure of the risk premium, as discussed in section 2.3 and as shown in equation (10). From the price series I have gathered I calculated the return series by calculating the log return, as shown in equation (9).

In the theoretical review I briefly discussed the APT and the CAPM with respect to the study I am doing. I chose to use both the APT and the CAPM. By using both asset pricing models I will be able to compare the results, and avoid missing possibly significant results that would not have been found if one method was excluded and if it turns out that for example the growth in total production was a better factor for estimating the return on weather futures together with the market risk premium, instead of the market risk premium only.

When using the CAPM, and the APT, I started by finding the log return from one month to the next for weather futures on both Chicago and New York. I then gathered monthly return data for a market index. I choose the Standard and Poor 500 to represent the market return. According to Bodie, Kane and Marcus (2018, 47) the Standard and Poor 500 index is a market index that is value weighted and that is computed by finding the aggregate market value of the 500 included firms and their aggregate market value on the last trading day. The change in the index is the change in the aggregate market value and the index return is the return that an investor would earn by holding a portfolio of the 500 firms included in the index with weights equal to the weights in the index (Bodie, Kane and Marcus 2018, 47). I gathered data from Thomson Reuters Eikon's application Datastream on the monthly return on the Standard and Poor 500 Index back until 2000 and the return was quoted on the 31st each month. With the return on the market portfolio and the risk-free interest rate I found the market risk premium as the difference between the two, based on the definitions in the theoretical review.

As stated in the review of methodology, I will build regressions by using both the CAPM and the APT. In addition, I will use insight from Ferson and Harvey (1999) to build interaction terms between the risk factors in the asset pricing models and the climate variables. As defined previously and as defined by Bodie, Kane and Marcus (2018, 247-249), beta represents the sensitivity to macroeconomic factors and is a measure of the systematic risk. Beta is defined by using the covariance of the asset with the market and changes in beta would therefore indicate a change in the covariance with the market (Brealey, Myers and Allen 2017, 182-183). Hence, changes in beta would indicate changes in the systematic risk and therefore changes in the return required by investors. Tying climate changes to changes in the systematic risk through the interaction terms means that the beta coefficients in the regression would indicate changes in the sensitivity to systematic risk factors, and changes in the risk premium, when a risk factor or a climate variable changes, in which the effects due to climate changes will be visible through the beta coefficients on the interaction terms.

5.4 Economic variables

5.4.1 Industrial production growth

When the total production goes up and firms produces more there is also an increase in emissions and the amount of carbon dioxide (CO2) in the atmosphere goes up. As the climate gets adversely affected by increased pollution, a lot of firms might become more exposed to weather risk due to more unstable climate. Some firms also might specialize in trading derivatives for speculative purposes and might choose to invest in weather derivatives. As mentioned earlier I plan to use the APT to try to explain the weather futures return and since I want to include a measure of total production as an explanatory variable I need to find data that expresses total production in the US.

In Datastream I could only access quarterly Gross Domestic Product, but since my other data is at a monthly frequency I decided to find another measure of the total production in the US. Therefore I decided to use the industrial production index for the US as a measure of total production in the country as this time series was at a monthly frequency. According to Board of Governors of the Federal Reserve System (2020 b) the industrial production index indicates the real output within for example manufacturing, mining and electric utilities for facilities in the US. I found monthly values of the industrial production index back until 2000 in Thomson Reuters Eikon's application Datastream.

The variable I plan to use in the APT model is the growth in the industrial production, which I find by calculating the percentage change in the industrial production index from one month to the next.

5.4.2 Interest rate

Interest rates affect the attractiveness of different types of investments. From the theoretical review the risk premium was defined as the difference between the market return and the risk-free rate of return (Brealey, Myers and Allen 2017, 199). It can be seen from the definition of the risk premium that the risk-free interest rate affects the expected return required by investors. The futures price on a traded asset is calculated as the expected future value of the spot price and in order to find the future value of the traded underlying the risk free interest rate is used (Hull 2018 a, 129).

According to Bodie, Kane and Marcus (2018, 128), interest rates earned on assets that are considered to be risk-free can be used as the risk-free interest rate. Treasury bills (T-bills) is a way for the government to raise money in which investors buys T-bills at a price lower than the maturity value and at maturity the government pays back the face value of the bond (Bodie, Kane and Marcus 2018, 28). The probability of the US government going bankrupt or not being able to repay their bondholders is infinitely small and therefore the interest rate on

T-bills is often viewed as a measure of the risk-free rate. I found the monthly 3-month T-bill interest rate from Board of Governors of the Federal Reserve System (2020 a). Since my data of returns are on a monthly frequency I need the monthly interest rate. Interest rates are often quoted on an annualized basis and in order to find the monthly interest rate I multiply the interest rate found by 30/360, or divide by 12.

5.4.3 Financial crisis

During certain periods the volatility in global financial markets might be higher than normal. A financial crisis is often characterized as periods with higher risk and recessions. In bad times investors might become reluctant to invest and in order to invest they might require a higher risk premium to be compensated for higher risk. In the theoretical review above I explained that weather futures are used both by hedgers and speculators (Jewson and Brix 2005, 6). In periods with high volatility, some investors might prefer financial instruments with lower risk and that could be considered as safe compared to the more volatile ones.

I plan to run a regression in which I plan to control for financial crisis. As previously mentioned, the intercept in the CAPM should be zero in order for the model to hold (Bodie, Kane and Marcus 2018, 288). I plan to include the variable to check if the CAPM holds when controlling for financial crisis. In order to control for financial crisis I create a dummy variable. The dummy variable created for indicating whether there is a financial crisis or not has a value of zero if the data gathered was in a period in which it was not a financial crisis and a value of 1 if the data gathered was in a period that can be considered to be a financial crisis. Hence, the dummy variable shows the difference in the average weather futures return when going into a period of financial crisis.

In order to classify if a period is a financial crisis or not I am going to set certain requirements that must be fulfilled. If the requirements are fulfilled, the period is classified as a financial crisis. By making my own set of requirements from the definitions of a recession or a financial crisis, my results might not be consistent with market consensus. Therefore I chose to use already well-established market requirements. According to The National Bureau of Economic Research (NBER), a recession is a significant reduction in economic activity and that is visible for example in employment or in a country’s production (NBER 2020). My data starts from the year 2000. Since 2000, NBER has identified two recessions (NBER 2020). The first was from March 2001 to November 2001 while the second lasted from December 2007 until June 2009 (NBER 2020). The first recession lasted for 8 months and the second lasted for 18 months (NBER 2020).

5.5 Climate variables

In this section I will describe the climate variables I will control for in the regression. Auffhammer (2018, 37) defined climate as the distribution of weather outcomes. The past years the weather has been very volatile and deviated from what can be seen as normal many places. For example winters lack snow and the ice in the arctic is melting, Europe has experienced severe heat waves and several places have been experiencing a lot of rain leading to floods. But some argue that weather varies from decade to decade and that a lot of the extreme weather we see today is not due to climate changes but is due to normal variation. Some claims that some of the extreme weather events occurring today also occurred several years ago, for example that winters several years ago also could lack snow or that summers many years ago also were unusually warm. Some of the evidences of how climate changes have affected the climate today might be hard to quantify and the outcomes from Auffhammer (2018) is therefore valuable. In addition, other important questions are if the climate changes have been visible through the data gathered to find evidences of changes in the risk premium due to climate changes or if the data gathered properly shows the effects of climate changes on weather futures.

5.5.1 Temperature

In the theoretical review I explained how weather futures is related to temperature and how the payoff on a weather futures depends on an index built on temperatures (Jewson and Brix 2005, 4). In Datastream I found temperatures, in Fahrenheit, for the United States back until 2000. The financial markets in the US are entangled. As defined earlier, both hedgers and speculators uses weather futures. With many different investors having different purposes for using the weather futures, everyone can take one side in the weather futures. For example an investor in California might take a position in a weather futures to speculate on the temperature while a chicago firm might enter the opposite position in the same contract to hedge their weather-related risk by having a HDD on Chicago. When the US climate, and hence temperatures, becomes more volatile and the weather becomes more extreme, the risk premium might go up as less people want to take the speculative position in weather futures. As less people want to take one side of the futures and maybe even more want to take the opposite side to hedge their risk, a higher risk premium might be needed to make sure that enough investors enters the opposite positions of the hedgers.

5.5.2 The actual weather compared to normal weather

Climate changes is often viewed to be an upward trend in the temperature meaning that the global temperatures becomes higher due to emissions related to consumption and production (Auffhammer 2018, 37). More extreme weather might lead to an increased demand from firms or investors wanting to hedge their weather exposure, and as with temperature, might lead to a higher risk premium to attract investors to take the opposite positions of the hedgers seeking to reduce their risk.

When it comes to creating a variable that compares the weather to normal weather there are three potential issues. The first issue is regarding what is “normal weather”? How much snow is normal during the winter in the US or how much rain is normal during a year? The question leads to the second important issue, could it be that there are natural variations in weather that is not the result of climate changes and that causes some years to stick out as more extremes when it comes to weather events? In a lot of discussions about whether climate changes are created by humans and if there is a climate crisis going on, some say that extreme weather are not particularly special for our decade. For example they point to winters lacking snow or summers being extremely warm 50 or 60 years ago and claim that extreme weather is not evidence enough that climate changes are currently affecting the life on our planet. Weather might vary due to natural variations and changes due to nature, and all weather outcomes might not be the result of climate changes.

The third issue is what aspect of weather should be used in order to compare the weather that has occured recently to what could be classified as normal weather? Should for example temperature be compared to normal, or should the amount of snow during a period be compared to normal? The US is a large country that stretches across a large geographical area. Within the US there are several regions that have different climate structure, for example

California's climate in west differs from New York's climate in east. This aspect makes it even harder to find a «normal» weather situation as weather differ between the regions.

To compare the weather that have occured recently to a measure of «normal» I decided to use temperature. The occurance of some weather types might have different probabilities in the different regions in the US. Temperatures are relatively easy to measure and it might be easier to find relevant data for the temperature than for example rain or snow. I decided to try to find data that could represent a normal weather outcome for the US by looking at the weather before climate changes would have contributed to a large impact on climate. During the middle of the 19th century the Industrial Revolution led to technological innovations and thus more pollution (History 2009). The effects of the pollution first became visible during the middle of the 20th century (History 2009). Since the level of pollution has continued from the industrial revolution due to more production and consumption, the middle of the 20th century could be considered to be quite early when it comes to the visible effects of the pollution and climate changes, therefore I decided to try to find average data for the 20th century.

According to the National Climate Report 2017 published by National Oceanic and Atmospheric Administration(NOAA), which is the National Centers for Environmental Information, the average annual temperature for the 20th century was 52 Fahrenheit (NOAA 2018). In order to include the variable in my regression I make a dummy variable. The dummy variable will have a value of 1 if the temperature in a given month is larger than 52 Fahrenheit and 0 otherwise. The expectation regarding the risk premium is the same as with temperature, when the temperature is higher than normal and the weather is more volatile, a higher risk premium is required to attract investors to take the opposite positions of those wanting to hedge their risk.

5.5.3 Emission of carbon dioxide

The amount of carbon dioxide emissions is an important variable to control for when it comes to climate changes and its magnitude. It is still an ongoing debate about what causes the temperatures on earth to increase and about what causes the weather to become more extreme. In the empirical review I explained how some see the weather as outcomes from a distribution of the climate (Auffhammer 2018, 37). According to a lot of science, these weather changes are caused by emissions, mainly due to production or consumption. Within the theory about how the earth and the atmosphere works, the greenhouse effect is a process in which the emissions, of for example carbon dioxide, trap heat coming from the sun and therefore leads to warmer temperatures (NASA Climate Kids 2020). A lot of activities on earth release greenhouse gases like carbon dioxide and therefore changes the natural greenhouse effect (NASA Climate Kids 2020). NASA has seen an increase in the amount of greenhouse gases in the atmosphere that causes higher temperatures on earth (NASA Climate Kids 2020).

My expectation is that emissions and the industrial production should be highly correlated as higher levels of production leads to higher emissions and that this should be visible in the regression using the APT and therefore affect the sensitivity to the risk factor growth in the industrial production. Higher temperatures on earth leads to more days in which the temperatures might be higher than 65 Fahrenheit. In other words, less days in which there are need for heating and more days in which there is need for cooling. As shown in the empirical review from Cao and Wei(2004, 1392) the risk premium consist of covariances and we need to check whether the covariances becomes more extreme, which happens if temperatures leads to more damages.

I found total yearly CO2 emissions for the US from IEA from 2000 to 2019 (IEA 2020 a and b). The problem is the same as with Gross Domestic Product when it comes to different frequencies of the data, all the other data is collected at a monthly frequency while the data on CO2 emissions is on a yearly basis. In order to solve this problem I make the assumption that the country pollute at a constant rate and therefore pollute about the same quantity each month. Therefore the total CO2 emissions during a year is the sum of the pollution in each month. Hence, I find the monthly CO2 emission as the yearly emissions divided by 12. When it comes to the CO2 emissions in 2019, IEA (2020 a) claims that the emissions fell by 2,9 percent for the US and I therefore calculated the 2019 emissions based on the emissions in 2018 and the percentage change.

5.5.4 Cooling degree days

As defined earlier, the variable cooling degree days is a measure of how many days in which cooling services are needed due to warm weather (Benth and Benth 2012, 5). Hence, we can relate cooling degree days to droughts, low harvest and low yields from agricultural commodities. Some of the high temperatures experienced leads to massive heat waves, which is leading to droughts, destructions of grains and bushfires. Due to some of the droughts experienced, electricity prices increased several months afterwards several places.

During a period of time, the more cooling degree days, the less heating degree days. Global warming is often seen as an upward-sloping trend in the temperature. If there are more droughts fewer people might want to speculate on weather futures on CDD and more people might want to hedge their exposures by using weather futures on CDD, which might reduce the risk premium included in weather futures on HDD. In Datastream I found the monthly cooling degree days volume for the US from 2000 to 2020.

5.5.5 Number not at work due to bad weather

When people travel to work by car they contribute with a lot of emissions compared to those using public transportation. By using cars or other forms of private transportations the workers contribute to the climate changes that gives rise to higher temperatures. When the employees cannot get to work due to the bad weather, firms suffer financially due to reduced production capacity. The financial losses might incentivize them to become hedgers. Weather stopping people from coming to work could be a sign of how rough the climate is and how it affects business and firms. But not being able to go to work due to weather may not be a unique characteristic of climate changes as weather might have stopped people from going to work for decades. For example a lot of snow can make it harder for employees to reach their workplace or too warm weather might lead to national restrictions to protect workers from the heat. Being stopped from coming to work due to the weather is not a problem that have emerged in the past years and is not solely due to climate changes. Despite difficulties regarding the issue about whether these data represents absence due to climate changes, the data says something about the cost for the society and firms when workers are not able to come to work due to the weather. A question that can arise is regarding how bad weather is defined. Bad weather might not be due to climate changes, but climate changes can lead to more days in which the weather is so extreme that people might not be able to go to work. For example more heatwaves, tornadoes or floods. In addition the data could be a good indication about how changing climate and higher probability of incidents involving extreme weather affects firms when it comes to work absence.

In Datastream I found data on how many people did not make it to work due to bad weather. The data had a monthly frequency and I found data for the same period as for the weather futures, from 2000 to 2020. According to the US Bureau of Labor Statistics (BLS 2017), bad weather increases the likelihood of increased absences from work. Therefore, the US Bureau of Labor Statistics (BLS 2017) have investigated work absences due to bad weather. The reference week is the week that includes the twelfth day of the month and the absence must occur during this week in order to occur (BLS 2017).

5.5.6 Precipitation

As another indicator of climate changes I chose to use precipitation. More climate changes could lead to more extreme weather in which the amount of rain and snow could be affected for example through floods, less rain due to heatwaves or lack of snow. The data says something about the development in the amount of precipitation. By comparing the amount of precipitation to what could be considered normal, I would experience some of the same difficulties as when comparing the temperature to normal. Therefore, I chose to control for precipitation. In Datastream I found the average precipitation in millimeters each month for the US from 2000 and until January 2020.

5.6 Year

As explained earlier, I also create a dummy variable that indicates whether the year is in the time period 2000 to 2010 or 2011 to 2020. The dummy variable has a value of one if the year is in the time period between 2011 and 2020, and a value equal to zero otherwise. Therefore, the coefficient on the variable will show the difference in the average return when going to the preiod after 2011 compared to the period before 2011.

Chapter 6

Results and analysis

In this chapter I will conduct regression analyses in order to test whether climate changes have led to a significant change in the risk premium included in weather derivatives. In other words, does climate changes become a more systematic source of risk? I will then review the regression results and discuss them. Finally I will provide recommendations for further research.

6.1 Calculating the return and the market risk premium

In section 2.3 and 5.3 I explained the choice of how to measure the return on the weather futures, the risk premium in weather futures and the market risk premium. I decided to use both the CAPM and the APT to describe the return of the weather futures. The market risk premium is calculated as the difference between the market return and the risk-free interest rate, in which the monthly T-bill interest rate is used as a measure of the risk-free interest rate. The risk premium in weather futures is calculated in accordance with the discussion in section 2.3 and equation (10).

6.2 Regressions using the CAPM

In this section I will test my thesis by making a linear regression by using the CAPM. I will conduct two regression analyses, one is a general test for changes in the sensitivity to systematic risk and I will also conduct a Chow break test by using the results from the regression to look for breaks, in other words evidence of changes in the systematic risk. The other is a regression in which changes in the systematic risk is tied to climate changes. As presented in equation (10), the one-period return is used as an estimate of the one-period risk premium for the weather futures.

6.2.1 Changes in the systematic risk using the CAPM

In the first regression I plan to use only the variable that indicates if the year is in the time period before or after 2011 in addition to the risk premium. This is to look for changes in beta, and therefore the systematic risk, without controlling for climate changes. The results will indicate whether there has been a change in the systematic risk in weather derivatives. A reason for why I run this regression is that I want a general model to investigate changes in the risk premium in weather derivatives. If the climate variables I have chosen does not capture the effects of the climate changes properly or if they do not properly capture how weather futures are affected by climate changes, so that the regression is not showing the true changes in the systematic risk in weather futures that is due to changes in climate, I have a general model for investigating changes in the risk premium on weather futures.

I make an interaction term between the market risk premium and the dummy variable indicating the year, and make a linear regression model for weather futures on Chicago and New York in which the dependent variable is the futures return. The regression model will be the following

$$Log\ return\ weather\ futures_i = \alpha_i + \beta_{1i} * Market\ risk\ premium_i$$
$$+\beta_{2i} * Year_i + \beta_{3i} * Year_i * Market\ risk\ premium_i + e_{it}$$

Alpha (α_i) represents the intercept. In the regression table below the futures return on weather futures on both Chicago and New York are used as the dependent variables, and the results are presented in column one and two respectively.

The beta coefficient on the interaction term in the regression will be interpreted as the change in the return when the market risk premium changes by one unit after 2011, when controlling for the other explanatory variables included in the regression. In other words, the beta coefficient on the interaction term is the change in the sensitivity to the market risk factor after 2011. When a null hypothesis stating that the true value of the coefficient is actually zero fails to be rejected, the coefficient can not be said to be significantly different from zero at the significance level chosen (Stock and Watson 2015, 123-124). When the conclusion of a hypothesis test is that the null hypothesis fails to be rejected, the regression results do not provide evidence that the coefficient is actually different from zero (Stock and Watson 2015, 267). By making the conclusion that the coefficient on the interaction term is not significantly different from zero, the consequence would be that one can not be certain that the sensitivity of the risk premium in the weather futures to the market risk factor, when the market risk premium changes by one unit, changed after 2011. It could be that the change in the sensitivity of the risk premium in weather futures to the market risk factor is the same before and after 2011 when the market risk premium increases by one unit, and that the systematic risk is the same.

Table 1: Regression of the return on weather futures on the market risk premium, the dummy variable year, and the interaction term between the market risk premium and the dummy variable year by using CAPM.

	(1) returnC	(2) returnNY
MRpremium	0.326	0.0774
	(0.636)	(0.791)
Year	-0.0115	-0.0179
	(0.0445)	(0.0554)
MRPyear	0.137	0.721
	(1.137)	(1.414)
_cons	0.00515	0.00786
	(0.0298)	(0.0371)
N	239	239
R-sq	0.002	0.002

*In column (1) the dependent variable is the return on weather futures on Chicago. In column (2) the dependent variable is the return on weather futures on New York. * indicates p-value smaller than 5 %. ** indicates p-value smaller than 1 %. *** indicates p-value smaller than 0,1 %. The standard error of the coefficients are presented in the parantheses below each coefficient.*

The constants in the regression table shows the average return on the weather futures if the coefficient on the market risk premium, and the coefficient on the interaction term between the market risk premium and the dummy variable year is zero, and if the time period is between 2000 to December 2010. The constants in the regression results are nonzero, but neither of the constants are significantly different from zero at a 0,1, 1 or 5 percent significance level. The constants are not significantly different from zero and the null hypothesis of zero coefficients fails to be rejected. According to Bodie, Kane and Marcus (2018, 288) the CAPM holds if the intercept is zero, as explained earlier. A reward without bearing systematic risk would cause investors to alter their portfolios which would make the alpha zero (Bodie, Kane and Marcus 2018, 288).

In the first column the dependent variable is the return on weather futures on Chicago. From the coefficient on the market risk premium variable, a one unit increase in the market risk premium is associated with an increase in the average return on the weather futures when controlling for the interaction term between the market risk premium and year, and when the variable year has a value of zero. As the return is an estimate of the risk premium, as defined in equation (10), the higher market risk premium the higher risk premium in the Chicago weather futures. The t-statistic is 0,51 (0,326/0,636) by using Stock and Watson (2015, 122) and the coefficient is not significantly different from zero at a 0,1, 1 or 5 percent significance level. The dummy variable year shows the difference in the average futures return when going from the time period before 2011 to the time period after 2011, which in this case shows a reduction in the average return when the market risk premium has a value of zero, and when controlling for the interaction term between the market risk premium and the dummy variable year. The interaction term is interpreted as the change in the futures return when the market risk premium increases by one unit given that the year is in the time period after 2011. The results provide evidence of an increase in the sensitivity to the market risk factor per unit increase in the market risk premium during the time period 2011 to 2020, when controlling for the market risk premium and the dummy variable year. But neither of the coefficients on the variables included in the regression are significantly different from zero at a 0,1, 1 or 5 percent significance level.

In column two the dependent variable is the return on weather futures on New York. From the regression results, a one unit change in the market risk premium is associated with an increase in the return on the New York weather futures when controlling for the variable that is the product of the dummy variable year and the market risk premium, and when the year is in the time period between 2000 to December 2010. The t-statistic for the coefficient is 0,10 (0,0774/0,791) and it is not significantly different from zero at a 0,1, 1 or 5 percent significance level. The dummy variable year shows a reduction in the return when going from the time period before 2011 to the time period after 2011, when controlling for the interaction term between the market risk premium and year, and when the market risk premium is zero. This is the same finding as for weather futures on Chicago. The interpretation of the coefficient on the interaction term, which is the product of the variable market risk premium and the dummy variable year, is the effect of an increase in the market risk premium on the return when the year is in the time period between 2011 to 2020, when controlling for the market risk premium and the dummy variable year. As the beta coefficient says something about the systematic risk, the results indicates that there is an increase in the sensitivity to the market risk factor when the market risk premium increases by one unit in the time period 2011 to 2020. None of the coefficients in column two is significantly different from zero at a 0,1, 1 or 5 percent significance level.

From R squared the explanatory variables seems to have low predictive power over the futures return on both Chicago and New York, and therefore seems to predict little of the variation in the dependent variable (Stock and Watson 2015, 242). As defined in equation (10), the one-period return is an estimate of the one-period risk premium. The regression results therefore indicates a higher risk premium for both weather futures when the market risk premium increases after 2011, but neither of the coefficients on the interaction terms are significantly different from zero at a 0,1, 1 or 5 percent significance level in column one nor column two. Since the intercepts are not signifcantly different from zero, the CAPM appears to hold. As mentioned earlier, that the coefficients are not significantly different from zero indicates that the change in the sensitivity to the market risk factor when the market risk premium increases by one unit, and the systematic risk, after 2011 appears to be the same as before 2011.

6.2.2 Testing for breaks

In this section I will conduct a Chow break test. The test is used when you have an idea about the break date (Stock and Watson 2015, 609). I want to run the Chow break test in order to test whether there was a structural break around 2011. 2011 is in the middle of the time span of my data and it is highly likely that possible consequences of the climate changes would be visible in 2011. If climate changes have had an effect on the risk premium, and therefore the sensitivity to systematic risk factors, in weather futures, I want to see if a break happened in 2011 and by break I want to test whether the systematic risk changed after 2011. In this case the regression for testing for breaks in the data will be the same as the regression in 6.2.1 when it comes to testing for breaks in the regression using the CAPM. Therefore, the regression model, and the null and alternative hypotheses will be (Stock and Watson 2015, 609)

$$Log\ return\ weather\ futures_i = \alpha_i + \beta_{1i} * Market\ risk\ premium_i + \gamma_{0i} * Year_i$$
$$+\gamma_{1i} * Year_i * Market\ risk\ premium_i + e_{it}$$

$$H_0: \gamma_0 = \gamma_1 = 0$$
$$H_1: \gamma_0 = 0 \ \ or \ \ \gamma_1 = 0$$

In other words, the null hypothesis is that there is no change in the systematic risk after 2011 and it is tested against the alternative hypothesis that the systematic risk has changed. After running the individual regressions I performed a F-test in Stata testing the null hypothesis with the two restrictions for both weather futures on New York and Chicago.

Table 2: Chow test using results from 6.2.1 by using Chicago weather futures

```
. test Year MRPyear

 ( 1)  Year = 0
 ( 2)  MRPyear = 0

       F(  2,   235) =    0.04
            Prob > F =    0.9631
```

Table 3: Chow test using results from 6.2.1 by using New York weather futures

```
. test Year MRPyear

 ( 1)  Year = 0
 ( 2)  MRPyear = 0

       F(  2,   235) =    0.16
            Prob > F =    0.8482
```

According to the results, the p-value is high such that the null hypothesis fails to be rejected at a 10 percent significance level using both Chicago and New York weather futures. Therefore, the regression results does not provide evidence of a break and the systematic risk does not appear to be different after 2011. But despite not finding evidences of a break around 2011, there might have been breaks in other time periods in the sample. In the regression results in section 6.2.1 the coefficients provided evidence of changes in the systematic risk after 2011 but none of the coefficients were significantly different from zero at a 0,1, 1 or 5 percent significance level. Therefore, the results in section 6.2.1 and the results from the chow test provide evidence of no change in the systematic risk after 2011. The null hypotheses in the Chow test fails to be rejected and the cofficients on the interaction terms in the regression in section 6.2.1 are not significantly different from zero.

6.2.3 Controlling for climate variables in the CAPM

I would like to both control for general economic factors and factors related to climate changes that could have affected the risk premium. This is in order to make statistical conclusions regarding changes in the systematic risk that we can say with a high level of confidence is related to climate changes and in an attempt to avoid the omitted variable bias. In an attempt to tie potential changes in the risk premium to climate changes I include the variables I have chosen to represent measures of the climate changes. Before running the regressions I made interaction terms between the climate variables and the market risk premium by using insight from Ferson and Harvey (1999). By making the interaction terms I will be able to directly tie changes in the systematic risk, represented by beta, to climate changes. If the beta coefficients on the interaction terms between the market risk premium and the climate variables are zero, the climate variables does not affect the systematic risk of the weather futures and beta is constant. On the other hand, if the beta coefficients on the interaction terms are nonzero climate changes have affected the sensitivity to systematic risk factors and hence the risk premium.

I will run one regression for weather futures on New York and then one for Chicago weather futures with the dependent variable being the return on the weather futures series I have gathered. The regression model will be

$$\begin{gathered}
Log\ return\ weather\ futures_i = \alpha_i + \beta_{1i} * Market\ risk\ premium_i \\
+\beta_{2i} * Precipitation_i * Market\ risk\ premium_i \\
+ \beta_{3i} * NotWork_i * Market\ risk\ premium_i + \beta_{4i} * CDD_i * Market\ risk\ premium_i + \\
\beta_{5i} * CO2_i * Market\ risk\ premium_i + \beta_{6i} * TF_i * Market\ risk\ premium_i \\
+ \beta_{7i} * Temptonormal_i * Market\ risk\ premium_i + \beta_{8i} * Precipitation_i \\
+ \beta_{9i} * NotWork_i + \beta_{10i} * CDD_i + \beta_{11i} * CO2_i + \beta_{12i} * TF_i \\
+ \beta_{13i} * Temptonormal_i + e_{it}
\end{gathered}$$

Table 4: Regression of the return on weather futures on the market risk premium, the climate variables chosen, and the interaction terms between the climate variables and the market risk premium by using the CAPM.

	(1) ReturnC	(2) ReturnNy
MRpremium	-10.81	-5.189
	(12.06)	(15.15)
Precipitation	-0.00316	-0.00384
	(0.00175)	(0.00220)
NotWork	-0.000710**	-0.000523
	(0.000221)	(0.000278)
CDD	-0.000215	-0.000428
	(0.000488)	(0.000613)
CO2	-4.62e-10	-4.93e-10
	(7.45e-10)	(9.36e-10)
TF	-0.00798	-0.0118
	(0.00633)	(0.00795)
Temptonormal	0.286**	0.455***
	(0.106)	(0.133)
MRPprec	-0.0613	-0.0608
	(0.0430)	(0.0540)
MRPnwork	0.00934	0.00411
	(0.00851)	(0.0107)
MRPCDD	-0.0221	-0.0139
	(0.0132)	(0.0165)
MRPCO2	6.34e-10	-3.01e-09
	(2.12e-08)	(2.66e-08)
MRPTemp	0.327	0.257
	(0.177)	(0.222)
MRPtempton	-2.324	-3.302
	(2.314)	(2.906)
_cons	0.796	0.968
	(0.434)	(0.545)
N	237	237
R-sq	0.126	0.109

*In column (1) the dependent variable is the return on weather futures on Chicago. In column (2) the dependent variable is the return on weather futures on New York. * indicates p-value smaller than 5 %. ** indicates p-value smaller than 1 %. *** indicates p-value smaller than 0,1 %. The standard error of the coefficients are presented in the parantheses below each coefficient.*

The constants in the regression table shows the return on the weather futures if all of the explanatory variables included in the regression was zero. Neither of the intercepts can be said to be significantly different from zero at a 0,1, 1 or 5 percent significance level. The t-statistic is 1,78 (0,968/0,545) and 1,83 (0,796/0,434) for the intercept on the regression using New York and Chicago weather futures respectively. With a two-sided test and a 10 percent significance level the critical value is 1,29 (Stock and Watson 2015, 804). Since the t-statistic of both intercepts are larger than the critical value, both constants are significantly different from zero at a 10 percent significance level (Stock and Watson 2015, 195). But increasing the significance level increases the probability of making a type 1 error (Stock and Watson 2015, 124). Therefore, the rejection of the null hypothesis of a zero coefficient at a 10 percent significance level comes with a tradeoff, where the cost is higher probability of making a type 1 error. As in section 6.2.1, according to Bodie, Kane and Marcus (2018, 288), a zero intercept is required for the CAPM to hold. The rejection of the null hypotheses that the constant is zero at a 10 percent significance level is evidence that the CAPM does not appear to hold.

The coefficient on the market risk premium is negative and therefore indicates lower return when the market risk premium increases by one unit for both weather futures on New York and Chicago. The coefficient is not significantly different from zero at a 0,1, 1 or 5 percent significance level for neither weather futures on Chicago nor New York. Since the coefficients are not significantly different from zero the risk factor does not significantly explain the return on the weather futures. The coefficients on the climate variables NotWork and Temptonormal are both individually significantly different from zero at a 1 percent significance level for weather futures on Chicago. The coefficient on the dummy variable Temptonormal is significantly different from zero on a 0,1 percent significance level for weather futures on New York and indicates a higher return when the temperature is higher than normal compared to when the variable has a value of zero.

When looking at the interaction terms in column one for the regression with the return on Chicago weather futures as the dependent variable, it appears that none of the coefficients are significantly different from zero at a 0,1, 1 or 5 percent significance level. When it comes to the interpretation of the interaction terms, for example the coefficient on MRPprec shows the change in the return when the market risk premium goes up by one unit per unit of precipitation. A negative coefficient indicates a lower sensitivity to the market risk factor when precipitation increases by one unit per unit of market risk premium and since the return is an estimate of the risk premium, the negative coefficient indicates a lower risk premium on the weather futures. The coefficients on the interaction terms between the market risk premium, and precipitation(MRPprec), CDD(MRPCDD) and the dummy variable comparing temperature to normal(MRPtempton), when controlling for all the other included variables, appear to indicate a reduction in the systematic risk when the market risk premium increases by one unit per unit of precipitation, CDD and when the temperature is higher than normal, for the weather futures on Chicago. The coefficients on the three remaining interaction terms provides evidence of a higher systematic risk when the market risk premium increases given the temperature, CO2 emissions and the amount of people not at work due to bad weather, when controlling for the other explanatory variables included. In chapter 5 I wrote down an expectation that higher temperatures and higher temperatures than normal would lead to higher risk premiums as more firms would want to hedge when the weather becomes more volatile and in order to attract speculators to take the opposite positions of the hedgers they must be offered a higher compensation. This expectation could explain a positive coefficient on the variable MRPTemp, but the expectation appears to be wrong for the variable MRPtempton. Neither of the two coefficients are significant at a 0,1, 1 or 5 percent significance level. In total, the effect seems to be a reduction in the systematic risk when tying the changes in systematic risk to climate changes for the weather futures on Chicago and therefore a lower risk premium. But none of the coefficients on the interaction terms are significantly different from zero at a 0,1, 1 or 5 percent significance level, providing evidence of no change in the systematic risk due to climate changes.

Neither any of the coefficients on the interaction terms between the market risk premium and the climate variables appears to be significant in the regression in column two using the return on New York weather futures as the dependent variable. When controlling for the explanatory variables included in the regression in column two, the coefficients on the interaction terms between the market risk premium, and precipitation(MRPprec), CDD(MRPCDD), CO2(MRPCO2) and temptonormal(MRPtempton) appears to indicate a reduction in the systematic risk when the market risk premium increase by one unit given the level of precipitation, CDD, CO_2 emissions and when the temperature is higher than normal. The two remaining coefficients appear to indicate a higher return when the market risk premium increases by one unit given the temperature and the value of the NotWork variable. The effect in total for New York weather futures appears to be a reduction in the systematic risk tied to climate changes, which is the same result as the regression in column 1 for weather futures on Chicago. The reduction in the sensitivity to the market risk factor tied to climate changes indicates a lower risk premium on the New York weather futures, as the return is used as a measure of the risk premium as stated in equation (10). But none of the coefficients are significantly different from zero at a 0,1, 1 or 5 percent significance level, which is the same finding as with weather futures on Chicago.

R squared is 12,6 and 10,9 percent for the regression in column one and two respectively, and shows that the independent variables explain 12,6 and 10,9 percent of the variation in the dependent variables (Stock and Watson 2015, 242). As already discussed previously in the theoretical review, a lot of the CAPM assumptions might not hold perfectly when it comes to the weather derivatives market. In addition, the nonzero intercepts at a 10 percent significance level leans towards the result that the CAPM does not seem to hold. The findings with few significant results and the evidences of nonzero intercepts, at a 10 % significance level when controlling for climate changes, indicates that the CAPM might not be the right asset pricing model to investigate changes in the sensitivity to systematic risk due to climate changes for the weather futures data collected. The findings in the regression in section 6.2.1 indicates a positive beta coefficient after 2011 when the market risk premium increases on Chicago and New York weather futures. None of the coefficients on the interaction terms in the regression results above or on the interaction terms in section 6.2.1 are significantly different from zero. Overall, the evidences of changes in the systematic risk and changes in the systematic risk tied to climate changes shows no significant changes.

6.3 Regressions using the APT

As mentioned in the previous section, all the CAPM assumptions might not hold perfectly for the weather futures market and therefore I also use the APT. In this section I use the growth in the industrial production index(IP), in addition to the market risk premium, to explain the return on weather futures and to run the regressions. As stated earlier in chapter 5, emissions are expected be highly correlated with total production and therefore I expect the model to show a better fit than the CAPM and better explain the return on weather futures. In this section I will run the regression using the APT and hence include the growth in the industrial production index (IP growth) as an explanatory variable in addition to the market risk premium. As defined before, according to Bodie, Kane and Marcus (2018, 247-249) the beta coefficient represents the sensitivity to macroeconomic factors and therefore the systematic risk. The return on the weather futures is used as an estimate of the risk premium in the weather futures, as discussed in section 2.3 and as defined in equation (10).

6.3.1 Changes in the systematic risk using the APT

In this section I will run a linear regression using the APT, and I will include both the market risk premium and the variable for the growth in the industrial production index (IP growth). I will make an interaction term between both risk factors and the dummy variable year. The reasoning behind the regression is the same as the similar regression using the CAPM in section 6.2.1, to have a model looking at changes in the systematic risk if the climate variables chosen does not properly capture climate changes or its effect on weather futures. In addition, the growth in the industrial production index is included to see if the model using the APT and the risk factor industrial production growth, in addition to the market risk premium, better explains the return on the weather futures than the regression using the CAPM and the market risk premium only.

The regression model is the following

$$Log\ return\ weather\ futures_i = \alpha_i + \beta_{1i} * Market\ risk\ premium_i$$
$$+\beta_{2i} * IP\ growth_i + \beta_{3i} * Year_i + \beta_{4i} * Year_i * Market\ risk\ premium_i$$
$$+\beta_{5_i} * Year_i * IP\ growth_i + e_{it}$$

Alpha (α) represents the intercept. The regression is performed for both the return on the weather futures on both Chicago and New York, and the results are presented in column one and two respectively in the regression table below.

As explained in section 6.2.1, if the beta coefficient on the interaction terms are not significantly different from zero, the coefficients provide evidence that the systematic risk did not change after 2011. In other words, the sensitivity to the market risk factor and the sensitivity to the risk factor representing the growth in the industrial production index, is the same before and after 2011.

Table 5: Regression of the return on weather futures on the risk factors market risk premium and the growth in the industrial production index, the dummy variable year, and the interaction terms between the two risk factors and the dummy variable year, by using the APT.

	(1) ReturnC	(2) ReturnNY
MRpremium	0.317	0.0508
	(0.634)	(0.795)
Ipgrowth	0.715	2.191
	(3.816)	(4.785)
Year	-0.0317	-0.0277
	(0.0452)	(0.0567)
MRPyear	0.402	0.875
	(1.137)	(1.426)
IPGyear	14.40	5.355
	(7.821)	(9.807)
_cons	0.00504	0.00751
	(0.0296)	(0.0372)
N	239	239
R-sq	0.023	0.006

*In column (1) the dependent variable is the return on weather futures on Chicago. In column (2) the dependent variable is the return on New York weather futures. * indicates p-value smaller than 5 %. ** indicates p-value smaller than 1 %. *** indicates p-value smaller than 0,1 %. The standard error of the coefficients are presented in the parantheses below each coefficient.*

The intercepts in the two regressions shows the expected return in the time period 2000 to 2010 when the explanatory variables have a value of zero. None of the intercepts are significantly different from zero at a 0,1, 1 or 5 percent significance level. Both the coefficients on the variables market risk premium and industrial production growth in the two regressions provides evidence of an increase in the sensitivity to the risk factors and an increase in the systematic risk when the variables increase by one unit, and therefore an increase in the risk premium. But neither of the individual coefficients on the variables market risk premium nor growth in the industrial production index are significantly different from zero at a 0,1, 1 or 5 percent significance level for either weather futures on New York or Chicago.

In the regression results in column one, in which the return on weather futures on Chicago are used as the dependent variable, the coefficient on the interaction term IPGyear provides evidence of an increase in the systematic risk when the industrial production index grows by one unit after 2011 when controlling for the market risk premium, the growth in the industrial production index, the dummy variable year, and the interaction term between year and the market risk premium. But the coefficient is not signifiantly different from zero at a 0,1, 1 or 5 percent significance level. The interaction term between the market risk premium and the dummy variable year also gives evidence of an increase in the systematic risk after 2011 when the market risk premium increase by one unit, when controlling for the other included variables. But the beta coefficient on the interaction term MRPyear is not significantly different from zero at a 0,1, 1 or 5 percent significance level.

In column 2, in which the regression uses the return on New York as the dependent variable, the interaction terms indicating whether the systematic risk has changed after 2011 indicates positive beta coefficients for both MRPyear and IPGyear. The results are evidence of an increase in the risk premium on New York weather futures when the market risk premium or the growth in the industrial production go up by one unit in the time period 2011 to 2020, when controlling for the other explanatory variables included. But, the null hypotheses that the individual coefficients are zero fails to be rejected such that the coefficients are not significantly different form zero at a 0,1, 1 or 5 percent significance level.

The R squared is low in the regression using the APT when adding the growth in the industrial production index as an explanatory variable in addition to the market risk premium.

It is not yet clear whether the APT better explains the return on weather futures than the CAPM. My expectation was that the APT would be a better model for explaining the return, but it does not appear to be correct when only using the interaction term between the risk factors and the dummy variable year, and by comparing the regressions using the APT and the CAPM in section 6.2.1 and 6.3.1. Until now there has not been any significant coefficients and the R squared is low in the regression results. The finding of no significant coefficients means that the true value of the coefficient could be zero which provides evidence that the systematic risk is unchanged after 2011 when using both the APT and the CAPM.

6.3.2 Testing for breaks

In the review of methodology I presented the Chow break test. The regression I will run in order to test for breaks and the hypotheses to be tested are expressed below, and the regression is the same as the one in 6.3.1. I will therefore test for a break in 2011, and my dummy variable year will be the same as before.

$$Log\ return\ weather\ futures_i = \alpha_i + \beta_{1i} * Market\ risk\ premium_i + \beta_{2i} * IP\ growth_i + \gamma_{0i} * Year_i + \gamma_{1i} * Year_i * Market\ risk\ premium_i + {\gamma_2}_i * Year_i * IP\ growth_i$$

$$H_0: \gamma_0 = \gamma_1 = \gamma_2 = 0$$
$$H_1: \gamma_0 = 0, \gamma_1 = 0\ or\ \gamma_2 = 0$$

In other words, as previously noted, the null hypothesis of no change in the systematic risk in 2011 is tested against the alternative of a change in the systematic risk. After running the regressions and the tests in Stata, it appears from the results below that the null hypotheses fails to be rejected for weather futures on New York and Chicago. The results provides evidence of no break and therefore no change in the systematic risk.

Table 6: Chow test using results from 6.3.1 by using Chicago weather futures

```
. test Year MRPyear IPGyear

 ( 1)  Year = 0
 ( 2)  MRPyear = 0
 ( 3)  IPGyear = 0

       F(  3,   233) =    1.19
            Prob > F =    0.3157
```

Table 7: Chow test using results from 6.3.1 by using New York weather futures

```
. test Year MRPyear IPGyear

 ( 1)  Year = 0
 ( 2)  MRPyear = 0
 ( 3)  IPGyear = 0

       F(  3,   233) =    0.25
            Prob > F =    0.8644
```

Despite not finding evidences of a break during a year, breaks could have happened in other time periods. But that the null hypotheses fails to be rejected both for New York and Chicago weather futures fits well with the conclusions in section 6.3.1 that the coeefficients are not significantly different form zero at a 0,1, 1 or 5 percent significance level. Both results therefore indicates no change in the systematic risk tied to the two risk factors and therefore no change in the risk premium. Therefore, the evidences does not appear to indicate breaks in other time periods.

6.3.3 Controlling for climate changes using the APT

In this section I will run a linear regression using the APT, and the two risk factors market risk premium and the growth in the industrial production index. In addition I will include all the climate variables by making interaction terms between the market risk premium and the growth in the industrial production index, and the climate variables. The regression model looks like the following

$$Log\ return\ weather\ futures_i = \alpha_i + \beta_{1i} * Market\ risk\ premium_i$$
$$+\beta_{2i} * Precipitation_i * Market\ risk\ premium_i$$
$$+\beta_{3i} * NotWork_i * Market\ risk\ premium_i + \beta_{4i} * CDD_i * Market\ risk\ premium_i +$$
$$\beta_{5i} * CO2_i * Market\ risk\ premium_i + \beta_{6i} * TF_i * Market\ risk\ premium_i + \beta_{7i} *$$
$$Temptonormal_i * Market\ risk\ premium_i + \beta_{8i} * IP\ growth_i + \beta_{9i} * Precipitation_i *$$
$$IP\ growth_i + \beta_{10i} * NotWork_i * IP\ growth_i + \beta_{11i} * CDD_i * IP\ growth_i$$
$$+\beta_{12i} * CO2_i * IP\ growth_i + \beta_{13i} * TF_i * IP\ growth_i$$
$$+\beta_{14i} * Temptonormal_i * IP\ growth_i + \beta_{15i} * Precipitation_i + \beta_{16i} * NotWork_i$$
$$+\beta_{17i} * CDD_i + \beta_{18i} * CO2_i + \beta_{19i} * TF_i + \beta_{20i} * Temptonormal_i + e_{it}$$

The regression is made using the return on both Chicago and New York weather futures as the dependent variables, and the results are presented in the regression table below in column one and two respectively.

Table 8: Regression of the return on weather futures on the risk factors market risk premium and the growth in the industrial production index, the climate variables chosen, and the interaction terms between the two risk factors and the climate variables by using the APT.

	(1) returnC	(2) returnNY
MRpremium	-16.33	-7.844
	(12.79)	(16.26)
Ipgrowth	150.8*	63.29
	(71.99)	(91.54)
Precipitation	-0.00268	-0.00362
	(0.00178)	(0.00227)
NotWork	-0.000739**	-0.000537
	(0.000232)	(0.000296)
CDD	-0.000113	-0.000457
	(0.000501)	(0.000637)
CO2	-2.17e-10	-3.08e-10
	(7.61e-10)	(9.68e-10)
TF	-0.00995	-0.0128
	(0.00650)	(0.00826)
Temptonormal	0.313**	0.483***
	(0.109)	(0.139)
MRPprec	-0.0394	-0.0529
	(0.0444)	(0.0564)
MRPnwork	0.0123	0.00579
	(0.00924)	(0.0117)
MRPCDD	-0.0280*	-0.0172
	(0.0139)	(0.0177)
MRPCO2	1.57e-09	-3.96e-09
	(2.20e-08)	(2.80e-08)
MRPTemp	0.408*	0.316
	(0.192)	(0.244)
MRPtempton	-2.966	-4.148
	(2.521)	(3.206)
IPGPrec	-0.350	-0.182
	(0.318)	(0.404)
IPGnwork	-0.00245	0.00130
	(0.0432)	(0.0549)
IPGCDD	-0.0143	0.0279
	(0.0824)	(0.105)
IPGCO2	-0.000000290*	-0.000000139
	(0.000000135)	(0.000000172)
IPGTemp	0.112	0.292
	(0.900)	(1.144)
IPGTempton	-2.037	-12.85
	(17.77)	(22.60)
_cons	0.732	0.907
	(0.446)	(0.567)
N	237	237
R-sq	0.154	0.115

*In column (1) the dependent variable is the return on weather futures on Chicago. In column (2) the dependent variable is the return on New York weather futures. * indicates p-value smaller than 5 %. ** indicates p-value smaller than 1 %. *** indicates p-value smaller than 0,1 %. The standard error of the coefficients are presented in the parantheses below each coefficient.*

The constants show the expected return on the weather futures when all the explanatory variables included have a value of zero. As mentioned in the theoretical review and stated in equation (10), the return is a measure of the risk premium and therefore the constants show the expected risk premium when all the explanatory variables included have a value of zero. Neither of the intercepts are significantly different from zero at a 0,1, 1 or 5 percent significance level. The R squared is 15,4 percent for the regression in column one and 11,5 percent in the regression in column two.

In the regression in column one, using the return on Chicago weather futures as the dependent variable, the coefficient on the variable industrial production growth is significant on a 5 percent significance level. The coefficient on Ipgrowth indicates a higher sensitivity to the risk factor growth in the industrial production index when the industrial production index grows by one unit and therefore indicates a higher risk premium in Chicago weather futures. The coefficient on the MRpremium variable indicates a lower return when the market risk premium increases by one unit and therefore a lower sensitivity to the market risk factor when the market risk premium increases by one unit. But the coefficient on the market risk premium variable is not significantly different from zero at a 0,1, 1 or 5 percent significance level. The significance level of the coefficient on the growth in the industrial production variable in the regression output supports the expectation that the APT with industrial production better explains the return on Chicago weather futures in the regression than the CAPM. The significant coefficient indicates that the coefficient is statistically significantly different from zero at a 5 percent significance level. Therefore the regression using the APT and the growth in the industrial production index as a risk factor appears to significantly explain the return on Chicago weather futures and therefore appears to fit better than the CAPM.

For the regression in column two in which the dependent variable is the return on New York weather futures, the beta coefficient on MRpremium indicates a reduction in the sensitivity to the market risk factor when the market risk premium increases by one unit. The coefficient on the Ipgrowth variable indicates a higher sensitivity to the risk factor growth in the industrial production index when the industrial production index grows by one unit. But neither of the coefficients for any of the two variables are individually significant at a 0,1, 1 or 5 percent significance level when controlling for the climate variables, the same finding as in section 6.3.1.

For the weather futures on Chicago the APT seems like the best model compared to the CAPM to explain the return, which supports the expectation from earlier. On the other hand, it is surprising that the return on the New York weather futures is not best explained by the APT as well. As reviewed earlier, the APT uses the growth in the industrial production as well as the market risk premium to explain the return. Higher production often go together with high levels of pollution due to firms' eagerness to produce at the lowest cost possible. The higher levels of pollution leading to a larger extent of adverse climate effects and which would be expected to lead to an increased demand for hedging instruments built on weather, in which more investors are needed to take the speculative position. It is therefore surprising that the APT does not appear to significantly explain the return on New York weather futures as well as it does for Chicago weather futures. An explanation could be that the climate variables chosen does not properly capture the effects of climate changes and how it affects New York weather futures, or the effects of climate changes have not been extreme enough to significantly affect the risk premium on New York weather futures.

In the first column, in addition to the coefficient on the risk factor growth in the industrial production index, the coefficient on the climate variables Temptonormal and NotWork are significantly different from zero at a 1 percent significance level. The variables seem to lead to higher return on the weather futures when the temperatures are higher than normal and a reduction in the return when the amount of people not at work due to bad weather increases by one unit. In addition, the coefficient on the interaction terms between the market risk premium and CDD(MRPCDD), and between the market risk premium and temperature(MRPTemp) are significant at a 5 percent significance level. A possible explanation for the finding on the coefficient on MRPCDD could be that a higher number of CDD would lead to more firms that are exposed to CDD buys weather futures on CDD to hedge their risks which leads to higher risk premiums to attract speculators to take the opposite positions, and lower risk premium on HDD futures as the amount of hedgers and investors using that type of contract is reduced. When it comes to the explanation of the significant coefficient on the the variable MRPTemp that indicates a positive beta coefficient, from section 5.5.1, the expectation was that more volatile temperatures leads to a higher risk premium to make sure that enough investors enters the opposite side of the hedgers wanting to reduce their risk. The expectation of the effect on weather futures of the variable Temptonormal was the same as for the temperature variable, that higher temperatures than normal could be an indication of the effects of high levels of pollution and could increase the need for hedging in which more speculators are required to take the opposite position and they are offered a higher risk premium to do so. The expectation could explain a positive signicant coefficient on MRPTemp, but it appears to be wrong for the MRPtempton variable in which the effect on the risk premium appears to be opposite and the coefficient is not significantly different from zero on a 0,1, 1 or 5 percent significance level. The coeffieicient on the Temptonormal variable however is positive and significant on a 1 percent significance level.

The coefficient on the variable NotWork indicates a lower return when the number of people not at work due to bad weather increases and is significant on a 1 percent significance level. However, the interaction term between the market risk premium and the NotWork variable appears to indicate a higher risk premium when the amount of people not at work increases given the market risk premium, but the coefficient is not significantly different from zero at a 0,1, 1 or 5 percent significance level. The coefficient on the interaction term between the growth in the industrial production and CO2 emissions is significantly different from zero at a 5 percent significance level. The coefficient indicates a reduction in the systematic risk when the amount of CO2 emissions increase per unit of growth in the industrial production index. The significant finding provides evidence in support of the expectation of the high correlation between production and emissions, but more emissions was expected to increase the need for speculators to enter the opposite side of the hedgers and thereby being offered a higher risk premium.

The interaction terms between the industrial production growth and the climate variables provides evidence of negative betas and hence a reduction in the systematic risk due to climate changes. The interaction terms between the market risk premium and the climate variables provides evidence of a reduction in the sensitivity to systematic risk due to climate changes as well. In total, the beta coefficients on the interaction terms provides evidence of a reduction in the risk premium due to climate changes, but not all of the coefficients are significantly different from zero. The interaction term between the growth in the industrial production index and CO2 shows evidence of a significant reduction in the systematic risk due to climate changes. The coefficients on the interaction terms MRPTemp and MRPCDD provides evidence of a significant increase and a significant reduction in the systematic risk due to climate changes respectively. Therefore, some of the coefficients shows evidence of significant changes in the sensitivity to the market risk factor and the risk factor growth in the industrial production index due to climate changes.

In the regression results in column two, in which the dependent variable is the return on New York weather futures, only the climate variable Temptonormal is significant and it is significantly different from zero on a 0,1 percent significance level. The coefficients on the interaction terms between the growth in the industrial production index and the climate variables provides evidence of a reduction in the systematic risk. The coefficients on the interaction terms between the market risk premium and the climate variables also provides evidence of a reduction in the systematic risk. The effect in total appears to be a reduction in the risk premium due to climate changes, but none of the interaction terms are significantly different from zero at a 0,1, 1 or 5 percent significance level.

The results does not provide as many significant results for the weather futures on New York as for the weather futures on Chicago as expected. The evidence from the regression using the return on New York weather futures as the dependent variable does not provide as good indication as for the weather futures on Chicago, whether the APT is better at explaining the return for weather futures on New York compared to the CAPM. Earlier I discussed some possible explanations. The results from column two in the regression indicates that when the temperature is higher than normal the return is higher compared to when the dummy variable has a value of zero and the coefficient is significant on a 0,1 percent level. The result is evidence that the APT provides some evidence of significant changes in the return for New York weather futures.

6.4 Robustness during financial crises

A financial crisis affect financial markets to a huge extent. A financial crisis affect the return on many assets trading on exchanges and one would expect that to also include weather futures. As explained by Hull (2018 a, 51 and 65) futures are exchange traded and also requires the two parties in a contract to hold a margin account to reduce the credit risk, therefore some of the risk and consequences involved in a financial crisis might not hit the futures contracts as hard as other exchange traded assets. In addition, futures are often viewed as assets containing low risk which might increase their attractiveness during financial crises.

Up until now the regressions have not been controlling for whether there has been a financial crisis or not. Could controlling for the variable financial crisis affect the results? In these regressions I will add the dummy variable indicating whether there is a financial crisis or not to check whether the results from the regressions above holds.

6.4.1 Regression using the CAPM

In this section I will use the regression made earlier by using the CAPM with the market risk premium as an explanatory variable together with the interaction terms between the climate variables and the market risk premium. In addition, I will add the dummy variable FinCrisis made as an explanatory variable that indicates whether there is a financial crisis in a certain period or not. The regression model will look like the following

$$
\begin{gathered}
Log\ return\ weather\ futures_i = \alpha_i + \beta_{1i} * Market\ risk\ premium_i \\
+\beta_{2i} * Precipitation_i * Market\ risk\ premium_i + \beta_{3i} * NotWork_i * \\
Market\ risk\ premium_i + \beta_{4i} * CDD_i * Market\ risk\ premium_i + \beta_{5i} * CO2_i * \\
Market\ risk\ premium_i + \beta_{6i} * TF_i * Market\ risk\ premium_i \\
+ \beta_{7i} * Temptonormal_i * Market\ risk\ premium_i + \beta_{8i} * Precipitation_i \\
+ \beta_{9i} * NotWork_i + \beta_{10i} * CDD_i + \beta_{11i} * CO2_i \\
+ \beta_{12i} * TF_i + \beta_{13i} * Temptonormal_i + \beta_{14i} * FinCrisis_i + e_{it}
\end{gathered}
$$

The regession is made using weather futures return on Chicago and New York, and the results are presented below.

From the review of methodology, the intercept should be zero for the CAPM to hold (Bodie, Kane and Marcus 2018, 288). The intercepts in the linear regressions built on CAPM in section 6.2.1 were not significantly different from zero at a 0,1, 1 or 5 percent significance level. On the other hand, the intercepts in the regression in section 6.2.3 when controlling for climate changes were significantly different form zero at a 10 percent significance level. Does the regression from section 6.2.3 above using the CAPM hold when controlling for the dummy variable indicating whether it is a financial crisis or not?

Table 9: Results from the regression in section 6.2.3 and adding the dummy variable FinCrisis as an explanatory variable.

	(1) ReturnC	(2) ReturnNY
MRpremium	-10.83	-5.193
	(12.09)	(15.19)
Precipitation	-0.00318	-0.00385
	(0.00175)	(0.00220)
NotWork	-0.000711**	-0.000524
	(0.000222)	(0.000279)
CDD	-0.000210	-0.000427
	(0.000489)	(0.000615)
CO2	-4.95e-10	-5.04e-10
	(7.63e-10)	(9.58e-10)
TF	-0.00802	-0.0119
	(0.00635)	(0.00797)
Temptonormal	0.287**	0.455***
	(0.106)	(0.133)
MRPprec	-0.0626	-0.0612
	(0.0435)	(0.0546)
MRPnwork	0.00941	0.00413
	(0.00853)	(0.0107)
MRPCDD	-0.0218	-0.0138
	(0.0133)	(0.0167)
MRPCO2	1.09e-09	-2.86e-09
	(2.14e-08)	(2.68e-08)
MRPTemp	0.324	0.256
	(0.178)	(0.223)
MRPtempton	-2.279	-3.287
	(2.329)	(2.925)
FinCrisis	0.0147	0.00490
	(0.0707)	(0.0888)
_cons	0.811	0.974
	(0.441)	(0.554)
N	237	237
R-sq	0.127	0.109

*In column (1) the dependent variable is the return on weather futures on Chicago. In column (2) the dependent variable is the return on weather futures on New York. * indicates p-value smaller than 5 %. ** indicates p-value smaller than 1 %. *** indicates p-value smaller than 0,1 %. The standard error of the coefficients are presented in the parantheses below each coefficient.*

According to the definitions made by NBER regarding what can be defined as a financial crisis, NBER has not classified any periods after 2011 as a financial crisis (NBER 2020). Therefore, the value of the variable FinCrisis is zero for both weather derivatives on New York and Chicago from 2011 to 2020 in the regressions. The R squared indicates that the explanatory variables explain 12,7 and 10,9 percent of the variation in the dependent variables in column one and two respectively (Stock and Watson 2015, 167 and 169).

The coefficient on the FinCrisis variable is not significantly different from zero in either of the regressions in column one or two. The coefficients on both intercepts increase when controlling for the financial crisis variable. As stated in equation (10), the return is an estimate of the risk premium in weather derivatives, therefore the intercept shows the risk premium when all of the explanatory variables have a value of zero and hence when there are no financial crisis. When the value of the financial crisis variable is one, the effect on the risk premium in weather derivatives is $\alpha_i + \beta_{14i}$ (Stock and Watson 2015, 328). In other words, the sum of α_i and β_{14i} is the value of the new intercept when there is a financial crisis (Stock and Watson 2015, 328). The positive coefficient on the FinCrisis variable indicates a higher return during a financial crisis compared to a year in which the value of the variable is zero, when controlling for the other included variables. The intercepts in the regression output is nonzero, but none of the intercepts are significantly different from zero at a 0,1, 1 or 5 percent significance level. As stated by Bodie, Kane and Marcus (2018, 288), a zero intercept is required for the CAPM to hold and the conclusion that the coefficients are not significantly different from zero provides evidence that the CAPM holds during financial crises.

A possible explanation for the higher return during financial crisis could be that investors are attracted to safer investments with lower risk compared to for example stocks and that therefore some uses weather futures to bet on weather, and that a higher return is offered to attract hedgers or other investors to take the opposite positions in the futures. In addition the credit risk is zero in futures contracts due to the process of daily settlements, as explained in the theoretical review, which might further increase the attractiveness of weather futures (Hull 2018 a, 51). In the regression results, both for the weather futures on Chicago and New York, adding the dummy variable FinCrisis only affects the intercept, and have almost no effect on the coefficients of the other included variables and the significance of the results. But the coefficient on the FinCrisis variable is not significantly different from zero in column one or two.

6.4.2 Regression using the APT

In this section I will use the regression made earlier by using the APT with the risk factors market risk premium and the growth in the industrial production index as explanatory variables, together with the interaction terms between the two market risk factors and the climate variables. In addition, the dummy variable FinCrisis will be added. The regression will look like the following

$$Log\ return\ weather\ futures_i = \alpha_i + \beta_{1i} * Market\ risk\ premium_i + \beta_{2i} * Precipitation_i * Market\ risk\ premium_i + \beta_{3i} * NotWork_i * Market\ risk\ premium_i + \beta_{4i} * CDD_i * Market\ risk\ premium_i + \beta_{5i} * CO2_i * Market\ risk\ premium_i + \beta_{6i} * TF_i * Market\ risk\ premium_i + \beta_{7i} * Temptonormal_i * Market\ risk\ premium_i + \beta_{8i} * IP\ growth_i + \beta_{9i} * Precipitation_i * IP\ growth_i + \beta_{10i} * NotWork_i * IP\ growth_i + \beta_{11i} * CDD_i * IP\ growth_i + \beta_{12i} * CO2_i * IP\ growth_i + \beta_{13i} * TF_i * IP\ growth_i + \beta_{14i} * Temptonormal_i * IP\ growth_i + \beta_{15i} * Precipitation_i + \beta_{16i} * NotWork_i + \beta_{17i} * CDD_i + \beta_{18i} * CO2_i + \beta_{19i} * TF_i + \beta_{20i} * Temptonormal_i + \beta_{21i} * FinCrisis_i + e_{it}$$

Table 10: Results from the regression in section 6.3.3 and adding the dummy variable FinCrisis as an explanatory variable.

	(1) returnC	(2) returnNY
MRpremium	-16.33	-7.840
	(12.82)	(16.30)
Ipgrowth	149.5*	62.47
	(72.76)	(92.53)
Precipitation	-0.00268	-0.00362
	(0.00179)	(0.00227)
NotWork	-0.000737**	-0.000535
	(0.000234)	(0.000297)
CDD	-0.000111	-0.000457
	(0.000502)	(0.000638)
CO2	-2.44e-10	-3.23e-10
	(7.85e-10)	(9.98e-10)
TF	-0.00992	-0.0127
	(0.00652)	(0.00829)
Temptonormal	0.312**	0.483***
	(0.110)	(0.140)
MRPprec	-0.0401	-0.0534
	(0.0447)	(0.0569)
MRPnwork	0.0123	0.00577
	(0.00926)	(0.0118)
MRPCDD	-0.0278*	-0.0171
	(0.0140)	(0.0178)
MRPCO2	1.94e-09	-3.74e-09
	(2.22e-08)	(2.82e-08)
MRPTemp	0.405*	0.314
	(0.194)	(0.246)
MRPtempton	-2.918	-4.119
	(2.548)	(3.240)
IPGPrec	-0.351	-0.182
	(0.319)	(0.405)
IPGnwork	-0.00348	0.000683
	(0.0438)	(0.0557)
IPGCDD	-0.0143	0.0280
	(0.0825)	(0.105)
IPGCO2	-0.000000285*	-0.000000136
	(0.000000139)	(0.000000177)
IPGTemp	0.110	0.291
	(0.902)	(1.147)
IPGTempton	-2.134	-12.90
	(17.83)	(22.67)
FinCrisis	0.0122	0.00721
	(0.0830)	(0.106)
_cons	0.741	0.912
	(0.451)	(0.574)
N	237	237
R-sq	0.154	0.115

*In the first column the dependent variable is the return on weather futures on Chicago. In the second column the dependent variable is the return on weather futures on New York. * indicates p-value smaller than 5 %. ** indicates p-value smaller than 1 %. *** indicates p-value smaller than 0,1 %. The standard error of the coefficients are presented in the parantheses below each coefficient.*

Just as with the CAPM regression in 6.4.1, the coefficient on the dummy variable FinCrisis has a value of zero after 2010 as NBER did not classify any periods after 2010 as a financial crisis (NBER 2020). The R squared is 11,5 percent for the regression using the return on New York weather futures as the dependent variable and 15,4 percent for the regression using the return on Chicago as the dependent variable.

When controlling for the FinCrisis variable, the intercept in both columns increase compared to the regression in section 6.2.3. The constants shows the expected risk premium on the weather futures when all the explanatory variables included are zero, and hence when it is not a financial crisis. When there is a financial crisis, the effect on the risk premium is $\alpha_i + \beta_{21i}$ (Stock and Watson 2015, 328). The changes in the coefficients on the other explanatory variables are small or no changes. The intercepts are still not significantly different from zero at a 0,1, 1 or 5 percent significance level. The APT still appears to be the best model and neither of the coefficients on the interaction terms lost their significance after controlling for FinCrisis. Neither of the coefficients on the FinCrisis variable are significantly different from zero for either the weather futures on New York or Chicago on a 0,1, 1 or 5 percent significance level.

The results provide evidence of a positive coefficient on the variable FinCrisis in the regression results in both columns and therefore indicates an increase in the return during a financial crisis. The positive coefficients could have the same explanation as in 6.4.1. In addition, a financial crisis might affect firms and their earnings such that more people might get fired and the production capacity might go down. Firms that experience exposure to weather risk could therefore become further incentivized to hedge their weather exposure when earnings are more volatile than normal. But the coefficient on the FinCrisis variable is not significantly different from zero in column one or two.

6.5 Recommendations regarding further research

After doing the analysis, thinking about the thesis in addition to taking into account the limitations of this paper, I have the following recommendations to further research.

As mentioned in the introduction, climate changes are expected to get even rougher in the future. From the empirical review, the insight from Auffhammer (2018, 33-34) was that local emissions leads to global damages and that emissions today will affect the life on our planet in the future. A similar study in a couple of years with more variables and data reflecting the consequences of climate changes might give more significant results. In addition, another recommendation is doing the break test on other years or use the Quandt-Likelihood Ratio test to look for breaks, which is suggested as another break test by Stock and Watson (2015, 609-610). When working with this paper the outbreak of the coronavirus had a large impact on financial markets. In addition, the restrictions on travelling and other activities, and countries shutting down led to large reductions in the global emissions. These effects could lead to more volatility in many variables representing climate changes and the effects would have been interesting to include in the analysis after the outbreak of the virus is over. In addition, it could be interesting to find more data on the prices of weather futures other geographical places and to compare the results.

Chapter 7

Conclusion

In this study I have investigated whether climate changes have led to a significant change in the risk premium in weather derivatives. Several regressions have been performed by using the return on weather futures on Chicago and New York as an estimate of the risk premium, as stated in equation (10). By using interaction terms I have tested for changes in the systematic risk in general, in case the climate variables chosen does not properly capture climate changes or their effect on weather futures, and tied changes in the systematic risk to climate changes by using interaction terms between the two risk factors chosen to explain the risk premium in weather futures and the climate variables I have chosen to include.

In the CAPM, beta shows how sensitive the return of an asset is to changes in the market risk premium and is a measure of the systematic risk (Bodie, Kane and Marcus 2018, 247-249). In the regression using the APT, beta shows the sensitivity of the return of the asset to changes in the risk factors, in this case the market risk premium and the growth in the industrial production index (Bodie, Kane and Marcus 2018, 311). After estimating the risk premium in the weather derivatives and running the regressions I found some evidence of changes in beta, and therefore changes in the systematic risk which indicates a change in the risk premium.

In the regression using the CAPM to look for changes in the systematic risk by using the interaction term between year and the market risk premium, none of the resulting coefficients are significantly different from zero. In the Chow test testing for breaks, there is no evidence of a break in 2011 for weather futures on Chicago and New York. The results therefore indicates that the systematic risk did not change after 2011. The results from the regression using CAPM and the interaction term between the market risk premium and year supports the finding of no break since the coefficient on the intercation term were not significantly different from zero. The CAPM appears to hold in the regression as the intercepts are not significantly different from zero.

In the regression using the APT and the interaction term between year and the market risk premium, the regression results does not indicate significant changes in the sensitivity to the market risk factor or the risk factor growth in the industrial production index after 2011. The findings in the Chow break test does not provide evidence of a break for New York or Chicago weather futures in 2011. The results in the regressions using the APT, and the interaction terms between the risk factors and the dummy variable year therefore supports the finding of no break as the null hypothesis that the coefficients on the interaction term between the risk factors and the variable year are zero fails to be rejected. That the coefficients are not significantly different from zero is evidence that the the systematic risk did not change after 2011.

In the regression results using the CAPM when controlling for the climate variables, none of the interaction terms that tie changes in the sensitivity to the market risk factor to climate changes appears to be significantly different from zero for either weather futures on New York or Chicago. In addition, the intercepts are significantly different from zero at a 10 percent significance level which indicates that the CAPM does not appear to hold. When using the APT and controlling for the climate variables, the results provide evidence that the risk factor growth in the industrial production index significantly explains the futures return on Chicago weather futures, which makes the APT a better model for explaining the return on Chicago weather futures, as expressed in the expectations. In addition, the regression using the APT, and controlling for the interaction terms between the risk factors and the climate variables, provides evidence of significant changes in the sensitivity to systematic risk factors due to climate changes for some variables. The coefficients on the variables IPGCO2, MRPTemp and MRPCDD are significantly different from zero at a 5 percent significance level for Chicago weather futures. The results therefore provides evidences of significant changes in the sensitivity to the systematic risk factors for Chicago weather futures. According to equation (10) in the theoretical review, the return is an estimate of the risk premium in weather futures and therefore the coefficients on the three variables provide evidence of significant changes in the risk premium due to climate changes per unit of the risk factors.

When using the CAPM, and the interaction term between the market risk premium and the dummy variable year to explain the futures return, none of the intercepts are significantly different from zero in any of the regressions. When controlling for the climate changes, the CAPM does not appear to hold as the intercepts are significantly different from zero at a 10 percent significance level. In the robustness test by adding the variable indicating whether there is a financial crisis or not, the regression does not provide evidence of nonzero coefficients as the intercepts are not significantly different from zero and the CAPM appears to hold during a financial crisis when controlling for climate changes.

From the empirical review, Cao and Wei (2004, 1088) found evidences of a significant risk premium for the variable temperature and that the risk premium can constitute a significant part of the price of a derivative built on weather. The regression results provide evidence that the APT seems like the best model for explaining the return on the weather futures for Chicago, as was the expectation. For weather futures on New York there are not found the same significant results that indicates that the APT is better than the CAPM. To conclude, in the regression for the weather futures on New York there is hard to find significant changes in the risk premium due to climate changes. But from the evidences in the data some coefficients indicates significant changes in the systematic risk and significant changes in the risk premium due to climate changes for weather futures on Chicago when using the APT.

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Appendices

```
. regress LogrChicago MRpremium Year MRPyear
```

Source	SS	df	MS
Model	.060610222	3	.020203407
Residual	26.8765753	235	.114368406
Total	26.9371855	238	.113181452

Number of obs	=	239
F(3, 235)	=	0.18
Prob > F	=	0.9121
R-squared	=	0.0023
Adj R-squared	=	-0.0105
Root MSE	=	.33818

LogrChicago	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	.3256466	.6360318	0.51	0.609	-.927406	1.578699
Year	-.0115259	.0445325	-0.26	0.796	-.0992597	.076208
MRPyear	.137348	1.137238	0.12	0.904	-2.103136	2.377832
_cons	.0051545	.0298094	0.17	0.863	-.0535732	.0638822

```
. regress LogrNY MRpremium Year MRPyear
```

Source	SS	df	MS
Model	.091478662	3	.030492887
Residual	41.5600543	235	.176851295
Total	41.6515329	238	.175006441

Number of obs	=	239
F(3, 235)	=	0.17
Prob > F	=	0.9150
R-squared	=	0.0022
Adj R-squared	=	-0.0105
Root MSE	=	.42054

LogrNY	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	.0774137	.7909152	0.10	0.922	-1.480776	1.635604
Year	-.0178919	.0553768	-0.32	0.747	-.1269903	.0912064
MRPyear	.7208651	1.414172	0.51	0.611	-2.06521	3.50694
_cons	.0078626	.0370684	0.21	0.832	-.0651663	.0808914

```
. regress LogrChicago MRpremium Ipgrowth Year MRPyear IPGyear

      Source |       SS           df       MS      Number of obs   =       239
-------------+----------------------------------   F(5, 233)       =      1.09
       Model |  .618157302         5  .12363146   Prob > F        =    0.3641
    Residual |  26.3190282       233  .112957203   R-squared       =    0.0229
-------------+----------------------------------   Adj R-squared   =    0.0020
       Total |  26.9371855       238  .113181452   Root MSE        =    .33609

------------------------------------------------------------------------------
 LogrChicago |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   MRpremium |   .3169445   .6337977     0.50   0.617    -.9317622    1.565651
    Ipgrowth |   .7154041    3.81612     0.19   0.851    -6.803107    8.233916
        Year |  -.0316926   .0451993    -0.70   0.484    -.1207442    .0573589
     MRPyear |   .4016488    1.13703     0.35   0.724    -1.838525    2.641822
     IPGyear |   14.39749   7.820971     1.84   0.067    -1.011372    29.80634
       _cons |   .0050399   .0296312     0.17   0.865    -.0533395    .0634192
------------------------------------------------------------------------------
```

```
. regress LogrNY MRpremium Ipgrowth Year MRPyear IPGyear

      Source |       SS           df       MS      Number of obs   =       239
-------------+----------------------------------   F(5, 233)       =      0.30
       Model |  .266730635         5  .053346127   Prob > F        =    0.9123
    Residual |  41.3848023       233  .177617177   R-squared       =    0.0064
-------------+----------------------------------   Adj R-squared   =   -0.0149
       Total |  41.6515329       238  .175006441   Root MSE        =    .42145

------------------------------------------------------------------------------
      LogrNY |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   MRpremium |   .0507621   .7947603     0.06   0.949    -1.515073    1.616597
    Ipgrowth |   2.191039   4.785283     0.46   0.647    -7.236913    11.61899
        Year |  -.0276676   .0566784    -0.49   0.626    -.1393352    .0839999
     MRPyear |    .875141   1.425796     0.61   0.540    -1.933959    3.684241
     IPGyear |   5.355054   9.807226     0.55   0.586    -13.96712    24.67723
       _cons |   .0075114   .0371565     0.20   0.840    -.0656942    .0807171
------------------------------------------------------------------------------
```

Source	SS	df	MS		
				Number of obs =	237
				F(13, 223) =	2.48
Model	3.40051524	13	.261578095	Prob > F =	0.0035
Residual	23.4835897	223	.105307577	R-squared =	0.1265
				Adj R-squared =	0.0756
Total	26.884105	236	.113915699	Root MSE =	.32451

LogrChicago	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	-10.81229	12.06421	-0.90	0.371	-34.58674	12.96215
Precipitation	-.0031646	.0017481	-1.81	0.072	-.0066096	.0002804
NotWork	-.0007099	.0002212	-3.21	0.002	-.0011458	-.0002741
CDD	-.000215	.0004878	-0.44	0.660	-.0011762	.0007463
CO2	-4.62e-10	7.45e-10	-0.62	0.536	-1.93e-09	1.01e-09
TF	-.0079758	.0063302	-1.26	0.209	-.0204505	.0044988
Temptonormal	.2862832	.1059486	2.70	0.007	.0774946	.4950718
MRPprec	-.0613298	.0430126	-1.43	0.155	-.146093	.0234335
MRPnwork	.0093381	.008507	1.10	0.274	-.0074262	.0261025
MRPCDD	-.0220977	.0131659	-1.68	0.095	-.0480433	.0038478
MRPCO2	6.34e-10	2.12e-08	0.03	0.976	-4.11e-08	4.24e-08
MRPTemp	.3267521	.1766568	1.85	0.066	-.0213782	.6748824
MRPtempton	-2.324177	2.313612	-1.00	0.316	-6.883517	2.235163
_cons	.7958715	.4341457	1.83	0.068	-.0596817	1.651425

Source	SS	df	MS		
				Number of obs =	237
				F(13, 223) =	2.10
Model	4.53162053	13	.348586195	Prob > F =	0.0152
Residual	37.0416834	223	.166106204	R-squared =	0.1090
				Adj R-squared =	0.0571
Total	41.573304	236	.176158068	Root MSE =	.40756

LogrNY	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	-5.188752	15.15172	-0.34	0.732	-35.04763	24.67013
Precipitation	-.0038409	.0021955	-1.75	0.082	-.0081676	.0004857
NotWork	-.0005234	.0002778	-1.88	0.061	-.0010708	.0000241
CDD	-.0004281	.0006126	-0.70	0.485	-.0016354	.0007792
CO2	-4.93e-10	9.36e-10	-0.53	0.599	-2.34e-09	1.35e-09
TF	-.0118368	.0079502	-1.49	0.138	-.027504	.0038304
Temptonormal	.4546747	.1330633	3.42	0.001	.1924523	.7168971
MRPprec	-.0608187	.0540206	-1.13	0.261	-.1672749	.0456375
MRPnwork	.0041094	.0106841	0.38	0.701	-.0169453	.0251642
MRPCDD	-.0139263	.0165354	-0.84	0.401	-.046512	.0186593
MRPCO2	-3.01e-09	2.66e-08	-0.11	0.910	-5.55e-08	4.95e-08
MRPTemp	.2566548	.2218674	1.16	0.249	-.1805701	.6938797
MRPtempton	-3.302354	2.905719	-1.14	0.257	-9.028535	2.423828
_cons	.9684661	.5452537	1.78	0.077	-.1060431	2.042975

Source	SS	df	MS
Model	4.13245358	20	.206622679
Residual	22.7516514	216	.105331719
Total	26.884105	236	.113915699

Number of obs	=	237
F(20, 216)	=	1.96
Prob > F	=	0.0101
R-squared	=	0.1537
Adj R-squared	=	0.0754
Root MSE	=	.32455

LogrChicago	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	-16.3334	12.7867	-1.28	0.203	-41.53609	8.869289
Ipgrowth	150.8327	71.98615	2.10	0.037	8.947405	292.7179
Precipitation	-.002677	.0017819	-1.50	0.134	-.0061892	.0008352
NotWork	-.0007391	.0002325	-3.18	0.002	-.0011973	-.0002809
CDD	-.0001126	.0005006	-0.22	0.822	-.0010994	.0008741
CO2	-2.17e-10	7.61e-10	-0.29	0.776	-1.72e-09	1.28e-09
TF	-.0099466	.0064982	-1.53	0.127	-.0227546	.0028614
Temptonormal	.3127691	.1094908	2.86	0.005	.0969618	.5285763
MRPprec	-.0394413	.0443655	-0.89	0.375	-.1268861	.0480034
MRPnwork	.0122815	.009239	1.33	0.185	-.0059286	.0304915
MRPCDD	-.0280075	.0139094	-2.01	0.045	-.055423	-.000592
MRPCO2	1.57e-09	2.20e-08	0.07	0.943	-4.18e-08	4.50e-08
MRPTemp	.4078041	.1921842	2.12	0.035	.0290076	.7866006
MRPtempton	-2.965928	2.521298	-1.18	0.241	-7.935425	2.003569
IPGPrec	-.3502296	.318099	-1.10	0.272	-.9772051	.2767458
IPGnwork	-.0024468	.0431574	-0.06	0.955	-.0875102	.0826167
IPGCDD	-.0142717	.0823601	-0.17	0.863	-.1766041	.1480606
IPGCO2	-2.90e-07	1.35e-07	-2.14	0.033	-5.57e-07	-2.32e-08
IPGTemp	.1122512	.8999512	0.12	0.901	-1.661559	1.886062
IPGTempton	-2.037427	17.77451	-0.11	0.909	-37.07113	32.99627
_cons	.7319988	.4461829	1.64	0.102	-.1474309	1.611429

Source	SS	df	MS
Model	4.78646209	20	.239323105
Residual	36.7868419	216	.170309453
Total	41.573304	236	.176158068

Number of obs	=	237
F(20, 216)	=	1.41
Prob > F	=	0.1217
R-squared	=	0.1151
Adj R-squared	=	0.0332
Root MSE	=	.41269

LogrNY	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	-7.843755	16.25917	-0.48	0.630	-39.8907	24.20319
Ipgrowth	63.28786	91.53533	0.69	0.490	-117.129	243.7047
Precipitation	-.0036162	.0022659	-1.60	0.112	-.0080823	.0008498
NotWork	-.0005369	.0002956	-1.82	0.071	-.0011196	.0000457
CDD	-.0004574	.0006366	-0.72	0.473	-.0017122	.0007973
CO2	-3.08e-10	9.68e-10	-0.32	0.751	-2.22e-09	1.60e-09
TF	-.01276	.0082629	-1.54	0.124	-.0290463	.0035262
Temptonormal	.4832996	.1392251	3.47	0.001	.2088858	.7577133
MRPprec	-.0529482	.0564138	-0.94	0.349	-.1641402	.0582438
MRPnwork	.0057896	.011748	0.49	0.623	-.0173658	.0289449
MRPCDD	-.0171865	.0176867	-0.97	0.332	-.0520472	.0176742
MRPCO2	-3.96e-09	2.80e-08	-0.14	0.888	-5.91e-08	5.12e-08
MRPTemp	.3156161	.2443754	1.29	0.198	-.1660496	.7972818
MRPtempton	-4.147624	3.206003	-1.29	0.197	-10.46668	2.171432
IPGPrec	-.1816813	.4044847	-0.45	0.654	-.9789237	.615561
IPGnwork	.0012976	.0548775	0.02	0.981	-.1068665	.1094616
IPGCDD	.027946	.1047265	0.27	0.790	-.1784708	.2343627
IPGCO2	-1.39e-07	1.72e-07	-0.81	0.421	-4.78e-07	2.00e-07
IPGTemp	.2919117	1.14435	0.26	0.799	-1.96361	2.547434
IPGTempton	-12.8475	22.60151	-0.57	0.570	-57.39525	31.70026
_cons	.9071473	.5673521	1.60	0.111	-.2111079	2.025403

Source	SS	df	MS			
				Number of obs	=	237
				F(14, 222)	=	2.30
Model	3.40508209	14	.243220149	Prob > F	=	0.0058
Residual	23.4790229	222	.105761364	R-squared	=	0.1267
				Adj R-squared	=	0.0716
Total	26.884105	236	.113915699	Root MSE	=	.32521

LogrChicago	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	-10.82647	12.09037	-0.90	0.372	-34.65304	13.00011
Precipitation	-.0031794	.0017533	-1.81	0.071	-.0066347	.0002759
NotWork	-.0007112	.0002218	-3.21	0.002	-.0011482	-.0002742
CDD	-.0002102	.0004894	-0.43	0.668	-.0011746	.0007542
CO2	-4.95e-10	7.63e-10	-0.65	0.517	-2.00e-09	1.01e-09
TF	-.0080171	.0063469	-1.26	0.208	-.020525	.0044908
Temptonormal	.2865454	.1061841	2.70	0.007	.0772876	.4958033
MRPprec	-.0625574	.0435082	-1.44	0.152	-.1482993	.0231845
MRPnwork	.0094103	.0085324	1.10	0.271	-.0074045	.0262252
MRPCDD	-.0217911	.0132765	-1.64	0.102	-.0479552	.0043731
MRPCO2	1.09e-09	2.14e-08	0.05	0.959	-4.10e-08	4.32e-08
MRPTemp	.3237719	.177617	1.82	0.070	-.0262591	.6738029
MRPtempton	-2.278598	2.328943	-0.98	0.329	-6.868263	2.311068
FinCrisis	.0146835	.0706619	0.21	0.836	-.1245703	.1539374
_cons	.8111188	.441224	1.84	0.067	-.0584046	1.680642

Source	SS	df	MS			
				Number of obs	=	237
				F(14, 222)	=	1.94
Model	4.53212991	14	.323723565	Prob > F	=	0.0237
Residual	37.041174	222	.166852135	R-squared	=	0.1090
				Adj R-squared	=	0.0528
Total	41.573304	236	.176158068	Root MSE	=	.40848

LogrNY	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	-5.193485	15.18595	-0.34	0.733	-35.12054	24.73357
:ecipitation	-.0038459	.0022022	-1.75	0.082	-.0081859	.0004941
NotWork	-.0005238	.0002785	-1.88	0.061	-.0010727	.0000251
CDD	-.0004265	.0006147	-0.69	0.488	-.0016379	.0007848
CO2	-5.04e-10	9.58e-10	-0.53	0.600	-2.39e-09	1.38e-09
TF	-.0118506	.007972	-1.49	0.139	-.027561	.0038599
:emptonormal	.4547623	.1333712	3.41	0.001	.1919267	.7175978
MRPprec	-.0612287	.0546479	-1.12	0.264	-.1689237	.0464663
MRPnwork	.0041336	.010717	0.39	0.700	-.0169865	.0252536
MRPCDD	-.0138239	.0166758	-0.83	0.408	-.0466871	.0190392
MRPCO2	-2.86e-09	2.68e-08	-0.11	0.915	-5.57e-08	5.00e-08
MRPTemp	.2556595	.2230934	1.15	0.253	-.1839924	.6953114
MRPtempton	-3.287131	2.925238	-1.12	0.262	-9.05192	2.477658
FinCrisis	.0049039	.0887539	0.06	0.956	-.1700041	.1798119
_cons	.9735583	.5541936	1.76	0.080	-.1185951	2.065712

Source	SS	df	MS			
				Number of obs	=	237
				F(21, 215)	=	1.86
Model	4.13472031	21	.196891443	Prob > F	=	0.0149
Residual	22.7493846	215	.105811091	R-squared	=	0.1538
				Adj R-squared	=	0.0711
Total	26.884105	236	.113915699	Root MSE	=	.32529

LogrChicago	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	-16.32719	12.81584	-1.27	0.204	-41.58796	8.933587
Ipgrowth	149.4525	72.76333	2.05	0.041	6.03172	292.8734
Precipitation	-.002679	.0017861	-1.50	0.135	-.0061995	.0008414
NotWork	-.0007366	.0002336	-3.15	0.002	-.0011971	-.0002761
CDD	-.0001111	.0005019	-0.22	0.825	-.0011004	.0008781
CO2	-2.44e-10	7.85e-10	-0.31	0.756	-1.79e-09	1.30e-09
TF	-.009921	.0065153	-1.52	0.129	-.0227631	.0029211
Temptonormal	.3121762	.1098144	2.84	0.005	.0957255	.528627
MRPprec	-.040122	.0447089	-0.90	0.371	-.1282459	.0480019
MRPnwork	.0122506	.0092624	1.32	0.187	-.006006	.0305073
MRPCDD	-.027795	.0140164	-1.98	0.049	-.0554221	-.0001679
MRPCO2	1.94e-09	2.22e-08	0.09	0.930	-4.18e-08	4.57e-08
MRPTemp	.4048203	.1936968	2.09	0.038	.0230326	.7866081
MRPtempton	-2.918477	2.54774	-1.15	0.253	-7.940223	2.103268
IPGPrec	-.3510899	.3188762	-1.10	0.272	-.9796137	.2774339
IPGnwork	-.0034826	.0438306	-0.08	0.937	-.0898754	.0829102
IPGCDD	-.0142551	.0825474	-0.17	0.863	-.1769609	.1484506
IPGCO2	-2.85e-07	1.39e-07	-2.05	0.042	-5.60e-07	-1.11e-08
IPGTemp	.1100992	.9021166	0.12	0.903	-1.668026	1.888224
IPGTempton	-2.134217	17.82718	-0.12	0.905	-37.27265	33.00422
FinCrisis	.0121534	.0830355	0.15	0.884	-.1515145	.1758213
_cons	.740841	.4512591	1.64	0.102	-.1486174	1.630299

Source	SS	df	MS			
				Number of obs	=	237
				F(21, 215)	=	1.33
Model	4.78725966	21	.227964746	Prob > F	=	0.1567
Residual	36.7860443	215	.17109788	R-squared	=	0.1152
				Adj R-squared	=	0.0287
Total	41.573304	236	.176158068	Root MSE	=	.41364

LogrNY	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MRpremium	-7.840069	16.29685	-0.48	0.631	-39.96213	24.28199
Ipgrowth	62.4692	92.52717	0.68	0.500	-119.9073	244.8457
Precipitation	-.0036175	.0022712	-1.59	0.113	-.0080941	.0008592
NotWork	-.0005355	.0002971	-1.80	0.073	-.001121	.0000501
CDD	-.0004566	.0006382	-0.72	0.475	-.0017145	.0008014
CO2	-3.23e-10	9.98e-10	-0.32	0.746	-2.29e-09	1.64e-09
TF	-.0127448	.008285	-1.54	0.125	-.0290751	.0035854
Temptonormal	.4829479	.139642	3.46	0.001	.2077052	.7581906
MRPprec	-.053352	.0568527	-0.94	0.349	-.165412	.0587079
MRPnwork	.0057713	.0117782	0.49	0.625	-.0174442	.0289868
MRPCDD	-.0170604	.0178235	-0.96	0.340	-.0521916	.0180707
MRPCO2	-3.74e-09	2.82e-08	-0.13	0.895	-5.94e-08	5.19e-08
MRPTemp	.3138462	.2463083	1.27	0.204	-.171642	.7993345
MRPtempton	-4.119477	3.239752	-1.27	0.205	-10.50522	2.266266
IPGPrec	-.1821916	.4054887	-0.45	0.654	-.9814339	.6170506
IPGnwork	.0006831	.0557358	0.01	0.990	-.1091755	.1105418
IPGCDD	.0279558	.1049688	0.27	0.790	-.1789438	.2348554
IPGCO2	-1.36e-07	1.77e-07	-0.77	0.443	-4.85e-07	2.13e-07
IPGTemp	.2906352	1.147148	0.25	0.800	-1.970461	2.551731
IPGTempton	-12.90491	22.66937	-0.57	0.570	-57.58758	31.77776
FinCrisis	.0072091	.1055894	0.07	0.946	-.2009139	.2153322
_cons	.9123923	.5738293	1.59	0.113	-.2186592	2.043444

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Generating interaction term between year and the market risk premium:
gen MRPyear = MRpremium*Year



Generating interaction term between year and the growth in the industrial production index:
gen IPGyear = Ipgrowth*Year



CAPM with dummy variable Year
regress LogrChicago MRpremium Year MRPyear
regress LogrNY MRpremium Year MRPyear

presentable results
eststo returnC: regress LogrChicago MRpremium Year MRPyear
eststo returnNY: regress LogrNY MRpremium Year MRPyear
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APT with dummy variable Year
regress LogrChicago MRpremium Ipgrowth Year MRPyear IPGyear
regress LogrNY MRpremium Ipgrowth Year MRPyear IPGyear

presentable results
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eststo ReturnNY: regress LogrNY MRpremium Ipgrowth Year MRPyear IPGyear
esttab ReturnC ReturnNY, se r2 mtitles varwidth(16)





Generating interaction terms between market risk premium and climate variables:
gen MRPprec = MRpremium*Precipitation
gen MRPnwork = MRpremium*NotWork
gen MRPCDD = MRpremium*CDD
gen MRPCO2= MRpremium*CO2
gen MRPTemp = MRpremium*TF
gen MRPtempton = MRpremium*Temptonormal
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Generating interaction terms between growth in industrial production index and climate variables:
gen IPGPrec = Ipgrowth*Precipitation
gen IPGnwork = Ipgrowth*NotWork
gen IPGCDD = Ipgrowth*CDD
gen IPGCO2 = Ipgrowth*CO2
gen IPGTemp = Ipgrowth*TF
gen IPGTempton = Ipgrowth*Temptonormal




CAPM with climate variables
reg LogrChicago MRpremium Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPTempton
reg LogrNY MRpremium Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPTempton

presentable results
eststo ReturnC: reg LogrChicago MRpremium Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton
eststo ReturnNy: reg LogrNY MRpremium Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton
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reg LogrNY MRpremium Ipgrowth Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton IPGPrec IPGnwork IPGCDD IPGCO2 IPGTemp IPGTempton

presentable res:
eststo returnC: reg LogrChicago MRpremium Ipgrowth Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton IPGPrec IPGnwork IPGCDD IPGCO2 IPGTemp IPGTempton
eststo returnNY: reg LogrNY MRpremium Ipgrowth Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton IPGPrec IPGnwork IPGCDD IPGCO2 IPGTemp IPGTempton
esttab returnC returnNY, se r2 mtitles varwidth(16)









CAPM with the dummy variable fincrisis:
eststo ReturnC: regress LogrChicago MRpremium Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton FinCrisis
eststo ReturnNY: regress LogrNY MRpremium Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton FinCrisis
esttab ReturnC ReturnNY, se r2 mtitles varwidth(16)
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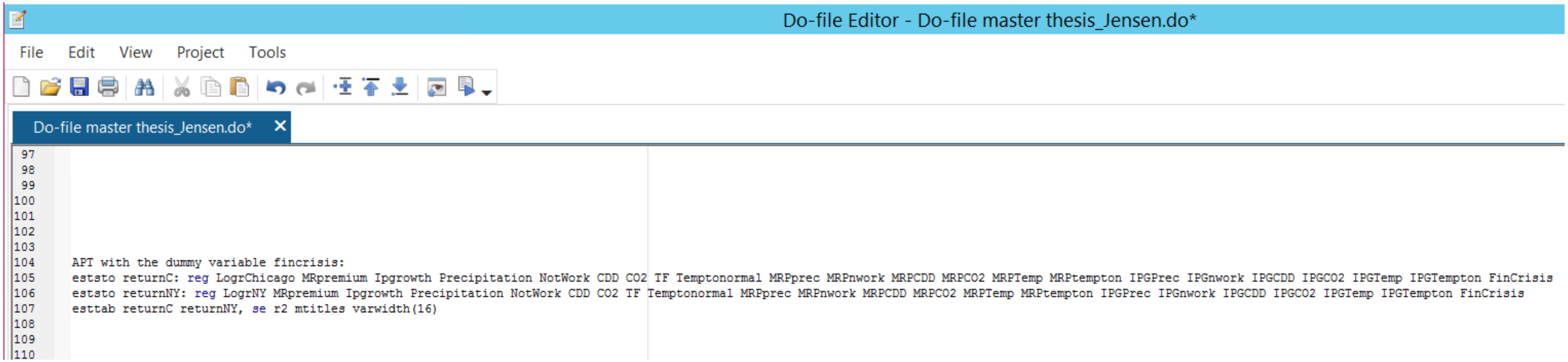
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APT with the dummy variable fincrisis:
eststo returnC: reg LogrChicago MRpremium Ipgrowth Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton IPGPrec IPGnwork IPGCDD IPGCO2 IPGTemp IPGTempton FinCrisis
eststo returnNY: reg LogrNY MRpremium Ipgrowth Precipitation NotWork CDD CO2 TF Temptonormal MRPprec MRPnwork MRPCDD MRPCO2 MRPTemp MRPtempton IPGPrec IPGnwork IPGCDD IPGCO2 IPGTemp IPGTempton FinCrisis
esttab returnC returnNY, se r2 mtitles varwidth(16)

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CAPM with dummy variable Year
regress LogrChicago MRpremium Year MRPyear
regress LogrNY MRpremium Year MRPyear

presentable results
eststo returnC: regress LogrChicago MRpremium Year MRPyear
eststo returnNY: regress LogrNY MRpremium Year MRPyear
esttab returnC returnNY, se r2 mtitles varwidth(16)


F-test for the Chow break test:
test Year MRPyear








APT with dummy variable Year
regress LogrChicago MRpremium Ipgrowth Year MRPyear IPGyear
regress LogrNY MRpremium Ipgrowth Year MRPyear IPGyear

presentable results
eststo ReturnC: regress LogrChicago MRpremium Ipgrowth Year MRPyear IPGyear
eststo ReturnNY: regress LogrNY MRpremium Ipgrowth Year MRPyear IPGyear
esttab ReturnC ReturnNY, se r2 mtitles varwidth(16)


F-test for the Chow break test:
test Year MRPyear IPGyear
```