Climate Change Risk in Stock Markets

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Climate change is becoming a common threat to the world and has been studied by scholars in various fields. In the field of finance, many papers have discussed financial market efficiency toward climate change in order to better manage related risks. Our work focuses on the topic of climate change risk in the stock market. We use long-term trends of a newly released climate index, Actuaries Climate Index (ACI), as proxies for climate change risk. As a type of production risk, ACI trends have an adverse impact on the agricultural production and corporate profitability of agriculture-related companies. We find significant predictability of climate change risk on corporate profits. This motivates us to further test the predictability of the ACI on stock returns. We construct a risk-adjusted stock trading strategy that adjusts to climate change risk. With a one-year holding period, our non-overlapping strategy earns positive returns with zero cost at the beginning over a 26-year test period. The outperformance suggests the predictive ability of the ACI and creates potential arbitrage opportunities in the stock market. Thus, the stock market is believed to be inefficient toward climate change risk. We get similar results and conclusions for different versions and extensions of the non-overlapping strategy. However, these conclusions are no longer attainable when we look at strategy returns in shorter periods. From subsample tests, we find that our strategy performs considerably well in terms of abnormally positive returns before 2015. But the predictability on stock returns degenerates quickly over a short period of time in 2017. This "overturn" of market inefficiency highlights the importance of follow-up studies and we suggest that future research could be devoted more toward discovering evidence about market efficiency and the impact of climate events on investors' attention toward climate change risk.

Acknowledgements

First of all, I would like to express my sincere gratitude to my supervisor, Professor Chengguo Weng, for his great instructions and encouragements. Without his efforts, I could not make this thesis possible. I am deeply grateful for his patience and support through my study at the University of Waterloo. Secondly, I would like to thank my second readers, Professor David Saunders and Professor Tony S. Wirjanto, for their precious time and advice. Many thanks also go to administrative coordinators Mary Lou Dufton and Lisa Baxter for their help. In addition, I would like to thank all my friends and fellow students for their company and help. Last but not least, I would like to especially thank Keying Xu, who gives me confidence and brings unlimited happiness to my life.

Dedication

To my family.

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Chapter 1

Introduction

There is a growing consensus that climate change has become a major threat to the world. With greenhouse gas accumulating in the atmospheric layer, the global climate[1] is altered and this induces a chain of climate events. Extreme climate events are more frequently reported these years such as sea level rise, earthquakes, tornadoes, flooding, and wildfires. Social and financial damages caused by these climate events have drawn more public attention to the problem of climate change. There is rich literature studying the impact of climate change and potential risk management mechanisms for climate change risk.

1.1 Climate Change and the Agriculture Industry

The agriculture industry is always one of the natural industries in which scholars want to assess the influences of climate change since agricultural products are directly connected with climate elements such as temperature and precipitation. The risk of climate change is transmitted into the agriculture industry through many channels. For example, on the one hand, warmer temperatures would cause higher water demand and less growing season

[1]Climate refers to aggregated weather in a location over a certain period of time. Weather refers to atmosphere status such as temperature, precipitation, and humidity in a location during a short period of time (Deschnes and Greenstone, 2007 [9]).

precipitation for field crops, which would encourage the spread of diseases and reduce production. It would also affect forage and grain production in drought seasons and put pressure on livestock. High temperatures would further intensify wildfires and threaten local farms. On the other hand, redundant rainfall or precipitation would degrade soil and water resources and therefore destroy the ecosystem (Fourth National Climate Assessment (NCA4) Volume II, Reidmiller et al., 2017 [25]).

However, the impacts of climate change tend to vary among different areas since the agricultural production is affected by various factors such as types of products, technology and adaptation methods. Evidence has shown that climate change may not affect the agriculture industry or relevant industries as a whole substantially but there is considerable variation across different regions. Deschnes and Greenstone (2007) [9] estimate the impacts of climate change on the United States agricultural industry. They find that the overall impact of temperature and precipitation increase on agricultural profits is small but the state-level variation is large. Across the country, the impacts of climate change vary from \$720 million (South Dakota) to -\$750 million (California). One possible explanation for this discrepancy in regional influences may be seen in different patterns of climate change. Some states are experiencing a higher frequency of heat waves and drought and therefore tend to have lower agricultural productivity. Among all regions in the United States, Delta, Northeast and Southeast are more vulnerable to climate extremes (Wang et al., 2018 [32]). Another reason may be due to a nonlinear linkage between climate and aggregated agricultural production. Yields of popular crops would have consistently similar patterns under temperature or precipitation increase. Crop yields would slightly increase when temperature or precipitation is under certain thresholds. However, yields would decline sharply under the effects of extremely warm temperatures or high precipitation (Schlenker et al., 2009 [27]). So in short-term, a slight change in climate may benefit some crops and areas in terms of production. But in a long-run during which both temperature and precipitation are expected to become extreme, the national and global agriculture industry would be adversely influenced.

1.2 Climate Change and the Financial Market

Besides the agriculture sector, other relevant markets will also be affected by climate change through the supply chain among different industries. The risk of climate change will be transmitted into other markets through business activities. This thesis focuses on the consequent risks in the financial market. There are four general forms of transformed risk in the financial market (Painter, 2019 [24]). The two types of most frequently studied risk are physical risk that is related to financial assets valuation, and production risk that directly affects agricultural production or relevant profits. These two types of climate change risk have been analyzed by many scholars and received different degrees of market recognition by investors. Most physical risk studies concentrate on bond pricing with a climate discount and find that the risk is identified by the market. Battiston and Monasterolo (2019) [2] find that countries that are highly dependent on carbon-intensive sectors would have larger climate spreads on their sovereign bonds. Investors holding these sovereign portfolios would be affected more by physical climate risk. Similarly, long-term municipal bonds are also affected by physical climate risk. Coastal counties in the United States have to pay more issuance fees to issue their municipal bonds and the penalties are enlarged after the release of a review that demonstrates the potential damage caused by climate change in 2006 (Painter, 2019 [24]).

Nevertheless, production risk is remaining unrecognized by investors according to many scholars. For instance, Dell et al. (2012) [8] study the temperature effects on aggregated economic outcomes and identify a negative effect of high temperatures on agricultural outputs. Hong et al. (2019) [16] exploit production risk of drought in the stock market. They find that the market is underreacting to the risk. In Fang et al.'s (2019) [14], they build a sustainable portfolio under a Markowitz mean-variance portfolio optimization framework and find that controlling the investment in carbon-intensive sectors improves the mean returns and standard deviations of the portfolio. Also analyzing under the standard mean-variance framework, Benedetti et al. (2019) [3] find that institutional investors are less aware of climate change risk and the market is not adequately pricing the risk. As a result, investors could reduce ex-post risks through divestment in some fossil fuel stocks and the cost of their de-risking Bayesian portfolio is considerably low. The failure of correctly pricing climate change risk also leads to discussions about market efficiency. The Efficient Market Hypothesis (EMH) stipulates that under a semi-strong form of market efficiency, stock prices should reflect all available public information (Fama, 1970 [10]). Opponents of EMH try to disprove this hypothesis by exploiting arbitrage opportunities on public climate information or translated information such as climate trends[2]. For instance, Liesen (2015) [21] constructs a green investment strategy by buying companies with more greenhouse gas emission disclosure and selling companies with less disclosure. His strategy earns significantly positive returns and these abnormal risk-adjusted returns may serve as evidence for market inefficiency toward climate change risk. Parallel to the green investment strategy, a long-short strategy by Hong et al. (2019) [16] also adjusts to systematic climate risk in the stock market and rejects the EMH.

1.3 Outline

In light of the literature, this thesis studies climate change risk in the stock market. We want to study if the stock market correctly prices production climate risk. We use a newly released climate index, the Actuaries Climate Index (ACI), as proxies for climate change risk. We find that the risk indexed by the ACI has significantly adverse impacts on agricultural production and relevant companies' financial performance. Based on this evidence, we focus on stocks that are highly connected to climate change and we group stocks in agriculture, food and beverage sectors together to define a new sector called agriculture-related sector. We construct a risk-adjusted trading strategy to test the predictability of the ACI on agriculture-related stock returns. Through multiple versions and extensions of the default strategy, we find that the predictability does exist over a long-term period but degenerates after 2015. The existence of predictability on stock returns rejects the classical hypothesis of market efficiency. Thus, the degeneration in a short period implies

[2]Some papers test the EMH based on translated information such as climate trends. This type of information is extracted from available public information such as climate indices. So they actually study the translation of market efficiency. Our thesis also focuses on the translation of market efficiency. In the rest of the thesis, we may use the term "market efficiency" to refer to the translation of market efficiency for simplicity.

changes of market recognition towards climate change risk. Our thesis contributes to the study of climate change risk and stock market efficiency toward the risk. We use the composite climate index to measure climate change risk in Canada and the United States. Our comprehensive analysis supplements current research on climate change and financial market efficiency. The distinct finding of a transition process from inefficiency towards efficiency refutes the efficacy of the claim about stock market inefficiency and generates further interests in future research.

The rest of the thesis proceeds as follows. Chapter 2 introduces the climate index, which provides proxies of climate change risk, and stock data used in the analysis. Chapter 3 introduces the motivation for the predictability on stock returns and tests the predictability with a relative strength trading strategy. Chapter 4 assesses the stock return predictability of the ACI in extended fields and with various suitable modifications. Chapter 5 concludes the thesis.

Chapter 2

Actuaries Climate Index and Stock Data

A key quantity of climate research is the proxy of climate change risk since various weather elements can contribute to a location's climate. Proxies can be values of weather elements or composite climate indices. For weather elements, the two most popular proxies are levels of temperature and precipitation, which are good indicators of climate change and can be easily obtained. Representing regional status of heat and humidity respectively, temperature and precipitation are found to be influential in agricultural production and other human activities according to the literature. They are also main resources for building climate indices (Schlenker et al., 2009 [27]; Reidmiller et al., 2017 [25]). Climate indices are frequently used as measurements of climate (change) risk. Different from weather elements, composite climate indices combine different aspects of weather conditions in an endogenous way and thus can provide more comprehensive knowledge of regional climate. Climate indices numerically measure the severity of the climate and the magnitude of climate change in a fixed period of time. So they provide helpful information for the identification of climate change risk. So far, more climate indices are constructed for global or regional research and more quantitative studies on climate change are based on climate indices. Hong et al. (2019) [16] use the Palmer Drought Severity Index (PDSI) to estimate drought risk in different countries. Wang et al. (2018) [32] use the Temperature

Humidity Index (THI) and Oury Index for measuring risk of heat waves and drought. In our work, we want to extract risk information from a new climate index and analyze the relevant risk in the stock market. The following sections introduce two important types of data used: climate index and stock data.

2.1 Climate Index

Climate indices have a long history in quantitative research, serving as measures of climate severity and fluctuations. Well-known indices are the Palmer Drought Severity Index (PDSI), the United States Climate Extremes Index (CEI), and the International Geosphere-Biosphere Program (IGBP), etc., which are widely used in the fields of environmental science, agriculture, economics, and finance. These indices measure climate change risk from different perspectives. For example, the PDSI focuses more on drought risk while the CEI gives an overview of multivariate climate extremes in the United States. In 2016, the Actuaries Climate Index (ACI) was released by four Northern American actuarial organizations (the Canadian Institute of Actuaries, the Society of Actuaries, the Casualty Actuarial Society and the American Academy of Actuaries) and Solterra Solutions. The index is aimed at measuring extreme climate from an actuarial perspective and is the main source of the climate information in our work.

2.1.1 Overview of the ACI

The ACI is a composite climate index that provides a glance at climate extremes in Canada and the United States (American Academy of Actuaries et al., 2019 [5]). It covers 52 states and 11 provinces (Alaska, the conterminous United States, and all Canadian provinces). Provinces and states are grouped into 15 regions by geographical locations: Alaska (ALA), Central East Atlantic (CEA), Central West Pacific (CWP), Midwest (MID), Southeast Atlantic (SEA), Southern Plains (SPL), Southwest Pacific (SWP), Central Arctic (CAR), Northeast Atlantic (NEA), Northeast Forest (NEF), Northen Plains (NPL), Northwest Pacific (NWP), Canada (CAN), the United States (USA), and a combined region of two countries (USC). For each region, values are based on grid-level data. The fundamental databases are the National Oceanic and Atmospheric Administration (NOAA)'s Earth System Research Laboratory (ESRL) and the Global Historical Climatology Network (GHCN)'s Daily gridded dataset. These two databases are designed for climate extremes and are operationally updated and publicly available. With data starting from January 1961, the ACI is now updated on an indistinct frequency of around three months[1]. We work on the version of the ACI released in August 2019. It has the data up to February 2019 (or the first quarter of 2019)[2]. We work on the complete monthly data from 1961 to 2018.

Similar to the CEI, the ACI aims at measuring overall extreme climate changes. It consists of six components that represent high temperatures (T90), low temperatures (T10), precipitation (P), drought (D), wind power (W) and sea level (S) in the extreme case, respectively. A common computational problem of composite indices is how to combine components with different measurements together. For example, in the ACI, temperatures are measured in degree Celsius (C) while precipitation and drought components are measured in percentage. One way to address this problem is to calculate standardized anomalies. The published ACI also follows this adjustment and the values of the aggregated index and the components are all standardized anomalies based on a 30-year reference period from 1961 to 1990, *i.e.* values are subtracted by average levels of the reference period and then divided by standard deviations of the reference period. Therefore, six anomalies are able to be combined into the composite ACI while preserving the accuracy of components. The key metric ACI is the average of component anomalies[3]. On every update, the ACI is provided with four versions: monthly smoothed data, monthly unsmoothed data, seasonally smoothed data, and seasonally unsmoothed data. For the smoothed data, values are five-year moving averages. Table 2.1 presents a summary of the seasonally smoothed ACI as well as all six components in region USC.

[1]Generally, the ACI is updated every three months based on historical updates. But after the November 2018 release, the ACI was under improvement of methodology and the first version of the ACI using improved methodology was released in May 2019, around six months after November 2018.

[2]For every update, the ACI is on both monthly and seasonal basis.

[3]Mathematically, ACI = (T90 - T10 + P + D + W + S)/6 where the minus sign is to reserve the extreme change towards lower temperatures according to the ACI design.

Panel A: Statistics Summary							
	Mean	*Std*	Min	25*th*	50*th*	75*th*	Max
ACI	0.29	0.37	-0.39	0.02	0.16	0.66	1.02
T90	0.37	0.62	-0.64	-0.17	0.32	0.85	1.90
T10	-0.42	0.58	-1.42	-1.03	-0.28	0.02	0.51
P	0.26	0.42	-0.56	-0.09	0.26	0.61	1.41
D	0.08	0.67	-1.50	-0.43	0.17	0.59	1.45
W	0.15	0.30	-0.50	-0.12	0.21	0.39	0.68
S	0.42	0.72	-1.02	-0.08	0.46	0.88	2.20

Panel B: Correlation							
	ACI	T90	T10	P	D	W	S
ACI	1						
T90	0.85	1					
T10	-0.93	-0.93	1				
P	0.72	0.56	-0.60	1			
D	0.26	0.03	-0.18	-0.33	1		
W	0.50	0.35	-0.41	0.39	0.02	1	
S	0.78	0.55	-0.63	0.87	-0.15	0.27	1

Table 2.1: Summary of Seasonally Smoothed Data in USC (1961-2018)

The above summary statistics indicate that all six climate elements are changing towards more extreme cases. Tendencies of component T90, P, D, W, and S are reflected in positive averages and medians and negative values of T10 measure the decrease of low temperatures, which means that daily low temperatures become colder or more extreme. Generally, all components exhibit trends towards extremes. These trends in total make the ACI an increasing measurement of extreme climate. All trends are also observed in Figure 2.1 which presents time series of the ACI and components in USC.

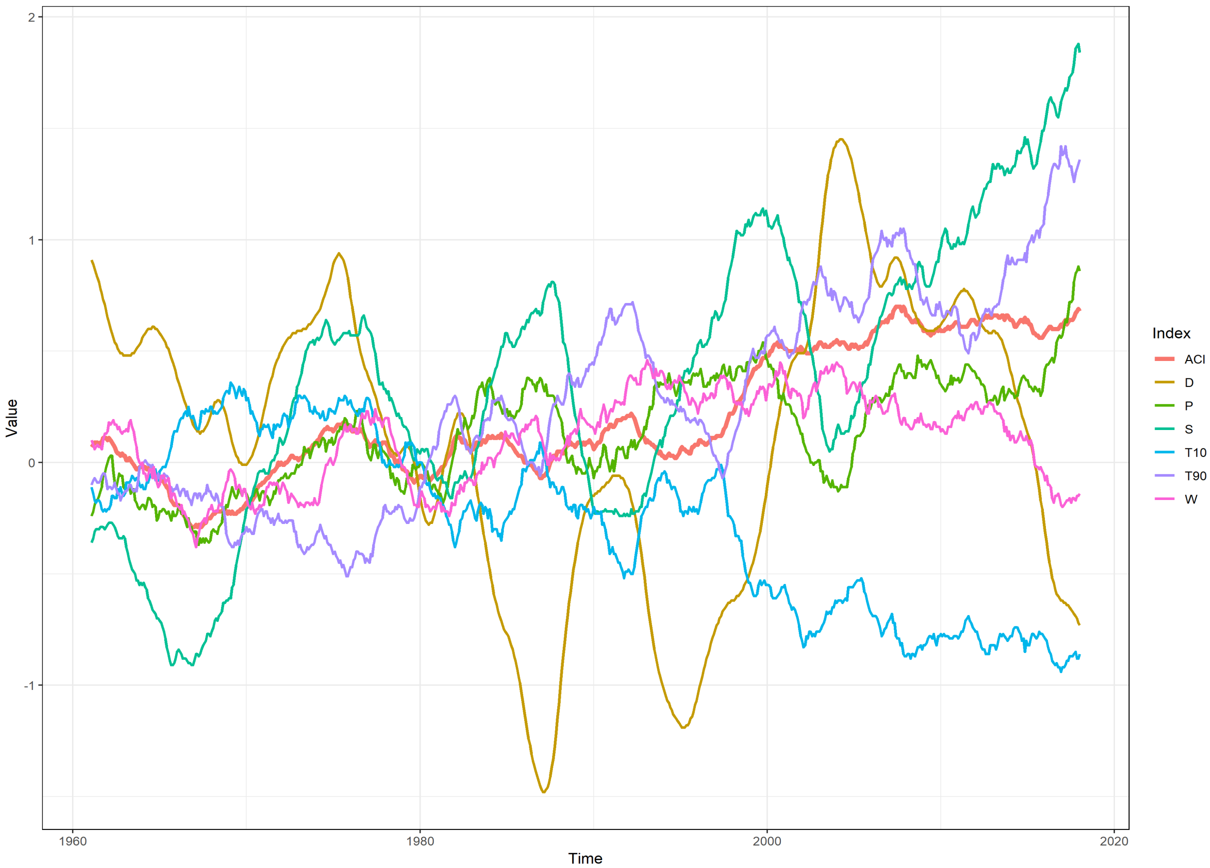

Figure 2.1: Time Series of ACI in USC (1961-2018)

Since six components are standardized from the reference period, only 32% of the data is expected to go beyond -1 or 1 (16% for each part) in cases of a Gaussian distribution. If the value is out of the range, it will be considered as an extremum. Because ACI and component values are already extreme changes, extrema imply more severe changes of climate since the reference period. Among all components, temperatures (T10 and T90) and sea level have the biggest change towards extremes. They have the largest absolute means as well as absolute 75% quantiles (25% quantile for T10). This evidence is not surprising in the context of global warming and sea level rise. Seasonal time series of the drought measurement are more volatile than others in terms of standard deviations and minimums. Drought risk is a major part of climate change risk so that the PDSI and some literature focuses on it. However, the influence of wind power seems to be mild when we compare summary statistics. The data of wind power and drought components have a similar pattern of right skewness but the wind power anomalies sit in a narrower range and have less dispersion. This may cast doubts on the contribution of this component to the index and the equivalence weights among components. A similar concern about other components may arise when we look at the correlation matrix of the ACI and components. Based on the correlation coefficients, component D and W are not much correlated with other components and thus the ACI. This might be good news since it suggests that ACI components may capture climate change from various perspectives. On the other hand, components T90, T10, P, and S are highly correlated with each other, which may bring on concern that these elements would stem from the same source such as greenhouse gas emissions and therefore the ACI would double or triple count climate change risk. Although we do not plan to discuss the selection of ACI components as well as the rationality of averaging components to obtain the ACI, we could still follow these insights to make more use of the index for risk management purposes.

2.1.2 Time Trends

The increasing trends of the ACI and its elements are consistent with common observations of climate change such as global warming and sea level rise. The ACI thus can be considered as a good measurement of climate extremes. In the implementation of climate indices, we hope to find clues about how regional climate would change in the future so that we can prepare for severe volatility. Therefore, climate trends become reasonable indicators for predicting prospective climate fluctuations. We exploit the ACI trends in this subsection in order to capture long-term time trends of the ACI and reconfirm the relationship between the ACI and real world climate events before proceeding to applications.

Figure 2.1 already shows monthly series of the ACI and components in region USC. This graph also includes a visual presentation of Table 2.1. For example, the wind component is more stable during the period than others and only fluctuates in a small range. On the contrary, values of sea level and drought are more volatile and also reach to wider scopes. Figure 2.1 starts from a component-wise perspective and only shows the data in the combined region USC. Since we are more interested in the composite index and dispersion among ACI regions, the rest of this subsection will only concentrate on the ACI data for all provincial regions.

A glance at regional indices over the entire time period is in Figure 2.2. The clustering of regional indices in the first 30 years might be due to the way in which standardized anomalies are defined. In the calculation of standardized anomalies, values of the first 30 years of the period (1961-1990) are used as benchmarks and all values are standardized with reference averages and standard deviations. Thus, most of the anomalies over the reference period are expected to be in the range of [-1,1] and have less volatility. This reminds us that if we want to investigate differences among regions, the reference period is not a good object to be tested since observations in different regions do not significantly differ from each other over this time interval. Values after 1990 would show more dispersion and are of most interest to us. After the reference period, regional indices spread along the time in three general directions: generally decreasing (ALA and NPL), level between origins and termini of the period (MID and NEF) and generally increasing (other regions). This dispersion of the ACI brings on the significance of regional analysis. All ACI regions together cover most land of Canada and the United States, which are indisputably diverse in climate, population, economy, technology, etc. Also, we can observe that even under a serious trend of global warming, some regions may not be affected largely or even could benefit from climate change. Indeed, some states in the United States, for example, South Dakota, Georgia, and Arizona, are projected to have higher agriculture production in the process of increasing temperature and precipitation (Deschnes and Greenstone, 2007 [9]).

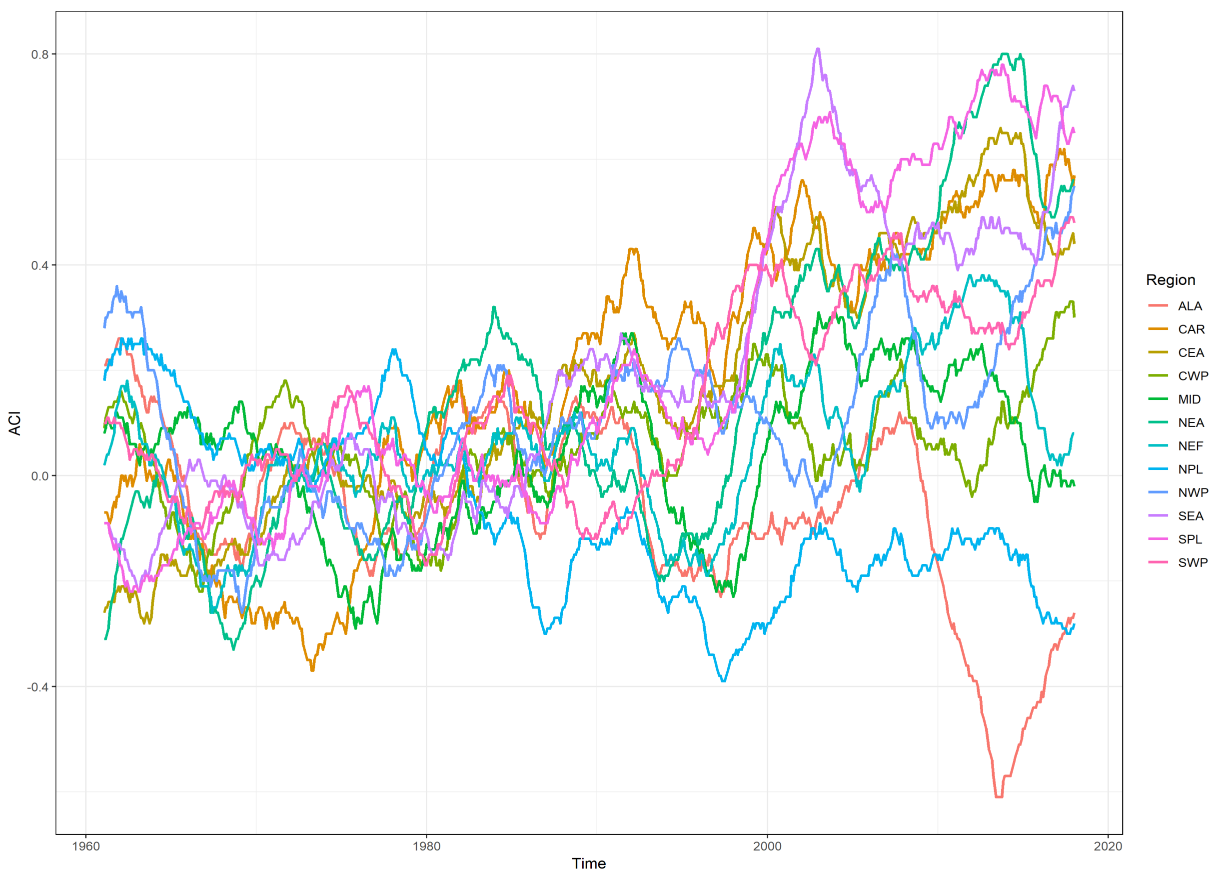

Figure 2.2: Time Series of the ACI (1961-2018)

Based on the observation, we choose a period from 1993 to 2018 as the test period. The 26-year test period is chosen to avoid the clustering effect over the reference period and capture the most recent change of the index. ACI values in the test period are clearer in Figure 2.3 and follow the same patterns as those over the entire time period. Among 12 regions, ALA and NPL experienced overall decreasing trends from other regions throughout the period. The ACI in MID and NEF fluctuated around zero from 1998 to 2017 and ended up near zero in 2017. The ACI in other regions generally shows upward trends. As mentioned earlier, the ACI measures climate extremes and definitions of the ACI and its components make higher ACI values indicating more extreme climate situations.

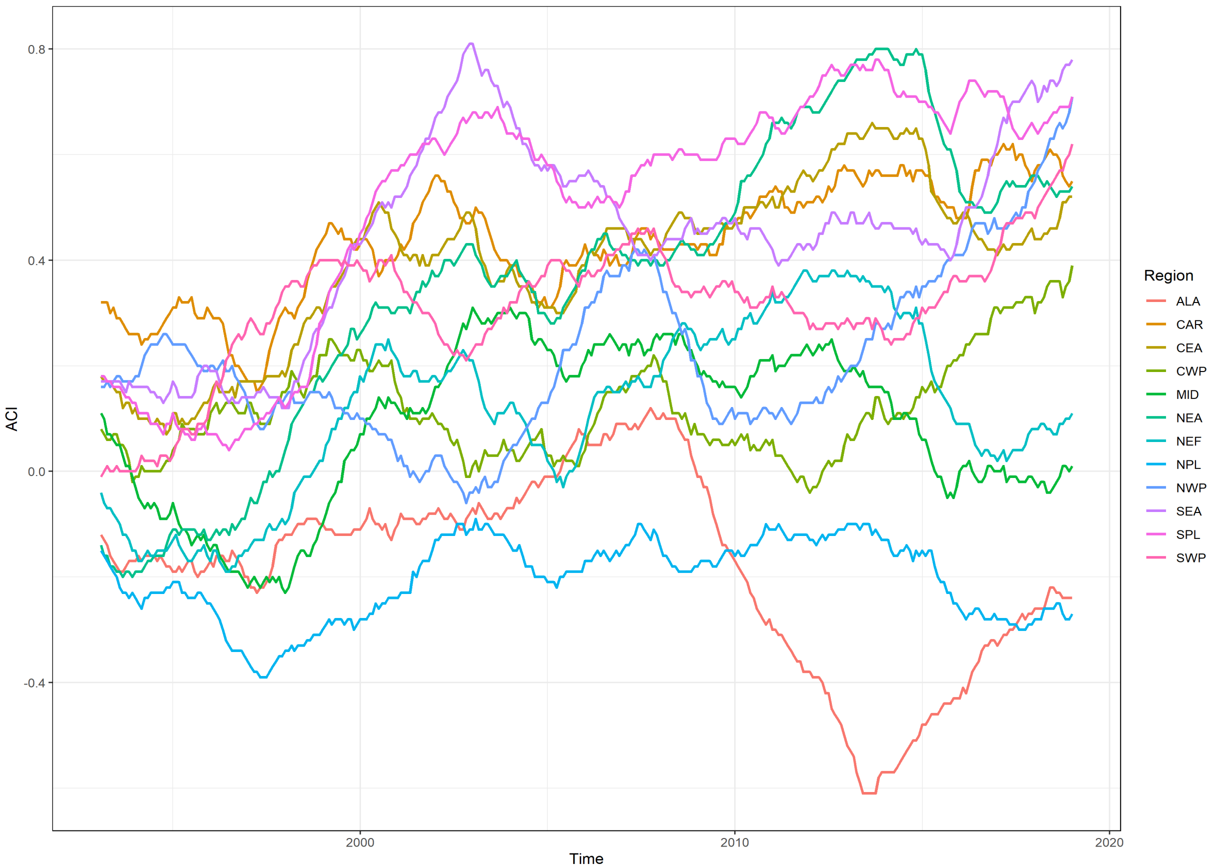

Figure 2.3: Time Series of the ACI (1993-2018)

Regional ACI has similar patterns in the test period and the full data period. To further quantify patterns, differential ACI may be a choice for very-short-term investigation. However, simple differences cannot capture the long-term change of the index as the whole picture of climate change might vary from snapshots over short terms. For the need for long-term analysis, we want to estimate long-term time trends of the ACI by time series models. From Figure 2.3, the ACI of many regions looks like a nonstationary and seasonal process. This may require to fit the time series with complex models such as Auto Regressive Integrated Moving Average (ARIMA) models in order to precisely capture the dynamics of the ACI. However, our purpose is to use the ACI data to develop a simple proxy of climate change risk for each region and consequently develop a ranking of these regions based on the proxy variable. Thus, it is imperative to maintain the model consistency among different regions. In other words, the fitted models need to convey comparable information on long-term trends of the ACI across all the regions. So, we fit the ACI data of each region with the following model and hope the approximated measurements can be taken as proxies of climate change risk in Canada and the United States.

$$ACI_{i,t} = \alpha_i + \beta_i t + \theta_i ACI_{i,t-1} + \epsilon_{i,t} \tag{2.1}$$

This time series model is a modified AR(1) model with a deterministic trend term and is used in Hong et al. (2019) [16] and Kumar et al. (2019) [20]. As $ACI_{i,t}$ measures the autocorrelation effect of prior observations and $\epsilon_{i,t}$ wraps up disturbances, the deterministic trend term $\beta_i t$ captures a long-term direction of the ACI, *i.e.* long-term time trend. At the end of each month in the test period, we use past monthly smoothed ACI data to capture approximated deterministic time trends based on Equation (2.1). Table 2.2 reports average monthly trends in the test period for all ACI regions. Trends are reported in basis points and regions are ordered according to their trends in an ascending order. The order is similar to what is shown in the above figures. NPL, NEA, and ALA have the smallest or negative time trends among all regions and MID and NEF's ACI then have almost zero trends in terms of sign and significance during the years. Nearly half of the regions have experienced high and relatively significant ACI trends (averages are larger than 0.05 bps and t test statistics are larger than 1.4), which means the extreme climate is steadily deteriorating in these regions. The last column reports average year-end time trends. Year-end trends are estimated using the same data and model from 1993 to 2018 but only estimated at the end of each year. Average year-end trends are close to average monthly trends and reserve the order of regions except for NEA.

Region	$\hat{\beta}_i$(bps)	t-stat	YET
NPL	-0.0403	-0.6040	-0.0046
NEA	-0.0040	-0.0438	0.0814
ALA	0.0049	0.1011	-0.0419
NEF	0.0290	0.8921	0.0315
MID	0.0341	0.9688	0.0310
CWP	0.0540	1.4041	0.0541
SWP	0.0783	2.1890	0.0831
SEA	0.0835	1.4815	0.0683
SPL	0.0914	1.6538	0.1202
NWP	0.1089	2.8794	0.0742
CAR	0.1399	1.9019	0.1951
CEA	0.1405	1.5700	0.1591

Table 2.2: Average Long-term Trends (1993-2018)

However, the rank of regions is not the same as in Figure 2.4 as the averages and statistics in the above summary. In Figure 2.4, monthly trends are displayed based on ranks, *i.e.* we combine trends at the same rank. Several regions may contribute to the trends of a specific rank. For example, the smallest trends are on the lowest line in Figure 2.4 and NEA, NPL, and ALA all have been the region that has the smallest trend during the test period. Thus, the lowest line is built on several pieces of different colors which represent different regions. We can still observe some stable tendencies in Figure 2.4. For example, trends in NEA, NPL, and ALA are in the lowest ranks most of the time while those in CAR and CEA are steadily high-ranked, which is anticipated through the evidence of average trends in Table 2.2. We can also conclude from the graph that the partition based on ACI trends significantly separates regions with different exposure to climate change. Compared with raw ACI data, long-term time trends $\hat{\beta}_i$ capture the effect of magnitude and capture climate change in most recent years and therefore have higher predictability on future climate situations. Since larger ACI trends imply the greater potential of climate deterioration, instead of using raw ACI values, we now focus on long-term ACI trends as proxies of climate change risk. Higher trends represent a greater possibility of climate degeneration, *i.e.* higher climate change risk. Therefore, Table 2.2 also provides a risk rank about ACI regions and gives us an overview of climate change risk in Canada and the United States.

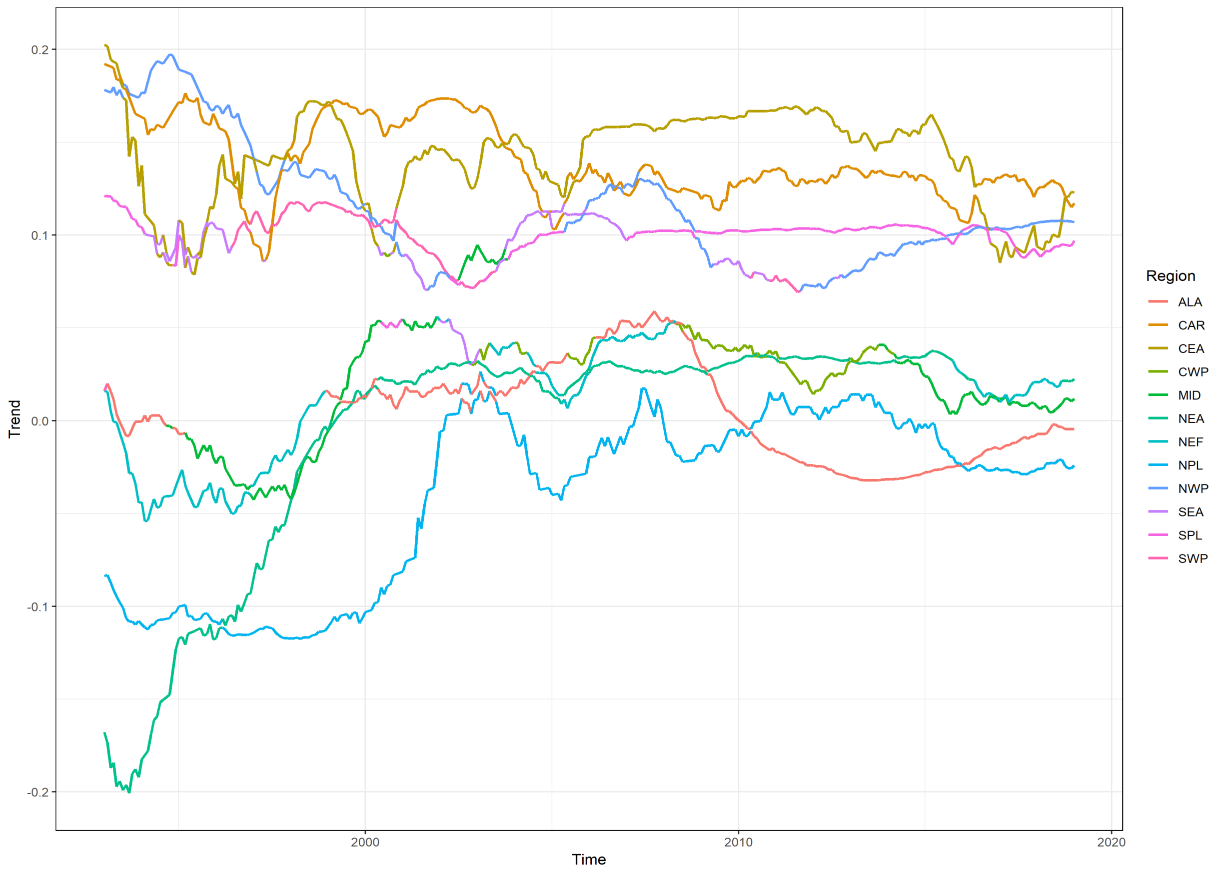

Figure 2.4: Highest Four Trends and Lowest Four Trends (1993-2018)

2.1.3 Risk and Production

So far, we have a climate index that stores historical extreme climate in Canada and the United States. We defined proxies of how severe climate change is, *i.e.* ACI time trends. We want to use them to quantify climate change risk indexed by the ACI. Our primary confidence about the measurement comes from the credibility of the ACI since we do observe several common climate events from ACI time series. However, in order to apply our proxies in further analysis, the credibility of ACI trends reflecting the underlying risk is still to be validated since ACI trends are approximated.

Painter (2019) [24] summarizes general genres of climate-induced risk existing in the financial market, among which production risk is the main focus of our work. We believe that climate change risk captured by ACI time trends will affect the agriculture industry most. Thus, climate change risk in our work should also belong to the type of production risk the industry faces. In order to verify the reliability of ACI trends as proxies for production climate risk, we assess the correlation between ACI trends and the farm production in Canada and the United States using fixed effects (FE) and random effects (RE) models. The idea of the assessment is that if ACI trends have a significantly negative impact on the farm production (yields and revenues), then we could trust them to be used as proxies of risk.

We use wheat yields and revenues (yields times price) to represent the farm production in Canada and the United States. Yields are measured in tonnes per hectare (t/ha) and prices are measured in dollars per ton ($/t). Thus, revenues are measured in dollars per hectare ($/ha). Because we have ACI trends for twelve regions, we need popular agricultural products to match the geographical diversity. Wheat is a common type of field crop grown in most ACI regions. As crop farms are considerably stable in locations and field crops highly depend on soil, temperature, precipitation and other climate elements, wheat is a good sample to assess the reliability of ACI trends. We collect regional wheat yield and price data for 9 provinces (Canada) and 42 states (the United States), which cover 10 ACI regions except for ALA and CRA, from 1988 to 2018. The models we used are as follows:

$$FP_{i,t} = a_i + b\hat{\beta}_{i,t-1} + \epsilon_{i,t},\ t = 1, ..., T,\ i = 1, ..., N \tag{2.2}$$

$$FP_{i,t} = \mu + X_i + Y_{i,t} + b\hat{\beta}_{i,t-1} + \epsilon_{i,t},\ t = 1, ..., T,\ i = 1, ..., N \tag{2.3}$$

The first one is the fixed effects (FE) model. $FP_{i,t}$ is the farm production (yield or revenue) of region i at time t. a_i is the unobserved fixed effect in region i. $\hat{\beta}_{i,t-1}$ is the ACI trend in region i at time *t-1*. We do not use contemporary ACI trends in order to test if $\hat{\beta}$

predicts future farm production. Equation (2.3) is the random effects (RE) model. μ is the intercept. The random effects are figured by random variables X_i and $Y_{i,t}$. $Y_{i,t}$ captures a deviation of the level at time t from the average level in region i, while X_i captures a deviation of the average level in region i from the average level in all regions. We report results of these two models in Table 2.3.

	Yield		*Revenue*	
	FE	*RE*	*FE*	*RE*
$\hat{b}$	-0.4441^{***}	-0.4436^{***}	-0.4739^{***}	-0.4735^{***}
Intercept		3.4670^{***}		6.2664^{***}

Note: *: 0.1; **: 0.05; ***: 0.01.

Table 2.3: Impact of Risk on Production

In spite of the nuance between FE model and RE model, for both yields and revenues, results suggest a significantly negative correlation between ACI time trends and the farm production. This implies that climate change risk in our work belongs to the type of production risk in Painter (2019) [24]. Meanwhile, our usage of ACI time trends as proxies of climate change risk is confirmed, allowing us to conduct further analysis based on this climate information for the regions in Canada and the United States.

2.2 Stock Data

Besides the climate index, another important part of our data is stock data used to analyze climate change risk in a financial market. As mentioned earlier, one focus in climate change research is the regional deviation under a general background. Thus, financial data should also have a regional classification in order to match up with the climate change information. This requires our stock data to have at least two parts: price and location information. Price data is used to calculate stock returns which are of most concern in this thesis. Location data is used to group relevant stocks together under the climate background and connect financial performance to climate change risk. Moreover, since the location information is almost included in company fundamental databases, other financial scales in fundamental databases such as total assets, net income, book-to-market ratio can also help to assess a company's financial performance in the market. In line with these data requirements, we choose the Compustat database, which provides these two types of data simultaneously, as our main database.

The Compustat database is a well-known database that provides financial, statistical and market information. It is available in the Wharton Research Data Services (WRDS) by the University of Pennsylvania. It has easy search and link functions that allow users to quickly access different types of data as well as to link the database with another popular financial database for stock price data, the Center for Research in Security Prices (CRSP) database. Indeed, there is a merged database called the CRSP/Compustat Merged (CCM) database between the Compustat and the CRSP database in the WRDS. However, the Compustat database is more mature and complete than the CCM database. The Compustat database provides data not just in the United States markets but also in Canadian markets and other international markets while the CRSP database mainly has data for common stocks traded on the NYSE, AMEX, and NASDAQ. As a consequence, the CCM database loses some common stocks that are located in Canada but not in those three stock exchanges. Thus, we use the Compustat database rather than the CCM database. We focus on common stocks in four influential stock exchanges in Canada and the United States: the New York Stock Exchange (NYSE), NASDAQ, American Stock Exchange (AMEX), and Toronto Stock Exchange (TSX). Then we match these common stocks to ACI regions based on location information (state or province) in the Compustat database. However, during the test period, many stocks became delisted for various reasons such as bankruptcy, acquisitions, and mergers. For delisted stocks, we follow traditional adjustment methods (Shumway, 1997 [29]; Shumway and Warther, 1999 [30]; Trecartin, 2003 [31]) to assign different delisting returns to stocks delisted for different reasons.

Table 2.4 summarizes the numbers of common stocks in 12 ACI regions during the test period from 1993 to 2018. Each column in sequence presents average numbers, numbers at the end of the period, minimum numbers, and maximum numbers in a year, respectively. Not surprisingly, there is no listed stock in region CAR and are few stocks in the region ALA due to the extreme weather. There is also a huge difference in stock numbers between Canada (CAR, NEA, NEF, NPL, and NWP) and the United States (ALA, CEA, CWP,

MID, SEA, SPL, SWP).

	Avg. #	# in 2018	Min. #	Max. #
ALA	3	2	2	4
CAR	0	0	0	0
CEA	1814	1738	1581	2059
CWP	139	106	106	178
MID	1045	955	931	1212
NEA	25	22	15	32
NEF	885	1157	510	1180
NPL	288	186	186	377
NWP	209	174	137	260
SEA	843	692	692	1041
SPL	574	580	517	662
SWP	1158	1176	943	1300

Table 2.4: Regional Numbers of Companies (1993-2018)

However, stocks in the whole market do not perform in high correlation with climate change (Fang et al., 2019 [14]; Hong et al., 2019 [16]; Kumar et al., 2019 [20]). In most climate change research, analysis is limited to certain industrial sectors. For example, carbon-intensive sectors including energy and utilities industries are chosen to study the effect of greenhouse gas emission (Liesen, 2015 [21]; Fang et al., 2019 [14]; Benedetti, 2019 [3]; Bertolotti et al., 2019 [4]). In Hong et al. (2019) [16], they study drought risk in food markets. Kumar et al. (2019) [20] select trading industries based on temperature sensitivities. In our case, because we are more interested in stocks that are expected to be correlated with climate change risk (or production climate risk), we filter stocks which are in relevant sectors by their Standard Industrial Classification (SIC) codes. Stocks with SIC codes between 0100 and 0999 (agriculture, forestry and fishing division) and between 2000 and 2099 (food and beverage subdivisions in manufacturing division) are grouped as a new sector, the agriculture-related sector. The agriculture-related sector is believed to be highly exposed to production risk, which is shown in the last section and will also be shown in the next chapter. Table 2.5 summarizes the numbers of stocks and stock returns of the agriculture-related sector in our database.

	Avg. #	# in 2018	Min. #	Max. #	Avg. Return (%)	Min. Return (%)	Max. Return (%)
ALA	0	0	0	0	-	-	-
CAR	0	0	0	0	-	-	-
CEA	28	26	23	33	1.38	-18.51	19.87
CWP	4	5	1	5	1.08	-25.39	62.52
MID	25	16	16	36	1.17	-13.98	10.70
NEA	3	2	2	5	1.41	-32.02	83.67
NEF	20	12	12	26	1.07	-21.94	24.57
NPL	3	2	2	4	0.91	-32.11	83.67
NWP	7	5	2	8	0.54	-26.70	20.19
SEA	25	13	13	28	1.79	-11.65	99.90
SPL	9	7	7	11	1.39	-22.26	29.27
SWP	21	14	14	26	1.36	-18.34	27.76

Table 2.5: Summary of Agriculture-related Sector (1993-2018)

From Table 2.5, there are fewer stocks in the agriculture-related sector and stocks at the end of the test period are generally fewer than the average level. The last three columns in Table 2.5 summarize regional returns in the sector. Stocks in one region are equally weighted[4] to build a regional portfolio. All returns are presented as monthly values and are in percentage. Generally, regional returns in all Canadian regions are smaller than those in the United States. Nevertheless, the correlation between stock returns and climate change risk is not clear when we link Table 2.2 and 2.5 together. For example, SEA has the largest average monthly return among all regions as well as a higher average ACI trend, *i.e.* higher climate change risk, than half of the regions. The linkage between returns and risk

[4]It is also interesting to consider value-weighted portfolio for each region. For simplicity, we follow the "1/N" strategy in this thesis.

is still to be studied. Moreover, the issue of no company in some regions is also important in our analysis and we will discuss more in the next chapter.

Chapter 3

Return Predictability and Market Efficiency

Long-term ACI trends and agriculture-related stock returns exhibit significant regional disparities. While higher ACI time trends indicate higher climate change risk, differences in regional returns between regions with high climate change risk and regions with less climate change risk are not marked at the average level. Does this mean that climate change risk is involved in stock pricing? Or in other words, do stock returns fully reflect climate change risk embraced? If it is, it could be taken as evidence to support the presence of market efficiency toward climate change risk and investors would have less concern about managing climate change risk in the stock market. The idea comes from the well-known Eugene Fama's (1970) [10] Efficient Market Hypothesis (EMH). According to his semi-strong form of market efficiency, it is impossible for stocks or portfolios to outperform the market in an efficient market based on public information. Stock prices at any time should fully reflect all public information. Nevertheless, the market efficiency in the real world is still subject to controversy (Liesen, 2015 [21]). We cannot simply conclude whether the stock market is efficient[1] toward climate change risk or not just based on the above tables because the above tables and graphs exhibit not only summaries, but also fluctuations of

[1] As mentioned earlier, we use the term "market efficiency" to refer to the translation of market efficiency toward risks.

regional ACI trends and stock returns during the test period.

3.1 Motivation

We have shown a negative correlation between climate change risk and agricultural production in Canada and the United States. Before we could draw a conclusion about the market efficiency, it is worthy to assess whether there is a significant difference in financial performance between companies in regions with higher climate change risk and those in regions with less climate change risk since the linkage between average returns and average climate change risk is not clear. If there is not a huge difference between them, then climate change risk indexed by the ACI may not be a significant force driving a company's revenue. Thus, it is inappropriate to discuss this type of risk in the financial market. However, since the previous literature has provided evidence about the impact of climate change on the agriculture industry (Deschenes et al., 2007 [9];), we could expect an adverse relationship between our climate change risk and financial performance.

Our test is built on a modified Fama-MacBeth regression model. The Fama-MacBeth regression model (Fama and MacBeth, 1973 [13]) is a famous model in asset pricing. It is an extension of the classical asset pricing model, Capital Asset Pricing Model (CAPM; Sharpe, 1964 [28]; Lintner, 1965 [22]), in estimating risk premia of general risk factors. Our model is as follows:

$$DROA_{i,t} = a_i + f_i^{'} X_{i,t} + e_{i,t}, \; i = 1, ..., n \tag{3.1}$$

$$DROA_{i,t} = \mu_t + \eta_t Risky_{i,t-1} + \lambda_t^{'} \hat{f}_i + \epsilon_{i,t}, \; t = 1, ..., T \tag{3.2}$$

$$\eta = \frac{1}{T} \sum_{t=1}^{t=T} \eta_t \tag{3.3}$$

X in Equation (3.1) is optional variables to control common factors such as market returns and earnings per share. $DROA_{i,t}$ in Equation (3.1) and (3.2) is the difference of return on assets (ROA) in region i at time t. It is defined as $NI_{i,t}/TA_{i,t} - NI_{i,t-1}/TA_{i,t-1}$ where $NI_{i,t}$ is aggregated net income in region i at time t and $TA_{i,t}$ is aggregated total assets. *DROA* is used as a measurement of corporate profitability of agriculture-related companies. *Risky* is a dummy variable indicating if a region has higher climate change risk in terms of ACI time trends. A region is considered risky if its ACI time trend is in the upper 33% quantile group. Here, we do not use contemporary ranks of risk. At time t, ACI trends at time *t-1* are used to separate risky and riskless regions. Besides *Risky*, we also consider another straightforward measurement of risk, the value of ACI trend $\hat{\beta}$ from Equation (2.1), with which Equation (3.2) becomes:

$$DROA_{i,t} = \mu_t + \eta_t \hat{\beta}_{i,t-1} + \lambda_t' \hat{f}_i + \epsilon_{i,t},\ t = 1, ..., T \tag{3.4}$$

Our parameter of interest is the time-averaging η. If η is not significantly different from zero, then we can conclude that there is no marked difference in regional profitability when we control the level of risk. Thus, the stock market might be efficient with respect to climate change risk. Table 3.1 shows a summary of USC data and the correlation among ACI trends, profitability and optional controls in the test. $\hat{\beta}$ represents ACI time trends as proxies of climate change risk. Optional controls are *AEPS* (value-weighted earnings per share of agriculture-related stocks), *DPS* (value-weighted dividends per share), *BV* (value-weighted book values per share), *MR* (value-weighted returns), *AMR* (value-weighted returns of agriculture-related stocks), and *ABV* (value-weighted book values per share of agriculture-related stocks). $\hat{\beta}$ is in basis points and *DROA*, *MR*, and *AMR* are in percentage. Other control factors are in dollars. We observe a negative correlation between ACI trends and *DROA* from Panel B of Table 3.1. This suggests an adverse impact of climate change risk on agriculture-related stocks.

Panel A: Statistics Summary							
Variable	Mean	*Std*	Min	25*th*	50*th*	75*th*	Max
$\hat{\beta}$	0.1590	0.1853	-0.1960	0.0100	0.1629	0.2693	0.4950
$DROA$	-0.0255	0.9506	-1.9923	-0.4221	-0.0116	0.5629	1.9074
$AEPS$	2.0858	0.7361	0.7880	1.6417	1.9868	2.3804	4.1928
DPS	1.1265	0.2784	0.7566	0.8971	1.1129	1.2500	1.8758
BV	341.8365	492.5144	34.4396	76.4497	206.0014	439.7754	2484.0777
MR	1.1349	0.2060	0.5752	0.9835	1.1782	1.2700	1.4342
AMR	1.1038	0.1451	0.7423	1.0349	1.1164	1.1970	1.3233
ABV	15.6793	4.9522	8.4173	10.5926	15.4094	18.8811	25.8143

Panel B: Correlation								
	$\hat{\beta}$	$DROA$	$AEPS$	DPS	BV	MR	AMR	ABV
$\hat{\beta}$	1.0000							
$DROA$	-0.1089	1.0000						
$AEPS$	-0.3475	0.1459	1.0000					
DPS	-0.3354	-0.3173	0.2534	1.0000				
BV	0.2402	0.0237	-0.1126	-0.0935	1.0000			
MR	-0.1667	0.4957	0.0480	-0.2721	0.1865	1.0000		
AMR	-0.1547	0.2039	0.1773	-0.3341	0.2550	0.7311	1.0000	
ABV	-0.3161	-0.1891	0.8018	0.5506	-0.1744	-0.0467	0.0777	1.0000

Table 3.1: Summary of Regression Variables

	(1)	(2)	(3)		(4)	(5)	(6)
Intercept	-0.0001	-0.0028	-0.0359	*Intercept*	-0.0012	-0.0005	-0.0456
	(-0.0557)	(-1.1384)	(-0.7225)		(-0.5010)	(-0.1474)	(-1.1531)
Risky	0.0016	-0.0040	-0.1419^{*}	$\hat{\beta}$	0.0002	-0.0010	-0.0035^{*}
	(0.4271)	(-0.7944)	(-1.9559)		(0.2219)	(-1.2592)	(-1.8050)
AEPS		0.0003	0.0303	*AEPS*		0.0002	-0.0045
		(0.1204)	(0.9910)			(0.1448)	(-0.5401)
DPS		-0.0020^{*}	-0.0131^{*}	*DPS*		0.0007	-0.0041
		(-1.7840)	(-1.7755)			(0.6532)	(-0.9153)
BV		0.0120	0.2334	*BV*		0.0280	-0.0972
		(0.6995)	(1.1531)			(0.9778)	(-0.8719)
MR		0.0941	4.4162	*MR*			0.4356
		(0.8184)	(1.5480)				(1.3978)
AMR			0.9503	*AMR*			0.8180
			(0.9401)				(1.1051)
ABV			0.2454	*ABV*			-0.0436
			(1.1854)				(-0.5925)
R^2	0.0849	0.7616	0.9482	R^2	0.1875	0.616	0.9384

Note: *: 0.1; **: 0.05; ***: 0.01.

Table 3.2: Results of Fama-MacBeth Regression

Table 3.2 shows two sets of results of the regression on a yearly basis under different choices of controls and measurements of risk. We use the Newey-West approach with data-based lags to adjust estimates of the regression and t statistics are reported in brackets. The last row of results is the average R^2 of the regression over the test period. The left panel of Table 3.2 is from the regression with dummy variable *Risky* and the right panel is from the regression with numerical variable $\hat{\beta}$. For each panel, results under three choices of control factors are displayed. In the first set of controls (no optional control), the coefficients of *Risky* and $\hat{\beta}$ are positive, suggesting that companies in risky regions tend to be more profitable than others. However, the results are not significant in terms of the t statistics and p-values. The conclusion is overturned by adding optional controls to the model. In the second model where we control some regional differences, η's become negative but not significant yet. As opposed to the positivity, negative coefficients imply that companies' profits are weakened if they undertake more climate change risk. In the last model, we add more optional controls and the coefficient estimates of *Risky* and $\hat{\beta}$ become significantly negative, from which we could reject the null hypothesis and conclude that there is a significant difference between risky and riskless regions in terms of *DROA*. This conclusion supports our approach of using ACI trends as proxies of climate change risk. Thus, we can conduct more analysis of this type of risk in the financial market.

We also learn from the regression results that climate change risk has negative impacts on companies' profitability. Because we compare regional profitability at time t with year-end ranks or ACI trends at time *t-1*, climate change risk of the last year also helps to predict this year's profitability. In other words, the ACI provides significant predictions about the profitability of agriculture-related stocks, *i.e.* the ACI may have some predictability on corporate revenues of agriculture-related stocks.

Since stock prices and returns are connected with companies' profits, the adverse impact on corporate profitability (*DROA*) motivates us to further test the relationship between climate change risk and stock returns and the predictability of the ACI on stock returns. In an informationally efficient market, investors would not have opportunities to predict future stock returns based on climate change risk, *i.e.* the ACI would lose its predictability on stock returns in an efficient market. Notably, the predictability on corporate profitability (*DROA*) does not contradict the absence of the predictability on stock returns. Companies' profitability depends on their production, market prices, and supply-demand relationship. It will influence investors' trading behavior upon stocks. If investors foresee the business gains of an agriculture-related company based on the ACI, they would buy the company's stock before the realization of profits, which would increase the stock price through the stock buy-sell mechanism. This would drive the stock price quickly reaching to or even passing its intrinsic value. Then at the realization of business gains, investors would turn out to have no profit on trading this stock. Therefore, an efficient market would not allow the arbitrage opportunity based on the ACI to exist.

However, the EMH theory seems to be vulnerable under some tests by critics (Liesen, 2015 [21]; Hong et al., 2019 [16]; Kumar et al., 2019 [20]). In an inefficient market, investors who collect public but unrecognized information can take advantage of it. On the other hand, if some collections of information in the market can generate arbitrage opportunities, the market is then inefficient. Our tests of predictability on stock returns and stock market efficiency are built upon this idea.

3.2 Strategies

According to the results of the Fama-MacBeth regression, we have general knowledge that if we rank ACI regions based on their ACI time trends, there is a significant difference in regional profitability between risky regions and riskless regions. This difference is an indicator of the predictability of the ACI on corporate performance and motivates us to further test the recognition of climate change risk information in the stock market. We want to establish stock portfolios based on the information extracted from ACI time trends. If the ACI is also helpful in predicting future stock returns, investors can speculate in the stock market using these portfolios. The existence of the predictability on stock returns would reflect that climate change risk is not fully identified by the market, *i.e.* the market is not efficient toward the climate change risk. In this section, we will introduce a trading strategy that exploits the ACI information and conclude our opinions about the predictability on stock returns and the market efficiency according to the strategy's performance.

Our trading strategy is a risk-adjusted trading strategy. The idea of this popular strategy comes from Jegadeesh and Titmans (1993) [18] relative strength strategy and modified versions by Hong et al. (2019) [16] and Kumar et al. (2019) [20]. The relative strength strategy is also called a "buy winner and sell loser" strategy, which may be understood better literally. In the J-K relative strength strategy, all stocks are ranked according to their past J-month returns. High-ranked stocks have more relative strength (momentum) in returns and are denoted as winners in the momentum theory, while low-ranked stocks are losers. The combination of longing winners and shorting losers is a zero-cost portfolio so that it should be risk-free. By investing in zero-cost portfolios, Jegadeesh and Titman (1993) [18] find that their performance is significantly positive and exceeds risk-free returns. This strategy has been widely accepted and studied for empirical or theoretical purposes. Hong et al. (2019) [16] modify the strategy to test the efficiency of the stock market toward drought risk. Instead of using ranks based on stock momentum, they rank 31 international markets by their geographical drought risk. Then winners would have less drought risk and losers would have more drought risk. Similarly, Kurmar et al. (2019) [20] construct a zero-cost portfolio based on temperature sensitivities of stocks. In our case, the basis for classifying winner stocks and loser stocks is the ACI time trends, or climate change risk.

Since we use the ACI trends to rank, ranking objectives are 12 ACI regions. The whole test period is divided into several ranking periods with equal lengths of time. For each region, at the beginning of each ranking period, we use Equation (2.1) to estimate a historic ACI time trend up to then. Because higher ACI trends imply more extreme climate fluctuations, time trends approximate climate change risk in the future. Larger trends suggest a greater climate change risk in the corresponding ACI regions. Ordered by contemporaneous ACI trends, regions with smaller values are expected to be less risky in the following years, *i.e.* winners in our rank basis. Likewise, regions with large ACI trends are classified as losers. In our scale, we define regions with their trends in the lower 33% quantile group as winner regions and regions with trends in the upper 33% quantile group as loser regions. Other regions are mediums. Thus, in each ranking period, we have four winner regions, four loser regions and four medium regions. Then at the same time, we construct three portfolios on the basis of ranks. Stocks in the same region are grouped to form a regional portfolio by equivalent weights. A winner portfolio equally invests in winner region portfolios and loser and medium portfolios are also constructed by their elementary regional portfolios. Equivalent weights and equally weighted investment here mean that all portfolios constructed are "1/N" portfolios. The key portfolio in our strategy is a zero-cost portfolio by shorting the loser portfolio and longing the winner portfolio using the payment of short-selling. By this construction, our expense to hold this composite portfolio is zero at every time. We hold these four portfolios (winner, medium, loser and zero-cost portfolios) through the ranking period and close them at the end of the period. If there are stocks entering or quitting the market, we will revise weights in regional portfolios to maintain all stocks equally weighted. We repeat the procedure in the following ranking periods. Our default ranking period is one year, which means that we will hold portfolios for one year and close them. In this case, we have to construct 26 times in the 26-year test period.

In the calculation of regional returns, we encounter the problem of no stock in some regions mentioned in the last chapter. When this happens, we construct the regional portfolio with only risk-free bonds (the United States Treasury Bills) with maturities matching the ranking period. For example, in the first year of the test period, there is no stock in ALA. We then only invest in one-year United States Treasury Bills in the ALA regional portfolio. This idea is still on the basis of risk ranks. If one region is in the winner group, it has a smaller exposure to climate change risk. We want to find financial products to match its risk. Since we cannot compare risks between other winner portfolios in our strategy and financial products, even climate-based products, in the market, we invest in risk-free bonds to keep the lowest level of risk. We make the same choice for loser portfolios since we cannot find other returns that are at the same level of risk as other loser returns. By this adjustment, at most one region in the loser (winner) portfolio would have no stock. This may cause a small change in regional returns. But for most of the time when we have to invest in risk-free bonds, winner and loser portfolios both are subject to this adjustment. Therefore, changes in regional returns are offset by the long-short action and the problem of no stock is not a critical issue in assessing portfolio performance.

We evaluate our strategy with several measurements of trading portfolios. The classical and most straightforward measurement is the average return of the strategy over the test period. For risky portfolios (winner, loser, and medium portfolios), we calculate their average returns net of risk-free returns. Positive net returns are expected since these three portfolios do not diversify over systematic risk stemmed from climate change and should be rewarded with higher returns. For the zero-cost portfolio, because we adjust climate change risk of this portfolio, we simply calculate its average return over the test period as the risk-adjusted return. Three other measurements of portfolios from asset pricing models are also used in evaluation: CAPM alpha (Sharpe, 1964 [28]; Lintner, 1965 [22]), Fama-French 3-Factor alpha (Fama and French, 1973 [13]), and Carhart 4-Factor alpha (Carhart, 1997 [6]). Models to estimate alphas are as follows:

$$r_t - r_{f_t} = \alpha_{CAPM} + \beta(r_{mt} - r_{f_t}) + \epsilon_t \tag{3.5}$$

$$r_t - r_{f_t} = \alpha_{3F} + \beta(r_{mt} - r_{f_t}) + b_s SMB_t + b_v HML_t + \epsilon_t \tag{3.6}$$

$$r_t - r_{f_t} = \alpha_{4F} + \beta(r_{mt} - r_{f_t}) + b_s SMB_t + b_v HML_t + b_m MOM_t + \epsilon_t \tag{3.7}$$

In the above three models, r is the return of the target portfolio and r_f is the risk-free return[2]. Four market portfolios are the excess market portfolio ($r_m - r_f$), size portfolio *SMB* (small-size minus big-size portfolio), value portfolio *HML* (high-value minus low-value portfolio), and momentum portfolio *MOM*. Notably, in estimating alphas for the zero-cost portfolio, we use portfolio returns instead of excess portfolio returns. Three alpha measurements are α_{CAPM} of the CAPM model, α_{3F} of the Fama-French 3-Factor model, and α_{4F} of the Carhart 4-Factor model. By using these alphas, we compare our portfolios to common market factors. The purpose of this is to clarify that climate change risk is a new type of risk in the market and can not be explained by traditional factors. If alphas are not significantly different from zero, then climate change risk could be managed by investing in market factors.

In Table 3.3, we report the performance of our strategy under different choices of ranking periods. Besides our default period of one year, we also have other lengths of time from one month to three years. As mentioned in the last chapter, we create ACI time trends in order to estimate long-term directions of climate change. So in our strategy, we choose the one-year ranking period as the default because the length of the period is neither too short to reflect the long-term effect of the ACI rank nor too long to be close to reality. Our objectives are stocks related to agriculture and most of the agricultural products have production cycles no longer than three years. Periods less than or equal to six months are also tested because we want to know if the strategy is effective in a short period of time. For every choice of ranking periods, we report the performance of three portfolios where those of winner and loser portfolios are net of risk-free returns. Three types of alpha are shown in the last three columns of the table. We also report Newey-West adjusted p-values for zero-cost portfolios. Returns and alphas in Table 3.3 and the following tables are displayed in monthly percentages and are period averages.

[2] We use returns from the 3-month United States Treasury Bills as default risk-free returns.

Period	Portfolio	R_{ex}	α_{CAPM}	α_{3F}	α_{4F}
1 Month	Loser	0.68	0.44	0.38	0.37
	Winner	0.82	0.60	0.56	0.57
	Zero-Cost	0.14	0.16	0.18	0.20
	p-value	0.52	0.47	0.42	0.36
3 Months	Loser	0.67	0.43	0.37	0.35
	Winner	0.82	0.60	0.56	0.57
	Zero-Cost	0.15	0.18	0.19	0.21
	p-value	0.48	0.43	0.39	0.34
6 Months	Loser	0.69	0.45	0.39	0.37
	Winner	0.79	0.57	0.53	0.53
	Zero-Cost	0.11	0.12	0.14	0.16
	p-value	0.63	0.58	0.54	0.48
1 Year	Loser	0.69	0.45	0.38	0.37
	Winner	0.93	0.72	0.67	0.68
	Zero-Cost	0.25	0.28	0.29	0.31
	p-value	0.28	0.23	0.21	0.17
2 Years	Loser	0.76	0.52	0.46	0.45
	Winner	0.91	0.70	0.66	0.67
	Zero-Cost	0.14	0.18	0.20	0.23
	p-value	0.54	0.45	0.41	0.34
3 Years	Loser	0.81	0.58	0.52	0.51
	Winner	0.81	0.59	0.53	0.55
	Zero-Cost	0.01	0.01	0.01	0.04
	p-value	0.98	0.98	0.96	0.87

Table 3.3: Summary of Strategy Performance

The positivity of all excess returns (winner and loser returns) validates the strategy. Otherwise, our strategy is meaningless if its returns are lower than risk-free returns. Excess returns become smaller when adjusted by traditional market factors, but still remain positive. This implies that positive returns of our portfolios are driven by two parts of factors or risk. One part is traditional market factors such as size factor and value factor. This common systematic risk contributes to a small part of the returns. Most of the returns cannot be explained by market factors, which means that climate change is a new source of systematic risk. When we compare loser and winner portfolios, average excess returns, as well as alphas of winner portfolios, are always larger than those of loser portfolios. This evidence is similar to the results of Fama-MacBeth regression and suggests that ACI time trends have the predictability on stock returns. Regions with lower ACI time trends tend to have higher regional returns. The differences in average excess returns between winners and losers lead to positive risk-adjusted returns of zero-cost portfolios. For the default one-year ranking period, the average monthly return of the zero-cost portfolio over the test period is 0.25%, or equivalently around 3% annually. According to our previous discussion, positive returns of zero-cost portfolios also confirm the existence of the market inefficiency. By starting with a zero expense, investors can earn positive returns over the 26-year period. This arbitrage opportunity, similar to some opposite views about the Efficient Market Hypothesis (Liesen, 2015 [21]; Hong et al., 2019 [16]; Kumar et al., 2019 [20]), rejects the ideal assumption of stock market efficiency. When information about climate change risk can be extracted from the public climate index, the stock market does not recognize it or correctly price it. If the stock market is efficient enough toward climate change risk, then most investors will invest in the same method and erode the arbitrage opportunity immediately. In this case, our strategy cannot obtain positive returns over a long-term period.

Table 3.3 provides more information than positive returns about our strategy. A period-length effect is also shown in the results. As we use ranking periods longer than one year, *i.e.* hold portfolios for a longer period before closing them, the zero-cost returns decrease generally to almost zero. This effect is clearer when we test our strategy with more choices of ranking periods (see Table 3.4). With longer ranking periods, the predictability is weakened. The change in risk ranks could contribute to this effect. But we can observe relatively stable ranks among regions from Figure 2.4, which is expected by using a rolling window to estimate ACI trends. Then the main explanation for this period-length effect could be the spread of risk information over the market. For the default ranking period, we hold portfolios for an entire year and they generate arbitrage opportunities on public information that other investors are not aware of. However, when the ranking period becomes longer, the information about climate change risk could be absorbed by the stock market so it becomes irrelevant in speculating in the stock market. This short-life of outperformance is similar to the staleness of temperature sensitivity in Kumar et al. (2019) [20]. The vanishing of arbitrage opportunities again confirms that the source of positive zero-cost returns is the mispricing by the market. Thus, the market is not efficient toward climate change risk but reacts to the risk slowly. However, if we hold for a shorter period of time, the decrease in returns is not clear. Actually, since climate change risk is realized through production cycles, we cannot expect risk would be reflected by stock returns contemporaneously. The relative stability of risk ranks may explain positive returns with shorter holding periods.

Period	R_{ex}	α_{CAPM}	α_{3F}	α_{4F}
1 Month	0.14	0.16	0.18	0.20
3 Months	0.15	0.18	0.19	0.21
6 Months	0.11	0.12	0.14	0.16
9 Months	0.10	0.12	0.15	0.17
12 Months	0.25	0.28	0.29	0.31
18 Months	0.15	0.18	0.19	0.21
24 Months	0.14	0.18	0.20	0.23
30 Months	0.11	0.13	0.15	0.18
36 Months	0.01	0.01	0.01	0.04

Table 3.4: Zero-Cost Returns with Different Ranking Periods

Relatively stable ranks should not be considered as limitations of our strategy since we wish to capture long-term climate change. Indeed, if the market is efficient, stock prices should include all public information in an efficient market. Public information should contain historical information such as past stock prices, present information such as contemporary fundamental evaluation, and future information projected from historical and present information such as stock momentum and prediction of risk ranks. Thus, if the market is efficient, then not only contemporary ranks, but also past ranks of regions would be included in stock pricing as past ranks may predict current ranks.

Therefore, based on the previous conclusion of market inefficiency and relatively stable ranks in Figure 2.4, we compare the performance of the strategy with two choices of risk ranks: the risk rank at the beginning of 1993, *i.e.* the year-end rank of 1992, and dynamic ranks used in the default strategy. With the default one-year ranking period, the strategy performance with the fixed rank is unsurprisingly close to that with dynamic ranks in Table 3.5. Dynamic ranks are still better than the fixed rank in terms of strategy alphas.

Rank	Portfolio	R_{ex}	α_{CAPM}	α_{3F}	α_{4F}
1992	Loser	0.68	0.46	0.39	0.38
	Winner	0.98	0.69	0.64	0.65
	Zero-Cost	0.30	0.23	0.24	0.27
	p-value	0.18	0.30	0.28	0.23
Dynamic	Loser	0.69	0.45	0.38	0.37
	Winner	0.93	0.72	0.67	0.68
	Zero-Cost	0.25	0.28	0.29	0.31
	p-value	0.28	0.23	0.21	0.17

Table 3.5: Comparison Between Fixed and Dynamic Ranks

3.3 Cross-Sector Test

In the above analysis, we implement the trading strategy only in the agriculture-related sectors including fishing, forestry, food, and beverage. The intuition of this arrangement is that revenues of these subsectors are expected to be mostly related to climate change risk. Therefore, portfolio returns should have no significant differences if the market appropriately prices climate change risk. However, there are nine other sectors according to the Standard Industrial Classification (SIC) and some industries other than agriculture also have relationships with climate change such as energy, utilities, and material (Andersson et al., 2016 [1]; Fang et al., 2019 [14]). In this section, we repeat the trading scheme on stocks in other SIC sectors to examine whether the ACI time trends have return predictability in other sectors.

In the original SIC list, there are ten divisions but no one specific division called an agriculture-related sector. In our analysis, we combine the agriculture, fishing, forestry, food, and beverage industries to become the agriculture-related sector. Other SIC divisions left are mining, construction, manufacturing, TCEGS (transportation, communications, electric, gas and sanitary service), wholesale trade, retail trade, FIRE (finance, insurance and real estate), service and public administration division. Because there is no stock in the public administration division in our database, we have overall nine divisions including the agriculture-related sector that can be tested with the trading strategy. In the agriculture-related sector, we also have two subsectors: farm (agriculture, fishing, and forestry) and food and beverage. We also test our strategy in these two subsectors. A summary of strategy performance under a one-year ranking period is in Table 3.6. We report Carhat 4-Factor alphas for nine SIC sectors in descending order as well as the entire stock market (the last row) in Panel A.

Panel A: SIC Sectors		
Sector	α_{4F}	p-value
Agriculture-related	0.31	0.17
Construction	0.23	0.51
TCEGS	0.11	0.64
Mining	-0.07	0.98
Wholesale Trade	-0.20	0.34
Manufacturing	-0.75	0.04
Services	-1.34	0.48
Retail Trade	-1.42	0.27
FIRE	-3.57	0.35
All	-0.98	0.31

Panel B: Subsectors		
Sector	α_{4F}	p-value
Farm	0.61	0.07
Food & Beverage	0.09	0.71

Table 3.6: Strategy Performance in SIC Sectors

Among all SIC sectors, the agriculture-related sector has the highest return in the risk-adjusted strategy. If we assume that the level of recognition about climate change risk is the same among all sectors, then the outperformance of the agriculture-related sector is not a coincidence because this sector is mostly related to climate change according to literature and common sense. Besides the agriculture-related sector, our strategy does not gain positive returns in most of other sectors. The negativity does not suggest the market efficiency as well. By investing in a reverse strategy, *i.e.* buying losers and selling winners, investors can still earn positive returns. However, in that case, we do not have the intuition of investment. The only two sectors aside that have positive strategy performance are construction and TCEGS. Main industries in these two sectors are utilities and transportation which are carbon-intensive. So they are also connected with climate change and have heterogeneity in returns between risky stocks and riskless stocks.

On the other hand, the predictability on agriculture-related stock returns is robust in two subsectors. For the subsectors, strategy returns are all positive, especially in the farm subsector. Comparing the two subsectors, the farm sector is more directly related to climate change since climate events would affect farm production first then the impact is transmitted into the food and beverage industries through supply chains. Moreover, food and beverage companies would have more remedy approaches against production losses in underlying materials such as importing raw materials. However, adaptations by farms, for example using advanced technology and changing types of crops, cannot increase contemporary yields. When facing production losses, farms' profits may be only compensated through limited channels such as price increasing by the supply-demand mechanism and some public subsidies.

3.4 Discussion

In this chapter, we test the relationship between climate change risk and corporate performance of agriculture-related companies. We find that companies with higher climate change risk tend to have less corporate profitability. This validates our method of using ACI time trends as proxies of climate change risk and motivates us about the predictability of ACI trends on stock returns. By investing in a risk-adjusted portfolio, we are able to adjust climate change risk in the stock market. The portfolio generates positive returns over a long run, which verifies the return predictability on agriculture-related stocks. Meanwhile, since the portfolio is adjusted to climate change risk, positive returns also demonstrate that the market misprices the risk. The hypothesis of stock market efficiency is then rejected by the outperformance of the default portfolio as an arbitrage opportunity in the market. The inefficiency stems from the spread of risk because the results of the Fama-MacBeth regression confirms the existence of production risk and it takes time for risk to be absorbed by the market. Even though the risk is not identified by investors within one year, it starts to spread over the market and is realized by the market a few years later. Thus, the return predictability degenerates when we use the same climate information for trading in a longer period of time.

Chapter 4

Exploiting Strategy Performance

From the results of our risk-adjusted strategy, significantly positive zero-cost returns over a long term have implied the market inefficiency toward climate change risk. We also find some subtle clues that the stock market does identify some climate change risk, but at a slow pace. The delayed reaction towards climate change risk would be a signal of a transition process from the market inefficiency to market efficiency. Moreover, our default strategy is a modified relative strength strategy and we invest in a fixed cycle. There are still some improvements in our strategy that may help us to better understand the market efficiency problem. In this section, we replicate the efficiency test with more modifications to the strategy.

4.1 Lag Effect

In our original strategy, we analyze six scenarios of the ranking period. We use a default ranking period of one year on the basis of common production cycles to allow risk in the yields to be transmitted into stock prices. Extreme climate events do not immediately affect industrial revenues. Especially for the farm industry, the impact may take several months or years on productivity and the productivity may also take months to be reflected in revenues. Other lengths of periods are also tested to see how fast the information is transmitted. Even though our strategy succeeds with most of the periods, we find significant evidence that the outperformance is short-lived. It is because the market misprices contemporary climate change risk but starts to identify and react to the risk slowly. The effect only appears when the ranking period is at least three years. However, with a three-year holding period, strategy performance is averaged over the period. So the average returns or the use of long holding periods may mitigate the impact. By the construction of the strategy, we invest in stocks only based on the rank at the beginning of the ranking period and hold them throughout the period. But the impact of the rank may differ across months. Therefore, we want to analyze how long will the market take to absorb the climate information.

In order to perform the test, at the start of every ranking period, we use the region rank several months or years ago and then invest in stocks based on this lagged rank. In order to only capture the effect of delayed information, instead of using the one-year holding period, we monthly rebalance our portfolios, *i.e.* we hold each portfolio for only one month. If we use the rank one year ago and hold portfolios for another one year, then in the last month of the period, there is almost a two-year lag since the rank. The lag effect will be amplified by the ranking period. Therefore, with the holding period of one month, all risk ranks are used for investment. Results of the test are shown in Table 4.1. As lags between the time of ranks and the time of investment increase, average returns and alphas decrease generally. When the lag reaches one and a half years, we lose any arbitrage opportunity in investment according to average returns and corresponding p-values. This suggests that the climate information is fully absorbed by the market 18 months after its disclosure. The consumption happens in a short period. This also explains the decrease in strategy returns in Table 3.3 when the ranking period increases from one year to three years. From Table 3.3, we may conclude that the outperformance of the strategy would live for at most three years. Actually, it fades away much faster and disappears in one and a half years.

Lag	R_{ex}	α_{CAPM}	α_{3F}	α_{4F}
0 Month	0.14	0.16	0.18	0.20
	(0.52)	(0.47)	(0.42)	(0.36)
1 Month	0.08	0.10	0.12	0.14
	(0.73)	(0.66)	(0.60)	(0.54)
3 Months	0.07	0.10	0.11	0.13
	(0.76)	(0.68)	(0.63)	(0.57)
6 Months	0.12	0.14	0.16	0.18
	(0.60)	(0.54)	(0.50)	(0.45)
9 Months	0.01	0.04	0.07	0.09
	(0.95)	(0.85)	(0.77)	(0.71)
12 Months	0.02	0.05	0.07	0.09
	(0.94)	(0.83)	(0.76)	(0.69)
18 Months	-0.04	-0.01	0.02	0.04
	(0.86)	(0.96)	(0.95)	(0.85)
24 Months	-0.05	-0.01	0.02	0.04
	(0.84)	(0.90)	(0.98)	(0.94)
30 Months	-0.08	-0.08	-0.07	-0.04
	(0.73)	(0.73)	(0.78)	(0.87)
36 Months	-0.21	-0.22	-0.21	-0.18
	(0.39)	(0.38)	(0.41)	(0.47)

Table 4.1: Summary of Lag Effect

4.2 Starting Investment in Different Months

Another variate in our trading strategy is the start month for the investment. In the default strategy, we start the investment at the beginning of 1993 and revise portfolios after every ranking period, *i.e.* we use a non-overlapping strategy. Therefore, we only rank regions in the months of January and hold portfolios for an entire year. Only ranks in the months of January are used and thus our strategy may be referred to as a January strategy. While it is reasonable since most agricultural and business activities follow the calendar, investors do not have the restriction of only investing in the months of January. Even though we have clues from the average returns that strategy performance starting from other months will not differ greatly, it is still worthy to test the performance for different months. Moreover, the ACI has two calculation bases: monthly and seasonal. In the above tests, we use the monthly ACI to estimate ACI monthly trends. Seasonal ACI does not differ from monthly values largely since the impact of extreme climate would not last only in a few months and disappear. From the results of our strategy, we could expect seasonal ACI trends would also have the return predictability. So we replicate the strategy with different starts (months and seasons) of the investment.

Panel A		
Month	α_{4F}	p-value
Jan	0.31	0.17
Feb	0.21	0.36
Mar	0.14	0.54
Apr	0.08	0.73
May	0.08	0.72
Jun	0.09	0.69
Jul	0.09	0.71
Aug	0.14	0.56
Sep	0.14	0.54
Oct	0.18	0.44
Nov	0.11	0.63
Dec	0.20	0.39

Panel B		
Season	α_{4F}	p-value
Spring	0.16	0.50
Summer	0.09	0.70
Fall	0.14	0.56
Winter	0.08	0.76

Table 4.2: Strategy Performance of Different Starts

From Panel A of Table 4.2, Carhart 4-Factor alphas of twelve zero-cost portfolios show an approximate U shape along starting months. Among all results, the strategy beginning in January has the largest return. Returns in the following months are still positive. The smoothness of the series is expected because we rank regions on a rolling basis and thus risk ranks are relatively stable from month to month. Similar conclusions could be drawn for seasonal tests from Panel B of Table 4.2. With different starting seasons, our strategy still earns positive returns over a long run. The U shape along time is not obvious in Panel B and average returns are lower since we lose some variation in ACI trends with seasonal data.

4.3 Overlapping Strategy

In our original strategy, we use the non-overlapping strategy and introduce ranking periods during which we only follow the rank at the start of the period. This method has been proved to be most effective with the default one-year ranking period. However, by using this trading scheme, beginning ranks may remove fluctuations in ranks during holding periods. Other than the non-overlapping strategy, there are also two types of trading strategies that are widely accepted: monthly rebalanced strategy and overlapping strategy. In relevant tests about the market efficiency, only limited strategies are used. Indeed, in order to prove the market efficiency, all possible trading strategies should be tested (Liesen, 2015 [21]). However, it is practically prohibited. So in this thesis, we consider three popular types of strategies.

The use of monthly rebalanced strategies is common in stock trading, which literally means rebalancing portfolio weights or reinvesting in stocks at the start of each month. We apply this method in testing the lag effect. The overlapping strategy is a general version of the monthly rebalanced strategy. As explained by Jegadeesh and Titman (1993)[18], at the end of each month, an overlapping strategy establishes one portfolio and holds it for k months. As a result, in month t, there are k portfolios in effect established from t-k to t-1. The strategy return in month t is then the average return of k portfolios. At the end of month t, the portfolio from t-k closes and a new portfolio emerges. This strategy is more general than the monthly rebalanced strategy because portfolios in the strategy do rebalance at the end of each month and this strategy becomes the traditional monthly rebalanced strategy when k is equal to one. Likewise, our strategy is also the monthly rebalanced strategy when the ranking period is one month. Therefore, we can conclude from the above results that the monthly rebalanced strategy still works in our framework.

In Table 4.3, we report the performance of the overlapping strategy. Results under the one-month ranking period are exactly the same as in Table 3.3. Other results are also similar to the results of the non-overlapping strategy as the overlapping returns are moving averages of non-overlapping returns. We still observe similar predictability degeneration when holding periods increase.

Period	Portfolio	R_{ex}	α_{CAPM}	α_{3F}	α_{4F}
1 Month	Loser	0.68	0.44	0.38	0.37
	Winner	0.82	0.60	0.56	0.57
	Zero-Cost	0.14	0.16	0.18	0.20
	p-value	0.52	0.47	0.42	0.36
3 Months	Loser	0.75	0.51	0.44	0.42
	Winner	0.83	0.61	0.57	0.57
	Zero-Cost	0.08	0.10	0.12	0.14
	p-value	0.72	0.65	0.60	0.54
6 Months	Loser	0.75	0.51	0.45	0.44
	Winner	0.84	0.62	0.58	0.59
	Zero-Cost	0.09	0.11	0.13	0.15
	p-value	0.63	0.58	0.54	0.48
1 Year	Loser	0.79	0.55	0.49	0.47
	Winner	0.86	0.65	0.61	0.61
	Zero-Cost	0.07	0.10	0.12	0.14
	p-value	0.74	0.66	0.60	0.54
2 Years	Loser	0.82	0.59	0.52	0.51
	Winner	0.86	0.65	0.61	0.62
	Zero-Cost	0.04	0.06	0.09	0.11
	p-value	0.87	0.78	0.70	0.64
3 Years	Loser	0.84	0.61	0.55	0.53
	Winner	0.83	0.62	0.58	0.59
	Zero-Cost	-0.01	0.01	0.03	0.05
	p-value	0.97	0.97	0.89	0.82

Table 4.3: Summary of Overlapping Strategy Performance

4.4 Tests on ACI Components

In the design of the ACI data, the key metric is the average of standardized anomalies of six components: high temperature, low temperature, precipitation, drought, wind power and sea level. The key index has been shown to have the predictability on stock returns. To test the return predictability of ACI components, we dig into six ACI components and implement the strategy based on their time trends estimated by the same time series model. Table 4.4 displays the results of these tests with a one-year ranking period. For temperature anomalies (T90 and T10), we combine them together for the investment. For five components, there is huge heterogeneity in predictability on stock returns. Components precipitation, drought, and winder power all have similar predictability on stock returns as the composite ACI. The result of drought is consistent with the conclusion of Hong et al. (2019) [16] even though we are using different measurements. They suggest that the drought index PDSI has strong predictability on stock returns and therefore the market underreacts to drought risk. For components temperature and sea level, our strategy does not work in obtaining abnormally positive returns. Indeed, the market seems to be relatively efficient toward the temperature anomaly.

Element	R_{ex}	α_{CAPM}	α_{3F}	α_{4F}
Temperature	0.00	-0.06	-0.05	-0.07
	(0.99)	(0.81)	(0.84)	(0.80)
Precipitation	0.07	0.15	0.20	0.22
	(0.75)	(0.50)	(0.38)	(0.33)
Drought	0.31	0.30	0.33	0.36
	(0.20)	(0.21)	(0.17)	(0.14)
Wind	0.44	0.41	0.37	0.38
	(0.05)	(0.07)	(0.10)	(0.09)
Sea Level	-0.30	-0.18	-0.11	-0.13
	(0.24)	(0.47)	(0.65)	(0.60)
ACI	0.25	0.28	0.29	0.31
	(0.28)	(0.23)	(0.21)	(0.17)

Table 4.4: Predictability of ACI Components

4.5 Subsample Tests

From Table 3.3, we have already tested the effectiveness of our default strategy over the 26-year test period. However, the outperformance is not statistically significant in terms of p-values. Even though the non-significance does not obstruct our conclusions in terms of the predictability on stock returns, it is still worthy to test the strategy in subsamples of the 26-year period to see if similar issues exist over shorter test periods.

Taking the one-year default ranking period as an example, we divide the 26-year test period into four time blocks: 1993-1999, 2000-2006, 2007-2013, and 2014-2018. We implement our risk-adjusted strategy in each subsample and report results in Panel A of Table 4.5. The performance of the strategy over subsamples varies. Strategy average returns between 1993 and 1999 and between 2007 and 2013 are much larger than those in other subsamples and over the whole 26-year test period. This can be also observed when we draw the time series of strategy cumulative wealth (see Figure 4.1). To obtain the cumulative wealth series, we assume the strategy was activated by an institutional investor in

January 1993 in the stock market. We assume that the investor holds a short and a long position based on the risk rank with $1 respectively with an assumption of no transaction costs and short margins. Thus, the beginning wealth is zero. When the first ranking period ends, the investor will liquidate the stock trading accounts and put the remaining cash in a risk-free account to earn the United States Treasury Bill yields. Then it will reopen the stock accounts based on a new risk rank and hold portfolios for the next ranking period. By following this trading scheme, the investor will have a time series of account accumulative wealth and end up with more than $1.5 in December 2018 with no expense at the beginning. Figure 4.1 is a direct visualization of Table 3.3, from which we can clearly conclude that the risk-adjusted strategy starting from 1993 does provide an arbitrage opportunity in the stock market. Investors can start with a zero input and receive a significant payoff[1].

However, there are several declines in the account wealth around 2000, 2011 and after 2015. These declines are reflected in average returns in Panel A of Table 4.1. The average returns and alphas during 2000 and 2006 are significantly close to zero, while those in the last five years of the test period are negative, causing the cumulative wealth to decrease sharply. It seems that the market efficiency toward climate change risk is periodical and has been through some transition periods. This is reasonable since the emergence of new technology, natural resources, natural disasters, and climate policies, for example, the biotechnology at the beginning of the 21st century and the release of the Paris Climate Agreement (PA) in 2016, would draw the world's attention to climate change and increase the awareness of climate change risk. But, the majority of relevant literature does not discuss the market efficiency problem in different periods or provide evidence of the transition of efficiency. For example, Liesen (2015) [21] finds that the market inefficiently prices climate systematic risk during a five-year period. In Hong et al. (2019) [16], the evidence to support the market inefficiency is averaged from 1985 to 2014 and only two 15-year subsamples are tested. Based on the average performance of our strategy over a long run (at least 20 years), we can still conclude that the market was inefficient from 1993 to 2014.

[1]The conclusion is based on the assumption of no transaction costs and short margins. We do not discuss the problem in the realistic scenario where transaction fees could be overwhelming in stock trading.

Panel A: Splitting the Test Period				
Subsample	R_{ex}	α_{CAPM}	α_{3F}	α_{4F}
1993-1999	0.67	0.48	0.54	0.47
	(0.16)	(0.33)	(0.29)	(0.35)
2000-2006	0.03	0.01	0.00	-0.01
	(0.93)	(0.97)	(0.99)	(0.98)
2007-2013	0.73	0.77	0.82	0.86
	(0.08)	(0.06)	(0.05)	(0.04)
2014-2018	-0.72	-0.64	-0.66	-0.56
	(0.19)	(0.24)	(0.24)	(0.32)

Panel B: Before and After 2015				
Subsample	R_{ex}	α_{CAPM}	α_{3F}	α_{4F}
1993-2014	0.50	0.53	0.55	0.57
	(0.05)	(0.04)	(0.03)	(0.03)
2015-2018	-1.13	-1.09	-1.11	-1.03
	(0.01)	(0.02)	(0.01)	(0.03)

Table 4.5: Strategy Performance in Subsamples

Unlike the obvious evidence of market inefficiency before 2015, the evidence of market inefficiency starting from 2015 is not convincing from our results. Thus, in addition to the tests in four subsamples, we also compare the performance before and after 2015 as there is a significant loss in account wealth after 2015 from Figure 4.1. We report the comparison in Panel B of Table 4.5. The results indicate that there is a significant arbitrage opportunity before 2015, which is quite consistent with the conclusion of Hong et al. (2019) [16]. Nevertheless, the overwhelming loss from 2015 to 2018, especially in 2017, is unexpected based on our knowledge. While positive returns are signals of market inefficiency, negative returns do not suggest that the market is efficient. In an efficient market, information is absorbed in stock prices so there should not be any significant performance difference between winner and loser portfolios. Since our strategy did experience declines in wealth around 2000 and 2011, we cannot exclude the possibility of normal fluctuations from 2015 to 2016. But for the huge loss in a short period (around six months) in 2017, one possible explanation might be a transition from inefficiency towards efficiency, during which investors may overreact to the disclosure of climate change risk such as the release of the PA in late 2016 and the announcement of withdrawal from the PA by the United States in the middle of 2017. Indeed, evidence is found that basic resources stocks in the German market are affected by the release of the PA in terms of risk and returns (Pham et al., 2019 [17]). So far, we cannot draw any clear conclusion about the market efficiency over this sample period based on the currently available data. Future research about the change of investors' attention towards climate change and event studies of worldwide climate policies should follow up in order to identify the presence of the market efficiency.

Figure 4.1: Cumulative Wealth of the Risk-Adjusted Strategy

4.6 Discussion

In this chapter, we focus on addressing some limitations found in our default strategy. Based on the results from Table 3.3 that the market reacts to risk slowly, we test the speed of market recognition about climate change risk. By investing in a monthly rebalanced portfolio, we find that climate information is absorbed by the market 18 months after its disclosure. Moreover, in terms of the issue that only beginning risk ranks are used for investment in the non-overlapping strategy, we modify the strategy to start trading in different months or seasons. Since our measurements of climate change risk are stable within three years, strategy performance starting from all calendar months is relatively good in terms of Carhart 4-Factor alphas, which again confirms the return predictability of the ACI. Another solution to the issue is to use overlapping strategies. The monthly rebalanced strategy, as a special case of a (non-)overlapping strategy, has been proved to support our points towards predictability and market inefficiency. Indeed, general overlapping strategies also generate positive returns since their returns are moving averages of returns of the non-overlapping strategies.

Because the ACI is composite based on six components, we also estimate components' time trends and run the analysis with them. Most of the componentwise tests have similar results and suggest the market inefficiency toward the corresponding risk, among which we find comparability with conclusions in other literature. However, the market seems to correctly price the risk stemming from temperature anomalies and overreact to information about sea level anomalies.

For all of the above tests and other tests conducted in most literature, a long test period of at least 20 years is used to run the stock trading strategies. However, statistical insignificance of our positive returns motivates us to test in short-term periods. We run several subsample tests where we split the 26-year test period into two and four subsamples. We find that the inefficiency is considerably stable before 2015. After 2015, our strategy does not perform well and loses money quickly in a short term in 2017. One explanation of this inversion could be a transition process from the market inefficiency to market efficiency. However, due to the limitation of data, we are not able to conclude whether investors have started to recognize climate change risk following several important actions to mitigate global warming. This would be an interesting topic for future research.

Chapter 5

Conclusion

Climate change has become a common threat to the world and has been studied by scholars in various fields. In the field of finance, many papers have discussed the financial market efficiency toward climate change. Our work focuses on the topic of climate change risk in the stock market. To initiate the analysis, we use the long-term trends of a newly released climate index, Actuaries Climate Index (ACI), as proxies for climate change risk. We find significant evidence that, as a type of production climate risk, ACI trends have an adverse impact on agricultural production in Canada and the United States. This verifies the credibility of ACI trends reflecting climate change risk.

With a good proxy of risk, we assess the correlation between climate change risk and the corporate profitability of agriculture-related companies. Results imply that there are significant differences in profits. Companies in regions with higher climate change risk tend to have worse financial performance and higher ACI trends predict less profitability of relevant companies. This motivates us to further test the predictability of ACI trends on stock returns. We construct a risk-adjusted stock trading strategy that adjusts to climate change risk. With a one-year holding period, our non-overlapping strategy earns positive returns with zero cost at the beginning over a 26-year test period. The outperformance suggests the predictability of the ACI on stock returns and creates an arbitrage opportunity in the stock market. Therefore, we claim that the stock market is inefficient toward climate change risk. We get similar results and conclusions for different versions and extensions of the non-overlapping strategy, for example, strategies with different holding periods, strategies starting from different months or seasons, and overlapping strategies. Meanwhile, we also find the slow reaction of the stock market toward the climate information, which confirms the point that the outperformance of our strategies stems from the mispricing of risk.

However, conclusions are no longer attainable when we look at strategy returns in shorter periods. From subsample tests, we find that our strategy performs considerably well in terms of abnormally positive returns. But the return predictability degenerates quickly over a short sample period in 2017. This distinct evidence has never been mentioned in the literature since many scholars previously working in this topic seldom test short-term market efficiency nor on recent stock data. This "overturn" of market inefficiency is beyond our ability to test due to the limitation of currently available data. However, it highlights the importance of follow-up studies and we suggest that future research could be devoted more toward discovering evidence about the market efficiency and the impact of climate events, for example, the release of the Paris Climate Agreement (PA), on investors' attention towards climate change.

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