Weather Exposure and the Market Price of Weather Risk

Submitted by Kingkan Ketsiri to the University of Exeter as a thesis for the degree of Doctor of Philosophy in Finance, July 2012.

I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

Signature ……..

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Abstract

Whilst common intuition and the rapid growth of weather derivative practices effectively support the notion that equity returns are sensitive to weather randomness, empirical support is fragile. This thesis is the first study that investigates weather exposure and weather risk-return trade-off consistent with the arbitrage pricing theory (APT). It explores weather risk and its premium in the U.S. market during January 1980 to December 2009, based on three of the most weather-influenced industries.

The research starts with the construction of ten seasonally-adjusted weather measures as the proxies of unexpected temperature, gauged in Fahrenheit degree and percentage terms. The weather exposures of individual firms are estimated based on each of the ten measures and the market return. Although average weather exposure coefficients are small, the number of firms with significant estimates is more than attributable to chance and results are more profound in utilities. The weather coefficients are mainly stable over the sample period, indicating that the introduction of weather derivatives does not significantly impact a firm's weather exposure. Further investigation into summer and winter time reveals that most of the significant weather betas are found in winter. However, only a minority of firms have statistically different weather betas between the two seasons. Results are robust with respect to the ten measures.

The finding that unpredictable weather broadly affects groups of stocks has a direct implication in asset prices, as weather risk may be one of the priced factors. In this study, the weather risk premium is estimated using the standard two-pass Fama and MacBeth (1973) methodology, enhanced with Shanken's adjustments for the errors in variables problem. The tests are based on firm-level and portfolio-level regressions, assessed by different model specifications and repeated for the ten weather measures. In the unconditional setting, there is little support that the market price of weather risk is not zero. Although the estimates are insignificant, the magnitudes of weather premiums are relatively high compared with those of other macroeconomic factors in previous literature. Most of the estimated weather pricings are negative; thus, stocks exposed to weather should be hedged against an unanticipated increase in temperature. The main pricing results are robust to alternative sample sets, portfolio formations, base assets and weather measures. Nonetheless, the significance of weather premium is slightly affected by model specifications. In few cases, the pricings of weather risk are significant when the positive values of weather betas are used in cross-sectional regressions.

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Chapter 1

Introduction

1.1 Research motivation

The existence of weather derivatives has drawn my interest to weather risk, which has been recently identified as another major potential candidate for hedging activities. Not only do catastrophic weather events cause damage, but also small undesirable weather conditions can lead to adverse effects on revenues, costs, and the financial performances of companies. It is revealed by the National Science Foundation (2011) that routine weather events such as rain and cooler-than-average days can add up to huge annual economic impacts of as much as $485 billion in the U.S., and the effects seem to prevail in every sector. Although there is now an array of instruments available to hedge against weather exposure, evaluating that exposure is far harder than quantifying standard exposures such as commodity price risks (Renne and Hatch, 2011). Related studies are inadequate and there is a great deal of disagreement in the research as to what extent firms are exposed to weather fluctuations.

The literature shows that weather has largely impacted on companies through various economic activities; however, the body of knowledge has evolved on a piecemeal basis. One research strand has identified the economic effects of weather, while another has verified that these effects can influence the returns on equities. Although this linkage points to the likelihood of financial effects of the weather on share prices, it lacks empirical evidential back-up. Previous studies in relation to weather and financial markets have only focused on psychological effects, which may not reflect the real weather effect on asset prices. Indisputably, changing weather conditions are likely to affect weather-related firms' expected cash flows, and these effects could be passed on to equity returns. Existing literature reveals a gap in empirical knowledge of weather risk; therefore, this research is motivated to bridge the gap in this under-researched area.

In addition, the area of weather derivatives is quite new and unique, and little research has been done up to the present comparable to the research interest shown in traditional derivative topics. A critical element in the area is the debate on reliable pricing techniques, where the notion of the weather risk premium may turn out to be a key. This thesis is also motivated by this fact; hence, it makes a start on the task of pricing

weather risk. It is believed that the findings of this study would contribute more or less to the future of weather derivative valuations as well as the management of risks associated with unexpected weather conditions.

1.2 Background and context

To begin with, it is worthwhile defining the difference between weather and climate. There has been much concern over global climate change over the past decade; many studies may appear similar in scope but different in their timeframe of analysis. Thus, it is important to make the distinction between weather and climate to clearly understand the purposes of individual research, including this thesis.

> *Climate in a narrow sense is usually defined as the "average weather", or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. The classical period is 30 years, as defined by the World Meteorological Organization (WMO). These quantities are most often surface variables such as temperature, precipitation, and wind* (Baede, 2001, p.788).

The time horizon for climate projections is much longer than that of weather forecasts. Larsen (2006) pointed out that climate change studies have usually employed mid to long-term projections of weather to estimate the future impact of change on ecological and societal populations. In addition, they have often focused on individual sectors such as agriculture, and extended the timeframes they consider into decades or even centuries. As a consequence, the accuracy of the results is doubtful. This thesis, however, will take another perspective and rest on the analyses of financial impacts of 'weather' on firms. The chief interest is on the risk of small deviations from everyday weather which is not covered by weather insurance and can be detrimental to a company's financial health.

It is self-evident that weather is ever changing and unpredictable. Even in the current technology-based era, human wellbeing depends largely on weather. It influences our daily lives and choices, and many companies in a variety of industries face a risk affected by weather change (Carabello, 2005). The importance of weather risk is clear in the case of firms such as energy utilities, where demand for electricity and natural gas is strongly correlated with temperature, and agricultural commodity producers where the effects of weather can be seen on crop yields. Other industries are also affected by surprise weather events even though this may be less apparent. For example,

construction companies may have schedules influenced during periods of poor weather or a clothing company may sell fewer clothes in a cold summer. In fact, the profitability and earnings of virtually every industry depend to some extent on the vagaries of weather. William Daley, former Secretary of Commerce, estimated that about $1 trillion of the $7 trillion U.S. economy is weather sensitive (Challis, 1999; Hanley, 1999). Larsen (2006) evaluates the sensitivity of eleven U.S. economic sectors to weather and finds that 16.2% of the aggregate U.S. economy, in terms of production, is sensitive to weather on an annual basis. Although Lazo et al. (2011) reports the inconsistent figure that only 3.36% of U.S. annual GDP is exposed to weather, they cannot deny that every sector is statistically sensitive to at least one measure of weather variability.

Empirical evidence in relative to economic impacts of weather is abundant; however, the individual studies have examined the effects of different weather variables on various aspects of business such as productivity and profitability. Thus, the results are diverse and disconnected. In addition, these studies have usually focused on a particular sector, and weather effects on the wider economy have not been subject to much empirical research. For example, Yu, Yang and Chou (2002) suggested a potential risk from warming-induced evapo-transpiration in rice production on paddy fields in southern Taiwan. Al-Zayer and Al-Ibrahim's (1996) analysis shows a very high correlation between monthly electricity consumption and degree days in Eastern Saudi Arabia.[1] In retail sales, Starr-McCluer (2000) believes that weather was often identified as the cause of month-to-month fluctuations in consumer spending that exaggerates and departs from the seasonal cycle. These studies confirmed the economic importance of weather impacts through different channels, and, in fact, firms' accounting information such as earnings reflects these effects to a great extent.

On another research strand, the studies of the relationship between disclosed accounting information and the characteristics of common traded stocks are quite far advanced, in the area of market-based accounting research (MBAR). Ball and Brown (1968) first revealed the evidence of a statistically significant association between unexpected

[1] A degree day value is the difference between a day's average temperature and a previously set temperature (in the U.S., 65˚ F). Degree days above 65˚ F are called Cooling Degree Days and degree days below 65˚ F are called Heating Degree Days. More details can be found in Chapter 2.

earnings and residual returns. Lev and Ohlson (1982) concluded that accounting data convey useful and timely information to investors.

Indirectly, weather variability tends to impact on stock returns through unexpected earnings. It is surprising that no study has been carried out to date. Even though the relationship between weather and the stock market has been investigated earlier, researchers have only concentrated on the psychological effect. In this case, the impacts of total weather conditions on the performances of financial markets are analysed. However, investors are only rewarded for taking non-diversifiable risks, which to a certain extent relate to the unpredictable weather rather than total weather. The literature has yet to demonstrate, on a market-wide basis, the full extent of the unforeseen weather effects on share prices. These financial effects are considered as 'weather risks' in this study.

Considering weather as another fundamental risk, it is possible that this risk is priced in the market. If economic variables such as an interest rate or an exchange rate can generate security returns, a natural basic phenomenon like weather ought also to have the potential to fundamentally influence equity values. This is due to the fact that the occurrences are random and inevitable even with the advancement of today's technology. If the weather risk is systematic and cannot be diversified away, it will be priced. This initiative is shown to be consistent with the well-accepted asset pricing theories such as the capital asset pricing theory (CAPM) and the arbitrage pricing theory (APT).

It is surprising that none of the previous studies has ever incorporated the natural-type variables in modelling return generating processes, although an interest was shown up in the early history of asset pricing. In fact, Chen, Roll and Ross (1986) was interested in treating natural forces as one of the systematic factors, but they had a limited ability of including these factors at the time. Chen et al. (1986, p.384) suggested that *"…stock prices are usually considered as responding to external forces (even though they may have a feedback on the other variables). It is apparent that all economic variables are endogenous in some ultimate sense. Only natural forces, such as supernovas, earthquakes and the like, are truly exogenous to the world economy…*" Although weather and natural forces are not exactly the same, they share a common characteristic that they are outside of human control for which no one can hold responsible. In addition, forces of nature play a very important role in shaping the surface of the Earth

including weather. Incorporating weather risk in asset pricing may bring forth an initial step towards understanding of stock price correspondence to natural forces, such truly external effects as Chen et al. (1986) claimed.

This research will make a start on the task of pricing weather risk in an asset pricing framework, by investigating the effect of weather risk on expected stock returns and attempting to derive a market price of weather risk. The market price of weather risk is important as it does provide a promising avenue of attack in the search for reliable methods of pricing weather derivative contracts. The conventional risk-neutral valuation methodology does not apply to a weather derivative because an underlying asset is not a traded commodity and trader cannot create a risk-free portfolio by combining the derivative with its underlying weather. Since the risks associated with weather are non-diversifiable, the prices of weather derivatives should reflect the weather risk premiums (Richards, Manfredo and Sanders, 2004). Empirical studies related to weather derivative valuations have also found that the implied market price of weather risk is not zero, and is significant in some cases (Richards et al., 2003; 2004; Cao and Wei, 2004; Hardle and Cabrera, 2009). Thus, using the risk free rate to discount the expected payoff is inappropriate and weather derivatives must be priced so as to reflect weather risk premiums.

The previous literature has only inferred the market price of weather risk from equivalent-derivative quotes or simulations, but this thesis will take a different approach that will directly estimate the weather pricings from the stock market information. Following the Fama-MacBeth (1973) procedure, the research can measure the weather risk premium and easily compare results of other recent asset pricing studies at the same time. The approach, in the vein of factor models, is appropriate because it is intuitive, easy to implement and based on the well-known asset pricing theory.

1.3 Research objectives

The overall study aims to obtain an insight into the financial effects of weather on stock returns in weather-sensitive industries. In order to achieve this, research objectives are three-fold. Firstly, the study aims to quantify the unexpected weather events for the first time in academic practice. Secondly, it gives a unique definition of weather exposures and provides comprehensive empirical evidence of those exposures across industries. Thirdly, it attempts to research the possibility that weather might be one of the

fundamental variables affecting stock returns. A key object of the study is to price such weather effects, if any, using the factor models such as the APT.

1.4 Research contribution

This thesis can contribute to a great extent to the theoretical background of weather risk, as it is able to connect the two individual research strands within an objective setting. Not only does it determine the under-researched area and fulfil the gap in literature, but it also locates weather risk into the well-developed asset pricing framework.

This research will provide the first evidence of weather risk and its market price in the U.S. stock market. The findings will add to the knowledge of weather risk in another aspect that has never been examined before, the fundamental effects of 'unexpected' weather conditions on a firm's equity returns. Comprehension of such effects is useful for at least two reasons. First, an understanding of the effects of weather risk on stock returns may provide new insights into the dynamics of the market. Weather, being a package of natural phenomena more basic than fundamental economic variables, may turn out to be an important driver of stock returns. Second, studying the weather risk premium may relate to the pricing of weather derivatives, as previously mentioned.

Hopefully, the knowledge would enable better management of risks associated with the unforeseen weather events. In addition, the study of weather risks in the asset pricing context will be useful for capital budgeting, cost-benefit analysis, portfolio management, and for other economic problems requiring knowledge of weather risk.

1.5 Structure of the thesis

This thesis is organized into seven chapters. Chapter 2 illustrates the existence of weather risk for businesses by reviewing previous studies relating to weather risk in various aspects. The body of research indicates that routine weather events have economically impacted on corporations. A recent weather risk management tool developed in the late 1990s, *weather derivative*, has mitigated the risk of these small variations of weather. Thus, this chapter provides a brief explanation related to the weather derivative, including the history, the market, the unique characteristics and the valuation techniques used at the moment. As this type of asset is new and relatively different from traditional derivatives, the pricing approaches remain in a rather

rudimentary state and are largely unsatisfactory on theoretical grounds. However, the market price of weather risk seems to be the key to this issue.

If we accept that weather risk does exist, then it becomes imperative to find satisfactory and reliable methods of pricing such risk. This thesis proposes a promising avenue to price weather risk through a factor model, consistent with the asset pricing theory. Chapter 3 mainly focuses on the framework used for the research. It first discusses the literature in market-based accounting research, which suggests that the economic effect may be transferred to the financial effect on a firm. As this reveals the possible effect of weather on security returns, the chapter clearly identifies an area that is still under-researched and develops the research hypotheses. Following the assumption, this chapter explains the asset pricing theory, which the research methodology will be based on, and reviews related literature of CAPM and APT. The chapter finally suggests the inclusion of weather as another fundamental determinant of stock returns, and presents the contributions of this thesis.

Chapter 4 details and analyses the data used in the research. It describes the logical process of sample and variable selections, sources of data, problems and resolution of missing observations, as well as preliminary statistical results. Central to the chapter is the exploration of weather variables that will be used throughout the study. The unexpected element of weather is defined and measured here, followed by an analysis of the statistical properties of the weather variables developed in this chapter.

Chapter 5 analyses weather risk in the market by estimating individual firms' exposures to weather based on the previously-developed weather factors. The chapter begins with a review of the various measurements of weather exposures in prior empirical studies. Then, it discusses a new approach in estimating weather exposure, which conforms to the standard approach of estimating exchange rate exposure in previous literature. It elaborates the methodology as well as specifying alternative models used in this examination. It subsequently provides a number of empirical findings about weather exposure in the U.S. stock market. Finally, it discusses the results, acknowledges limitations and suggests further research in relation to weather risk.

Chapter 6 empirically investigates whether the market rewards weather risk, as individual stocks that do not hedge themselves against weather fluctuations would be expected to be correlated with the weather that affects them. In other words, it generally

contributes to the experimental search for weather as a potential pricing factor in asset pricing models. The chapter reviews relevant literature of the market price of weather risk, which is relatively scanty. It then proposes to study the weather pricing in an alternative way, consistent with the well-accepted pricing theory. The Fama-Macbeth two-stage regression procedure is explained and weather is included in the asset pricing model. Various modifications of the model are proposed, and empirical results are reported afterwards. The evidence is discussed and further research relative to the market price of weather risk is suggested here. Finally, Chapter 7 provides a summary of all major findings in the thesis. It concludes with a discussion of the limitations of the study and recommendations for future research.

Chapter 2

Weather Risk and Weather Derivatives

2.1 Introduction

Weather is beyond human control. In ancient times, people found this fact so frightening that they created gods such as Zeus or Jupiter to explain weather phenomena. Nowadays, we can explain such events but we have yet to forecast them precisely. In addition, climate is changing: global warming is a universal topic and it tends to increase not only in temperatures but also in the unpredictability of weather patterns. Scientists expect this trend to damage the world's environment and thereby human wellbeing.

In the view of William Clay Ford, Jr., a chairman of Ford Motor Company, this climate change becomes not only an environmental but also a business issue (Collins, 2006). This is because bad weather costs money and there are many businesses-- such as energy, agriculture, construction, and travel-- whose corporate revenues and earnings are extremely dependent on weather. ABN AMRO revealed findings of the impacts of adverse weather conditions on production in Western Europe, Scandinavia and North America during 1980-2003 (Anon, 2005). The study included 15 sectors which cover most of the economy and it was found that many industries were vulnerable to unfavourable weather. The greatest risk was reported in the Netherlands and Denmark, in which greater than 30% of all production was subject to loss from poor weather. In addition, industries in large sections of the U.S. retained the highest levels of exposure to adverse weather, with 25-30% of production at risk. Similarly, Larsen (2006) evaluated the sensitivity of eleven U.S. economic sectors to weather and found that 16.2% of the aggregate U.S. economy, in terms of production, was sensitive to weather on an annual basis. By estimation, almost 20% of the U.S. economy was exposed to weather (Carabello, 2005) and more than a third of the U.S. economic growth was related to weather circumstances according to Commerce Department figures (Morrison, 2009).

This fact has inclined financiers to the possibility of transforming this inconsistency in nature into money. Before 1997, there were only few financial instruments offering a protection against weather risks. The use of insurance is known to be an effective tool to

shield the high-impact events such as hurricanes or floods, but it does not cover the losses from small fluctuations in daily weather. This suggests an inception of the weather derivatives concept where weather turns to be a tradable commodity. The first transaction of a weather derivative was traded over the counter in 1997, and Chicago Mercantile Exchange (CME) launched a series of exchange-traded futures and options in 1999 (Geman, 1999; Jewson and Brix, 2005; Cao, Li and Wei, 2004). To date, the weather derivatives market has actively expanded, especially from 2003 when the exchange began offering clearing services for traded transactions. Even with the economic downturn recently, the 2008 volume has not contracted as much as the other sectors in the futures industry (Morrison, 2009) and the market still has potential to reach every business sector globally via continued innovations (Dischel, 1999b; WRMA, 2006).

This chapter attempts to emphasize that weather risk does exist and it impacts on a wide economy through different aspects in various industries. The effects are important and quite unique in the sense that weather conditions tend to affect volume rather than price. As a result, weather derivatives were created to offer an additional protection for volume hedging which the traditional derivatives market still lacks. In other words, they could be seen as direct hedging tools for businesses where their activities depend tremendously on weather. As the weather derivatives concept has not been long established in comparison with other types of asset class, this chapter also aims to provide a background of weather derivatives and their market.

The content of the chapter is divided into two sections: weather risk and weather derivatives. The first part firmly establishes the importance of weather risks on academic grounds by reviewing the previous studies of diverse weather effects on various sectors including stock markets. The literature review is divided into four subsections by business sectors: energy utilities, agriculture, other sectors and the financial market. In the following section, the management of weather risk through weather derivatives is introduced. This part briefly illustrates how the weather derivative was created, how it differs from insurance and traditional derivatives and how it works as a financial instrument. It also mentions the development, current situation, limitations and possible growth of weather-related trading markets. Last but not least, it touches on a variety of valuation techniques used at the moment to price the weather derivative instruments.

2.2 Weather risk

Not only do disastrous weather events result in severe damage to lives and properties, but also changing weather conditions create adverse financial conditions for companies. The weather impacts range from small reductions in revenues to devastation of the company. Many studies have been carried out on the effects of weather on various kinds of business activity in different sectors, focusing on a variety of weather parameters. For example, temperature is central to electricity and gas consumption. Although there have been a number of examinations of the relation between energy consumption and other weather factors such as wind and humidity, the proportion is smaller. Agricultural produces, on the other hand, are sensitive to more diverse weather elements, for example, temperature, precipitation, and humidity. In most respects, weather effects on these two industries are evident and direct. Even so, other industries such as construction, retailing and tourism also suffer from the impact of unpredicted weather occurrences. For instance, construction companies struggle to meet schedules during periods of poor weather, an amusement park would attract fewer visitors when it rains, and consumers can postpone purchases if shopping is more difficult due to weather.

In this section, academic work and press reports on weather impacts in different frameworks are reviewed in order to give a thorough understanding of the weather sensitivity of economic sectors via wide-ranging business elements such as production, demand, pricing and sales. The review is divided into parts by industry to provide a conception of weather risk in distinctive settings.

2.2.1 Energy utilities

The energy sector is strongly dependent on the weather. Cold winters create higher demand for heating while hot summers stimulate air conditioning needs. It is clear that demand in this industry is substantially subject to weather variability, and the literature has explored, to a great extent, the impact of weather variability on the change of energy consumption such as electricity and gas. Most studies include seasonal weather factors in the models of energy consumptions, and they have shown that temperature is usually the most significant weather variable affecting electricity demand (Li and Sailor, 1995). Sailor and Munoz (1997) suggested that temperature is the most important climatic factor in explaining not only electricity but also gas demand. They used a methodology of historical analysis to confirm the relationship between temperature and electricity

consumption in eight of the most energy-intensive states in the U.S. In their research, the different energy consumption models were developed using two sets of independent variables, either primitive or derived forms. Examples of primitive variables are temperature, precipitation, relative humidity, wind speed, atmospheric pressure, and solar radiation. On the other hand, derived variables are the value calculated from the observed primitive variables and include heating degree-days (HDDs), cooling degree-days (CDDs), and enthalpy latent days (ELDs).[2] It was shown in the study that the primitive variable approach was as good as the derived variable models in explaining natural gas consumption, whereas the degree-day models approach was better for electricity. Sailor and Munoz (2007) justified that electricity is used for heating and cooling applications while natural gas is normally for heating only.

Researchers suggest that the relationship between energy demand and weather is non-linear and exhibits a seasonal pattern. Bolzern, Fronza and Brusasca (1982) showed that the relation between daily temperature and winter-daily electric load in Milan, from winter 1976 to winter 1978, is significant and increases over time. Likewise, Valor, Meneu and Caselles (2001) found the non-linear relationship between electricity load and daily temperature in Spain from 1983 to 1999. The results showed the comfort zone of ±3°C around 18°C and two saturation points beyond which the electricity load no longer increases. The authors asserted that the derived variable model allowed a better fit of the electricity demand functions.

Pardo, Meneu and Valor (2002) examined the relationship between derived weather variables such as HDDs and CDDs and Spanish daily electricity demand, and found clear evidence of the existing seasonal structure. Regarding the consequences of serial correlation and autoregressive behaviour, the model with lagged temperature variables appeared to have the higher predictive power, as the electricity demand was affected by both current and previous temperatures. The authors found that HDDs' lagged coefficients were significant up to the fourth lag, whereas only CDDs' first lag was significant. As expected, the size and significance of the coefficients decreased for increasing lags. Peirson and Henley (1994) discovered a similar conclusion in Great

[2] A degree day value is the difference between a day's average temperature and the base temperature (65˚F or 18˚C), HDD = max ($T_0 - T_i$, 0) and CDD = max ($T_i - T_0$, 0). The ELD value represents the amount of energy required to lower the humidity to the ASHRAE (the American Society of Heating, Refrigerating, and Air-Conditioning Engineers) comfort level without reducing air temperature.

Britain. The out-of-sample was drawn in this study to test the predictive power, and a high correlation between observed and predicted values of 94.16% was obtained.

Gabbi and Zanotti (2004) investigated the relationship between gas consumption and climate parameters such as average temperature, degree days, humidity, pressure and rain in the Italian market using a stepwise scheme. They applied different models, from the simplest regression to extended models, adding lagged variables, dummy variables, and autoregressive error term. Even though other studies in different countries suggested that variables other than temperature were not significant, the authors found that humidity and pressure were also significant in this study. The estimations showed that the derived variables (degree days) achieved better statistical results than temperature. Moreover, it was found that the estimated coefficients decreased over time, confirming that present effects were more relevant than the lagged effects. As expected, the HDD had a positive expected sign and the holiday weekend dummy had a negative sign. The overall results from the study seemed to point to the fact that, among the explicative variables, the most significant was the temperature, both present and lagged. In addition, the seasonal component was very important as confirmed by the considerable improvement of R^2 from 70% to approximately 80%.

Al-Zayer and Al-Ibrahim (1996) analysed the effect of temperature on electricity consumption in Eastern Saudi Arabia, which is subject to hot humid summers and cool dry winters. They used monthly data, from 1986 to 1990, of electricity consumption and degree days to obtain a forecasting model for assessing the impact of ambient temperature on electricity usage. The electricity consumption data appeared to have a yearly cyclical pattern of a significant increase in summer and decrease in winter, with a peak in July and August during the investigated periods. The results exhibited a very high correlation between electricity consumption and degree days, ranging between 0.80 and 0.96.

Hor, Watson and Majithia (2005) developed a multiple regression model to forecast monthly electricity demand in England and Wales, using weather, GDP, and population growth as independent variables. Comparing statistical error indices, their simple multiple regression models proved to be better than commonly used models such as an artificial neutral network, a socioeconomic model, and the Box-Jenkins model. Weather variables in their models included different parameterizations of temperature and humidity, such as HDDs, CDDs, ELDs, wind speed, sunshine hours and rainfalls.

However, all models underestimated the winter demand because the correlation of extreme low temperature and electricity demand was weak.

The non-weather factors tend to be more important in long-term forecasting since long-term energy consumption is related to the change in other socio-economic factors as well as climate change. The actual response may be underestimated if we consider only variations in weather variables in sensitivity models. Petterson (1994) pointed out that variability in residential consumer behaviour was more significant than climate variations in determining energy consumption in his simulation model. It is suggested that the key socio-economic factors that affect the behaviour include household income, household size and electricity price (Lam, 1998). Sailor and Pavlova (2003) investigated the potential of changes in market saturation to exacerbate the increased electricity demand resulting from climate change. Based on air conditioning market saturation data from 39 U.S. cities, the authors developed a generalized functional relationship between market saturation and CDDs. The focus of this study was on the residential sector in three cities within each of four states. There were convincing results that market saturation's changes in some cities may be two to three times more significant than weather sensitivity to current loads. This study also showed a strong exponential relationship between saturation and CDDs. There was a potential that long-term increases in CDDs could result in increasing saturation that may be more important than the weather sensitivity. Their research demonstrated that it was crucial to include long-term saturation adjustment to the air-conditioning electricity consumption model responding to climate changes.

The weather impacts not only on energy demand but also on spot prices. Energy prices in the market rise when cold weather is forecast and plunge with the prediction of warm weather. Research in this area intends to find the appropriate models to explain the power price behaviour. Rambharat, Brockwell and Seppi (2005) introduced a discrete-time model for electricity prices, including transitory spikes as well as temperature effects. Electricity prices exhibit occasional jumps, making them highly non-Gussian. In addition, temperatures generally have significant non-linear effects on electricity prices. Therefore, the models that do not account for these characteristics can misprice financial derivatives and lead to inferior operational decisions. The authors proposed the improved model to incorporate more realistic mean reversion and jump dynamics, and they found that it provided a better fit for their sample. Their results confirmed that

temperature had a significant effect on electricity prices and the effect of temperature was positive.

In summary, electricity load and gas consumption show strong correlations with weather variables, especially temperature. Empirically, the relationships are non-linear and the derived variables such as degree days seem to explain energy consumption better than primitive variables like temperature. There exists a seasonal and autoregressive pattern in an energy demand also so many studies propose to include a seasonal component and/ or lagged variables into their models. Moreover, researchers advocate incorporating non-weather variables such as GDP, population growth and household income for a better explanation of energy consumption as they can influence user behaviours. These socio-economic and demographic variables tend to be even more crucial than weather variables in the long term studies. In addition, weather tends to be an important factor in determining energy spot prices as well through a demand-supply mechanism.

2.2.2 Agriculture

Farming has long been known to depend on weather as growing conditions rely mostly on the appropriate temperature and precipitation. Despite the advancement in technology and know-how, unexpected change in weather conditions or extreme weather events can undermine productivity which in turn affects farmers' incomes. During this time of global climate change and environmental concern, the sector yields seem to be more vulnerable to weather changing conditions. Lansigan, Delos Santos and Coladilla (2000) reported that rice yields in Philippines were directly influenced by both short-term weather fluctuations and longer-term climate variability. Hence, researchers have attempted to establish a clear relationship between weather variables and crop yields, to better understand weather effects and in order to mitigate the risk. Schelenker, Hanemann, and Fisher (2006) reviewed the literature so far and found mixed results regarding the weather impacts on agriculture. They summarized the three broad approaches most researchers have used to examine agriculture's sensitivity to weather, which are the agronomic approach, the computable general equilibrium approach and the Ricardian approach. The following sections aim to clarify each approach in detail and discuss results obtained from different empirical studies.

Firstly, a considerable amount of research interest has addressed an issue of crop yield vulnerability to changing weather conditions based on the agronomic models. This method applies different climatic variables into models to find the optimal growing conditions and to measure the extent to which climatic changes impact on crop yields. For instance, Kaylen, Wade, and Frank (1992) proposed the models of corn yield by incorporating stochastic trends, prices and weather variables which are precipitation, temperature, soil moisture, and dispersions of those weather factors.

Chen and Chang (2005) used econometric methods to investigate the changes of yield distributions in respond to weather change. They adopted maximum likelihood regression to study weather impacts on the yields of seven major crops—rice, corn, soybean, peanut, adzuki bean, sweet potato, and potato—in Taiwan based on pooled panel data of productions in 15 regions for ten years. Both climatic and non-climatic effects were included in a set of explanatory variables. The estimated results showed that management had a positive and significant impact on yield, whereas land slopes were damaging. In addition, weather variables exhibited diversified effects on crop yields though they were all significant. For example, an increase in temperature variation reduced yields for rice and adzuki beans but improved corn yields. More precipitation increased the variability of rice and corn yields while lessening that of adzuki bean yields. However, technology of crop production and agronomic practices generally improved yields over the sample period after controlling for weather and management effects.

Alternatively, simulation-based models for crop growth may be developed to study changes in crop yields corresponding to changes in weather conditions. For example, Adams (1989) used crop simulation models to predict changes in yields of both irrigated and rain-fed wheat, corn, and soybeans. Based on simulation results of specific crops in the Chinese agriculture, Smith and Yunlong (1996) found that the major cereal crops' yields such as rice declined with climate change, except where additional irrigation was available. Schlenker and Roberts (2006) combined the strengths of the reduced-form approach and simulation models into their research to find the relationship between weather and corn yields. Using unique data of daily weather of the U.S. for 1950-2004, they proposed a significant non-linear association between temperature and corn yields. A result showed that yields were increasing with temperature if it was moderate but

damaging when temperatures exceeded 30˚C. This is more or less in keeping with the concept of degree days.

Researchers noticed that the analysis of agronomic approach focuses only on the agricultural sector, but ignores the possible connections with the remainder of the economy. Therefore, the second approach, computable general equilibrium (CGE), is introduced to remedy this problem. Higgs and Powell (1990) presented the general equilibrium model of the Australian economy, which was previously called ORANI, to forecast agricultural incomes for farmers in the south-western of Victoria. They had broken a new ground in the CGE literature by using independently made long-run forecasts for the economy at large to provide the shorter term predictions on quite a small regional level.

Kumar and Parikh (2001) used an integrated modelling framework to estimate the impact of climate change on Indian agriculture. They started by using a crop simulation model to estimate the potential changes in rice and wheat yields, and then integrated those predicted yields with an applied general equilibrium model, AGRIM, to estimate the economic and welfare implications of climate change. Results showed that the projected large-scale changes in climate would significantly reduce crop yields, consequently cause a harmful effect in agricultural production. The study of economic and welfare impacts indicated that climate change would create significant problems for the economy, and people in poorer sections tended to bear a greater share of such burden.

Whilst the agronomic models seem not to fully capture the adaptation and alleviation strategies of farmers in response to climate change, the CGE models are only appropriate to highly aggregated industries of the economy (Schlenker et al., 2006). Thus, the third approach called the Ricardian analysis is introduced. Mendelsohn, Nordhaus, and Shaw (1994) proposed this technique to examine the effects on land values and farm revenues instead of crop yields as the traditional production-function approach did. They believed that the traditional crop-yield models often neglect adaptations such as crop switching that farmers make in response to economic and environmental changes. Therefore, the proposed technique took these adaptations into account by focusing on the value of land, assuming that the economy has fully adapted to climate change so that land prices have achieved long-term equilibrium. This approach is based on the discounted future values of all profits or rents gained from the

land. However, Cline (1996) criticized the validity of the approach when assuming constant output prices, perfectly elastic irrigation, and the application of global mean impacts for the U.S. Mendelsohn and Nordhaus (1996) accepted that an ignorance of variant relative prices may lead to underestimated damage from welfare loss; however, it was shown that the bias was small around five per cent. They agreed that criticism on a uniform climate-change scenario was a useful addition so they recommended further work of Williams, Shaw and Mendelsohn (1996) where seasonal and regional variation were examined. Nonetheless, the irrigation assumption response was that water price, implicitly, was a function of climatic or geographical variables so the model was unbiased. Also, it was pointed out that this approach is well-suited to tremendously heterogeneous sectors because it can rely upon reduced-form estimation and does not require the tedious task of constructing models of different crops in dispersed locations.

Mendelsohn et al. (1994) suggested that temperature and precipitation had a systematic influence on agricultural rents. These effects tended to be non-linear and seasonally varied. The overall impact of climate as measured by marginal impacts was largely the same across the different models even though the quantities estimates varied. They found that higher temperatures in all seasons apart from autumn reduced average values of farmland, while higher precipitations outside of summer or autumn increased those values. Results were robust and climate effects on agriculture were stable over time.

Schlenker et al. (2006) also applied the Ricardian approach in their study of the effect of global warming on the U.S. agriculture. They related farmland values to climate, soil, and socio-economic variables for U.S. counties east of the 100th meridian, where agriculture is not primarily dependent on irrigation. Instead of using some month's average to represent seasonal effect, the authors captured the concept of degree days to reflect the agronomists' perspective that plant growth is linear in temperature only within a specific range. The estimated coefficients of climatic variables in this study were consistent with the previous agronomic literature, as the number of growing degree days and precipitation were close to optimal growing condition for many agricultural products. In addition, degree days above 34°c were always dangerous in the findings. By adding the fixed effects to account for the likelihood of unobserved common characteristics such as crop subsidies and state-specific taxes, it was found that these inclusions did not decrease the significance of climatic variables and concurrently the parameter of spatial correlation was nearly unchanged. Additionally, it was

predicted in the study that the farmland values would decrease by 10%-25% in the middle term, depending on climatic scenarios, due to global warming while a distribution of such an impact expanded in the longer run (Schlenker et al., 2006).

Kurukulasuriya and Ajwad (2004) also adopted the Ricardian technique to estimate the climate change impacts at the household level in Sri Lanka, allowing a control for factors such as human and available capital as well as adaptation mechanisms. The use of farm-level data can capture a variation within a district and control socio-economic factors better than the aggregate data. It was found in the study that climate variables explained roughly 14% of the variation in net income across farms, and changes in revenue fluctuated from -23% to 22% depending on climate change scenarios. These effects were also predicted to vary considerably across regions: the dry areas were expected to be adversely affected from warm weather whereas the wet zones might benefit from it. The authors also pointed out the importance of precipitation for tropical farmlands as such changes can dominate temperature especially during the key months of the growing seasons.

It is obvious that there are diversified effects of weather conditions on crop yields. Different crops in distant locations require distinct growing conditions. Although a conclusive pattern may not be drawn for all crops, one could at least expect an ongoing increase in crop yield variation attributable to greater climate deviations and more frequent occurrences of extreme events (Chen and Chang, 2005). Analysis of impacts of climate change on agriculture is vital as it deals with food security. Besides, the effects are not only confined to agricultural productivity, but also pass such burdens on to product prices and farmers' incomes. A study of Roll (1984) indicated that cold temperatures cause orange juice futures price movements, and a small yet statistically significant relation was also found between orange juice futures returns and unpredicted weather. Additionally, long-run climate change is likely to bring about $1.3 billion or 4% increase in annual agricultural sector profits by Deschenes and Greenstone (2006)'s estimates. Climate is also found to be a considerable fraction of the variation in rural income across the U.S. and Brazil (Mendelsohn et al., 2004). It is asserted that adverse weather clearly leads to rural poverty, and global warming is affecting each region to a different extent.

Hence, a clear comprehension of the relationships between weather and crop yield distributions is critical to minimize the negative impact of climate change on the wide

economy. Even though weather cannot be controlled and an agriculture sector is still extensively responsive to nature, this information can assist farmers as well as governments in preparing possible options to cope with the variation of weather conditions. One of them is to use financial derivatives to hedge against weather risk, and it is predicted that weather derivatives will be more actively traded in this sector.

2.2.3 Other industries

It is apparent that there is a prevalence of weather effects on agricultural productivity and utilities consumption. At the same time, it is highly probable that other industries are affected from unexpected weather to some degree. For instance, a construction company can experience delays when it is cold or raining because labourers cannot work outside. Such delays could lead to cost overruns or claims on construction projects. Researchers have attempted to quantify these impacts in an objective way and included more industries into their studies. Larsen (2006) studied the impact of weather on 11 sectors of the U.S. and tried to quantify the historical sensitivity of each sector's production to annual weather variability. The 11 sectors included agriculture, wholesale trade, retail trade, transportation, utilities, communications, manufacturing, services, mining, construction and FIRE (finance, insurance, and real-estate). The weather parameters were HDD, CDD, precipitation and precipitation standard deviation. The outcomes showed that the impact varied from region to region and sector to sector. The manufacturing sector exhibited consistently negative signs for HDD, which means sector output drops when temperature decreases. Surprisingly, both manufacturing and mining sectors were more sensitive to weather than previously thought.

Tol (2000) included tourism, fire, water consumption, energy consumption, and agriculture in one study of weather impacts on nature, social, and economics in the Netherlands. For tourism, it was confirmed in his research that more tourists chose to travel during a hot summer and visits declined immediately by the following year. Likewise, Galeotti et al. (2004) investigated similar industries in Italy to find the impacts of extreme weather events on the socio-economic system. They found that more dry weather significantly increased the number of fires and higher summer rainfalls tended to reduce the yearly number of forest fires. Meanwhile, high monthly regional temperatures had a positive effect on domestic tourism flows. Results also showed that last year's temperature in the corresponding month appeared to trigger monthly

domestic tourism, whereas last year's rainfall impeded domestic movements. More weather effect reviews on tourism are shown in the subsequent section.

Tourism is considered by many to be a luxury and unnecessary. Nevertheless, its impact on the economy is huge and many local economies greatly depend on tourism. Concurrently, this source of income may fluctuate due to many factors and weather is one of them. The attractiveness of destinations or the motives to travel is sensitive to weather and weather change because tourist decisions can be changed if the weather is expected to be adverse. Not only does the presence of extreme weather events but also unusually hot or cold seasons change people's decisions on their holidays.

Until recently, most studies have concentrated on recreation demand and centred on demand functions for recreation and tourist facilities across populations. Lancaster (1966) as cited in Bigano et al. (2005) originally argued that the characteristics of a good are more important to consumers than the actual good in itself, and that climate and country attributes should be considered in the influential characteristics of tourism. However, according to a review by Gallarza, Saura and Garcia (2002), climate was included as a destination attribute in only 12 out of 25 studies of destination choice; however, it was ranked the seventh among the 20 most frequently used attributes. Hu and Ritchie (1993) reviewed several studies and found that natural beauty and weather were general desirables in choices of destination. Nonetheless, there is little interest in tourism research to specifically examine weather as the destination image. Pike (2002) as cited in Bigano et al. (2005) found only one, which is the survey conducted in Germany by Lohmann and Kaim (1999), of the 142 destination image papers assessing weather. The study asserted that landscape was the most important for destination image, while weather and bio-climate were the third and eighth respectively. Yet, destinations were still chosen despite the likely bad weather even if weather was found to be a significant factor. Arbel and Ravid (1985) addressed another aspect of recreation demand using a time-series approach to detect characteristics which vary with time. They studied the factors associated with the use of park recreational facilities in New York, which were weather, energy prices, energy shortages and the currency value. Weather index used in the study is the proportion of average temperature to precipitation, based on the assumption that people would not attend state parks even if the temperature is high when it is raining. The impact of weather patterns was normally hard to detect in a cross-section study, but showed quite clearly in this study. It was

verified that weather played a major role in the short term but had no long term effect on park attendance, which was as expected.

Outdoor sports like golf or skiing also rely heavily on weather conditions. These sports also induce other activities, especially for the use of accommodation facilities. Researchers have conducted a series of studies on golf demand, golfers' experiences, or the prediction of golf course expansion. One interesting research is by Correia and Pintassilgo (2006), who investigated the motivations behind golf demand in the Algarve based on the survey results in 2002. It was the first to address the behavioural side of golf demand in this area. They identified four driving motivations to play golf, which were the social environment, the leisure opportunities provided by the region, the golf courses and the game conditions, as well as the price and accessibility. Weather was one of these motives, considered as a part of leisure opportunities. Also, the analysis of monthly golf demand clearly related to weather conditions as it exhibited the seasonal pattern in the monthly number of golf rounds.

In spite of the global warming trend, the tourism literature attention on weather or climate change has been fairly limited. Bigano et al. (2005) reviewed the impact studies of climate change on tourism and categorize those quantitative studies into four groups. The first group related to the forecast of changes in the supply of tourism services when applied to winter sports. For example, Abegg (1996) as cited in Bigano et al. (2005) evaluated the consequences of temperature changes, which impacts on snow depth and coverage, on ski season length and the facilities used in the Swiss Alps. Secondly, the tourism index approach was used to assess the impact of climate change on tourism. Thirdly, statistical techniques were applied to find a relationship between demand and weather. Lastly, with grounded economic theory, the estimated demand equations were estimated within the climate change framework. Loomis and Crespi (1999) predicted a sharp reduction of 52% in skiing days under the scenarios of 2.5˚C increase and 7% decline in precipitation in their study. Climate change can affect international tourist flows too since cool countries may be more or less attractive as they get warmer. Hamilton, Maddison and Tol (2003) presented a simulation model called the Hamburg Tourism Model that traces the international tourist flow from 207 countries, using variables of distance, population, income, and temperature. This model was used as an input to a computable general equilibrium model for examining the economy-wide implications of climate change.

Most of these previously mentioned studies seem to neglect the impact of extreme weather conditions, which may affect short-term demand such as the choice of destinations or the holiday lengths. Therefore, Bigano et al. (2005) empirically analysed the relationship between climate characteristics, weather extremes and domestic and international tourism demand across Europe, particularly in Italy. They found that temperature was generally the strongest indicator of domestic tourism and they were positively related in the same-month all across Europe, except in winter sports regions. A summer warming of 1˚C increases domestic demand by approximately 0.8-4.7%. Also, the climate impact relied on destination type; for example, coastal resorts responded more favourably to rising temperature in summer than inland resorts. However, more research is needed to draw a clear conclusion as far as extreme weather events are concerned.

While holiday decisions are socio-economically made, it is admitted that weather is among the relevant factors influencing a shift in demand in the industry. The relationship between tourism and weather is generally seasonal and varies according to different destination types. Although empirical studies regarding associations between tourism and weather are few and no clear quantitative message is drawn, the degree of interest is now gradually increasing and more aspects of the relationship are being covered.

The other sector worth mentioning in greater detail is retailing. A retail sector usually observes predictable sales patterns related to seasonal weather, but somehow endures losses due to abnormal weather. For example, a cloth retailer would sell fewer clothes in a cold summer or a warm winter. Steele (1951) suggested that weather might affect the sales of a retail store in four ways; inconvenience, physical prevention, psychological change towards shopping habits, or impulse purchase. However, the research focused on the extent of correlation between daily sales and weather, rather than finding which of these factors affect sales, by estimating four weather variables to a store's rectified sales during seven weeks before Easter.[3] The analyses based both on the years of early Easter and late Easter. Results were different for the reason that early Easter seasons are typically colder and stormier than late Easter seasons. The amount of snow cover was the outstanding weather cause of sales variation for the early Easter years, whereas precipitation had more effect than temperature, snow cover, and sunshine during the late

[3] Rectified sales denote sales after the total process of correcting data for seasonal and trend variation.

Easter season. However, the influence of sunshine was minor in both cases. It was shown that, from 88% of sales variance, 42% was accounted for weather factors and the rest was due to the rectification process.

There were reports later on also suggesting the influence of weather on sales. Peter Gibbs, a BBC weatherman, took the view that global warming could have a direct impact on the supply and demand for food and drink within five to ten years. He addressed, according to one manufacturer, a 10% increase in ice cream sales for each one degree rose in temperature and added further that soft drink sales rose four-times faster above 18˚C whereas sales of soup rose exponentially below that (Pendrous, 2003). This information confirms the impulse purchasing type of Steele's suggested relationship, whereby weather can drive a desire for particular merchandises for certain types of weather. On the other facet, some economic experts conceive of unusual weather as a period to delay purchasing only. Therefore, they expect the next period's sales to pick up. Starr-McCluer (2000) believes that weather causes month-to-month fluctuations in consumer spending apart from the seasonal cycle. The study rested on the notion that weather, via time and money constraints, can induce substitution in spending across goods and over time. It also discussed how sales levels may be affected by retailers' incentives to clear out inventories. From the analysis based on U.S. retail sales, there were modest but significant effects of unusual weather on nominal monthly retail sales, even after taking other determinants of consumer spending into account. The data showed considerable evidence of weather-related dips and swings. However, lagged effects often offset original effects, tending to wash out at a quarterly frequency. The quarterly data exhibited a tendency for sales to slump in a cold first quarter and then bounce back in the second. Nonetheless, it was unclear in the study regarding the relative importance of such effects due to the lack of related data on prices or physical quantities of goods.

The online market surprisingly also has evidence of weather impacts when TradeDoubler, a digital marketing company, found that online sales from more than 1,000 advertisers across Europe peaked on bad-weather days (Bainbridge, 2006). Reasons might be similar to Steele's suggestion that weather make people feel uncomfortable about going to stores or physically prevent them from going out. Likewise, Bainbridge also reported TBG's research finding that DatingDirect campaign performed 27% better on bad weather days than on sunny days as people turned to the

web for amusement. However, some advertisers benefit from good weather considering Ocean Finance campaigns performed 54% worse in bad weather. Thus, it is possible for online media companies to take advantage of the correlation of weather and online sales by adapting their advertising and marketing activities according to weather change. One plan is through allocating one email list to advertisers with similar target audiences, and sending out to different companies' emails according to the type of weather. The author raised an example of HotBlocks strategy that a team can send out a pre-loaded campaign within minutes when temperature hits an agreed level, allowing advertisers of beer or ice cream to exploit hot weather more rapidly. In this way, the digital media certainly has a quick response to changes in weather and obviously reaps benefits over other advertising channels.

Weather not only affects demand of retailing but also indirectly influence product prices in accordance with the demand-supply-price relationship. Thus, Brunner (2002) studied the historical effects of the El Niño weather system on world product prices and economic activities, primarily focusing on real prices of non-oil primary commodities. Based on two widely cited measures of the El Niño-Southern Oscillation (ENSO) which are sea surface temperature (SST) anomalies and Southern Oscillation Index (SOI) anomalies, the study found that ENSO appeared to have economically and statistically significant effects on world commodity prices.[4] Its influence was mostly on food prices in the short run, but the effect was much stronger over the longer horizon, accounting for almost 20% of commodity price inflation movement during the study period. A positive standard deviation surprise in ENSO, for example, could raise real commodity price inflation about 3.5-4%.

All in all, it is clear that nearly all sectors are directly or indirectly affected by weather. Research on these impacts in any other industries than agriculture and utilities is quite limited; however, they are very interesting and help make up the whole picture of how much impact unpleasant weather could have on the economy and society. Larsen (2006) revealed an objective finding that U.S. GDP had expanded on average by 16.2% annually with historical weather variability. Certainly, industry productivity or demand is a multi-faceted issue and relevant factors are different by industry. Weather might be only a small part but it is common and inevitable. In addition, it is not only current weather that counts, but also the expectation of future weather and the degree of

[4] Anomalies measure deviations from a region's historical average.

weather extremes. Understanding the industries' weather sensitivities would allow policymakers to direct resources in an effort to mitigate this risk, especially during this time of global warming and climate change. Further research is expected to bring more comprehension to this complicated topic.

2.2.4 Financial markets

Surprisingly, weather seems to have an influence on the financial market as well. There is a considerable amount of research studying the weather effect on equity pricing on the ground that trading strategies are influenced by investors' moods as well as the other economic factors. Psychological research supports this view in that weather conditions tend to be an important determinant of everyday emotional states and behaviours in modern life (Persinger, 1980; Watson, 2000). Good weather induces positive moods and actions: people are likely to evaluate future prospects more optimistically when they are in a good mood. Howarth and Hoffman (1984) showed that sunshine is positively related with a good mood, while cloud cover and precipitation were negatively associated. This is in line with studies of, to name a few, Cunningham (1979), Sanders and Brizzolora (1982), and Parrott and Sabini (1990). These conceptions have led to an interest in the relationship between weather and equity pricing.

The research area has, to date, concentrated on the association between financial market performances and a variety of mood-induced variables. Such proxies could have been divided into two major groups, simply as weather and biorhythm variables.[5] Examples of biorhythm factors are seasonal affective disorder (SAD), daylight savings time changes (DSTC) and lunar phases. The season effects on depression are relatively well documented and Keller et al. (2005) provided consistent survey results that pleasant springtime weather can improve moods and broaden cognitions because time spent outside in the fresh air increases. The following section of this thesis will discuss two research lines in the literature of behavioural finance whereby the weather effects in capital markets are investigated by employing two different types of aforementioned weather-related mood proxies.

Most of the studies on the weather variables centre on cloud cover, sunshine, and temperature. Saunders (1993) discovered a long history of significant correlation

[5] Biorhythms are the body's natural biological cycles and they have been related with mood fluctuation in a large body of psychological research.

between local New York weather and daily changes in three major U.S. stock indices. The study found that both very sunny and cloudy weather influence stock prices, but the effects on sunny days were more pronounced. Moreover, the New York cloud cover remained significantly related with index returns when considered simultaneously with non-weather variables such as the January, weekend, and small-firm effects. The effect appeared to be robust with respect to time and not influenced by infrequent, large daily index changes. This research contributed knowledge in this area by establishing the causal direction between a temporal, economically insignificant, local, mood influence and asset prices. A great body of replicated studies has followed with an attempt to verify the findings in different markets and using alternatives to aggregate equity prices. Trombey (1997) utilized essentially identical data but tested with different statistical methodology. It was reported that cloud cover effect results appeared to be mixed and fairly weak in the analysis, which was similar to the conclusion of Kramer and Runde (1997) in their replicated work using German data. However, Hirshleifer and Shumway (2003) provided strong international evidence to support the view that cloudiness was correlated with returns. While the magnitude of the index return was not prominently related to cloudiness, the sign test produced much stronger results in that 25 out of 26 indices were found to be negatively related to the markets. A pooled test, where parameters were constrained to be the same across markets, also presented very statistically significant results. Findings were still robust after controlling the other weather conditions such as rain and snow, which are unrelated to returns. Researchers also suggested that investors could have benefited from weather-based trading strategies if they can trade with small transaction cost. Likewise, results obtained by Chang et al. (2006) had implied the significance of investors planning to invest in the Taiwan stock market should include behavioural weather variables in asset pricing models. The empirical evidence showed that temperature and cloud cover had the greatest threshold effects on stock market returns in Taiwan.

Research in this field has also been developed by taking account of other factors; for example, the different trading system, the improved econometric technique, or the use of other weather proxies. Pardo and Valor (2003) investigated the links between the Madrid Stock Exchange index and sunshine hours and relative humidity, considering different trading systems in two periods. The weather effect, if any, in the modern period should be less because investors are geographically scattered and use computer-based trading systems. However, the authors found no evidence of sunshine hours or

humidity on stock prices in either outcry or computerized systems. Tufan and Hamarat's (2003) argument was also similar in the sense that weather seemed not to affect investor decisions, even if they live in the area. To take Istanbul as an example, brokers and dealers whose trading volume was high usually lived in Istanbul, but no evidence of the cloudy day effect was found in the Istanbul Stock Exchange. Literature on other weather variables such as wind has also been produced, but is relatively small. Keef and Roush (2002) examined daily returns of the value-weighted all shares stock index of New Zealand using cloud, temperature, and wind factors. Results were interesting in that wind was the most significant variable, while cloud had no influence on equity returns and temperature effects were, as suggested, treated with caution. The authors pointed out that the results were not astonishing as the capital city is known as Windy Wellington. At this point, it could be implied that climatic settings should be prioritized when carrying out a research about weather effects. Limpaphayom, Locke and Sarajoti (2005) also tested the wind effect and found that the bid-ask spread on the Chicago Mercantile Exchange widened on windy days. Morning high wind speed appeared to be correlated with trade imbalance and lower trader income in the day. Geomagnetic storms were of an interest to Krisvelyova and Robotti (2003) as they were believed to induce depression and anxiety and should lead to lower equity returns. The research's findings were moderately favourable with the storm effects in four out of nine countries, and the effects were more prominent for small capitalization equities.

The other research line emphasizes the studies of mood mis-attribution in equity pricing related to biorhythms. An increase in depression and anxiety has been linked to sleep disruptions following daylight savings time change (Coren, 1996) and the shortness of the days due to the seasonal variation. The seasonal affective disorder (SAD) is the medical condition whereby the shortness of the days in fall and winter leads to depression. Both SAD and DTSC are extensively studied as mood proxies in an asset pricing context.

Kamstra, Kramer, and Levi (2000) suggested adding the DSTC impact to the other rational explanation of weekend effect on the financial market performances on two particular weekends a year. They discovered the average returns on DSTC weekends were particularly lower than expected and these were roughly 200-500% larger than the regular weekend effect. This was both statistically and economically significant in several international markets such as the U.S., Canada, and the U.K. It was implied that

a one day loss on DSTC, only in the U.S., was as large as $31 billion on the NYSE, AMEX and NASDAQ exchanges. Though, Pinegar (2002) provided further robustness tests for these results and reported that the DSTC effect was significant only for the autumn change. Such effect was, however, driven by two outliers associated with international stock crises, and it was further revealed that by adjusting for heteroscedasticity the significant fall effect would vanish. Yet, Kamstra et al. (2002) refuted the argument. They drew attention to their compilation of international evidence, while Pinegar only presented the U.S. one. In addition, they cast doubt on the methodologies used in the Pinegar's study. It seems the DSTC significance remains uncertain.

In the following study of Kamstra et al. in 2003, they shifted their interest to the seasonal affective disorder or the SAD effects. By controlling for well-known market seasonal variables and other environmental factors, stock returns appeared to be significantly related to seasonal day lengths through fall and winter in an international context and the overall magnitude was large. In addition, the research discovered that the SAD relationship was reversed in the Southern Hemisphere compared to the Northern, which was in accordance with reversed seasons in these two areas. Also, higher latitude markets showed more pronounced SAD effects. The findings were compelling evidence for the authors' hypothesis that the reduction of hours would be related with lower returns due to risk aversion following investor depression, whereas the increase in hours would be associated with higher returns as investors become more willing to take risk when mood heightens. However, Kelly and Meschke (2005) argued their SAD findings, and others, excessively relied on positive returns during December 21st to January 20th, which was already known as a positive return anomaly (Hawawini, Keim and Ziemba, 2000). Furthermore, according to Jacobsen and Marquering (2004), it was premature to conclude that evidence on seasonality in stock returns were from induced mood change and actually the correlation might be spurious. The observed seasonal effect could be explained by many other possible explanations such as the old market saying 'Sell in May and go away'. Bouman and Jacobsen (2002) analysed 37 stock exchanges and found that it was indeed presented in stock market returns. The argument was also consistent with the study of Goetzmann and Zhu (2005), where the weather effect plainly existed in the data, but virtually there was no difference on an individual's propensity to buy/sell equities on cloudy/sunny days. They found little link between the behaviour of market makers and local weather.

Some researchers have mixed both weather- and biorhythm-based proxies in one study. Dowling and Lucey (2005) examined an association between eight mood variables, including both weather and biorhythms, and daily Irish stock returns during 1988 to 2001. They reported a significant relationship between Irish equity returns and rain, DSTC, SAD, and lunar phrases, when controlled for the cloud cover levels. The evidence was more conspicuous in times of positive market performance, which was in accordance with psychological research showing that people in good moods were more likely to be influenced by irrelevant mood factors in their decision makings. Dowling and Lucey extended their study in 2008 using the global equity dataset based on seven mood factors; they concluded that SAD and low temperatures show the greatest relationship with equity pricing. Overall, the SAD effects in different locations were in the predicted direction and the relationship was more significant for small capitalization indices as expected (Dowling and Lucey, 2008). Even though some findings were contradicted with Kamstra et al. (2000) on the DSTC finding, the authors suggested that this was unnecessarily in conflict with psychological research on the DSTC and mood. The research further drew attention to an interesting relationship between mood proxies and equity variances: the presence of mood-influenced investors should lead to increased variance.

The existence of weather's influence on human emotions and decision making has shed light on a research interest in the area of the psychological impacts of weather on stock market performances. Recent research in behavioural finance has tested for evidence of mis-attributed mood by weather on equity pricing. The area has been explored by using a wide spread of weather-related mood proxies, which are broadly categorized into weather and biorhythmic variables. The former examines the psychological effects of sunshine hours, cloud cover, temperature and other weather variables on stock prices and variances. On the other hand, the latter emphasizes biological cycle effects from seasons and daylight savings time changes in the studies. Both research strands have produced mixed results. For researchers who find supportive evidence, their findings are difficult to reconcile with fully rational price setting. They believe that stock market anomalies have not been fully justified by economically relevant news and suggest an inclusion of behavioural variables, including weather-induced factors, in asset pricing models. By contrast, many studies have found no evidence on the weather effects. Some might have either replicated or extended previous work but obtained different results. Their arguments lie on different statistical methods, data-driven inferences, or spurious

regressions. They find it sceptical to conclude that the market anomaly is induced by weather-related mood swings, even when the weather effects are there in the data. More research is needed to explain the weather effects, if any, in a financial market setting.

After all, researchers are aware of the potential weather risk in capital markets when it drives investors' state of mind and decision making in equity trading. However, results remain inconclusive and research continues. Future studies could attempt other hypothesized proxies as weather is multifaceted. It is suggested that all other influencing factors should be accounted for in research such as small versus big, trading system, and market timing. Hypothesis and analysis should also be made cautiously as the nature of climate in different locations is dissimilar. For instance, the effect of temperature on stock indices in warm countries might be negative while it could be positive in colder countries. SAD also varies based on latitude, where more extreme latitudes experience more extreme seasonal depression and thereby the stock market reactions.

2.3 The management of weather risk: introduction to weather derivatives

The previous section has shown that weather risk is vital and common. Even though no all-encompassing solution is available for managing a firm's exposure to weather, it does not mean that companies should leave these risks unhedged. Businesses usually protect their losses from catastrophic weather events by buying weather insurances, yet attempting to control the impact that weather has on their bottom line. Thanks to the development of weather derivatives, now firms can seek a certain level of protection against even small variations of weather. However, Ramamurtie (1999) noted that those companies should understand the relationship between the weather event and the economic activity before protection was sought. Otherwise, these become taking more risks. This section provides the basic understanding for the use of weather derivatives as a tool to mitigate weather risk. It begins with an introduction to weather derivative products, explaining the specification of a contract, the payoff and the special characteristics of the instrument. Next, the origin and development of this type of market, current trading, and a future potential are reviewed. Lastly, the section reviews current valuation techniques of weather derivatives.

2.3.1 Overview of weather derivatives

A weather derivative is a financial instrument used to hedge against weather-related risk. Jewson and Brix (2005) stated that a standard weather derivative contract is defined by the following attributes: the contract period, a measurement station, a weather variable, an index, and a pay-off function. Weather risk is highly localized so that a weather derivative contract has to specify a measurement station-- in some cases a back-up station is to be used in case the main station fails. Weather variables could be temperature, snowfall, rainfall, wind, precipitation, etc.

A weather index is calculated by aggregating a weather variable at a specified station over the contract period, and a payoff depends on this. The most commonly used weather variable is temperature, and degree-day indices are the most frequently seen (Morrison 2009).[6] Dischel (1999b) explained two reasons for the popularity of degree-day derivatives. Firstly, weather derivatives were originated to serve a need for weather risk management in a power market, where apparently its demand is associated with the outdoor temperature. In addition, many studies have claimed that derived variables, which are degree days, can explain gas and electricity demand better than a primitive temperature factor. Secondly, temperature is continuous so it is easier to measure and manage than discontinuous weather parameters such as rainfall. It may rain on one side

[6] According to the Chicago Mercantile Exchange (CME), the term 'degree day' originates in the energy industry where it is used to assess and acknowledge the expected demand for energy. A degree day value is the difference between a day's average temperature and a previously set temperature (65˚F or 18˚C) and it is a measure of how hot or cold it is on any given day at a specific location. Degree days above 65˚F are called cooling degree days (CDDs) because they are days when people are likely to use energy for air conditioning. Heating Degree Days or HDDs refer to days when people are likely to use energy for heating. They are typically used in winter when temperatures are usually below 65˚F. Typically, the summer season covers from April to October and the winter season is from November to March (Ramamurtie, 1999).

In the weather market, the number of HDDs Z_i on a particular day is defined as

$$Z_i = \max(T_0 - T_i, 0)$$

and the CDDs Z_i is

$$Z_i = \max(T_i - T_0, 0)$$

where T_i is the average temperature on day i and T_0 is the base temperature. The baseline is 65 degrees Fahrenheit in the U.S., and it is usually 18 degrees in other countries where the temperature is measured in Celsius. For example, if a day's average temperature in November is 40˚F, HDD is 65 – 40 = 25. If the temperature exceeds 65˚F, the value of HDD would be zero. It is noted that neither CDDs nor HDDs can ever be negative.

of the street and not on the other, and this measurement challenge causes uncertainty and a difficulty in pricing.

In a degree-day derivative contract, an HDD or CDD index is aggregated for *n* days, as specified in a contract period. A monthly HDD or CDD is simply the sum of all daily HDD or CDD recorded that month.[7] Then, the value of a weather futures contract is determined by multiplying the monthly HDD or CDD by an agreed price and the contract would settle at this price (Carabello, 2005).

In other cases, a contract could be purchased with a specified strike index and a payoff would be calculated accordingly. For example, it could specify a payment of $10,000 for every HDD above 200 HDDs in a defined period. However, degree-day indices are not the only type of indices used in temperature derivatives trading. There are also average of average temperature indices, cumulative average temperature indices, and even event indices known as critical day indices. In addition, CME provides weather derivatives based on other weather parameters such as snowfall, frost, and hurricane. Examples of individual contracts are calendar-month futures (swap) contracts on HDD and CDD as well as options on futures.[8] Weather derivatives are able to be traded over-the-counter and thus traders may tailor a weather variable, a contract type, a strike index and a location to suit their needs. In practice, actual weather derivative contracts are extensive and constantly evolving. Their structures are similar to those of standard derivatives such as forwards, swaps, calls, puts, collars, straddles, or strangles.

In general, weather derivatives can give a measure of protection against the impact of weather events deviating from expectations or the norm. This is useful due to the fact that weather forecasts tend not to be precise and these small deviations are highly likely to happen in everyday life. Only a few degrees cooler than normal during summer may affect the demand for soft drinks, and beverage producers might want to protect themselves against lower sales and revenues. The degree of impact may be more intense in cases of non-storable products like gas and electricity. Energy companies would clearly like to protect their losses from an oversupply when the actual weather deviates

[7] If there were 10 HDD daily values recorded in November 2004 in Chicago, the HDD index would be the sum of all 10 values. For instance, if the HDD values for the month are 25, 15, 20, 25, 18, 22, 20, 19, 21 and 23, the monthly HDD index will be 208 (Carabello, 2005).

[8] For specifics on weather contracts, visit the Chicago Mercantile Exchange's website http://www.cme.com/weather/index.html .

from weather forecasts. Unfortunately, insurance does not cover these kinds of variances in the revenue streams.[9] Therefore, a weather derivative exists to serve this purpose: to protect against low-risk but high-probability weather events. For example, a power utility company, who committed to sell power at a fixed price based on load expectation and is also concerned about load variability around such expectations, may employ weather derivatives as a hedge.

The unique character of weather risk leads to a specialty of weather derivatives that they provide protection against weather-related change in quantities rather than price (Jewson and Brix, 2005). Although price may be adjusted according to changing demand, it might not compensate for revenues lost associated with volume sensitivity to weather. For that reason, the use of traditional financial derivatives for price hedging is not efficient enough to tackle challenges in variations of volume sales due to weather, and the use of weather derivatives can be complimentary to the traditional risk management tools. It is obvious that weather derivatives are different from insurance and traditional derivatives in a number of respects. Table 2.1 summarises these differences.

[Insert Table 2.1 here]

2.3.2 Weather derivatives market

The new and cutting-edge tools for trading weather came into practice in the late 1990s when the first transaction of weather derivatives took place in 1997 in the energy industry.[10] These tools resulted from the need of power providers to protect their revenues from weather variability and fierce competition attributable to the deregulation of the U.S. energy market (Geman, 1999; Climatrix, n.d.). The El Niño winter of 1997-1998 was one of the primary drivers to market growth. At the same time, the insurance industry faced a cyclical period of low premiums in traditional businesses and started to

[9] A typical example of insurance policy would be to cover a loss due to plant or business shut down resulting from extreme weather events.

[10] Early pioneers in the market—energy traders Aquila, Enron, and Koch Industries—executed the first transaction to protect against warmer or cooler than average weather in Wisconsin for the winter of 1997-1998 (Cao et al., 2004). The participants saw weather derivatives as both a mechanism to hedge inherent weather exposure in core energy assets and a new risk management product to offer to regional utilities alongside with other products they were already providing.

write options to make sufficient capital, which in turn provided the liquidity in the swap market in weather (Considine, n.d.).

Early transactions were traded over-the-counter (OTC), privately negotiated, and individualized agreements. The weather derivative has been a new edition to the OTC market, but further expansion is fairly limited due to credit issues. Thus, the Chicago Mercantile Exchange (CME) started trading weather derivatives publicly in 1999, initially based on U.S. cities only. Weather futures in European cities were launched afterwards when the demand became apparent. By 2003, the CME products included exchange-traded weather futures and options on futures, reflecting monthly and seasonal average temperatures of 15 U.S. and five European cities (Carabello, 2005; Cao et al., 2004).[11] They are standardized contracts and publicly traded, with continuous negotiations on prices and complete price transparency. The CME offers all traders, either small or large, equal access to the best bids and offers on all weather products, which in turn allows investors to take immediate market action in response to unanticipated changes in weather occurrences.

The weather derivative market has continued to grow. According to Valerie Cooper, a former executive director of the Weather Risk Management Association (WRMA), an $8 billion weather-derivatives industry developed within a few years of its inception (Carabello, 2005; Saha, 2005). Nevertheless, the trading volume did not reach meaningful levels until 2003 when the exchange began offering clearing services, which currently account for 91% of volume (Morrison, 2009). The CME clearing house ensures the elimination of default risk and the integrity of all transactions because it serves as the counterpart of each trade. "*The trading volume of CME weather futures in 2003 was more than quadrupled from the previous year, totalling roughly $1.6 billion in notional value and the momentum of this volume seems continuing to increase*" (Carabello, 2005). The WRMA reported $4.57 billion worth of the market at the close of 2004 (Anon, 2005), marking a 10% increase over the previous year (WRMA, 2004). A WRMA survey in 2005/06 showed the total value of traded weather contracts surged

[11] CME offers additional products responding to customer demand from time to time. For the latest product offer, check www.cmegroup.com.

to $45.2 billion compared to only $9.7 billion in 2004/05.[12] Figure 2.1 presents the number and notional limit of weather contracts reported by survey participants during 2001-2006. The CME trade increased substantially after 2004, both in terms of value and volume trading. Declines in the OTC market may offset some of this rise, but they were small relative to the size of the market. Specifically, at the beginning weather derivatives were traded more during winter, but summer transactions started to gain more momentum in 2005/06.

[Insert Figure 2.1 here]

According to WRMA (2008), the weather risk market experienced robust growth for 2007-2008, with the number of contracts traded increasing 35% and notional value of the contracts grew 76% compared to the previous year. This increase in trading volume is having positive impacts on market liquidity and price discovery. Figure 2.2 exhibits CME weather derivatives volume trading during January 2002 to October 2008 from another source, and it clearly supports the previous WRMA survey findings that the CME trading started rocketing in 2004. Morrison (2009) viewed that the growth was continuing but the volume in 2008 descended due to the global economic recession and the turmoil in financial markets, yet not as much as other sectors of the futures industry.

[Insert Figure 2.2 here]

In 2010, the weather trading market sees the expansion again for 19%. This growth is bolstered by 29% increase in OTC contracts and roughly by 15% in the broader market of CME trades (Anon, 2011). The emergence of the CME clearly facilitates the weather market expansion as in recent years there has been more trading on the exchange market. Standardized weather derivative contracts are now listed on other exchanges, such as the London International Financial Futures and Options Exchange (LIFFE) and the Intercontinental Exchange (ICE). The weather market is also expanding into India, Latin America, and Southeast Asia. India developed a rainfall index in the National Commodity and Derivatives Exchange (NCDEX) in 2005 to track the progress of the monsoon, and this was a forerunner to a weather derivative to be launched subsequently

[12] Price Waterhouse Coopers conducted annual surveys for WRMA, focusing on activity in the weather risk industry and providing quantification of transaction volumes and various breakdowns of trading activity. Their findings included size of the weather market, types of contracts, numbers and notional values of traded contracts, participants' main lines of business and locations of respondents.

(Saha, 2005). A survey finds that the Indian weather market grew four-fold in 2010 and it expects major growth over the next few years, although the huge growth is attributable to weather insurance (WRMA, 2010).

Not only has the weather market expanded geographically, but it has also increased diversity in terms of participants. There are a growing awareness and signs of potential growth in the trading of weather futures among agricultural firms, restaurants and companies involved in tourism and travel (Carabello, 2005). In addition, as the market grows, traders see the opportunities to trade weather derivatives on a speculative basis. It attracts the involvement of insurers, reinsurers, investment banks and hedge funds. The WRMA survey participants, during 2002-2006, are reviewed by locations and business lines. The report indicates a greater proportion of participants from other regions outside North America, while demonstrating an increased participation from non-energy traders over the period.

[Insert Figure 2.3 here]

An increasing diversity and depth of established players in the market is largely attributed to the emergence of exchange traded contracts as this increases transparency, creditworthiness, and liquidity to the market. To serve the various needs of the diverse traders, broader products are offered to enhance the weather risk management capabilities of all market participants. The range of weather contracts has been continuously increased and updated to cover more weather aspects such as rainfall and snow, to have terms ranging from a week to years and to have payouts from small to large exposures (Climatrix, n.d.). Throughout the time, CME has advanced more product innovations and provided greater coverage in different locations around the world. CME started trading snowfall in 2006 and has since added 50 new contracts of weather such as rainfall in various countries, for a total of 67 offerings (Anon, 2011). In 2009, the exchange offered contracts on temperature and precipitation indices in 24 cities in the U.S, six in Canada, ten in Europe, and two in Asia-Pacific (Morrison, 2009). Along with the CME exchange, the market education, regulatory framework and legal documentation around the world have laid the foundation for considerable market expansion (WRMA, 2006).

The weather market has grown impressively, yet remains significantly smaller than most of the other commodity markets. The use of weather derivatives is more common

in an energy sector, followed by construction and agriculture. Morrison (2009) stated that the energy sector accounted for more than half of total trading; nonetheless, just 35% of energy companies managed their business exposures to weather according to the CME/ Strom Exchange study. Likewise, only 10% of several hundred businesses in the survey used weather derivatives to manage weather risk even though most of them believed that the weather factor was significant for their earnings. As the global economy is exposed to over a trillion dollars of unmanaged weather risk, the growth in this market will continue its exponential gains (CME, 2005). Clemmons, Haminski, and Hrgovcic (1999) claimed industry experts' belief that one day the trading volume of the weather market can eventually surpass all futures and options contracts traded worldwide. This is because weather materially affects a large number of industries and weather risks in these businesses usually offset one another. By swapping such risks, each company can maintain sales and profits from the particular weather types. This prospect is attractive to companies, whose shareholders need earning stability, and unquestionably stimulates further market growth.

Additionally, weather derivatives could be seen as a good complement or hedge of commodity positions. Investment and commercial banks can cross-sell weather derivatives along with other financial products, and some commodity traders and hedge funds may trade them speculatively (Climatrix, n.d.). Furthermore, weather contracts are attractive investment opportunities due to the fact that they have minimal correlated returns to other financial products such as bonds and equities (Jewson and Brix, 2005). It is demonstrated that an investor could enhance a portfolio performance while maintaining a low standard deviation by including weather derivatives in a conventional portfolio (Lennep et al., 2004). Cao et al. (2004) constructed efficient frontiers consisting of equity, fixed income, commodities, and temperature instruments. They found that including the temperature index over, and above all other indices, led to a noticeable improvement of the risk-return trade-offs especially for the higher range of standard deviations, and concluded that weather derivatives held a potential in asset allocation and portfolio management. For all these potentials, some experts assert that the weather derivatives market one day will reach into every sector of the world economy and potentially grow to trillions of U.S. dollars in value if innovative products are evolved (Dischel, 1999b).

2.3.4 Weather derivatives valuation

Although weather derivatives are beneficial to companies, their market is relatively illiquid and underdeveloped due to few potential hedgers in the market. The bid-ask spread is high and a fair value of the instruments are still not determined. The conventional risk-neutral valuation methodology does not apply to a weather derivative because an underlying is not a traded commodity and a trader cannot create a risk-free portfolio by combining the derivative with its underlying. In addition, meteorological variables are likely to be predictable, especially over a longer horizon. This predictability property does not suggest arbitrage opportunities (Cao et al., 2004). Also, their statistical processes do not follow the random walk without mean reversion, which is against the assumption of the pervasive Black-Scholes model (Garman, Blanco and Erickson, 2000).

Both Dischel (1998) and Garman et al. (2000) advised that The Black-Scholes model may also be inadequate for weather derivatives pricings for another reason. That is, weather derivative payoffs typically accumulate value over a period of time; for example, every day's HDD for the term of the option is added to the total payout at expiry date. This is in contrast to Black-Scholes option payoffs that are determined by the underlying values at maturity. The researchers perceived this style as more similar to Asian or average price options. McIntyre and Doherty (1999) also pointed out that the daily return of weather derivatives are not log normally distributed, which means the use of the Black-Scholes technique to price a weather derivative is not realistically satisfactory.

Unfortunately, weather derivative is a more recent development from the financial services industry; thus, little research has been done up until the present compared to other derivatives. Even though pricing methodology is one of the main areas of study, it remains in an early stage on theoretical grounds, and valuation techniques are rather self-formulated by each institution. The pricing models seem to be too complicated and are not publicly revealed. Unquestionably, this is a great impediment to the development, both in terms of transparency and liquidity, of the weather market. This section generally reviews methods developed so far for weather derivative valuation, which are classified into three broad categories: actuarial method, market-based pricing and equilibrium approach.

2.3.4.1 Actuarial method

Typically, the actuarial or insurance methodology estimates the expected loss using the statistical distribution of outcome and sets a premium within the context of a large portfolio of identical and independent risks (Ramamurtie, 1999). It is a straightforward method, but at the same time requires a large diversified portfolio to make the pricing approach reasonable.

The simplest approach used for weather derivatives is *the burn analysis,* by which the historical payout of the derivative is computed to find an expectation as the key concept in the past always reflects the future on average. It neglects a seller's premium, demand and supply pressure, and weather forecasts at the moment. The basic form of burn can be extended to include cases where the data is cleaned and de-trended prior to evaluating how the contract would have performed, but it explicitly does not include fitted distributions or simulations (Jewson and Brix, 2005). Since the burn analysis is based on historical data, it is intuitively straightforward and has minimal assumptions. However, by assuming that historical index time series is stationary and statistically consistent with the weather during the contract period, the analysis is subject to large pricing errors since it does not describe enough future possibilities. Also, disparate views on the choice of historical record length draws variability in prices and wide bid-ask spreads in the market (Dischel, 1999b). Going back 10 years versus 20 years would lead to a difference of more than 300% in estimated values of Atlanta call option, according to the study of Cao et al. (2004). It was also pointed out that a longer time series does not always enhance valuation accuracy, and this is especially critical when the maturity of weather derivatives is short. Practitioners have to trade-off between statistical power and data representation.

The *statistical modelling* is investigated in the hope of more accuracy than that of burn analysis because the distribution can be fitted to the historical data. Researchers can use statistical models to at any stage of the settlement process of a weather derivative: either modelling the weather index or the payoff value. According to Jewson and Brix (2005), the former stochastic process is, however, slightly preferable because the index distribution has smooth tails while the payoff distribution for capped swaps stops at the limit values and for call options consists of two spikes.

Index modelling attempts to fit the distribution to the historical indices, then estimates the parameters of that distribution or simulates a future behaviour. Most of previous studies model temperature directly (daily modelling), not heating or cooling degree days. Garman et al. (2000) and Cao et al. (2003) made the comment that a lot of information is lost when modelling HDDs or CDDs since they are derived variables and bound to zero. Also, Jewson and Brix (2005) viewed that HDD/ CDD distribution is not normal because of the cut-off at the baseline. Moreover, HDDs/ CDDs are period-dependent and path-dependent, but the temperature process is universal. Modelling temperature is therefore superior because it can apply to temperature contracts at any strikes and maturity. It is apparent that temperature is mean-reverting, seasonal, and incorporating a weak trend of global warming; thus, any models that only assume Black-Scholes style random walk behaviour will be inadequate to model temperature (Garman et al., 2000). Researchers have suggested diverse models to capture every characteristic of temperature behaviour; for example, those based on Brownian motion, AR, ARMA, ARFIMA (autoregressive fractionally integrated moving average), AROMA (autoregressive on moving average), CAR (continuous autoregressive), GARCH, etc.

Once the stochastic process of an underlying or index is estimated, the value of a contingent claim can be calculated by combining this with a payoff structure to derive the distribution of financial outcomes. This stage can be done in a number of ways. Firstly, one can derive closed-form expressions of the expected payoff; for example, the study of Brix, Jewson and Ziehmann (2002), Jewson (2003) and Jewson and Penzer (2004a). Secondly, Monte Carlo is used to generate a great number of simulated scenarios of weather and determine possible payoffs. Subsequently, the present value of the average of all simulated payoffs is the fair price of a weather derivative. Examples in certain cases are Dischel (1998) and Torro, Meneu and Valor (2001). Lastly, Jewson and Brix (2005) mentioned numerical integration, which is similar to simulation but dividing the range of possible index values into intervals and using only one index value within each interval. This method is numerically efficient because the sampling of index values need include only relevant ones. However, it is not practical for the large portfolios, unlike simulation.

Weather traders depend on meteorological forecasts in the same way as financial traders rely upon economic outlooks. They need these predictions for inputs on expected

temperatures, and statistical modelling can do the task. Many studies have focused on weather forecasting as a key to weather derivative pricing such as Diebold and Campbell (2000), Jewson and Caballero (2002), Taylor and Buizza (2006) and Jewson and Penzer (2004b; 2006). By incorporating the possible futures, statistical modelling may sound more accurate than burn analysis. Nonetheless, by enforcing a certain shape onto the distribution, an assumption has been made, which may be wrong and introduces an extra source of error. It is important to keep in mind that complexity does not necessarily mean accuracy. Even though a comparison of burn analysis and statistic modelling is hardly possible in practice, Jewson (2004a) sought out how much better index modelling was than burn. It was reported that, in the case of fitting the right distributions, there is little benefit in using modelling when a small amount of data is used and for options with strikes near the mean. However, modelling gives significantly better results than burn when estimating the variance of payoffs and delta.

2.3.4.2 Arbitrage-free or market-based pricing

The arbitrage-free or market-based approach is similar to the traditional option pricing technique, which replicated a portfolio using an underlying asset and a risk-free security to mimic the value of the derivative claim. In case of a weather derivative where an underlying asset (weather index) is not a tradable asset, a proxy is used instead. The proxy could be a portfolio of other correlated assets such as weather derivatives on similar index. Although this practice is not a perfect hedge, at least it is possible to reduce risk to a more acceptable level according to the arbitrage pricing principle. An outstanding feature of the arbitrage-free technique is that all risk preferences do not play a role since they are hedged away. There is no task for risk loadings, and this makes arbitrage prices unique and independent on the trader (Jewson and Brix, 2005).

Geman (1999) proposed to hedge weather derivatives by using electricity contracts that have prices correlated with the weather. Likewise, Davis (2001) asserted that weather derivatives should be priced using a portfolio of gas and weather contracts. These initiatives are plausible because undoubtedly a number of energy companies do trade correlated gas and weather contracts in a combined portfolio. Nonetheless, Brix et al. (2002) pointed out that the gas price was more related to the demand than to the temperature. Instead, they suggested the use of weather futures contracts for pricing weather options on similar indices. Jewson and Brix (2005) justified an example, where weather swaps were used to dynamically hedge weather options. Given the swap price

process, one can price options on the same index based on the assumption that the swap is liquidly tradable without transactions costs and is used to continuously delta hedge the option. Under certain assumptions, researchers derived analogies of the Black and Scholes (1973) and Black (1976) equations for weather options (McIntyre, 1999; Jewson and Zervos, 2003). Jewson (2004b) extended the previous study to price the weather derivatives that are based on non-linear indices. Given a stochastic process model for the expected weather index, it is shown in the study how to derive the arbitrage price for options following Jewson and Zervos's (2003) methodology.

In reality, the weather market is rather illiquid so incomplete market pricing models should be more appropriate than the Black-Scholes style models. The indifference pricing approach, based on the expected utility arguments, is attractive to many researchers. Davis (2001) explored the marginal utility approach, with an assumption that agents in the weather derivatives market are not representative but face very specific weather risks related to the weather effect on their business. Consequently, agents will buy or sell weather derivatives if it increases their utility. In a suggested framework, a general pricing formula, based on optimal consumption and investment rules, was applied to price swap and option values. It was revealed in his study that pricing by taking the real-world expected value discounted at the risk free rate is incorrect. Brockett et al. (2006), also basing the study on the indifference pricing framework, contributed to the literature by incorporating both hedgeable and unhedgeable weather risks in explaining portfolio effects on the weather derivatives prices. Their analysis showed how the magnitude of portfolio effects is related to the correlation between weather indices and other risky assets, the correlation between weather indices, and the payoff structures of other weather derivatives already in an investor's asset portfolio.

Hamisultane (2008) reviewed other possible strategies that can be used to treat the liquidity problem when duplicating the weather option payoff. When choosing the quantities of the securities in the portfolio, one can decide to maximize the expected utility of the agent or to reduce the variance of the difference between the portfolio value and the option value at maturity. To obtain the price of a contingent claim from these strategies, the expectation of its terminal payment has to be calculated. Two ways were advised to estimate such an expected payoff, either by extracting a risk-neutral distribution or solving the partial differential equation for a market price of risk from a

quoted price. Hamisultane (2007) proposed to use information contained in the New York futures prices to value New York weather options. The study inferred the risk-neutral distribution from market prices by using Monte-Carlo simulations and the optimization problem suggested by Jackwerth and Rubistein (1996), whilst extracted the market price of risk by solving a partial differential equation following Pirrong and Jermakyan (2001)'s finite difference method. Similarly, Hardle and Cabrera (2009) used the implied market price of risk from the Berlin Cumulative Average Temperature (CAT) futures to price other temperature derivatives such as HDD and CDD for Berlin. Huang, Shiu and Lin (2008) intuitively used the market price of risk of the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) as a proxy for weather options because there is no weather options contract in Taiwan. Actually, it is possible to compute the market price of risk instead of inferring it from quotations but that would be time-consuming. A requirement of observed prices sets a critical drawback to this pricing method as most of weather derivatives quoted prices are not generally available, especially for those traded over the counter.

Even dynamic hedging looks promising in pricing weather derivatives, as it seems that such trading neither strongly affects the market price of weather derivatives nor determines an arbitrage opportunity. Therefore, it is considered not to be a practical pricing method (Jewson and Brix, 2005). The authors suggest that the market-based pricing is appropriate when investors want to know the level at which they could expect to buy more equity or sell a current holding. However, the hedging should continuously be more dynamic along with the weather market development.

2.3.4.3 Equilibrium approach

Cao and Wei (1999; 2001; 2004) were the first researchers who proposed and implemented an equilibrium valuation framework for weather derivatives, specialized for temperature contracts. The authors extended Lucas (1978)'s equilibrium asset pricing model in that the fundamental sources of uncertainty in an economy are generated not only by aggregate dividend but also by the weather condition. A contingent claim on temperature can be priced once the weather process and the dividend process are combined with the valuation model. It was shown in their studies that the equilibrium prices of weather derivatives depend on the agent's risk preference and the correlation between aggregate consumption and weather process. Given the temperature risk embedded in the aggregate output, the risk aversion will determine the

risk premium via equilibrium valuations. In the study, an arbitrary risk aversion variable needs to be identified to calculate the risk premium and option prices. The authors applied the Monte Carlo simulation to calculate the expected temperature derivatives prices.

One featured objective of their work is to show whether the market price of weather risk significantly affects weather derivatives valuations. Numerical analyses indicated that the market price of risk related to the temperature does not appear to be significantly different from zero in most cases, which indirectly warrants the use of the risk free rate to derive weather derivatives as many experts normally do in the industry (Cao and Wei, 1999). However, it was acknowledged that the result is not universal as the special class of utility function was employed and only the contemporaneous correlation between the aggregate dividend and the temperature was allowed. Their following studies (2001; 2004), however, appeared to incorporate both the contemporaneous and lagged effects in correlations. Cao and Wei (2004) found that the temperature significantly associated with the aggregate consumption and that the risk premium could represent an important portion of the derivatives' price. The proportion of risk premium in weather options and futures was determined by comparing prices when the correlation coefficient between the temperature and consumption was assumed to be zero and non-zero. According to the results, using a risk free rate to discount the expected payoff will lead to a sizeable error. This is similar to findings of Richards et al. (2004). In addition, it was found that the market price of risk affects option values much more than forward prices. Extra caution was suggested when valuing derivative securities with non-linear payoffs (Cao and Wei, 2004).

Hamisultane (2010) contributed to the literature of consumption-based pricing by estimating the risk aversion coefficient instead of assuming constant arbitrary values. It was found that the estimated coefficient from the simulated method of moments approach must have questionably high values in order to match the calculated weather futures prices with the observations. The study inferred the information from the quoted price in the market, similarly to Pirrong and Jermakyan (2001) and Huang et al. (2008), and applied it into the equilibrium pricing framework. This could be considered as an application in between market-based and equilibrium pricing.

With a common practice of using historical simulations in pricing derivatives, Cao and Wei (1999) also demonstrated that this method tended to overestimate option prices

because simulations assume that the future temperature can resemble any of the past seasons in the sample whereas a typical weather contract covers a period and does not project very far into the future.

In a nutshell, an actuarial valuation is achieved basically by estimating the exposure of each outcome and a corresponding probability of occurrence obtained from a sample of historical observations or meteorological forecasts. This method depends on a statistical modelling of a stationary time series to derive a prediction for the distributions of outcomes for the settlement index. Although this approach is easy to implement and widely used, it appears to ignore the financial market and generally assumes the zero market price of weather risk (Brockett et al., 2006). Most of the study emphasizes on the underlying index and payoff distribution but little mention is made of the risk premium.

Market-based pricing is analogous to the no-arbitrage option models, but being adapted to reflect the fact that an underlying asset is non-tradable. The use of proxy, such as other weather derivatives on the same weather index, is recommended in order to form a self-financing portfolio. In practice, traders should find it difficult to form an active hedge in such an illiquid weather market. Nonetheless, as long as the market price of risk is obtained, the Martingale method can be applied to valuate weather derivatives even if the underlying is not tradable (Huang et al., 2008). Hamisultane (2007) believed that the weather derivative value predictions can be improved by incorporating the information contained in the prices of most transacted contracts. For that reason, market-based research attempts to find the arbitrage-free price of an option by inferring a risk-neutral probability or extracting the market price of weather risk from the existing quotations in the market. However, it might not always be possible to infer the market information as weather market prices are not constantly available.

Equilibrium pricing, on the other hand, does not need market quotations. It aims to evaluate weather derivatives through an equilibrium framework where fundamental uncertainties in the economy are driven by two state variables, aggregate dividend and weather (Cao and Wei, 1999; 2001; 2004). Once the temperature process, agent's preference and dividend process are determined, the price of a contingent claim is derived. In this case, the risk premium depends on the correlation between weather and the aggregate dividend process. It is evident that the literature in both the market-based and equilibrium pricing address the importance of the market price of weather risk but

through a different foundation. Empirically, it is observed that the market price of weather risk of many contracts is significant and not zero. Thus, using the risk free rate as a discount factor might lead to a sizable error in weather option pricing. This suggests that actuarial techniques might not be appropriate.

Hamisultane (2008) computed the prices of weather contracts from three major pricing methods for comparison and found that the consumption-based pricing (or equilibrium approach) was the most appropriate for weather derivatives valuation. The prices obtained from methods concerning the inference of the market price of risk, both arbitrage-free and consumption-based approaches, were closer to the actual level of the index than the actuarial method. In fact, though, the actuarial approach is the most extensively used in practice when applied to weather pricing. Up to the present, there is no harmony in methodologies used to value weather derivatives.

However, all approaches for weather derivatives pricing need a weather process as a part of their valuation. After all, it is highly important to choose the right random process for an underlying as small misspecifications may lead to large pricing errors. A number of empirical studies have been devoted to finding the right model for temperature, but no proposal is all-embracing and widely accepted. Since the weather process is rather local, it is more difficult to find a standard model which can represent a worldwide or even a countrywide effect. This is the first inconsistency in pricing contingent claims on weather, by choosing a different model for an underlying process. In addition, the choices of different pricing frameworks can add larger discrepancies in valuation. These are preventing the market from development at a faster pace. Both a standard model for the weather process and a satisfactory valuation framework are yet to be establishing to bring in growth and liquidity for the weather market.

2.4 Summary

This chapter offers a comprehensive understanding of weather influences on different sectors in an economy and reviews the literature of such effects. Even though a weather risk is not the only corporations' source of exposures, it prevails in almost every line of business including financial markets. Technological advancements may have made it possible for weather forecasts to be timely and more accurate, but weather and climate changes are relatively out of control. Weather exposures, either small or large, are inevitable and adverse weather conditions are continuously undermining the financial

states of companies. Changes in weather do not only vary volume outputs in an industry, but they also impact equilibrium market prices through the demand-supply mechanism. In addition, these weather impacts are versatile across sectors and products. No clear message can be drawn for weather impacts to the general economy, as some weather dependent industries may benefit from hot weather whereas others may not. Such effects also vary in response to dispersed locations and different significant weather variables consistent with the nature of the business.

Temperature-related variables are common in most studies of weather effects in every industry. In the power industry, temperature is one of the most significant weather parameters influencing consumption, and derived variables such as degree days are widely accepted to explain gas and electricity demand, better than a primitive temperature factor. However, demand and supply in other industries are responsive to more assorted weather elements and researchers have focused mostly on primitive variables in these studies. For example, both temperature and precipitation are considered to be equally important for growing conditions in crop yields, snowfall level is a major matter in decision-making for holiday makers in winter, and cold rainy days may delay purchasing in retail businesses. Likewise, research interests on the psychological impact of weather to stock markets have based the studies on various weather-induced factors such as temperature, sunshine hours, cloud cover, SAD and DSTC.

As weather is seasonal, the relationships between weather and economic activities show strong seasonal patterns. Lagged effects are present in some cases also. Nonetheless, the norms are different across product types and locations. Therefore, the mitigation of weather risk should be customised to an individual business depending on the characteristics of the relationship between the company's performance and the weather. In the past, businesses could buy weather insurance to cover the losses from extreme weather events but they were not able to control the financial inconsistency attributable to small weather variations. An increase in the volatility of weather and unusual weather conditions, with regards to the scientific facts about climate change, also urges corporations to call for better weather risk management tools.

On account of the invention of the weather derivative, it is possible for businesses to alleviate risk relating to short spells of unpleasant weather. In other words, they are now able to seek protection against fluctuations in revenue streams owing to weather

variability. Stabilising corporate cash flows brings further benefits, according to Jewson and Brix (2005), in that a company is likely to have more internal funds available and thereby avoids the cost of raising external capital. Even with a need for outside funds, low volatility in profitability means a company can borrow money at a lower rate and better terms because the likelihood of going into financial distress is less. In a publicly traded company, this low volatility in profits also frequently relates to a less volatile share price and higher share value. Researchers also suggest the inclusion of weather derivatives into a portfolio, for the purpose of risk diversification, because of its low correlations with other financial products. Therefore, there is a high potential that weather derivatives will be common to all traders worldwide one day.

While the weather derivative market growth is somewhat impressive, its size remains much smaller compared to other financial products. However, there is still a large room to grow as only a small fraction of the weather dependent businesses uses weather derivatives to mitigate the risk nowadays. One impediment to the market growth is a lack of product price discovery. The usual risk-neutral approach cannot be applied to value weather derivatives since the underlying asset, weather, is not tradable in the market. A number of research projects into weather derivatives pricing have been done but no consensus has emerged to date. The techniques have been developed based on few theoretical frameworks, including actuarial, equilibrium and market-based approaches. These approaches, however, still require knowledge of the weather risk premiums or the market price of weather risk. Whilst the industrial norm uses the risk free rate to discount the expected payoff, the empirical studies find mixed results.

As the market price of weather risk is a key to weather derivatives pricing, this thesis will centre on this issue. However, instead of inferring it from quoted prices or complicated numerical analyses, the research proposes to directly estimate it from the financial data that is publicly available in the market. The framework used in this study will be different from the previous research so far, and the justification of the methodology will be discussed in the next chapter.

Table 2.1: Weather derivatives and other risk management tools

The table summarises the main differences between weather derivatives and previously-invented risk management tools. Panel A compares weather insurance and weather derivatives, whereas Panel B reviews the characteristics of traditional traded derivatives and weather derivatives.

A. Weather insurance and weather derivatives

Weather Insurance	Weather Derivatives
1. For high risk, low probability events	1. For low risk, high probability events
2. Substantial claims, evidence required	2. Payoffs depend on weather indices
3. Non-tradable instrument	3. Tradable instrument
4. Standardized policies by nature of business and types of risk	4. Flexible to construct desired coverage by choosing location, index, strike, etc.
5. Fixed premium for full terms	5. Able to re-evaluate derivative positions frequently
6. Tax liabilities	6. No tax liabilities
7. Different accounting treatments and contractual details	

B. Traditional derivatives and weather derivatives

Traditional Derivatives	Weather Derivatives
1. Tradable underlying assets	1. Non-tradable underlying assets
2. Arbitrage free pricing	2. Market pricing
3. Either financial settlement or physical delivery settlement	3. Only financially settled
4. Price hedging	4. Volume hedging

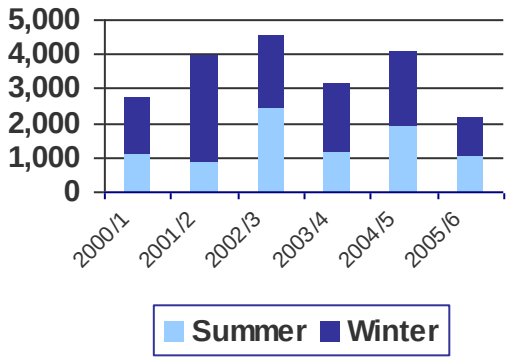
Figure 2.1: Volumes and notional values of traded weather contracts, 2001-2006

Graphs below display the number and notional values (in millions of U.S. dollars) of traded weather contracts by over-the-counter and CME trades during 2001-2006. These figures were reported by WRMA surveys, in which their findings included the size of the market, various breakdowns in trading activity, and the participants' main lines of business and locations. Figure A and B account for the number of contracts reported by survey respondents, while figure C represents the notional limit of these transactions.

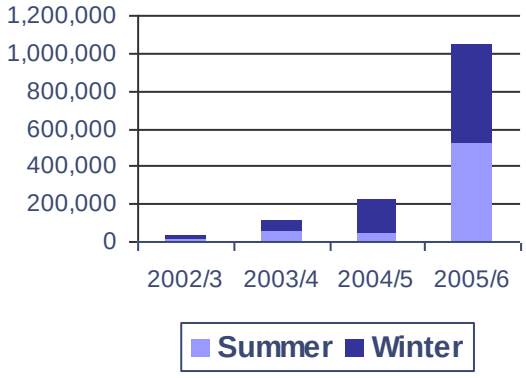
The CME trade increased substantially after 2004, both in terms of value and volume. Declines in the OTC market may offset some of this rise, but they were small relative to the market size. Specifically, at the beginning weather derivatives were traded more during winter, but summer transactions started to gain a momentum in 2005/06.

Note—CME notional values for all years have been revised to reflect CME-reported values.

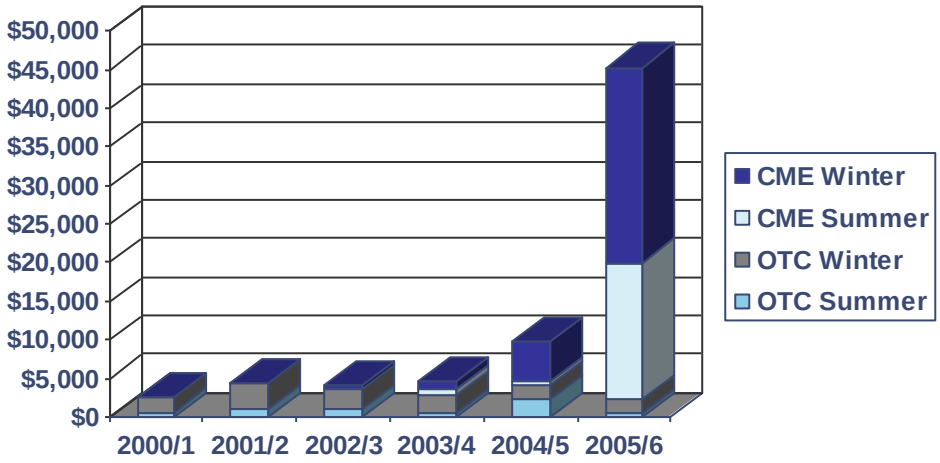
A. OTC trades



B. CME trades



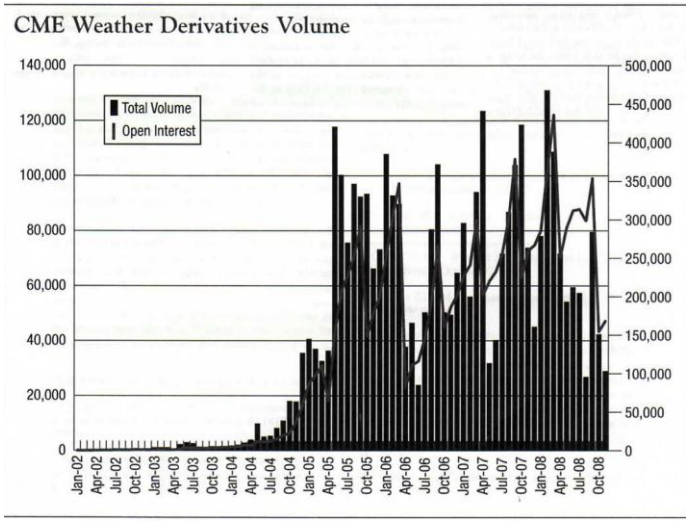
C. Notional values of traded weather derivatives



Source: Weather Risk Management Association

Figure 2.2: CME weather derivatives trading volume

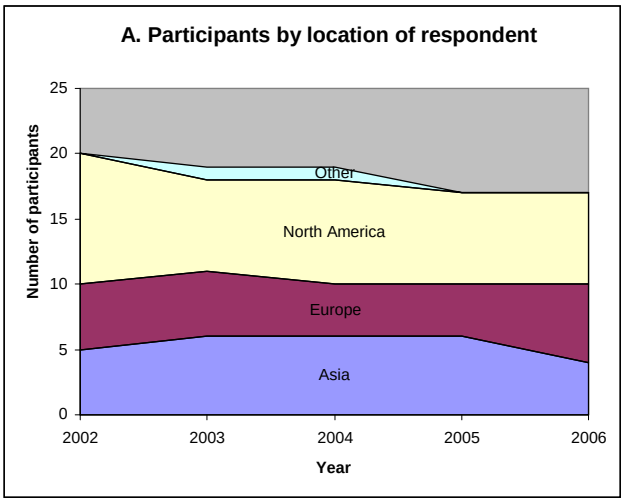
The figure exhibits CME weather derivatives volume trading from January 2002 to October 2008, and it clearly supports the earlier WRMA survey findings that the CME trading started taking off in 2004. The growth continued but the volume in 2008 fell due to the global economic recession and the turmoil in financial markets. However, the decline was not as much as in other sectors of the futures industry.

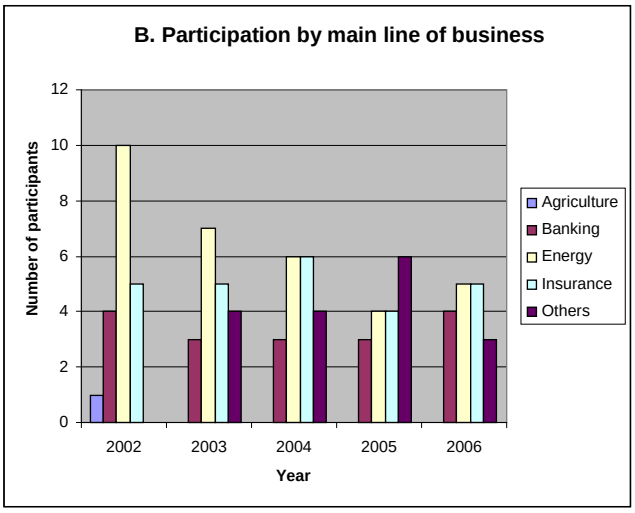


Source: Futures Industry, Jan/ Feb 2009, p.28

Figure 2.3: Weather derivatives geographic trading and business lines, 2002-2006

As the weather derivative market grows, it attracts the involvement of more diverse investors. WRMA reviewed its survey participants during 2002-2006 according to their locations and business lines. Panel A indicates a greater proportion of participants from other regions outside North America, while panel B demonstrates an increased participation from non-energy traders over the period of time.





Source: Annual surveys by Weather Risk Management Association (WRMA)

Chapter 3

Weather Risk in Asset Pricing Context

3.1 Introduction

It has been pointed out through the last chapter that weather exposures on economic activities are general and corporations begin to absorb those risks by the use of recently-invented weather derivatives. However, pricing of such tools is still ambiguous and under-researched. Among attempts to find an appropriate pricing technique, one promising possibility is addressing the market price of weather risk. Both market-based and equilibrium approaches in weather derivative valuations are concerned with assessing of these weather risk premiums, and there are supporting studies which suggest that they are significantly different from zero. Therefore, this thesis will focus on the determination of the market price of weather risk, seeing them as offering potential for the valuation of weather derivatives. Although this study also concentrates on weather risk premiums, the methodology used is distinct from the previous literature on weather derivatives pricings so far. Instead of extracting information from the market or generating weather processes themselves, the research applies the well-known asset pricing context in order to derive the weather risk premiums.

Ever since the seminal work of Sharpe, researchers have sought to determine the precise set of factors that determine security returns. Factor models and the arbitrage pricing theory (APT) of Ross (1976) have been used in an attempt to extend the basic insights of the Capital Asset Pricing Model (CAPM) to encompass multiple sources of market risk. Such factor models were seen as a possible solution to the disappointing results of empirical tests of the CAPM itself, and it was hoped that such models would lead to a greater understanding of the pricing of securities in practice by financial markets. The APT, however, is still ambiguous in the sense that it does not advise on how many and which factors are the fundamental determinants of stock returns. This study investigates whether natural phenomena can be one of those basic variables.

In attempting to include a weather factor into an asset pricing context, there should be at least one rational assumption to support the view that weather is a possible source of risk in determining equity returns. Previous empirical studies of weather risks, as reviewed in Chapter 2, are concentrated in two areas: either the economic effects on

corporate activities or the psychological influences on stock market performances. Unfortunately, neither of these directly investigates the sensitivity of equity returns to weather randomness. One potential implication, however, rests on a connection through the context of market-based accounting research, which examines how accounting information associates with characteristics and prices of traded securities.

It is conceivable that weather may affect corporate finances through economic impacts on operations and these effects, to some extent, will influence security prices. This assumption fills in a gap between two distinctive research strands and also potentially fits well within an asset pricing framework. It is therefore sensible to presume that weather economically and financially affects equity returns. If this is the case, weather randomness, being a package of natural phenomena more basic than fundamental economic variables, will turn out to be an important driver of stock returns and therefore it will be priced.

This chapter discusses related literature and background theory fundamental to the development of a hypothesis. As the research assumption lies between two research areas but the methodology is situated within another research strand, the whole chapter is dedicated to arriving at an understanding of all related literature in order to derive the main assumption of the thesis. The associated research strands are the weather effects in business, the market-based accounting research and the theory of asset pricing. While the first area was empirically reviewed in the previous chapter, studies of the other two areas will be given in the following sections.

3.1.1 Objective of this chapter

The ultimate objective of this chapter is to develop the hypotheses this thesis will be based on. By so doing, it conveys the knowledge and ideas that have been previously established on the related topics by accredited scholars and researchers. Concurrently, it aims to identify the areas of controversy or those areas still under-researched. This helps to define the research questions and build on the hypotheses of the thesis: that weather is one of the fundamental risks and that it is priced in a financial market. The other objective is to show the contribution of this thesis to the research area.

3.1.2 Structure of this chapter

The rest of the chapter is divided into three parts. The next section begins by establishing how weather exposures can be related to security returns. It addresses an incomplete knowledge on a market-wide basis of the weather effects on security prices, with reference to two stand-alone research areas that can actually be connected in order to understand the fullest extent of weather risks and returns. While weather effects have already been discussed in the previous chapter, this part reviews literature on market-based accounting research (MBAR) and proposes a possible link between the two areas. The development of research hypotheses of the fundamental weather risk and its market price is also explained here.

Following an assumption of the significance of weather to security returns, Section 3 suggests the framework to investigate weather exposure empirically. The renowned asset pricing theory is reviewed both in terms of its background theory and literature studies. CAPM and APT are discussed in this section.

Finally, Section 4 brings all aspects under a single framework, where weather risk becomes a potential factor included within an asset pricing model. The proposal fills a gap in the research into weather effects and asset pricing. This segment not only provides a rationale behind the hypotheses but also indicates the contribution to knowledge on the dynamics of a financial market which this thesis makes. It also clarifies how this empirical study is unique and important to research, especially in weather risk and weather derivative pricings.

3.2 Weather exposures and share values

The section begins with a perspective of the market-based accounting research (MBAR) and its findings. Subsequently, it indicates how this area can possibly be connected to weather effects. Corporate earnings or profits are a key to link the two research schemes, and help in identifying the under-researched area of a financial impact of weather in a stock market.

3.2.1 A review of market-based accounting research

Market-based accounting research examines the relationship between share prices, stock returns, trading volumes and published accounting numbers. The research uses

contemporaneous accounting data as independent variables to determine stock return or price as the dependant variable (Lee, 1999). Lev and Ohlson (1982) asserted that MBAR builds on the foundation of financial principles such as portfolio selection theory and CAPM. This makes it unique in that it contributes to other disciplines. They also pointed out that the empirical work of MBAR would contribute to the knowledge of relationships of fundamental or firm-based variables and the systematic risk of common equities, and any inconsistent evidence with market efficiency theory may call for a reconsideration of these equilibrium models such as CAPM.

Starting in the 1950s/60s as a result of significant developments in finance theory, most of earlier studies on the information content of accounting data were announcement-related, investigating impacts of the announcement of some events on the mean and variance of the stock return distributions. Ball and Brown's (1968) research has compiled consistent information of a statistically significant association between the sign of unexpected earnings, derived from the first difference in earnings, and residual returns. The stock-price reaction occurred prior to earnings announcements, with no significant relationship between earnings and returns following the disclosure. Beaver (1974) extended Ball-Brown's methodology to consider the size rather than just the sign of unexpected earnings. The largest (either positive or negative) unexpected earning portfolios were found to have higher absolute residual returns than moderate portfolios. This suggested that both the magnitude and sign of unexpected earnings added to the statistical association between unexpected earnings and residual returns. The Ball-Brown methodology has been extensively used in related contexts, but is limited in that the assumption is based on unexpected earnings, which means a specific earning expectation model is needed. Patell (1976) substituted 'management's earning' forecasts for the Ball-Brown model, and his findings confirmed those results. This forecast model was only marginally better in explaining excess returns than Ball-Brown's expectation model.

Researchers not only investigated the mean of unexpected return distribution, but also, more recently, have examined the variance and trading volumes. However, these later empirical studies are relatively few compared to the first type. Based on intraday stock price data, Patell and Wolfson (1981) observed that the variance of stock price during earnings announcement period was larger than normal. The return variance was also changed significantly at this time, and the regular pattern of negatively serially-

correlated intraday return was interrupted. This confirms the hypothesis that earnings data bring new information to the market. Beaver (1968) introduced another element to the study by analysing trading volumes, reflecting possible asymmetry in firms' future prospects. The results also supported the information content hypothesis in that above-average trading volume was noticed around earnings announcement dates. Theoretically, the stock reactions in either price or volume can be observed independently but both variables might often be positively correlated in practice. However, an interpretation of this correlation should be made with caution. It should be kept in mind that these variables capture two different aspects of individuals' thought processes (Lev and Ohlson, 1982).

Lev and Ohlson (1982) assessed the available empirical evidence in MBAR and concluded that earnings announcements affect the stochastic properties of stock prices (mean, variance, and serial correlation). Their conclusion was based on a number of studies using different dataset, in terms of both time periods and stock exchanges, and various statistical methodologies. These observations were consistent with the prior assumption of the relevance and timeliness of earnings information to investment decisions in financial markets.

From its inception, MBAR has become a norm for many industries (Sambharya, 2011) and can be used for predictive research goals (Bernard, 1995; Lee, 1999). Accounting research has been developed as an essential tool for the professional world. Since 1995, there have been even more refinements in the methodology, making it an increasingly strong research tool. While there are still criticisms of MBAR, as the literature review will demonstrate, its strengths have increased over time as it has adapted. MBAR deals specifically with evaluating the financial status of a company. The validity of MBAR, therefore, depends on the validity of the underlying relationship upon which it is based. Literature discusses the relationship, if any, between corporate returns or earnings and stock returns as well as difficulties that exist in drawing a correlation between the two types of data.

Hirschey and Wichern (1984) considered accounting and market measures independently for evaluating profitability. The study examined the correlation of both accounting and market information to profitability indicators in several industries, including food processing, transportation equipment, chemicals, and primary metals. The researchers noted that accounting information was useful in historical company

data and allowed interpretation of that history. Market measures, on the other hand, were forward-looking, providing a different measure of profitability. The authors concluded that the relationships between accounting measures (corporate earnings) and market measures (stock prices) are the key to explaining the firm-profit phenomenon. This research does not provide a direct analysis of the correlation between corporate and stock returns, but contextualises its importance.

Lev (1989) utilised twenty years of data from nineteen studies on the correlation between corporate earnings and equity returns to determine the validity of the assumed relationship between them. This empirical research showed that the correlation was negligible, if present at all. The author concluded that there was little significant relationship between earnings and returns. However, this research is outdated and more recent studies have made contrary findings. The response of Strong and Walker (1993) responded to Lev (1989), explained why the earnings-returns relationship which is a foundation for MBAR exists and can be useful. This study utilised regression analysis and applied adaptations to improve the data and correlation results. Additionally, regression should account for a variation in earnings components. These adaptations resulted in a significant increase in the correlation between corporate earnings and stock returns. Data modifications are suspect if not based on fact but help in defining the parameters.

Nichols and Wahlen (2004) tested the existence of a relationship between earnings and returns by using annual data from 31,923 firms from NYSE, AMEX, and NASDAQ. The authors examined the correlation between stock and corporate returns or earnings. They found that earnings correlated with contemporaneous stock market return information and changes in market value. Liu and Thomas (2000) built on the existence of a relationship between earnings and returns to explain the type of relationship. The researchers used annual data from I/B/E/S from 1981 to 1994. They confirmed a relationship between corporate and stock returns, but noticed that it was nonlinear. The relationship changed annually, with the coefficient of the nonlinear correlation being unpredictable.

Maditinos, Sevic, and Theriou (2009) examined the correlation between stock returns and performance measures including earnings per share, returns on investment, returns on equity, economic value added, and shareholder value added. The researchers used data listings in the Athens Stock Exchange. The data was pooled, with time series data

for the period from 1992-2001. The results of the study indicated that the correlation was strongest between stock returns and earnings per share than any of the other performance indicators. Though limited to the Athens Stock Exchange, it provides the clearest evaluation of the correlation between stock returns and earnings against other comparable measures of performance.

Boyacioglu and Akdogan (2010) considered the problem of measuring the accuracy and ethical relationship between corporate returns and stock returns. The authors identified corporate governance as the solution. More precise contemporaneous data translates to more accurate MBAR. The specific type of corporate governance can also alter the data. Clark and Wojcik (2005) noted the cultural differences between different nations and their effects. For instance, German values translate into governance with more concentrated ownership. By studying this effect in the firms of the DAX100, the authors found that concentrated ownership resulted in higher returns, without a change in earnings. Ownership structures can affect the relationship between earnings and returns.

Shen and Lin (2010) tested the importance of corporate governance and found that it affected stock return data. When comparing strong governance regimes to weak in Taiwan, the authors found that strong resulted in significantly higher stock returns. This indicates that the relationship between corporate and stock returns may be altered by outside influences on the governance regime. This conclusion is similar to one of Lev and Ohlson (1982)'s which notes that differences in accounting practices compromised the validity of MBAR. Specifically, the researchers believed that differences in accounting techniques and regulatory systems influenced the data of a given firm. Thus, the relationship between that data, particularly corporate returns, and stock returns was altered.

Similarly, market data can also be manipulated. Bartov and Mohanram (2004) collected data on stock option award decisions by the executives of more than 1,200 public companies. Their findings indicated that earnings improved prior to stock option awards, but deflated afterwards. This suggested that earnings management can manipulate the return on stocks. Beaver, Clarke, and Wright (1979) made similar findings decades earlier, suggesting that residual stock returns were inconsistent with expected earnings and demonstrating instability in the returns/earnings relationship. The researchers based their findings on a cross-sectional regression of residual returns and

earnings data of 25 NYSE firms. Similar findings were also found by Cheng and Warfield (2005). Their results showed that the equity incentives for managers resulted in bad management practices, such as reporting earnings lower than actual, can alter the value of returns.

Easton and Sommers (2003) considered the correlation between balance sheet and income sheet data and market data, specifically examining how regressions of financial statement can skew market data. The researchers completed a series of regressions to explain market indicators, particularly a stock price. The results showed that the firms which comprised the top five per cent of the financial data have a dominant, or scale, effect on the dependent variable or stock price.[13] Using MBAR, the correlation between earnings and stock prices may be skewed by the other firms in the data pool. Studies in MBAR employing regressions in this manner should account for scale effects. Nichols and Wahlen (2004) also confirmed scale effect issues in their research. One set of empirical results in their article addressed the relationship between earnings and stock returns at firms with persistently high earnings compared to those with lower. The authors found that a higher rate of earnings persistence was correlated with a stronger relationship between corporate earnings and stock returns. MBAR should be used with caution, particularly with companies that have lower rates of earnings persistence.

In conclusion, MBAR adds a new tool for analysing a company's financial status by predicating a relationship existing between accounting and market information. Bringing together accounting and financial theories, it creates a multi-disciplinary and multi-faceted approach; however, it cannot be proved conclusively that earnings are more relevant than numerous other items. A more conservative interpretation of the information-content findings, as Lev and Ohlson (1982) suggested, is therefore that accounting reports, rather than earnings in particular, provide timely and relevant information to the market. While there are weaknesses in the MBAR methodology, there is evidence of the relationship between corporate and equity prices or returns, which supports the assumption of this thesis.

[13] The regressions of market capitalization on financial statement variables are driven by a small subset of the very largest firms in the sample, and such overwhelming influence is referred to as 'scale effect' (Easton and Sommers, 2003).

3.2.2 Identifying the under-researched area

Previous literature on one hand suggests that weather has impacts on corporate accountings such as earnings or profits, and on the other hand MBAR advises that such accounting numbers provide useful information to investors in financial markets. Thus, it implies a possible relation of weather influence in security prices. The earlier studies most related to this area is the weather impacts on stock market performances, but their research focuses are on psychological effects rather than the bottom-line effects.

Fundamentally, stock returns are payoffs for taking risks, which are related to unanticipated events. As weather forecasting is not always accurate and variation of weather hits unexpectedly, a firm's earnings is exposed to these unforeseen weather events. Consequently, stock prices of a firm should reflect an unexpected change in future cash flows attributable to unanticipated weather, and the change here can be considered as the fundamental impact of weather on a firm or the genuine 'weather risk'. Thus, the financial impacts of weather on security prices should base on unexpected weather occurrences, rather than total weather conditions. Surprisingly, as far as is known, no study has been carried out in this area. Figure 3.1 provides a picture of an overlay in literature and identifies an interesting under-researched area.

[Insert Figure 3.1 here]

A gap in previous research strands raises a question as to what extent weather unpredictability affects share values. Moreover, can investors be rewarded when holding securities exposed to weather? Answering these questions involves, together with the development of weather factors, the estimates of weather risk and the assessment of weather risk premiums. By doing so, this helps researchers and investors to gain more insights into the market-wide effects of weather and to relate empirical findings to the pricing mechanism of weather derivatives.

This thesis is different from the previous literature in three aspects. Firstly, it brings in a new set of weather factors. The construction of unpredictable weather variables has never been identified in the previous literature but will be proposed for the first time in this thesis. Secondly, the research draws an interest on to the direct relationship between unpredictable weather and share values, or what is considered weather risk. The weather exposure of companies will be analysed by estimating the sensitivity of the firm values to unanticipated weather events. This can be measured by the regression coefficient of

the change in return of the equity on a weather variable, called a 'weather beta'. Simultaneously with an arrival of the weather beta, the third advantage is the discovery of a market price of weather risk. Theoretically, stock returns are determined by the product of factor exposures and factor premiums. Therefore, this weather premium can be empirically estimated. The subsequent section will elucidate more on the theory, the framework and the methodology of this thesis.

3.3 Asset pricing theory

This section mainly explains and reviews literature related to the methodological framework of this study. It begins with a brief historical development of asset pricing theory and the theoretical grounds of asset pricing models: the well-known CAPM and APT are discussed here. The aim is to arrive at an understanding of the way securities are valued in the market and to seek a possible way to examine a weather risk in that setting. The latter part of the section primarily reviews studies on CAPM and APT, discussing previous empirical findings related to factors driving asset returns.

3.3.1 History of asset pricing

The investment theory can be dated back to 1952 when Markowitz presented a mean-variance analysis to a competitive market. Given the level of risk, he derived an efficient frontier of investment portfolios such that each of them had the highest possible expected rate of return. However, the technique was too sophisticated for a computation according to the technology of that time. A major development was introduced in the 1960s by Sharpe, with a simplified single-index model. This version allowed researchers to manage large numbers of securities and made portfolio theory more practical. Sharpe (1964), Lintner (1965), and Mossin (1966) as cited in Milne (2003) have observed that with all market clearance, investors would choose portfolios that were a linear combination of the risk-free and the market-portfolio. This became known as the capital asset pricing model (CAPM), which became the premier model and which became popular in terms of a useful application in the real world for decades. It has been widely used to measure portfolio performances, value equities and make decisions on capital budgeting (Haugen, 2001). Milne (2003) added that this was the first time in finance that a theory created such a simple model that could be tested, and CAPM has been one of the popular subjects for empirical studies until the present day. The standard CAPM is actually derived under restrictive assumptions, but sometimes in

any economic model the fruitfulness of statistical results is traded off for the simplicity of a theory. Therefore, these assumptions were relaxed later on with the development of extensions of CAPM. A continuation of the CAPM, for example, includes a zero-beta CAPM (no riskless asset), a model extension to a multi-period economy, the introduction of restrictions on borrowing, and the introduction of taxes and transaction costs.

Although CAPM appeared to provide a good fit for the data at an initial stage, a later article by Roll (1977) criticized the model, claiming that its predictive power was exaggerated by the test methodology (Milne, 2003) and that it was impossible to verify its single economic prediction unless researchers had the true market portfolio. As an alternative to the CAPM, Ross (1976) developed the arbitrage pricing theory (APT) which related expected returns to risk in such a way that no investors could create unlimited wealth through arbitrage. By pure arbitrage and diversification arguments, he showed that asset prices could be obtained by a linear function of a few basic factors. This theory is also testable (Dybvig and Ross, 1985), and less demanding in terms of assumptions. Broadly speaking, the APT is more general than CAPM as it allows a number of factors, instead of only the covariance between returns of a security and the market portfolio, to affect the equity rate of return. However, the problem with this theory is that there is no indication of how many and what these factors are, so they need to be empirically determined. In a later decade, while CAPM was being called into question, APT seemed to gain momentum in empirical research. However, CAPM still receives 2-3 times the coverage in standard finance texts compared to APT (Groenewold and Fraser, 1997).

3.3.2 Theoretical background of CAPM and APT

The following section describes the theoretical background of the basic CAPM and APT in brief, as detailed explanations and extensions of these basic models can be found in well-known academic references such as Haugen (2001) and Cuthbertson (1996).

The CAPM concept builds on the Markowitz's modern portfolio theory, efficient frontier and mean-variance analysis. In the investment theory, the minimum variance frontier contains combinations of expected return and risk for portfolios of risky assets that minimize return variance given the levels of expected return. To obtain the mean-

variance-efficient portfolios available with risk-free borrowing and lending, all efficient portfolios must be combinations of the risk free asset and a single risky tangency portfolio on efficient frontiers (Fama and French, 2004). With homogeneous expectations, all investors hold the same tangency portfolio with the risk free asset. Consequently, the capital market line (CML), along which all investors invest, can be derived by drawing a straight line from the risk-free asset tangential to the efficient frontier. That tangency portfolio, therefore, represents a bundle of stocks held in certain fixed proportions by all investors and it is called the market portfolio (M).

The CML identifies an individual expectation of returns on a portfolio, and it is a linear relationship between risk and return on efficient portfolios that can be written as:

$$E(R_p) = R_f + \sigma_p \left[\frac{E(R_m) - R_f}{\sigma_m} \right] \qquad (3.1),$$

where R_p is the portfolio return, R_f is risk-free asset return, R_m is market portfolio return, σ_p is standard deviation of portfolio returns an σ_m is standard deviation of market portfolio returns.

It is worth noting that the amounts of riskless and risky assets held by any individual investor depend upon his preferences. The only thing they have in common is that the optimal portfolio of risky assets for all investors lies on the CML; therefore, the slope of CML is often referred to as the market price of risk since it is the rate at which individual will trade off for risk and return.

Investors are generally concerned with a final portfolio position; therefore, they assess the risk of an individual asset on the basis of its contribution to the portfolio variance. Since they all hold the same market portfolio, a security's risk can be measured by the covariance between an asset and the market portfolio, and this is called the beta.

$$\beta_i = \frac{\text{cov}(R_i, R_m)}{\sigma_m^2} \qquad (3.2)$$

As implied in CAPM that the market portfolio M is on the minimum variance frontier, a perfect linear relationship should exist between the beta of assets and their expected returns.[14] Given the linear relationship, one can draw the security market line (SML)

[14] See proof of the linear relationship between the beta of the stocks and their expected return with reference to any portfolio in the minimum variance set in Haugen (2001), pp. 114-116 and Cuthbertson (2007), pp. 40-41.

which expresses the expected return in terms of a risk-free rate and the relative risk of a stock or portfolio. The relationship is given by

$$E(R_i) = R_f + [E(R_m) - R_f]\beta_i \qquad (3.3).$$

As a result, the basic one-period CAPM connects a portfolio to a single risk factor, which is the covariance with the market portfolio. It predicts that only the covariance of returns between asset *i* and the market portfolio drives the excess return on asset *i*. In other words, the expected return on any asset is the risk-free rate plus a risk premium, which is the asset's beta times the premium per unit of beta risk.

Essentially, the CAPM model is based on the following assumptions (Black et al., 1972).

i. All investors are single period risk-averse utility of terminal wealth maximizers and can choose among portfolios on the basis of expected return and variance.
ii. There are no impediments to the free flow of capital and information throughout the market, for example, no taxes or no transaction costs.
iii. All investors have homogeneous views regarding the parameters of the joint probability distribution of all security returns.
iv. All investors can borrow and lend at a given riskless rate of interest.

Many of assumptions of CAPM are admittedly unrealistic; however, the variant models have been derived later on under the relaxation of some of these assumptions.[15]

Alternative to the CAPM, APT formulated by Ross (1976) directly relates the asset price to the fundamental factors driving it. It is assumed that the covariances existing between security returns can be attributed to the fact that securities respond, to some degree, to the pull of one or more factors and that the relationship between the security returns and the factors is linear (Haugen, 2001).

$$R_{it} = \alpha_{it} + \beta_{i1}F_{1t} + ... + \beta_{ij}F_{jt} + \varepsilon_{it} \qquad i = 1, 2, \ldots, n \qquad (3.4),$$

[15] For example, Haugen (2001) suggested further readings on Chen, Kim and Kon (1975) for a derivation of the CAPM under transaction costs, Brennan (1973) for a derivation under personal income taxes, and Lintner (1970) for a derivation under heterogeneous expectations.

where F_{jt} are factors or measures of non-diversifiable risks, β_{ij} are factor loadings or sensitivities of the security price to the particular factors, ε_{it} is a random variable with $E(\varepsilon_i) = 0$, $E(\varepsilon_i^2) = \sigma_i^2$, $E(\varepsilon_i \varepsilon_k) = 0, i \neq k$, and $\text{cov}(\varepsilon_i, F_j) = 0$ for all *i* and *j*.

By assuming that (i) no arbitrage possibilities and (ii) the law of large numbers, the relationship between the expected return of asset and the factor sensitivities can be given by:

$$E(R_{it}) = \lambda_0 + \lambda_1 \beta_{i1} + ... + \lambda_j \beta_{ij} + \varepsilon_{it} \qquad (3.5),$$

where λ_0 usually equals the risk-free rate and λ_j has the interpretation of price of risk with unit sensitivity to factor *j* and zero sensitivity to all other factors (Cheng, 1996).[16] Therefore, APT implies that, for an arbitrary asset, its expected return depends only on its factor exposures.

According to Cuthbertson (1996), the security return comprises of both an expected and an unexpected or surprise element, which, for any individual security, can be further broken down into general news and specific news. The APT predicts that general news will affect the rate of return on all stocks but to the different extent because the risk is systematic and non-diversifiable. The idea of systematic risk is similar to the case of CAPM, but the difference is that CAPM has a single non-company factor whereas APT separates out the factor into as many as proved necessary.[17]

The principal idea of APT that only a small number of systematic risk influences the long-term average returns of assets may appear similar to the multi-factor Merton (1973) ICAPM, but the APT is much more an arbitrage relation than an equilibrium condition (Dimson and Mussavian, 1999).[18] Proponents of APT remark two major advantages of the model over CAPM that assumptions regarding investors' preferences are less restrictive and it can be verified empirically (Haugen, 2001). APT neither

[16] In a statistical context, the law of large numbers implies that the average of a random sample from a large population is likely to be close to the mean of the whole population.

[17] The covariance is interpreted as a measure of risk that investors cannot avoid by diversification. See the consistency of the APT and CAPM in Haugen (2001, pp.261-262) and Cuthbertson (1996, pp.61-65).

[18] Dimson and Mussavian (1999, p.1759) explains that "*If the factor model holds exactly and assets do not have specific risk, then the law of one price implies that the expected return of any asset is just a linear function of the other assets' expected return. If this were not the case, arbitrageurs would be able to create a long-short trading strategy that would have no initial cost, but would give positive profits for sure.*"

requires that all investors behave the same, nor does it argue that the market portfolio is the only risk asset which will be held. In addition, it avoids the problem over testability dispute in CAPM. Nonetheless, the APT model involves some relatively subtle arguments and it is not easily interpreted at an intuitive level (Cuthbertson, 1996). Since APT provides no indication of appropriate factors for the model, the choice of variables and their interpretations have been intensely debated almost from its inception.

3.3.3 Literature review on CAPM and APT

The development of CAPM has changed the financial world, and a great deal of related empirical research has been undertaken. Fama and French (2004) reviewed the theory and findings on CAPM from its initial stage. For the early tests, they asserted that the Sharpe-Lintner CAPM has never been an empirical success, while the Black version, which relaxes the risk-free borrowing or lending assumption and only predicts that the beta premium is positive, has had some success. This is consistent with the view of Black et al. (1972) that previous research is likely to point out an inadequate description of the traditional CAPM in explaining security returns.[19]

The Sharp-Lintner CAPM predicts that assets have expected returns as specified in equation (3.3), and most of these predictions are tested either by cross-section or time-series regressions. In early cross-section studies, empirical evidence firmly rejected the traditional Sharp-Lintner CAPM. It was found that the intercept is larger than the average risk-free rate and that the beta coefficient is less than the average excess market return.[20] These previous cross-section tests found two problems: estimates of individual assets' betas are imprecise, creating an error-in-variables problem (EIV), and the regression residuals have common sources of variation (Fama and French, 2004). To improve the precision of beta estimates, researchers work with portfolios instead of

[19] It was shown in Black et al. (1972) that research by Douglas (1969), Lintner (1965a) and Miller and Scholes (1972) seemed to indicate that the traditional CAPM model does not provide a complete description of the structure of security returns although evidence presented by Jensen (1968; 1969) on the relationship between the expected return and systematic risk of a large sample of mutual funds indicated that the expected excess return on any asset is directly proportional to its beta.

[20] Evidence cited in Fama and French (2004) includes studies by Douglas (1968), Black et al. (1972), Miller and Scholes (1972), Blume and Friend (1973), Fama and MacBeth (1973). More recent cross-section tests, such as those of Fama and French (1992) and Fama and French (2004), also supported the earlier findings.

individual assets.[21] However, the combination into portfolios reduces statistical power by decreasing the range of betas. Therefore, researchers tend to sort securities on beta when constructing portfolios and this sorting procedure has become a standard method in empirical studies (Fama and French, 2004). Additionally, Fama and Macbeth (1973) proposed a two-stage rolling regression method to account for the inference problem caused by correlation of residuals in cross-section regressions, and their approach has also become a common practice in an empirical study.

Jensen (1968 cited in Fama and French, 2004) initiated a time-series regression test for the Sharpe-Lintner CAPM, and the intercept term in his regression model, or Jensen's alpha, has been implied to be zero for each asset. However, results from time-series regressions confirmed the early cross-section regression findings that the relation between beta and average return is too flat: the intercepts in time-series regressions of excess asset returns on the excess market return are positive for assets with low betas and negative for assets with high betas (Friend and Blume, 1970; Black et al., 1972; Stambaugh, 1982 cited in Fama and French, 2004).

Following a rejection of the traditional CAPM, Black et al. (1972) indicated that expected return on a security can be represented without risk-free borrowing or lending. With unrestricted short-selling of risky assets, the expected return can be expressed in terms of the return on portfolio that has a zero covariance with the return on the market portfolio, $E(R_z)$, instead of the risk free rate. They found that the factor had a positive trend over 1931-1965 and that the values appeared to be statistically different from the average risk-free rate. Instead, they roughly equalled to the average market return. The $E(R_z)$ seemed to be an important determinant of asset returns in the study. According to Fama and French (2004, p.15), evidence from early tests of CAPM suggested that *"the central predictions of the Black version of the CAPM, that the market betas suffice to explain expected returns and that risk premium for beta is positive, seem to hold. But the more specific prediction of the Sharpe-Lintner CAPM that the premium per unit of beta is the expected market return minus the riskfree interest rate is consistently rejected."*

However, in the late 1970s, a body of empirical research appeared to challenge the CAPM's Black version and evidence has shown that much of the variation in expected

[21] Fama and French (2004) suggest seeing the work of Blume (1970), Friend and Blume (1970) and Black et al. (1972).

return does not relate to market beta (Fama and French, 2004). An increasing number of studies have discovered that the cross-sectional variation in average equity returns is not subject to the market beta alone. Fundamental variables such as earnings-price (E/P) ratios, size, debt-equity ratios and ratios of book-to-market value (BE/ME) also contained information about expected returns that are not captured by market betas (Fama and French, 2004; Galagedera, 2007).[22] Fama and French documented the empirical failures of the market model in their important series of research (1992; 1993; 1996a) and saw these variables as prime candidates to expose the shortcomings of CAPM.

The compelling evidence on average-return anomalies of the CAPM suggests that a multifactor version of Merton's (1973) intertemporal capital asset pricing model (ICAPM) or Ross's (1976) APT can provide a better approximation of average returns.[23] Fama and French (1993; 1996a) implemented ICAPM by proposing a three-factor model for expected return: the market excess return, the size effect (small minus big, SMB), and the effect of BE/ME (high minus low, HML) were included in the model. They argued that, although size and BE/ME are not state variables, two classes of stocks-- small caps and value stocks (high BE/ME) -- are likely to perform better than the market and these covariances in returns cannot be explained by the market return. It is worth noting that the excess market return was one of the factors included in the model, due to its strong theoretical standing, and tests on long sample periods showed that this premium is reliably positive; however, the positive market premium does not lend support to CAPM and justify the use of it in applications (Fama and French, 1996b).

The Fama-French three-factor model provides an improved explanation of average returns than CAPM, and it captures most of the average-return anomalies unobserved by CAPM. The constructed model is now generally used in empirical tests and has become

[22] They reviewed literature related to fundamental variables as follow. See earnings-price (E/P) ratios in Basu (1977), size in Banz (1981), debt-equity ratios in (Bhandari, 1988) and ratios of book-to-market (BE/ME) value in Rosenberg et al. (1985); Chan et al. (1991); Capaul et al. (1993).

[23] ICAPM is an extension of CAPM, acknowledging that investors of ICAPM are concerned not only with their end-of-period payoffs but also with the opportunities for investment of the payoffs. Consequently, investors also consider how their wealth may vary with relevant state variables in the future. Thus, the demand for risky assets will be made up both of the mean-variance component and a demand to hedge adverse shocks to the investment opportunity set. Therefore, optimal portfolios are multifactor efficient, in that the expected returns are the highest possible given the level of return variances and the covariances of their returns with the relevant state variables. (See Fama and French, 2004; Dimson and Mussavian, 1999)

a benchmark to proxy for risks (Xue, 2003). Nevertheless, the three factors have also been challenged by the documented financial anomalies. The most serious problem is the momentum effect raised by Jegadeesh and Titman (1993) as cited in Fama and French (2004), where high-performing stocks over the past three to twelve months tend to continue to do well for the next few months and *vice versa*. Carhart (1997), therefore, added an additional momentum factor as an extension of the Fama-French model. Moreover, Kothari, Shanken and Sloan (1995) contended that Fama-French results were largely due to survival bias. Fama and French (1996b) later argued that the survival bias does not explain the relationship between B/M and average return and their argument is in accordance with that of Chan, Jegadeesh and Lakonishok (1995).

Another strand of research argues that the market portfolio, central to the model of CAPM, is theoretically and empirically indefinable. Instead, proxies are used to test CAPM and, consequently, nothing about CAPM is learnt. Roll's famous critique (1977) of CAPM testability appeared to shed light on the APT model of Stephen Ross (1976). The APT has been widely discussed in literature and empirically researched in many markets as it has the potential to overcome CAPM's alleged weaknesses of unrealistic assumptions and empirical shortcomings. Groenewold and Fraser (1997) pointed out that CAPM typically displays insufficient explanatory power as well as overestimating the risk-free rate and underestimating the market risk premium. Consequently, the prediction of an asset return by using market betas alone becomes impractical.

In contrast to CAPM, APT allows for a number of risk factors and permits researchers to determine variables providing the greatest explanation for the specific sample at hand. Berry et al. (1988 cited in Paavola, 2007) suggested simple instructions about the qualifications of legitimate risk factors in the APT framework: (i) at the beginning of every period, the factor must be completely unpredictable to the market; (ii) each APT factor must have a pervasive influence on stock returns; and (iii) relevant factors must influence expected return; for example, they must have non-zero prices. These properties imply that the factor must be unpredictable and the risk must be systematic and can be priced empirically.

However, empirical work has found mixed support for APT as the theory itself does not describe the relevant factors in asset pricing and thus it cannot explain variation in security returns by referring to a limited number of distinguishable factors. Studies in the field have concentrated on attempting to determine the set of these variables through

two distinct methodologies: either using statistical techniques to extract significant factors or assuming pre-specified random factors. In the literature, the common factors driving asset returns may include unanticipated change in macroeconomic factors such as interest rate, inflation, GDP, oil prices and exchange rate.

The initial classic empirical test of APT was conducted by Roll and Ross. They adopted a similar methodology to that used by Black et al. (1972) in testing CAPM to estimate factor betas in the first stage and then estimate the cross-sectional relationship between security betas and average rates of return in the second stage (Haugen, 2001). Roll and Ross (1980) estimated the factor betas, by using a statistical technique called factor analysis, which best explains the covariances existing between the securities in the sample. They found that four different factors were priced in the U.S. market. Later studies of APT, such as those by Reinganum (1981), Chen (1983), Connor and Korajczyk (1986), Lehman and Modest (1988), Martikainen, Yli-Olli, and Gunasekaran (1991) and Groenewold and Fraser (1997), also adopted factor analysis or principal component analysis to determine the significant factors; however, the number of factors that influence equity returns extracted by factor analysis has been the source of much contention.

Although factor analytic techniques provide a benefit in that the extracted factors can explain a large proportion of the risks in the particular dataset over the period under consideration (Dimson and Mussavian, 1999), several critical issues have emerged when testing APT with this approach. The main criticism is probably that the number of factors is likely to increase when the sample size expands (Dhrymes, Friend and Gultekin, 1984; Trzcinka, 1986). Roll and Ross (1984) responded that the increased number of factors in expanding samples could be due to new factors depending on the companies included in the sample. Nonetheless, the appropriate number of variables seems to vary significantly across studies and the contents of priced factor are likely to differ across samples (Martikainen et al., 1991).[24] Antoniou et al. (1998) support the argument that the empirical evidence to-date, especially with regard to the U.S. and the U.K., indicate that APT is far from robust, with different numbers of factors being priced in different samples.

[24] See Lehman and Modest (1988) and Cho and Taylor (1987) for different number of factors in empirical studies. See Kryzanowski and To (1983); Cho, Eun and Senbet (1986); Conway and Reinganum (1988); Booth et al., (1991b) as cited in Martikainen et al. (1991) for the different contents of priced factors across different groups of securities.

In addition, in empirical work using factor analysis, the extracted factors are artificially generated and therefore have no economic interpretation at all. Errors in factor identification may have led to the inconsistencies (Haugen, 2001). From this perspective, arriving at a model that offers economic insight is needed. This is similar to Roll and Ross (1980 cited in Dimson and Mussavian, 1999, p.14)'s argument that *"an effort should be directed at identifying a more meaningful set of sufficient statistics for the underlying factors"*.

Hence, researchers try to pre-specify general factors that explain asset returns in the stock market. The seminal work of Chen et al. (1986) initiated an APT test with macroeconomic variables, and their results showed that industrial production, changes in the risk premium and twists in the yield curve have a significant explanatory influence on asset prices. Their argument for using the set of macroeconomic variables rests on a fundamental valuation that the stock price will be discounted by expected future dividends. Therefore, the choice of factors should include any systematic risks that impact on future dividends and the discount rates. The set of variables investigated in Chen et al. (1986), or else very similar to it, has been used in a number of studies, more recently, and some of them have been found to be important and priced in those research.[25]

Burmeister and McElroy (1988) and Azeez and Yonezawa (2003) pointed that the advantages of using macroeconomic factors are not only an economic interpretation but also additional information by linking asset-price behaviour to macroeconomic events. In addition to the macroeconomic-type, aggregated accounting numbers have been suggested as state variables such as the work of Martikainen and Yli-Olli (1990), and firm-characteristic based variables such as Fama-French factors can also be used as factors in APT. By identifying specific factors in a model seems to provide a meaningful analysis; however, Huberman and Wang (2005, p.11) argued that this method *"…is implemented without regard to the factor structure. Its attempt to relate the assets' expected returns to the covariance of the assets' returns with other variables is more in the spirit of Merton's (1973) intertemporal CAPM than in the spirit of APT."*

Besides, Fama (1991) contended that offering economic insight does not sufficiently generate a valid model as the relations may be spurious without robustness checks.

[25] For example, the growth rate of money supply, oil and gold price, consumer price index and exchange rates.

"…although the returns and economic factors used by Chen, Roll and Ross are available for earlier and later periods, to my knowledge we have no evidence on how the factors perform outside their sample" (Fama, 1991, p.1595). Connor and Korajczyk (1992 cited in Antoniou et al., 1998) also supported the argument that any valuation of the empirical performance and validity of APT must concentrate on its ability to price assets outside the sample used for estimation. They suggested that the prices of specific risk factors should be the same across different subsamples of assets. Antoniou et al. (1998) found that only three out of five priced factors in their study are unique in the sense that the carry the same prices of risk in the two samples. However, only with the unique factors are able to explain the cross-sectional behaviour of excess returns of securities in the study. Thus, the model appeared to be robust and this does not invalidate APT.

While the two approaches in APT have been tested separately in general, not many studies have compared the factors and the explanatory power of these two techniques. Martikainen et al. (1991) carried out a test in Finnish market and found that macroeconomic factors add incremental information with respect to the traditional factor analysis. Connor (1995) compared the explanatory power of three methods of multi-factor models-- macroeconomic, fundamental and statistical factor analysis. Although the two latter methods outperformed a macroeconomic model in terms of an explanatory power, he concluded that using a macroeconomic factor model was probably the strongest out of the three approaches due to its intuitive appeal and theoretical consistency.

Some of later empirical research such as Xue (2003) introduced a new approach for APT. He used principal components analysis to extract the principal components in the first step, and then adopted Semi-parametric reduced rank regression technique to estimate the factors as the underlying forces driving these components. His estimation procedure discovered five empirical factors, which can be explained by commonly used macroeconomic variables. It was also claimed that the discovered set of factors can capture additional risk information that Fama-French three factors leave out. However, the issue was that these empirical factors are not pre-specified, but rather derived by capturing features in the data. Thus, it is required to establish a strong relation between these factors and macroeconomic variables to persuade researchers that these factors are risk-based. Nonetheless, it seems difficult to explain the relatively large variations in

stock returns by means of small variations in monthly macroeconomic variables (Xue, 2003). Therefore, the author recommended future research on an investigation of the link between the common forces of macroeconomic variables and the factors estimated in the study to identify a set of economically interpretable risk factors.[26] In some sense, this approach is in accordance with Chen (1988)'s statement that factor analysis can be helpful in testing the APT against specified alternatives, as well as in linking identifiable economic variables to common-stock return fluctuations.

In summary, CAPM is a theory of equilibrium based on investors' portfolio demand. The key insight is that higher expected returns come with greater risk and a beta is a measure of that. CAPM is simple and theoretically appealing in that it connects a portfolio to a single risk factor, which is the covariance of an asset return with the market return. However, the empirical records of CAPM are discouraging. Although the behavioural researchers may argue that sorting firms on price ratios (firm-based characteristics) exposes investor overreaction to good and bad times and thus violations of CAPM are due to mispricing, the CAPM empirical results are unsatisfactory enough to invalidate its applications (Fama and French, 2004).[27]

The CAPM's empirical problems may also reveal theoretical flaws. The model does not fit well with reality as the real market return is not observable. In addition, the restrictive assumptions of CAPM seem to limit the model in theory because, in reality, some of them are likely to be violated. For example, investor expectations are not homogeneous and investors in fact hold different portfolios. Instead of everyone being interested solely in the market portfolio, APT discards this view and replaces it with an explanatory model of what influences asset returns. Like CAPM, the APT argues that discount rates are based on the systematic risk exposure of the security, as opposed to the total risk. However, it allows many possible sources of risk that cannot be diversified away to be compensated in terms of expected return for holding assets exposed to these uncertainties. In particular, under an arbitrage argument, APT assumes a factor model of asset returns. The model seems to be more valid than CAPM in terms of its less restrictive assumptions and testability. However, one main drawback of APT

[26] It will be interesting to specify a series of macroeconomic variables *a priori* but model these series as dynamic processes, and estimate factors as *common forces* driving the movements of these macro variables (Xue, 2003).

[27] See DeBondt and Thaler (1987), Lakonishok et al. (1994) and Haugen (1995) as cited in Fama and French (2004).

is its generality given that it does not specify the right factors and additionally these factors can change over time.[28] To estimate factor sensitivities and premiums, the theory requires investors to identify the risk sources, the identity of which in fact cannot be agreed. The set of factors ultimately relies on empirical work, in which the results are often mixed, depending on the sample data and methodologies used.

A number of studies have compared CAPM and APT, and suggested that APT may produce superior estimates of expected return than CAPM (Chen, 1983; Bower, Bower and Logue, 1984; Conner and Korajczyk, 1988; Lehmann and Modest, 1988; Burmeister and McElroy, 1988). More recent studies also support these earlier findings. Groenewold and Fraser (1997) found that both macro-factor and artificial-factor versions of APT clearly have higher within-sample explanatory power than CAPM. They suggested that the strength of APT comes from its multi-factor structure rather than customization, as only little explanatory power was lost by specifying macroeconomic factors *a priori*. However, the authors accepted that some data-mining may present in the specification searches. Similar conclusions were derived by Chen and Jordan (1993) using the U.S. data set. Dhankar (2005) analysed the Indian stock market using monthly and weekly returns for 1991-2002 and found that APT explained both return generation processes better than CAPM. The adjusted R^2 of APT was higher than that of CAPM, and the error sum of squares was significantly lower for the individual stocks, alphabetical and industry portfolios. Nonetheless, the result was contradictory for beta-sorted portfolio so the author addressed that portfolio dissimilarity is critical in estimating common factors explaining returns. As results may vary according to the sample, period and methods used, it seems premature to conclude that APT outperforms CAPM. The recommendation is, therefore, that researchers should not solely rely on beta but should give due consideration to multifactor models like APT (Dhankar, 2005).

In the author's view, CAPM should not be totally discarded as it is still intuitively appealing in terms of its simplicity and economic interpretation. Asset return anomalies have been found and these anomalies can be described using multi-factor models to fit the empirical evidence. However, if a proxy of market portfolio can represent all market risk, as CAPM claims, anomalies found in empirical research should rest on the

[28] Groenewold and Fraser (1997) suggest this is the main reason for APT's failure to replace CAPM despite its distinct advantages.

effects of any exogenous factor unrelated to the market at all. Chen et al. (1986) viewed that all economic variables are endogenous and only natural forces are truly exogenous to the economy. However, their study did not base an asset-pricing model on these systematic factors due to the limited abilities at the time and so they take the stock market as endogenous relative to other markets.

While tests of multi-factor asset pricing models have been carried out using pre-specified macroeconomic or firm-based factors, no published study has been reported with weather factors, based on the author's awareness. In the context that weather is common, uncontrollable, unpredictable and uncorrelated with general economic conditions; it should be considered as exogenous to the world economy, similar to Chen et al. (1986)'s concept of natural forces. Such an exogenous factor may be able to explain the returns incremental to the market portfolio's effect, and this assumption reconciles with both spirits of ICAPM and APT. From this perspective, it is worth considering the inclusion of weather risk into the asset pricing model.

3.4 Weather as a fundamental determinant of stock returns

Considering weather as representing the common source of volume risks for weather-related businesses, we can make an assumption that weather risk will be priced in the market. Bringing together seminal empirical evidence from several disciplines, the hypothesis is that weather is one of the fundamental factors driving the price of a security. As previously mentioned, this under-researched area should deliver a deeper understanding of asset pricing and the weather market.

If economic variables such as an interest rate or an exchange rate can generate security returns, a natural basic phenomenon like weather should also have the potential to fundamentally determine equity values. This is due to the fact that the occurrences are random and inevitable even with the advancement of today's technology. Its fluctuations and unpredictability enable weather to be another common source of risk in financial markets. Because of its wide impacts, the risk is systematic and cannot be diversified away; thus, it will be priced.

To find out how sensitive stock returns are reacting to the randomness of weather, the estimate of an exposure coefficient can be obtained from the time-series regression,

$$R_{it} = \beta_{0i} + \beta_{1i} W_t + \varepsilon_{it} \quad (3.6),$$

where R_{it} is the rate of return on the i company's common stock and W_t is a weather variable. This specification is appropriate if changes in stock prices and weather are basically unanticipated.[29] The weather beta, β_{1i}, describes the stock's sensitivity or reactivity to a weather factor, which is estimated as the relationship between the return on the stock and the weather randomness.

However, a company is not exposed to only weather but also to a market condition in general, so an alternative model to (3.6) is to control for a market movement. One may consider this specification fitting within the APT context discussed earlier, which is

$$R_{it} = \beta_{0i} + \beta_{2i} R_m + \beta_{3i} W_t + \varepsilon_{it} \quad (3.7),$$

where R_m is the rate of return on the market index. The weather exposure, β_{3i}, in this case is considered as a market-adjusted weather beta. If the weather beta is significant, the effect of weather will meaningfully impact the equity returns and thus investors should be compensated for bearing it. Although other macroeconomic factors, such as inflation and exchange rate, may also influence stock returns, the market subsumes these macroeconomic determinants. For this reason, the most well-known asset pricing model such as CAPM includes only a single market portfolio factor. Thus, this thesis employs only two factors, one of which is the market portfolio representing the market condition as a whole.

One of the potential explanations to the equity premium is the standard asset pricing models mentioned earlier. In the APT setting where it relates the assets' expected returns to a number of relevant variables, such returns are considered to be a linear function of each factor's beta. If asset returns follow a factor structure in (3.7) then the following relation exists between expected returns and the factor sensitivities.

$$E(R_i) = \delta + \lambda_1 \beta_{2i} + \lambda_2 \beta_{3i} \quad (3.8),$$

where λ is the risk premium of the factor and δ is the risk-free rate. In this study, the λ_2 or the market price of weather risk will be empirically examined whether it is statistically different from zero or not. Yet, the specification needs to satisfy

[29] If the expected rate of return on the common stock and the expected change in weather are constant over time, then the intercept β_{0i} will represent these expected values and the slope coefficient β_{1i} will correctly measure the effect of unanticipated change in weather.

assumptions of the APT. The factor model in (3.8), therefore, takes as given the premium that the market generally places on an exposure to the risk but requires the estimation of a particular stock's exposure to the risk. This type of model makes sense for factors which represent external risks in the marketplace that affect all stocks.

While the study has focused on the exposure to weather and its market price, it has also demonstrated a difficulty in identifying an appropriate representative for the weather factor. As deliberated, weather itself is not expressed in risk forms, and weather risk should be related to 'unexpected' weather conditions rather than general weather events. Then, the study needs to find out how to extract the unexpected component of weather, which have been somewhat neglected in previous studies. This thesis, therefore, begins to form variables representing unpredictable weather by using simple statistical approaches. By discarding complex meteorological models, it makes weather variables uncomplicated and more applicable to non-scientists and as such hopes to encourage more reflections on the study of weather risk.

To date, a number of theoretical papers have investigated the possible sources of assets' returns. However, no study has yet addressed the possibility of inclusion of weather even though the risk is actually natural and basic. All the hypotheses in this study are new to the research area, so the empirical evidence found should add on to the comprehension of the weather risk and its premium in general. To be more specific, the research undertaken contributes knowledge in a number of respects.

First of all, it proposes innovative but simple concepts of how to quantify weather randomness as a weather factor which is testable in an asset pricing context. The methodology used in this thesis is much simpler than complex scientific models that meteorologists generally use to predict the future weather. Investors need no comprehension in meteorology to forecast weather, but rather use historical data to estimate the unpredicted weather factor.

Secondly, the sensitivity of equity values to weather surprise is examined for the first time. An obtained weather beta represents weather exposure of a firm, which is a relation between unexpected change in weather and a security's return. The weather beta is likely to be a key parameter for a risk management of the weather-related firms.

Following an estimation of weather risk, the third advantage of this study is the discovery of its market price. With the approach used in this study, the market price of weather risk can be estimated without the need of information from weather derivatives' market prices, which remain in a rather rudimentary state on one hand and are difficult to obtain on the other hand.[30] The estimated price of weather risk may provide a basic method for pricing weather derivatives in the future, in that a weather premium can be used as a discount rate instead of a risk free rate in a weather derivative valuation.

Last but not least, the study is located at an under-researched area and thus seeks to bring a connection to other research strands. This would enable researchers and investors to understand mechanics of the financial market to a fuller extent.

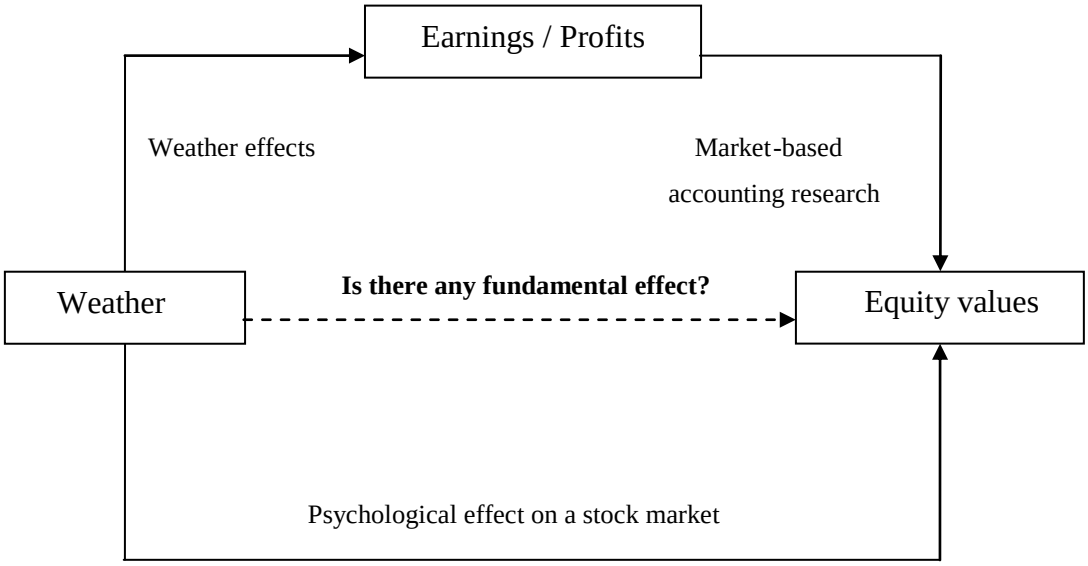
The research questions in this thesis are still at an early stage for weather risk study and further research could be carried out in several ways. However, the impact of this thesis would positively encourage researchers to study further into these issues and as such it would bring more academic and empirical knowledge to the public. In this way, it is hoped that more understanding of weather risk will be achieved and the estimated price of weather exposure in the vein of APT may provide a reliable method for pricing weather derivative contracts.

[30] It is likely difficult to obtain the market prices of weather derivatives, in which the market price of weather risk can be implied, because one cannot obtain price information for OTC contracts while that of traded contracts in the market are subject to a liquidity issue of the instruments. For example, researchers may not be able to find a resemble contract, with the specific maturity and location, to be used in the study of an equilibrium pricing.

Figure 3.1: An assumed weather-security price relationship

The diagram illustrates the relevant research strands and pinpoints the interesting under-researched area. Previous literature on one hand suggests that weather impacts corporate accountings such as sales or profits, and on the other hand expresses the fact that those accounting numbers provide useful information to investors in financial markets. Through these linkages, it implicitly recommends a connection between weather effects and security returns.

In literature, only a psychological effect has been examined with respect to this connection. The research has yet to be carried out for a fundamental effect of weather on security prices: how unpredicted weather has impacted on equity values through a changing investment opportunity set (expected future cash flows). Therefore, this thesis aims to fulfil the gap in literature by examining bottom-line weather exposures, if any, and its premiums.



Chapter 4

Data Analysis and Quantifications of Unexpected Weather

4.1 Introduction

The thesis investigates corporate weather exposures in terms of their effects on equity prices, if any, and examines the pricings of such risks. In every study, it is highly important for researchers to carefully review the quality of sample data since their inherent characteristics are critical to statistical inferences. Therefore, this chapter is dedicated to analysing the sample data and developing innovative weather variables that will be used later on in the study. The principal objective is to investigate every facet of the sample data, and present them as preliminary results on which the interpretation of the subsequent findings will hinge.

Central to this chapter is the exploration of unexpected weather components, which is essential to the study of weather exposures and risk premiums. As previously mentioned, consistent with the ability of investors to diversify, no additional return can be earned by bearing diversifiable risk. In fact, a company would set a plan ready to deal with any foreseeable related factors so only cash flow fluctuations in relation to an unpredictable element would be considered a non-diversifiable risk. If such risk is fundamental, theoretically it will be priced in the market. In the same vein, weather-related companies should not be exposed to a weather condition at any period but rather its randomness. Unexpected weather is a conventionally used notion and yet it is a concept difficult to define precisely. An approach to quantify this element has not been derived in literature, thus this chapter intuitively proposes ideas to construct such a measurement. All the identifications and analyses of the innovative weather factor are presented in the second half on the chapter.

As weather derivatives originated in the U.S. and this market has been considered as the largest in terms of trading, the study is carried out for the U.S. market and the sample data are 484 weather-related companies operating there. On the ground that not all companies are exposed to the same level of risk from weather variability, the research is restricted to a few industries for which it is believed that the weather exposures tend to be fairly evident and direct. Hopefully, the results found in this study may bring forth a potential price of existing weather risk in general.

The study uses the series of monthly average temperature as a representative for weather because temperature tends to affect the sample firms in common. This parameter is also more manageable than others, such as rainfall and snowfall, because it is continuous. Measurement challenges such as discontinuity can cause uncertainty which eventually impacts the market price. Additionally, it is observed that the weather derivative market has developed from temperature-based derivatives and these instruments have been extensively traded up until the present. Therefore, it is valid to start the investigation of weather effects with this simple and widely-accepted parameter. The monthly frequency is picked out for the reason that it is long enough to allow the effects of weather surprise to reflect in stock prices, through companies' economic and financial activities. The effect of one day's weather on a stock market is seen in terms of its psychological effect, which is not the intention of this study. On the other hand, a quarter or annual data may not efficiently capture weather exposures as the effects may be washed out in the next season. A monthly average temperature should be sufficient for issues studied in the research, but any later explorations may consider a finer time resolution.

The sample period is from January 1980 to December 2009, which covers time both before and after the invention of weather derivatives. Thus, the study can examine weather exposures of companies with respect to the arrival of this weather risk management tool. A decision on historical lengths of data is critical due to the fact that climate patterns are shifting, especially in the most recent decades. In addition, weather forecasts today are more precise than the past so current weather randomness may be different over a long historical period. This study opts for an intermediate record length of thirty years because meteorologists, such as those from the U.K. Met Office or the U.S. climate services, define climate on a normal base period of 30 years. Moreover, the period does not go back so far but still cover enough observations to study the stability of weather exposures before and after the coming of weather derivatives.

The rest of the chapter is organised into three sections. Section 2 describes data description and the analysis of returns on sample stocks, the market portfolio return and meteorological records (temperature). It describes the logical process of sample and variable selections, sources of data, problems and resolutions of missing observations, as well as some key statistics of those factors. Section 3 is intended to establish the time-series of quantified unpredictable temperature and to analyse statistical properties

of such variables. Owing to the fact that there is no cohesive assumption on how to measure unexpected weather in the financial world, this section is set to explore and construct potential variables. Different hypotheses are proposed in order to develop innovations of the weather proxies used in the research. The statistical properties of unexpected weather variables and preliminary findings are analysed thoroughly and presented in this part. Section 4 provides a summary of the chapter.

4.2 Data description and analysis

The data used in this thesis are as follows: (i) the time-series of 484 security returns from three selected industries, (ii) the time-series of returns on the CRSP value-weighted market index, and (iii) monthly average temperature series at national level, on which a construction of ten weather risk measures will be based. This section provides detailed data descriptions, analyses, problems of, and resolutions for all these preliminary data series in the research.

4.2.1 The sample

Although recently Lazo et al. (2011) have shown that weather variability has a statistically significant relationship to U.S. economic activity in all sectors, not all businesses are responsive to the same level of weather swings and this fact is reflected in this study.[31] Given that this thesis is the first study to investigate weather exposures and its pricings in the stock market, it is important to start at a basic level, focusing on the industries most affected by weather. This study intends to find weather exposures of U.S. companies in which, it is believed, the weather impacts are likely to be considerable in regard to their economic activities. By reviewing literature and news related to weather derivative markets, three important sectors are selected for the sample set: utilities, agriculture, and tourism.[32]

The first, and conceivably the most important, group is utilities recalling that the weather derivative market was first established there. Temperature directly impacts the

[31] Lazo et al. (2011) finds that all 11 nongovernmental sectors in the U.S. is significantly sensitive to at least one measure of weather variability (HDD, CDD, total precipitation and precipitation standard deviation) in the study. They define weather sensitivity as the variability in gross product owing to weather variability, controlling for changes in technology and for changes in the level of economic inputs.

[32] News includes articles, press release and information on websites, which related to weather effects, weather risk and weather derivative market.

consumption of gas and electricity in residential, commercial and industrial areas. Energy demand, therefore, is very sensitive to volatile weather and precise predictions of demands are needed given that the power is non-storable. An oversupply means a cost increase, profit deterioration and possibly lower share value of a company. Thus, utilities firms need to predict the future weather conditions and mitigate exposures attributable to unexpected temperatures. Being the largest traders of weather derivative contracts reaffirm that small weather fluctuations can be translated into considerable weather exposures within this sector.

Next, agricultural companies should also be included in the sample because their products rely highly on the mercy of the weather. Warmer or colder than normal will destroy produce and cause a high volatility of supplies. Adverse weather apparently affects an ability of companies to maintain a stable environment, to achieve sales growth, and to effectively manage and secure costs.[33] Again, this poor financial performance will be reflected in stock returns. It is worth mentioning that agriculture has been the most studied sector for weather impacts on productions, and it is one of the most relatively weather-sensitive sectors measured by changes in gross domestic products due to weather variability (Lazo et al., 2011). However, it should be noted that agricultural firms are exposed to more varied weather than just the temperature. A body of literature, to a great extent, has also explored the impacts of precipitation on crop yields, bundled with the temperature and other non-weather effects. According to the WRMA annual surveys, agricultural companies appear to be active traders in weather derivative markets and recently they have been seen as potential users in the weather market worldwide.[34] For example, the Indian weather market for agriculture grew four-fold in 2010 (WRMA, 2010) and the Australian agriculture sector is seeing more weather risk products tailored for the needs of farmers, growers and traders such

[33] It is noted in Lazo et al. (2011)'s analysis that agriculture most likely experiences greater sensitivity due to longer-term constraints in cropping decision at longer time scales than available weather information.

[34] The Weather Risk Management Association (WRMA), the international trade organization of the weather risk management industry, conducted an annual survey regarding the value of weather risk management contracts from year 2000 to 2006. Their objectives were to establish sizes of the market and provide consistent measure of a market development over a specified time period. Survey participants' main lines of business are energy, agriculture and bank and insurance.

as YieldShield (WRMA, 2011).[35] Thus, it is imperative to add this sector in the sample set.

Tourism is the last sector included in the sample. In fact, little research has been carried out on the association between weather and leisure companies' revenues and profits. However, it is predicted that weather impacts should be reasonably noticeable because travelling decisions to a great extent are confirmed by weather. Providing that leisure is non-necessity products, holiday makers would easily switch their choices of locations if they experience weather fluctuations and surprises. They even cancel their trips when there is an extreme weather warning. The revenue of this industry is tremendously dependent on the number of tourists, and that is obviously affected by weather conditions. Therefore, it is expected that the equity values of tourism firms should also be exposed to weather variables. The interface between weather and tourism, however, is multifaceted and highly complex. The tourism industry is characterized by considerable diversity; consequently, substantial differences exist in effects of on travel demand. For example, ski resorts would attract fewer skiers in unusually warm winter while the amusement park nearby might benefit from that. Although varied conceptualisations of the subsectors comprise the tourism sector, weather, besides distance, cost and timing, tends to be the most important influence on the choice of leisure travel destinations and thus affects all firms' earnings in the industry. Then, the weather effects tend to be rather evident.

In brief, the aforementioned three sectors appear to be distinctive among others in the market in terms of the degree of weather effects, thus it is advantageous to start the exploration of weather exposures within these industries. Utilities seem to be the most outstanding sector affected by unusual temperature, followed by agriculture. The structure of the tourism sector is rather diverse and disintegrated, hence a selection of sample firms and an analysis of weather effects must be formed with caution.

4.2.1.1 Source of data

The research intends to include both active and dead stocks, during the study period, in the sample to avoid survivorship bias and for better estimations. The University of Chicago Center for Research in Security Prices (CRSP) is the database used for the

[35] YieldShield is a pilot tool to transfer the risk of a growing season not reaching its reasonable expectations.

thesis because it provides information on both active and inactive securities and efficiently categorizes those shares corresponding to Standard Industrial Classification (SIC) by the U.S. government.

Prior to 1999, the U.S. government uses the SIC code to group companies with similar products and services, and the standard provides benefits in terms of statistics and easy comparison with other measures. From 1999, the North American Industry Classification System (NAICS) has replaced the old SIC system to provide a high level of comparability in business statistics across North America. NAICS codes, though, are available in the CRSP database only from August 2001 onwards. The sample period for this thesis starts from January 1980, thus the SIC code is a more appropriate standard to classify securities for this study. According to the standard, the research focused primarily on the major group number 01 (Agricultural production crops), 49 (Electric, Gas and Sanitary services), 70 (Hotels, Rooming Houses, Camps, and Other Lodging Places) and 79 (Amusement and Recreation Services).[36] Within the utilities and tourism-related major groups; however, there are some industries which do not particularly rely on temperature such as water supply, sanitary services, irrigation systems, boarding houses, membership-based hotels, dance studios, theatrical producers and indoor sports facilities membership sport clubs. Consequently, securities from these unrelated industries are removed from the sample. After all, data in the study, for utilities, is mainly based on businesses of natural gas and electric production, distribution and services. Meanwhile, the tourism sample includes firms primarily engaged in hotels, sporting and recreation campsites, recreational vehicle parks, golf courses, amusement parks and racing.

It is a matter of fact that a company can have more than one class of share; however, each security in this study should represent only one company at any time. Therefore, the sample includes only ordinary shares, which is the most common class. The research uses the CRSP Permanent Company Number (PERMCO) to provide the unique identifier for each individual company in the database. This number is permanent for all securities issued by this company regardless of name changes, which helps ensuring the consistency of an investigation (CRSP, 2011).

[36] Information related to SIC code can be found at Occupational Safety& Health Administration, U.S. department of Labour's website. http://www.osha.gov/pls/imis/sic_manual.html.

Additionally, the U.S. weather impacts only companies operating within the States so any shares from companies running businesses outside the U.S. are omitted. Any securities with missing data of more than three periods or with observations less than 24 months are also excluded for more accurate approximation. Table 4.1 summarizes the whole process of the sample selection, explaining how 484 sample stocks are derived. These securities belong to companies expected to be most influenced by the U.S. temperature, and they are listed on different exchanges such as NASDAQ, NYSE, and AMEX.

[Insert Table 4.1 here]

4.2.1.2 Equity returns

The dependent variable in the thesis, R_{it}, are month t^{th} total returns of each stock *i* in the sample from January 1980 to December 2009, and the data is collected from the CRSP database. The return is defined as the change in the total value, including dividends, of an investment over a holding period per dollar of initial investment, and it is calculated as follows:

$$R_t = \left[\frac{P_t * F_t + D_t}{P_{t-1}} \right] - 1 \qquad (4.1)$$

where ,

P_t = last sale price or closing bid/ ask average at time *t*

F_t = price adjustment factor for *t*

D_t = cash adjustment for *t*

P_{t-1} = last sale price or closing bid/ ask average at time *t-1*.

The holding period return is appropriate in the study due to an assumption that temperature risk should take some time to reflect its impacts into stock prices, via the effects of earning surprises. As mentioned earlier, only one day temperature surprise should not significantly impact companies' cash flows, especially for agricultural or tourism corporations. Day-to-day weather variations should impact a security market in terms of a psychological rather than financial effect.

4.2.1.3 Missing observations and resolutions

When returns are missing, the subjective resolutions criteria are used as follows. If the period of missing observations is more than three periods, the securities are excluded from the sample. However, if the period of missing observations is considered short, which only applies to a few periods, returns are replaced by the market return of the same period.

4.2.2 The market proxy

The market portfolio of all risky assets is not observable. Ideally, the market proxy should include all U.S. stocks and bonds, foreign stocks and bonds, real estate etc. However, this is often limited by data availability and cost. Besides, CRSP calculates returns for equal-weighted and value-weighted portfolios of all available stocks for each trading period, based on individual stock returns. Each of these portfolios is calculated in two ways, including dividends or excluding dividends. The CRSP stock data files include data from NYSE, AMEX, NASDAQ and NYSE Arca stock exchanges, so it offers broad indices across the U.S. market (CRSP, 2011).

The market proxy of CRSP value-weighted market index return including dividends is employed in this research. It is a total return index, which takes into account both the changes in the price of the stock and the dividend paid to investors and then reinvested. The index return $R(I)$ is the change in value of a portfolio over some holding period, calculated as the weighted average $W_n(I)$ of the returns $r_n(I)$ for individual securities in the portfolio.

$$R(I) = \frac{\sum_n W_n(I) * r_n(I)}{\sum_n W_n(I)} \tag{4.2}$$

In a value-weighted portfolio, the weight $W_n(I)$ assigned to each security is its total market value $V_n(I)$, which are the product of its price $P_n(I-1)$ and its number of share outstanding at the end of the previous trading period $S_n(I-1)$.

$$W_n(I) = P_n(I-1) * S_n(I-1) \tag{4.3}$$

[Insert Figure 4.1 here]

Figure 4.1 illustrates the movement of monthly rates of market return series (R_m) from January 1980 to December 2009, together with a histogram and basic descriptive statistics. For a given market index, the returns are fluctuated around zero with an average mean value of 0.984%. The mean is statistically different from zero at 1% level, with *t*-statistic at 4.06. The probability distribution of the returns is asymmetric and non-normal as it is negatively skewed and leptokurtic. This is also supported by the Jarque-Bera statistic at 144.1824, which rejects the null hypothesis that the series is normally distributed at 1% confidence level. It should be noted that all descriptive statistics of all series in the research are conducted using EViews 7.0. Brief explanations on these statistics are explained in Appendix I.

In any estimation involving time-series data, a theory behind it is based on stationary time series.[37] Ignoring this assumption can result in a spurious regression and it is difficult to make any inferences of findings to the other time period.[38] Throughout this thesis, all stationary or unit root tests are based on the Augmented Dickey-Fuller (ADF) test developed by Dickey and Fuller, which is briefly explained in Appendix II. The ADF test is carried out for the market return series to ensure its stationary property before a further analysis. The results are reported in Table 4.2, in which each panel represents different exogenous regressors including a constant, a constant and linear trend, or neither of them. It indicates that the null hypothesis of the presence of unit root can be rejected at 1% level in all cases. The market return series is undoubtedly stationary.

[Insert Table 4.2 here]

4.2.3 The weather variable

There are many possibilities in the search for weather variables. At first, it is important to find out which aspect of weather is of interest. Different weather aspects range from temperature levels, humidity, the levels of rainfalls or snowfalls, to precipitations. Most of the previous literature on the effects of weather found that temperature and

[37] A stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two periods depends only on the lag between the two time periods and not the actual time at which the covariance is computed (Gujarati, 2003).

[38] If a relationship between two variables is allowed to change arbitrarily in each time period, then we cannot hope to learn much about how a change in one variable affects the other variable if we only have access to a single time series realization (Wooldridge, 2009).

precipitation affect most of business activities such as sales, productivities and demands in weather-influenced industries. They show significant relationships of these weather parameters with demands of gas and electricity, growing conditions of agricultural produce and even tourist decisions to travel. Nevertheless, temperature is selected for this study due to the fact that its effects are dominant in every sector. Although precipitation also greatly impacts on agricultural products, its effect on utility demand and travel decision is not as outstanding as the temperature effect. Moreover, its continuous measurement property makes it easier to monitor. Additionally, temperature contracts remain the most-traded customised weather hedge even though growth of products in other parameter has been reported such as rainfall, snow and wind contracts (Dudley, 2011). They are still widely traded on exchange markets in terms of heating and cooling degree days. The above reasons and the small sample of agricultural firms make it possible for this research to exclusively focus on temperature effects. This thesis will use *monthly average temperature* as a measure of weather

If temperature is actually affecting investors' cash flow forecasts for the firm, then it should not be subject to short-range weather such as one day's temperature variation. Rather, corporate operations and earnings are exposed to persistent changes in day-to-day temperature, such as a warmer than average winter. Larsen (2006) stated that, typically, weather data can be grouped into short-range forecasts (up to 3 days), medium range (3 to7 days), long or extended range (7 to 14 days) and seasonal (14 days to 1 year). This study will consider monthly data as opposed to that of other timeframes, since it appropriately captures abnormal weather deviating from a seasonal pattern and, in addition, it is the customary period used in the study of asset pricing. Additionally, the period is not too long for temperature effects to be diminished, in the case that temperature variations are averaged out during that period. Moreover, mean temperature seems to capture the temporal variation of temperature during a day better than the minimum or maximum temperature.

4.2.3.1 Source of data

Weather data are central to this research, thus the desirable properties of weather data are its high quality, reliability, consistency and long historical records. Dunis and Karalis (2003, p.1) stated that "*Without an appropriate quantity of relevant, high-quality data, pricing and management of weather risk would be unfeasible*". Therefore, all temperature data in this thesis are selected from a well-known source and the series

used are chosen with a high precision and appropriate historical length. The thesis mainly bases investigations on the 30-year data, in accordance with a base period of climate *normal* as defined by the meteorological organizations in the U.S. and the U.K.

The temperature series are obtained from a website of National Climatic Data Centre (NCDC), U.S. department of commerce. Specifically, average monthly temperature data is obtained from NOAA Satellite and Information Service. It is available at http://www1.ncdc.noaa.gov/pub/data/cirs/drd964x.tmpst.txt. NCDC reports monthly time bias-corrected average temperature at state-wide, regional and national levels. The period of records starts from 1895 onwards; however, the monthly data for the most recent one to two years are based on preliminary data and will be updated when the final data are analysed.

There are thousands of weather stations across the U.S., and the records from these stations have been pieced together for the weather data at the state-wide, regional and national level. The state-wide values are available for the 48 contiguous states, excluding Alaska and Hawaii. As the climatic divisions of Alaska and Hawaii have data with lengths of record that are shorter than for the contagious U.S. divisions, they provide dataset separately and their records are not included in the computation for regional or national values (Guttman and Quayle, 1996). Each of the 48 states has been subdivided into as many as 10 climatic divisions, depending upon the size of the state. A divisional dataset has been compiled and averaged by simple unweighted arithmetic means of monthly data from all representative stations within a given division. A state-wide value has been computed via regression techniques, from divisional values weighted by area, and the resulting temperature data are adjusted for observation time bias (Guttman and Quayle, 1996).[39] The regional and national values are also computed in the same way, proportionate to the area weights.

Information of the states and area weights can be found at http://www1.ncdc.noaa.gov/pub/data/cirs/state.README. It should be noted that the temperature records may be different from values published in other NCDC publications due to the differences in the way the regions are defined, the adjustment of

[39] Observers usually take one observation at the same time during the day, but the 24-hour period at any station can vary from station-to-station and year-by-year. This affects reports of data and eventually the calculation of monthly mean temperatures. These potential biases, however, are rectified by adjusting for the various observation times using the model recommended by Karl et al. (1986 cited in NCDC, 2007).

temperature data for time of observation bias, and the use of preliminary data. The descriptive statistics of state-wide temperature data can be found in Table 4.3.

[Insert Table 4.3 here]

4.2.3.2 Principal component analysis of state-wide temperature data

Each company is situated in a different location so it should be exposed to weather from a different region. Applying weather data at a state level may help in estimating a security's weather sensitivity more accurately but this will add a complexity to the model, especially when one company has operations in more than one place. As the variables are measuring the same construct, which is temperature, at different locations, it is possible to reduce some redundancy in these variables and extract only a few factors that account for most of the variance. Principal component analysis (PCA) is a variable reduction procedure used in the thesis and it is conducted by SPSS 16.0. PCA provides information about the patterns of data and reduces the number of dimensions without much loss of the information (Smith, 2002). Its concept is to form new variables that contain as much variability of the original data as possible (Pahor, 2011). Schelns (2005, p.1) claimed that "*PCA is used abundantly in all forms of analysis... because it is a simple, non-parametric method of extracting relevant information from confusing data sets.*"

To ensure that PCA is appropriate for the data set, a preliminary analysis is based on the correlation matrix, Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. Fortunately, state-wide temperatures from the 48 states are highly correlated at more than 90%, indicating that these variables could be reduced to a smaller set of components in order to handle data more easily. All states' temperatures correlate fairly well; thus, there is no need to eliminate any of them before PCA. This is not surprising because temperature in the same country tends to vary together, and neighbouring states should have higher correlations than more distant areas. These extremely high correlations among state temperatures suggest that they should not be used together as explanatory variables in estimations to avoid a multicollinearity problem. Rather, these observed variables should be reduced into a smaller number of principal components.

Field (2005), Wuensch (2010) and SPSS (2007)'s user guide provide useful explanation and guidance on interpretations of PCA results in SPSS, and this study bases analyses on those references. The KMO statistic is measuring sampling adequacy and it usually varies between 0 and 1. A value of 0 indicates that the sum of partial correlations is large relative to the sum of correlations, which means diffusion in the pattern of correlations and hence factor analysis is unlikely to be appropriate (Field, 2005). Kaiser (1974 cited in Field, 2005) recommends accepting values greater than 0.5 as acceptable. Ideally, values more than 0.7 are preferred. Besides, Bartlett's test of sphericity is used to test the null hypothesis that the correlation matrix is an identity matrix which advises that the factor model is inappropriate (Field, 2005; Wuensch, 2010). These statistics provide justifications of whether the data set is suitable for a variable reduction process. In this case, the KMO statistic is 0.978 and Bartlett's test of sphericity is significant at 0.00, indicating patterns of correlations are relatively compact and thus factor analysis should yield distinct and reliable factors.

PCA uses a factor extraction method to form uncorrelated linear combinations. The first component has the maximum variance, while successive components incrementally explain portions of the variance and are all uncorrelated with each other. Table 4.4 lists the eigenvalues associated with each linear component before and after extraction. Each eigenvalue represents the variance that has been captured by the particular linear component, and the results are displayed in terms of the percentage of variance explained. The result from the table obviously shows that factor 1 already explains the very large amount of total variance at 97.37%; therefore, after extraction, SPSS leaves only one factor with an eigenvalue greater than 1.[40] Each successive component is explaining only smaller amounts of the total variance, and components with an eigenvalue of less than 1 account for less variance than did the original and so are of little use.

[Insert Table 4.4 here]

[40] The "eigenvalues greater than one" rule by Kaiser has been most commonly used due to its simple nature and availability in various computer packages. It states that the number of factors to be extracted should be equal to the number of factors having an eigenvalue greater than 1.0 (ACITS, the University of Texas at Austin, 1995).

The above result recommends only one extracted factor, and this is strongly supported by the high degree of communalities after extraction in Table 4.5.[41] The table indicates communalities before and after extraction, specifying how much of the variance in the variables has been accounted for by the extracted factors. Since principal component analysis works on an initial assumption that all variance is common, the communalities before extraction are all 1. After extraction, however, it reflects the common variance of the data structure. The result advises that all variables distribute large common variance, ranged from 92.8% to 98.8%.

[Insert Table 4.5 here]

The other useful tool to identify the number of factors extracted is a scree plot, which graphs the eigenvalue against the component number. It offers a visual aid for a decision at which point additional components no longer meaningfully increase the amount of variance accounted for. Figure 4.2 confirms that only one component should be retained, as seen by the curve reaches a stable plateau suddenly after one factor.

[Insert Figure 4.2 here]

The component score coefficient matrix is the factor weight matrix used to compute the factor scores for each factor. The result shows that coefficients of all variables appear to be equal at 0.021, signifying that a linear combination of equally-weighted observed variables would be optimal. If that is the case, the use of average temperature at national level is likely to be more accurate as it is also adjusted by area weights. Therefore, national values of average monthly temperature have been used for later analyses throughout the study. Lazo et al. (2011, p.717)'s finding that "*no one part of the country appears significantly more weather sensitive than another region in relative terms*" also supports the choice.

Corresponding to PCA results, the thesis utilizes the nationwide average monthly temperature series from January 1970 to 2009 for estimations in the research. The period goes backwards ten years longer than other series in the research because more observations are needed when constructing weather innovations by statistical methods. For example, unexpected weather of January 1980 needs to be estimated from historical

[41] Field (2005) commented that Kaiser's criterion is accurate when there are less than 30 variables and communalities after extraction are greater than 0.7 or when the sample size exceeds 250 and the average communality is greater than 0.6.

data. The use of autoregressive moving average (ARMA) process in estimating predicted weather component will consume some lagged periods. To ensure the full-length of weather variables is consistent with that of the other return series, more periods of data are prepared for the coverage.

It is worth noting that the study uses PCA to extract principal components of state temperature series because readers in finance and economics are familiar with this variable reduction method. Nonetheless, geophysical research alternately uses empirical orthogonal function (EOF) in order to analyse the spatial and temporal variability of climate. Basically, the method is similar to PCA in examining variability of scalar fields and the term can be used interchangeably (Bjornsson and Venegas, 1997). To the best of my knowledge, there were few studies using EOF to analyse the variability of sea surface temperature (SST) for specific locations.[42] For example, Keiner and Yan (1997) used a time-series of satellite images to determine the patterns of SST variance in Delaware Bay, and discovered that the seasonal solar heating cycle accounted for 95.3% of the total variance. Armstrong (1995) found the first EOF mode described 65% of the spatial variability of SST off northern and central California, whereas the second EOF mode accounted for 11% of the remaining variability in the data set. Even though these findings are not analogous to the data used in this study, it can be observed that there were only few principal components have been identified for variability in temperature.

4.2.3.3 Preliminary analysis of temperature series

Temperature is undoubtedly seasonal in its nature, and scientists have given a warning of the trend to global warming throughout the past few decades. It is fairly evident that many weather stations have indicated the existence of long-term warming, and this could be due to increasing urbanization, more local fossil fuel usage, or global warming (Garman et al., 2000). In order to examine a trend and seasonality in the temperature series, Table 4.6 reports descriptive statistics while Figure 4.3 illustrates graphs and a histogram of the series for 30 years during the study period.

[42] More details of EOF for climate can be referred to *'A guide to empirical orthogonal functions for climate data analyses* by Navarra and Simoncini (2010). Empirical work using EOF also explore the structure of the variability in SST with different data sets (both in space and time) such as Singleton (n.d.), and the variability in precipitation such as Widmann and Schar (1997).

Average temperature in the 30-year period is 53.56°F. In general, the coldest month is January with an average monthly mean of 32.30°F and the warmest month is July with an average monthly mean of 74.79°F. The standard deviations of colder months are slightly higher than others, probably suggesting that companies will face higher weather fluctuations or, in other words, weather risks in winter. This is similar to Cao and Wei's finding that temperature tends to be more volatile in winter than in summer (Richards et al., 2004).

[Insert Table 4.6 here]

A graph of national monthly average temperature against time apparently shows a clear and consistent seasonal pattern throughout the period: July is the hottest month and December is the coldest month. Surprisingly, no obvious trend is observed from the data, which is contrary to scientists' belief about global warming. The mean and variance of the series seem to be constant across time, implying a stationary time series. However, this may be due to the manipulation of data at the source, for which the obtained series is averaged and corrected for potential biases. When rearranging the data in the year-by-month format, it helps observing a seasonal pattern clearer. The graph in panel B presents the obvious movement of temperature mean and season within a year, in that a season can be evidently defined for subsequent analyses. The histogram in panel C reports that the temperature series is not normally distributed.

[Insert Figure 4.3 here]

Although it is clear that a seasonal pattern exists in a temperature series, it is worthwhile to conduct formal tests to examine the presence of seasonality. Hylleberg (1992) defines a seasonal component in time-series data as a systematic intrayear variation that is not necessarily regular. Thus, the intrayear variation can be either constantly repeated or evolving each year. While the former is known as a stable seasonality, the latter is recognized as a moving seasonality. In order to test for seasonality in the dataset, it is useful to test both types of variation separately as well as conducting a test for a combined variation together. The study carries out seasonality tests of temperature series by using ARIMA X-12 features in EViews 7.0, and a brief description of these tests is in Appendix III.

Table 4.7 reports all the results of stable seasonality tests, a moving seasonality test, and a combined test are shown in panel A-D respectively. In section A, an F-statistic is the ratio between-month variance and residual variance. A large F-value indicates that a significant amount of intra-year variation is due to months, or in other words seasonality exists. In this case, the null hypothesis of no seasonality can be rejected at 0.1% level. In addition, the Kruskal-Wallis Chi-squared test, which tests whether all the medians of temperature for each month are the same, shows that seasonality present at the 1% level. The statistic in section C is the moving seasonality test, which investigates the presence of seasonality that repeats itself from year to year in an evolving fashion. The null hypothesis is that there is no significant effect due to years after controlling for variation due to months, or no evolving seasonality. It cannot be rejected at 5% level in this case. The final analysis, in panel D, combines together the two F-tests described earlier and the nonparametric Kruskal-Wallis test, indicates that the presence of seasonality is identifiable for monthly average temperature series. As expected, the results points out that seasonality present in the series, and it can be identified as stable.

[Insert Table 4.7 here]

Not only is weather seasonal, but it is also likely to slightly vary around the previous period's level. It is not frequent to see extreme weather swings in a day. Changes in daily temperature are not entirely random as weather systems tend to lead to "warm spells" or "cold snaps" (Richards et al., 2004). In other words weather can be, to some extent, predictable even it is uncertain, and a forecast will be more accurate when the time frame is nearer. Garman et al. (2000, p.6) also mentioned this fact in his study that *"Weather dynamics are governed by the laws of physics, from which yesterday's cold and damp overcast unfolds into today's warm, clear blue sky – albeit with a measure of uncertainty. Uncertainty prevails when forecasting the weather, although short-term trends exist. In practice, this means that today's weather is more predictable than tomorrow's, and tomorrow's is more predictable than the next week."*

From this perspective, it may suggest that the temperature series is serially correlated and may follow a random walk process, thus violating a condition of stationary.[43] The

[43] Random walk model is a classic example of non-stationary time series. The process, e.g. random walk without drift, shows that the value of Y at time *t* is equal to its value at time *t-1* plus a random shock,

ADF test is conducted to test whether this series contains unit root or not. Table 4.8 presents ADF statistics, which can reject the null hypothesis at 5% level. In other words, the temperature series is stationary. It should be noted that a constant is needed as one of exogenous regressors in a model because temperature should seasonally vary around some fixed value.

[Insert Table 4.8 here]

Although the temperature series is stationary, it may still be serially correlated. A correlogram analysis is introduced here to investigate the autocorrelation (ACF) and partial autocorrelation (PACF) functions of the temperature time series up to the specified order of lags. Figure 4.4 displays the correlogram of the series for 20 lags, and the autocorrelation coefficients clearly show a seasonal pattern.[44] They start at very high value and decline, but rising up to reach a peak again around every six lags. Most of ACFs are individually significantly different from zero, in that they are outside the 95% confidence bounds. The PACFs exponentially decays after the second lag and most of them are statistically insignificant after lag 11. The value of *Q*-statistic up to lag 20 is 3329.1, and the probability of obtaining such a value, under the null hypothesis that the sum of 20 squared estimated autocorrelation coefficients is zero, is practically zero. Hence, the null hypothesis of no autocorrelation can be rejected.

[Insert Figure 4.4 here]

Ashley (2001) stated that sometimes seasonal movement can conceal other features in the observed series, such as small movement, direction and turning points. When re-examining the correlograms for the first and second difference of temperature series, the seasonal pattern still exists although the magnitude is lesser. The repeated cyclical patterns reinforce the fact that the seasonal effect is very strong and therefore it should be removed before subsequent analyses. The removal of seasonal fluctuations can provide an improved observation of the behaviour of a series, which is important to economic analysts (Ashley, 2001), and it is often suggested to remove the seasonal

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$Y_t = Y_{t-1} + u_t$. If the series is non-stationary, it is not possible to generalize any findings from the data to other time periods.

[44] Quantitative Micro Software, LLC (2007) recommends that if the autocorrelations appear to have a wavy cyclical pattern, this would suggest the presence of a *seasonal* autoregressive moving average (ARMA) structure.

factors from the series that do display seasonal patterns before reporting for the public use (Wooldridge, 2009). Therefore, the temperature series is seasonally adjusted in the following section.

4.2.3.4 Seasonal adjustment of temperature series by X-12-ARIMA

Analysing and establishing the general pattern of data may not be clear if the series contains a short-term effect associated with the time of year which obscures other movements.[45] Pierce (1980 cited in Buranavitayawut, 2008) states that researchers can better interpret, recognize and react to other important non-seasonal component in a series by removing seasonality. Therefore, seasonal adjustment is desirable to remove systematic calendar related variation from the temperature series before pursuing further investigations.

There are several methods of deseasonalising a time series; for example, the method of dummy variables and the application of the ARIMA model.[46] Seasonal adjustment is very complicated and detailed process indeed, and the practical implementation is not simple. However, there are several advantageously standardized seasonal adjustment programs, which are used commonly by many statisticians around the world. For example, the Bank of England has used X-12-ARIMA to seasonally adjust the monetary and related statistical series since 2004 (Thorp, 2003). The method has been favoured by the bank partly because of its consistency with the methodology used by the Office for National Statistics UK as well as its well-documented records and continuous support by the U.S. Census Bureau (Hussain and Maitland-Smith, 2010).

In this study, X-12-ARIMA developed by the U.S. Consensus Bureau has been applied, and EViews 7.0 provides an access to these X-12-ARIMA features. According to X-12-ARIMA Reference Manual V0.3 (U.S. Census Bureau, 2007) and Release Notes (Monsell, 2007), briefly, The X-12-ARIMA enhances the X-11-ARIMA by including more a variety of new tools and diagnostics to enlarge the range of economic time series that can be adequately seasonally adjusted. The essential source of these tools is

[45] A time series may contain four components: a seasonal, a cyclical, a trend and one that is strictly random.

[46] Gujarati (2003) implies that the seasonal influence can also be removed, for example, by taking the fourth-quarter differences of the quarterly original series and then decide what kind of ARIMA model to fit.

regARIMA models, or regression models with ARIMA errors. There are build-in regressors for directly estimating various flow, disruptions or the sudden change in the series, stock trading day effects and holiday effects. It is claimed that the use of regARIMA models can extend the series with forecasts in order to improve the seasonal adjustment to the most recent data. The benefits, both theoretical and empirical, were documented in many publications (U.S. Census Bureau, 2007). More detailed explanation for X-12-ARIMA, an up-to-date documentation of the program and the program itself can be found on U.S. Census Bureau's website, http://www.census.gov/srd/www/x12a/.[47]

The X-12-ARIMA program allows users to fit ARIMA models to the series prior to seasonal adjustment, and it uses the standard (p d q) $(P\ D\ Q)_s$ notation for seasonal ARIMA model. The (p d q) refers to the orders of non-seasonal autoregressive (AR), differencing, and moving average (MA) operators, while the $(P\ D\ Q)_s$ refers to the seasonal AR, differencing and MA orders. The *s* subscript means the seasonal period, for example, s=12 for monthly data. In general, X-12-ARIMA performs seasonal adjustment by decomposing the original series into a trend cycle, a seasonal component and an irregular component. Although there are many ways in which these components could fit together in a time series (Hyndman, 2004), the program offers two options of either additive model or multiplicative model. National Statistics UK (2007) recommends that multiplicative decomposition is suitable if the seasonal effects change proportionately with the trend, and most of economic series seems robust with this type. However, the fact that seasonal variation of temperature should not move with the trend makes the valid assumption for an additive model in this case.

The following additive model is suggested.

$$T = C + S + I \qquad (4.4),$$

where T is temperature series, C is the trend cycle, S is the seasonal component and I is irregular component.

[47] Additional sources for references of guidance on model estimations and diagnostics include, for example, EViews 6 User's Guide, SAS/ ETS User's Guide Version 8, Findley et al. (1990; 1998), Findley and Hood (1999), National Statistics UK (2007), Hungarian Central Statistical Office (2007) and Catherine Hood Consulting website http://www.catherinechhood.net/safaqx12arima.html.

The obtained temperature series in the analysis is from January 1979 to December 2009, so as to compensate for any lost periods when modelling the series later on. This research runs a number of models and selects the best fit model by the following criteria, as suggested by the standard of Chiu et al. (See Murdoch et al., 2000) and U.S. Census Bureau research (McDonald-Johnson et al., 2010; Lytras et al., n.d.; Findley and Hood, 1999).

1. The fitted model should be stationary, as evidenced by the absolute value of the coefficients of the AR characteristic equation being less than 1.
2. The fitted model should be invertible, as evidenced by the absolute value of the coefficients of the MA characteristic equation being less than 1.
3. Residuals are random, as measured by the value of *Q*-statistic greater than 0.05.
4. Monitoring and Quality assessment statistics are acceptable.
5. The series has acceptable seasonal adjustment stability diagnostic values, by sliding spans or historical revisions.
6. Seasonally adjusted series should not have residual seasonality. F-tests for residual seasonal effects should be non-significant after the series is seasonally adjusted.
7. Out-of-sample forecast errors should be less than 15 per cent.
8. Simpler regARIMA model is preferred, by avoiding high-order or mixed ARIMA models.

Table 4.9 presents some important results from the best fitted seasonal decomposition model found using X-12-ARIMA program. It is an additive regARIMA (1 0 1) (0 0 1) model with constant and seasonal dummies. The most appropriate model is determined by all significant regression coefficients, as reported in panel A and B of the table, and the smallest AIC shown in panel D compared with the other models which were run but their results have not been shown here. The estimated AR and MA coefficients in panel C of the selected model are stationary and invertible, with the absolute value less than one.

[Insert Table 4.9 here]

Additionally, residuals appear to be random as measured by the *Q*-statistics, which are more than 0.05 for all lags, indicating the adequacy of the fitted ARIMA model. Table 4.10 demonstrates more diagnostics of the chosen model, and there is no evidence of

residual seasonality from the model. The *Q*-stat is accepted at 0.70, and all important M-stats falls within an acceptance level between 0 and 1.[48] M3 and M5 are designed to observe if there is too much irregular in the series relative to the trend. Hood (n.d.) suggests that both M3 and M5 may fail if there is a very flat trend in the series because the change in the irregular will always be more than the change in the trend. In this case, there is no cause for concern and nothing needs to be done. According to Hood (n.d.) and X-12-ARIMA reference manual, M7 is the most important M statistic, which tests for moving seasonality relative to stable seasonality. Too much moving seasonality may cause problems in estimations. However, M7 is very low at 0.048 for the selected model. Lytras et al. (n.d.) interprets M7 value less than 1 that the series has identifiable seasonality, which is vital for any seasonal decomposition process.

[Insert Table 4.10 here]

The program also produces out-of-sample forecasts for 2010, and the figures have been compared with available actual temperature data from the same source. They fall within the forecast ranges produced from the model. All of the above findings verify that the selected model is proper and then the seasonally adjusted series is practical for further analyses. Figure 4.5 shows the graph and descriptive statistics of the seasonally adjusted temperature series (*TSA*), while Table 4.11 reports its ADF test statistics. The new series appears to be more random, with no pattern of seasonality present. The probability distribution seems closer to be the Gaussian function; however, it is still asymmetric with a negative skewness and a more acute peak around the mean. Compared to the temperature series, the seasonally adjusted series has a similar mean temperature but a standard deviation remarkably drops, from around 15°F to 2°F. It can be inferred that seasonality has a great influence in the data, and thus the removal of a seasonal effect should make the other patterns are more observable. The ADF statistics in Table 4.11 confirmed that the series is stationary at 1% significance level.

[Insert Figure 4.5 and Table 4.11 here]

[48] M-stat and Q-stat are monitoring and quality assessment statistics provided by X-12-ARIMA, and their definitions are mentioned in the reporting table.

4.3 Measures of unexpected weather

In asset pricing theory, only unexpected component should be considered as a risk, which will be rewarded in holding risky assets, and weather is no exception. As mentioned earlier in Chapter 3, the theoretical framework explains the mechanism through which weather risk may be fundamental and significant in explaining the security returns. Unfortunately, it has not been clearly identified in literature how to quantify the exposure as well as the unexpected weather that such risk is based upon. At this point, it comes to one of the most critical parts of this research, which is the exploration of proxies of unexpected weather. As only unforeseeable future weather should play an important role, in that it will be priced in the market, the question is how this unpredictable element is captured. It may be described as an uncertainty concerning the future, presuming as the difference between actual temperature and expected temperature. Nevertheless, expected temperature could be variously identified as there is no general consensus on the methodology for predicting temperature in theory. For example, it can be based on a historical average, the previous season, an official forecast, or a prediction from meteorological models.

Therefore, this section is devoted to arriving at the practical quantifications of unexpected weather factors. In order to develop appropriate measurements, firstly, implications of weather uncertainty are discussed by reviewing definitions and measurements of weather and macroeconomic factors in previous empirical studies. Due to a limited study of weather variables in finance literature, it is hoped that the methods employed for obtaining proxies of macroeconomic shocks can be applied for weather. One of the well-accepted approaches used for extracting these shocks from time-series economic data is Autoregressive Integrated Moving Average (ARIMA) model, so this study employs the process to extract unpredictable temperature in the same vein. Following the first subsection, the second part constructs various weather risk proxies according to different underlying assumptions. Finally, the last part contains descriptive statistics of these innovative weather risk factors.

4.3.1 Implications on unexpected weather measures

NCDC expresses an old saying that *"climate is what you expect, weather is what you get"*, indicating the existence of uncertainty in daily weather although it is predictable. Similarly to financial traders who believe in economic forecasts, weather traders may

rely on meteorological forecasts for information on expected temperatures. While meteorological organizations provide more precise weather forecasts at the present, basing expected temperature upon these predictions can still be problematic for economic decisions. This is because more accurate forecasts are always derived with shorter time spans, which, undoubtedly, is less useful for business planning. In addition, the changing weather forecasts make it more complicated for researchers to determine the right forecast values in quantifying weather risk, as no one can identify the appropriate forecast window for a study. Moreover, forecasting firms are still confronted with prevailing uncertainty although they employ a variety of sophisticated models, involving tens of parameters, to predict evolving weather conditions. In brief, using scientific weather forecasts in identifying expected weather seems not to be practical as it cannot be proved to be accurate while being too complicated and unstable.

Instead of relying on meteorological forecasts, this thesis suggests using the data at hand to construct 'unexpected weather innovations' as proxies of the real uncertainty in weather conditions. To the best of my knowledge, there are not many studies related to weather randomness within an asset pricing context and none of them concentrates on measuring weather risk. Indicators used for representing temperature variability often are the number of heating degree days (HDD), cooling degree days (CDD), energy degree days (EDD) and changes in these variables. Nevertheless, these factors seem not to account for seasonal effects which obviously are what people expect. In other words, they do not truly capture the unpredictability in daily temperature.

Due to the limited study in weather risk compared to other macroeconomic risks in finance literature, approaches to extract an uncertainty in economic time series can be applied to this study. The potential methodology is to estimate an econometric model to extract surprises from the temperature time series. One of the most popular models used for economic forecasting based on time series data is Autoregressive Integrated Moving Average (ARIMA) model. Known as the Box-Jenkins (BJ) methodology, it utilizes an analysis of the stochastic properties of the time series on their own rather than constructing single or simultaneous equation models. In many cases, the forecasts obtained by this method are more reliable than those obtained from the traditional econometric modelling, particularly for short-term forecasts (Gujarati, 2003).

A number of empirical studies have applied ARMA models to mimic the true generating processes of economic series, and have used the residuals from those models as representatives for economic shocks. For example, Chatrath, Ramchander and Song (1997) used ARMA model to derive the expected and unexpected components of inflation series. Buranavitayawut (2008) and Boyd, Hu and Jagannathan (2005) employed ARMA models to obtain unemployment shocks.

Although numerous studies benefit from using this tool for forecasting or obtaining an unexpected component from the time series of interest, Buranavitayawut (2008) addressed several drawbacks of the application of ARIMA model in a research. First, the identification of models is subjective and thus the reliability depends on the skill and experience of a researcher. Second, there is no underlying theory or structural relationship so the economic significance is subject to a debate. Last but not least, the model is backward looking and it may be poor at capturing turning points especially in the long-run.

Nevertheless, ARIMA's philosophy on 'let the data speak for themselves' makes it simpler to explain temperature by past values of temperature itself and stochastic error terms. The approach is appropriate for the study of the temperature behaviour because it does not need any derived theory, so the complexity of science in natural phenomena can be kept away. Hence, an ARIMA approach is one of the key tools for extracting unpredictable temperature in this thesis, and its theoretical explanation can be found in Appendix IV. It should be noted that the terms 'temperature' and 'weather' can be used interchangeably throughout this thesis.

In addition to an ARIMA approach, this research proposes rational assumptions and uses statistical methods to help extracting unexpected components from historical temperature records, and the procedures will be mentioned in the following section. All proposed quantifications of weather randomness in this study are basically conforming to the standard methodology used in finance, in which they are more accessible to financial investors who do not have strong knowledge on climatological system. All in all, weather surprise can be generated either from simple unobserved component based on specific assumptions or autoregressive models with time varying parameters which allow agents to update their expectations regularly based on available information.

4.3.2 Constructing measures of unpredictable weather events

This thesis proposes various methodologies to obtain the weather innovations. There are ten constructed measures that will be used as representatives for unexpected weather in the study. By doing this, the empirical performance of all these measures can be compared and checked for the sensitivity of results. Five approaches are proposed based on different assumptions and methodologies, ranging from simple statistical method to the use of ARMA models for temperature forecasting. Additionally, the other five measures are raised to quantify the risk in percentage, as analogous to measurement units of economic variables in literature. Expressing weather in percentage terms helps investors to easily compare weather exposure with any economic exposures. For example, how large is the weather effect to a security return for 1% variation of weather, compared with 1% variation of inflation. The next section explains all ten measures of unpredictable weather with respect to their assumptions, calculations, descriptive statistics and preliminary analyses.

4.3.2.1 W1: Deviations from monthly means

As most people expect future weather from past experience, the unexpected weather could be deviations from seasonal norms. The first variable is intuitively simple and straightforward, which is a series of deviations from average monthly temperature mean of the specific month. Considering a mean temperature of the month as an estimated temperature, the unexpected component can be derived from actual temperatures of month *m* year *y* minus the average temperature of the month ($\overline{T_m}$) from the entire period.

$$W1_t = T_m^y - \overline{T}_m \tag{4.5}$$

where $\overline{T_m} = \left(\dfrac{\sum_{y=1980}^{2009} T_m^y}{30} \right)$ and *m* represents each month, Jan-Dec.

This method, to some extent, already deseasonalises the weather factor because it considers the uncertainty on an account of a particular month. This simplification establishes a good starting point for the exploration of weather variables. In order to quantify the first weather variable in term of percentage, the deviation is compared to the standard deviation of temperature in the particular month.

$$\%W1_t = \frac{T_m^y - \overline{T}_m}{\sigma_m} \qquad (4.6),$$

where σ_m is a standard deviation of temperature series of a specific month. This formula indicates the proportion of the standard deviation of a particular month to the historical standard deviation. To put it simply, it is the percentage of the individual month's temperature deviation compared to the norm's deviation.

4.3.2.2 W2: Residuals from the ARMA model of W1

The previous variable, however, may still contain some predicted elements as temperature deviations are possible to correlate with deviations from the previous period. For example, if January's temperature this year is hotter than the norm by 5 degrees, investors may expect February's temperature to be higher than norms at more or less the same level. In order to find the real uncertainty of temperature at a period, temperature deviation series (*W1*) can be modelled by following the Box-Jenkins approach and the residuals derived from the model can be used as a proxy of weather randomness.

The unit root test is applied to *W1* series first to check if the series is integrated, or non-stationary, or not. Table 4.12 exhibits the ADF-statistics of the series, and it is clearly evident that the series is stationary. Therefore, an ARMA process is appropriate for modelling *W1*.

[Insert Table 4.12 here]

Recalling that ARMA is a univariate model in which a time series is expressed in terms of past values of itself, or the autoregressive component, plus current and lagged values of white noise error terms, or the moving average component, ARMA (*p*,*q*) of $W1_t$ process can be written as

$$W1_t = \theta_t + \sum_{i=1}^{p} \alpha_i W1_{t-i} + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i} + \varepsilon_t \qquad (4.7),$$

where θ = Constant term

α_i = Autoregressive Coefficient

γ_i = Moving Average Coefficient

ε_t = Error term

To identify the appropriate values of *p* and *q*, the correlogram as illustrated in Figure 4.6 aids in this task. Although there is no clear pattern found in the correlogram, the ACFs and PACFs at some lags, for example, 1, 2, 3 and 7 are statistically different from zero. As a rule of thumb, a given autocorrelation coefficient is classed as significant if it is outside the 95% confidence bound, where the dotted lines are (Quantitative Micro Software, 2007). The Ljung-Box joint test statistic rejects the null hypothesis of no autocorrelation at the 1% level for all number of lags considered. This indicates that ARMA process is appropriate for the data. Therefore, various ARMA models are estimated with the combination of these significant lags, *p* and *q*, and both with and without constant.

[Insert Figure 4.6 here]

Then, results from those estimations are compared and selected based upon the significance of all estimated coefficients, the lowest values of information criteria (AIC and SBC) and Sum Square Residual (SSR), the highest R^2 and the white-noise residuals. According to these criteria, the most parsimonious model for *W1* is ARMA (1,1) with no constant. Table 4.13 reports all estimated results, with coefficients of AR and MA terms are significant at 1% confidence level. Compared with other models, the process of ARMA (1,1) without a constant reports the lowest AIC at 4.197 and the highest adjusted R^2 at 0.064.[49] The estimated ARMA model is also stationary and invertible because the AR and MA roots lie within the unit circle.

[Insert Table 4.13]

Since an ARMA model should reduce the error term into the white noise process, then *Q*-statistic is used to test residuals, ε_t, of the model. According to a correlogram of residuals from ARMA (1,1), as illustrated in Figure 4.7, all the *Q*-Stats for 20 lags in the

[49] In comparing two models on the basis of the coefficient of determination, either R^2 or adjusted R^2, the sample size *n* and the dependent variable must be the same. Theil (1971 cited in Gujarati 2003, p.218) argues that *"…it is a good practice to use adjusted R^2 rather than R^2 because R^2 tends to give an overly optimistic picture of the fit of the regression, particularly when the number of explanatory variables is not very small compared with the number of observations".*

model cannot reject the null hypothesis of no autocorrelation. Hence, we can conclude that the residuals process from the model is white noise process.

[Insert Figure 4.7 here]

Therefore, *W1* should follow the process of ARMA (1,1) as given below.

$$W1_t = 0.63W1_{t-1} - 0.49\varepsilon_{t-1} + \varepsilon_t \tag{4.8}$$

Thus, the difference of the actual and the estimated values, or residuals, are representing another weather variable, *W2* in this study.

$$W2_t = \varepsilon_t \tag{4.9}$$

To measure the *W2* in percentage term, it is suggested to be scaled by the actual temperature, as follows.

$$\%W2_t = \frac{\varepsilon_t}{T_t} \tag{4.10}$$

However, it should be remembered that the adjusted R^2 of the estimation is relatively low at 6.4%, suggesting that the model does not fit well with data. Only 6.4% of the total variation in *W1* can be explained by ARMA (1,1) model. Consequently, the residuals are considerably large and fairly the same size as *W1*. Therefore, the *W1* and *W2* series should be closely correlated, and both weather measures may not yield significantly different results of weather sensitivity or pricing.

4.3.2.3 W3: Residuals from the ARMA model of seasonally adjusted temperature

Another proposed measure for unexpected temperature is to model temperature itself by applying ARMA methodology directly, and use the residuals as the unanticipated temperature or temperature surprise. Because the temperature process is autoregressive, as weather today depends on yesterday's value, it is sensible to fit an ARMA model to extract unexpected components (residuals). Recalling that the ACFs of the temperature series in Figure 4.4 exhibit the seasonal pattern, it is therefore more appropriate to fit a seasonal ARMA rather than an ordinary ARMA model. However, seasonal ARMA is more or less the same as a deseasonalisation process by regARIMA in X-12-ARIMA program. Removing the seasonal disturbance from the data arrives at the seasonally

adjusted temperature series *(TSA)*, in which the other characteristics can be revealed. To establish the general pattern of *TSA* and extract for an unexpected component in temperatures, an ARMA model may be fitted to the series and residuals from the model represents the time-series of weather surprise. It should be noted that the *TSA* series is stationary and follows *I(0)* process; hence, an ARMA *(p,q)* model is suitable.

To identify *p* and *q*, Figure 4.8 reports the correlogram of the *TSA* series at level, which is visually different from Figure 4.4 as there is no more seasonal pattern in ACFs observed. The values of ACFs and PACFs here significantly drop and are not persistent. Since a given autocorrelation coefficient is classed as significant if it is outside the dotted line, it can be deduced that the first three and the seventh ACFs and PACFs are significant under this rule. The first ACF coefficient is highly significant, and the Ljung-Box joint test statistic rejects the null hypothesis of no autocorrelation at the 1% level for all the lags considered. Therefore, a mixed ARMA process could be appropriate, although it is hard to precisely determine the appropriate order given the output. To find the soundest ARMA model, a combination of significant lags has been estimated and results are compared by the same criteria used for *W1* model.

[Insert Figure 4.8 here]

The ARMA (1,1) is the most parsimonious model for mimicking an expectation on seasonally adjusted temperature. The coefficients of constant, AR (1) and MA (1) are all significant. The Durbin-Watson statistic is around 2, assuming that there is no first-order autocorrelation. The AR and MA roots lie within a unit circle, implying that the model is (covariance) stationary and invertible. The adjusted R^2 at 6.1% of ARMA (1,1) is the highest, as well as with the smallest AIC, among the other candidate models. However, the adjusted R^2 is relatively low: only 6.1% of the variation in *TSA* can be explained by the model. This may imply that the temperature series do not have any other exceptional patterns apart from seasonality.

[Insert Table 4.14 here]

Figure 4.9 displays the correlogram of residuals of the estimated model. The insignificant Ljung-Box Q-statistics of all lags considered indicate that there is no autocorrelation in the residuals for the selected ARMA (1,1) model. Therefore, the residuals are white-noise.

[Insert Figure 4.9 here]

From the estimated results, the seasonally adjusted temperature (*TSA*) follows the process of

$$TSA_t = 53.56 + 0.68TSA_{t-1} - 0.54\delta_{t-1} + \delta_t \qquad (4.11),$$

where δ_t is the residual which represents the weather innovation (*W3*).

$$W3_t = \delta_t \qquad (4.12)$$

Similar to *%W2*, the percentage value of *W3* is standardized by the actual temperature.

$$\%W3 = \frac{\delta_t}{T_t} \qquad (4.13)$$

4.3.2.4 W4: Temperature irregularity

Through the process of seasonal adjustment of temperature series, there is one derived series that is very interesting, which is irregular components. According to the National Statistics UK (2007), irregular fluctuations may occur due to a combination of unpredictable factors such as unseasonal weather, natural disaster or sampling errors. By the definition, it can be implied that the irregular fluctuations, contrary to the regular behaviour of seasonal effects, can also proxy for weather surprise. Therefore, the *I* component from equation (4.4) is proposed to be included in a set of weather variables for the study. Equation (4.14) and (4.15) illustrates *W4* in degree and percentage measurement, respectively.

$$W4_t = I_t \qquad (4.14)$$

$$\%W4 = \frac{I_t}{T_t} \qquad (4.15)$$

4.3.2.5 W5: Time-varying deviations from historical mean

All prior proposals compute a weather factor by using the temperature data of the entire sample period. In reality, the temperature data at the period after estimation is not obtainable because the real temperature in the future has never been known. Therefore,

only the historical data before the estimated period should be used for calculation. Then, the researcher obtains the temperature data back to January 1970, and estimates weather risk by computing temperature deviations from the historical 10-year mean temperature prior to the estimated period. The idea behind this variable is similar to that of *W1*, but it reflects the fact that researchers do not know actual temperatures in the future.

In addition, the calculations of temperature mean and standard deviation are rolled monthly over the entire period to ensure that every point estimations base on the difference of actual and estimated mean of ten years earlier. For example, value of unexpected weather for January 1980 is computed from the actual temperature at January 1980 minus the mean January temperature from 1970-1979, whereas that of February 1981 risk is based on the difference of actual temperature in February 1981 and the mean February temperature from 1971-1980. The time varying parameter, *W5*, allows investigators to update their expectations every period based on information available to them at the time their expectations are formed.

$$W5_t = T_t - \frac{\sum_{i=-1}^{-10} T_m^i}{10} \qquad (4.16),$$

where *t* is the period, *m* represents each month and *i* is the year lagged from one to ten years. Corresponding to equation (4.5) and (4.6), the percentage measure of W5 is also adjusted by the rolling 10-year standard deviation of historical temperature.

$$\%W5_t = \frac{W5_t}{\sigma_m^i} \qquad (4.17),$$

where σ_m^i is a standard deviation of temperature series of a specific month, computed from the last ten years. Table 4.15 summarizes all proposed measures of weather risk used in the study, with description and calculation methods.

[Insert Table 4.15 here]

4.3.4 Statistical properties of weather variables

This section reports the basic statistics of previously-constructed weather variables, and all descriptive statistics in Table 4.16 are conducted using EViews 7.0. Most of the mean values of unexpected weather are also close to zero. The simple hypothesis test regarding mean value has been carried out, with the null hypothesis that the mean, μ_w, of the series is equal to zero. It is reported that only the series of *W5* and its percentage term have a mean value statistically different from zero. All the reported Jarque-Bera probabilities for weather factors, apart from that of *W1*, do not exceed the value to reject the null hypothesis of normal distribution. Therefore, only *W1* series is normally distributed.

[Insert Table 4.16 here]

If any time series is non-stationary, its behaviour can be studied only for the time period under consideration. This is not useful for researchers when they cannot be able to generalize or draw an inference from the data to other time periods. Therefore, the unit root test is very important and has been applied to all weather variables before being used in subsequent analyses. The ADF tests are conducted to test whether derived weather risk series exhibit a mean reversion process, and the estimated coefficients and ADF statistics of weather innovations are reported in Table 4.17. The results clearly show that ADF-statistics for all series are much larger than the critical value at 1% confidence level. Therefore, all of them are stationary and ready to be utilized for regressions in the further study.

[Insert Table 4.17 here]

Table 4.18 displays a correlation matrix between the weather variables and the market return series. The first column is the most important, as it reports the correlation coefficients between the market variable and each weather factor. Ideally, correlations should be low because each of these proxies will be used together with market return as explanatory variables in further investigations, and, in fact, they should not be strongly related to each other anyway. As expected, the reported correlation coefficients between weather variables and market return are very low, which fairly assures that the problem of correlated regressors should not exist. It is interesting to find that only *%W1* has negative correlation to the market factor. The other columns show the correlation

coefficients among weather factors, and they are as high as expected because these measures intend to gauge the same thing but with different in methodologies. All correlations between degree and percentage term of the similar factor varies around 90-95% because they are dissimilar only in scaling. The strongest correlation is between *W1* and *W2*, which is 99%. This reinforces the earlier finding that the derived ARMA model does not fit well to *W1* series, and thus its residuals (*W2*) are likely to have similar values. This may suggest that either *W1* or *W2* can be dropped out in examinations later. The correlation between *%W4* and *%W5* are reported as the mildest among weather factors at 65%.

[Insert Table 4.18 here]

4.4 Summary

In summary, this chapter is discussing the data used in the thesis: the first half explains how the sample and variables are selected while the second half constructs the weather variables that will be used for further examinations in the study. The statistical properties of all these variables are also reported. The sample includes 484 securities from three weather-influenced industries, which are agriculture, utilities and tourism. In this study, dependent variables are the total return series of these equities from January 1980 to December 2009, whereas independent variables are the series of market portfolio returns and unpredictable temperatures. The research employs the CRSP value-weighted market index return including dividends as the proxy for the market return because the index covers broad indices across the U.S. market. Temperature is chosen as a representative for the weather factor owing to the fact that it significantly relates to businesses' activities in the literature, the measure is continuous and easy to monitor, and it is extensively traded in the weather derivative market.

Temperature series are obtained both at nation-wide and state-wide levels; however, only the national average temperature series is used for further analysis. Based on the high correlations among state-wide temperatures, a principal component analysis (PCA) is applied to reduce the redundancy of information and to extract only the few factors that account for most of the variance. PCA results show that the first factor already accounts for 97.37% of the total variance while the subsequent factors are marginal. In addition, the degree of communalities within the dataset of state temperatures is high and the component score coefficients of each state are equal. These findings lead to the

use of national temperature series in the following analysis as the series is the average of state values weighted by area. Undoubtedly, the series of monthly average temperature clearly exhibits seasonal pattern. However, it is seasonally adjusted by using the well-accepted X-12-ARIMA method developed by the U.S. Consensus Bureau.

The latter part of the chapter contributes to quantitatively defining unpredictable components of temperatures. Based on different assumptions and methodologies, ten measures of weather randomness, gauged in Celsius degree and percentage terms, are developed. The first measure (*W1*) is very simple: subtracting the actual temperature of the month by the average mean of thirty years. This represents an idea that average mean temperature is what investors expect and that any deviations from the mean are unpredictable and risky. They can also be interpreted in term of percentage by adjusting the deviation of the month with the standard deviation of the series.

The second and third measures apply an econometric method, autoregressive-moving average (ARMA) process, to derive the unexpected components of temperatures. Due to the fact that weather today is generally influenced from yesterday's weather, the temperature time-series is autocorrelated. Therefore, ARMA is an appropriate model to fit the values of the parameter while minimizing the error terms. The model can predict values of the series and error terms represent uncertainty in temperature. The model of ARMA (1,1) is best fitting to both series of *W1* and seasonally adjusted temperature series (*TSA*), and the derived time-series of error terms from these models represent *W2* and *W3* respectively.

The fourth measure (*W4*) of unpredictable temperature is acquired from the process of temperature deseasonalisation. When the temperature series is seasonally adjusted by the X-12-ARIMA, the program decomposes the original series into a trend cycle, a seasonal component and an irregular component. The last element denotes the irregular fluctuations in temperature or, in other words, weather surprise. The *W2, W3* and *W4* are proportionated to the actual temperature of the month for their percentage measurements.

Finally, the last measure (*W5*) is suggested owing to the fact that researchers cannot actually obtain the data in the future. Thus, only historical records before the estimated period, not the entire sample period, should be used for calculation. With the similar

assumption to *W1*, a temperature deviation in each month is computed from the difference between an actual temperature and the historical mean of 10 years earlier. These computations are rolling from period to period to obtain the time-series of *W5*. Also, the percentage values of the series are obtained from scaling *W5* with rolling standard deviations.

It is worth noting that all the proposed weather variables are estimated backwards rather than forwards. This is because weather forecasts are basically unstable and keep changing when the timeframe is nearer, thus basing expected weather upon the forecasts is problematic. Therefore, it is suggested that historical records are more practical than future predictions in this study.

Preliminary statistics of all variables are reported, as well as correlations among them. All weather variables exhibit mean values near zero, but *W5* mean is statistically different from zero at 5% level of significance. Only *%W1* series is normally distributed among all factors. These weather variables are highly correlated because they tend to measure the same element but taking different approaches. The highest correlation at 99% is between *W1* and *W2*, which suggests one of them may be dropped later in the study. On the other hand, *%W4* and *%W5* appear to have the lowest correlation coefficient at 65%. The correlations between weather risk series and market return series are also examined, and only weak correlations are reported. This is favourable as it is likely to guarantee that multicollinearity problem can be avoided in later studies.

The development of proxies for unexpected weather is highly important for a further study in weather exposures and the market price of weather risk. Due to the limited study of weather in asset pricing, investors have no idea how the market gives rewards for bearing weather exposure, the factor which is more basic than economic risks. Hopefully, understanding this issue may lend a support to find the conformity of weather derivative valuations in the future. However, this thesis studies only one aspect of weather, while other weather parameters such as precipitation are also proved in literature to have impacted businesses and they have yet to be examined. The work for appropriate weather factors, apparently, can be another interesting future research area.

Appendix I: The Normal Distribution and the Jarque-Bera Test

Skewness (S) is a measure of symmetry whereas kurtosis (K) measures if the data are peaked or flat relative to a normal distribution. They are calculated by

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \bar{y}}{\hat{\sigma}}\right)^3 \qquad (4.18),$$

and

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \bar{y}}{\hat{\sigma}}\right)^4 \qquad (4.19),$$

where $\hat{\sigma}$ is an estimator for the standard deviation that is based on the biased estimator for the variance ($\hat{\sigma} = sd\sqrt{(N-1)/N}$). A distribution is asymmetric if it has a long tail on the left or right from the centre, and it is high or low kurtosis when it tends to have a distinct peak or flat top near a mean correspondingly. A normal distribution usually has zero skewness and kurtosis value at 3.

Although several tests of normality are discussed in literature and standard references, the Jarque-Bera (JB) test is considered in this thesis. It measures the difference of a skewness and kurtosis of the series with those from the normal distribution. The statistic is computed by

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \qquad (4.20),$$

where n = the sample size, S = skewness, and K = kurtosis coefficient. The null hypothesis of a normal distribution bases on the joint hypothesis that S=0 and K=3, and the JB statistic follows the chi-square distribution with 2 degrees of freedom. The reported probability in the study is the probability that the JB statistic exceeds the observed value under the null hypothesis, which leads to a rejection of the normal distribution.

Appendix II: The Unit Root Test

By necessity, the discussion on stationary or unit root test will be brief. More details can be found on standard references such as Davidson and MacKinnon (1993), chapter 20, Wooldridge (2009), chapter 18 and Gujarati (2003), chapter 21.

A series is considered stationary if the mean and variance of the process are constant across time and its autocovariances do not depend on time. Throughout this thesis, all stationary or unit root tests are based on the Augmented Dickey-Fuller (ADF) test developed by Dickey and Fuller. The ADF test is augmenting the preceding simple Dickey-Fuller test by adding the lagged values of the dependent variable Δy_t. This is in order to construct a parametric correction for higher-order correlation by assuming that *y* series follows AR(*p*) process. Consider the following regression,

$$\Delta y_t = \alpha y_{t-1} + x_t \delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + \varepsilon_t \qquad (4.21),$$

where y_t is the time series of interest, x_t are optional exogenous regressors which may consist of constant or a constant and trend, and ε_t is the error term. Basically, this augmented specification is used to test the null hypothesis H_0: $\alpha = 0$ against the alternative hypothesis H_1: $\alpha < 0$. It should be noted that there are two practical issues in performing an ADF test. First, it is the choice of exogenous regressors to be included in a regression: one can include a constant, a constant and trend, or neither of them. The standard recommendation is to choose a specification for plausible description of data under both the null and alternative hypotheses. On the other hand, it is also accepted that another approach is to include both constant and trend as the other two cases are special cases of this more general specification.

Appendix III: The Seasonality Tests

The following part provides only a brief description of the seasonality tests in the ARIMA-X-12 program. Further details can be referred to SAS Institute Inc. (1999), chapter 21.

Firstly, the stable seasonality test analyses the intrayear variation that is repeated constantly each year, and it is based on a one-way analysis of variance on the final unmodified SI Ratios with seasons (months or quarters) as the factor.[50] A large F-statistic and small significance level indicates that a significant amount of variation in the SI Ratios is due to months or quarters and thus the null hypothesis of no month/ quarter effect is rejected. It should be noted that several assumptions for constructing an F-test can be violated when performing this test; therefore, SAS Institute Inc. (1999) states that the seasonality is not identifiable if the null hypothesis is not rejected at 0.1% level.

Next, comparable to a one-way analysis of variance, a non-parametric test can also be performed to test the stable seasonality. One of the most widely accepted non-parametric tests is the Kruskal-Wallis Chi-squared test, which has the null hypothesis that the populations from which the samples originate have the same median. In this case, it is to test whether all the medians of temperatures for each month are the same. According to Larsen and Marx (2000), the Kruskal-Wallis statistic is given by

$$KW = \frac{12}{N(N+1)} \sum_{k=1}^{12} \frac{r_k^2}{n_k} - 3(N+1) \qquad (4.22),$$

where $r_k = \sum_{i=1}^{n} r_{i,m}$ (rank sum), when ranking temperature values for year i (i= 1, 2,…,n) by month k (k=1,2,…,12). In parentheses are the rank, $r_{i,k} \in [1,2,...,N]$, assigned corresponding to the temperature values from the lowest to highest across the entire set of $N = \sum_{k=1}^{12} n_k$. The KW has approximately a χ^2_{k-1} distribution with k-1 degree of

[50] The SI Ratio is the ratio of the original series to the estimated trend, so it is an estimate of the detrended series. It can also be thought of as the seasonal-irregular component.

freedom. The null hypothesis can be rejected at the conventional level of significance α if $KW \geq \chi^2_{1-\alpha,k-1}$, indicating that seasonality presents.

Thirdly, for the moving seasonality test, the F-test is performed by a two-way analysis of variance with two factors of both seasons (months) and years. Total variation consists of three variances: between-month variance measuring the magnitude of seasonality, between-year variance capturing year-to-year movement of seasonality, and residual variance. The year effect is tested separately by the F-statistic from the ratio of between-year variance and the residual variance. The null hypothesis is that there is no effect due to years after accounting for variation due to months. In other words, there is no evolving seasonality in the time series. In contrast to the interpretation of the stable seasonality test, the null hypothesis of no moving seasonality can be rejected with low F-value owing to the fact that high F-value reduces the probability of a reliable estimate of the seasonal factors.

The X-12 program also reports a combined test of the simultaneous presence of both stable and moving seasonalities, known as the test for identifiable seasonality. The test is important because sometimes seasonal component cannot be accurately identified and estimated due to, for example, little evidence of stable seasonality but larger moving seasonality which dominates most of the process. The combined test is performed as follows.

1. If the null hypothesis in the stable seasonality test is not rejected at 0.1%, the seasonality is not identifiable.
2. If the null hypothesis in (1) is rejected, but the null hypothesis of the moving seasonality is not rejected at 5% level, the following measures are computed:

$$T_1 = \frac{7}{F_m - F_s} \qquad (4.23),$$

$$\text{and} \qquad T_2 = \frac{3F_m}{F_s} \qquad (4.24),$$

where F_s and F_m denote the F-value for the stable and moving seasonality tests respectively. Let T denotes the simple average between T_1 and T_2, the null hypothesis of identifiable seasonality *not* present is accepted if $T \geq 1$.

3. If the moving seasonality f-test (F_m) passes, but one of statistics based on T fails, or the Kruskal-Wallis Chi-squared test fails at the 1% level, the program reports “Identifiable Seasonality Probably Present”.
4. If the F_s, F_m and the Kruskal-Wallis Chi-squared test pass, then the seasonality is identifiable.

Appendix IV: ARIMA Model

Autoregressive Integrated Moving Average (ARIMA) models involve with three main processes, which are autoregressive AR(p), integrated I(d) and moving average MA(q). The following part will describe these processes in brief, as the explanation of these terms is easily accessible in standard texts of econometrics. Let X_t be a random variable X at time t, where its entire sequence, denoted as $\{X_t\}$, can be considered as a realization of a stochastic process.

(i) Autoregressive process

An autoregressive model is one where the current value of a variable, X_t, depends upon only its value in the previous time period(s) and a random term. If X_t follows a p order of autoregressive process, an AR(p) model is given by

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad (4.25),$$

where ε_t is Gaussian (white noise) error term.

(ii) Moving average process

A moving average model is simply a linear combination of white noise processes, ε_t, so that X_t depends on the current and previous values of a white noise disturbance term. If X_t follows a q order of moving average process, an MA(q) model can be expressed as

$$X_t = \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (4.26).$$

(iii) Integrated process (stationarity)

It should be advised that the stationarity of variables is very crucial in time-series analysis since the variable that is non-stationary leads to the spurious regression. To avoid the problem, non-stationary time series has to be transformed to make it stationary. In general, if a non-stationary time series has to be differenced d times to make it stationary, that time series is said to be integrated of order d, denoted

as $X_t \sim I(d)$. A careful attention is needed when combining two or more time series that are integrated at different order.

It is likely that *X* has characteristics of both AR and MA and is therefore ARMA. Thus, an ARMA (*p,q*) process for X_t contains *p* lags of autoregressive component of X_t and *q* lags of moving average stochastic error terms, ε_t, as illustrated below.

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{4.27}$$

It should be noted that the ARMA model in equation (4.27) requires that its characteristic roots must be within the unit circle, which is the case when the $\{X_t\}$ sequence is stationary.[51] If $\{X_t\}$ is said to be non-stationary or an integrated process, the ARMA model becomes ARIMA (*p,d,q*) with the integrated component *I(d)*.

In estimating ARIMA, the objective is usually to form a parsimonious model, which is one that describes all of the features of data under the study using as few parameters as possible (Brooks, 2002). The specification of the appropriate ARIMA model for a study is achieved by three steps: identification, estimation and diagnostic checking (Brooks, 2002). The first step finds out the appropriate value of *p, d,* and *q* to suggest a subclass of parsimonious models to describe how the data have been generated. The correlogram view of a series can be helpful for this task. Next, this stage is to estimate the parameters of the autoregressive and moving average terms included in the model. As the goal of ARIMA analysis is a parsimonious representation of the process; only enough AR and MA terms should be used to fit the properties. The Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (BSC) provided with each sets of estimates may also be used as a guide for the appropriate lag order selection. After fitting the possible ARIMA model, diagnostic checking, such as a test of white-noise residual, should be performed to ensure that the model fits the data reasonably well and is appropriate for forecasting. It should be noted that the identification and estimation of ARMA models is more of an art than a science, and it is an iterative process (SAS Institute Inc., 1999 and Gujarati, 2003).

[51] If the estimated ARMA process is (covariance) stationary and invertible, then all AR and MA roots should lie inside the unit circle respectively. For explanation about the stationary condition of AR(*p*) and invertability condition of MA(*q*), see Brooks (2002), chapter 5.

Identification

The principal tool in identification of *p* and *q* lags is correlogram, which is the plots of autocorrelation function (ACF) and partial autocorrelation function (PACF) against the time lag.[52] It is also a commonly used tool for checking randomness in a dataset, ascertained by computing autocorrelations for data values at varying time lags. If the series is random, such autocorrelations should be near zero for any and all time-lag separations.

The autocorrelation (AC) between X_t and X_{t-k} can be calculated as a ratio of the autocovariance between them to the variance of X_t, as given in the following equation.

$$\rho_k = \frac{E[(X_t - \bar{X})(X_{t-s} - \bar{X})]}{E[(X_t - \bar{X})^2} \tag{4.28}$$

Note that $-1 \leq \rho_k \leq 1$ and $\rho_0 = 1$. The ACF can be constructed by plotting ρ_k against lag *k*; it shows the correlation coefficient for values of the series *k* periods apart. If ρ_k dies off more or less geometrically with increasing lag k, it is a sign that the series follow a low-order AR process. However, if ρ_k drops to zero after a small number of lags, it signifies a low-order MA process.

The partial autocorrelation (PAC) at lag *k*, ϕ_k , measures the correlation between X_t and X_{t-k} after removing the correlation from the intervening lags. It can be obtained by simply run the regression:

$$X_t = \beta_0 + \beta_1 Y_{t-1} + ... + \beta_{k-1} Y_{t-(k-1)} + \phi_k Y_{t-k} + \varepsilon_t \tag{4.29}$$

Again, the PACF can be constructed by plotting ϕ_k against lag *k*. It is worth noting that the estimation of ρ_k and ϕ_k by EViews differ slightly from theoretical description and the equations can be found in its user's guide, chapter 11. The program also offers the boundary lines in the correlogram plots, which are approximately two standard error

[52] The autocorrelation is the correlation between a time series and lags of itself, while the partial autocorrelation is the amount of correlation between a variable and a lag of itself that is not explained by correlations at all lower-order-lags.

bounds, $\pm 2/\sqrt{T}$. If AC or PAC is within these bounds, it is not significantly different from zero at approximately 5% significance level.

The values of AC and PAC can be tested for statistical significance by the Ljung-Box *Q*-statistic, which tests the null hypothesis that there is no autocorrelation up to order *k*. It is computed as

$$Q_{LB} = T(T+2)\sum_{j=1}^{k}\frac{\rho_j^2}{T-j} \qquad (4.30),$$

where ρ_j the jth autocorrelation, *k* is the maximum lag length and T is the number of observations. If the series is not based upon the results of ARIMA estimation, then under the null hypothesis, *Q* is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of autocorrelations. However, if *Q*-statistic is used to test the residual series from ARIMA estimation, the degrees of freedom should be adjusted to $j - p - q$.

The *Q*-statistic is also often used as a test of whether the series is white noise, and the decision rule is that if the calculated value of *Q* exceeds the critical value of χ^2 with appropriate degrees of freedom at the specified significance level, then the null hypothesis can be rejected. EViews cautions users for the practical problem of choosing the order of lag to use for the test. By choosing too small a lag, the test may not be able to detect serial correlation at high-order lags whereas selecting too large a lag may lower the power of the test.

Estimation

The estimation of the parameters of the model can be done using least squares or maximum likelihood, depending on the model. At the estimating stage, two well-known information criteria, Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (BSC), are usually produced with other estimating results. These information criteria are helpful in providing a subjective decision to specify the most parsimonious model when the ACF and PACF patterns are hard to interpret. They embody two factors: a term which is a function of the residual sum of squares (RSS) and some penalty for the loss of degrees of freedom from adding extra parameters. The AIC and SBC are expressed algebraically as follows.

$$AIC = T\ln(SSR) + 2n \quad (4.31);$$

$$SBC = T\ln(SSR) + n\ln(T) \quad (4.32),$$

where *SSR* is the sum of squared residuals, *T* is the number of usable observations and *n* is the number of estimated parameters. From these equations, it is intuitively clear that adding an additional lag to a model will have two competing effects on the information criteria: the RSS will fall but the value of the penalty term will increase. Therefore, adding a regressor with no explanatory power to the model will only increase the information criteria, which is not desirable. To obtain the most parsimonious model, the objective is to choose the number of parameters, *p* and *q*, which minimize the value of the information criteria. It should be noted that, all models must be estimated over the same period when comparing them based on these criteria.

Sometimes these two information criteria can suggest different order of *p* and *q*, but no criterion is superior to others (Diebold, 1998). Brooks (2002) advises that SBC is strongly consistent but inefficient: it will asymptotically deliver the correct model but the average variation in selected model orders from different samples will be greater in SBC context than that of AIC. On the other hand, AIC is not consistent but is generally more efficient: it tends to be biased toward selecting an over-parameterised model. Enders (2004) advocates that SBC has superior large sample properties while AIC does better in small samples. Nevertheless, both criteria should be used in choosing an ARMA model, and when different views from these criteria appear, a decision can also be made based on the significance of coefficients as well as the white-noise residuals of the model.

Diagnostic checking

This step involves determining whether the model specified and estimated is adequate. The appropriate ARMA model must contain not only statistically significant coefficients but also a white-noise residual. The correlogram and Ljung-Box *Q*-statistic described in equation (4.30) can be used to test the white-noise process of the residuals. It is worth noting that diagnostic testing in the Box-Jenkins approach essentially involves only autocorrelation tests rather than the whole tests of which are for the classical linear regression model.

Table 4.1: Summary of equities in the sample

A sample consists of 484 common equities listed on NASDAQ, NYSE and AMEX in selected weather-influenced industries during January 1980 to December 2009—they are from agricultural, tourism and utilities major group.

The table shows the construction of the final sample. The SIC code is useful to classify securities into each industry, in that any unrelated industry within the industry group is dropped out from the sample. For a reason that each security in the sample should represent only one company at any time, non-ordinary shares are also excluded. The CRSP Permanent Company Number (PERMCO) is used to provide the unique identifier in this case. Additionally, the U.S. weather impacts only companies operated within the States so any shares from companies operated outside the U.S. are omitted. For more accurate estimations in the study, the securities with missing data more than three periods or with observations less than 24 months are also dismissed. The last column shows the numbers of shares after all eliminations for each industry, and the last row indicates the total shares in the sample. It should be noted that the research intends to include both active and dead stocks in the study; therefore, the number of observations for each security is unbalanced.

MAJOR GROUP	INDUSTRY GROUP	Number of Companies					FINAL SAMPLES
		Total	operated outside U.S.	From deselected industries	Less than 24-month observations	missing data more than 3 periods	
Agriculture	Crop Products	27	4	0	4	0	19
							19
Tourism	Hotels	134	19	0	11	3	101
	Campsites	10	0	0	1	1	8
	Sports	32	5	2	2	0	23
	Recreations	120	7	14	18	5	76
							208
Utilities	Electricity	136	27	0	8	0	101
	Gas	137	30	8	6	0	93
	Combined Electricity and Gas	64	1	0	6	1	56
	Steam& Air Conditioning	8	0	0	1	0	7
							257
Numbers of firms in the final sample							**484**

Table 4.2: Unit root test results for the market return series, Jan 1980 – Dec 2009

The table reports the estimated coefficient α and the ADF-statistics of the market return series. Lag length is based on minimum Akaike Info Criterion. The ADF test is estimated by

$$\Delta y_t = \alpha y_{t-1} + x_t\delta + \beta_1\Delta y_{t-1} + \beta_2\Delta y_{t-2} + \ldots + \beta_p\Delta y_{t-p} + \varepsilon_t ,$$

where y_t is the time series of the value-weighted market return, x_t are optional exogenous regressors which may consist of constant or a constant and trend, and ε_t is the error term. The null hypothesis of the presence of unit root is that α = 0. The asterisks *** means that the null hypothesis of unit root in market returns can be rejected at 1% level of significance.

Panel A: ADF Test with both Constant and Trend	
α	-0.8906
ADF-stat	-16.93***
Panel B: ADF Test with Constant Only	
α	-0.8847
ADF-stat	-16.86***
Panel C: ADF Test with no exogenous regressor	
α	-0.8469
ADF-stat	-16.25***

Note: ***Significant at 1% level

Table 4.3: State-wide temperature for 48 states, Jan 1980 – Dec 2009

The table presents means and standard deviations of average monthly temperatures for the sample period. Temperature means range from 40°F to 70°F whereas standard deviations are between 8 to 21 degrees.

Variables	State	Mean	Std. Deviation	Analysis N
VAR00001	Alabama	63.0569	12.7609	360
VAR00002	Arizona	61.0556	13.7449	360
VAR00003	Arkansas	60.6708	14.6234	360
VAR00004	California	59.8417	11.1083	360
VAR00005	Colorado	45.7856	15.4405	360
VAR00006	Connecticut	49.3503	15.9264	360
VAR00007	Delaware	55.6675	15.0729	360
VAR00008	Florida	70.9136	8.8216	360
VAR00009	Georgia	63.7078	12.2871	360
VAR00010	Idaho	44.8203	15.2330	360
VAR00011	Illinois	52.1194	17.4800	360
VAR00012	Indiana	52.0000	16.7456	360
VAR00013	Iowa	48.1369	19.2914	360
VAR00014	Kansas	54.5772	17.2376	360
VAR00015	Kentucky	55.9331	15.1492	360
VAR00016	Louisiana	66.7403	12.0084	360
VAR00017	Maine	41.1911	18.1586	360
VAR00018	Maryland	54.5753	15.2645	360
VAR00019	Massachusetts	48.1203	15.8411	360
VAR00020	Michigan	44.8575	17.3719	360
VAR00021	Minnesota	41.7203	21.0547	360
VAR00022	Mississippi	63.5819	13.0077	360
VAR00023	Missouri	54.7914	16.6449	360
VAR00024	Montana	43.2472	16.9057	360
VAR00025	Nebraska	49.1694	17.8924	360
VAR00026	Nevada	50.3500	14.7556	360
VAR00027	New Hampshire	44.0689	17.2550	360
VAR00028	New Jersey	53.0550	15.3854	360
VAR00029	New Mexico	53.9367	13.9479	360
VAR00030	New York	45.7453	16.9355	360
VAR00031	North Carolina	59.2608	13.3156	360
VAR00032	North Dakota	40.9433	21.1676	360
VAR00033	Ohio	51.1256	16.2164	360
VAR00034	Oklahoma	59.8128	15.7240	360
VAR00035	Oregon	48.7547	12.0114	360
VAR00036	Pennsylvania	49.0683	15.8115	360
VAR00037	Rhode Island	50.3906	14.9587	360
VAR00038	South Carolina	62.6344	12.8739	360
VAR00039	South Dakota	45.5831	19.5103	360
VAR00040	Tennessee	57.9289	14.3737	360
VAR00041	Texas	65.2275	13.0752	360
VAR00042	Utah	49.2172	16.3119	360
VAR00043	Vermont	42.9675	17.8456	360
VAR00044	Virginia	55.4167	14.3179	360
VAR00045	Washington	48.6331	12.4197	360
VAR00046	West Virginia	52.0083	14.7362	360
VAR00047	Wisconsin	43.6244	19.2026	360
VAR00048	Wyoming	42.4389	16.6172	360

Table 4.4: Principal component analysis: total variance explained

The table lists the eigenvalues associated with each linear component before and after extraction of state-wide temperature data from 48 states. The result obviously shows that factor 1 already explains very large amount of total variance at 97.366% whereas subsequent factors explain a little. After extraction, it leaves only one factor with an eigenvalue greater than 1.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	46.736	97.366	97.366	46.736	97.366	97.366
2	.565	1.178	98.544			
3	.239	.498	99.041			
4	.193	.401	99.443			
5	.067	.139	99.581			
6	.038	.080	99.661			
7	.031	.065	99.726			
8	.025	.052	99.778			
9	.020	.041	99.820			
10	.015	.031	99.850			
11	.012	.025	99.875			
12	.008	.018	99.893			
13	.006	.014	99.906			
14	.006	.013	99.919			
15	.005	.009	99.928			
16	.004	.009	99.938			
17	.003	.007	99.944			
18	.003	.006	99.950			
19	.003	.005	99.955			
20	.002	.005	99.960			
21	.002	.004	99.964			
22	.002	.004	99.968			
23	.002	.003	99.971			
24	.001	.003	99.974			
25	.001	.003	99.977			
26	.001	.002	99.979			
27	.001	.002	99.981			
28	.001	.002	99.983			
29	.001	.002	99.985			
30	.001	.002	99.987			
31	.001	.001	99.989			
32	.001	.001	99.990			
33	.001	.001	99.991			
34	.001	.001	99.992			
35	.000	.001	99.993			
36	.000	.001	99.994			
37	.000	.001	99.995			
38	.000	.001	99.996			
39	.000	.001	99.996			
40	.000	.001	99.997			
41	.000	.001	99.997			
42	.000	.000	99.998			
43	.000	.000	99.998			
44	.000	.000	99.999			
45	.000	.000	99.999			
46	.000	.000	99.999			
47	.000	.000	100.000			
48	.000	.000	100.000			

Table 4.5: Principal component analysis: communalities

The table specifies how much of the variance in the variables, average monthly temperature data from 48 states, has been accounted for by the extracted factor. The results advise that, after extraction, all variables distribute large common variance from 92.8% to 98.8%. This indicates the high degree of communalities within the dataset.

	Initial	Extraction
VAR00001	1.000	.978
VAR00002	1.000	.955
VAR00003	1.000	.987
VAR00004	1.000	.928
VAR00005	1.000	.973
VAR00006	1.000	.983
VAR00007	1.000	.982
VAR00008	1.000	.946
VAR00009	1.000	.976
VAR00010	1.000	.952
VAR00011	1.000	.988
VAR00012	1.000	.987
VAR00013	1.000	.982
VAR00014	1.000	.985
VAR00015	1.000	.987
VAR00016	1.000	.977
VAR00017	1.000	.972
VAR00018	1.000	.987
VAR00019	1.000	.980
VAR00020	1.000	.982
VAR00021	1.000	.976
VAR00022	1.000	.980
VAR00023	1.000	.988
VAR00024	1.000	.953
VAR00025	1.000	.980
VAR00026	1.000	.943
VAR00027	1.000	.979
VAR00028	1.000	.983
VAR00029	1.000	.968
VAR00030	1.000	.978
VAR00031	1.000	.983
VAR00032	1.000	.966
VAR00033	1.000	.985
VAR00034	1.000	.986
VAR00035	1.000	.935
VAR00036	1.000	.985
VAR00037	1.000	.973
VAR00038	1.000	.978
VAR00039	1.000	.974
VAR00040	1.000	.985
VAR00041	1.000	.977
VAR00042	1.000	.958
VAR00043	1.000	.975
VAR00044	1.000	.987
VAR00045	1.000	.941
VAR00046	1.000	.984
VAR00047	1.000	.983
VAR00048	1.000	.966

Extraction Method: Principal Component Analysis

Table 4.6: Statistics of nationwide monthly temperature, Jan 1980 – Dec 2009

The first column TEMP represents statistics of the time-series of temperature data from the whole sample period whereas the others show the results of the particular month within a year. Average temperature in 30 years is 53.56°F, whereas the coldest monthly mean is 32.30°F in January and the warmest monthly mean is 74.79°F in July. The standard deviations of temperature of months in winter (Dec-Feb) are slightly higher than the other season.

	TEMP	***JAN***	***FEB***	***MAR***	***APR***	***MAY***	***JUN***	***JUL***	***AUG***	***SEP***	***OCT***	***NOV***	***DEC***
Mean	53.56	32.30	36.18	43.92	52.74	61.79	69.85	74.79	73.44	65.82	54.65	43.38	33.84
Median	53.85	31.90	36.80	43.75	53.15	61.90	69.75	74.70	73.30	65.70	54.80	43.50	34.70
Standard Deviation	15.07	2.91	2.95	2.11	1.94	1.39	1.24	1.13	1.30	1.46	1.31	2.42	2.90
Minimum	26.00	26.60	29.70	39.90	48.10	58.90	67.10	72.10	70.50	63.40	51.20	38.60	26.00
Maximum	77.30	39.70	40.60	48.40	56.30	64.10	71.80	77.30	75.80	69.70	57.40	48.50	36.90
Count	360	30	30	30	30	30	30	30	30	30	30	30	30

Table 4.7: Tests for the presence of seasonality in temperature data

Seasonality tests are conducted for temperature data, using the ARIMA X-12 features in EViews 7.0. In section A, an *F*-statistic is the ratio between-month variance and residual variance. A large *F*-value indicates that a significant amount of intra-year variation is due to months, or in other words seasonality exists. In this case, the null hypothesis of no seasonality can be rejected at 0.1% level. In addition, the Kruskal-Wallis Chi-squared test in Panel B, which examines whether all the medians of temperature for each month are the same, shows that seasonality present at the 1% level (*p*-value = 0.00).

The statistic in section C is the moving seasonality test, which investigates the presence of seasonality that repeats itself from year to year in an evolving fashion. The null hypothesis is that there is no significant effect due to years after accounting for variation due to months, or no evolving seasonality. It cannot be rejected at 5% level in this case. The final analysis in Panel D combines together the two F-tests described earlier and the nonparametric Kruskal-Wallis test, EViews reports that the presence of seasonality is identifiable for monthly average temperature series.

A. F-tests for seasonality

Test for the presence of seasonality assuming stability.

	Sum of Squares	**Degrees of Freedom**	**Mean Square**	**F-Value**
Between Months	83054.5146	11	7550.4104	2281.397**
Residuals	1191.4403	360	3.3096	
Total	84245.9549	371		

***Seasonality present at the 0.1 per cent level.*

B. Nonparametric Test for the Presence of Seasonality Assuming Stability

Kruskal-Wallis Statistic	**Degrees of Freedom**	**Probability Level**
362.1878	11	0.00%

Seasonality present at the one per cent level.

C. Moving Seasonality Test

	Sum of Squares	**Degrees of Freedom**	**Mean Square**	**F-Value**
Between Years	104.4519	30	3.4817	1.115
Error	1030.3476	330	3.1223	

No evidence of moving seasonality at the five per cent level.

D. COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY

IDENTIFIABLE SEASONALITY PRESENT

Table 4.8: Unit root test results for temperature series, Jan 1980 – Dec2009

The table reports the estimated coefficient α_1 of the first autoregressive term and the ADF-statistics of the temperature series. Lag length is based on minimum Akaike Info Criterion. The ADF test is estimated by

$$\Delta T_t = \alpha_1 T_{t-1} + x_t\delta + \beta_1 \Delta T_{t-1} + \beta_2 \Delta T_{t-2} + \ldots + \beta_p \Delta T_{t-p} + \varepsilon_t ,$$

where T_t is the time series of temperature, x_t are optional exogenous regressors which may consist of constant or a constant and trend, and ε_t is the error term. The constant is needed as an exogenous regressor in a model because temperature (in Fahrenheit) should fluctuate around some fixed value. The null hypothesis of the presence of unit root is that $\alpha_1 = 0$. The asterisks ** means that the null hypothesis of unit root in temperature can be rejected at 5% level of significance. Therefore, the temperature series has no unit root.

Panel A: ADF Test with both Constant and Trend	
α_1	-0.6454
ADF-stat	-3.78**
Panel B: ADF Test with Constant Only	
α_1	-0.4697
ADF-stat	-3.08**

Note: **Significant at 5% level

Table 4.9: Seasonal decomposition of temperature series by X-12-ARIMA

The X12 program allows users to fit ARIMA models to the series prior to seasonal adjustment, and it uses the standard (p d q) $(P\ D\ Q)_s$ notation for seasonal ARIMA model. The (p d q) refers to the orders of non-seasonal autoregressive (AR), differencing, and moving average (MA) operators, while the $(P\ D\ Q)_s$ refers to the seasonal AR, differencing and MA orders.

The regARIMA (1 0 1)(0 0 1) additive model with constant and seasonal dummies are the best fitting model for average monthly temperature series, providing that all coefficients are significant and AIC is the smallest compared with other estimated models. The table presents the estimations and statistics of this model.

Panel A reports constant and seasonal coefficients of the model together with their *t*-statistics. All of them appear to be statistically different from zero at the 5% significance level, with the absolute value more than 1.96. The chi-squared test for group of regressors is reported in panel B, and all regressors are jointly significant at 1% level.

Panel C reports the estimated coefficients and standard errors for the most parsimonious model, ARIMA (1 0 1) (0 0 1). The results also imply that the fitted model is stationary and invertible as evidenced by the absolute value of the coefficients of the AR and MA characteristic equation being less than 1.

Panel D estimates the likelihood statistics, in which the AIC is reported. This statistic is compared among different models estimated for the same data set. The chosen model minimizes the AIC value, which is the distance between the model and the truth.

A. Regression Model

Parameter Variable	Estimate	Standard Error	*t*-value
Constant	53.4311	0.2261	236.28
Seasonal			
Jan	-21.4627	0.2974	-72.18
Feb	-17.5280	0.2973	-58.96
Mar	-9.5913	0.2972	-32.27
Apr	-0.7969	0.2971	-2.68
May	8.24	0.2971	27.74
Jun	16.3181	0.2971	54.93
Jul	21.2675	0.2971	71.59
Aug	19.8830	0.2971	66.93
Sep	12.3298	0.2971	41.50
Oct	1.1809	0.2972	3.97
Nov	-10.2336	0.2973	-34.43
†Dec (derived)	-19.6068	0.2974	-65.94

† For full trading-day and stable seasonal effects, the derived parameter estimate is obtained indirectly as minus the sum of the directly estimated parameters that define the effect.

B. Chi-squared Tests for Groups of Regressors

Regression Effect	df	Chi-Square	*p*-value
Seasonal	11	24919.51	0.00

C. ARIMA Model (1 0 1)(0 0 1)

Standard Parameter	Estimate	Errors
Non-seasonal AR		
Lag 1	0.9130	0.0315
Non-seasonal MA		
Lag 1	0.7871	0.0478
Seasonal MA		
Lag 12	0.1050	0.0524
Variance	4.08E+00	

D. Likelihood Statistics

Effective number of observations	372
Number of parameter estimated	16
Log likelihood	-789.3595
AIC	1610.7190
AICC (F-corrected AIC)	1612.2514
Hannan Quinn	1635.6198
BIC	1673.4213

Table 4.10: Diagnostics for the regARIMA (1 0 1)(0 0 1) of temperature series

The table displays diagnostic results of the seasonally adjusted model for the temperature series performed by X-12-ARIMA. Panel A clearly reports that there is no evidence of residual seasonality from the model both in the entire series and in the last 3 years. This implies that the selected model can remove seasonality from the data relatively well, which is desirable.

Additionally, panel B shows the monitoring and quality assessment statistics which are unique to the X-12 program. The first column describes the meaning of these statistics, while the second column reports the values. Remember that the *M*-stats and *Q*-stat should fall within an acceptance level between 0 and 1. M3 and M5 are designed to observe if there is too much irregular in the series relative to the trend. However, both M3 and M5 may fail if there is a very flat trend in the series because the change in the irregular will always be more than the change in the trend. In this case, there is no cause for concern and nothing needs to be done. The M7 is the most important M statistic, which tests for moving seasonality relative to stable seasonality. Too much moving seasonality may cause problems in estimations. However, M7 is very low at 0.048 for the selected model, indicating that the series has identifiable seasonality which is vital for any seasonal decomposition process. Ultimately, the *Q*-stat summarises all *M*-stats and it displays "accepted", meaning that the model falls within the acceptance range and should bring a practical seasonal adjustment to the time series.

It is worth noting that the last column in panel B and texts in parentheses at panel descriptions identify the sources of the results considered here. As X12 program produces a great deal of estimated results, only those which are significant and relevant will be illustrated.

A. Test for the presence of residual seasonality (D11)

No evidence of residual seasonality in the entire series at 1% level	F = 1.00
No evidence of residual seasonality in the last 3 years at 1% level	F = 0.67
No evidence of residual seasonality in the last 3 years at 5% level	

Note: sudden large changes in the level of the adjusted series will invalidate the results of this test for the last three year period.

B. Monitoring and Quality Assessment Statistics (F3)

M Statistic		
Description	**Statistic**	**Source**
The relative contribution of the irregular over 3 months span	M1 = 0.052	F 2.B
The relative contribution of the irregular component to the stationary portion of the variance	M2 = 0.066	F 2.F
The amount of month to month change in the irregular component as compared to the amount of month to month change in the trend-cycle	M3 = 1.716	F 2.H
The amount of autocorrelation in the irregular as described by the average duration of run	M4 = 0.367	F 2.D
The number of months it takes the change in the trend-cycle to surpass the amount of change in the irregular	M5 = 3.000	F 2.E
The amount of year to year change in the irregular as compared to the amount of year to year change in the seasonal	M6 = 0.865	F 2.H
The amount of moving seasonality present relative to the amount of stable seasonality	M7 =0. 048	F 2.I
The size of the fluctuations in the seasonal component throughout the whole series	M8 = 0.068	
The average linear movement in the seasonal component throughout the whole series	M9 = 0.012	
Same as M8, calculated for recent years only	M10 = 0.06	
Same as M9, calculated for recent years only	M11 = 0.054	
Q Statistic		
Q	0.62	ACCEPTED
Q (except M2)	0.70	ACCEPTED

Note: All measures are in the range from 0 to 3 with and acceptance region from 0 to 1

Table 4.11: Unit root test results of seasonally adjusted temperature series *(TSA)*

The table reports the estimated coefficient α_1 of the first autoregressive term and the ADF-statistics of the deseasonalised temperature series. Lag length is based on minimum Akaike Info Criterion. The ADF test is estimated by

$$\Delta TSA_t = \alpha_1 TSA_{t-1} + x_t\delta + \beta_1 \Delta TSA_{t-1} + \beta_2 \Delta TSA_{t-2} + \ldots + \beta_p \Delta TSA_{t-p} + \varepsilon_t ,$$

where TSA_t is the time series of seasonally adjusted temperature, x_t are optional exogenous regressors which consist of constant or a constant and trend, and ε_t is the error term. In this case, the constant is needed as an exogenous regressor in a model because temperature should fluctuate around some fixed value.

The null hypothesis of the presence of unit root is that $\alpha_1 = 0$. The asterisks *** means that the null hypothesis of unit root in temperature can be rejected at 1% level of significance. Therefore, the seasonally adjusted temperature series contains no unit root and the series is stationary.

Panel A: ADF Test with both Constant and Trend	
α_1	-0.7292
ADF-stat	-9.13***
Panel B: ADF Test with Constant Only	
α_1	-0.6661
ADF-stat	-8.74***

Note: ***Significant at 1% level

Table 4.12: Unit root test results for *W1* series

The table reports the estimated coefficient α_1 of the first autoregressive term and the ADF-statistics of the *W1* series. Lag length is based on minimum AIC. The ADF test is defined by

$$\Delta W1_t = \alpha_1 W1_{t-1} + x_t\delta + \beta_1 \Delta W1_{t-1} + \beta_2 \Delta W1_{t-2} + \ldots + \beta_p \Delta W1_{t-p} + \varepsilon_t ,$$

where $W1_t$ is the time series of temperature deviations from norms, x_t are optional exogenous regressors which consist of constant or a constant and trend, and ε_t is the error term.

The ADF statistics in all panels clearly determine that the null hypothesis of the presence of unit root in *W1* can be rejected at the 1% significance level. Hence, the *W1* series is stationary.

Panel A: ADF Test with both Constant and Trend	
α	-0.8634
ADF-stat	-16.33***
Panel B: ADF Test with Constant Only	
α	-0.6860
ADF-stat	-8.69***
Panel C: ADF Test with no exogenous regressor	
α	-0.6859
ADF-stat	-8.70***

Note: ***Significant at 1% level

Table 4.13: The model of ARMA (1,1) of *W1*

Ultimately, The ARMA (1,1) process without a constant is the most parsimonious model for *W1* series as it shows the lowest AIC at 4.197 and the highest adjusted R^2 at 6.49%. The below table reports all estimated results of the model, with coefficients of AR and MA terms and its *t*-statistics. They are all significant at the 1% confidence level. The estimated ARMA process is also stationary and invertible because the AR and MA roots lie within the unit circle.

Therefore, *W1* should follow the process of ARMA (1,1) as given below.

$$W1_t = 0.63W1_{t-1} - 0.49\varepsilon_{t-1} + \varepsilon_t ,$$

where ε_t is an error term or residual. However, the adjusted R^2 of the estimation is relatively low at 6.4%, suggesting that the model does not fit well with data. Only 6.4% of the total variation in *W1* can be explained by ARMA (1,1) model. Consequently, the residuals are considerably large and fairly the same size as *W1*.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.6321	0.1067	5.92	0.0000
MA(1)	-0.4875	0.1265	-3.85	0.0001
R-squared	0.0674	Mean dependent var		0.0253
Adjusted R-squared	0.0649	S.D. dependent var		2.0350
S.E. of regression	1.9679	Akaike info criterion		4.1972
Sum squared resid	1429.003	Schwarz criterion		4.2183
Log likelihood	-776.5785	Hannan-Quinn criter.		4.2056
Durbin-Watson stat	2.0080			
Inverted AR Roots	.63			
Inverted MA Roots	.49			

Table 4.14: The model of ARMA (1,1) of *TSA*

The ARMA (1,1) is the most parsimonious model for mimicking an expectation on seasonally adjusted temperature (*TSA*). The table reports the estimated results of this model. The coefficients of constant, AR (1) and MA (1) terms are strongly significant at 1% level of confidence. The Durbin-Watson statistic is around 2, assuming that there is no first-order autocorrelation. The AR and MA roots lie within a unit circle, implying that the model is (covariance) stationary and invertible.

The adjusted R^2 at 6.1% of ARMA (1,1) is the highest, as well as with the smallest AIC, among the other candidate models. However, the adjusted R^2 is relatively low: only 6.1% of the variation in *TSA* can be explained by the model. This may imply that the temperature series do not have any other exceptional patterns apart from seasonality.

From the estimated results, the seasonally adjusted temperature (*TSA*) follows the process of

$$TSA_t = 53.56 + 0.68TSA_{t-1} - 0.54\delta_{t-1} + \delta_t$$

where δ_t is the residual which represents the measure of weather risk (*W3*).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	53.5626	0.1453	368.60	0.00
AR(1)	0.6798	0.1045	6.51	0.00
MA(1)	-0.5428	0.1250	-4.34	0.00

R-squared	0.0612	Mean dependent var	53.523
Adjusted R-squared	0.0561	S.D. dependent var	2.0027
S.E. of regression	1.9457	Akaike info criterion	4.1772
Sum squared resid	1393.13	Schwarz criterion	4.2088
Log likelihood	-771.863	Hannan-Quinn criter.	4.1897
F-statistic	12.0049	Durbin-Watson stat	2.0233

Inverted AR Roots	.68
Inverted MA Roots	.54

Table 4.15: Summary of innovative weather measures

The table summarises all measures for weather proxies. The first column identifies the variable abbreviations that will be used throughout the rest of the study, while the second column explains the descriptions. The last column shows how to derive the quantifications of these factors algebraically.

Variables	Description	Methodology
W1	Deviations from monthly mean temperature (norms)	$T_t - \overline{T}_m^y$
%W1	Deviations scaled by standard deviation of the month	$\frac{T_t - \overline{T}_m^y}{\sigma_m}$
W2	Residuals ε from ARMA(1,1) of W1	$\varepsilon_t = W1_t - 0.63W1_{t-1} + 0.49\varepsilon_{t-1}$
%W2	Residuals to actual temperature	$\frac{\varepsilon_t}{T_t}$
W3	Residuals δ from ARMA(1,1) of seasonally adjusted temperature (*TSA*)	$\delta_t = TSA_t - 53.56 - 0.68TSA_{t-1} + 0.54\delta_{t-1}$
%W3	Residuals to actual temperature	$\frac{\delta_t}{T_t}$
W4	Irregular temperature produced from X-12-ARIMA seasonal decomposition process	$I_t = T_t - C_t - S_t$
%W4	Irregularity to actual temperature	$\frac{I_t}{T_t}$
W5	Deviations from 10-year historical mean of temperature	$T_t - \frac{\sum_{i=-1}^{-10} T_m^i}{10}$
%W5	Deviations scaled by historical standard deviation of the period	$\frac{W5_t}{\sigma_m^i}$

Table 4.16: Descriptive statistics for the time series of the constructed weather measures

The table reports the descriptive statistics of all innovations of weather measures. Most of the mean values of weather factors are close to zero. The simple hypothesis test regarding mean value has been carried out, with the null hypothesis that the mean, μ_w, of the series is equal to zero. It is reported that only the series of W5 and its percentage value have the mean value statistically different from zero. The standard deviations of weather proxies are approximately 2 degrees Fahrenheit, but ranges from around 0.05 to 1.20 in percentage terms. All the reported Jarque-Bera probabilities for these weather variables, apart from that of %W1, do not exceed the value to reject the null hypothesis of normal distribution. Therefore, only %W1 series is normally distributed.

	W1	**%W1**	**W2**	**%W2**	**W3**	**%W3**	**W4**	**%W4**	**W5**	**%W5**
Mean	0.0000	0.0000	0.0613	-0.0011	-0.0020	-0.0029	-0.0431	-0.0034	0.2797**	0.1428**
Median	0.0617	0.0410	0.0807	0.0017	0.0494	0.0009	-0.0088	-0.0002	0.3300	0.2298
Maximum	7.4000	2.6588	7.7129	0.1943	7.6329	0.1923	5.9655	0.1503	6.7900	4.3528
Minimum	-7.8367	-2.7015	-7.9258	-0.3048	-9.4610	-0.3639	-9.1173	-0.3507	-8.2200	-4.3732
Standard Deviation	2.009	0.985	2.012	0.053	1.993	0.053	1.748	0.047	2.128	1.204
Skewness	-0.292	-0.119	-0.234	-1.202	-0.427	-1.741	-0.612	-2.101	-0.095	-0.343
Kurtosis	4.208	2.818	4.299	8.621	5.723	12.410	6.933	15.398	4.002	4.377
Jarque-Bera	26.98	1.34	28.61	560.74	122.21	1509.99	254.48	2570.27	15.59	35.50
Probability	0.000001	0.5123	0.000001	0	0	0	0	0	0.0004	0

Note—the asterisks ** indicate a statistical significance at 5% level.

Table 4.17: Unit root tests for the constructed weather measures

The table provides results of ADF tests for all weather variables. These tests are conducted to test whether derived weather risk series exhibit a mean reversion process, and the estimated coefficients and ADF statistics of weather risk innovations are reported. The results clearly show that ADF-statistics for all series are much larger than the critical value at 1% confidence level. Therefore, all of them are stationary and ready to be utilized for regressions in the further analysis.

	W1	%W1	W2	%W2	W3	%W3	W4	%W4	W5	%W5
Panel A: ADF Tests with both Constant and Trend										
α_1	-0.8634	-0.7643	-0.8628	-0.8775	-0.7276	-0.8988	-2.1493	-1.2445	-0.7348	-0.7828
ADF-stat	-16.334***	-8.762***	-16.32***	-16.52***	-8.805***	-16.92***	-12.02***	-15.99***	-8.922***	-9.05***
Panel B: ADF Tests with Constant Only										
α_1	-0.6860	-0.5319	-0.6855	-0.8526	-0.6738	-0.8734	-2.0378	-1.4479	-0.7256	-0.7758
ADF-stat	-8.691***	-5.203***	-8.681***	-16.16***	-8.474***	-16.54***	-11.62***	-11.91***	-8.846***	-9.00***
Panel C: ADF Tests with no exogenous regressor										
α_1	-0.6859	-0.5319	-0.6833	-0.8523	-0.6738	-0.7521	-2.0276	-1.4128	-0.695	-0.587
ADF-stat	-8.702***	-5.212***	-8.674***	-16.18***	-8.485***	-9.092***	-11.60***	-11.72***	-8.638***	-5.505***

Note: ***Significant at 1% level

Table 4.18: A correlation matrix for independent variables

The table displays a correlation matrix between the weather variables *(W)* and the market return *(MR)* series. The first column is the most important, as it reports the correlation coefficients between the market variable and each weather risk factor. Ideally, correlations should be low because each of these weather proxies will be used together with market return as explanatory variables in further investigations, and they should not strongly related to each other as a matter of fact. The reported correlation coefficients between weather variables and market return are very low, which fairly assures, to some extent, that the problem of multicollinearity should not exist. It is interesting to find that only *%W1* has negative correlation to the market factor.

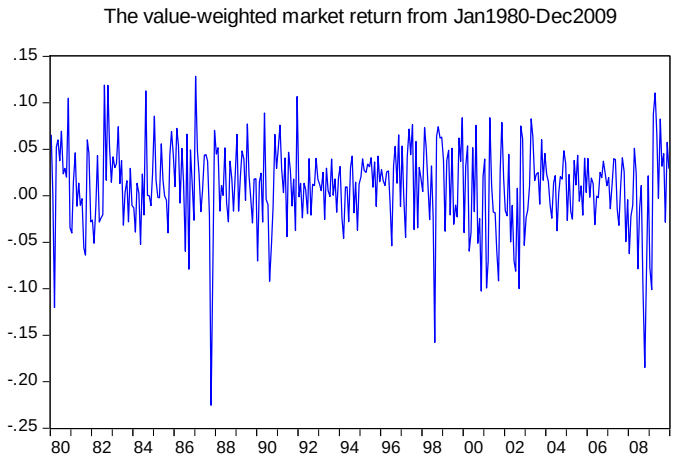
The other columns show the correlation coefficients among weather factors, and they are as high as expected because these measures intend to gauge the same thing but with different in methodologies. All correlations between degree and percentage term of the similar factor varies around 90-95% because they are dissimilar only in scaling. The strongest correlation is between *W1* and *W2*, which is 99%, while the mildest relationship is between *%W4* and *%W5* at 65%.

	MR	W1	%W1	W2	%W2	W3	%W3	W4	%W4	W5	%W5
MR	1										
W1	0.0177	1									
%W1	-0.0063	0.9422	1								
W2	0.0183	0.9986	0.9409	1							
%W2	0.0251	0.9616	0.8299	0.9621	1						
W3	0.0229	0.9591	0.9029	0.9628	0.9349	1					
%W3	0.0281	0.9135	0.7866	0.9166	0.9639	0.9608	1				
W4	0.0246	0.8692	0.797	0.8736	0.8692	0.9145	0.9013	1			
%W4	0.0184	0.8355	0.7056	0.8395	0.9008	0.888	0.9435	0.9619	1		
W5	0.0772	0.9261	0.8765	0.9304	0.8882	0.9148	0.8643	0.8548	0.8133	1	
%W5	0.027	0.8363	0.9077	0.8376	0.7275	0.8245	0.7093	0.7504	0.6544	0.8891	1

Figure 4.1: The market return series: graph and descriptive statistics

While the figure in panel A illustrates a movement of monthly rate of value-weighted market return series (R_m) from January 1980 to December 2009, panel B shows the histogram and descriptive statistics of the series. For the given market index, the returns are fluctuated around zero with an average mean value of 0.984%. The histogram looks asymmetric, negatively skewed and leptokurtic. It appears not to follow the normal distribution, with the values of skewness at -0.8355 and the kurtosis at 5.6115. The Jarque-Bera probability of 0.00 supports the non-normality of the series. It is less than 0.01, so the null hypothesis that the series is normally distributed can be rejected at 1% confidence level.

Panel A: Graph of the value-weighted market returns from Jan 1980 - Dec 2009.



Panel B: Histogram and descriptive statistics of the market return series.

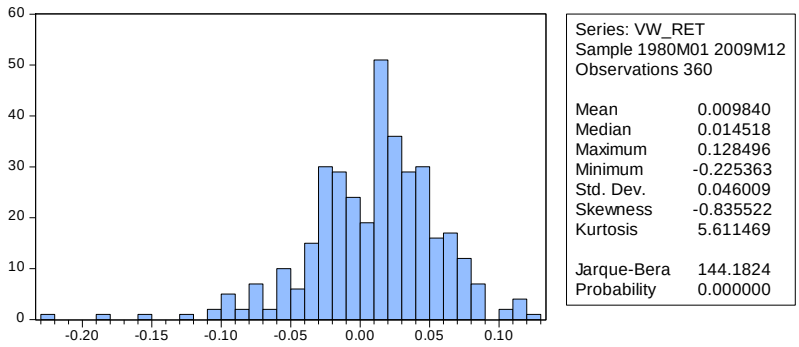


Figure 4.2: Scree plot of state-wide monthly average temperatures

A scree plot illustrates the rate of change in the magnitude of the eigenvalues for the factors. In general, the rate of decline tends to be fast for the first few factors but levels off later, indicating the maximum number of factors to be extracted. For 48 state-wide temperature series, the data should reduce to only one factor as the scree plot clearly drops after the first component. It is clearly noticeable that only one component has the eigenvalue greater than 1.

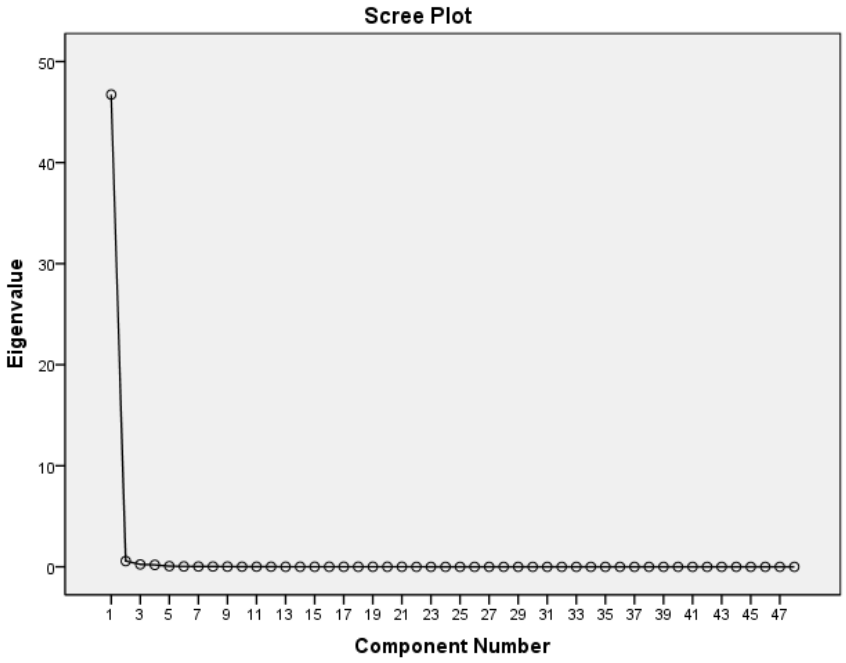
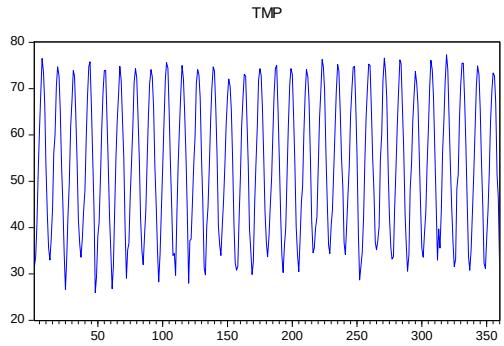


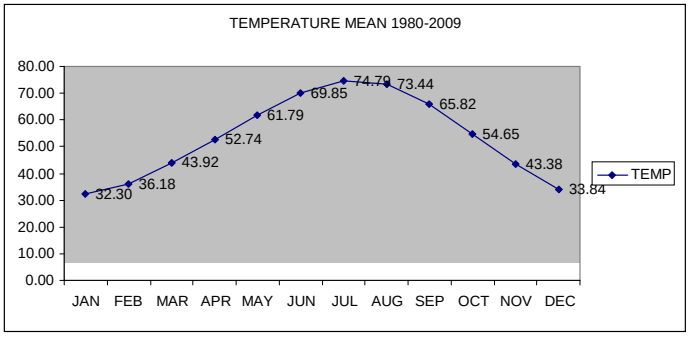
Figure 4.3: Monthly average nation-wide U.S. temperature, Jan 1980 - Dec 2009

The figure illustrates monthly average temperature from the sample period. While panel A shows the normal plot of the series against time, panel B rearranges the data and graphs the means for a particular month during the period for a greater analysis of the seasonal pattern. Panel C summarises the descriptive statistics and a histogram of the series. At a glance, the distribution of the series does not resemble the bell-shaped normal distribution at all. The Jarque-Bera probability firmly assures that this series is not normally distributed.

Panel A: Monthly average temperature (national values)



Panel B: Monthly average temperature mean



Panel C: Histogram and descriptive statistics

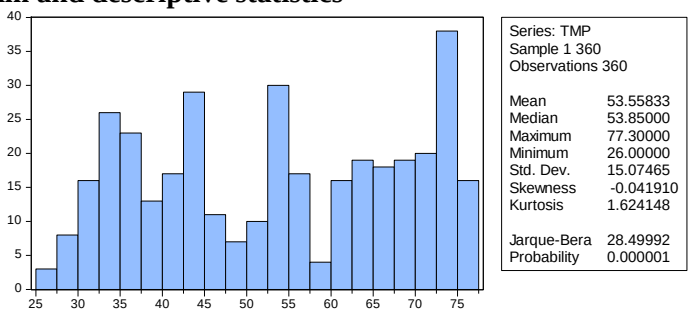
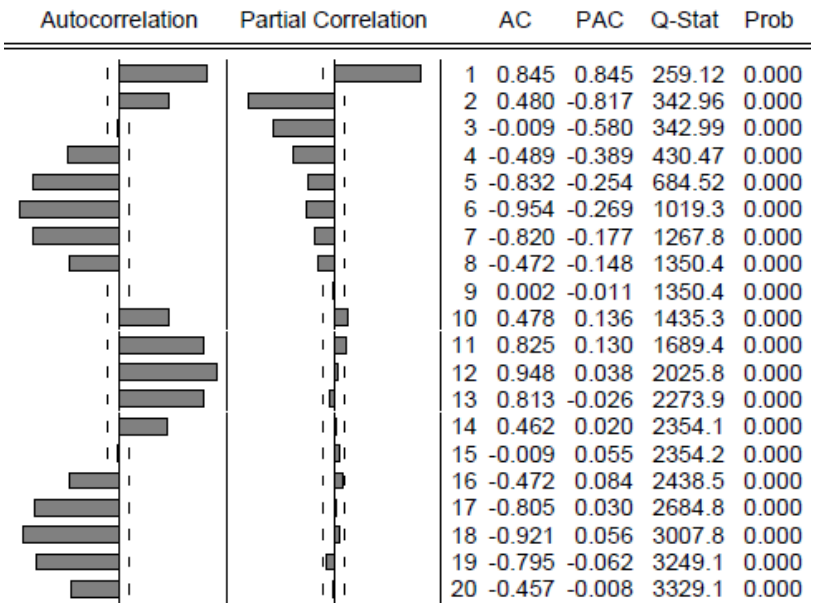


Figure 4.4: Level correlogram of national monthly average temperature series (*T*)

A correlogram characterizes the pattern of temporal dependence by displaying the autocorrelation (ACF) and partial autocorrelation (PACF) functions up to the specified order of lags. For the monthly temperature series, the correlogram at level for 20 lags is reported here, and the autocorrelation coefficients clearly display a seasonal pattern. Most of ACFs are individually significantly different from zero, in that they are outside the 95% confidence bounds. It should be noted that the dotted lines in the plots of the autocorrelations are the approximate two standard error bounds. If the autocorrelation is within these bounds, it is not significantly different from zero at the 5% significance level.



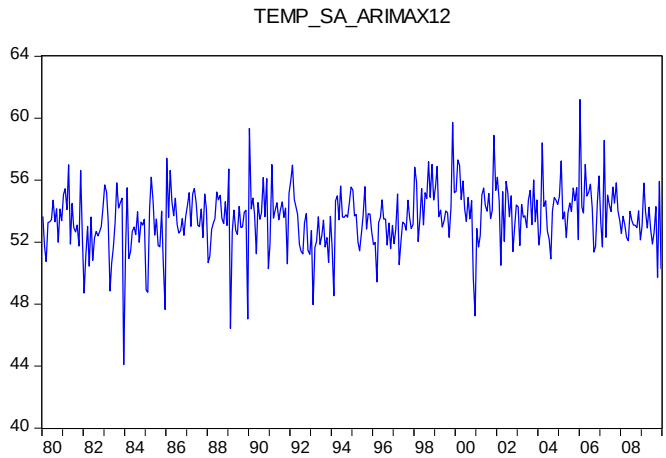
	AC	PAC	Q-Stat	Prob
1	0.845	0.845	259.12	0.000
2	0.480	-0.817	342.96	0.000
3	-0.009	-0.580	342.99	0.000
4	-0.489	-0.389	430.47	0.000
5	-0.832	-0.254	684.52	0.000
6	-0.954	-0.269	1019.3	0.000
7	-0.820	-0.177	1267.8	0.000
8	-0.472	-0.148	1350.4	0.000
9	0.002	-0.011	1350.4	0.000
10	0.478	0.136	1435.3	0.000
11	0.825	0.130	1689.4	0.000
12	0.948	0.038	2025.8	0.000
13	0.813	-0.026	2273.9	0.000
14	0.462	0.020	2354.1	0.000
15	-0.009	0.055	2354.2	0.000
16	-0.472	0.084	2438.5	0.000
17	-0.805	0.030	2684.8	0.000
18	-0.921	0.056	3007.8	0.000
19	-0.795	-0.062	3249.1	0.000
20	-0.457	-0.008	3329.1	0.000

Figure 4.5: The seasonally adjusted temperature series (*TSA*)

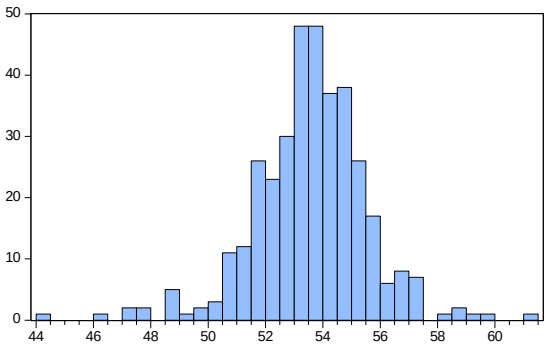
The monthly average temperature series is seasonally adjusted by the X-12-ARIMA, and the statistical characteristics of the obtained series are described here. Panel A graphs the seasonally adjusted temperature series, while Panel B reports its histogram and descriptive statistics. The series show no seasonality pattern and the probability distribution seems closer to be the Gaussian function.

It should be noted that the temperature series for 31 years is used for deseasonalisation, and the result yields 372 observations, from Jan 1979 to Dec 2009, for the seasonally adjusted temperature values. However, the graph and descriptive statistics reported here is based on 30-year data starting from Jan 1980 in order to make them comparable to which of the temperature series before seasonal adjustment.

Panel A: Graph of seasonally adjusted temperature, Jan 1980 – Dec 2009.



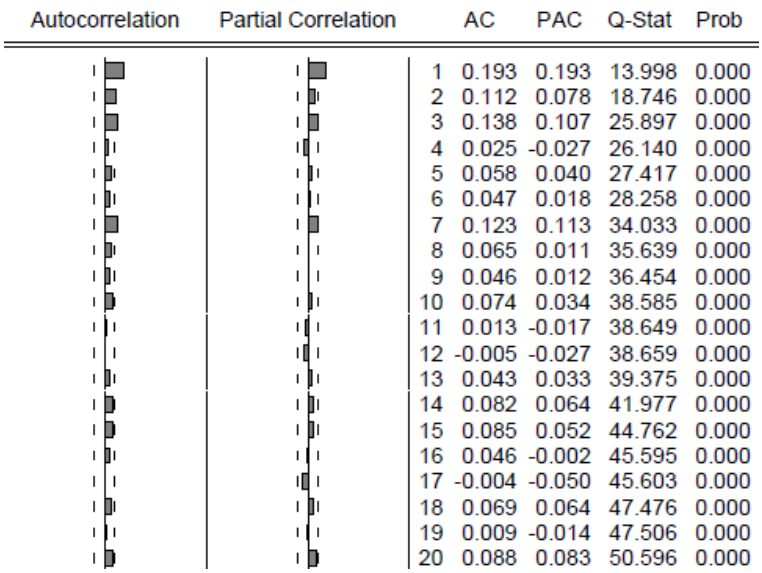
Panel B: Histogram and descriptive statistics



Series: TEMP_SA_ARIMAX12	
Sample 1980M01 2009M12	
Observations 360	
Mean	53.55993
Median	53.61210
Maximum	61.19550
Minimum	44.10170
Std. Dev.	1.993620
Skewness	-0.426722
Kurtosis	5.720301
Jarque-Bera	121.9260
Probability	0.000000

Figure 4.6: Level correlogram of *W1*, Jan 1979 - Dec 2009

The figure displays the level correlogram of *W1*, and it is examined in order to specify the appropriate lags, *p* and *q* for an ARMA model. The first and second columns represent autocorrelation (ACF) and partial autocorrelation (PACF) functions respectively. Even though there is no clear pattern found in the correlogram, some lags are spiked outside the 95% confidence bounds represented by the dotted lines. It can be deduced that the first three and the seventh ACFs and PACFs are statistically significant from zero. The penultimate column shows the Ljung-Box joint test *Q*-statistics, while the last column presents the probability. The null hypothesis of no autocorrelation at the 1% level for all number of lags cannot be rejected.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.193	0.193	13.998	0.000
		2	0.112	0.078	18.746	0.000
		3	0.138	0.107	25.897	0.000
		4	0.025	-0.027	26.140	0.000
		5	0.058	0.040	27.417	0.000
		6	0.047	0.018	28.258	0.000
		7	0.123	0.113	34.033	0.000
		8	0.065	0.011	35.639	0.000
		9	0.046	0.012	36.454	0.000
		10	0.074	0.034	38.585	0.000
		11	0.013	-0.017	38.649	0.000
		12	-0.005	-0.027	38.659	0.000
		13	0.043	0.033	39.375	0.000
		14	0.082	0.064	41.977	0.000
		15	0.085	0.052	44.762	0.000
		16	0.046	-0.002	45.595	0.000
		17	-0.004	-0.050	45.603	0.000
		18	0.069	0.064	47.476	0.000
		19	0.009	-0.014	47.506	0.000
		20	0.088	0.083	50.596	0.000

Figure 4.7: The correlogram and *Q*-Stats of residuals from the ARMA (1,1) of *W1*

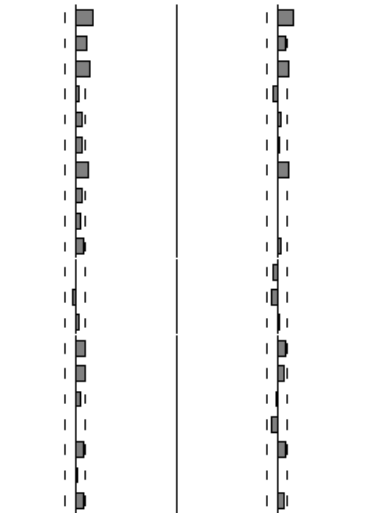
The figure displays the correlogram of residuals of the ARMA (1,1) model of *W1*. If the ARMA model is correctly specified, the residuals from the model should be nearly white noise. The first and second columns represent ACFs and PACFs respectively. The correlogram has no significant spike at any lag: all of ACFs and PACFs are within the dotted line of 95% confidence bounds.

The penultimate column of output gives the statistic resulting from a Ljung-Box test with number of lags in the sum equals to the row number in the third column. The *Q-stat* is asymptotically distributed as a χ^2 with degrees of freedom equal to k - p - q when the series represents the residuals from ARIMA estimation. The test statistics will follow a $\chi^2(1)$ for third row and $\chi^2(2)$ for the fourth row, and so on. The last column represents p-values associated with these test statistics, and they are insignificant for all lags considered in this case. This indicates that there is no autocorrelation in the residuals for the selected ARMA (1,1) model.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.011	-0.011	0.0431	
		2	-0.006	-0.006	0.0572	
		3	0.069	0.069	1.8465	0.174
		4	-0.054	-0.053	2.9325	0.231
		5	0.011	0.011	2.9764	0.395
		6	-0.000	-0.005	2.9764	0.562
		7	0.104	0.112	7.0929	0.214
		8	0.043	0.041	7.8087	0.252
		9	0.019	0.023	7.9494	0.337
		10	0.050	0.037	8.9265	0.349
		11	-0.001	0.006	8.9271	0.444
		12	-0.050	-0.051	9.9025	0.449
		13	-0.001	-0.006	9.9027	0.539
		14	0.049	0.042	10.837	0.543
		15	0.075	0.076	13.036	0.445
		16	0.028	0.020	13.336	0.500
		17	-0.031	-0.048	13.713	0.547
		18	0.076	0.067	15.975	0.455
		19	-0.020	-0.006	16.129	0.515
		20	0.092	0.106	19.458	0.364

Figure 4.8: Level correlogram of *TSA* series, Jan 1979 – Dec 2009

Figure 8 reports the level correlogram of the *TSA* series, which is visually different from Figure 4 as there is no more seasonal pattern in ACFs observed. The values of ACFs and PACFs significantly drop, compared with which of temperature series, and are not persistent. As a rule of thumb, a given autocorrelation coefficient is classed as significant if it is outside the dotted line. It can be deduced that the first three and the seventh ACFs and PACFs are significant under this rule. Since the first ACF coefficient is highly significant, the Ljung-Box joint test statistic rejects the null hypothesis of no autocorrelation at the 1% level for all number of lags considered.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.178	0.178	11.858	0.001
		2	0.120	0.091	17.270	0.000
		3	0.153	0.123	26.130	0.000
		4	0.025	-0.030	26.368	0.000
		5	0.067	0.045	28.091	0.000
		6	0.062	0.029	29.553	0.000
		7	0.135	0.121	36.498	0.000
		8	0.065	0.007	38.132	0.000
		9	0.050	0.010	39.083	0.000
		10	0.080	0.035	41.555	0.000
		11	-0.006	-0.037	41.567	0.000
		12	-0.025	-0.048	41.814	0.000
		13	0.028	0.021	42.129	0.000
		14	0.092	0.088	45.408	0.000
		15	0.098	0.070	49.172	0.000
		16	0.049	-0.004	50.116	0.000
		17	0.005	-0.050	50.125	0.000
		18	0.087	0.082	53.084	0.000
		19	0.019	0.000	53.233	0.000
		20	0.087	0.073	56.238	0.000

Figure 4.9: The correlogram and *Q*-Stats of residuals from the ARMA (1,1) of *TSA*

The figure displays the correlogram of residuals of the ARMA (1,1) model of *TSA*. The first and second columns represent ACFs and PACFs respectively, and the values hover around zero which resemble to the white noise process. There is no significant spike at a specific lag.

The penultimate column of output gives the statistic resulting from a Ljung-Box test with number of lags in the sum equals to the row number in the third column. It is worth noting that Q is asymptotically distributed as a χ^2 with degrees of freedom equal to k - p - q when the series represents the residuals from ARIMA estimation. The last column represents p-values associated with these test statistics, and they are insignificant for all lags considered in this case. This indicates that there is no autocorrelation in the residuals for the selected ARMA (1,1) model. The residuals are white-noise and hence the ARMA (1,1) is appropriate for the *TSA* series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.016	-0.016	0.0935	
		2	0.002	0.002	0.0956	
		3	0.075	0.076	2.2376	0.135
		4	-0.064	-0.062	3.7724	0.152
		5	0.009	0.007	3.8039	0.283
		6	0.006	0.001	3.8159	0.431
		7	0.109	0.120	8.3585	0.138
		8	0.037	0.035	8.8760	0.181
		9	0.023	0.024	9.0731	0.247
		10	0.058	0.042	10.354	0.241
		11	-0.035	-0.025	10.828	0.288
		12	-0.067	-0.070	12.545	0.250
		13	-0.013	-0.022	12.607	0.320
		14	0.065	0.064	14.249	0.285
		15	0.088	0.091	17.271	0.187
		16	0.027	0.018	17.560	0.228
		17	-0.027	-0.053	17.837	0.271
		18	0.086	0.085	20.739	0.189
		19	-0.012	0.015	20.792	0.236
		20	0.085	0.104	23.669	0.166

Chapter 5

The Weather Exposures of U.S. Corporations

5.1 Introduction

It is widely accepted that changing weather conditions affect companies' operations and services, leading to a financial impact on weather-exposed firms and a consequent effect on their stock prices. While the common intuition and the rapid growth of weather derivative practices effectively support the notion that equity return is sensitive to weather randomness, empirical support is fragile. Although the associations between weather and company operations or finances have been extensively analysed, as reviewed in Chapter 2, it is surprising that the relationship between weather and stock returns and the economic importance of the relation have not been subject to much empirical research. Most of studies in the area, however, have centred on psychological effects rather than financial effects of weather on security prices. Accordingly, it has intensively focused on the effects of weather conditions rather than those induced by unpredictable weather element. Given that a firm usually seeks protections for predicted weather events but is still exposed to unforeseeable weather surprises, any residual exposures would translate into potentially detrimental profit and share price. However, a lack of empirical evidence casts some doubt on the basic premise of how significantly the unexpected weather impacts the performance and stock return of firms.

To date, the literature on weather exposure has been limited and none of it has touched on the measurement of unpredictable weather and the effect of this component on asset prices. Researchers have often defined and measured weather exposure in a different way, focusing on exposure to the total weather variable comprising such elements as temperature, degree days, and precipitation. This study will take a new approach. It will develop a procedure which similar to that used for examining the relationships between the foreign exchange rate and security returns. On this basis it will estimate the weather exposure of each firm in the sample. In the context that stock returns are influenced by a wide variety of unanticipated events that cannot be hedged and one of which may include unforeseen weather, the weather exposure should be based on an unpredictable element rather than a total weather variable. Exposure, in this case, represents the sensitivity of equity return to unexpected temperature and can be measured by a

regression coefficient of equity return on the unexpected weather variable. The study herein refers to an estimate as a 'weather beta'.

Having sought to measure the component of unexpected temperature in the previous chapter, this study utilises those proxies to examine the relationship between each measurement and security returns. The chapter aims to provide the comprehensive empirical evidence of weather exposures, or weather betas, across U.S. companies in three of the most weather influential sectors, as well as examining their economic significance. By measuring the weather betas, it greatly simplifies the estimation of weather exposures in previous literature and gives rise to the possibility of large-scale empirical studies of this subject. Moreover, weather betas are likely to be a key to resolve the puzzle of the market price of weather risk which is now the critical issue in pricing of weather derivatives.

To the extent that this is the first study to define and measure weather exposure based on an unexpected weather element, considering a number of innovative weather factors helps determining if the effects are sensitive to the way of such variables are constructed or not. In addition, an analysis by sector gives a clearer picture of how weather can affect each industry to different extents. The study also provides additional informative results of the absolute weather betas as the magnitude of weather exposure probably matters more than the sign. According to Perez-Gonzalez and Yun (2010), utility firms can potentially gain from hedging weather risks irrespective of the sign of weather betas.

The research has added an analysis on weather exposures between the two sub periods, before and after the arrival of weather derivatives. By doing so, stability of coefficients can be tested and the significance of having weather derivatives in the financial market may be confirmed. Additionally, the study investigates further seasonal impacts. It explores the effects of temperature shocks on firm values during summer and winter time, and examines if these estimates are consistent between the two seasons. Finally, an investigation of market exposure is supplemented to the analysis.

The rest of the chapter is organized as follows. Section 2 reviews previous studies on weather exposures and describes various measurements proposed in the literature. Furthermore, it discusses a promising new methodology in estimating weather exposure, which is parallel to the standard approach of the estimation of exchange rate

exposure. The method is striking because it is in keeping with the sense of the asset pricing theory. This is consistent with other research for macroeconomic exposures in finance. Section 3 explains the approach used in the study in detail and specifies a variety of models that will be tested. Statistical and econometric tests are all addressed in this section, including a stability test and a test for equality of coefficients. Section 4 provides empirical findings on the estimations of weather exposures. The research considers the distribution of firm-level weather exposures within each industry, the stability of those exposure estimates, the seasonal effects and the market exposure to weather surprise. Section 5 discusses the results, acknowledges limitations of the study and suggests further research that may be carried out for greater understandings of the weather exposures. Finally, section 6 provides a conclusion.

5.2 Literature review

Due to limited research of weather risk in finance, the proxy for weather and the approach to measure weather exposure have remained vague. Prior empirical studies have identified various sets of weather-related parameters such as temperature, rainfall and precipitation, depending on the business they are interested in. For the most extensively-researched industry like utilities, researchers have often utilised derived variables such as degree days in their studies. Nevertheless, these previous studies seem to focus on general weather conditions but neglect the importance of unexpected weather. It was argued in the last chapter that total weather variables do not truly represent weather shock. What is needed is an exclusive focus on unexpected elements which relate to a weather risk and can be compensated for in an asset pricing context.

A number of studies over the past decade have investigated the financial impacts of weather but none of these have estimated the exposures on security returns. A handful of studies have suggested measuring weather exposure and making hedging decision by modelling the cash flows of the firms and simulating the impact of weather changes (Dischel, 1999a; Renne and Hatch, 2011).[53] However, this approach is useful only for specific situations and is too complicated to apply to cross-firm comparisons of weather exposures.

[53] This approach is similar to models in the early research discussing exchange rate exposures. Bodnar and Wong (2003) viewed that by using such a method it is difficult to incorporate other complexities into the models and it requires significant amounts of firm-specific information that is usually unavailable outside the firm. Consequently, the method is not easily applicable to a large-scale study of exchange rate exposures.

Elsewhere there have been studies identifying weather exposure as the sensitivity of specific economic measures to changes in weather variables, as reviewed in Chapter 2. For example, researchers have estimated relationships between various weather factors and utility consumptions (Valor et al., 2001; Pardo et al., 2002; Gabbi and Zanotti, 2004), agricultural yields (Lansigan et al., 2000; Chen and Chang, 2005; Schlenker and Roberts, 2006), farm revenues (Mendelsohn et al., 1994), retail sales (Starr-McCluer, 2000) and tourism demands (Correia and Pintassilgo, 2006; Bigano et al., 2005). These studies were focused on specific sectors and particular sets of weather parameters which generally impact firms within an industry. Therefore, those empirical findings were not ideally useful in aggregate setting.

A more recent research of Lazo et al. (2011) is claimed to be the first comprehensive empirical analysis of the sensitivity of the whole U.S. economy to weather variability based on a well-known economic theory and the use of generally accepted quantitative methods of economic analysis. The authors define and measure weather sensitivity as *"…the variability in gross product owing to weather variability, accounting for changes in technology and for changes in the level of economic inputs"* (Lazo et al., 2011, p.712).[54] They use a nonlinear regression analysis to model the relationships between sectoral GSP (gross domestic product by state) and economic inputs of capital, labour, and energy, and a set of weather indicators.[55] The relationships for 48 contiguous states for 11 sectors are estimated, and the study primarily finds that every sector is statistically sensitive to at least one measure of weather variability. Moreover, the mixture of positive and negative elasticity estimates reflects the fact that weather affects each sector differently. Aggregating over all sectors and states, Lazo et al. (2011) show that approximate 3.36% of U.S. annual GDP is exposed to weather variability.

Perez-Gonzalez and Yun (2010) focus on the effect of the use of weather derivatives in energy companies on firm value, investment and financing decisions, but part of their study touches on the measures of weather exposure because firms with higher exposures tend to use weather derivatives for hedging. The authors innovatively

[54] The gross domestic product by state, or GSP, for a sector is total revenue minus total cost for all firms in the sector across the entire state. Note that GSP is a monetary measure, thus the change in GSP may not be apparent if the quantity impacts from weather-related shifts in demand and supply are offset by price changes (Lazo et al., 2011).

[55] A set of weather variables include heating degree days (HDDs), cooling degree days (CDDs), total precipitation and precipitation standard deviation.

introduce two proxies of weather exposure: revenue volatility and weather-induced volatility. While the former proxy captures the total potential to hedge and may include reflections of other confounding variables, the latter one represents the historical volatility of revenue attributable to degree-day variables (HDDs, CDDs and EDDs).[56] The so-called weather-induced volatility can be found by two steps. Firstly, the research estimates the sensitivity of revenue to the quarterly level of a degree-day variable for each firm, in which the regression coefficient is referred to as weather beta. Afterwards, the meaningful weather exposure is obtained by the product of the absolute value of weather beta and the standard deviation of such weather variable.[57] For example, $\left|\beta_i^{EDD}\right| * \sigma_i^{EDD}$ captures the historical weather-induced volatility of revenue that results from energy degree days. The research finds a robust empirical support that firms in the highest weather exposure quartile, irrespective of the risk measure used, exhibit high cash flow sensitivity to changes in weather conditions. Moreover, pre-1997 weather exposure is found to be a strong predictor of weather derivative use after 1997, in that firms in the top weather exposure quartile are two or three times more likely to use weather derivatives after 1997 than the least weather-exposed firms.

In brief, weather exposure is a relatively recent area of study in finance, and empirical support is limited. Most previous studies have focused on specific situations, which is difficult for generalization. Among relevant research, weather risk is significant although its measurement differs from study to study. The research interests have been various, and the scattering of assumptions and methodologies can obstruct the strong foundation of the research strand. Researchers have yet to establish the definition, measurement and standard procedures for the examination of weather exposure in order to encourage more large-scale studies in the subject.

Although the literature suggests that weather risk significantly affects finances of firms through various economic activities, it has yet to identify how these effects translate into changes in securities' returns, in which investors are interested. Most importantly, none of the previous studies has examined the financial effects attributable to 'weather

[56] More specifically, EDDs are energy degree days which are the sum of heating degree days (HDDs) and cooling degree days (CDDs) during the specified period. They measure all deviations from 65°F to capture extreme hot and cold weather conditions.

[57] It is worth noting that the absolute values of weather betas are more informative about the firms' hedging opportunities because energy firms can potentially gain from hedging weather risks irrespective of the sign of those weather betas (Perez-Gonzalez and Yun, 2010).

surprise' on firms, the unexpected element that relates to investment risk in modern portfolio theory. The estimate of firm-level weather exposure is fundamental to making and understanding risk management and other corporate decisions of the firms.

5.3 Empirical methodology

Weather exposure is defined as the sensitivity of the security return to change in weather surprise. It can be estimated by separately running the Ordinary Least Square (OLS) regression of the individual equity return on each of the ten weather measures developed in Chapter 4 and the market return. As unpredictable temperature may affect firms' expected cash flows differently in summer and winter, the seasonal dummy variables are added to the standard model to capture the relationships. The equality of such effects is also examined. In addition, the weather exposure may not be constant over time, especially after the arrival of weather derivatives by which firms can hedge such exposures more effectively, thus the structural break test is also carried out.

This section explains the models and econometric methods employed in the research, and it is divided into three subsections. Firstly, all models are specified. Secondly, the Chow test and the dummy variable approach are explained in order to be used for an assessment of the stability of weather exposures over time. Lastly, the F-test is clarified for the test of equality of seasonal weather betas.

5.3.1 Model specifications

The sensitivity of the security return to weather randomness represents a firm's exposure to weather. Recalling from the equation (3.6), it can be measured by the slope coefficient of the following time-series regression.

$$R_{it} = \beta_{0i} + \beta_{1i} W_t + \varepsilon_{it} \qquad (5.1),$$

where R_{it} is the stock return of company i, W_t is a weather factor, β_{0i} is an intercept, β_{1i} is the elasticity of the security return to weather randomness and ε_i is an error term. The description of weather exposure in this study happens to be similar to Adler and Dumas

(1984 cited in Bodnar and Wong, 2003)'s explanation for foreign exchange rate (FX) exposure.[58]

In reality, the rate of return on the stock is also influenced from a number of economic factors. If we consider all these factors as endogenous to the market and the market portfolio can represent a market condition in general, the alternative model will be as follows.

$$R_{it} = \beta_{0i} + \beta_{2i} R_m + \beta_{3i} W_t + \varepsilon_{it} \qquad (5.2),$$

where R_m is the rate of return on the market index. The weather exposure, β_{3i}, in this case is considered as a market-adjusted weather beta. The market portfolio is included into the model in order to allow for the market movement and any non-weather effects that are spuriously correlated with the weather variable. This is consistent with the well-known asset pricing model such as CAPM, in which includes just a single market portfolio factor.

The model specification in (5.2) is comparable to the typical measurement of FX exposure, whereby the market return is usually included in the regression to control for other sources of systematic risk that are correlated with exchange rates.[59] Bodnar and Wong (2003) stated that the inclusion of the market portfolio dramatically reduced the

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[58] Bodnar and Wong (2003) explained Adler and Dumas (1984)'s intuition as follows. Under the assumption that the market value of the firm is the present value of all future cash flows, the FX exposure is defined as the elasticity of firm value with respect to exchange rate. Given that domestic inflation is non-stochastic, it in turn can be obtained from the coefficient on the exchange rate variable in the following regression:

$$R_i = \alpha_i + \delta_i XR + \varepsilon_i \ ,$$

where R_i is the stock return for firm i, XR is the percentage change in an exchange rate variable defined as home currency price of foreign currency, δ_i is the elasticity of firm value to exchange rate change and ε_i is an error term. The δ_i indicates the total exposure elasticity which comprises of two effects: the average change in the present value of cash flow caused by a unit change of FX and the non FX-related phenomena that affect valuations and are spuriously correlated with FX variable over the sample period. Obviously, a part of the latter effect includes macroeconomic effects that influence the valuation of all firms and investors believe that happen to be correlated with exchange rate. If the correlation of the macroeconomic effects with exchange rate could be modeled, it would be possible to remove the impact from the total exposure estimates. However, previous research has found limited success in identifying these relationships (Bodnar and Wong, 2003).

[59] The model with the market portfolio is preferably used in research relative to foreign exchange risk (e.g. Jorion, 1990; 1991; Allayannis, 1997; Doidge, Griffin and Williamson, 2002; Bodnar and Wong, 2003) and can be described as follows:

$$R_i = \alpha_i + \gamma_i XR + \beta_i R_m + \varepsilon_i \ ,$$

where R_m is the return on the domestic market portfolio, γ_i is the exchange rate exposure elasticity of firm i, β_i is the beta of the firm with respect to the market portfolio.

residual variance of the regression compared with the model without it, and this, to some extent, improves the precision of the exposure estimates. They also noted the often-overlooked fact that the definitions of the exposure coefficients from the two equations, parallel to (5.1) and (5.2), are different. While the coefficient from the model without the market return measures the *total* exposure, the coefficient from the market-adjusted model measures the *residual* exposure.[60] This understanding is critical because the interpretation of a firm having zero residual exposure does not mean the firm is not affected by exchange rate changes as often given in the analysis. Rather, a zero residual exposure implies that a firm has the same exposure as the market portfolio, in case that the market portfolio has a nonzero exposure (Bodnar and Wong, 2003). This fact is useful for the analysis in this study.

To begin the analysis, the impact of weather on stock return can be investigated using the following market-adjusted model.

$$R_{it} = \alpha_{it} + \beta_{MR} MR_t + \beta_w W_t + \varepsilon_{it} \qquad (5.3),$$

where R_{it} is the rate of return on the companies' common stocks as provided by CRSP, MR_t is the rate of return on the CRSP value-weighted market index, W_t is the weather measure under interest, α_{it} is the intercept, β_{MR} is the beta of the firm with respect to the market portfolio, β_w is the weather exposure elasticity or weather beta in this study and ε_i is the error term.[61] It should be remembered that the market portfolio return explicitly controls for market movement, reduces the residual variance of the regression, and to some extent improves the precision of the estimates.

The nature of exposure for a firm may not be the same over the year because its profits rely on a particular character of weather. For example, demand for natural gas has traditionally been highly cyclical due to the higher need for residential and commercial

[60] In foreign exchange risk literature, Bodnar and Wong (2003) pointed out that the coefficient γ_i from the market-adjusted model measures the FX exposure elasticity of the firm as the difference between the firm's total exposure elasticity and the market's exposure elasticity adjusted by the firm's market beta. This is the estimated *residual* exposure elasticity of the firm and it differs from the total exposure whenever the market portfolio has a nonzero exposure to exchange rate.

[61] It is the change in firm *i*'s returns that can be explained by changes in weather surprise after controlling for movements in the market. Similar to the FX literature, see Jorion (1990) and Bodnar and Wong (2000; 2003) for a discussion of why it is important to include the market return in the equation.

heating in winter, thus a gas company's profit and share price should be more exposed to a surprise in winter's temperature than that of summer. Therefore, the sensitivities of firm values to unpredictable weather should be reviewed and compared between different seasons.

Although Perez-Gonzalez and Yun (2010) verify that moderate weather realizations significantly affect operating results, the focus of this study is more on the extreme seasons of summer and winter as the effects are likely to be noticeable.[62] Effectively, weather exposures are now measured in three categories: summer, winter, and mild weather. To investigate these seasonal effects closely, the exposure estimates in different seasons are captured by the following seasonal dummy model.

$$R_{it} = \alpha_{it} + \beta_{MR} MR_t + \beta_{ws} W_t * D_s + \beta_{ww} W_t * D_w + \beta_{wm} W_t * D_m + \varepsilon_i \qquad (5.4),$$

where β_{ws} is the exposure elasticity in summer, D_s equals to 1 for months in summer (June to August) and zero otherwise, β_{ww} is the exposure elasticity in winter, D_w equals to 1 for months in winter (December to February) and zero otherwise, β_{wm} is the exposure elasticity in mild seasons, D_m equals to 1 for the rest of the year and zero otherwise.

Not only are the firm-level exposures investigated, but also the exposure of the market to weather is examined. The market-level exposure can be derived from a univariate regression of the market return on a weather measure, as follows.

$$MR_t = \alpha_t + \delta_w W_t + \varepsilon_t \qquad (5.5),$$

where δ_w is the exposure of the market to a specified weather measure.

As β_w from equation (5.3) accounts for residual exposure, examining the market exposure in equation (5.5) would provide an implication on the total-residual weather effect to some extent. Presumably, movements in unpredictable weather should not economically affect the market return because firms respond differently to warmer or

[62] Perez-Gonzalez and Yun (2010) present significant impacts of mild temperature (low energy degree days or EDDs) on measures of several operating performance, which are natural logarithm changes in revenue, natural logarithm changes in operating income and operating profitability on assets. Mild temperature is indicated by a dummy variable of 1 if the annual EDD values are in the lowest quintile or zero otherwise, for each sample firm.

colder than expectations and the effects are aggregated. If δ_w is not significantly different from zero, then β_w is more or less representing the firm's total exposure to weather.[63]

In addition, the market exposure to weather may be different across different seasons hence seasonal dummy variables are added to the model as follows.

$$MR_t = \alpha_t + \delta_{ws} W_t * D_s + \delta_{ww} W_t * D_w + \delta_{wm} W_t * D_m + \varepsilon_i \qquad (5.6),$$

where δ_{ws}, δ_{ww} and δ_{wm} are the market exposures in summer, winter and mild seasons respectively.

5.3.2 Parameter stability test

The time-series regression may have a structural change in the relationship between the regressand and regressors. This is due to the fact that, at any time during the entire sample period, there may be external or internal forces causing a change in values of parameters of the model. However, the regression of (5.3) contains an assumption that the parameters α, β_{MR}, β_W remain the same for the whole period. This implicit assumption can be tested by using the Chow test. The steps involved are as follows.

1. The regression is firstly estimated over the whole period as in equation (5.3). Splitting the data into two sub-periods, two separate estimations can be done over the two sub-periods (5.7 and 5.8). The residual sum of squares (RSS) for each regression is obtained.

   Period 1: $$y = \alpha_1 + \beta_{MR1} MR + \beta_{W1} W + u \qquad (5.7)$$

   Period 2: $$y = \alpha_2 + \beta_{MR2} MR + \beta_{W2} W + u \qquad (5.8)$$

2. Equation (5.3) is called the restricted regression since the restriction of equal coefficients across the sub-samples has been imposed. The restricted residual sum of squares (RSS_R) is taken from the regression of the whole period. On the other hand, the unrestricted residual sum of squares (RSS_u) is obtained from adding RSS of each regression of the sub-samples (RSS_1 +

[63] Theoretically, weather variables should not correlate with the market. They are truly exogenous variables that are determined by the nature.

RSS_2). The unrestricted regression contains both of each of the sub-samples because two sets of samples are deemed independent.

3. An F-test, which is based on the difference between these RSSs, is formed.

$$\text{F statistic} = \frac{RSS_R - RSS_U}{RSS_U} * \frac{n-2k}{k} \qquad (5.9),$$

where n is the number of observations and k is the number of regressors in each sub-sample.

4. The null hypothesis is that the intercept and slope coefficients are the same across the two periods, $H_0 : \alpha_1 = \alpha_2, \beta_{MR1} = \beta_{MR2}, \beta_{W1} = \beta_{W2}$. If the value of the test statistic is greater than the critical value from the F(*k*, *n-2k*), the null hypothesis can be rejected and the parameters are not stable over time.

The Chow test is basically about how much bigger the restricted RSS is than the unrestricted RSS. If the coefficients do not change much between the two samples, the residual sum of squares will not significantly increase upon imposing the restriction. Generally, the Chow test is useful and easy to generalize to handle more than one structural break. However, it can tell only if the two regressions are different or not, but not the source of such difference. It should also be noted that the assumptions underlying the test are that the error terms in the sub-period regressions are normally distributed with the same variance (homoscedastic) and that they are independently distributed.

As an alternative to the Chow test, one can use the dummy variable to investigate the stability test of a regression model. The key benefit of this approach is an ability to provide additional information, in that one can determine which part of the joint null hypothesis is causing a rejection. This is due to the fact that the significances of the coefficients on the dummy variables can be individually examined by pooling all observations and running just a multiple regression as shown below.

$$y = \alpha_1 + (\alpha_2 - \alpha_1)D_1 + \beta_{MR1}MR + (\beta_{MR2} - \beta_{MR1})D_2 + \beta_{W1}W + (\beta_{W2} - \beta_{W1})D_3 + u, \qquad (5.10),$$

where D_1 equals to 1 for period 2 or 0 for period 1, D_2 is corresponding to value of MR for period 2 or 0 for observation in period 1, and D_3 is the weather risk values for period 2 or otherwise equals to 0.

Estimating (5.10) is equivalent to estimating two individual regression functions (5.7) and (5.8). The coefficients of all dummy variables represent the differential intercept or slope, indicating how much the slope coefficient of the second's function period differs from the first period. Therefore, this single regression can be used to test a variety of hypotheses such as the differential intercept or each differential slope is zero or not. These can be examined by the standard t-test if they are different from zero. For example, if the differential intercept coefficient $\alpha_2 - \alpha_1$ is statistically insignificant, the null hypothesis is accepted that the two regressions have the same intercept.

For a stability test of the entire regression, the hypothesis of simultaneously differential coefficients equals to zero, H_0: $(\alpha_2 - \alpha_1) = (\beta_{MR2} - \beta_{MR1}) = (\beta_{W2} - \beta_{W1}) = 0$, can be tested by the usual F-test. This is similar to the Chow test: the unrestricted RSS is estimated from (5.10) whereas the restricted RSS is obtained by deleting the dummy variables corresponding to that hypothesis. For example, D_2 is deleted if only intercept and weather coefficient are tested for a change.

The focal point of the stability test in this thesis is the change of weather beta. With this respect, the dummy variable approach is appropriate as it can determine the structural stability of the weather beta individually. However, Maddala (2001) gives a warning of stability inferences by looking at *t*-ratios of dummy variables alone. It is possible that the *t*-ratios for all coefficients are insignificant and still the F-ratio for the entire set of coefficients is significant. Therefore, this study pursues both the F-test for the entire regression and the *t*-test for weather beta for more meaningful analysis. Gujarati (2003) also points out another advantage of the dummy method: pooling regression increases degrees of freedom because it includes all observations in one regression. By that, it may improve the relative precision of the estimated parameters.

5.3.3 F-test for equality constraints in models

It is assumed that stock returns in the sample should be more sensitive to change in weather, and possibly weather shocks, in winter than summer because utilities demand peaks during this season, tourists are more sensitive to cold than warm weather conditions and a hard freeze often ends the growing season for crops. Therefore, expected cash flows of these firms should be impacted by weather surprise to a greater extent in winter. It is interesting to test this assumption: whether weather coefficient in

summer and winter have equal effects on a firm value. Referring to the seasonal model in equation (5.4), the null hypothesis is

$$H_0 : \beta_{ww} = \beta_{ws} \tag{5.11}$$

There are several methods for testing for equality of parameters, but this thesis chooses to impose an equality of coefficients to a model and use an *F*-test to test such equality constraint. Firstly, a new dummy variable D_{ws} is created, which is equal to the sum of two previous dummy variables of D_w and D_s. By adding two seasonal dummies together, the estimated effects from both seasons are forced to be equal. Then, a restricted regression can be obtained as follows.

$$R_{it} = \delta_{it} + \beta_{MR} MR_t + \beta_{wws} W_t * D_{ws} + \beta_{wm} W_t * D_m + \varepsilon_{it} \qquad (5.12),$$

where D_{ws} equals to 1 if it is summer or winter, or zero otherwise. For an unrestricted regression where the summer and winter effects are not constrained, it is the same seasonal model as in equation (5.4). Finally, an incremental F-test can be performed by individually comparing the RSSs of restricted (5.12) and unrestricted (5.4) models for each firm in the sample. Again, *F*-statistic can be obtained by:

$$F = \frac{(RSS_R - RSS_U)/m}{RSS_U/(n-k)} \quad \sim \quad \mathrm{F}(m, n\text{-}k) \qquad (5.13),$$

where *m* is the number of restriction (1 in this case), *n* is the number of observations and *k* is the number of parameters in the unrestricted regression. If the null hypothesis can be rejected at 5% significance level, it indicates that the firm faces different weather effects between summer and winter.

5.4 Empirical results

In this section, the empirical results of the weather exposures are presented respective to each weather measure. When repeating the analyses of weather coefficients using ten alternative innovative factors, most of the findings are consistent and these show that the results are insensitive to constructed measures of weather shocks. The section is divided into four parts. Firstly, it discusses the distribution of firm-level temperature exposure coefficients for all weather measures. It should be noted that all estimated

results are subdivided according to industry so as to observe the temperature exposures within each industry and to be able to compare results. It is assumed that utilities should be more exposed to weather surprise than the other industries as the need for hedging weather exposure by weather derivatives emerged from this sector. In addition, the relationship between utility stock returns and unexpected weather is expected to be negative, given that warmer than expected weather would suppress demand in the industry, especially in winter. Unlike utilities, it is predicted that agricultural equity returns should be positively related to weather surprise because warmer conditions should increase crop yields and thus firm revenues in general. Since firms with high weather betas are more exposed to weather than those with low betas, irrespective of the sign, the absolute weather betas are also briefly examined in here.

Following the estimations of firm-level weather exposures, the second part reports a stability of these weather betas before and after weather derivatives emerged. Due to the fact that lengths of data are different among the sample equities, a stability check can be performed on those stocks that have available data in both periods for more than 24 consecutive months. Consequently, the sample size is reduced to only 172 firms within the three sectors. However, it is unlikely that there will be many firms with significant structural breaks and most of the weather exposures should be relatively constant between the two sub-periods. This is because weather derivatives have not been extensively traded until the end of the last decade, and they have yet to be developed further in order to reach every sector. Hence, not all firms in the sample are able to hedge their weather exposures and therefore levels of exposure should not have significantly changed in the second period.

Thirdly, the winter and summer weather effects are closely examined because these effects are supposed to be different between seasons. Presumably, the temperature risk should be more profound in winter than summer for utility companies, for example. This is due to the fact that consumers tend to use less energy if it is a mild winter but may not turn on air conditioners even though the temperature may be hotter than that expected in summer. By using the seasonal dummy model, the summer and winter coefficients are derived and can be compared by F-tests. In brief, this part mainly presents the distribution of firm-level exposures in summer and winter and reports on whether these coefficients are equal or not.

Fourthly, this section provides a partial explanation for the scarcity of studies on the market exposure to weather. Although the market seems to rarely correlate with unpredictable weather, this analysis provides an implication for the total-residual weather exposures of firms.

5.4.1 Distribution of firm-level weather exposure coefficients

The examination begins with the results of the weather exposure estimates for a standard market-adjusted model in equation (5.3), which includes the return to the CRSP value-weighted index as the market portfolio. Similar to the research practice of FX exposure, the market return implicitly controls for the related macroeconomic factors that may correlate with weather measures and therefore the reported weather betas represent the residual exposure of weather. To the extent that weather affects firms differently, the regression is estimated separately for each firm in the sample to obtain firm-level weather exposures. Numerous methods can be used to examine the significance of these coefficients, but this study concentrates on examining their distributions of weather betas and reviewing their absolute values.

Figure 5.1 presents the distributions of the weather coefficients of all equities in the sample: each histogram plots the density of weather betas derived by regressing equity returns on the market return and the different weather measure. A normal curve is also displayed together with a histogram, and it is clear that all distributions with respect to different weather measures are not normal. The area of the two adjacent rectangles representing the values close to zero accounts for much more than half of the observations, which makes a sharp spike in the middle of each histogram. The shape of the graph is similar for all weather measures, in that most weather betas are crowded near zero.

[Insert Figure 5.1 here]

Parallel to the seminal FX research of Jorion (1990), the percentage of weather coefficients that are significant at the 5% and 10% level are examined as a statistical measure of performance, and these distribution results are reported in Table 5.1. Each panel in the table presents results from a different industry, in that several firms in the sample were selected with representative statistical values (firms with minimum, median, and maximum β_w).

[Insert Table 5.1 here]

Panel A presents the cross-sectional weather beta distribution results of 19 agricultural firms and panel B reports those of 208 tourism companies, while panel C covers the results of 257 utility firms. Within each panel, an individual column presents results from a different weather measure. These results are generally aligned, which means empirical evidence is insensitive to the way the weather variables are specified in this study. Although *%W2, %W3* and *%W4* may present higher means and standard deviations of weather betas, the reported numbers of firms with significant weather coefficients are not apparently different from results of the other weather variables. As those measures are constructed similarly in the percentage terms, the magnitudes of weather betas may be different from those of others but the economic significances are similar.[64] Generally, if the independent variable is divided by some non-zero constant, which is *T* in this case, then the OLS slope coefficients are multiplied by such value (Wooldridge, 2009).

Nevertheless, different industries may respond in a slightly different way to each weather measure, in relation to the number of firms with significant weather betas. For example, *%W3* is the measure with the greatest number of significant weather betas in utilities whereas it is insignificant within agricultural sector, where *W5* and its percentage appear to be more effective than other variables in measuring weather exposure. However, a small sample from this industry makes this conclusion less solid. The *%W4* variable seems to stand out in tourism, followed by *W5*. Essentially, the coefficients of variables *%W2* and *%W3* appear to be relatively significant in all industries, even though variables fit differently among them.

Overall, the coefficient signs are plausible in all industries even though they are somewhat ambiguous in tourism. Around two-thirds of agricultural firms show positive weather betas, which means that agricultural companies perform better financially if temperature is warmer than expected, responsive to the prior assumption that crops grow better in warm weather conditions. In contrast, most of the utility firms have negative weather betas: a colder temperature than predicted leads to higher stock returns. Electric and gas companies account for most of the constituents in utilities, and as they experience higher demands and hence more profits if the temperatures are colder

[64] The %W2, %W3 and %W4 variables are scaled by actual temperature of the period to quantify these variables in percentage terms.

than normal, then negative weather betas are not surprising. However, an inconclusive coefficient sign in tourism does not mean it provides an odd result, but rather reflects the complexion of tourism sector. Naturally, tourism contains individual firms, some of which, e.g. ski resorts, may benefit from colder than normal temperatures, while the rest benefit from warmer conditions. Thus, the relationships between weather and equity returns within the industry are difficult to be agreed upon in practice. The standard deviations of coefficients in the industry are approximately double those of agriculture and utilities, and this may confirm the varied nature of businesses within this industry.

Average weather coefficients in utilities are negative whereas those of agriculture and most of tourism are positive. This is not surprising, bearing in mind the reasons explained above. However, all means are small in values around zero, implying that weather randomness slightly explains a variation of equity returns but it does not mean they can be negligible.

The number of firms that are exposed to weather surprise is greater than what can be attributed to chance although the percentage of firms that are exposed is not overwhelming. As expected, this finding is more substantial in utilities, considering that utility firms are so exposed to changing weather that they initially sought protection through weather derivatives. Regarding the obvious results of *%W3*, for example, 30 out of 257 firms (11.67%) find weather betas economically significant at 5% level and 52 firms' betas (20.23%) are statistically different at 10% significance level. In utilities, all weather measures excluding *%W1* exhibit higher percentages of significance betas than what could have been obtained by chance, and most of the significant relationships are negative.

On the other hand, the significant weather betas are less evident in agriculture: most exposures are small relative to their standard errors. However, this does not necessarily mean that the true exposure coefficients are all zero but rather that exposures are imprecisely estimated, specifically relative to the small sample size. In addition, according to Bodnar and Wong (2003), these weather coefficients are considered the residual exposure of firms and they differ from the total exposure whenever the market portfolio has a non-zero exposure to weather. In this sense, the market exposure should be examined before confirming that the agricultural firms' exposures to weather are actually zero. The evidence of market exposure will be reported later in the fourth subsection and more analysis of the firms' total exposures will be offered there.

Of all three industries, agriculture presents the highest magnitude of average weather betas although they are not significant, suggesting that firms in this industry may be more sensitive to unexpected temperature than those from tourism or utilities. This finding is similar to the analysis of Lazo et al. (2010) of sectoral sensitivity to weather. They compare the relative magnitude of impacts among sectors and find that agriculture is one of the most sensitive sectors, possibly because of longer term constraints in decision-making owing to cropping decisions at longer time scales than available weather information (Lazo et al., 2010).[65] Although the variables in this study are not identical to those used by Lazo et al., the implication is more or less comparable. Tourism firms, on the other hand, present the lowest size of average beta: very close to zero. This may indicate that weather risk is more diversifiable in tourism than agriculture: temperature is only one factor in tourists' decision-making, whereas in agriculture it is much more dominant. However, this result may also relate to offsetting values of positive and negative betas. For in-depth analysis, the absolute weather betas within each industry are investigated in the following paragraph.

The assessment of absolute coefficients is appropriate for weather because a firm's exposure to weather depends on the magnitude rather than the direction. For example, firm A with a weather coefficient of -1 would indicate that a 1% warmer than expected temperature leads to a 1% drop in a stock return whereas firm B with a weather beta of 0.5 can predict that a 1% colder than expected temperature will also decrease a stock return by 0.5%. In this case, firm A is considered to be more risky than firm B although the value is less. Thus, two firms with the same size of weather coefficients but a different sign are exposed to the same level of weather risk, but relative to either hotter or colder temperatures than expected. This is different from the general market beta definition, where firms with negative betas are moving against the market and portfolio managers may consider these stocks less risky than those with positive betas. A revision of absolute weather betas would indicate which firms, portfolios, or industries are highly exposed to unexpected weather, regardless of the weather conditions. Similar to the study of Doidge et al. (2002), this study provides an additional examination of the significance of weather coefficients in Table 5.2. The absolute values of each firm's

[65] Results are based on a numerical simulation to derive fitted values of gross domestic product by state (GSP) for each sector and each state, based on 70-year weather variability. They are looking at variations in state and sector GSP that are attributable solely to weather variability while controlling for variability in other economic inputs. See Lazo et al. (2010) for greater explanation.

weather beta and *t*-statistic are aggregated across firms in a given industry over the sample period.

[Insert Table 5.2 here]

Table 5.2 presents the average of the absolute value for all firms' weather betas and *t*-statistics over the sample period. Irrespective of the direction, the average weather coefficients are quite large in all sectors. Interestingly, the average of absolute weather betas for tourism is the highest among the three sectors despite its smallest magnitude from the previous results. This suggests that firms in this sector are highly exposed to unexpected weather but the effects are offset at the level of industry as a whole. However, the standard errors of coefficients are also large, resulting in small *t*-statistics. The last row of the result in each panel reports the average R^2 in regressions (5.3), and these values are small. It seems likely that unexpected weather and the market movement explain only around 10% of variations in stock returns. However, Wooldridge (2009) views that low R^2 in regression equations in the social sciences are not uncommon. It is still possible that they provide good estimates of the *ceteris paribus* relationships between stock returns and market return, and stock returns and weather measure.[66] Moreover, the focus of this research is on estimates of weather risk, rather than the explanation model of stock returns. Thus, the low R^2 is unlikely to be a problem.

5.4.2 Stability of weather betas

For the long sample period of 30 years, any external factor may impact on the extent to which weather randomness influences the value of equity through critical periods of time. In this case, crucial breaks were conceivably extreme weather, an introduction of weather derivative products in late 1997, or when these tools started being traded in the exchange market in 1999. Since damages from extreme weather are covered by weather insurance and hence should not greatly impact on corporate profits, a focus of the study is on the arrival of weather derivatives which offer greater ability to hedge the persistent day-to-day weather risk.

[66] "*A small R-squared does imply that the error variance is large relative to the variance of y, which means we may have a hard time precisely estimating the β_j. But remember….that a large error variance can be offset by a large sample size: if we have enough data, we may be able to precisely estimate the partial effects even though we have not controlled for many unobserved factors*" (Wooldridge, 2009, p.199).

Considering that the length of observations in the sample is unbalanced, choosing a break point will affect the number of samples in each sub-period and, in turn, the statistical results. It should be noted that only the equities with more than 24-month observations in each period remain in the sample for a stability test. As there should be sufficient observations in each period to ensure that inferences from a regression are still valid, the breakpoint is considered carefully in order to keep most of the stocks within the sample as well as to provide a meaningful interpretation for the particular time period. Taking everything into consideration, the year 1998 is assumed to be the point of the structural break because it is roughly when weather derivatives originated and it is also about half of the whole sample period. Most importantly, a satisfactory number of shares are still included in the sample if the break is set there.

The sample consists of 172 shares in which 5 are agricultural, 42 are tourism and the rest are utilities equities. The two sub-periods are from January 1980 to December 1997 and from January 1998 to December 2009. Responding to equation (5.7) and (5.8), regressions of each stock return series are estimated separately for the two periods and they are examined for every weather variable (*W*). With the two regressions, weather betas from the first and second period of the same firm can be compared. Obviously, any changes in a coefficient sign indicate that relationships between equity values and weather shocks have changed after the emergence of weather derivatives and this may signify a structural break. Therefore, a sign check of market-adjusted weather betas has been carried out and reported in Table 5.3.

[Insert Table 5.3 here]

The table indicates the number of equities with a change in sign of weather coefficients from the first to the second sub-period. The values in parentheses represent the number of equities in the sample of each industry, while the values in each column are the reported changes in sign of weather betas for each weather variable. The coefficients of unpredictable temperature appear to change over time as more than half of the samples have an exposure with a different sign in the first and second sub-periods. All weather variables exhibit similar results although *%W1* appears to have relatively few changes compared to other measures. It is interesting to observe that most of these changes are from positive to negative, irrespective of industry. However, these alterations are more profound in utilities. The negative exposure coefficient indicates that, at any time of the

year, a warmer than expected temperature decreases an equity value or a colder than expected temperature increases an equity value.

If weather coefficients are not constant over time, it seems important to test whether changes in these weather betas are significant or not. To investigate the stability, the dummy variable approach according to equation (5.10) is employed and results are presented in Table 5.4.

[Insert Table 5.4 here]

The standard *t*-test is employed to investigate whether the differential slope or coefficients is different from zero, whereas the *F*-test is carried out for the null hypothesis that simultaneously differential coefficients equal zero. Among 172 firms in the sample, the table shows the number of equities where the *t-stat* of coefficients or the *F-stat* is significantly different from zero at the 5% level of significance. Each column contains results from different weather variables, and results are also classified by industry.

Essentially, the structural break in weather coefficients presented in the table is greatly reduced to around one-third of the reported sign changes, and these results are consistent for all weather variables. This may be because most of weather betas are small in value and fluctuate around zero. Insignificant changes then lead to changes in the sign of the coefficients. Consistent with the sign change results, *%W1* appears to have the smallest number of stocks associated with a structural break in weather betas. Additionally, the unstable coefficients are found mostly in utilities. This is possible since utilities companies are the most extensive users of weather derivatives and thus weather exposures can be changed with superior hedging ability.

It is remarkable that market coefficients experience a structural break equivalent to or more than weather betas; however, these breaks are not necessarily from the same equity. Overall, around 19-25% of the samples have unstable coefficients simultaneously, as evidenced by the *F*-test results.

5.4.3 Corporate exposures to weather in winter and summer

Based on the assumption that some firms, especially utilities, are more exposed to cold than hot weather, the seasonal dummy model in (5.4) is estimated for each firm in the

sample to derive firm-specific weather coefficients in different seasons. Figures 5.2 and 5.3 display the distributions of weather exposures in winter and summer respectively. These histograms are similar to those found earlier by the standard model, in terms of the non-normality and a peak in the middle of the graph. However, for the values near zero, the frequencies of the negative bars are higher than the positive bars for all weather measures in both seasons, although the differences are less noticeable for summer coefficients.

[Insert Figure 5.2 and 5.3 here]

For a closer analysis, Table 5.5 illustrates the distributions of weather exposures in winter and summer seasons, for different sectors in each panel. Panel A shows the distribution of weather coefficients from agricultural companies, while panels B and C present results from tourism and utilities firms respectively. Again, representative values from three firms in each industry are reported with *t*-statistics in parentheses. It should be noted that the *t*-stat for median values of tourism firms are omitted due to the fact that the sample size is an even number and so the median is calculated from the middle values between two numbers.

[Insert Table 5.5 here]

Results are similar to those found earlier from the standard model, in which cross-sectional means and standard deviations from variables *%W2, %W3* and *%W4* are exceptionally higher than other factors. The findings are consistent in every weather variable, but any relative discrepancies are assumed to be mainly the result of different methods of measurement.

Agricultural firms report more positive relationships in both seasons, implying that hotter than expected temperatures increase share values in both summer and winter. Cross-sectional means are positive in both seasons but the values are rather small. There is less empirical support for significant weather coefficients in this industry in both seasons.

In contrast to agricultural firms' exposures, strong negative relationships between weather and share values remain present in the utilities sector, especially in winter. In addition, cross-sectional means are all negative except for *W4* in summer; however, the positive value is very close to zero. A number of significant weather betas in winter are

evidently higher than those of the standard model. Nearly 20% of the samples find the winter betas statistically significant at the 10% level: on average, 45 out of 257 weather coefficients are significant across weather factors. This is obviously more than can be attributed to chance. Among the significant coefficients, the majority show the negative sign. Even though the weather effects are marked in winter, unfortunately little evidence is found in summer. However, this is what to be expected because demand for utilities in summer is usually less than that in winter; thus, randomness in temperature during the period should marginally affect corporate profits and share values. It should be noted that the variables *W2, W3* and their percentages are still among the best representatives of weather randomness in terms of the highest numbers of significant betas found by using them in the model.

Tourism firms are distinct from the other industries in that a majority of weather beta signs are different between the two seasons. While there are more positive weather betas in winter, more negative weather betas in summer are found. Accordingly, means are positive in winter, whereas most are negative in summer. It seems that firms relying on winter weather will benefit if it is a warm winter, and *vice versa*. This would suggest that tourists prefer weather that is neither too cold nor too hot. To some extent, seasonal variables can separate groups of firms that rely on different seasons and the results clarify the earlier puzzle why coefficient signs in the industry are inconclusive. With the seasonal dummy model, a greater number of firms in the sample experience significant weather coefficients, especially in winter. However, it should be kept in mind that this sector is considerably diverse in structure and likely to have heterogeneity of weather effects even within the specific seasons or regions. There has been very limited evaluation of the extent to which weather information is being integrated into the tourism industry.

In general, the seasonal dummy model provides a clearer analysis, as the exposures are allowed to vary across different seasons. The fitness of the models, R^2, slightly improves to around 13%, but these predictive powers are still low. There are more significant winter exposures than summer exposures across sectors, and results are more apparent in utilities. One interesting discovery is that the summer exposures of firms in tourism seem to be more evident than those in the other two sectors. This may suggest that the weather effects are still important for this industry in summer: summer holidays

are also exposed to weather randomness, even though the impacts are less than for winter holidays.

While the distributions of exposures seem different between summer and winter, it is more reliable to pursue *F*-tests for testing the equalities of these coefficients. After imposing a restriction to the model, Table 5.6 presents the number of regressions that cause a rejection of the null hypothesis that a weather beta in summer is equal to a weather beta in winter.

[Insert Table 5.6 here]

Basically, weather coefficients are likely to be equal in both seasons even though the weather effects seem to be more profound in winter, based on the previous analysis. Around 9 to 14 firms indicate a strong rejection for the equality of seasonal betas, for most of the different weather measures. However, the variables *%W1* and *%W5* shows noticeably higher numbers of stocks, 22 (4.5%) and 28 (5.8%) of the sample respectively, with more unequal weather coefficients than the other factors. Both of them, however, are very similar in the way they are constructed and in the way they differ from others in terms of their scaling.

In brief, there is less empirical support that the weather betas of sample firms are not the same between seasons. Fewer than 5% of total samples experience a non-equality of weather betas between winter and summer seasons, and this may be attributed to chance. Agricultural companies do not have evidence for different weather coefficients in winter and summer, in accordance with the results from the previous findings. Generally, results found here contradict a prior assumption of different weather exposures between seasons. This may be because the exposures here are based not on total weather but on unpredictable weather, which is less volatile across seasons. Hence, small fluctuations in surprise weather conditions may not lead to a great difference in weather exposures between seasons.

For every OLS regression, a Durbin-Watson test is carried out to trace for autocorrelation in residuals, and results are reported in Table 5.7. Values in each column represent the number of regressions that reject the null hypothesis of no autocorrelation at 5% level. Results of a standard market-adjusted model are presented in Panel A whereas those of a seasonal dummy model are shown in Panel B.

[Insert Table 5.7 here]

Overall, regressions with seasonal dummy models are better specified in terms of serially uncorrelated residuals. Around 13% of samples yield significant Durbin-Watson statistics in the standard model, and the numbers are slightly reduced in the seasonal dummy models. All weather variables exhibit very similar results of autocorrelation in residuals. For a closer investigation, these serially correlated residuals are mostly from the same equities no matter what weather measures have been tested.

5.4.4 Market exposure to weather

Although several empirical studies argued that the stock market performance is psychologically derived by weather conditions (Saunders, 1993; Hirshleifer and Shumway, 2003; Kamstra et al., 2000; 2003), this research primarily assumes that the fundamental association between surprise in temperature and the market portfolio return will be trivial due to the aggregated effect. In essence, unexpected temperature should financially impact each company's expected cash flow differently, either the magnitude or direction. On the whole, these impacts should be compensated across firms and the market exposure should be insignificant.

This part attempts to provide an empirical economic explanation of the market exposure to unexpected weather, which can be derived by regressing the monthly market return on an individual weather factor. Table 5.8 reports the estimated coefficients from the standard model (5.5) in panel A, coupled with the seasonal model (5.6) in panel B.

[Insert Table 5.8 here]

As expected, the empirical evidence shows that weather surprise seems to have little impact to the market portfolio in both models for all weather measures. In the standard model, the relationships between market and weather surprises are positive, except for %W1 factor, but very small compared to their standard errors. They are all statistically insignificant.

For the seasonal dummy model, the market exposures are mostly negative in summer and positive in winter. It signifies that the market return increases if it is a warm winter or a cold summer, possibly suggesting that not too extreme weather conditions relates with the positive returns. However, the sizes are similar to those found earlier in the

standard regressions, which makes these coefficients not significant at 5% level. Although R^2 for the seasonal dummy models are higher than those of the standard models, they are all considered exceptionally low. This suggests that both models neither fit well nor sufficiently explain the market returns. Generally, the variation in unpredictable weather can explain less than 1% of the movement in market returns.

The findings in this study are opposed to those of the literature in behavioural finance because weather measures are different. While the previous studies have focused on the effects of overall weather conditions on investors' moods and their trading strategies, this research emphasizes on the financial effects of unpredictable weather on equity returns through the fundamental impacts on firms' expected cash flows.

In the market, each company economically and financially reacts to a different extent to the weather surprise, and the estimated coefficient is the exposure predicted for individual corporate finance. At the aggregate level, the market exposure to weather may be less evident as the effects are offset across firms in the market: for example, a utility firm gains more revenues in a cold winter, whereas an agricultural company may experience less crop production and profits. Nevertheless, the estimate of market exposure is not the focus of this research. The important point here is that, in case that the market portfolio has a nonzero correlation to weather, controlling for the large changes in market exposure will be an important issue when estimating firms' exposures to weather over longer sample periods.

The estimated market coefficients are tested for stability by using the Chow test between the period before and after 1998, similar to what were tested on individual firms. For all regressions of the standard model, the statistics cannot reject the null hypothesis that there is no break at a specified breakpoint. However, regressions of the seasonal model present more varied results. While results by most of the weather measures show that there appears to be a structural change in the relationship between the market return and the weather surprise during two sub-periods, the tests by *W4* and *%W4* variables cannot reject the null hypothesis. Residual tests of both models indicate that all residuals are not heteroskedastic, autocorrelated and normal.[67] It is worth mentioning that the finding of insignificant market exposures here suggests that the

[67] The results of Durbin-Watson statistics in residual diagnostics are indecisive zone and we cannot either accept or reject the null hypothesis of no autocorrelation. Therefore, serial correlation LM tests have also been used to test residual autocorrelations up to lag 2.

firms' weather exposures found in this study represent total exposures of companies attributable to unpredictable weather. This is possible because weather is truly exogenous to the market, thus non-weather related phenomena should neither spuriously correlate with weather nor confound the interpretation of these estimates. Therefore, the weather coefficient in this study can be interpreted as the average change in the present value of cash flow caused by a unit movement of unexpected temperature.

5.5 Discussion and further research

Although theory and limited empirical evidence do not provide explicit guidance on how to measure weather exposure, this chapter proposes a simple approach based on generally accepted economic theory, agreeable to an objective. The market-based estimate of weather exposure is promising to uncover the firms' financial effects attributable to changing weather conditions. Fortunately, this methodology is a close parallel to the investigation of economic exposures such as foreign exchange rate (FX), in which the research strand has long been developed.[68] This well-accepted approach brings a more standard method, on the large-scale level, to the weather risk literature as well as alleviating the discovery of empirical weather exposure and market price of weather risk consistent with the asset pricing theory. Furthermore, by making the approach consistent with the measurements of economic exposures it is now feasible to compare the empirical results of weather sensitivity with those of macroeconomic measures which have already been extensively studied in the literature. Nevertheless, interpretations must be formed with care, as the scale of estimated weather betas is different from other coefficients, such as the firm beta, due to the fact that the units of measurements of weather are not returns.

Examining the exposure on an expansive industry level is potentially problematic as changes in weather may lead to offsetting effects on different firms within an industry. To address this concern, the research basically examines the exposure of individual firms to weather and reports the regression results by industry. As such, the distributions

[68] FX risk literature has long been developed; thus, there has been a large body of literature and the typical approach in literature has been firmly established. As a result, some common methodologies used in the examination of FX exposures could be applied for the study of weather exposures later. A large body of literature in FX exposure appears to be a cornerstone for the growth of studying weather risk in finance. Researchers can rationally adopt the research designs and methodologies from FX exposure examinations for implementing the weather-related study in finance. A reconciliation of FX exposure framework in weather risk literature should establish agreeable methodologies and motivate more studies of this subject.

and economic significances of weather betas are revealed both within- and between-industry. However, while the firm-level weather-related exposures may benefit a firm's activity such as hedging, a portfolio manager, who holds a diversified portfolio, may be interested more in whether the change in unexpected temperature affects the returns on certain groups of stocks more than others. Therefore, in the future, the results can be re-examined by measuring the effects grouped by specific classifications such as firm size, level of *ex-ante* weather exposure and location.

This study appears to be in the vanguard in this area and the initial results are relatively appealing, as the number of firms that are exposed to weather surprise is greater than can be attributed to chance, especially in utilities. In addition, most of the results are in line with prior assumptions; for example, the sign and relative magnitude of weather betas among industries. The average cross-sectional weather coefficients for industries in this thesis are relatively small compared to the sectoral sensitivity to weather analysed by Lazo et al. (2011), in which, for example, agriculture's GSP is largely sensitive to weather variability at 12.1%. In contrast, this research finds only small magnitudes of agricultural firms' coefficients and they are rarely significant. Nonetheless, both Lazo et al.'s and this study, although similarly aiming to measure weather exposures, are based on different approaches and parameters. Therefore, it is unsurprising to find inconsistent results. In addition, the sample of agricultural firms in this study is rather limited; in consequence, the results may be imprecisely estimated. Thus, the empirical evidence in this study contradicts the common assumption that agriculture is highly exposed to changing weather conditions.

It should be reminded that this thesis measures a firm's exposure to weather based on unexpected temperature variables, rather than weather conditions at any time.[69] This feature is unique when compared with the little previous research related to weather exposures; hence, the study lends support to an under-researched area of the literature. The findings should also be of interest to individual firms seeking to effectively hedge their weather risk and to policy makers who wish to understand the impacts of unpredictable temperatures on certain sectors of the economy during different seasons.

[69] For example, while crop yields rely on temperatures, they may not be largely influenced by unpredictable temperatures.

Incidentally, the analyses of exposures in this study are conducted without knowledge of hedging positions taken in a firm's derivative portfolio; thus, the estimated weather exposures may not be close to the real exposure levels. The use of weather derivatives may reduce exposures; however, one cannot assume perfect hedging.[70] In addition, given that the weather derivatives were introduced in late 1997 but have gained momentum since 2003, not all companies during the sample period have used weather derivatives. Therefore, it seems reasonable to conclude that a lack of hedging data is not likely to be a large concern.

The empirical findings in this thesis are only the initial step towards an understanding of weather exposures as the limited set of weather variables are included and the approach is very straightforward. Future research could be carried out in a number of ways. The first and probably easiest way may be to extend this study across sectors, weather parameters, space and time.[71] Lazo et al. (2011, p.718) suggest that, *"...given the magnitude of weather sensitivity across sectors of the U.S. economy, there is most likely significant economic potential to mitigate weather variability impacts in many sectors that are not conventionally considered to be as weather sensitive as agriculture."* To this end, the expansion of the research to less weather-sensitive sectors should reveal sectoral impacts and determine complementary sectors. By so doing, it is practically useful for both hedgers and investors.

For weather measures, researchers can explore other weather parameters as well as developing other appropriate proxies for 'unexpected' components of weather. Although temperature apparently impacts on almost every line of business and extensively underlies weather derivatives, Lazo et al. (2011) find that variation in precipitation tends to have a larger impact on GSP than temperature. Therefore, exploring weather exposures using other parameters would convey more robust results. The system of weather is also inter-related and can influence financial results through multiple channels. This fact makes weather exposures typically challenging. Similar to what Renne and Hatch (2011) present as an example web of relevant correlations for

[70] Hedging is subject to basis risk as the traded weather indices may not perfectly track the firms' weather exposure. On the other hand, to minimize basis risk, OTC derivatives may lead to higher transaction costs and credit risk exposures (Perez-Gonzalez and Yun, 2010).

[71] The FX literature is rich as researchers have examined the variation of FX exposures across countries (Bodnar and Gentry, 1993; Muller and Verschoor, 2006; Doidge et al., 2002), time (Bodnar, Dumas and Marston, 1998; Allayannis, 1997), and model structures (Bodnar and Wong, 2003).

summer conditions in Alberta, it is encouraging to find a vector of weather-related variables in empirical work. However, this clearly requires intensive modelling and is difficult to achieve in practice, especially for cross-sectional research.

In the past, a relatively large share of economic research on the impacts of weather on firms was devoted to specific locations due to different weather in distant areas. More large scale research, however, including this investigation, fails to take account of location effects. Although there may be significant local effects, once these are aggregated the effect may be negligible. A lack of data on regional activities of sample firms restricts ability to investigate location effects, and future research should take this issue into account. Likewise, lengthened sample period in the analysis could have changed the initial results if the additional years represented significantly different weather than during the previous period. Future studies could focus on different time periods and horizons, as well as investigating sub-periods in a finer time scale in order to detect the change of coefficients over time.

Secondly, researchers may consider other choices of the market portfolio. As Bodnar and Wong (2003) found that the choice of market portfolio in the FX exposure regression directly impacts the size and the interpretation of the resulting exposure estimates, changing the market portfolio in the weather risk study may yield different results.

Thirdly, the current study only considers the contemporaneous effects of weather on equity returns. In view of the fact that it may take some time for investors to realise these effects through changing expected future cash flows of the firm, the future model may include the lagged weather variables.[72] In addition, one problem in modelling the relationship between weather and stock return is that it may be too simplistic to assume that weather randomness has a linear and constant impact on firm value. Doidge et al. (2002) addressed a similar concern with FX exposure in their study, and they proposed a method to examine exposures without assuming a linear or constant exposure relation

[72] It is interesting to acknowledge that some studies in FX risk have found an insignificant FX risk using contemporaneous exchange rates but a strong evidence of a lagged relation (Amihud, 1994; Bartov and Bodnar, 1994). In that case, it suggests an exploitable mispricing of FX risk. By the same token, a lagged effect of unexpected weather may be significant in explaining variations in stock returns.

by forming different portfolios which can be updated over the sample period.[73] However, in order to effectively form portfolios for a comparative analysis, sources of differential weather exposures should be formerly identified.

Then, the fourth avenue for further research is to examine the determinants of weather betas, which may take similar approaches to those used for testing sources of differential FX exposures.[74] Given that corporate size indicates the level of operation which is subject to change in weather, large firms' expected cash flows may be more exposed to weather surprise than smaller firms. To the extent that size proxies for a firm's operational levels, it may function as one of the determinants of weather exposure. Additionally, a recent study by Perez-Gonzalez and Yun (2010) shows that weather derivatives lead to higher market valuations of firms. Therefore, a potential determinant of weather exposures may also include the corporate hedging position. Alternatively, since weather is a natural variable and truly exogenous to the market, the sources of differences in exposure may not necessarily be economic indicators, as is the case with location. Owing to the fact that weather patterns in distant geographic areas differ, location is likely to determine the extent to which weather surprise affects corporate profits. The location effects may be captured by matching the firms' main business site to regional dummy variables.

Lastly, in light of the findings in this study, the existence of weather exposures presents an interesting research question: how is the exposure priced in the equity market? The question leads to a final suggestion regarding further research: this relates weather to an asset pricing context. In theory, investors should be compensated for investing in firms whose equity returns are correlated with pervasive risk factors, of which, according to the findings of this study, weather appears to be one. Testing whether weather exposure

[73] Doidge et al. (2002) formed different portfolios with high and no international sales and then computed the average returns of portfolios during periods of appreciating and depreciating currency movements. In that way, they were able to analyze FX exposures without assuming a linear or constant exposure relation.

[74] Researching into the determinants of exposures provides greater understandings of the risks. For example, in case of FX risk, Jorion (1990) examined the sources of the differential effects of FX exposure in U.S. multinational firms. It was shown that the level of foreign sales is the main determinant of exchange rate exposure. Following the Jorion's publication, many studies have attempted to identify the determinants of FX exposure. For example, several studies have related the nature of exposure to firm size, provided that large firms have more foreign activity relative to small firms and thus they may have more exposures (e.g. Bodnar and Wong, 2000; 2003; He and Ng, 1998; Doidge et al., 2002). Other motivating determinants include net foreign revenues (Marston, 2001), export ratios (Nydahl, 1999; Doidge et al., 2002), and industry markup and competition (Allayannis and Ihrig, 2001).

is one of the pricing factors in an asset pricing model is strong motivation for future research.[75]

5.6 Conclusion

It is believed that weather risk is pervasive and difficult to insure against or diversify. A number of studies have found that weather risk is a major source of fluctuations in cash flows of weather-exposed firms; however, there is a lack of evidence in the literature of the impacts on the expected cash flows and firm values. Due to an absence of previous empirical work and discrete methodology, this research suggests an alternative approach to investigate the magnitude and economic significance of weather exposures, parallel to the method which has long been established for the examination of FX exposures.

Providing ten measures of unpredictable temperature from Chapter 4, the analysis starts with the estimations of weather exposures for individual firms over the sample period, and the distributions of those estimates are reported by industry for each weather variable. Overall, the unconditional analysis of individual firms indicates that the average exposure coefficients are small in magnitude but the number of firms with significant weather betas is more than attributable to chance, especially in utilities. The direction of the effects is as expected for the majority of the firms in both agriculture and utilities, in that they are positive and negative respectively. This means that higher than normal temperatures would benefit agricultural firms and increase their returns, while deteriorating the expected cash flows of utility companies. On the other hand, tourism provides mixed results due to the fact that the nature of business is more diverse than the other two sectors. Interestingly, all weather measures show similar findings but the magnitude of weather coefficients for *%W2*, *%W3* and *%W4* variables are obviously larger than the others, possibly due to their scaling. This suggests that the interpretation must be considered with caution because of the scale effect, particularly when comparing the estimated weather betas with other economic coefficients.

[75] This is also parallel to the research strand in FX risk, where the existence of exchange rate exposure has led to an interesting question of whether the FX risk is priced in domestic equity markets. In theory, exposure to exchange risk factor should yield a risk premium if the effects of currency risk do not vanish in a well-diversified portfolio (Carrieri and Majerbi, 2006). Also supported by empirical evidence of deviations of purchasing power parity (PPP), research in FX pricing has grown and introduced international asset pricing models that explicitly include FX exposure as a pricing factor. The prevailing literature include those of, for example, Solnik (1974), Adler and Dumas (1983), Jorion (1991), Bekaert and Harvey (1995), Ferson and Harvey (1991; 1993), Choi, Hiraki and Takezawa (1998), Chang et al. (2005) and Carrieri and Majerbi (2006).

In evaluating the absolute beta, it is found that the magnitudes of the average exposure coefficients are quite large. Although the averages of absolute weather betas vary across sectors for each measure, results from the ten weather measures are still consistent. Tourism presents the highest magnitudes in average absolute weather betas, in contrast to the previous result of average coefficients. This confirms the diversity of firm exposure to weather within the industry that is confounded at the industry-wide level. It seems that firms in tourism are actually highly exposed to unexpected temperature, resulting in either positive or negative movement of equity returns.

The weather coefficients are evaluated for stability after the introduction of weather derivatives, given that these tools possibly provide shields for weather exposures. Almost half of 172 firms, which appear during the time both before and after the arrival of weather derivatives, experience a change in sign of their coefficients. Nonetheless, the two-third of these changes is not statistically significant. It is possible that the betas are actually small in magnitude and fluctuate around zero, rather than showing a structural break.

This study has investigated firm exposures to weather further into summer and winter. The findings are consistent with the earlier results of the standard model. Specifically, it is revealed that most of the significant weather exposures in every sector are discovered in winter time. This finding resolves the earlier puzzle about the inconclusive sign within a tourism sector, in that the coefficient means are in fact positive in winter but negative in summer. For utilities, strong negative relationships between weather and stock returns remain presents, and the effects are obviously stronger in winter. Although the number of firms with significant weather exposures in winter is substantially more than that in summer, less than 5% of the total sample find a non-equality of weather betas between these two seasons.

Finally, the market exposure has been found to be small and insignificant, which is possibly due to the offsetting weather effects at the aggregate level. This finding implies that the weather betas identified earlier may already represent total firm exposure to weather. The little association between the market and weather is not surprising, although it contrasts with evidence in behavioural finance literature. As opposed to the previous literature, the focus of this study is essentially on the impacts of weather surprise, rather than weather condition, on expected cash flow that potentially affect the stock price.

By and large, this chapter provides evidence that unexpected temperature do affect equity return consistent with the prior assumptions and that the number of firms that are exposed to weather surprise is greater than what can be obtained by chance. The consistency of findings across ten weather measures, to some extent, verifies that these results are robust. However, this study is only the first step towards the understanding of weather risk and further research can be conducted in a number of ways. The finding in this study that unpredictable weather broadly affects groups of stocks has a direct implication in asset prices, as it is possible that weather risk can be priced. Although weather insurances and weather derivatives are available tools for the diversification of weather exposures, it is still difficult and costly for firms' risk management teams to entirely hedge the risks of persistent day-to-day weather fluctuations and climate change. As a result, weather risk theoretically will be priced and the next chapter will investigate into this matter.

Table 5.1 : Distribution of β_w for U.S. firms, Jan 1980- Dec 2009

A market-adjusted regression model,

$$R_{it} = \alpha_i + \beta_{MR}MR_t + \beta_w W_t + \varepsilon_{it},$$

is estimated individually for each firm in the sample to obtain its weather sensitivity. The table displays the distribution of these weather coefficients, β_w, for 484 firms from three industries in each panel. Panel A reports results from 19 agricultural firms, while Panels B and C present the findings of 208 tourism firms and 257 utilities companies respectively. In each industry, three firms were selected with representative values for the cross-sectional distribution, with *t*-statistics in parentheses. These three representatives are the minimum, median and maximum weather betas within the industry. The numbers of positive and negative weather coefficients are reported, as well as those of the significant coefficients. Each column represents results from a different weather measure for comparison, bearing in mind that each of them is constructed by a particular method and thus probably different in scaling.

A. Agriculture

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
Minimum	-0.0144	-0.0157	-0.0167	-0.0190	-0.0185	-0.0388	-0.3159	-0.3329	-0.6011	-0.0376
	(-0.61)	*(-0.66)*	*(-0.73)*	*(-0.79)*	*(-0.84)*	*(-0.78)*	*(-1.39)*	*(-1.59)*	*(-0.69)*	*(-0.56)*
Median	0.0013	0.0020	0.0006	0.0011	0.0026	0.0050	0.1189	0.0646	0.0774	0.0046
	(0.18)	*(0.28)*	*(0.14)*	*(0.26)*	*(0.63)*	*(0.71)*	*(0.27)*	*(0.35)*	*(0.44)*	*(0.62)*
Maximum	0.0171	0.0181	0.0289	0.0725	0.0227	0.0584	0.6794	0.9119	2.7458	0.0572
	(0.97)	*(1.04)*	*(0.81)*	*(1.51)*	*(1.35)*	*(0.85)*	*(1.08)*	*(0.68)*	*(1.51)*	*(1.09)*
Cross-sectional mean	0.0023	0.0027	0.0018	0.0040	0.0016	0.0040	0.1037	0.0674	0.1667	0.0026
Cross-sectional SD	0.0077	0.0082	0.0098	0.0185	0.0096	0.0202	0.2760	0.3232	0.6922	0.0203
Observations	19	19	19	19	19	19	19	19	19	19
Positive	13	12	10	11	12	12	11	11	11	11
Negative	6	7	9	8	7	6	8	8	8	8
Significance at 5% level	0	0	0	1	1	0	1	0	1	1
				5.06%	5.26%		5.26%		5.26%	5.26%
Positive	0	0	0	1	1	0	1	0	0	0
Negative	0	0	0	0	0	0	0	0	1	1
Significance at 10% level	2	2	2	1	2	0	1	0	1	2
	10.53%	10.53%	10.53%	5.26%	10.53%		5.26%		5.26%	10.53%
Positive	2	2	1	1	2	0	1	0	0	1
Negative	0	0	1	0	0	0	0	0	1	1

Note—*t*-statistics are in parentheses.

B. Tourism

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
Minimum	-0.0666*	-0.0625	-0.0612	-0.0518	-0.0486	-0.1700	-2.9558*	-2.3418	-0.6011*	-0.1318
	(-1.69)	*(-1.59)*	*(-1.06)*	*(-0.74)*	*(-0.90)*	*(-1.51)*	*(-1.78)*	*(-1.19)*	*(-1.75)*	*(-1.33)*
Median	0.0000	0.0003	0.0004	0.0005	-0.0002	0.0000	0.0159	0.0279	0.0774	0.0003
Maximum	0.0498	0.0521	0.0708**	0.075***	0.0580*	0.1142*	2.421***	2.8048*	2.746***	0.0971**
	(1.51)	*(1.61)*	*(2.06)*	*(2.86)*	*(1.82)*	*(1.78)*	*(3.02)*	*(1.81)*	*(3.34)*	*(2.36)*
Cross-sectional mean	0.0002	0.0008	0.0124	0.0029	0.0005	-0.0007	0.0408	0.0615	0.1230	-0.0011
Cross-sectional SD	0.0147	0.0149	0.0156	0.0175	0.0141	0.0291	0.6175	0.6533	0.7451	0.0232
Observations	208	208	208	208	208	208	208	208	208	208
Positive	104	111	108	116	102	103	109	115	117	106
Negative	104	97	100	92	106	102	99	93	91	102
Significance at 5% level	11	10	11	10	12	8	13	10	13	8
	5.29%	4.81%	5.29%	4.81%	5.77%	2.40%	6.25%	4.81%	6.25%	3.85%
Positive	6	7	7	8	8	5	9	7	11	5
Negative	5	3	4	2	4	3	4	3	2	3
Significance at 10% level	20	18	18	21	21	13	20	20	21	19
	9.62%	8.65%	8.65%	10.10%	10.10%	6.25%	9.62%	9.62%	10.10%	10.89%
Positive	11	11	14	15	14	6	13	13	14	9
Negative	9	7	4	6	7	7	7	7	7	10

Note—*t*-statistics are in parentheses. * Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

C. Utilities

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
Minimum	-0.0685	-0.0699	-0.0596	-0.0792	-0.0634	-0.1038	-4.551**	-4.0444*	-5.0416*	-0.121**
	(-1.60)	*(-1.63)*	*(-1.32)*	*(-1.45)*	*(-1.65)*	*(-1.60)*	*(-2.22)*	*(-1.85)*	*(-2.06)*	*(-2.59)*
Median	-0.0012	-0.0013	-0.0011	-0.0008	-0.0081	0.0000	-0.0512	-0.0441	-0.0333	0.0000
	(-0.60)	*(-0.87)*	*(-0.82)*	*(-0.39)*	*(-0.70)*	*(0.00)*	*(-0.74)*	*(-0.71)*	*(-0.54)*	*(-0.03)*
Maximum	0.0363	0.0411	0.0532	0.0463	0.0405	0.0668	1.5485	1.9055	1.8507**	0.0538
	(0.88)	*(1.00)*	*(1.31)*	*(1.09)*	*(1.01)*	*(0.69)*	*(1.07)*	*(1.37)*	*(2.38)*	*(0.60)*
Cross-sectional mean	-0.0021	-0.0021	-0.0018	-0.0017	-0.0017	-0.0025	-0.0988	-0.0873	-0.0928	-0.0013
Cross-sectional SD	0.0092	0.0093	0.0090	0.0107	0.0086	0.0154	0.4400	0.4186	0.4999	0.0130
Observations	257	257	257	257	257	257	257	257	257	257
Positive	81	80	85	100	95	84	69	83	93	127
Negative	176	177	172	157	162	108	188	174	164	130
Significance at 5% level	24	25	30	13	24	12	29	30	17	14
	9.34%	9.73%	11.67%	5.06%	9.34%	4.67%	11.28%	11.67%	6.61%	5.45%
Positive	2	2	4	5	7	2	3	5	7	7
Negative	22	23	26	8	17	10	26	25	10	7
Significance at 10% level	38	42	43	34	38	17	51	52	39	28
	14.79%	16.34%	16.73%	13.23%	14.79%	6.61%	19.84%	20.23%	15.18%	10.89%
Positive	5	5	8	14	9	3	8	11	13	12
Negative	33	37	35	20	29	14	43	41	26	16

Note—*t*-statistics are in parentheses. * Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

Table 5.2: Analysis of absolute weather coefficients, $|\beta_w|$

The table presents the averages of the absolute values for all firms' weather betas and *t*-statistics, from the market-adjusted model, $R_{it} = \alpha_i + \beta_{MR}MR_t + \beta_w W_t + \varepsilon_{it}$, over the sample period. Each panel represents a specific industry within the sample. An exposure coefficient with an absolute value of one would indicate that a one unit movement in unexpected temperature leads to a one per cent positive or negative movement in equity returns. The last row of the results in each panel reports the average R^2 from all regressions within the industry.

	W1	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
A. Agriculture										
average absolute beta	0.0058	0.0063	0.0069	0.0097	0.0071	0.0138	0.2284	0.2471	0.3695	0.0139
average t-stat	0.7405	0.7654	0.7443	0.7429	0.8349	0.6567	0.7892	0.8239	0.8192	0.8062
average R-squared (%)	8.40	8.44	8.52	8.93	8.47	8.41	8.58	8.73	9.24	8.64
B. Tourism										
average absolute beta	0.0098	0.0099	0.0103	0.0117	0.0094	0.0185	0.4076	0.4236	0.4849	0.0144
average t-stat	0.8166	0.8315	0.8181	0.8220	0.8531	0.7514	0.8528	0.8319	0.8259	0.7637
average R-squared (%)	12.46	12.51	12.46	12.56	12.64	12.27	12.60	12.53	12.57	12.38
C. Utilities										
average absolute beta	0.0046	0.0046	0.0046	0.0051	0.0042	0.0074	0.1944	0.1897	0.2092	0.0063
average t-stat	0.9400	0.9627	0.9528	0.8892	0.8903	0.6109	1.0094	0.9871	0.9073	0.7987
average R-squared (%)	11.81	11.82	11.78	11.73	11.69	11.60	11.99	11.92	11.83	11.54

Table 5.3: Sign change of β_w from 1980-1997 to 1998-2009 period

The weather coefficients are investigated if they are stable over time. A breakpoint is set around the time weather derivatives have emerged, by the end of 1997. Then, two separate regressions from each sub-period are estimated to obtain market-adjusted weather betas for each firm, and a sign of weather betas before and after 1998 can be compared.

The table reports the number of equities with a change in sign of weather coefficients from the first to the second sub-period. The values in parentheses represent the number of equities in the sample of each industry while the values in each column are the reported changes in sign of weather betas for each weather variable. It should be noted that the sample size of this examination is reduced to 172 equities because some stocks do not have sufficient observations for valid inferences in a sub-period.

	W1	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
UTILITIES (125)										
positive to negative beta	61	56	57	61	68	28	56	58	65	69
negative to positive beta	13	8	7	9	7	8	6	6	8	8
total changes	***74***	***64***	***64***	***70***	***75***	***36***	***62***	***64***	***73***	***77***
AGRICULTURE (5)										
positive to negative beta	1	2	2	1	2	1	3	3	2	2
negative to positive beta	0	0	0	2	0	0	0	0	2	0
total changes	***1***	***2***	***2***	***3***	***2***	***1***	***3***	***3***	***4***	***2***
TOURISM (42)										
positive to negative beta	13	13	10	9	14	13	14	7	11	13
negative to positive beta	10	10	7	6	10	11	8	7	7	9
total changes	***23***	***23***	***17***	***15***	***24***	***24***	***22***	***14***	***18***	***22***
TOTAL (172)	**98**	**89**	**83**	**88**	**101**	**61**	**87**	**81**	**95**	**101**

Table 5.4: A stability test for β_w from 1980-1997 to 1998-2009 period

In a view that weather coefficients are not constant over time, it seems important to test whether changes in these weather betas are significant or not. The following equation is used to investigate the stability test of a regression model.

$$R_{it} = \alpha_1 + (\alpha_2 - \alpha_1)D_1 + \beta_{MR1}MR_t + (\beta_{MR2} - \beta_{MR1})D_2 + \beta_{W1}W_t + (\beta_{W2} - \beta_{W1})D_3 + u \quad ,$$

where D1, D2, and D3 respectively correspond to the value of 1, MR and W in the second period. Otherwise, they are zero.

The standard *t*-test is employed to investigate whether the differential slopes or coefficients are different from zero, whereas the *F*-test is carried out for a null hypothesis of simultaneously differential coefficients equals to zero. Of all 172 firms in the sample, the table reports the number of equities that *t*-stat of individual coefficient or *F*-stat is different from zero at 5% level of significance.

	W1	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
UTILITIES (125)										
F-test	27	29	28	29	29	25	38	39	38	30
T-test										
D1 (intercept)	4	7	5	4	4	5	7	7	4	5
D2 (MR)	27	28	27	27	28	28	26	26	28	28
D3 (W)	27	29	26	26	23	7	32	38	36	19
AGRICULTURE (5)										
F-test	2	2	3	2	2	2	2	2	2	2
T-test										
D1 (intercept)	0	0	0	1	0	0	0	0	1	0
D2 (MR)	1	1	1	1	1	1	1	1	1	2
D3 (W)	1	1	1	0	1	1	1	1	0	1
TOURISM (42)										
F-test	5	4	2	2	5	5	2	2	2	6
T-test										
D1 (intercept)	4	4	4	3	4	5	3	4	3	5
D2 (MR)	5	5	6	7	5	5	6	7	7	5
D3 (W)	1	1	2	2	2	0	1	2	2	1
TOTAL (172)										
F-test	***34***	***35***	***33***	***33***	***36***	***32***	***42***	***43***	***42***	***38***
T-test										
D1 (intercept)	8	11	9	8	8	10	10	11	8	10
D2 (MR)	33	34	34	35	34	34	33	34	36	35
D3 (W)	29	31	29	28	26	8	34	41	38	21

Table 5.5: Distribution of firm-level β_{ww} (winter) and β_{ws} (summer)

Seasonal dummy variables for winter and summer are added to a market-adjusted regression model to capture the effects of season on share values.

$$R_{it} = \alpha_{it} + \beta_{MR} MR_t + \beta_{ws} W_t * D_s + \beta_{ww} W_t * D_w + \beta_{wm} W_t * D_m + \varepsilon_i \quad ,$$

where D_w ,D_s, and D_m is 1 for winter, summer and mild weather respectively. They are zero otherwise.

The above-mentioned dummy regression model is estimated individually for each firm in the sample to derive firm –specific seasonal weather betas. Panel A reports the distribution of weather exposure coefficients from agricultural companies, while panel B and C presents results from tourism and utilities firms respectively. Within each panel, results of winter and summer coefficients are separately presented, with the average R^2 of all regressions within the industry reported in the last row. Representative values from three firms in each industry are illustrated with *t*-statistics in parentheses. It should be noted that the *t*-stats for median values of tourism firms are omitted due to the fact that the sample size is an even number and so the median is calculated from the middle values between two numbers. The numbers of positive, negative, and significant weather coefficients are also presented. Each column represents results from a different weather measure for comparison.

Note—*t*-statistics are in parentheses. * Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

A. Agriculture

Winter	**W1**	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
Positive	14	14	12	14	12	14	13	12	14	10
Negative	5	5	7	5	7	5	6	7	5	9
Minimum	-0.0125	-0.0131	-0.0184**	-0.023**	-0.0096	-0.0367	-0.443*	-0.5506**	-1.0398	-0.0406
	(-1.48)	*(-1.54)*	*(-2.32)*	*(-2.65)*	*(-0.39)*	*(-1.49)*	*(-1.88)*	*(-2.57)*	*(-0.82)*	*(-0.67)*
Median	0.003	0.0038	0.0045	0.0047	0.0016	0.0084	0.0954	0.1234	0.1299	0.0045
	(0.06)	*(0.15)*	*(0.79)*	*(0.76)*	*(0.18)*	*(0.06)*	*(0.56)*	*(0.76)*	*(0.74)*	*(0.30)*
Maximum	0.0322	0.0337	0.0298	0.0775	0.0353*	0.0938	0.9752	1.0470	2.716	0.1224*
	(1.53)	*(1.62)*	*(0.68)*	*(1.23)*	*(1.79)*	*(1.52)*	*(1.43)*	*(0.72)*	*(1.29)*	*(1.83)*
Cross-sectional mean	0.0057*	0.0064**	0.0045	0.0076	0.0036	0.0165*	0.1749*	0.1198	0.2203	0.0077
Cross-sectional SD	0.0120	0.0115	0.0116	0.0205	0.0107	0.0351	0.3658	0.3842	0.7168	0.0340
Significance at 5% level	1/ 19	1/ 19	1/ 19	1/ 19	1/ 19	1/ 19	1/ 19	1/ 19	1/ 19	1/ 19
Positive	1	1	0	0	1	1	1	0	0	1
Negative	0	0	1	1	0	0	0	1	1	0
Significance at 10% level	1/ 19	1/ 19	1/ 19	2/ 19	2/ 19	1/ 19	2/ 19	1/ 19	2/ 19	3/ 19
Positive	1	1	0	1	2	1	1	0	1	2
Negative	0	0	1	1	0	0	1	1	1	1
Summer	**W1**	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
Positive	13	13	10	9	8	13	12	10	10	10
Negative	6	6	9	10	11	6	7	9	9	9
Minimum	-0.0669	-0.0631	-0.0726	-0.0964	-0.0351	-0.0794	-4.5786	-5.3053	-7.1073	-0.0330
	(-0.70)	*(-0.66)*	*(-0.72)*	*(-0.83)*	*(-0.61)*	*(-0.66)*	*(-0.66)*	*(-0.73)*	*(-0.84)*	*(-0.51)*
Median	0.0059	0.0061	0.0045	-0.0007	-0.0009	0.0078	0.4321	0.3453	0.1496	0.0009
	(0.66)	*(0.67)*	*(0.17)*	*(-0.04)*	*(-0.02)*	*(0.70)*	*(0.66)*	*(0.19)*	*(0.08)*	*(0.08)*
Maximum	0.1013	0.1022	0.1127	0.0801	0.1042	0.1269	7.2591	7.9682	5.8300	0.0982
	(1.34)	*(1.33)*	*(1.24)*	*(1.58)*	*(1.25)*	*(1.39)*	*(1.33)*	*(1.25)*	*(1.60)*	*(1.47)*
Cross-sectional mean	0.0074	0.0075	0.0073	0.0016	0.0056	0.0093	0.5324	0.5377	0.1798	0.0065
Cross-sectional SD	0.0336	0.0332	0.0348	0.0420	0.0300	0.0417	2.3954	2.4923	2.9911	0.0292
Significance at 5% level	0	0	0	0	0	0	0	0	0	0
Positive	0	0	0	0	0	0	0	0	0	0
Negative	0	0	0	0	0	0	0	0	0	0
Significance at 10% level	0	0	1/ 19	0	2/ 19	0	0	1/ 19	0	0
Positive	0	0	0	0	1	0	0	0	0	0
Negative	0	0	1	0	1	0	0	1	0	0
Average R^2 (%)	11.01	10.99	10.93	11.31	10.24	10.88	11.26	11.21	11.6	10.45

B. Tourism

Winter	**W1**	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
Positive	105	116	117	120	105	105	110	116	120	105
Negative	103	92	91	88	103	103	98	92	88	103
Minimum	-0.0784*	-0.0752	-0.0696	-0.1707*	-0.0816**	-0.2299*	-2.7088**	-2.5101*	-5.4410	-0.2698**
	(-2.55)	*(-1.47)*	*(-0.92)*	*(-1.83)*	*(-2.10)*	*(-1.77)*	*(-2.47)*	*(-1.99)*	*(-1.68)*	*(-2.19)*
Median	0.0002	0.0010	0.0020	0.0034	0.0004	0.0004	0.0324	0.0516	0.1016	0.0006
Maximum	0.116***	0.114***	0.137**	0.2036**	0.116***	0.34***	4.217***	4.7352**	7.3540**	0.364***
	(3.90)	*(4.01)*	*(2.15)*	*(2.47)*	*(4.07)*	*(3.92)*	*(3.99)*	*(2.12)*	*(2.51)*	*(4.12)*
Cross-sectional mean	0.0008	0.0019	0.0036*	0.0064***	0.0018	0.0022	0.0665	0.1203*	0.2096**	0.0044
Cross-sectional SD	0.0235	0.0237	0.0268	0.0338	0.0221	0.0687	0.8307	0.9382	1.1641	0.0668
Significance at 5% level	15/ 208	15/ 208	14/ 208	11/ 208	13/ 208	15/ 208	16/ 208	15/ 208	11/ 208	12/ 208
Positive	10	10	10	9	10	10	11	12	8	10
Negative	5	5	4	2	3	5	5	3	3	2
Significance at 10% level	26/ 208	27/ 208	25/ 208	19/ 208	21/ 208	25/ 208	24/ 208	20/ 208	17/ 208	22/ 208
Positive	14	16	17	14	16	14	14	13	12	16
Negative	12	11	8	5	5	11	10	7	5	6
Summer	**W1**	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
Positive	81	81	88	95	85	80	80	87	94	83
Negative	107	127	120	113	123	128	128	121	114	125
Minimum	-0.3963	-0.3801	-0.4914*	-0.5015*	-0.170*	-0.5091*	-28.019	-36.65*	-34.4*	-0.2127
	(-1.62)	*(-1.57)*	*(-2.00)*	*(-2.00)*	*(-1.74)*	*(-1.71)*	*(-1.56)*	*(-1.99)*	*(-1.90)*	*(-0.97)*
Median	-0.0070	-0.0066	-0.0041	-0.0032	-0.0067	-0.0086	-0.5273	-0.3298	-0.2193	-0.0072
Maximum	0.2556**	0.2565**	0.2495**	0.3213*	0.2429**	0.3368**	18.35**	17.83**	23.00**	0.3127***
	(2.42)	*(2.43)*	*(2.38)*	*(2.03)*	*(2.67)*	*(2.60)*	*(2.40)*	*(2.35)*	*(2.08)*	*(2.99)*
Cross-sectional mean	-0.0051	-0.0051	-0.0050	0.0003	-0.0045	-0.0057	-0.3811	-0.3641	0.0407	-0.0040
Cross-sectional SD	0.0522	0.0519	0.0555	0.0583	0.0421	0.0663	3.7785	4.0842	4.1482	0.0474
Significance at 5% level	6/ 208	6/ 208	6/ 208	5/ 208	4/ 208	6/ 208	6/ 208	6/ 208	6/ 208	3/ 208
Positive	2	2	3	3	2	2	2	3	4	1
Negative	4	4	3	2	2	4	4	3	2	2
Significance at 10% level	14/ 208	14/ 208	11/ 208	14/ 208	13/ 208	15/ 208	14/ 208	12/ 208	14/ 208	9/ 208
Positive	5	5	3	7	3	6	5	4	7	3
Negative	9	9	8	7	10	9	9	8	7	6
Average R^2 (%)	15.41	15.49	15.41	15.32	15.58	15.39	15.46	15.43	15.3	15.46

C. Utilities

Winter	**W1**	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
Positive	65	61	73	82	69	65	65	76	85	78
Negative	192	196	184	175	188	192	192	181	172	179
Minimum	-0.2451**	-0.2651**	-0.2172**	-0.2147**	-0.1479**	-0.72**	-9.2563**	-8.0468**	-7.9253**	-0.3938**
	(-2.45)	*(-2.57)*	*(-2.12)*	*(-2.13)*	*(-2.55)*	*(-2.46)*	*(-2.70)*	*(-2.29)*	*(-2.30)*	*(-2.61)*
Median	-0.0018	-0.002	-0.0016	-0.0017	-0.0016	-0.0053	-0.0590	-0.0447	-0.0471	-0.0037
	(-0.71)	*(-0.27)*	*(-0.73)*	*(-0.49)*	*(-0.92)*	*(-0.71)*	*(-1.01)*	*(-0.46)*	*(-0.66)*	*(-0.65)*
Maximum	0.0370	0.0440	0.0606	0.063***	0.0442	0.1088	1.4385	1.8636	1.857***	0.1298
	(0.76)	*(0.92)*	*(1.29)*	*(3.86)*	*(0.98)*	*(0.77)*	*(0.93)*	*(1.25)*	*(3.61)*	*(0.85)*
Cross-sectional mean	-0.0044***	-0.0044***	-0.0038***	-0.004***	-0.0033***	-0.0128***	-0.1425***	-0.1236***	-0.1348***	-0.009***
Cross-sectional SD	0.0192	0.0203	0.0185	0.02	0.0133	0.0562	0.6905	0.6431	0.6902	0.0377
Significance at 5% level	27/ 257	28/ 257	33/ 257	22/ 257	23/ 257	27/ 257	27/ 257	31/ 257	19/ 257	28/ 257
Positive	3	4	5	4	6	3	3	5	4	7
Negative	24	24	28	18	17	24	24	26	15	21
Significance at 10% level	45/ 257	54/ 257	53/ 257	41/ 257	43/ 257	35/ 257	53/ 257	45/ 257	35/ 257	46/ 257
Positive	7	10	8	7	9	7	8	7	6	11
Negative	38	44	45	34	34	38	45	38	29	35
Summer	**W1**	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
Positive	103	104	97	120	113	98	103	97	120	97
Negative	154	153	160	137	144	159	154	160	137	160
Minimum	-0.0923	-0.0925	-0.0964	-0.1062	-0.0780	-0.1171	-6.6621	-6.9409	-7.8362	-0.0958
	(-1.50)	*(-1.47)*	*(-1.43)*	*(-1.25)*	*(-1.19)*	*(-1.52)*	*(-1.51)*	*(-1.46)*	*(-1.29)*	*(-1.20)*
Median	-0.0019	-0.0018	-0.0021	-0.0005	-0.0011	-0.0025	-0.1160	-0.1441	-0.0283	-0.002
	(-0.36)	*(-0.30)*	*(-0.31)*	*(-0.05)*	*(-0.21)*	*(-0.46)*	*(-0.30)*	*(-0.30)*	*(-0.05)*	*(-0.18)*
Maximum	0.0872*	0.0893*	0.0717	0.108*	0.058***	0.1059*	6.6918*	5.1044	7.7959*	0.0789
	(1.82)	*(1.88)*	*(1.49)*	*(1.82)*	*(3.20)*	*(1.81)*	*(1.85)*	*(1.44)*	*(1.81)*	*(1.53)*
Cross-sectional mean	-0.0009	-0.0009	-0.0014	0.0004	-0.0007	-0.0014	-0.0565	-0.0971	0.0358	-0.0012
Cross-sectional SD	0.0155	0.0155	0.0157	0.0194	0.0147	0.0191	1.1152	1.1264	1.3982	0.0159
Significance at 5% level	4/ 257	4/ 257	4/ 257	4/ 257	5/ 257	4/ 257	4/ 257	4/ 257	5/ 257	5/ 257
Positive	3	3	1	2	3	3	3	1	2	3
Negative	1	1	3	2	2	1	1	3	3	2
Significance at 10% level	11/ 257	12/ 257	8/ 257	17/ 257	7/ 257	9/ 257	11/ 257	9/ 257	15/ 257	8/ 257
Positive	6	7	3	9	4	6	6	3	9	5
Negative	5	5	5	8	3	3	5	6	6	3
Average R^2 (%)	13.36	13.41	13.32	13.41	13.26	13.34	13.46	13.36	13.48	13.29

Table 5.6: A test on an equality of seasonal weather coefficients

A null hypothesis that a weather beta of summer is equal to that of winter has been tested by using the standard F-test. It has been performed to compare the following restricted and unrestricted regressions.

Restricted regression: $R_{it} = \delta_{it} + \beta_{MR} MR_t + \beta_{wws} W_t * D_{ws} + \beta_{wm} W_t * D_m + \varepsilon_{it}$

Unrestricted regression: $R_{it} = \alpha_{it} + \beta_{MR} MR_t + \beta_{ws} W_t * D_s + \beta_{ww} W_t * D_w + \beta_{wm} W_t * D_m + \varepsilon_i$,

where D_s, D_w, D_{ws} and D_m are the dummy variables for summer (Jun-Aug), winter (Dec-Feb), winter-summer (Dec-Feb and Jun-Aug) and mild season (Mar-May and Sep-Nov), respectively. They correspond to 1 for the months in parentheses or zero otherwise.

The table demonstrates the number of regressions that causes a rejection of the null hypothesis $H_0 : \beta_{ww} = \beta_{ws}$ at 5% level of significance.

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
Agriculture	0	0	0	0	0	0	0	0	0	0
Tourism	9	9	6	4	7	9	7	7	3	13
Utilities	4	5	5	6	7	13	5	5	6	15
TOTAL	**13**	**14**	**11**	**10**	**14**	**22**	**12**	**12**	**9**	**28**

Note—the sample size is 484 firms.

Table 5.7: Number of equities with significant Durbin-Watson statistic

For every regression, a Durbin-Watson test has been carried out to trace for autocorrelation in residuals. The test statistic is:

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \quad ,$$

where $e_i = R_i - \hat{R}_i$. R_i and $\hat{R}_i$ are the observed and predicted stock returns of the company *i*. The upper and lower critical values, d_U and d_L, have been tabulated for different value of the number of explanatory variables (*k*) and observations (*n*).

Values in each column represent the number of regressions that their residuals reject the null hypothesis of no autocorrelation at 5% level: when $d < d_L$. Results of the standard market-adjusted model are presented in Panel A whereas those of the seasonal dummy model are shown in Panel B.

Panel A: Standard market-adjusted model										
	W1	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
Agriculture	5	5	5	5	5	5	5	5	5	5
Tourism	28	29	27	28	28	30	26	27	28	26
Utilities	31	30	31	30	32	30	32	33	31	32
TOTAL	***64***	***64***	***63***	***63***	***65***	***65***	***63***	***65***	***64***	***63***
Panel B: Model with seasonal dummy variables										
	W1	**W2**	**W3**	**W4**	**W5**	**%W1**	**%W2**	**%W3**	**%W4**	**%W5**
Agriculture	4	4	4	4	4	4	4	4	4	4
Tourism	23	23	24	23	24	23	23	24	23	23
Utilities	29	28	28	27	28	30	29	29	29	29
TOTAL	***56***	***55***	***56***	***54***	***56***	***57***	***56***	***57***	***56***	***56***

Note—the sample size is 484 firms.

Table 5.8: Market exposure to unexpected weather

The market exposure coefficient is derived from a univariate regression by regressing the monthly market return (MR_t) on weather factors (W).

$$MR_t = \alpha_t + \delta_w W_t + \varepsilon_t$$

Results are reported for both the standard market-adjusted in (a) and the seasonal dummy models in (b). The second and third columns contain weather coefficients, δ_w, and *t*-stats respectively. The estimated coefficients are tested for stability before and after 1998 by using the Chow test, and statistics are reported in the fourth column. The two following columns show statistical results for serial correlation in residuals, with the Durbin-Watson and LM tests respectively. The LM test is provided because *DW*-statistics are indecisive zone. The penultimate column presents the White statistics, which test for heteroskedasticity in residuals. The last column indicates the fitness of the model or R^2.

a. Standard model: $MR_t = \alpha_t + \delta_w W_t + \varepsilon_t$

	Market exposure	***t-stat***	***Chow Test***	***DW***	***LM Test***	***White Test***	R^2
W1	0.0004	***0.33***	2.55	1.76	2.87	0.16	0.03%
W2	0.0004	***0.35***	2.42	1.76	2.87	0.16	0.03%
W3	0.0005	***0.43***	2.51	1.76	2.91	0.25	0.05%
W4	0.0006	***0.47***	2.06	1.76	2.93	0.42	0.06%
W5	0.0017	***1.46***	2.03	1.77	2.97	0.10	0.60%
%W1	-0.0003	***-0.12***	1.83	1.77	2.80	0.12	0.00%
%W2	0.0220	***0.48***	2.67	1.77	2.86	0.26	0.06%
%W3	0.0243	***0.53***	2.62	1.77	2.90	0.30	0.08%
%W4	0.0179	***0.35***	2.02	1.76	2.90	0.38	0.03%
%W5	0.0010	***0.51***	1.76	1.76	2.94	0.13	0.07%

b. Seasonal dummy model: $MR_t = \alpha_t + \delta_{ws} W_t * D_s + \delta_{ww} W_t * D_w + \delta_{wm} W_t * D_m + \varepsilon_i$

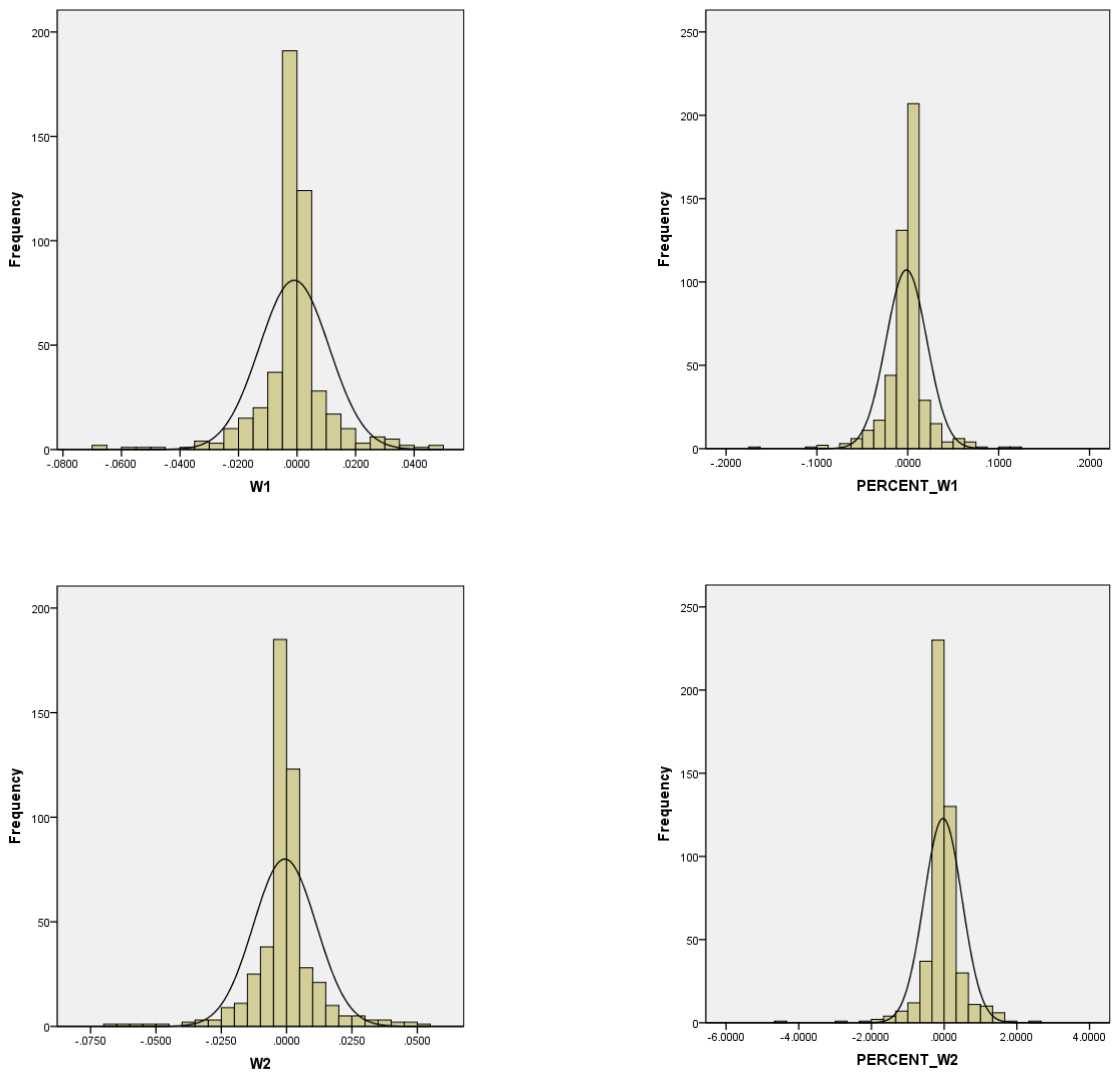
	Market exposure (summer)	***t-stat***	***Market exposure (winter)***	***t-stat***	***Chow Test***	***DW***	***LM***	***White***	R^2
W1	-0.0050	***-1.24***	0.0010	***0.58***	2.63†	1.78	2.76	0.75	0.58%
W2	-0.0051	***-1.26***	0.0009	***0.55***	2.54†	1.78	2.76	0.59	0.61%
W3	-0.0048	***-1.15***	0.0006	***0.36***	2.82†	1.77	2.77	0.89	0.60%
W4	0.0015	***0.28***	0.0001	***0.04***	1.75	1.76	2.96	0.74	0.12%
W5	-0.0038	***-1.02***	0.0027	***1.72***	3.04†	1.80	2.66	1.03	1.31%
%W1	-0.0062	***-1.25***	0.0028	***0.57***	2.40†	1.78	2.76	0.11	0.55%
%W2	-0.3600	***-1.24***	0.0213	***0.39***	2.65†	1.77	2.77	0.83	0.60%
%W3	-0.3357	***-1.12***	0.0138	***0.26***	2.84†	1.77	2.77	0.9	0.65%
%W4	0.0973	***0.25***	-0.0010	***-0.02***	1.69	1.76	2.95	0.73	4.62%
%W5	-0.0032	***-0.85***	0.0064	***1.47***	2.29	1.79	2.78	0.85	0.85%

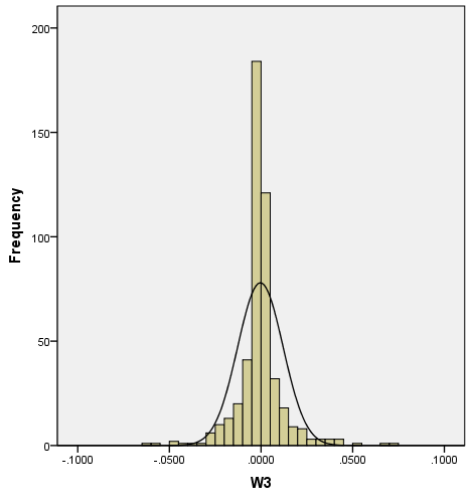
Note—† significant at the 5% level

Figure 5.1 : Distribution of β_w over the whole sample in 30-year period

The following ten figures present histograms of β_w over 484 firms in the sample, obtained from $R_{it} = \alpha_i + \beta_{MR}MR_t + \beta_w W_t + \varepsilon_{it}$. A histogram provides important information about distributions of data values in terms of shape, central value and spread. Each graph is labelled with the weather measure that regressions are based upon. Figures in the left side present results from the weather measures in degree scale, whereas those in the right side show results of their percentage measures.

The horizontal X-axis shows the scale of the values of weather coefficients, and they are generally groups into interval. A histogram consists of rectangle bars standing over these discrete intervals, where heights of the bars represent the frequency density of the interval. A line attached to a histogram represents a normal curve.

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.0500
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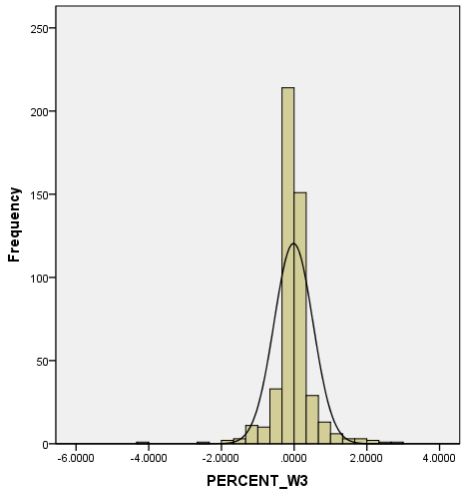
W3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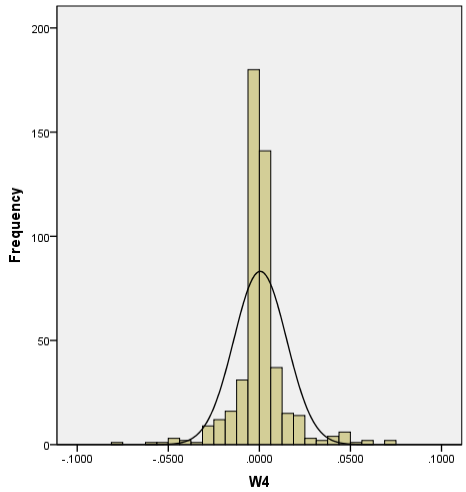
PERCENT_W3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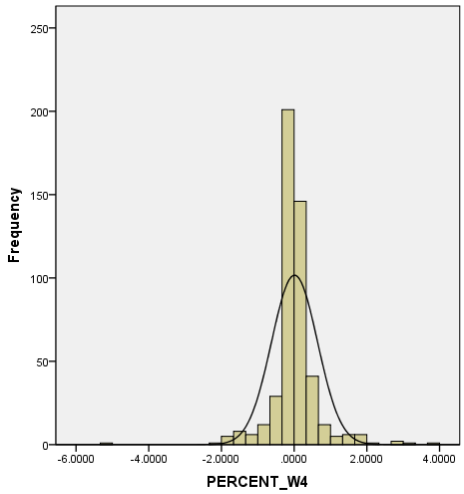
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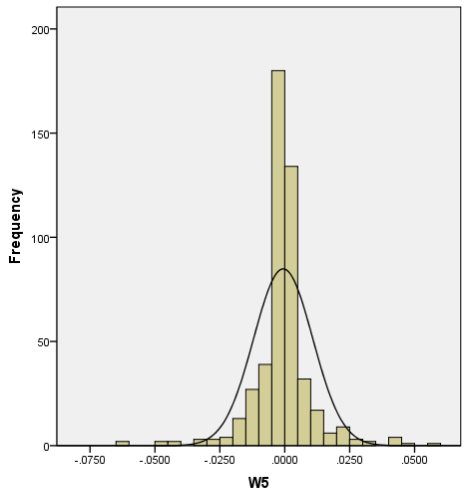
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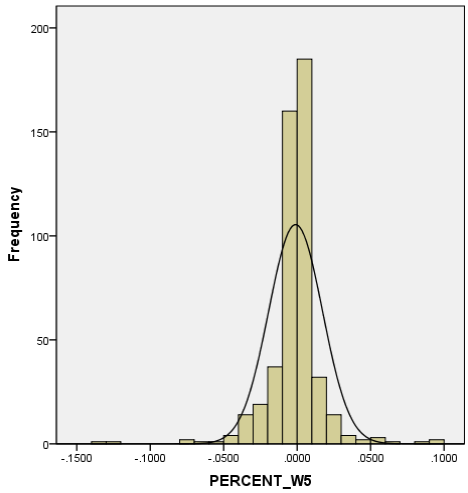
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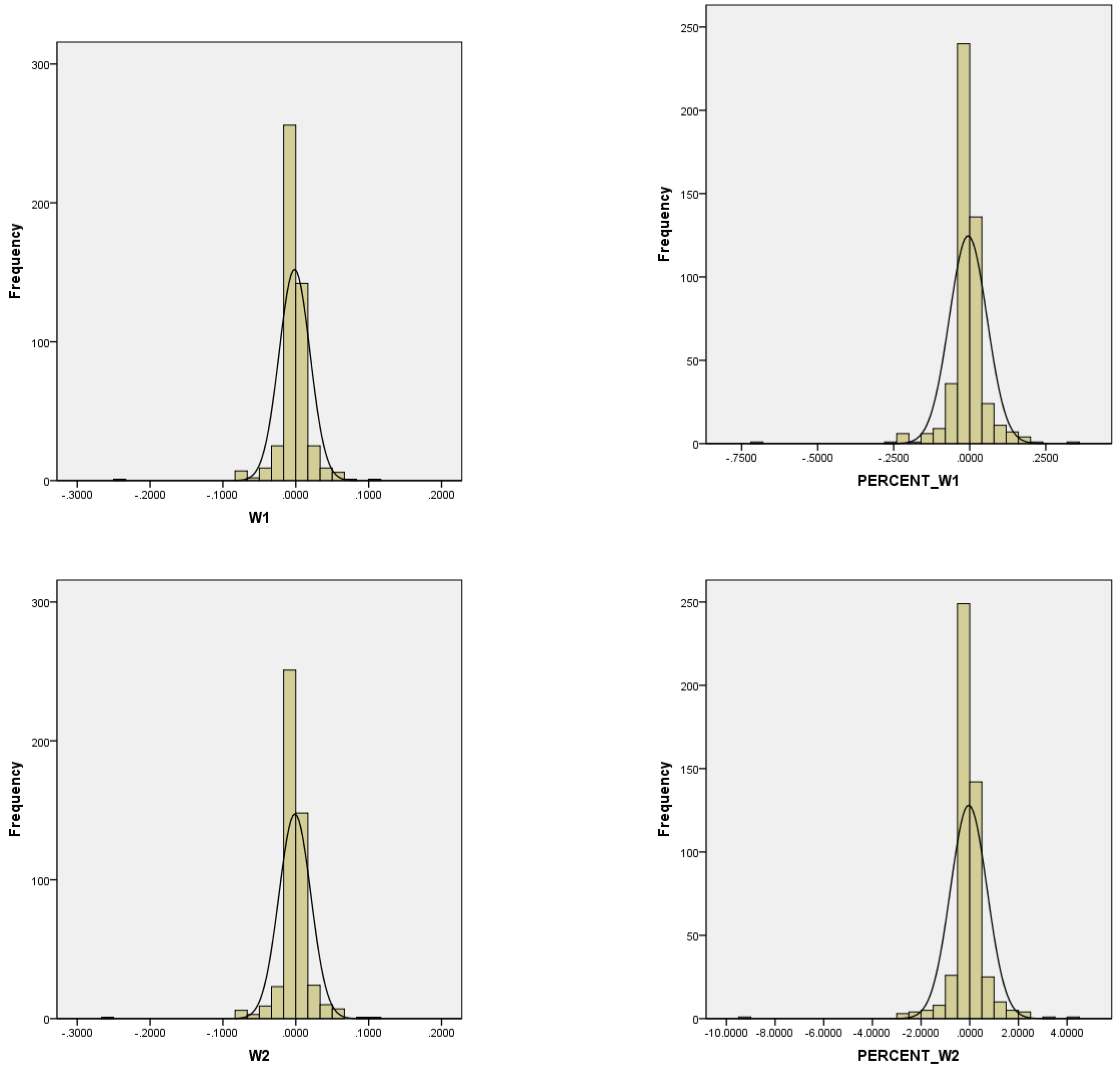
PERCENT_W5

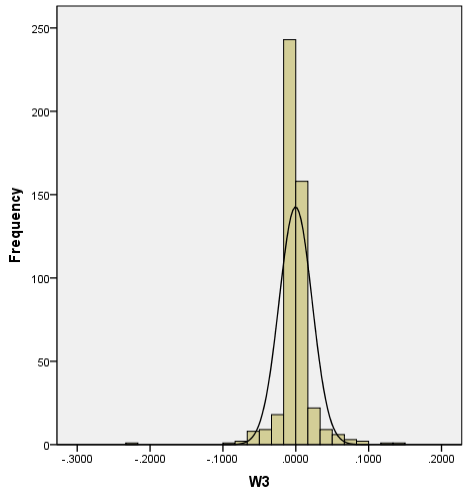
Figure 5.2: Distribution of β_{ww} over the whole sample in 30-year period

The following histograms show the distributions of weather coefficients in winter **(** β_{ww}) over the 484 firms, obtained from the seasonal dummy model.

$$R_{it} = \alpha_{it} + \beta_{MR} MR_t + \beta_{ws} W_t * D_s + \beta_{ww} W_t * D_w + \beta_{wm} W_t * D_m + \varepsilon_i$$

Each graph is labelled with the weather measure that regressions are based upon. Figures in the left side present results from the weather measures in degree scale, whereas those in the right side show results of their percentage measures. The horizontal X-axis shows the scale of the values of weather coefficients, and they are generally groups into interval. A histogram consists of rectangle bars standing over these discrete intervals, where heights of the bars represent the frequency density of the interval. A line attached to a histogram represents a normal curve.

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100
50
0
-.3000
-.2000
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.0000
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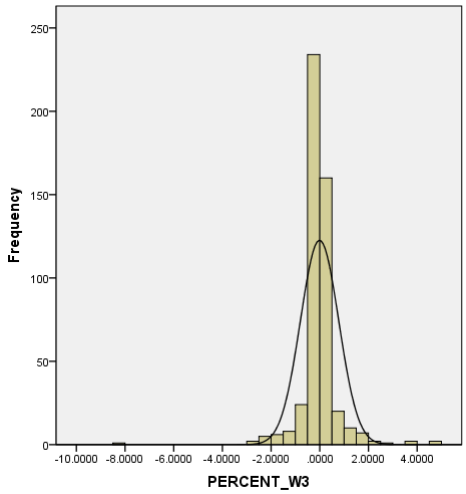
W3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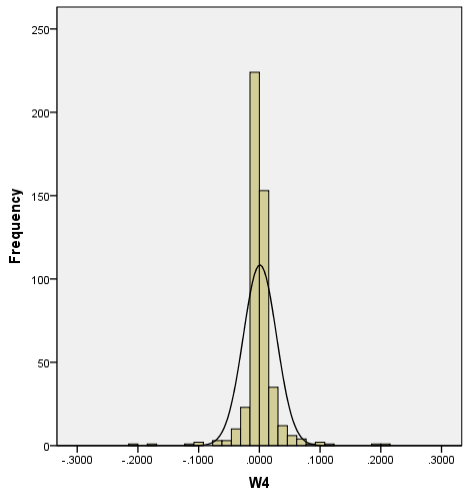
PERCENT_W3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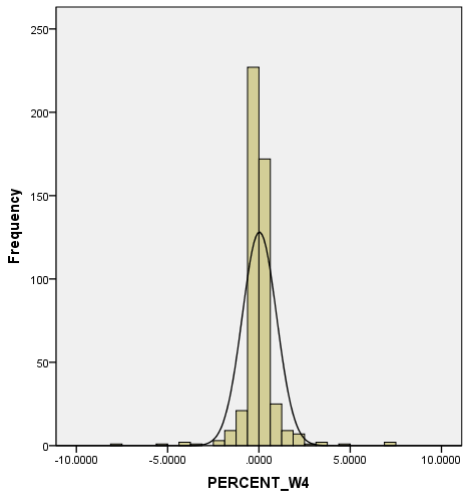
W4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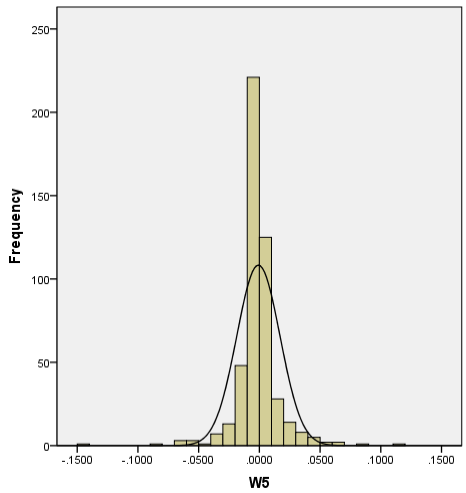
PERCENT_W4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.0000
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.1000
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W5

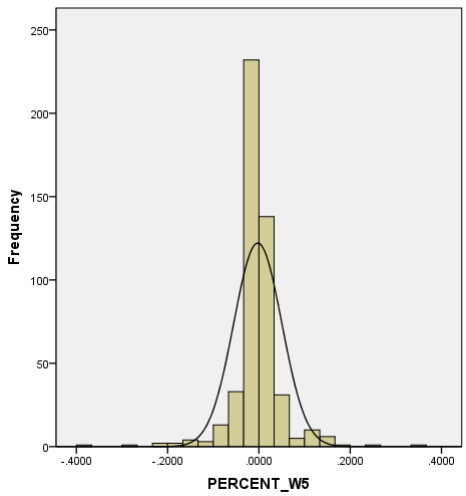
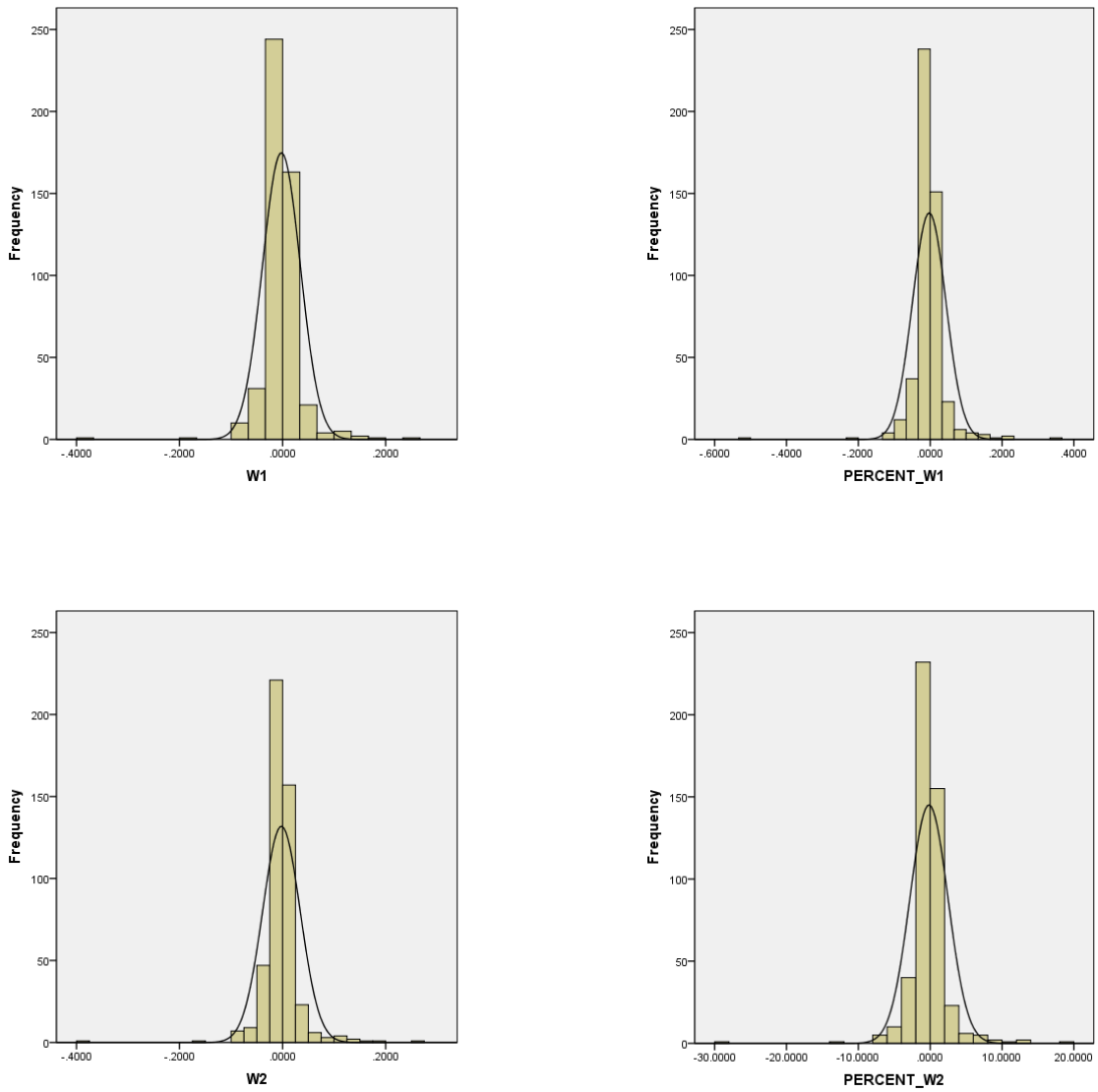

Frequency
250
200
150
100
50
0
-.4000
-.2000
.0000
.2000
.4000
PERCENT_W5

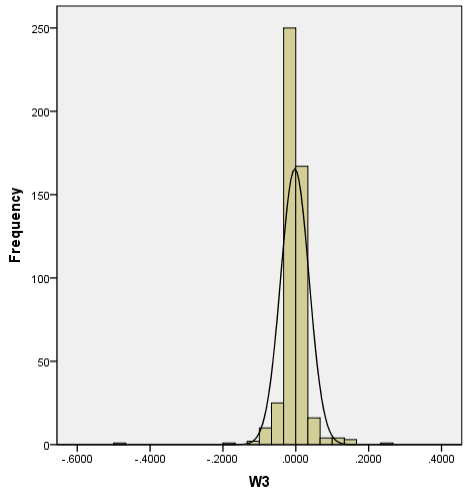
Figure 5.3: Distribution of β_{ws} over the whole sample in 30-year period

The following histograms show the distributions of weather coefficients in summer (β_{ws}) over 484 firms, obtained from the seasonal dummy model.

$$R_{it} = \alpha_{it} + \beta_{MR} MR_t + \beta_{ws} W_t * D_s + \beta_{ww} W_t * D_w + \beta_{wm} W_t * D_m + \varepsilon_i$$

Each graph is labelled with the weather measure that regressions are based upon. Figures in the left side present results from the weather measures in degree scale, whereas those in the right side show results of their percentage measures. The horizontal X-axis shows the scale of the values of weather coefficients, and they are generally groups into interval. A histogram consists of rectangle bars standing over these discrete intervals, where heights of the bars represent the frequency density of the interval. A line attached to a histogram represents a normal curve.

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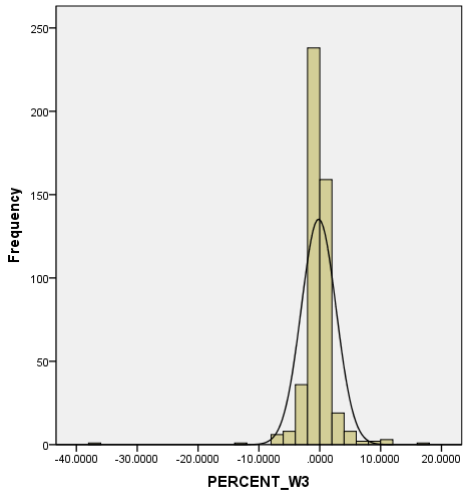
W3


Frequency
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-10.0000
.0000
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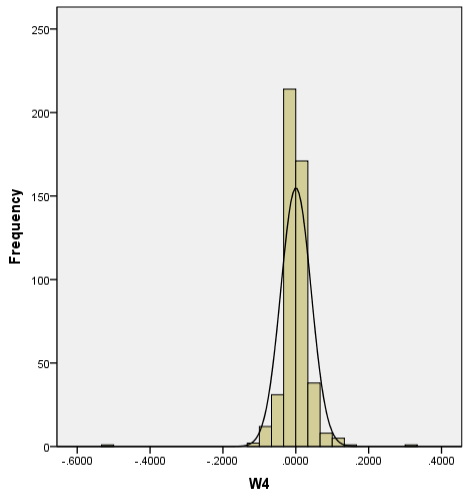
20.0000
PERCENT_W3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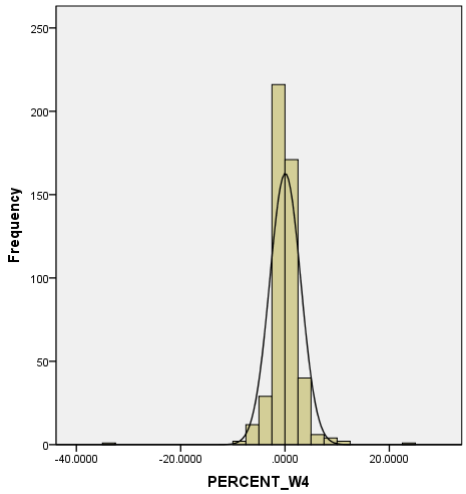
-.2000
.0000
.2000
.4000
W4


Frequency
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-20.0000
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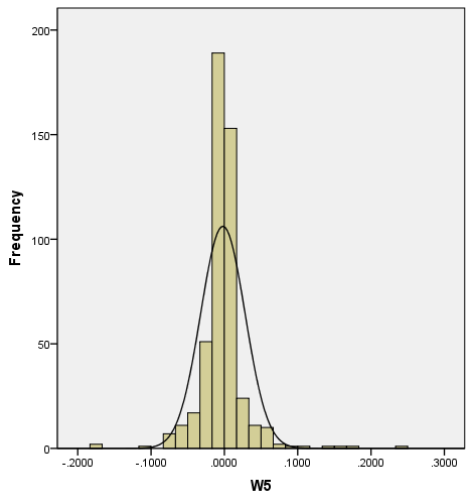
20.0000
PERCENT_W4


Frequency
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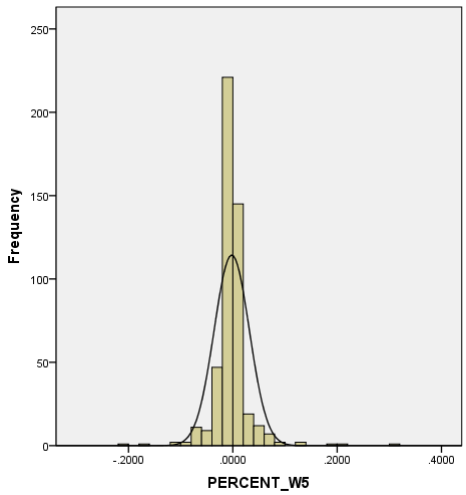
W5


Frequency
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Chapter 6

The Price of Weather Risk

6.1 Introduction

It was demonstrated empirically in the previous chapter that unpredictable temperature correlates with equity return and the number of firms that are exposed to these unexpected weather conditions is greater than can be attributable by chance. This finding has raised an important question: is the existing weather risk priced in the stock market? Given the natural climate fluctuations and an inadequacy of protections from adverse weather, firms can be substantially affected by the changing weather conditions and these exposures cannot be fully diversified.[76] In this case, investors who invest in weather-exposed firms must be compensated for bearing the weather risk. If weather risk is priced, the finding will provide suggestive implications for weather derivative valuation, portfolio selection, cost-benefit analysis and for other financial problems requiring comprehension of the relation between weather risk and equity returns.

Even though practitioners and researchers have become increasingly suspicious about the size and significance of the weather risk premium, it is in fact unobservable and must be estimated. The empirical research of the price of weather risk is not extensive, and unfortunately it is not the dominant subject in these studies. This line of research has actually taken its stand from the weather derivative pricing literature, where the market price of risk is a piecewise function of the variants of equilibrium models. Although some empirical work assumed a zero weather risk premium and justified the use of a risk-free rate to price weather derivative contracts (Davis, 2001), several studies (Richards et al., 2003; 2004; Cao and Wei, 2004; Hardle and Cabrera, 2009) empirically found that the implied market price of weather risk is significant.

The estimate of the market price of weather risk is actually interesting on its own; however, it has never been studied. Regarding the evidence of weather risk in the market, this chapter continues to investigate for the price of such exposure. It will

[76] It can be argued that weather risk should not be considered as a non-diversifiable risk because both weather insurance and weather derivatives do exist. However, the insurance covers only catastrophic weather events which seldom occur, while weather derivatives, which cope with day-to-day weather fluctuations, are subject to basis risks. See Pelez-Gonzalez and Yun (2010) for a discussion of possible weather risk management options for a utilities company. However, each option has its limitation and it is unlikely for weather risk to be fully hedged.

investigate whether or not investors are compensated for investing in firms whose equity returns are correlated with weather. This study sheds light on the assessment of this risk premium by pursuing an alternative approach to estimate the price of weather risk through a factor model, consistent with the arbitrage pricing theory (APT).[77] By so doing, it explicitly provides an additional test of the asset pricing model different from earlier studies.

Ever since the seminal work of Ross (1976), researchers have sought to determine the precise set of factors that determine security returns. In the spirit of APT, many factors have been tested if they can be one of the priced factors in an as yet undiscovered asset pricing model. These factors include macroeconomic, firm-specific and statistic-derived variables, as reviewed earlier in Chapter 3. However, none of these factors is similar to weather, the natural variable which is obviously more basic and truly unpredictable. In fact, the natural factors comparable to weather are of research interest since the early history of APT as Chen et al. (1986) intended to base an asset pricing model on such systematic physical factors as natural forces. However, the ability to incorporate these factors was limited at the time. Thus, they merely modelled equity returns as functions of macro variables and non-equity asset returns, viewing the stock market as endogenous relative to other markets.

This research is the first to empirically study the relationship between equity return and weather risk in relation to the well-accepted pricing theory. It provides evidence on the unconditional pricing of weather risk in the U.S. stock market, specifically for the most weather-influenced sectors. This chapter serves two objectives. Firstly, it studies the significance of the market price of weather risk. Secondly, it provides additional insights into the nature of the structure of security returns, as it may offer an adequate description of the relation between risk and return for securities.

The empirical tests follow the breakthrough methodology of Fama and MacBeth (1973), henceforth called FM, and employ cross-sectional regressions both at the firm- and portfolio-level to determine whether weather risk is priced. At the portfolio level, the analysis uses ten equally-weighted portfolios, sorted by either market beta or weather

[77] In asset pricing theories, such as the APT and the models of Merton (1973), the individual asset prices are influenced by a wide variety of unanticipated events, some of which may have a more pervasive effect than others. These factors may be priced in the sense that an additional return is required whenever a particular asset is influenced by non-diversifiable risks (Chen et al., 1986).

beta, which will be rebalanced monthly. All tests are repeated for the ten alternative weather measures developed in Chapter 4.

This chapter proceeds as follows. The next section reviews previous empirical studies related to the market price of weather risk and shows that the literature is different from this study. The third section elucidates the test procedure and technique used for measuring weather premiums, while the fourth section describes empirical findings. The penultimate section discusses these empirical results and the limitations of the study, as well as suggesting future research relative to this subject. The last section provides concluding remarks.

6.2 Literature review

The market price of weather risk has become a critical issue when researchers have sought a reliable method to price weather derivatives.[78] Since the risks associated with weather are non-diversifiable and are not fully hedged, weather derivative prices must reflect a potentially substantial risk premium (Richards et al., 2003; 2004; Cao and Wei, 2004). The capability to estimate and incorporate the weather risk premium is central to the pricing approaches used for the valuation of weather derivatives such as the market-based (arbitrage-free) and equilibrium valuation framework. However, there are insufficient theoretical or empirical studies in the literature that concerns the estimation the market price of weather risk with which to price the weather derivative contracts (Richards et al., 2003). Hardle and Cabrera (2009) affirmed that the majority of relevant studies so far have assumed a zero market price of weather risk and this assumption underestimates weather derivative prices. If the market price of weather risk is significant in valuing weather derivatives, discounting the derivative's payoff at the risk free rate, as assumed by several works, can lead to significant pricing errors (Cao and Wei, 2004).

[78] The non-tradable underlying assets of weather derivatives violate the no-arbitrage and market completeness assumptions; as a consequence, the direct application of the conventional derivative pricings to this asset is inappropriate. The well-known closed-form Black-Scholes option pricing, that renders the knowledge of a risky discount factor in the valuation of derivatives, cannot be used because investors cannot form portfolios with positions in the underlying security to yield an instantaneously riskless payoff. At present, techniques used to price weather derivatives remain in a rather rudimentary state and are largely unsatisfactory on theoretical grounds.

As the market price of risk is a key to price power derivatives, Pirrong and Jermakyan (2001) inferred it from the observed power forward prices in the marketplace using inverse methods because this risk premium is not known in reality.[79] Their findings revealed that the market price of risk was considerably large and likely to change over time. Thus, ignoring it will lead to sizeable errors in a power derivative valuation. It was emphasized by the authors that the market price of risk is an integral feature in power derivatives pricings.[80] They suggested that the approach advanced in their study should be extended to price contingent claims, which the traditional approaches cannot readily do, such as weather derivatives.

Several studies in weather derivative pricing adopted the Pirrong-Jermakyan framework to value weather-based contingent claims. In the process, the market price of weather risk was inferred from the observed derivative prices in the analysis. For example, Hamisultane (2007) solve the partial differential equation (PDE) by using the finite difference method to extract the market price of risk in order to value the New York weather futures and options. It is shown that this information can be inferred either from the equivalent futures contract or from other weather contracts with which the index is correlated. Although these results are quite different, the implied market prices of weather risk appear to be unstable in both cases. Hardle and Cabrera (2009) infer the market price of weather risk from Berlin cumulative monthly temperature futures traded on the CME by the bootstrapping method. They find that the weather risk premium is different from zero and shows a seasonal pattern that increases as the expiration date of temperature future increases.

However, this approach cannot find the market price of weather risk without a derivative contract of the similar weather index (Richards et al., 2004). Furthermore, the inference of market price of risk requires the liquidity of the quoted weather derivatives

[79] Pirrong and Jermakyan (2001) proposed an equilibrium model to price power derivatives, in that the price of a contingent claim must satisfy the partial differential equation (PDE) given a specification of the dynamics of the state variables and the relevant boundary conditions. Since the risk associated with the demand state variable is not hedgeable, any valuation depends on the market price of risk in relation to this variable. Taking the evidence of a market price of risk by the systematic differences between forward prices and realized spot prices, the data in Pirrong and Jermakyan's study clearly specified that the market price of risk is potentially large. Therefore, it is imperative to take it into consideration when valuing derivatives. They suggested valuing electricity options by extracting the market price of risk from the comparable forward contracts.

[80] It is necessary to incorporate a market price of risk into the valuation due to the non-stability of electricity and the non-tradable state variable (demand), which creates non-hedgeable risks.

(Hamisultane, 2008). Another promising way to proceed in the incomplete market framework is to identify an equilibrium pricing model that implicitly includes a risk premium for weather.

A series of Cao and Wei's studies (1999; 2001; 2004) extended the Lucas (1978)'s equilibrium asset pricing model to price weather derivatives, including weather as another fundamental source of uncertainty in the economy.[81] It was illustrated that equilibrium prices of weather derivatives are dependent on the agent's risk preference and the correlation between aggregate consumption and weather process. They claimed that the market price of risk would be zero if the dividend process and the temperature process are exclusively non-related, and that discounting the payoff at the risk-free rate can justify the price of a contingent claim. Given arbitrary values of the constant relative risk aversion coefficient and correlation case, numerical analyses in Cao and Wei (1999) demonstrated that the market price of risk associated with the temperature variable insignificantly affects weather derivative values.[82] However, the authors accepted that the result was not universal as they employed a particular class of the utility function and only allowed contemporaneous correlation between the aggregate dividend and the temperature. Thus, their subsequent studies allowed the current aggregate dividend to be affected by the lagged temperature.

Cao and Wei (2001) found that the market price of risk remained negligible in most cases. It became significant only when the risk aversion is high or when the mean reversion in the aggregate dividend process is weak. They stated that risk aversion is definitely one of the important factors affecting the risk premium in their study. The following research in 2004 additionally explored the higher risk aversion parameter to accommodate the equity premium puzzle. As opposed to their previous empirical results, Cao and Wei (2004) found that the market price of risk associated with the

[81] The ultimate objective of the studies was to propose an equilibrium framework for valuing weather derivatives, but they also aimed to establish whether the weather risk premium is significant in valuation of weather derivatives. The studies were based on temperature behaviour for five major cities in the U.S., and the model system was estimated using the 20-year data. Numerical analyses were performed for forward and option contracts on HDD's and CDD's.

[82] The values of derivatives with respect to correlation/ risk aversion scenarios are compared against the 'risk-neutral' values, and the difference determines the impact of market price of risk. In other words, the risk premium for forward prices is defined as the percentage difference between the forward price under various scenarios and the risk-neutral price.

temperature variable is important in most cases.[83] Based on the risk aversion and aggregate dividend process parameters conforming to empirical reality, the risk premium can represent a significant part of the temperature derivative price. The impact of the temperature risk premium is much more obvious for option prices than forward prices because of the non-linearity of payoffs.

Richards et al. (2003; 2004) adopted Cao and Wei's approach to estimate the market price of weather risk and found that derivative prices calculated under an assumption of a positive market price of risk are significantly different from those assumed to have a zero price.[84] Not only was the weather risk premium statistically significant, but it could also be economically large especially in case of the high risk aversion level. Although the level of risk aversion is rather extreme in their study, it shows the potential problem of neglecting risk preferences when valuing derivatives where a risk-neutral approach does not apply (Richards et al., 2004).

Similarly, Hamisultane (2010) adopt the consumption-based asset pricing model to price weather derivatives. The study estimates the relative risk aversion coefficient from the consumption data and temperature futures quotations, instead of assuming different values as in Cao and Wei's research.[85] In this research, there is no evidence of significant correlation coefficient between consumption and temperature process, which is equivalent to the state where the agents are risk-neutral and no market price of risk is required for weather derivatives. Although the result contrasts to those of Cao and Wei

[83] The market price of weather risk is not a significant factor if the dividend and temperature processes are only contemporaneously correlated and if the risk aversion is low. However, there is a marked increase in the significance of the risk premium when lagged correlations are introduced (Cao and Wei, 2004).

[84] The study used weather, yield and pricing data for nectarine growers in Fresno, California, in order to derive and estimate an equilibrium weather derivative pricing model that provides implicit estimates of the market price of risk. Using Monte Carlo simulation, it provided estimates of all derivative prices (calls and puts) and risk premiums. The study estimated the market price of risk over a range of risk aversion parameters for both types of derivatives. The implied market price of risk can be obtained by comparing the derivative prices that emerge from pure time-series behaviour of yields to those where yields depend on a weather index. If the market price of risk is zero, then the payoff will be independent of weather. By estimating a second yields function wherein yields are functions of time alone and re-calculating the implied derivative prices, the market price of risk can be estimated.

[85] This article estimates the coefficient by applying the well-known generalized method of moments (GMM) and the simulated method of moments (SMM).

(2004) and is inconsistent with the research's intuition, the author decides to keep this insignificant relation for her further analysis in the research.[86]

In summary, previous research related to the market price of weather risk seems scanty although it is a key to pricing weather derivatives. The literature takes two approaches to estimate the market price of weather risk, either by inferring it from the quoted prices of traded weather contracts or by implying it from equilibrium models.[87] However, these methods have limitations. While the former requires the liquidity of the quoted weather derivatives, the latter needs a determination of the risk aversion level. Empirical results by both approaches find mixed support on the assumption that the market price of weather risk is zero and the use of a risk-free rate to price weather derivatives is warranted. The size of weather risk premium and the appropriate technique to estimate such price is still the subject of an ongoing debate.

6.3 Empirical methodology

Perceiving weather risk as a risk that is partly non-diversifiable, investors need to be compensated for taking such an exposure. A weather risk premium is expected; however, the current methodologies used to estimate it are complicated and unsatisfactory on theoretical grounds. Instead of relying on the quoted derivative prices or the sophisticated numerical analysis, this thesis proposes to price the weather effects through a factor model. This method is consistent with the approach of well-known asset pricing models such as the CAPM and APT.

Recalling the justification described in Chapter 3, this section starts by including the weather risk in an asset pricing model. In the APT setting, the weather risk premium should be proportional to the regression coefficient between the risks and expected returns on the equities. In this study, the test methodology follows the Fama-MacBeth (1973) approach, which involves a two-stage procedure. The method is one of the most

[86] Hamisultane (2010) gives a number of reasons why the obtained result is different from Cao and Wei's. For example, the reasons may be the different choice of linear interpolation of the consumption data, the shorter sample period, and the temperature data at different locations.

[87] In a consumption-based method for weather derivative valuation, the market price of risk can be implied from comparing the derivative prices calculated under an assumption of a positive market price of risk relative to zero risk. These prices can be obtained from equilibrium models based on alternative weather process assumptions and coefficients of risk aversion.

common tests of the CAPM and APT and has been implemented by a number of seminal works, for example, Chen et al. (1986) and Fama and French (1992). It corrects for cross-sectional dependence by estimating standard errors from the estimated coefficients rather than the residuals. Serial correlation, however, is unlikely to be a problem under the market efficiency. This section also explains the test process and discusses the limitation of the method found in previous literature. Although the FM approach is subject to the errors-in-variables (EIV) problem, it survived most of the empirical results to become a standard methodology in literature due to its simplicity and clarity (Pasquariello, 1999).

The procedure clarification is followed by a discussion of two different approaches in specifying the universe of base assets in cross-sectional factor tests: the portfolio-level and the firm-level regressions. As each method has its own merit, this study uses both of them in the analysis. This also helps by checking the sensitivity of results in the research. The portfolio formation is described afterwards. Finally, the model specifications for all tests are shown.

6.3.1 Weather in asset prices

The APT states that the stock return is a linear function of a certain number of economic factors, assuming perfectly competitive and frictionless stock markets (Yli-Olli and Virtanen, 1992). This research hypothesizes that the cross-sectional differences in returns of weather-exposed stocks are determined by not only the endogenous market risk but also exogenous risk such as weather. The market portfolio reflects all sources of systematic risk in the economy and weather is a non-diversifiable exogenous risk specific to the sample firms. Thus, the returns on any stock are generated by the following factor structure.

$$R_i = \alpha_i + \beta_{MR} MR + \beta_w W_j + \varepsilon_i \qquad (6.1),$$

where R_i is the rate of return on the companies' common stocks, MR is the rate of return on the CRSP value-weighted market index, W_j is the weather measure under interest, α_i is the intercept, β_{MR} is the sensitivity of stock i with respect to the market portfolio,

β_w is the sensitivity of stock *i* to the weather factor and ε_i are the idiosyncratic risks of the stocks.[88]

If asset returns follow a factor structure in (6.1), the APT states that the following linear risk-return relationship can be written:

$$E(R_i) = \alpha_0 + \lambda_m \beta_{MR} + \lambda_w \beta_w \qquad (6.2),$$

where $E(R_i)$ is the expected return, α_0 is a constant riskless rate of return, λ_m is the risk premium on the market risk and λ_w is the risk premium on the weather risk. In this framework, an asset pricing model includes a risk premium term that contains the covariance of the return on asset with the weather factor. A weather risk is priced if the expected value of its premium is different from zero, $E(\lambda_w) \neq 0$, implying that expected returns differ across securities depending on their weather betas.

6.3.2 The two-stage regressions

The empirical tests in this thesis follow the FM procedure, which is carried out in two steps. The first stage is to estimate the firms' exposures to the state variables, which are the market return and the weather factor in this case, over a time interval by the time-series method. This is equivalent to estimation in (6.1). After that, the estimates of exposures or betas are used as independent variables in a cross-sectional regression, with expected asset return being the independent variable. The FM cross-sectional regression is given by:

$$R_{it} = \alpha_0 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}_{w,t-1} + e_i \qquad (6.3),$$

where R_{it} is the return at time *t* for a set of securities *i* on estimates of the systematic risks of each of the securities from the previous period, $\hat{\beta}_{MR,t-1}$ and $\hat{\beta}_{w,t-1}$. Each coefficient from the cross-sectional regression provides an estimate of the sum of risk premium, if any, associated with the state variable and the unanticipated changes of such factors.

[88] Idiosyncratic shocks are assumed to be uncorrelated across assets and uncorrelated with the factors.

The FM procedure suffers from the weakness of the two-step tests; in particular, the cross-sectional regression runs under the assumption that the estimated betas ($\hat{\beta}^i$) derived from the first step correspond to the true and unknown betas (β^i). In empirical tests, the use of estimated betas inevitably introduces errors-in-variables (EIV) problems. Fama and Macbeth (1973) avoided this phenomenon by forming portfolios because the portfolios' betas, $\hat{\beta}^p$, are likely to be more precise than individual betas.[89] In order to prevent clustering of positive and negative sampling errors within portfolios, they ranked $\hat{\beta}^i$ computed from data for one time period but used data from a subsequent period to obtain $\hat{\beta}^p$ for testing the model in the second stage.[90] It was hoped that the fresh data would minimize the effects of the regression phenomenon: errors in $\hat{\beta}^i$ within a portfolio would be extensively random across securities.

The FM solution is parallel to that of Black et al. (1972), who similarly concerned that a selection bias would be introduced into the procedure if the portfolios are constructed by using the ranked value of $\hat{\beta}^i$.[91] To avoid the bias, they recommended using an instrumental variable that is highly correlated with $\hat{\beta}^i$, but which can be observed independently. They demonstrated a ranking procedure similar to FM, which was shown to be independent of the measurement errors in the $\hat{\beta}^i$.

The month-by-month returns on the portfolios, with equal weighting of individual securities, can be computed for the study period. For each month *t* of this period, the following regression analogous to (6.3) is run.

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[89] Blume (1970 cited in Fama and Macbeth 1973, p.615) specified that "*If the errors in the $\hat{\beta}^i$ are substantially less than perfectly positively correlated, the $\hat{\beta}$'s of portfolio can be much more precise estimates of the true β's than the $\hat{\beta}$'s for individual securities*".

[90] Fama and Macbeth (1973) used the first 4 years of data to estimate $\hat{\beta}^i$, which was used to rank individual securities and group them into 20 portfolios. Then, the following 5 years of data were used to recompute the $\hat{\beta}^i$, and these were averaged across securities within portfolios to obtain $\hat{\beta}^p$. For each month *t* of the following years, the $\hat{\beta}^p$ was recomputed month by month to allow for delisting of securities. The component $\hat{\beta}^i$ for securities were themselves updated yearly.

[91] Black et al. (1972) stated that this selection bias would tend to cause the low-beta portfolios to exhibit positive intercepts and high-beta portfolios to show negative intercepts.

$$R_t^p = \gamma_0 + \lambda_m \hat{\beta}_{MR,t-1}^p + \lambda_w \hat{\beta}_{w,t-1}^p + u_p \qquad (6.4),$$

where R_t^p is the portfolio return, $\hat{\beta}_{MR}^p$ and $\hat{\beta}_w^p$ are the averages of the $\hat{\beta}_{MR}^i$ and $\hat{\beta}_w^i$ for securities in portfolio *p*. Again, the coefficients from the cross-sectional regression provide estimates of the risk premiums associated with the market risk and the weather risk. It should be noted that the equation (6.4) is actually (6.3) averaged across the securities in a portfolio.

Put it simply, the FM procedure estimates $\hat{\beta}^i$ from (6.1) in the first period to rank individual stocks and group them into portfolios. In this study, the first five years are lost for computing the factor loadings in this first-pass regression. As the observation periods for sample securities are unbalanced, the betas are calculated from the historical data of preceding 24-60 months depending on available periods. In the second period of subsequent five years, the $\hat{\beta}^i$ for each security was recomputed and averaged across securities within a portfolio to get $\hat{\beta}^p$. Then, the cross-sectional regression (6.4) was run repeatedly for each month *t* in the third period. The portfolio is rebalanced monthly, the regression is rolling forward, and the estimated coefficients moves forward through time. Thus, the time-series of the estimated slope coefficient in each of the cross-section regressions is obtained and the point estimate is the mean of that time-series. Ultimately, the point estimate is tested under the null hypothesis that the market price of risk relative to the state variable is zero, $E(\lambda) = 0$.

In order to examine if a weather risk is one of the priced factors, it involves testing the null hypothesis that $E(\lambda_w) = 0$ against the alternative that $E(\lambda_w) \neq 0$. Usually, the slope coefficient λ_w can be estimated by the OLS estimator; however, the null hypothesis cannot be tested using a straightforward OLS *t*-statistic because the error terms seem to be cross-sectionally correlated under the null hypothesis.[92] The FM solution is to repeatedly estimate the cross section regression in (6.4) and to use the point estimate

[92] Consequently, the usual OLS estimate of the standard error of $\hat{\lambda}_w$ is biased and inconsistent. See Cochrane (2001) and Guermat et al. (2004) for a discussion.

instead, which is an average of the time-series of the estimated slope coefficient in each of the regressions (Guermat et al., 2004).[93]

$$\hat{\lambda}_{FM} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t \qquad (6.5).$$

The FM *t*-statistics are given by:

$$t_{FM} = \frac{\hat{\lambda}_{FM}}{sd(\hat{\lambda}_t)/\sqrt{T}} \qquad (6.6),$$

where $\hat{\lambda}_{FM}$ and $sd(\hat{\lambda}_t)$ is the mean and the standard deviation of the time-series of estimated slope coefficient and *T* is the number of months in the period.

Shanken (1992) asserted that although the FM rolling and time-series procedure improves the naive OLS approach, the independence assumption is not strictly satisfied due to measurement errors in the overlapping beta estimates.[94] Thus, an adjustment to the standard errors of the $\hat{\lambda}_{jt}$ is proposed for correcting the bias introduced by the EIV. It is argued by Shanken that when estimating the *ex ante* price of risk, the factor-related variation in the *ex post* price should also be considered. Hence, the *t*-statistic in (6.6) should be asymptotically adjusted by a scalar *c*, which is given by:

$$c = \left[\frac{\bar{\hat{\lambda}}_j}{sd(R_j)}\right]^2 \qquad (6.7),$$

where $\bar{\hat{\lambda}}_j$ is the estimated average price of risk of associated variables, and $sd(R_j)$ is the standard deviation of the state variables. To account for the EIV problem, the standard error of the estimates of the corresponding $\hat{\lambda}_{jt}$ should be multiplied by $\sqrt{1+c}$, which yields the following *t*-statistic (Karanikas, 1997).

$$t^* = \frac{t(\hat{\lambda}_{FM})}{\sqrt{1+c}} \qquad (6.8).$$

[93] A solution exploits the fact that, " *while the estimated standard error in the regression will be biased, the estimated slope coefficient will be unbiased*" (Guermat et al., 2004, p.9)

[94] This is because the non-scalar covariance structure of returns is reflected in the variance of the monthly estimates (Shanken, 1992).

6.3.3 Portfolio versus individual stocks regression

Usually, portfolio formation is justified for reducing the EIV problem that arises from estimating the sensitivities and the prices of risk in two separate steps (Antoniou et al., 1998). The original motivation for this resolution raised by Blume, who suggested that the estimation errors of α_i and β_i would tend to offset each other when the assets are grouped into portfolios if they are imperfectly correlated (Ang, Liu and Schwarz, 2010). Blume (1970) as cited in Ang et al. (2010) argued that the more precise estimates of factor loadings enable researchers to estimate factor risk premiums more accurately. The intuition of running cross-sectional regression using portfolios as base assets were adopted in seminal work such as by Black et al. (1972) and Fama and Macbeth (1973). Later on, it has been implemented in the majority of modern asset pricing literature, possibly due to the easy accessibility of portfolios constructed by Fama and French (Ang et al., 2010).

Although the literature has shown that creating portfolios allows risk premiums to be estimated more precisely, Ang et al. (2010) empirically argues that this motivation is wrong. [95] They show that using portfolios actually leads to wider standard error bounds than using stocks in estimates of their models, which is contrary to Blume's intuition. While forming portfolios reduces the standard errors of factor loadings, it destroys information because the spread of betas is shrunk. Ang et al. (2010) believe that this loss of information is the major determinant for the larger standard errors found in their study. [96] Lo and MacKinlay (1990) also pointed out that the data-snooping biases can be inherent in portfolio-based tests. Thus, several studies estimate cross-sectional risk premiums by using the entire sample of stocks as suggested by Litzenberger and Ramaswamy (1979). For example, Avramov and Chordia (2006) used single securities in their empirical tests of asset pricing models to guard against the loss of information and data-snooping biases. Karanikas (1997) found that it was difficult to form portfolios in his research due to the small numbers of stocks and the relatively short observations of data. Therefore, he used individual stocks as base assets in tests of cross-sectional factor models.

[95] However, their setting considers only efficiency and ignores the power of the test. Also, the analysis is from an econometric, rather than an investment, perspective.

[96] The more dispersed the cross section of betas, the more information the cross section contains to estimate risk premiums. While creating portfolios reduces the sampling uncertainty of factor loadings, the standard errors of factor risk premiums actually increase due to the reduced dispersion of the betas.

Both approaches in specifying base assets have their own advantages and disadvantages. To minimise the EIV problem, the FM approach suggests that stocks should be grouped into portfolios in order to increase the precision of the beta estimates, which contributes to more accurately estimated risk premiums. Nevertheless, this induces a shrinking dispersion of betas, thus leading to the loss of information about the relationship between risk and expected return. The portfolio-level regression is instructive and more popular in recent empirical studies, but firm-level regression can also be done with respect to the issue of fuller information, especially when there are not many securities in the sample as in this case.[97] This study employs both individual stocks and portfolios as base assets in the analysis.

6.3.4 Portfolio formation

The sample period in this study is from January 1980 to December 2009. The first five years of data is used to estimate $\hat{\beta}^i_{MR}$ and $\hat{\beta}^i_w$ for the purpose of allocating stocks into ten portfolios. There are only ten constructed portfolios in this study due to the small numbers of stocks in the sample. However, these portfolios can be formed with respect to a choice of coefficients ($\hat{\beta}^i_{MR}$ or $\hat{\beta}^i_w$) and samples (tourism, utilities or all stocks). In grouping portfolios, the appointed betas are ranked in an ascending order and the individual securities are allocated into ten deciles. Then, the individual betas are re-estimated again using the following five years of data and averaged for the portfolio risk coefficients. Thus, stocks must have at least 85 consecutive observations in order to be included in a portfolio-level test.[98]

With rolling regression, the constructed portfolios are updated monthly and the estimated coefficients move onward. The first period of cross-sectional regressions starts from January 1990, and the time-series of estimated risk premiums contains 240 observations. Table 6.1 summarises the portfolio formation, estimation and testing periods according to the FM approach.

[97] Remembering that the observations of each security in the sample are unequal, the number of stocks in each month of the sample period is different and there may not be many of them in some periods.

[98] The procedure needs information for at least 24 prior months for estimating the first-pass regression and assigning stocks into portfolios. Then, the subsequent 60 periods are needed to estimate portfolios' coefficients, and the security returns in the 85th period are needed for the average of the expected portfolio returns.

[Insert Table 6.1 here]

Nonetheless, the portfolio weather coefficients calculated in the subsequent periods seems not to appropriately represent the spreading of betas in the first period. The inconsistency is clear when the portfolios are allocated by the ranked $\hat{\beta}_w^i$. As shown in Table 6.2, the portfolios constructed from low-$\hat{\beta}_w^i$ tend to have high values of portfolio weather betas. This happens in several weather measures and in all sample sizes. The irrational information of $\hat{\beta}_w^i$ and $\hat{\beta}_w^p$ indicates that the ranking procedure and portfolio formation described earlier may not be appropriate for this study.[99] These diverging values imply that the $\hat{\beta}_w^i$ obtained from the estimation period may not be highly correlated with the $\hat{\beta}_w^i$ estimated from the portfolio formation period.

[Insert Table 6.2 here]

This may be caused by the fact that the estimated weather beta of each security seems to be highly fluctuating over time. For a closer examination, Figure 6.1 presents examples of time-varying weather coefficients estimated from (6.1) of five random securities. The sample is randomly selected from the stocks with data available for the whole sample period in each industry: it should be noted that there is only one qualified stock in agriculture. The graphs are portrayed in three panels, within each panel the rolling weather betas of random stocks from a specific industry are represented. With a rolling window of 60 months, the graphs illustrate the movement of these coefficients for 300 periods. They confirm that weather betas are varying over time. In some cases, such as an agricultural stock, the coefficients are not mean-reverting.

[Insert Figure 6.1 here]

The inordinate movements of betas make it possible for a stock to move from the highest-$\hat{\beta}_w^p$ portfolio to the lowest-$\hat{\beta}_w^p$ portfolio, and vice versa, within the 60-month time frame. Using a random check, for the estimated betas associated with W5, several tourism stocks in portfolio 10 at the 240th period will move to portfolio 1, 3 and 5 if the portfolios at the 300th period are formed.

[99] This thesis also studies the risk premiums by using the portfolio formation approach, but in order to conserve space the results are not shown. Mainly, the market price of weather risk is insignificant.

In that case, the portfolio coefficients may not accurately represent the disperse information of high-beta and low-beta portfolios. Therefore, this study discards the use of the subsequent period to estimate portfolio betas. Instead, the $\hat{\beta}^i$ of individual firms during the portfolio formation period are averaged to obtain the portfolio betas. These portfolios are called 'pre-ranking beta' portfolios, as opposed to 'post-ranking beta' portfolios of FM, throughout the study.

The pre-ranking beta portfolio has several advantages, although it may induce measurement errors and selection bias. Firstly, it brings more observations for the estimates in the study. As only five years of data is lost for computing the factor loadings, the time-series of estimated risk premiums now contains 300 observations derived from the monthly rolling second-pass regressions. This is similar to the test periods using the firm-based regressions. In addition, the shorter required period for portfolio's coefficient estimations also increases the number of stocks in the sample within each period. Since the process of pre-ranking beta portfolio formation requires only 25 observations for a stock to be qualified, portfolios are now constructed with more stocks compared to using the original FM approach. Table 6.3 briefly summarizes the number of stocks in portfolios when using the pre-ranking and post-ranking beta approaches. It is obvious that the pre-ranking beta portfolios contain more stocks in all sample sizes.

[Insert Table 6.3 here]

Last, and most importantly, the portfolio weather coefficients obtained by this method can capture information of the wide spread of $\hat{\beta}_w^i$ more efficiently than those calculated by the post-ranking beta approach. There is a distinct difference between low beta, middle-range beta and high beta portfolios. All these benefits should bring more sampling variations, consequently leading to higher statistical reliability and accuracy of the estimates of weather betas and the pricings of weather risk.

In brief, the research forms ten portfolios according to the ranked $\hat{\beta}_w^i$ by running the OLS regression of (6.1) using the previous five years of data, and the ten portfolios are rebalanced monthly. The $\hat{\beta}_w^i$ is calculated from historical data of 24-60 months prior to

the year of testing, as available. [100] As the initial estimation and portfolio formation period requires 60 prior periods, the testing period starts from January 1985 to December 2009. The portfolios are reformed in different samples with respect to the selected industries, and they are also reallocated by the ranked $\hat{\beta}^{i}_{MR}$. The results of this study should be robust by testing on the different base assets as well as the alternative weather measures.

6.3.5 Models and Hypothesis

Essentially, this part shows all model specifications used for estimations in the study. To determine whether the market and weather variables are related to the underlying factors which explain stock prices, a version of the FM technique is applied. The first-pass regression determines the assets' exposure to the factors. These risks are estimated by regressing stock returns on unanticipated changes in the variables, using equation (6.1), over five years. It is noted that a qualified stock must have at least 24 observations for this regression. Then, the estimates of exposure, or betas, are used as the independent variables in the following second-pass regressions.

6.3.5.1 Portfolio-level regressions

For portfolios ranked by the $\hat{\beta}^{i}_{w}$:

$$R^{p}_{t} = \alpha_1 + \lambda_m \hat{\beta}^{p}_{MR,t-1} + \lambda_w \hat{\beta}^{p}_{w,t-1} + u_1 \qquad (6.9);$$

For portfolios ranked by the $\hat{\beta}^{i}_{MR}$:

$$R^{p}_{t} = \alpha_2 + \lambda_m \hat{\beta}^{p}_{MR,t-1} + \lambda_w \hat{\beta}^{p}_{w,t-1} + u_2 \qquad (6.10),$$

where R^{p}_{t} is the return of the portfolio at time *t*, $\hat{\beta}^{p}_{j,t-1}$ are the average betas of stocks in the portfolio, α is an intercept, and λ_j are the risk premiums associated with the state variables. The expected return of the portfolio is defined as the average returns of stocks in the portfolio at time *t*, and the betas at time *t-1* are calculated from the 24-60 preceding periods of data.

[100] The stock has to have recorded returns for at least 24 months before the testing period in order to be qualified, and any disqualified stock is discarded for that period.

6.3.5.2 Firm-level regressions

The sample size in this study is not large, especially when the test focuses on a particular industry. Therefore, the firm-level regression is useful for the spread of expected return over a wide range in an effort to improve the discriminatory power of the tests. In addition, it is helpful for a deeper analysis when the investigations are based on the absolute, positive and negative weather betas. As firms which are highly exposed to weather have high values of weather betas regardless of the sign, the analysis can be done considering only the absolute values of weather coefficients. Also, individual firms benefit from different weather conditions. This study explores further for a group of securities that gains an advantage from warmer than expected temperature (positive weather betas) and colder than expected temperature (negative weather betas). These cross-sectional regressions are given by:

$$R_{it} = \alpha_3 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}_{w,t-1} + u_3 \qquad (6.11);$$

$$R_{it} = \alpha_4 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \left|\hat{\beta}\right|_{w,t-1} + u_4 \qquad (6.12);$$

$$R_{it} = \alpha_5 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}^{+}_{w,t-1} + u_5 \qquad (6.13);$$

$$R_{it} = \alpha_6 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}^{-}_{w,t-1} + u_6 \qquad (6.14),$$

where $\left|\hat{\beta}\right|_{w,t-1}$, $\hat{\beta}^{+}_{w,t-1}$, and $\hat{\beta}^{-}_{w,t-1}$ are the estimated absolute, positive and negative weather betas respectively.

6.3.5.3 Hypothesis

The time-series and cross-sectional regressions are repeated for each month in the sample, yielding a time-series of estimated market and weather risk premiums. The time-series mean of these estimates are tested by a *t*-test for significant difference from zero. Both the market risk and the weather risk premiums are tested whether they are priced although the analysis is more focused on the prices of weather risk. In other words, the null hypothesis is $H_0 : \lambda_j = 0$, against the alternative hypothesis $H_1 : \lambda_j \neq 0$, where λ_j is the price of risk of the associated variable.

This study assumes that the weather risk premium is different from zero as the weather exposure is pervasive and non-diversifiable. Therefore, it should be priced and investors who invest in weather-exposed firms should be compensated for taking the risk. By the same token, prices of weather derivatives should embed the price of weather risk as they shield buyers from adverse weather. However, no specific assumption about the sign of this premium is presumed, as it may depend on the sign of the weather beta of individual firms. While the sign of weather premium is inchoate, it is assumed that the market risk premium is positive, according to the CAPM theory.

6.4 Empirical results

In this section, the analysis is begun by investigating portfolio results. These portfolios are constructed with respect to the choices of coefficients and samples. The average returns, market betas and weather betas of each pre-ranking beta portfolio are shown here. Afterwards, the estimates of risk premiums from (6.9) to (6.14) are mainly presented, and these prices of risks are tested by a *t*-test for significant difference from zero. Both *t*-statistics of FM and Shanken's corrections are reported, and the adjustments to the standard errors do not make a great difference to the inferences drawn in this study. The cross-sectional regression results here are reported in two parts: the portfolio-level and firm-level regressions. It should be noted that all analyses in the research are subdivided into three subsamples, which are tourism, utilities and all firms, to allow comparability between industries. Due to the exceptionally small sample size of agricultural industry, agricultural firms cannot be tested within the industry but they are included in the all-firm sample.[101] The last subsection illustrates the time-series graphs of the estimated weather premiums over time. It also reveals the serial correlations of these weather risk premiums by examining their autocorrelation coefficients.

6.4.1 Portfolio results

As mentioned before, all portfolio-level tests are based on ten portfolios, which are reconstructed in relation to a choice of the ranked $\hat{\beta}_w^i$ and $\hat{\beta}_{MR}^i$ in the three samples, tourism, utilities, and all firms. It is important to examine the characteristics of these portfolios before further analysis because the returns, market and weather coefficients

[101] There are 19 agricultural stocks in the research, but some observation periods contain only few data.

are used as independent variables in the second-pass regressions. Tables 6.4 to 6.6 present these results of the pre-ranking $\hat{\beta}_w^i$ portfolios, while Tables 6.7 to 6.9 show those of the pre-ranking $\hat{\beta}_{MR}^i$ portfolios. Each panel in these tables displays results of different sample sets. The portfolios are formed by 208 tourism, 257 utilities, or 484 securities: bearing in mind that the all-firm sample combines not only tourism and utilities stocks but also 19 agricultural firms. The portfolios are grouped by industry as well as by the whole sample so that the results from different industries can be compared. The first column in each table presents the specific portfolio number, where portfolio 1 consists of the lowest-decile betas and portfolio 10 contains the highest. The rest of the columns display results of individual portfolios with respect to different weather variables, consistent with the ten weather measures developed in Chapter 4. Since portfolios are rebalanced monthly on the rolling window of 60 periods, the mean of time-series results are shown in the following tables.

[Insert Table 6.4 to 6.9 here]

Table 6.4 and 6.7 present the average returns of $\hat{\beta}_w^i$-ranked portfolios and $\hat{\beta}_{MR}^i$-ranked portfolios, respectively. Basically, the portfolio returns are calculated by averaging returns of individual securities within the portfolio in a subsequent period, but results shown in these tables are the average returns of rebalanced portfolios over time. Regardless of the ranking-coefficients or weather factors, the average of all ten portfolios should yield the same returns because the sample is the same. No matter what portfolio the securities are assigned to, the average returns of all portfolios within the identical sample will be the same as averaging the returns of all securities. The results in Table 6.4 and 6.7 confirm that.

On average, the stocks in all three samples have the mean monthly returns around 1% over the entire period. The returns of these ranked portfolios look scattered with no systematic pattern, but the highest weather-beta portfolios (portfolio 10) in tourism seem to exhibit negative returns in most of the weather factors. This may suggest that stocks with high (positive) weather betas in this industry show signs of lower expected returns. This is possible as the much hotter than expected temperature can deteriorate tourism firms' expected cash flows and thus stock prices.

Table 6.5 and 6.6 display the portfolio market betas ($\hat{\beta}_{MR}^{p}$) and weather betas ($\hat{\beta}_{w}^{p}$) of the pre-ranking $\hat{\beta}_{w}^{i}$ portfolios, respectively. Table 6.8 and 6.9 similarly exhibit these results, which are of the pre-ranking $\hat{\beta}_{MR}^{i}$ portfolios. As the estimates of portfolio coefficients are the averages of the individual firms' betas obtained in the same portfolio formation period, the portfolio betas of the ranked variable are shown in an ascending order. Specifically, the average values of $\hat{\beta}_{w}^{p}$ for portfolio 1 to 10 in Table 6.6 are ranked from the lowest to the highest, while Table 6.8 explicitly shows the same pattern of the $\hat{\beta}_{MR}^{p}$. Although these portfolio betas can characterize each portfolio in terms of high-low betas, it should be remembered that they may introduce selection bias.

The $\hat{\beta}_{MR}^{p}$ of the pre-ranking $\hat{\beta}_{w}^{i}$ portfolios 1 to 10 in Table 6.5 are spreading randomly, but all values regarding the different weather factors, within the same sample, are closed to each other. The market betas in tourism portfolios are obviously higher than those in utilities portfolios, signifying that they are more risky. For the $\hat{\beta}_{w}^{p}$ in Table 6.6, more than half of constructed portfolios show negative values, which means that their expected returns are either negative when the temperature is higher than predicted or *vice versa*. The magnitudes of these weather betas are relatively small, usually less than 0.02. However, it is notable that the portfolios' weather coefficients associated with %W2, %W3 and %W4 are exceptionally higher than those of the other weather factors, consistent with the findings in the previous chapter.

When forming portfolios according to the ranked-$\hat{\beta}_{MR}^{i}$, the $\hat{\beta}_{MR}^{p}$ as shown in Table 6.8 are largely dispersed, especially in tourism. For example, in a case of *W1*, the values range from -0.05 in portfolio 1 to 2.23 in portfolio 10. In contrast, the $\hat{\beta}_{w}^{p}$ in Table 6.9 are not as scattered as the $\hat{\beta}_{MR}^{p}$, probably due to the small association between stock returns and unexpected weather. Most portfolios formed by $\hat{\beta}_{MR}^{i}$ depict negative weather coefficients, particularly in the utilities sample. Again, the portfolio weather betas are small in magnitude in most of the weather factors, except those associated with %W2, %W3 and %W4 variables.

6.4.2 Portfolio-level cross-section regressions

This subsection presents the estimates of the weather risk and market risk premiums using portfolios as base assets in cross-sectional regressions. The null hypothesis that the price of weather risk is zero cannot be rejected at the 5% level of significance in all cases. Similarly, the market risk premiums are not statistically different from zero, which is consistent with empirical evidence in modern asset pricing such as Chen et al. (1986), Jorion (1991) Fama and French (1992).

Table 6.10 reports the results of the second-pass regressions (6.9) of portfolios, grouped according to the ranked $\hat{\beta}_w^i$. The three panels show findings based on different samples: tourism, utilities or all-sample portfolios. Each column of the table is broken into ten weather factors, and this choice of variables reflects different methodologies in capturing unanticipated temperatures. For each weather measure, the table exhibits the averages of month-by-month coefficient estimates ($\overline{\lambda}_w$ and $\overline{\lambda}_m$), the standard errors of these monthly estimates, the *t*-statistics of the estimates and the average R^2 of monthly cross-sectional regressions.

[Insert Table 6.10 here]

While there is no theoretical foundation for the sign of the price of weather risk, all results relative to different weather factors and various sample sizes show that the estimated weather risk premiums are negative. This probably means that stock market assets are generally perceived to be hedged against warmer than expected weather. The negative premium indicates that stocks whose returns are inversely related to increases in unexpected temperature are more profitable, *ceteris paribus*. The magnitudes of estimated weather premiums are large compared with the estimated market risk premiums or the intercepts, but their standard errors are also large. Therefore, they are never significant.

The prices of weather risk estimated by the weather variables in Fahrenheit degrees are obviously greater than those obtained by the percentage factors, which is not surprising. As changing temperatures are always larger in a percentage than a degree term, the

price of weather estimated from this scaling variable is usually lower.[102] However, the magnitudes of weather risk premiums in percentage terms in this table are comparatively large, considering risk premiums associated with macroeconomic variables in previous literature. In the utilities sample, the weather risk premiums in relation to these percentage-weather variables range from -0.42% to -12.50% per month. However, in economic terms, the average value of -0.1250 means that a firm with a negative weather exposure of 0.0013, a mean $\beta_{\%w4}$ for utilities stocks, would have returned only 0.2% per annum more than a firm with no exposure. Although the estimated weather premiums seem to be high, the weather coefficients are so small that weather-exposed stocks would yield little extra return compared with securities with no weather risk. This is the case for all weather variables, either degree-based or percentage-based. The situation is confirmed by the fact that the sizes of estimated $\overline{\lambda}_w$ of variables *%W2*, *%W3* and *%W4* are smaller than those associated with the other weather factors, considering the weather risks estimated from these measures are usually higher.[103]

Turning to the estimated market risk premiums, some of them appear to disagree with the economic theory as they are negative. However, none of them is statistically different from zero. The estimated intercepts, on the other hand, are significant in most cases. The average coefficients of determination, R^2, improve when the tests are based on larger samples. In the all-firm sample, the R^2 with respect to each weather factor is in the narrow range of 45-49%.

[Insert Table 6.11 here]

Table 6.11 shows estimates of (6.10), and these results differ from the previous table because the cross-sectional regressions were run based on the portfolios sorted by the ranked $\hat{\beta}^i_{MR}$. The prices of weather risk are significant at 10% level only in cases of regressions based on all-sample firms and weather betas associated with *W4* and *%W4* variables.[104] However, the average weather premium estimated by *%W4* is no more

[102] Due to the fact that normal temperatures are much lower than 100°F, the degree and percentage terms cannot be directly compared. Changes in temperatures will be always larger in a percentage than a degree term.

[103] See findings in Chapter 5.

[104] Both W4 and %W4 represent temperature irregularities obtained by the ARIMA-X-12 procedure.

significant when the *t*-statistics is corrected for EIV. The results in Panel C, based on portfolios by the whole sample, reveal that the estimates of $\bar{\lambda}_w$ remain negative but their magnitudes are much larger compared with results of the $\hat{\beta}_w^i$-portfolios. The way portfolios are constructed seems to have a great impact on the magnitudes but not on the significance of these estimate coefficients. The average R^2 of these regressions are similar to previous tests though, around 47-49%.

Panels A and B show results based on portfolios formed within tourism and utilities industry respectively. The estimates of $\bar{\lambda}_w$ in these two samples are inconclusive in terms of comparative size to findings of the previous test. Nevertheless, their magnitudes are still high compared with those of the market risk. Regardless of the sign, the weather factors associated with large weather exposures remain experiencing the relatively small prices of weather risk. Several estimated $\bar{\lambda}_w$ are positive, and most of them are derived by tests based on tourism portfolios. The positive value for $\bar{\lambda}_w$ suggests that firms with positive exposures, whose returns increase when it is warmer than expected temperatures, are likely to have a slightly higher rate of return than otherwise. However, none of these estimates are statistically different from zero.

The findings of the estimated market risk premium are similar to previous tests based on (6.9), in that they are never significant. These results provide evidence against the CAPM model and its underlying assumption that the stock market information is efficiently reflected into the security prices. In contrast, the intercepts are statistically different from zero in all cases. On average, they slightly vary around 1% per month.

6.4.3 Firm-level cross-section regressions

This part demonstrates findings of the risk premiums estimated by using individual securities as the base assets. Although this approach is subject to the EIV problem, it reflects the full extent of information of the relationship between risk and expected return. This is appropriate when the number of stocks in the sample is not that large, as in this case. Results are mainly presented for 4 different models of the risk-return regression, (6.11) to (6.14), and within each specification the analysis is based on 10 weather measures and 3 sample sets. The first two regressions examine the risk-return relationship by using the whole dataset, while the other two investigate the association using only a group of selective securities.

The first version of firm-level regressions is estimated by (6.11), which is mainly similar to the portfolio-level regressions performed previously. In each period, a cross-section regression is done across the whole set of securities that have estimates of betas from the first-pass regression. Results are reported in Table 6.12, and they are mainly consistent with the evidence of portfolio-level regressions found earlier. All of the estimated weather premiums are negative, except the one estimated from *%W4* in the utilities sample. However, none of these coefficients are significant. Again, the prices of weather risk estimated from the percentage variables usually have smaller magnitudes than those associated with the degree factors due to the scaling effect. The weather premiums estimated by tourism firms appear to show the widest range, from -0.55% to -28.93% per month, across the ten weather measures.

The estimated market risk premiums remain trivial and the null hypotheses still cannot be rejected in all cases. The negative market risk premiums, although insignificant, are reported in all weather measures except when tourism firms are included in the sample. There is one interesting finding: both weather and market risk premiums estimated by tourism firms are larger in size than those estimated by the other two samples, in all weather factors. However, in economic terms, the tourism and utilities firms should not have widely different premiums associated with weather because the tourism firms have smaller sizes of weather betas than utilities firms on average. The average values of R^2 in the firm-level regressions are greatly reduced from those with the portfolio-level cross sections. The expected return predicted by this model can explain less than 10% of the cross-sectional variation in average stock returns.

[Insert Table 6.12 here]

The next table reports on tests that have been purposely designed to suit the nature of the weather risk. Results are estimated by (6.12), which is different from the earlier model where the cross-sections are run with the normal betas of weather. This test is based on the notion that one unit movement of unexpected temperature can lead to a 1%, either positive or negative, movement in equity returns. As the weather risk, to what extent the stock prices are sensitive to unexpected weather events, depends on the magnitude rather than a direction, tests relative to absolute weather betas should provide the comprehension of how variations of the weather risk explain stock returns.

[Insert Table 6.13 here]

The weather premiums in this model are mostly negative, and significant in some cases. In the combined sample, the prices of weather risk associated with *%W2* and *%W3* are significant at the 5% level, while the premiums estimated with *W1*, *W2* and *W5* are statistically different from zero at the 10% level of significance. In tourism, the weather premiums are also found to be significant in few cases. The *t*-statistics of these significant estimates range from -1.77 to -2.57. All of these significant weather premiums are negative, and this may be interpreted as investors not being compensated for undertaking the weather risk but experiencing losses in investment returns of approximately 1-3% per month for every unit of risk.

In cases of the market index, neither the estimates nor the significance of the factor betas are altered substantially by running regressions of the absolute weather betas. The intercepts and coefficients of determination also show similar results with those in the previous tests of normal weather betas.

To gain additional insight into the weather risk premiums in groups of securities that benefit from hotter weather or colder weather than expected, two alternative model specifications, (6.13) and (6.14), are investigated. Table 6.14 shows results of the tests across firms with only positive weather betas, while Table 6.15 presents findings based on firms with negative weather betas. It should be noted that the members of these groups within each period may change if a sign of the firm's weather beta changes over time.[105]

[Insert Table 6.14 here]

Conceivably, the most interesting results are found in Table 6.14, where only the firms that benefit from warmer temperatures than normal are included in the sample. The average weather risk premiums estimated in the all-firms sample are significant for half of the weather factors. These estimates are negative and they are obtained from the same group of significant weather factors as the previous tests of absolute weather beta.

The pricings of the market index are significant for the first time, in the utilities sample. However, they are inconsistent with the asset pricing theory as they are negative. The largest estimated market risk premium is associated with the variable *W3*, and investors may lose their investment returns over 1% per month for every 1% market risk.

[105] With rolling regression, the beta coefficients measured over the subsample move forward through time. The number of observations is held constant, but the start and end points are shifted.

Although these estimates contrast with the theory, previous seminal work has reported a negative market risk premium before. For example, Fama and French (1992) found a negative but insignificant market risk premium for a sub-period covered in their tests between 1977 and 1990.

In contrast, neither weather nor market risk premiums estimated by the groups of firms that benefit from colder weather than that predicted are significant, in all sample sets. The estimated results of this final test are shown in Table 6.15. There are several differences between the results in this table and the previous one, in terms of signs and magnitudes of the estimates. Some weather factors in specific samples experience considerable alteration of these estimates.

[Insert Table 6.15 here]

One notable difference between the estimates by the whole sample and a group of selected securities is that the average R^2 obtained from the latter models improve by nearly double. For estimates of (6.13) and (6.14), the average R^2 range from 8% to 19%.

All in all, the premiums pertaining to the weather exposures of the bivariate asset pricing models estimated in (6.9) to (6.14) are insignificant, except in a few cases.[106] The weather risk is often significant when the positive values of the weather betas are used in the regressions. Nonetheless, the significant estimates are typically negative. In all tests, the weather premiums anticipated from the variables associated with a degree term yield smaller magnitudes of the estimates than those from the percentage measures, which makes sense in terms of the scaling effect. The sizes of estimated weather risk premiums are exceptionally high compared to the premiums of macroeconomic variables in previous literature. However, this should not be conveyed to the high expected return in economic terms due to the fact that the weather betas are generally low even in the sample of firms highly-exposed to weather.

In every model, results of utilities and all-firms samples are likely to be similar whereas those of tourism may differ substantially. This is not surprising because utilities firms dominate the all-firms sample due to the large number of firms and the long observation

[106] Note that the Shanken's adjustments to the standard errors do not make a significant difference to the inferences drawn in this study.

of each security. The standard errors of weather risk coefficients in tourism are usually larger than those in the other samples. The weather premiums in tourism seem to vary more than pricings of weather in utilities. This is possibly due to the fact that weather is a more dominant factor affecting the expected cash flows of utilities rather than tourism.

Generally, the market index fails to have a statistically significant effect on pricings. The only case where the market risk premiums are significant is when cross sections are run across utilities firms with positive betas. It is inconsistent with the theory to discover that betas on the market portfolio are insufficient to capture the pricing, and in the case that they did, the relationships are negative. The insignificance of pricing of the stock market index contrasts sharply with their significance in the first-pass regressions. The time-series regressions are not reported here to conserve space, but the market index is statistically significant in many more cases than the weather variables. This is similar to what were found in Chen et al. (1986). They suggested that the explanatory power of the market indices in their tests may relate to statistical rather than economic interpretations.[107]

The intercept terms are statistically different from zero in general, and they are on average 1% per month. Theoretically, these estimates should reflect the risk-free rate. Nevertheless, the historical risk-free rate during January 1985-December 2009 according to CRSP is approximately 4.2% per annum.[108] This discrepancy, coupled with the non-priced factors in the tests, leads to an assumption that there are priced factors that pertain in the intercept term. This assumption is consistent with the fact that the average monthly return of all stocks in the sample is 1% overtime and the R^2 of all tests found in this study are relatively low. Although the R^2 of portfolio-based regressions improve substantially compared with those of firm-based tests, these models can explain, roughly, 40% of the cross-sectional variation in expected returns. The bivariate asset pricing models proposed in this research is unable to explain cross-sectional variations of returns. However, the omitted variables are undisclosed in this study and are left for further research.

[107] *"Although stock market indices explain much of the intertemporal movements in other stock portfolios, their estimated exposures (their betas) do not explain cross-sectional differences in average returns…."* Chen et al. (1986, p. 399).

[108] The historic risk-free rate is obtained by averaging the time-series of the Fama risk-free rate in the CRSP database.

6.4.4 The movement of estimated weather risk premiums over time

The previous subsection reveals the cross-section explanatory power of market and weather for the stock returns. The estimated slope coefficients in each of monthly cross-section regressions can be viewed as the *ex post* risk premium on each variable. The following section specifically presents the movements of these *ex post* weather risk premiums, with respect to each weather measure, and investigates if they are serially correlated.

To save space, only the time-series of weather risk premiums estimated from the whole sample are presented. Figure 6.2 illustrates the monthly movements of the weather risk premiums estimated for 300 periods from January 1985 to December 2009 inclusive. Parts A-F show the estimates from (6.9) to (6.14) respectively. Because the magnitudes of the estimated prices of weather risk are different to a great extent in relation to the weather measures, three figures are displayed within each panel. The first graph shows the time-series of weather risk premiums associated with the degree variables. The second figure depicts those of *%W2-%W4*, which usually estimate the smallest magnitudes of the premiums. The last one presents the premiums of the rest of the variables.

[Insert Figure 6.2 here]

All charts present unsystematic patterns, and the estimates from some particular periods exhibit outlier values. For example, the estimated weather premiums, with respect to most of weather factors and regressions in the 14th period, show exceptionally high magnitudes compared to the other periods. However, all estimates of the premiums seem to be random around zero and cannot be predicted.

In an efficient market, the risk premium should not be serially correlated and investors should not be able to predict future value from past values. Thus, the series of weather risk premiums are tested for the serial correlation by the visual correlogram tests and the Ljung-Box statistics up to lag 16. Overall, none of the autoregressive processes are detected in these time-series by examining ACF and PACF.[109] However, there are spikes at different lags depending on model specifications. The autocorrelation

[109] Autoregressive processes have an exponentially declining ACF and spikes in the first one or more lags of the PACF. The number of spikes indicates the order of the autoregression. Correlograms are not reported in this research, but no observation matches the autoregressive process.

coefficients are examined for a closer analysis, but serial correlation results are mixed.[110] The coefficients and the Ljung-Box statistics are not shown, but major findings are reviewed in Table 6.16.

[Insert Table 6.16 here]

The table summarizes the presence of serial correlations in the estimated weather premium time-series. Each row reveals findings of each model specification, while each column presents results in relation to the weather measure used for estimations of the premiums. The numbers in the table represent the specific lags that can reject the null hypothesis of no autocorrelations at 5% level of significance. Regarding the ten weather measures, the estimates by *W4* and *%W4* seem to show a serial correlation in the series in most of the model specifications. The Ljung-Box statistics are rejected at varied lags. On the other hand, there is no autocorrelation found in the premium time-series estimated by *W3* and *%W5* in any model.

The weather premiums estimated by (6.10) seem to be serially correlated more than those estimated by the other models: seven of the ten series in relation to each weather measure are found to be auto correlated at some lags. These serial correlation results may suggest that the pricings of weather risk found in this research are to some extent serially correlated, but they cannot give a precise conclusion about the predictability of the weather premiums. The results here are subject to the weather measure and model specification.

6.5 Discussion and further research

A recent debate over the size and significance of weather risk premium has emerged with the birth of weather derivatives. Because it is central to weather derivative pricings, previous literature proposes different methods to estimate it. Unfortunately, the existing approaches require information such as the quoted price of equivalent weather derivatives or the assumption about the risk-averse level. Ignoring these concerns, this study provides the first effort to tackle the weather risk premium by means of a factor model consistent with the theory of asset pricing. The merits of this approach are three-

[110] It should be noted that the underlying process is assumed to be independent and the Ljung-Box statistic is used to test the null hypothesis that all *n* lags of the correlation coefficients are simultaneously equal to zero. The test is based on the asymptotic chi-square approximation.

fold. Firstly, it does not need the quoted price data of the weather derivatives, which may not be easy to obtain.[111] Secondly, the estimates of the weather premium are based on the well-accepted theory and the conventional methodology. Results from the proposed model are more or less comparable with the asset pricing models investigated previously in many empirical studies. Lastly, the estimates do not involve the complicated numerical analysis, for example, deriving the temperature process. Only the standard OLS regression is used.

In general, the empirical results do not suggest that weather risk is typically priced in the U.S. stock market as the unconditional risk premium related to weather exposure appears to be small and not significant in most cases. They are robust with respect to the choice of weather measures, portfolio formations and sample sizes. Although this finding is contrary to the prior assumption, it is consistent with evidence in Cao and Wei (1999 and 2001) and Hamisultane (2010). With regard to the zero price of weather risk, the industrial practice of using risk free rates in pricing weather derivatives is to some extent assured. In rare cases, the weather risk may be priced when the absolute or positive weather betas are used in the cross-sectional tests. However, results depend largely on the sample sets and weather measures. The *%W2* and *%W3* factors seem to be the outstanding candidates in terms of achieving the significance of weather exposures in the testing models. Both are the percentage measures of the residuals of ARMA processes in temperature series.

Although results are not fully comprehensive in the sense that the risk premiums are not strictly significant at the 5% level of significance, they have some important implications to investment. While there is no strong a prior presumption that would sign the weather risk premium, most of the estimates are negative, including all which are found significant. It contrasts sharply with findings of Richards et al. (2003; 2004) where the implied market price of weather risk is large and positive. The negative weather premiums seem to be in favour in firms whose weather betas are negative, as the expected returns of those firms would turn to positive for bearing weather risk. Actually, as shown in the last chapter, most securities in the sample carry negative weather coefficients, especially utilities firms. In the other aspect, negative weather premiums could mean that weather-exposed stocks need to be hedged against adverse weather.

[111] It is difficult to find equivalent weather derivatives that are liquidate. In addition, sometimes the equivalent assets are traded over-the-counter, where their prices are not publicly available.

The time-series of estimated weather premiums seem to be fluctuating over time and this is consistent with the unstable prices of weather risk found in Hamisultane (2007) and Hardle and Cabrera (2009). The time-series of estimated pricings in several cases appear to be auto correlated, which implies that the weather premiums may be predictable. However, serial correlation results are mixed and no general conclusion is drawn. The predictability of the weather risk premiums need to be examined further. In addition, no investigation in this study has been done in the sub-periods or seasons, thus whether the results are used in the pricing of weather risk in different time frames would be the subject of further research.

The tests in this study are just the beginning and have caveats. They are based on a small sample and may be subject to selection bias coupled with the errors in variables problem. In addition, the weather measures used in this thesis are different in scaling with economic variables. Therefore, results should be interpreted with relatively high caution. Nevertheless, two kinds of experiment were made to assess the sensitivity of these results. Firstly, the alternative weather betas with respect to ten unexpected weather measures were used in all tests. Secondly, the investigations are replicated using the firm-level and portfolio-level regressions. In addition, portfolios are formed according to the different ranked coefficients.

Given that the weather and market risk are inadequate in fully explaining the returns of the sample equities, this might be due to several reasons. Firstly, the proxies may be poor. As some weather measures are superior in explaining the equity prices than others, more exploration of the weather proxy may be needed. Secondly, the information taken into account here does not consider the lagged effects, as the information may not be priced as quickly as assumed before. Comparatively, Cao and Wei did not find the significant price of weather risk until adding the lagged correlation between temperature and dividend processes in their later work. Thirdly, results may be subject to a choice of market portfolio, and researchers may consider other proxies such as equally-weighted market indices. Last but not least, the model may be incorrectly specified and there are priced variables left unexamined. This requires considerable work, but research in APT is going on extensively at the present.

Further investigations can also be done in several ways. For example, researchers may consider other alternative methods to FM for the tests of CAPM and APT such as Hansen's (1982) generalized method of moments (GMM). Jagannathan and Wang

(2002) argued that the GMM-based methods are superior to FM because both normality and conditional homoscedasticity assumptions are relaxed. However, the approaches do not lead to fully efficient estimates (Vorkink, 2003), while Ferson and Foerster (1994) suggested that they lead to asset pricing tests with anomalous properties. On the other hand, Harvey and Zhou (1993) find little support for the difference between OLS and GMM based tests. Recently, Shanken and Zhou (2007) conducted a simulation analysis of cross-sectional expected return models by the FM procedure, the maximum likelihood (ML) and GMM estimators. They found that the GMM estimate is often much more precise than that of the OLS, but it also displays more bias. The reduced form of ML seems to perform well in terms of bias and precision; however, their inferences are less reliable than those of the OLS estimators.

The empirical tests implemented here rest on an assumption that the price of weather risk is constant through time, or an unconditional risk premium. However, the evidence of unstable and possibly seasonal weather risk premium motivates for the use of a conditional version of the asset pricing model that allows for time variability of the prices of risk. Empirical results may be changed substantially, as shown in the previous literature of APT. For instance, in estimating the price of exchange risk, Choi, Hiraki and Takezawa (1998) found that the exchange risk in Japan is priced regardless of the exchange rate measure used in the conditional model, while results are more mixed in the unconditional model. Jorion (1991) found little evidence in his tests of unconditional risk premium that U.S. investors require compensation for bearing exchange risk, but he was aware that there has been accumulating evidence of non-zero conditional risk premium in the foreign exchange market. In the case of weather risk, different firms will be affected by seasonal weather in different ways. Thus, the conditioning information may include the month or season of the year, instead of just stock market or economic information as in the previous literature associated with macroeconomic variables. By allowing the time-variant risk premium, the analysis can be done further by decomposing the predictable part of the asset returns to examine the portion explained by the model and how the weather risk captures predictability of the returns, similar to what Ferson and Harvey (1991; 1993) did for foreign exchange risk.

If weather risk appears to be diversifiable and not priced, active hedging policies cannot affect the cost of capital. Pricing arguments seem not to be able to explain the increasing use of weather derivatives and there must be other reasons. The reason for hedging

weather risk is probably to reduce the expected costs of financial distress from adverse weather. However, under the assumptions of Modigliani and Miller (1958), managers may not be able to increase firm values by hedging. This argument is interesting, but contrasts with the empirical evidence of Pelez-Gonzalez and Yun (2010) that the use of weather derivatives lead to higher valuations, investments and leverage in U.S. electricity and natural gas firms. Possibly, further research may also explore if the use of weather derivatives can increase firm values.

6.6 Conclusion

The support of significant correlations between stock returns and unpredictable weather has motivated the investigation of compensation for such exposures. To the extent that weather shocks affect firms differentially, cross-sectional variation could appear in the relation between stock prices and weather. In theory, if the effects of weather risk do not vanish in a well-diversified portfolio, exposure to weather should yield a risk premium and investors who invest in a weather-exposed stock should gain an extra return.

Although experts assume that the market price of weather risk is not zero, there is insufficient evidence to reach a general conclusion on pricing of weather exposure. The previous studies have estimated these weather premiums by inferring them from the quoted prices of weather derivatives and simulations. Instead, this chapter provides new evidence on the pricing of weather risk in the vein of a factor model, consistent with the well-known asset pricing theory. As far as is known, there is no previous study that investigates the weather risk premium in this framework. This approach requires neither complicated models nor information which may not be publicly available. It also allows a direct comparison of empirical results of weather risk with economic or idiosyncratic risk variables.

As the CAPM theory provides some motivation for the market portfolio, this research tests the variants of the bivariate asset pricing model, where the value-weighted stock index is the first state variable and the unexpected temperature is the second one. The tests employ ten weather measures developed earlier in this thesis to fully account for the effects of changing temperatures. The investigations are done in three samples of tourism, utilities, and all firms. They are conducted by the customary FM methodology at the portfolio- and firm- level data. At the portfolio level, the tests are based on alternative portfolio formations either by the pre-ranking weather beta or by the pre-

ranking market beta. At the firm-level analysis, four alternative models are analysed according to the normal, absolute, positive and negative weather betas.

In the unconditional setting, there is little evidence that the weather risk is priced in the U.S. stock market. Overall, the main pricing results are robust to the alternative sample set, portfolio formations, base assets and weather measures. However, the significance of weather pricing seems to be affected by model specifications, as in several cases weather premiums turn out to be statistically different from zero when the positive value of weather betas are used in cross-sectional regressions. Most of the estimated pricings of weather risk are negative, and although insignificant, this may imply that assets exposed to weather need to be hedged against unexpected increases in temperatures. In other words, investing in stocks whose returns are inversely correlated to unexpectedly warm temperatures is more profitable than otherwise. The magnitudes of estimated weather risk premiums are relatively high; however, weather risk should only yield little extra return in economic terms due to the evidence of small weather coefficients found on average.

It seems that the models proposed in this study are incapable of explaining a substantial amount of the cross-sectional variations in average returns for the securities considered. The failure of the model specification documented here does not necessarily mean that investors do not price weather risk, but rather that the tests focus on specific sectors that effectively hedge weather risk. In addition, the model may not capture the time-varying risk and risk prices during the period of significant changes. This study is an initial exercise in empirical work of weather risk in asset pricing and further analysis in a range of scenarios would be worthwhile. Examinations can be done in larger samples, using different proxies of weather and market variables, and different asset pricing models, either by adding lagged or macroeconomic variables, or by using a different estimating methodology. In addition, a conditional framework to allow time-variation of weather risk may be applied.

In conclusion, even though the results found here are not significant and contrast with the prior assumption, this research establishes a new way of understanding weather risk and its premium. The approach is new to the field but promising because it is based on the strong and well-developed theory. It is much hoped that this study will stimulate more research into the empirical viability of weather exposure, leading to better understanding of the weather risk-return trade-off. This knowledge is useful in weather

derivative valuations, cost-benefit analysis of weather-exposed firms, hedging policy as well as investors' portfolio management.

Table 6.1: Portfolio formation, estimation and testing periods in the post-ranking beta portfolios

The sample period is from January 1980 to December 2009. According to the FM approach, the first five years of data are used to estimate the coefficients for the purpose of allocating stocks into portfolios. Then, the portfolio coefficients are obtained from averaging the individual firms' betas of the subsequent five years, and the portfolios returns are the average of individual returns in the next observation period. The portfolios are reformed monthly, yielding the total estimate of risk premiums for 240 periods. The table shows examples of portfolio formation, initial estimation and testing period of the post-ranking beta portfolios.

	Periods				
	1	***2***	***…***	***239***	***240***
Portfolio formation period	1/1980 - 12/1985	2/1980 - 1/1986		11/1999 - 10/2004	12/1999 - 11/2004
Initial estimation period	1/1986 - 12/1990	2/1986 - 1/1991	…	11/2004 - 10/2009	12/2004 - 11/2009
Testing period	Jan-91	Feb-91	…	Nov-09	Dec-09

Table 6.2: The portfolio weather coefficients for the post-ranking $\hat{\beta}_w$ portfolios

Ten portfolios are formed by ranking $\hat{\beta}_w^i$ in ascending order: portfolio 1 is the lowest decile and portfolio 10 is the highest. The weather betas of these portfolios are the averages of $\hat{\beta}_w^i$ in the subsequent period. The rolling window is five years, and the portfolios are rebalanced monthly. The table reports the averages of portfolio weather betas during January 1990 to December 2009.

A. Tourism

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0018	0.0016	-0.0007	0.0011	0.0008	0.0030	0.0717	0.0026	0.0523	0.0026
2	0.0017	0.0025	0.0014	0.0040	0.0015	-0.0004	0.1227	0.0373	0.1131	0.0049
3	0.0015	0.0021	0.0025	0.0027	0.0029	0.0036	0.0950	0.0967	0.1304	0.0020
4	0.0018	0.0023	0.0012	0.0024	0.0033	0.0016	0.0761	0.0403	0.0496	0.0026
5	0.0007	0.0006	0.0008	0.0033	0.0006	-0.0006	0.0034	0.0546	0.0576	-0.0007
6	0.0000	-0.0001	0.0007	0.0020	-0.0010	-0.0004	0.0177	0.0267	0.1501	-0.0011
7	-0.0007	-0.0004	0.0005	0.0029	-0.0018	-0.0006	0.0318	0.1190	0.1376	-0.0003
8	-0.0012	-0.0008	0.0011	0.0042	-0.0010	-0.0012	-0.0058	0.0716	0.1616	-0.0018
9	-0.0009	0.0001	0.0006	0.0037	0.0000	-0.0023	0.0169	-0.0128	0.1480	-0.0009
10	0.0005	0.0009	0.0016	0.0032	0.0009	0.0007	-0.0061	0.0581	0.1170	0.0022
ALL	*0.0005*	*0.0009*	*0.0010*	*0.0029*	*0.0006*	*0.0004*	*0.0424*	*0.0494*	*0.1117*	*0.0009*

B. Utilities

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0021	-0.0022	-0.0024	-0.0015	-0.0020	-0.0034	-0.0926	-0.0972	-0.0767	-0.0019
2	-0.0019	-0.0021	-0.0023	-0.0017	-0.0015	-0.0034	-0.0961	-0.1055	-0.0947	-0.0013
3	-0.0018	-0.0021	-0.0018	-0.0021	-0.0018	-0.0038	-0.0916	-0.0875	-0.0906	-0.0022
4	-0.0021	-0.0021	-0.0023	-0.0024	-0.0017	-0.0037	-0.0844	-0.0946	-0.1183	-0.0015
5	-0.0021	-0.0021	-0.0022	-0.0021	-0.0018	-0.0039	-0.0844	-0.0991	-0.1113	-0.0018
6	-0.0022	-0.0023	-0.0024	-0.0024	-0.0018	-0.0041	-0.1056	-0.1064	-0.1228	-0.0022
7	-0.0024	-0.0025	-0.0023	-0.0032	-0.0018	-0.0041	-0.1079	-0.1092	-0.1349	-0.0026
8	-0.0026	-0.0027	-0.0025	-0.0032	-0.0023	-0.0043	-0.1043	-0.1121	-0.1494	-0.0027
9	-0.0026	-0.0027	-0.0031	-0.0030	-0.0024	-0.0052	-0.1106	-0.1101	-0.1507	-0.0033
10	-0.0031	-0.0031	-0.0033	-0.0031	-0.0027	-0.0061	-0.1300	-0.1294	-0.1385	-0.0040
ALL	*-0.0023*	*-0.0024*	*-0.0025*	*-0.0025*	*-0.0020*	*-0.0042*	*-0.1007*	*-0.1051*	*-0.1188*	*-0.0024*

C. All firms

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0005	-0.0005	-0.0010	0.0005	-0.0005	-0.0001	-0.0192	-0.0412	-0.0022	0.0009
2	-0.0011	-0.0013	-0.0016	-0.0010	-0.0005	-0.0021	-0.0628	-0.0813	-0.0624	-0.0007
3	-0.0014	-0.0015	-0.0015	-0.0014	-0.0013	-0.0027	-0.0643	-0.0586	-0.0687	-0.0013
4	-0.0017	-0.0019	-0.0017	-0.0018	-0.0014	-0.0033	-0.0698	-0.0808	-0.0933	-0.0014
5	-0.0017	-0.0017	-0.0019	-0.0018	-0.0015	-0.0036	-0.0782	-0.0935	-0.0956	-0.0013
6	-0.0019	-0.0020	-0.0020	-0.0022	-0.0016	-0.0036	-0.0861	-0.0878	-0.1096	-0.0019
7	-0.0022	-0.0023	-0.0021	-0.0027	-0.0017	-0.0038	-0.0857	-0.0963	-0.1251	-0.0025
8	-0.0020	-0.0020	-0.0021	-0.0021	-0.0019	-0.0040	-0.0797	-0.0696	-0.1041	-0.0023
9	-0.0019	-0.0017	-0.0017	-0.0013	-0.0022	-0.0036	-0.0777	-0.0647	-0.0668	-0.0026
10	-0.0021	-0.0018	-0.0013	0.0007	-0.0012	-0.0044	-0.0655	-0.0389	0.0302	-0.0025
ALL	*-0.0016*	*-0.0017*	*-0.0017*	*-0.0013*	*-0.0014*	*-0.0031*	*-0.0689*	*-0.0713*	*-0.0698*	*-0.0016*

Table 6.3: The number of stocks in pre-ranking $\hat{\beta}^i$ and post-ranking $\hat{\beta}^i$ portfolios

The table compares the number of stocks within portfolios formed by the pre-ranking $\hat{\beta}^i$ and post-ranking $\hat{\beta}^i$ **.** The first column displays the different samples, while the second column shows the total number of stocks for each sample. The two last columns give the min-max number of stocks in portfolios formed by the two different approaches. These numbers are observed across all ten constructed portfolios over the whole sample period. It should be noted that the number of stocks in portfolios are different for each monthly observation due to the different sample sizes in each period.

Sample	**Number of stocks**	**Pre-ranking $\hat{\beta}^i$ portfolios**	**Post-ranking $\hat{\beta}^i$ portfolios**
Tourism	208	3 - 7	1 - 4
Utilities	257	9 - 19	8 - 16
All stocks	484	13 - 24	10 - 19

Table 6.4: The $\hat{\beta}_w$-ranked portfolio returns

The $\hat{\beta}_w^i$ of each security is estimated by $R_i = \alpha_i + \beta_{MR} MR + \beta_w W_j + \varepsilon_i$, from time *t-60* to *t-1*. The portfolios are constructed by ranking $\hat{\beta}_w^i$ ascending, and the portfolio returns are calculated by averaging returns at time *t* for individual securities within the portfolio. The portfolios are rebalanced over time by re-estimating $\hat{\beta}_w^i$ every month, and stocks can transfer from one to another portfolio. The table shows the average returns of ten rebalanced portfolios over January 1985-December 2009.

A. Tourism

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0100	0.0134	0.0105	0.0085	0.0124	0.0171	0.0133	0.0087	0.0075	0.0107
2	0.0159	0.0097	0.0141	0.0235	0.0136	0.0131	0.0170	0.0151	0.0202	0.0308
3	0.0068	0.0111	0.0151	0.0092	0.0157	0.0038	0.0075	0.0070	0.0074	-0.0036
4	0.0125	0.0139	0.0097	0.0111	0.0082	0.0084	0.0058	0.0170	0.0211	0.0080
5	0.0118	0.0085	0.0092	0.0126	0.0129	0.0078	0.0130	0.0112	0.0141	0.0044
6	0.0137	0.0110	0.0126	0.0137	0.0108	0.0120	0.0101	0.0120	0.0071	0.0098
7	0.0100	0.0079	0.0119	0.0041	0.0096	0.0115	0.0185	0.0187	0.0123	0.0110
8	0.0122	0.0113	0.0055	0.0043	0.0066	0.0110	0.0051	0.0027	0.0037	0.0115
9	0.0100	0.0136	0.0123	0.0149	0.0133	0.0108	0.0121	0.0136	0.0087	0.0094
10	-0.0018	-0.0004	-0.0004	-0.0016	-0.0014	0.0055	-0.0012	-0.0044	-0.0013	0.0078
ALL	*0.0101*	*0.0100*	*0.0101*	*0.0100*	*0.0102*	*0.0101*	*0.0101*	*0.0102*	*0.0101*	*0.0100*

B. Utilities

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0128	0.0127	0.0140	0.0125	0.0143	0.0135	0.0133	0.0134	0.0140	0.0136
2	0.0121	0.0124	0.0109	0.0120	0.0114	0.0119	0.0114	0.0122	0.0104	0.0113
3	0.0116	0.0116	0.0113	0.0112	0.0099	0.0090	0.0109	0.0101	0.0111	0.0097
4	0.0102	0.0101	0.0108	0.0101	0.0104	0.0108	0.0110	0.0107	0.0109	0.0098
5	0.0101	0.0086	0.0109	0.0107	0.0107	0.0119	0.0081	0.0102	0.0102	0.0107
6	0.0092	0.0109	0.0103	0.0111	0.0101	0.0098	0.0108	0.0118	0.0105	0.0116
7	0.0107	0.0100	0.0103	0.0103	0.0094	0.0114	0.0125	0.0102	0.0114	0.0114
8	0.0114	0.0118	0.0107	0.0107	0.0118	0.0092	0.0110	0.0099	0.0103	0.0101
9	0.0117	0.0109	0.0103	0.0094	0.0112	0.0108	0.0112	0.0103	0.0093	0.0093
10	0.0082	0.0089	0.0084	0.0099	0.0085	0.0097	0.0076	0.0090	0.0096	0.0105
ALL	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*

C. All firms

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0137	0.0128	0.0135	0.0121	0.0126	0.0131	0.0113	0.0111	0.0098	0.0140
2	0.0099	0.0111	0.0101	0.0112	0.0120	0.0080	0.0110	0.0103	0.0146	0.0085
3	0.0088	0.0097	0.0090	0.0091	0.0075	0.0087	0.0112	0.0127	0.0102	0.0097
4	0.0092	0.0091	0.0112	0.0114	0.0088	0.0095	0.0098	0.0092	0.0088	0.0104
5	0.0111	0.0092	0.0093	0.0109	0.0118	0.0124	0.0097	0.0104	0.0106	0.0090
6	0.0096	0.0112	0.0114	0.0094	0.0124	0.0093	0.0111	0.0108	0.0094	0.0104
7	0.0102	0.0100	0.0112	0.0095	0.0105	0.0103	0.0114	0.0096	0.0121	0.0104
8	0.0124	0.0125	0.0110	0.0135	0.0095	0.0128	0.0094	0.0104	0.0113	0.0108
9	0.0115	0.0098	0.0079	0.0086	0.0104	0.0112	0.0116	0.0112	0.0094	0.0093
10	0.0072	0.0082	0.0089	0.0079	0.0079	0.0082	0.0069	0.0078	0.0073	0.0110
ALL	*0.0104*	*0.0104*	*0.0103*	*0.0104*	*0.0103*	*0.0104*	*0.0103*	*0.0104*	*0.0104*	*0.0103*

Table 6.5: The portfolio market betas of the $\hat{\beta}_w$-ranked portfolio

By estimating $R_i = \alpha_i + \beta_{MR} MR + \beta_w W_j + \varepsilon_i$ from time *t-60* to *t-1*, portfolios are constructed by ranking $\hat{\beta}_w^i$ to ten deciles. The portfolio market beta is the average of individual $\hat{\beta}_{MR}^i$ within the portfolio during the portfolio formation period. These portfolios are rebalanced monthly, and stocks can transfer from one to another portfolio. The table shows the average portfolio market betas of ten rebalanced portfolios over January 1985-December 2009.

A. Tourism

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	1.0642	1.0597	1.0417	0.9872	1.0585	1.0284	1.1206	1.0818	1.0385	0.9552
2	1.0749	1.0642	0.9844	0.9800	1.0520	1.0726	1.0616	0.9666	0.9407	1.0199
3	0.9830	0.9951	1.0162	0.8738	1.0106	0.8852	0.9486	1.0425	0.9039	0.9852
4	0.8425	0.8662	0.9565	0.9394	0.9503	0.9441	0.9474	0.9726	0.9794	0.9744
5	1.0095	0.9840	1.0148	1.0543	1.0047	0.9161	1.0434	1.0244	1.0855	0.9533
6	1.0545	1.0683	1.0235	1.1274	1.0265	0.9824	1.0486	1.0267	1.0757	0.9799
7	1.0878	1.0553	1.0590	1.1197	1.0483	1.0533	1.0689	1.1334	1.1261	1.0778
8	1.0788	1.0633	1.0857	1.1169	1.0615	1.1359	1.0425	1.0875	1.1017	1.1213
9	1.0569	1.0803	1.0424	1.0101	1.0005	1.0994	1.0097	0.9965	1.0040	1.1229
10	1.0286	1.0416	1.0624	1.0881	1.0670	1.1554	0.9770	0.9509	1.0328	1.1012
ALL	*1.0281*	*1.0278*	*1.0286*	*1.0297*	*1.0280*	*1.0273*	*1.0268*	*1.0283*	*1.0288*	*1.0291*

B. Utilities

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.7834	0.7845	0.8193	0.7579	0.8123	0.7441	0.7950	0.8381	0.7640	0.7081
2	0.4985	0.4949	0.4966	0.4666	0.5266	0.4698	0.5362	0.5318	0.5031	0.4736
3	0.4488	0.4479	0.4433	0.4357	0.4458	0.4330	0.4412	0.4216	0.4400	0.4253
4	0.4251	0.4231	0.4198	0.4430	0.4320	0.4292	0.4272	0.4182	0.4205	0.4152
5	0.4274	0.4281	0.3993	0.4095	0.4094	0.4074	0.4049	0.4027	0.3973	0.3939
6	0.3917	0.3880	0.3947	0.4135	0.3946	0.3867	0.4096	0.3987	0.4018	0.4082
7	0.4037	0.4049	0.3955	0.4104	0.3970	0.3859	0.3859	0.3812	0.4001	0.4041
8	0.4061	0.4049	0.4175	0.4196	0.4205	0.4103	0.4021	0.4056	0.4245	0.4283
9	0.4354	0.4435	0.4573	0.4635	0.4331	0.4714	0.4417	0.4448	0.4729	0.4767
10	0.6193	0.6168	0.5884	0.6072	0.5797	0.6542	0.5972	0.5917	0.5847	0.6274
ALL	*0.4839*	*0.4837*	*0.4832*	*0.4827*	*0.4851*	*0.4792*	*0.4841*	*0.4834*	*0.4809*	*0.4761*

C. All firms

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.9879	0.9830	0.9980	0.9341	1.0056	0.9461	0.9848	1.0026	0.9354	0.9229
2	0.6337	0.6229	0.6130	0.5783	0.6530	0.6298	0.6501	0.6352	0.6060	0.6324
3	0.5487	0.5257	0.5222	0.5028	0.5495	0.5187	0.5512	0.5086	0.5057	0.5117
4	0.4960	0.5136	0.4824	0.4914	0.5085	0.4979	0.5067	0.4908	0.4771	0.4713
5	0.4861	0.4722	0.4691	0.4857	0.4752	0.4797	0.4747	0.4715	0.4711	0.4615
6	0.4712	0.4867	0.4872	0.4790	0.4888	0.4610	0.4825	0.4923	0.4907	0.4872
7	0.4937	0.4919	0.5062	0.4972	0.4903	0.4726	0.5081	0.5054	0.5150	0.5183
8	0.5664	0.5626	0.5637	0.6149	0.5383	0.5674	0.5390	0.5639	0.6058	0.5832
9	0.6763	0.6901	0.7077	0.7533	0.6705	0.7003	0.6767	0.7166	0.7441	0.7073
10	0.9217	0.9321	0.9247	0.9369	0.9042	0.9798	0.9061	0.8878	0.9109	0.9344
ALL	*0.6282*	*0.6281*	*0.6274*	*0.6274*	*0.6284*	*0.6253*	*0.6280*	*0.6275*	*0.6262*	*0.6230*

Table 6.6: The portfolio weather betas of the $\hat{\beta}_w$-ranked portfolio

By estimating $R_i = \alpha_i + \beta_{MR} MR + \beta_w W_j + \varepsilon_i$ from time *t-60* to *t-1*, portfolios are constructed by ranking $\hat{\beta}_w^i$ to ten deciles. The portfolio weather beta is the average of individual $\hat{\beta}_w^i$ within the portfolio during the portfolio formation period. These portfolios are rebalanced monthly, and stocks can transfer from one to another. The table shows the average portfolio weather betas of ten rebalanced portfolios over January 1985-December 2009.

A. Tourism

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0193	-0.0187	-0.0186	-0.0194	-0.0176	-0.0375	-0.7347	-0.7260	-0.7587	-0.0288
2	-0.0093	-0.0090	-0.0091	-0.0088	-0.0084	-0.0193	-0.3449	-0.3322	-0.3416	-0.0135
3	-0.0058	-0.0055	-0.0053	-0.0049	-0.0053	-0.0119	-0.2009	-0.1901	-0.1910	-0.0076
4	-0.0031	-0.0029	-0.0028	-0.0020	-0.0030	-0.0067	-0.1033	-0.1022	-0.0808	-0.0038
5	-0.0009	-0.0006	-0.0007	0.0006	-0.0010	-0.0024	-0.0183	-0.0209	0.0128	-0.0007
6	0.0012	0.0014	0.0014	0.0030	0.0009	0.0018	0.0543	0.0532	0.1045	0.0024
7	0.0032	0.0035	0.0037	0.0055	0.0031	0.0063	0.1365	0.1456	0.2050	0.0059
8	0.0057	0.0062	0.0063	0.0085	0.0056	0.0117	0.2409	0.2468	0.3139	0.0102
9	0.0092	0.0097	0.0100	0.0126	0.0091	0.0187	0.3683	0.3767	0.4716	0.0152
10	0.0186	0.0193	0.0194	0.0232	0.0178	0.0372	0.7435	0.7544	0.9229	0.0293
ALL	*0.0000*	*0.0003*	*0.0004*	*0.0018*	*0.0001*	*-0.0002*	*0.0141*	*0.0205*	*0.0659*	*0.0009*

B. Utilities

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0113	-0.0112	-0.0115	-0.0121	-0.0105	-0.0224	-0.4455	-0.4586	-0.5027	-0.0166
2	-0.0053	-0.0054	-0.0055	-0.0058	-0.0049	-0.0104	-0.2206	-0.2249	-0.2508	-0.0073
3	-0.0039	-0.0040	-0.0040	-0.0042	-0.0034	-0.0075	-0.1623	-0.1639	-0.1875	-0.0051
4	-0.0028	-0.0029	-0.0030	-0.0031	-0.0024	-0.0053	-0.1233	-0.1267	-0.1435	-0.0034
5	-0.0019	-0.0021	-0.0021	-0.0022	-0.0016	-0.0035	-0.0908	-0.0922	-0.1051	-0.0019
6	-0.0011	-0.0013	-0.0013	-0.0012	-0.0009	-0.0018	-0.0576	-0.0606	-0.0669	-0.0005
7	-0.0003	-0.0004	-0.0004	-0.0002	-0.0001	-0.0001	-0.0239	-0.0268	-0.0260	0.0009
8	0.0007	0.0006	0.0006	0.0011	0.0009	0.0019	0.0152	0.0125	0.0208	0.0026
9	0.0021	0.0021	0.0021	0.0028	0.0022	0.0050	0.0744	0.0678	0.0845	0.0053
10	0.0072	0.0073	0.0075	0.0087	0.0069	0.0145	0.2927	0.2974	0.3218	0.0134
ALL	*-0.0017*	*-0.0017*	*-0.0017*	*-0.0016*	*-0.0014*	*-0.0030*	*-0.0742*	*-0.0776*	*-0.0855*	*-0.0013*

C. All firms

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0145	-0.0142	-0.0143	-0.0148	-0.0133	-0.0290	-0.5648	-0.5670	-0.6083	-0.0220
2	-0.0062	-0.0062	-0.0062	-0.0065	-0.0057	-0.0125	-0.2466	-0.2500	-0.2753	-0.0089
3	-0.0041	-0.0042	-0.0042	-0.0044	-0.0037	-0.0081	-0.1693	-0.1705	-0.1905	-0.0056
4	-0.0028	-0.0029	-0.0029	-0.0029	-0.0024	-0.0054	-0.1203	-0.1200	-0.1338	-0.0034
5	-0.0017	-0.0018	-0.0018	-0.0017	-0.0014	-0.0031	-0.0773	-0.0782	-0.0833	-0.0016
6	-0.0007	-0.0008	-0.0007	-0.0004	-0.0005	-0.0011	-0.0355	-0.0382	-0.0331	0.0001
7	0.0004	0.0004	0.0004	0.0010	0.0006	0.0011	0.0112	0.0092	0.0223	0.0020
8	0.0019	0.0020	0.0020	0.0031	0.0019	0.0041	0.0715	0.0701	0.0999	0.0043
9	0.0044	0.0045	0.0046	0.0062	0.0042	0.0090	0.1777	0.1770	0.2260	0.0082
10	0.0125	0.0129	0.0131	0.0160	0.0120	0.0248	0.5175	0.5260	0.6347	0.0204
ALL	*-0.0011*	*-0.0010*	*-0.0010*	*-0.0004*	*-0.0008*	*-0.0020*	*-0.0436*	*-0.0442*	*-0.0342*	*-0.0006*

Table 6.7: The $\hat{\beta}_{MR}$-ranked portfolio returns

The $\hat{\beta}^{i}_{MR}$ of each security is estimated by $R_i = \alpha_i + \beta_{MR}MR + \beta_w W_j + \varepsilon_i$, from time *t-60* to *t-1*. The portfolios are constructed by ranking $\hat{\beta}^{i}_{MR}$ ascending, and the portfolio returns are calculated by averaging returns at time *t* for individual securities within the portfolio. The portfolios are rebalanced over time by re-estimating $\hat{\beta}^{i}_{MR}$ every month, and stocks can transfer from one to another portfolio. The table shows the average returns of ten rebalanced portfolios over January 1985-December 2009.

A. Tourism

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0085	0.0098	0.0073	0.0068	0.0062	0.0086	0.0088	0.0074	0.0076	0.0088
2	0.0132	0.0040	0.0137	0.0144	0.0156	0.0056	0.0125	0.0130	0.0137	0.0134
3	0.0072	0.0079	0.0084	0.0069	0.0089	0.0108	0.0067	0.0090	0.0073	0.0110
4	0.0155	0.0149	0.0127	0.0139	0.0090	0.0193	0.0145	0.0131	0.0129	0.0089
5	0.0068	0.0165	0.0067	0.0105	0.0090	0.0068	0.0084	0.0060	0.0090	0.0088
6	0.0112	0.0102	0.0131	0.0089	0.0132	0.0140	0.0113	0.0117	0.0102	0.0179
7	0.0168	0.0159	0.0198	0.0194	0.0182	0.0144	0.0179	0.0218	0.0203	0.0110
8	0.0098	0.0121	0.0081	0.0089	0.0094	0.0120	0.0088	0.0087	0.0083	0.0082
9	0.0063	0.0062	0.0061	0.0046	0.0061	0.0080	0.0067	0.0038	0.0057	0.0092
10	0.0058	0.0037	0.0067	0.0082	0.0057	0.0038	0.0064	0.0086	0.0084	0.0062
ALL	*0.0101*	*0.0101*	*0.0103*	*0.0103*	*0.0101*	*0.0103*	*0.0102*	*0.0103*	*0.0103*	*0.0103*

B. Utilities

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0120	0.0121	0.0123	0.0119	0.0119	0.0113	0.0124	0.0123	0.0119	0.0119
2	0.0096	0.0094	0.0094	0.0092	0.0098	0.0094	0.0096	0.0103	0.0103	0.0090
3	0.0108	0.0113	0.0114	0.0119	0.0107	0.0109	0.0113	0.0109	0.0108	0.0113
4	0.0120	0.0115	0.0109	0.0103	0.0117	0.0109	0.0110	0.0107	0.0110	0.0125
5	0.0102	0.0103	0.0110	0.0116	0.0104	0.0112	0.0103	0.0112	0.0106	0.0101
6	0.0096	0.0096	0.0092	0.0096	0.0097	0.0092	0.0098	0.0090	0.0101	0.0090
7	0.0100	0.0098	0.0100	0.0101	0.0099	0.0104	0.0101	0.0106	0.0101	0.0107
8	0.0124	0.0123	0.0124	0.0124	0.0124	0.0127	0.0122	0.0118	0.0117	0.0119
9	0.0115	0.0120	0.0114	0.0109	0.0112	0.0116	0.0120	0.0110	0.0108	0.0123
10	0.0100	0.0096	0.0100	0.0102	0.0103	0.0106	0.0094	0.0103	0.0108	0.0096
ALL	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*	*0.0108*

C. All firms

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0111	0.0110	0.0103	0.0099	0.0107	0.0096	0.0114	0.0107	0.0096	0.0098
2	0.0078	0.0082	0.0091	0.0092	0.0079	0.0099	0.0082	0.0090	0.0099	0.0088
3	0.0112	0.0111	0.0108	0.0106	0.0111	0.0106	0.0101	0.0100	0.0101	0.0117
4	0.0106	0.0104	0.0107	0.0110	0.0109	0.0101	0.0115	0.0106	0.0108	0.0100
5	0.0093	0.0092	0.0091	0.0097	0.0096	0.0097	0.0084	0.0099	0.0105	0.0097
6	0.0118	0.0123	0.0116	0.0113	0.0121	0.0118	0.0119	0.0114	0.0107	0.0116
7	0.0118	0.0114	0.0117	0.0119	0.0102	0.0123	0.0117	0.0114	0.0117	0.0110
8	0.0103	0.0102	0.0105	0.0113	0.0109	0.0119	0.0113	0.0115	0.0113	0.0110
9	0.0093	0.0092	0.0090	0.0084	0.0108	0.0075	0.0082	0.0076	0.0086	0.0097
10	0.0104	0.0106	0.0110	0.0104	0.0094	0.0103	0.0110	0.0115	0.0106	0.0106
ALL	*0.0104*	*0.0104*	*0.0104*	*0.0104*	*0.0104*	*0.0104*	*0.0104*	*0.0104*	*0.0104*	*0.0104*

Table 6.8: The portfolio market betas of the $\hat{\beta}_{MR}$-ranked portfolio

By estimating $R_i = \alpha_i + \beta_{MR} MR + \beta_w W_j + \varepsilon_i$ from time *t-60* to *t-1*, portfolios are constructed by ranking $\hat{\beta}^i_{MR}$ to ten deciles. The portfolio market beta is the average of individual $\hat{\beta}^i_{MR}$ within the portfolio during the portfolio formation period. These portfolios are rebalanced monthly, and stocks can transfer from one to another. The table shows the average portfolio market betas of ten rebalanced portfolios over January 1985-December 2009.

A. Tourism

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0512	-0.1176	-0.0475	-0.0403	-0.0573	-0.1166	-0.0506	-0.0480	-0.0403	-0.0488
2	0.4289	0.3886	0.4262	0.4287	0.4277	0.3798	0.4296	0.4274	0.4275	0.4162
3	0.6219	0.6000	0.6192	0.6200	0.6214	0.5937	0.6222	0.6196	0.6185	0.6152
4	0.7894	0.7873	0.7863	0.7865	0.7881	0.7846	0.7873	0.7846	0.7853	0.7814
5	0.9676	0.9504	0.9652	0.9632	0.9647	0.9536	0.9638	0.9622	0.9610	0.9636
6	1.1032	1.0956	1.1039	1.1005	1.1014	1.1024	1.1005	1.1012	1.0996	1.1067
7	1.2360	1.2443	1.2387	1.2342	1.2300	1.2462	1.2351	1.2372	1.2347	1.2353
8	1.4023	1.4168	1.4010	1.3994	1.4011	1.4194	1.4015	1.4028	1.4016	1.4058
9	1.5955	1.6451	1.5962	1.5934	1.5913	1.6458	1.5962	1.5973	1.5963	1.6006
10	2.2290	2.3149	2.2356	2.2386	2.2364	2.3208	2.2290	2.2329	2.2351	2.2517
ALL	*1.0323*	*1.0325*	*1.0325*	*1.0324*	*1.0305*	*1.0330*	*1.0315*	*1.0317*	*1.0319*	*1.0328*

B. Utilities

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0409	0.0408	0.0415	0.0396	0.0411	0.1066	0.0415	0.0420	0.0376	0.0338
2	0.2040	0.2040	0.2029	0.2023	0.2051	0.2246	0.2036	0.2026	0.2004	0.1977
3	0.2696	0.2697	0.2686	0.2686	0.2706	0.2786	0.2697	0.2686	0.2667	0.2634
4	0.3230	0.3229	0.3222	0.3219	0.3236	0.3297	0.3232	0.3224	0.3202	0.3148
5	0.3706	0.3704	0.3695	0.3692	0.3710	0.3674	0.3710	0.3699	0.3674	0.3620
6	0.4255	0.4252	0.4246	0.4248	0.4256	0.4189	0.4256	0.4248	0.4232	0.4168
7	0.4931	0.4928	0.4921	0.4922	0.4936	0.4786	0.4933	0.4924	0.4907	0.4838
8	0.5861	0.5857	0.5855	0.5845	0.5864	0.5654	0.5872	0.5865	0.5833	0.5744
9	0.7547	0.7542	0.7550	0.7523	0.7567	0.7232	0.7551	0.7553	0.7506	0.7458
10	1.3886	1.3876	1.3887	1.3866	1.3946	1.3141	1.3873	1.3882	1.3844	1.3822
ALL	*0.4856*	*0.4853*	*0.4851*	*0.4842*	*0.4868*	*0.4807*	*0.4858*	*0.4853*	*0.4824*	*0.4775*

C. All firms

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0144	-0.0141	-0.0129	-0.0128	-0.0157	-0.0187	-0.0132	-0.0126	-0.0145	-0.0206
2	0.2214	0.2214	0.2199	0.2200	0.2223	0.2179	0.2210	0.2200	0.2182	0.2151
3	0.3017	0.3019	0.3010	0.3005	0.3027	0.2979	0.3018	0.3010	0.2989	0.2946
4	0.3677	0.3675	0.3668	0.3665	0.3683	0.3633	0.3679	0.3669	0.3649	0.3596
5	0.4384	0.4382	0.4369	0.4377	0.4385	0.4355	0.4381	0.4370	0.4364	0.4322
6	0.5234	0.5232	0.5224	0.5223	0.5240	0.5195	0.5235	0.5226	0.5212	0.5160
7	0.6465	0.6462	0.6445	0.6451	0.6457	0.6415	0.6467	0.6453	0.6441	0.6374
8	0.8258	0.8254	0.8233	0.8227	0.8254	0.8226	0.8251	0.8233	0.8221	0.8186
9	1.1184	1.1181	1.1172	1.1141	1.1177	1.1207	1.1160	1.1151	1.1134	1.1175
10	1.8790	1.8789	1.8827	1.8822	1.8819	1.8779	1.8801	1.8835	1.8820	1.8839
ALL	*0.6308*	*0.6307*	*0.6302*	*0.6298*	*0.6311*	*0.6278*	*0.6307*	*0.6302*	*0.6287*	*0.6254*

Table 6.9: The portfolio weather betas of the $\hat{\beta}_{MR}$-ranked portfolio

By estimating $R_i = \alpha_i + \beta_{MR} MR + \beta_w W_j + \varepsilon_i$ from time *t-60* to *t-1*, portfolios are constructed by ranking $\hat{\beta}^i_{MR}$ to ten deciles. The portfolio weather beta is the average of individual $\hat{\beta}^i_w$ within the portfolio during the portfolio formation period. These portfolios are rebalanced monthly, and stocks can transfer from one to another. The table shows the average portfolio weather betas of ten rebalanced portfolios over January 1985-December 2009.

A. Tourism

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	0.0000	0.0014	0.0009	0.0019	0.0002	-0.0005	0.0684	0.0894	0.1133	-0.0008
2	-0.0014	-0.0009	-0.0010	-0.0005	-0.0009	-0.0019	-0.0130	-0.0049	0.0035	-0.0010
3	-0.0015	-0.0008	-0.0009	-0.0003	-0.0015	-0.0042	-0.0162	-0.0196	-0.0114	-0.0032
4	-0.0002	0.0002	-0.0005	0.0013	0.0005	-0.0018	0.0018	-0.0035	0.0348	-0.0001
5	-0.0003	0.0002	0.0002	0.0009	0.0007	0.0007	0.0051	-0.0056	0.0379	0.0025
6	0.0001	0.0003	-0.0002	0.0010	0.0001	0.0008	0.0279	0.0240	0.0478	0.0023
7	0.0009	0.0009	0.0016	0.0023	0.0009	0.0016	0.0353	0.0476	0.0651	0.0030
8	-0.0004	-0.0001	0.0000	0.0021	-0.0006	0.0000	-0.0113	-0.0079	0.0859	0.0006
9	0.0010	0.0010	0.0016	0.0040	0.0006	0.0017	0.0405	0.0485	0.1183	0.0032
10	0.0006	0.0003	0.0016	0.0047	0.0006	0.0004	-0.0273	0.0036	0.1249	0.0011
ALL	*-0.0001*	*0.0002*	*0.0003*	*0.0017*	*0.0000*	*-0.0003*	*0.0111*	*0.0172*	*0.0620*	*0.0008*

B. Utilities

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0015	-0.0016	-0.0016	-0.0012	-0.0011	-0.0042	-0.0625	-0.0615	-0.0641	-0.0012
2	-0.0014	-0.0015	-0.0015	-0.0015	-0.0010	-0.0033	-0.0609	-0.0664	-0.0784	-0.0009
3	-0.0012	-0.0013	-0.0013	-0.0014	-0.0009	-0.0029	-0.0568	-0.0577	-0.0727	-0.0011
4	-0.0013	-0.0014	-0.0014	-0.0015	-0.0011	-0.0027	-0.0635	-0.0640	-0.0826	-0.0009
5	-0.0014	-0.0015	-0.0015	-0.0015	-0.0011	-0.0026	-0.0684	-0.0686	-0.0780	-0.0010
6	-0.0012	-0.0014	-0.0015	-0.0015	-0.0010	-0.0025	-0.0631	-0.0649	-0.0733	-0.0009
7	-0.0015	-0.0016	-0.0016	-0.0014	-0.0013	-0.0027	-0.0660	-0.0682	-0.0743	-0.0012
8	-0.0019	-0.0019	-0.0019	-0.0017	-0.0016	-0.0028	-0.0871	-0.0895	-0.1009	-0.0013
9	-0.0021	-0.0021	-0.0020	-0.0017	-0.0019	-0.0029	-0.0929	-0.0900	-0.0923	-0.0016
10	-0.0031	-0.0030	-0.0035	-0.0030	-0.0031	-0.0034	-0.1282	-0.1529	-0.1486	-0.0029
ALL	*-0.0017*	*-0.0017*	*-0.0018*	*-0.0016*	*-0.0014*	*-0.0030*	*-0.0749*	*-0.0784*	*-0.0865*	*-0.0013*

C. All firms

Portfolio	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
1	-0.0012	-0.0011	-0.0010	-0.0007	-0.0007	-0.0022	-0.0422	-0.0383	-0.0412	-0.0009
2	-0.0012	-0.0012	-0.0013	-0.0013	-0.0008	-0.0027	-0.0530	-0.0607	-0.0694	-0.0011
3	-0.0013	-0.0014	-0.0013	-0.0014	-0.0009	-0.0025	-0.0564	-0.0571	-0.0686	-0.0010
4	-0.0013	-0.0014	-0.0013	-0.0013	-0.0011	-0.0025	-0.0592	-0.0578	-0.0633	-0.0010
5	-0.0009	-0.0009	-0.0009	-0.0006	-0.0006	-0.0018	-0.0398	-0.0428	-0.0465	-0.0006
6	-0.0011	-0.0011	-0.0010	-0.0007	-0.0009	-0.0023	-0.0462	-0.0408	-0.0398	-0.0008
7	-0.0011	-0.0011	-0.0010	-0.0004	-0.0009	-0.0025	-0.0481	-0.0461	-0.0399	-0.0011
8	-0.0009	-0.0007	-0.0007	-0.0001	-0.0005	-0.0012	-0.0352	-0.0338	-0.0166	0.0004
9	-0.0005	-0.0002	-0.0002	0.0010	-0.0002	-0.0012	-0.0033	-0.0064	0.0285	0.0002
10	-0.0017	-0.0013	-0.0014	0.0006	-0.0019	-0.0021	-0.0650	-0.0701	0.0021	-0.0009
ALL	*-0.0011*	*-0.0010*	*-0.0010*	*-0.0005*	*-0.0009*	*-0.0021*	*-0.0448*	*-0.0454*	*-0.0355*	*-0.0007*

Table 6.10: Regression coefficients estimated by the $\hat{\beta}_w$-ranked portfolios

The portfolio-level cross-sectional regression, $R_t^p = \alpha_1 + \lambda_m \hat{\beta}_{MR,t-1}^p + \lambda_w \hat{\beta}_{w,t-1}^p + u_1$, is rolling forward monthly from January 1985 to December 2009. The base assets are ten portfolios constructed by pre-ranking $\hat{\beta}_w^i$. The table reveals the averages of estimated coefficients over time, with their standard errors and *t*-statistics. The *t*-statistics are calculated both by the FM approach (in italic) and the Shanken's correction (in parentheses). The $\overline{R}^2$ is an average of R^2 of each monthly regression over 300 testing periods.

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
A. Tourism										
$\overline{\lambda}_w$	**-0.1609**	**-0.1706**	**-0.1633**	**-0.2279**	**-0.1164**	**-0.0749**	**-0.0592**	**-0.0624**	**-0.0630**	**-0.0865**
se(λ_w)	0.2437	0.2412	0.2527	0.2412	0.2658	0.1463	0.1476	0.1477	0.1476	0.1917
t-stat	*-0.66*	*-0.71*	*-0.65*	*-0.95*	*-0.44*	*-0.51*	*-0.40*	*-0.42*	*-0.43*	*-0.45*
	(-0.66)	(-0.70)	(-0.64)	(-0.94)	(-0.44)	(-0.51)	(-0.26)	(-0.27)	(-0.25)	(-0.45)
$\overline{\lambda}_m$	**-0.0011**	**-0.0046**	**0.0082**	**0.0020**	**0.0060**	**0.0044**	**0.0053**	**0.0081**	**0.0067**	**0.0078**
se(λ_m)	0.0064	0.0062	0.0075	0.0065	0.0070	0.0075	0.0070	0.0081	0.0069	0.0065
t-stat	*-0.17*	*-0.73*	*1.10*	*0.31*	*0.86*	*0.59*	*0.76*	*0.99*	*0.98*	*1.20*
	(-0.17)	(-0.73)	(1.08)	(0.31)	(0.85)	(0.59)	(0.75)	(0.98)	(0.97)	(1.18)
$\overline{\alpha}_1$	**0.0105**	**0.0143**	**0.0019**	**0.0073**	**0.0040**	**0.0049**	**0.0043**	**0.0006**	**0.0039**	**0.0019**
se(α_1)	0.0070	0.0069	0.0078	0.0066	0.0072	0.0074	0.0074	0.0086	0.0073	0.0068
t-stat	*1.50*	*2.07***	*0.25*	*1.10*	*0.56*	*0.67*	*0.58*	*0.07*	*0.53*	*0.28*
$\overline{R}^2$	26.37%	26.25%	27.65%	26.10%	25.37%	26.51%	26.13%	26.04%	27.41%	25.93%
B. Utilities										
$\overline{\lambda}_w$	**-0.1822**	**-0.1496**	**-0.2119**	**-0.0858**	**-0.2661**	**-0.0789**	**-0.0061**	**-0.0042**	**-0.0042**	**-0.1250**
se(λ_w)	0.1687	0.1696	0.1657	0.1428	0.1855	0.0834	0.0043	0.0045	0.0040	0.0985
t-stat	*-1.08*	*-0.88*	*-1.28*	*-0.60*	*-1.43*	*-0.95*	*-1.40*	*-0.93*	*-1.04*	*-1.27*
	(-1.08)	(-0.88)	(-1.27)	(-0.60)	(-1.42)	(-0.94)	(-1.39)	(-0.93)	(-1.03)	(-1.26)
$\overline{\lambda}_m$	**0.0058**	**0.0060**	**0.0042**	**-0.0017**	**-0.0001**	**0.0027**	**0.0009**	**0.0011**	**-0.0014**	**0.0046**
se(λ_m)	0.0061	0.0058	0.0059	0.0061	0.0063	0.0062	0.0065	0.0057	0.0060	0.0064
t-stat	*0.95*	*1.03*	*0.71*	*-0.28*	*-0.01*	*0.44*	*0.13*	*0.20*	*-0.23*	*0.71*
	(0.94)	(1.02)	(0.70)	(-0.280	(-0.01)	(0.44)	(0.13)	(0.20)	(-0.23)	(0.71)
$\overline{\alpha}_1$	**0.0083**	**0.0082**	**0.0084**	**0.0120**	**0.0108**	**0.0105**	**0.0106**	**0.0090**	**0.0111**	**0.0092**
se(α_1)	0.0032	0.0031	0.0031	0.0033	0.0033	0.0033	0.0033	0.0030	0.0032	0.0034
t-stat	*2.59***	*2.65****	*2.68****	*3.68****	*3.30****	*3.21****	*3.25****	*2.97****	*3.46****	*2.73****
$\overline{R}^2$	41.45%	40.78%	41.92%	42.12%	43.83%	43.29%	41.87%	43.62%	41.44%	39.58%
C. All firms										
$\overline{\lambda}_w$	**-0.1787**	**-0.1681**	**-0.1367**	**-0.1401**	**-0.0815**	**-0.0628**	**-0.0032**	**-0.0024**	**-0.0044**	**-0.0684**
se(λ_w)	0.1328	0.1338	0.1416	0.1291	0.1390	0.0694	0.0033	0.0034	0.0034	0.0797
t-stat	*-1.35*	*-1.26*	*-0.97*	*-1.09*	*-0.59*	*-0.90*	*-0.98*	*-0.69*	*-1.29*	*-0.86*
	(-1.34)	(-1.25)	(-0.96)	(-1.08)	(-0.59)	(-0.90)	(-0.97)	(-0.69)	(-1.29)	(-0.86)
$\overline{\lambda}_m$	**0.0013**	**0.0022**	**-0.0003**	**0.0025**	**0.0051**	**-0.0009**	**0.0006**	**-0.0038**	**-0.0018**	**0.0029**
se(λ_m)	0.0058	0.0059	0.0058	0.0061	0.0061	0.0057	0.0058	0.0061	0.0060	0.0058
t-stat	*0.22*	*0.37*	*-0.06*	*0.41*	*0.83*	*-0.15*	*0.10*	*-0.61*	*-0.29*	*0.51*
	(0.22)	(0.37)	(-0.06)	(0.41)	(0.82)	(-0.15)	(0.10)	(-0.61)	(-0.29)	(0.51)
$\overline{\alpha}_1$	**0.0104**	**0.0100**	**0.0118**	**0.0096**	**0.0077**	**0.0117**	**0.0110**	**0.0135**	**0.0116**	**0.0091**
se(α_1)	0.0034	0.0034	0.0033	0.0034	0.0034	0.0033	0.0034	0.0036	0.0035	0.0034
t-stat	*3.09****	*2.94****	*3.53****	*2.77****	*2.25***	*3.50****	*3.28****	*3.78****	*3.29****	*2.71****
$\overline{R}^2$	47.68%	48.80%	48.55%	47.27%	48.95%	47.91%	46.83%	49.00%	45.23%	45.04%

Note—* Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

Table 6.11: Regression coefficients estimated by the $\hat{\beta}_{MR}$-ranked portfolios

The portfolio-level cross-sectional regression, $R_t^p = \alpha_2 + \lambda_m \hat{\beta}_{MR,t-1}^p + \lambda_w \hat{\beta}_{w,t-1}^p + u_2$, is rolling forward monthly from January 1985 to December 2009. The base assets are ten portfolios constructed by pre-ranking $\hat{\beta}_{MR}^i$. The table reveals the averages of estimated coefficients over time, with their standard errors and *t*-statistics. The *t*-statistics are calculated both by the FM approach (in italic) and the Shanken's correction (in parentheses). The $\bar{R}^2$ is an average of R^2 of each monthly regression over 300 testing periods.

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
A. Tourism										
$\bar{\lambda}_w$	**0.2563**	**0.1678**	**0.3754**	**-0.0301**	**0.0586**	**-0.3536**	**-0.0540**	**-0.0524**	**-0.0602**	**0.2292**
se(λ_w)	0.4691	0.5599	0.4794	0.4261	0.4629	0.3464	0.1479	0.1479	0.1479	0.3144
t-stat	*0.55*	*0.30*	*0.78*	*-0.07*	*0.13*	*-1.02*	*-0.37*	*-0.35*	*-0.41*	*0.73*
	(0.54)	(0.30)	(0.77)	(-0.07)	(0.13)	(-0.96)	(-0.25)	(-0.25)	(-0.24)	(0.72)
$\bar{\lambda}_m$	**-0.0018**	**0.0003**	**-0.0010**	**-0.0002**	**-0.0010**	**-0.0020**	**-0.0006**	**-0.0001**	**-0.0002**	**-0.0037**
se(λ_m)	0.0043	0.0037	0.0044	0.0044	0.0042	0.0040	0.0042	0.0042	0.0043	0.0044
t-stat	*-0.43*	*0.09*	*-0.22*	*-0.05*	*-0.23*	*-0.49*	*-0.14*	*-0.02*	*-0.04*	*-0.84*
	(-0.43)	(0.09)	(-0.22)	(-0.05)	(-0.23)	(-0.49)	(-0.14)	(-0.02)	(-0.04)	(-0.83)
$\bar{\alpha}_2$	**0.0115**	**0.0094**	**0.0102**	**0.0099**	**0.0101**	**0.0102**	**0.0108**	**0.0099**	**0.0101**	**0.0122**
se(α_2)	0.0050	0.0043	0.0051	0.0050	0.0048	0.0046	0.0049	0.0049	0.0049	0.0050
t-stat	*2.31***	*2.17***	*2.01***	*1.99***	*2.10***	*2.23***	*2.20***	*2.04***	*2.08***	*2.46***
$\bar{R}^2$	26.74%	27.28%	26.81%	26.48%	26.60%	26.35%	26.57%	25.68%	26.01%	26.79%
B. Utilities										
$\bar{\lambda}_w$	**-0.0453**	**-0.0907**	**-0.4711**	**-0.2529**	**0.3051**	**-0.1215**	**-0.0062**	**-0.0171**	**-0.0117**	**-0.1036**
se(λ_w)	0.4280	0.4539	0.4415	0.4002	0.4705	0.1986	0.0116	0.0117	0.0107	0.2545
t-stat	*-0.11*	*-0.20*	*-1.07*	*-0.63*	*0.65*	*-0.61*	*-0.53*	*-1.46*	*-1.09*	*-0.41*
	(-0.11)	(-0.20)	(-1.04)	(-0.63)	(0.64)	(-0.61)	(-0.53)	(-1.38)	(-1.05)	(-0.41)
$\bar{\lambda}_m$	**-0.0015**	**-0.0021**	**-0.0011**	**-0.0005**	**-0.0012**	**0.0010**	**-0.0017**	**-0.0021**	**-0.0010**	**-0.0017**
se(λ_m)	0.0034	0.0033	0.0035	0.0033	0.0035	0.0038	0.0033	0.0034	0.0034	0.0034
t-stat	*-0.43*	*-0.64*	*-0.31*	*-0.16*	*-0.33*	*0.27*	*-0.52*	*-0.60*	*-0.28*	*-0.49*
	(-0.43)	(-0.64)	(-0.31)	(-0.16)	(-0.33)	(0.27)	(-0.52)	(-0.60)	(-0.28)	(-0.49)
$\bar{\alpha}_2$	**0.0096**	**0.0102**	**0.0098**	**0.0111**	**0.0104**	**0.0093**	**0.0110**	**0.0105**	**0.0092**	**0.0115**
se(α_2)	0.0023	0.0022	0.0022	0.0022	0.0022	0.0025	0.0023	0.0022	0.0024	0.0022
t-stat	*4.22****	*4.62****	*4.44****	*4.94****	*4.68****	*3.75****	*4.80****	*4.71****	*3.86****	*5.31****
$\bar{R}^2$	45.55%	45.79%	46.37%	46.29%	44.77%	45.28%	46.31%	47.08%	47.80%	44.33%
C. All firms										
$\bar{\lambda}_w$	**-0.6602**	**-0.6466**	**-0.4210**	**-0.8371**	**-0.4472**	**-0.1127**	**-0.0074**	**-0.0136**	**-0.0194**	**-0.3454**
se(λ_w)	0.5125	0.4917	0.4822	0.4558	0.5092	0.2171	0.0132	0.0137	0.0117	0.3081
t-stat	*-1.29*	*-1.32*	*-0.87*	*-1.84**	*-0.88*	*-0.52*	*-0.56*	*-0.99*	*-1.66**	*-1.12*
	(-1.22)	(-1.25)	(-0.85)	(-1.65*)	(-0.86)	(-0.52)	(-0.56)	(-0.96)	(-1.53)	(-1.08)
$\bar{\lambda}_m$	**0.0007**	**0.0012**	**0.0007**	**0.0007**	**0.0001**	**0.0008**	**-0.0001**	**-0.0007**	**-0.0003**	**0.0011**
se(λ_m)	0.0031	0.0031	0.0031	0.0031	0.0030	0.0031	0.0030	0.0031	0.0031	0.0032
t-stat	*0.22*	*0.38*	*0.24*	*0.22*	*0.03*	*0.26*	*-0.03*	*-0.23*	*-0.09*	*0.33*
	(0.22)	(0.38)	(0.24)	(0.22)	(0.03)	(0.26)	(-0.03)	(-0.23)	(-0.09)	(0.33)
$\bar{\alpha}_2$	**0.0089**	**0.0087**	**0.0094**	**0.0104**	**0.0098**	**0.0094**	**0.0105**	**0.0111**	**0.0110**	**0.0101**
se(α_2)	0.0023	0.0023	0.0022	0.0022	0.0022	0.0022	0.0023	0.0023	0.0023	0.0022
t-stat	*3.92****	*3.80****	*4.17****	*4.65****	*4.50****	*4.29****	*4.57****	*4.80****	*4.86****	*4.48****
$\bar{R}^2$	49.24%	49.38%	49.47%	49.36%	48.61%	47.43%	49.64%	49.63%	49.19%	48.99%

Note—* Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

Table 6.12: Coefficients estimated by firm-level regressions

The firm-level cross-sectional regression, $R_{it} = \alpha_3 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}_{w,t-1} + u_3$, is rolling forward monthly from January 1985 to December 2009. The table presents the averages of estimated coefficients over time, with their standard errors and *t*-statistics. The *t*-statistics are calculated both by the FM approach (in italic) and the Shanken's correction (in parentheses). The $\bar{R}^2$ is an average of R^2 of each monthly regression over 300 testing periods.

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
A. Tourism										
$\bar{\lambda}_w$	**-0.2034**	**-0.1965**	**-0.2307**	**-0.2893**	**-0.2743**	**-0.1124**	**-0.0036**	**-0.0040**	**-0.0055**	**-0.1516**
se(λ_w)	0.2256	0.2176	0.2277	0.2259	0.2106	0.1481	0.0050	0.0053	0.0054	0.1378
t-stat	*-0.90*	*-0.90*	*-1.01*	*-1.28*	*-1.30*	*-0.76*	*-0.72*	*-0.75*	*-1.03*	*-1.10*
	(-0.90)	(-0.90)	(-1.01)	(-1.26)	(-1.29)	(-0.75)	(-0.71)	(-0.75)	(-1.02)	(-1.09)
$\bar{\lambda}_m$	**0.0027**	**0.0027**	**0.0025**	**0.0026**	**0.0027**	**0.0023**	**0.0023**	**0.0022**	**0.0025**	**0.0021**
se(λ_m)	0.0036	0.0036	0.0036	0.0037	0.0036	0.0035	0.0036	0.0036	0.0036	0.0035
t-stat	*0.74*	*0.76*	*0.70*	*0.72*	*0.77*	*0.66*	*0.65*	*0.61*	*0.68*	*0.60*
	(0.74)	(0.76)	(0.70)	(0.72)	(0.77)	(0.66)	(0.65)	(0.60)	(0.68)	(0.60)
$\bar{\alpha}_3$	**0.0072**	**0.0072**	**0.0078**	**0.0075**	**0.0074**	**0.0070**	**0.0078**	**0.0082**	**0.0080**	**0.0078**
se(α_3)	0.0042	0.0042	0.0042	0.0042	0.0042	0.0042	0.0042	0.0042	0.0042	0.0042
t-stat	*1.71**	*1.73**	*1.85**	*1.77**	*1.77**	*1.68**	*1.86**	*1.94**	*1.90**	*1.87**
$\bar{R}^2$	7.58%	7.58%	7.80%	7.92%	7.50%	7.71%	7.61%	7.78%	7.88%	7.66%
B. Utilities										
$\bar{\lambda}_w$	**-0.1454**	**-0.1360**	**-0.1055**	**-0.0062**	**-0.1406**	**-0.0628**	**-0.0025**	**-0.0021**	**0.0002**	**-0.0539**
se(λ_w)	0.1905	0.1905	0.1865	0.1749	0.1989	0.0965	0.0046	0.0047	0.0045	0.1105
t-stat	*-0.76*	*-0.71*	*-0.57*	*-0.04*	*-0.71*	*-0.65*	*-0.53*	*-0.45*	*0.04*	*-0.49*
	(-0.76)	(-0.71)	(-0.56)	(-0.04)	(-0.71)	(-0.65)	(-0.53)	(-0.44)	(0.04)	(-0.49)
$\bar{\lambda}_m$	**-0.0004**	**-0.0004**	**-0.0007**	**-0.0008**	**-0.0009**	**-0.0004**	**-0.0008**	**-0.0010**	**-0.0011**	**-0.0013**
se(λ_m)	0.0032	0.0032	0.0032	0.0032	0.0032	0.0033	0.0032	0.0032	0.0032	0.0032
t-stat	*-0.12*	*-0.13*	*-0.22*	*-0.27*	*-0.28*	*-0.12*	*-0.24*	*-0.32*	*-0.36*	*-0.39*
	(-0.12)	(-0.13)	(-0.22)	(-0.27)	(-0.28)	(-0.12)	(-0.24)	(-0.32)	(-0.36)	(-0.39)
$\bar{\alpha}_3$	**0.0107**	**0.0108**	**0.0107**	**0.0112**	**0.0109**	**0.0110**	**0.0108**	**0.0108**	**0.0112**	**0.0115**
se(α_3)	0.0021	0.0021	0.0021	0.0021	0.0021	0.0021	0.0021	0.0020	0.0021	0.0021
t-stat	*5.12***	*5.18***	*5.17***	*5.39***	*5.17***	*5.16***	*5.28***	*5.28***	*5.46***	*5.41***
$\bar{R}^2$	9.26%	9.27%	9.18%	9.24%	9.25%	9.28%	9.07%	9.04%	9.11%	8.98%
C. All firms										
$\bar{\lambda}_w$	**-0.1605**	**-0.1528**	**-0.1299**	**-0.1277**	**-0.1534**	**-0.0610**	**-0.0037**	**-0.0030**	**-0.0029**	**-0.0609**
se(λ_w)	0.1342	0.1313	0.1342	0.1290	0.1370	0.0827	0.0032	0.0033	0.0032	0.0880
t-stat	*-1.20*	*-1.16*	*-0.97*	*-0.99*	*-1.12*	*-0.74*	*-1.18*	*-0.90*	*-0.92*	*-0.69*
	(-1.19)	(-1.16)	(-0.97)	(-0.99)	(-1.12)	(-0.74)	(-1.18)	(-0.90)	(-0.92)	(-0.69)
$\bar{\lambda}_m$	**0.0004**	**0.0004**	**0.0003**	**0.0004**	**0.0004**	**0.0000**	**0.0004**	**0.0004**	**0.0004**	**0.0002**
se(λ_m)	0.0030	0.0030	0.0030	0.0030	0.0030	0.0030	0.0029	0.0029	0.0030	0.0029
t-stat	*0.12*	*0.13*	*0.11*	*0.12*	*0.14*	*0.01*	*0.12*	*0.13*	*0.14*	*0.05*
	(0.12)	(0.13)	(0.11)	(0.12)	(0.14)	(0.01)	(0.12)	(0.13)	(0.14)	(0.05)
$\bar{\alpha}_3$	**0.0101**	**0.0101**	**0.0102**	**0.0102**	**0.0100**	**0.0105**	**0.0100**	**0.0100**	**0.0101**	**0.0105**
se(α_3)	0.0021	0.0021	0.0021	0.0021	0.0021	0.0021	0.0020	0.0020	0.0020	0.0021
t-stat	*4.86***	*4.88***	*4.91***	*4.92***	*4.83***	*4.94***	*4.89***	*4.89***	*4.93***	*5.00***
$\bar{R}^2$	5.61%	5.62%	5.68%	5.69%	5.64%	5.69%	5.58%	5.62%	5.66%	5.63%

Note—* Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

Table 6.13: Coefficients estimated by firm-level regressions with $\left|\hat{\beta}_w\right|$

The firm-level cross-sectional regression, $R_{it} = \alpha_4 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \left|\hat{\beta}\right|_{w,t-1} + u_4$, is rolling forward monthly from January 1985 to December 2009. The table presents the averages of estimated coefficients over time, with their standard errors and *t*-statistics. The *t*-statistics are calculated both by the FM approach (in italic) and the Shanken's correction (in parentheses). The $\overline{R}^2$ is an average of R^2 of each monthly regression over 300 testing periods.

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
A. Tourism										
$\overline{\lambda}_w$	**-0.2270**	**-0.2693**	**-0.3962**	**-0.2577**	**-0.5550**	**0.2009**	**-0.0140**	**-0.0214**	**-0.0149**	**0.1787**
se(λ_w)	0.2949	0.2779	0.2967	0.3014	0.3086	0.2451	0.0087	0.0099	0.0083	0.1768
t-stat	*-0.77*	*-0.97*	*-1.34*	*-0.86*	*-1.80**	*0.82*	*-1.61*	*-2.16***	*-1.80**	*1.01*
	(-0.76)	(-0.96)	(-1.31)	(-0.85)	(-1.74*)	(0.80)	(-1.55)	(-1.99**)	(-1.71*)	(1.00)
$\overline{\lambda}_m$	**0.0027**	**0.0026**	**0.0023**	**0.0024**	**0.0016**	**0.0029**	**0.0015**	**0.0013**	**0.0016**	**0.0019**
se(λ_m)	0.0036	0.0035	0.0035	0.0036	0.0035	0.0037	0.0036	0.0036	0.0036	0.0035
t-stat	*0.76*	*0.72*	*0.65*	*0.67*	*0.46*	*0.79*	*0.40*	*0.37*	*0.45*	*0.55*
	(0.76)	(0.72)	(0.65)	(0.67)	(0.46)	(0.78)	(0.40)	(0.37)	(0.45)	(0.55)
$\overline{\alpha}_4$	**0.0098**	**0.0101**	**0.0110**	**0.0099**	**0.0126**	**0.0053**	**0.0126**	**0.0144**	**0.0129**	**0.0062**
se(α_4)	0.0043	0.0042	0.0043	0.0042	0.0046	0.0052	0.0047	0.0048	0.0046	0.0043
t-stat	*2.31***	*2.40***	*2.59***	*2.34***	*2.74***	*1.02*	*2.66****	*3.01****	*2.80****	*1.43*
$\overline{R}^2$	7.40%	7.41%	7.53%	7.87%	7.66%	7.66%	7.50%	7.50%	7.68%	7.57%
B. Utilities										
$\overline{\lambda}_w$	**-0.0320**	**-0.0325**	**0.0916**	**0.0573**	**0.0758**	**-0.0599**	**-0.0013**	**0.0036**	**0.0032**	**0.0211**
se(λ_w)	0.2453	0.2449	0.2461	0.2277	0.2651	0.1286	0.0058	0.0060	0.0057	0.1518
t-stat	*-0.13*	*-0.13*	*0.37*	*0.25*	*0.29*	*-0.47*	*-0.22*	*0.60*	*0.56*	*0.14*
	(-0.13)	(-0.13)	(0.37)	(0.25)	(0.29)	(-0.47)	(-0.22)	(0.60)	(0.56)	(0.14)
$\overline{\lambda}_m$	**-0.0013**	**-0.0013**	**-0.0017**	**-0.0014**	**-0.0017**	**-0.0013**	**-0.0013**	**-0.0020**	**-0.0017**	**-0.0019**
se(λ_m)	0.0032	0.0032	0.0032	0.0031	0.0032	0.0032	0.0031	0.0031	0.0031	0.0032
t-stat	*-0.41*	*-0.42*	*-0.55*	*-0.44*	*-0.55*	*-0.41*	*-0.41*	*-0.63*	*-0.54*	*-0.58*
	(-0.41)	(-0.42)	(-0.55)	(-0.44)	(-0.55)	(-0.41)	(-0.41)	(-0.63)	(-0.54)	(-0.58)
$\overline{\alpha}_4$	**0.0111**	**0.0112**	**0.0106**	**0.0109**	**0.0110**	**0.0112**	**0.0115**	**0.0107**	**0.0109**	**0.0110**
se(α_4)	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023
t-stat	*4.80****	*4.84****	*4.59****	*4.65****	*4.81****	*4.86****	*5.11****	*4.71****	*4.71****	*4.81****
$\overline{R}^2$	9.18%	9.19%	9.33%	9.22%	9.24%	9.23%	8.87%	9.08%	9.17%	9.06%
C. All firms										
$\overline{\lambda}_w$	**-0.3235**	**-0.3232**	**-0.2404**	**-0.1488**	**-0.3607**	**-0.0445**	**-0.0114**	**-0.0107**	**-0.0068**	**-0.0128**
se(λ_w)	0.1830	0.1806	0.1867	0.1802	0.1989	0.1248	0.0044	0.0048	0.0044	0.1210
t-stat	*-1.77**	*-1.79**	*-1.29*	*-0.83*	*-1.81**	*-0.36*	*-2.57***	*-2.23***	*-1.54*	*-0.11*
	(-1.74*)	(-1.77*)	(-1.28)	(-0.82)	(-1.79*)	(-0.36)	(-2.51**)	(-2.19**)	(-1.52)	(-0.11)
$\overline{\lambda}_m$	**0.0012**	**0.0012**	**0.0010**	**0.0008**	**0.0011**	**0.0008**	**0.0015**	**0.0014**	**0.0010**	**0.0003**
se(λ_m)	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028
t-stat	*0.44*	*0.43*	*0.34*	*0.28*	*0.39*	*0.27*	*0.53*	*0.49*	*0.37*	*0.10*
	(0.44)	(0.43)	(0.34)	(0.28)	(0.38)	(0.27)	(0.53)	(0.49)	(0.37)	(0.10)
$\overline{\alpha}_4$	**0.0112**	**0.0112**	**0.0110**	**0.0109**	**0.0113**	**0.0104**	**0.0117**	**0.0116**	**0.0115**	**0.0102**
se(α_4)	0.0022	0.0022	0.0022	0.0022	0.0022	0.0022	0.0022	0.0022	0.0022	0.0022
t-stat	*5.18****	*5.18****	*5.03****	*4.89****	*5.14****	*4.70****	*5.39****	*5.33****	*5.21****	*4.72****
$\overline{R}^2$	5.89%	5.90%	6.00%	6.00%	6.01%	5.98%	5.79%	5.89%	5.87%	5.82%

Note—* Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

Table 6.14: Coefficients estimated by firm-level regressions with $\hat{\beta}_w^+$

The firm-level cross-sectional regression, $R_{it} = \alpha_5 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}_{w,t-1}^+ + u_5$, is rolling forward monthly from January 1985 to December 2009. Only firms that benefit from warmer than expected weather are included in the sample. The table presents the averages of estimated coefficients over time, with their standard errors and *t*-statistics. The *t*-statistics are calculated both by the FM approach (in italic) and the Shanken's correction (in parentheses). The $\overline{R}^2$ is an average of R^2 of each monthly regression over 300 testing periods.

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
A. Tourism										
$\overline{\lambda}_w$	**-0.3318**	**-0.2076**	**-0.4755**	**-0.4153**	**-0.2655**	**-0.0078**	**-0.0093**	**-0.0178**	**-0.0065**	**0.3036**
se(λ_w)	0.4396	0.4127	0.4314	0.4036	0.4581	0.2174	0.0117	0.0115	0.0107	0.3021
t-stat	*-0.75*	*-0.50*	*-1.10*	*-1.03*	*-0.58*	*-0.04*	*-0.79*	*-1.55*	*-0.61*	*1.00*
	(-0.74)	(-0.50)	(-1.07)	(-1.00)	(-0.58)	(-0.04)	(-0.78)	(-1.46)	(-0.60)	(0.97)
$\overline{\lambda}_m$	**0.0031**	**0.0038**	**0.0048**	**0.0064**	**0.0051**	**0.0020**	**0.0013**	**0.0024**	**0.0028**	**0.0054**
se(λ_m)	0.0044	0.0043	0.0040	0.0043	0.0045	0.0046	0.0046	0.0045	0.0044	0.0047
t-stat	*0.71*	*0.87*	*1.19*	*1.51*	*1.14*	*0.43*	*0.27*	*0.54*	*0.63*	*1.16*
	(0.71)	(0.87)	(1.19)	(1.49)	(1.13)	(0.43)	(0.27)	(0.54)	(0.63)	(1.15)
$\overline{\alpha}_5$	**0.0099**	**0.0077**	**0.0088**	**0.0048**	**0.0053**	**0.0105**	**0.0129**	**0.0129**	**0.0083**	**0.0022**
se(α_5)	0.0067	0.0064	0.0058	0.0059	0.0064	0.0062	0.0066	0.0063	0.0063	0.0059
t-stat	*1.48*	*1.21*	*1.51*	*0.82*	*0.83*	*1.71**	*1.97**	*2.06***	*1.32*	*0.38*
$\overline{R}^2$	13.44%	13.18%	12.74%	12.37%	13.68%	14.12%	13.48%	12.52%	12.30%	13.07%
B. Utilities										
$\overline{\lambda}_w$	**-0.1681**	**-0.0513**	**0.3328**	**0.0484**	**-0.5347**	**-0.3403**	**0.0024**	**0.0070**	**0.0100**	**-0.1631**
se(λ_w)	0.3750	0.3835	0.3910	0.3340	0.4599	0.2457	0.0089	0.0091	0.0091	0.2355
t-stat	*-0.45*	*-0.13*	*0.85*	*0.14*	*-1.16*	*-1.38*	*0.27*	*0.76*	*1.10*	*-0.69*
	(-0.45)	(-0.13)	(0.84)	(0.14)	(-1.13)	(-1.31)	(0.27)	(0.75)	(1.07)	(-0.69)
$\overline{\lambda}_m$	**-0.0075**	**-0.0069**	**-0.0132**	**-0.0060**	**-0.0087**	**-0.0024**	**-0.0065**	**-0.0039**	**-0.0072**	**-0.0069**
se(λ_m)	0.0044	0.0044	0.0044	0.0041	0.0046	0.0050	0.0044	0.0043	0.0042	0.0044
t-stat	*-1.72**	*-1.54*	*-2.97****	*-1.45*	*-1.89**	*-0.49*	*-1.47*	*-0.90*	*-1.73**	*-1.56*
	(-1.70*)	(-1.53)	(-2.86***)	(-1.43)	(-1.86*)	(-0.49)	(-1.45)	(-0.90)	(-1.71*)	(-1.55)
$\overline{\alpha}_5$	**0.0136**	**0.0130**	**0.0120**	**0.0139**	**0.0153**	**0.0143**	**0.0119**	**0.0097**	**0.0111**	**0.0137**
se(α_5)	0.0028	0.0028	0.0027	0.0028	0.0027	0.0029	0.0028	0.0027	0.0030	0.0026
t-stat	*4.81****	*4.58****	*4.49****	*4.92****	*5.74****	*5.00****	*4.26****	*3.66****	*3.74****	*5.28****
$\overline{R}^2$	15.88%	16.29%	16.12%	17.50%	15.94%	17.31%	16.92%	17.87%	18.65%	13.97%
C. All firms										
$\overline{\lambda}_w$	**-0.5039**	**-0.4104**	**-0.2894**	**-0.2240**	**-0.5137**	**-0.1627**	**-0.0153**	**-0.0128**	**-0.0069**	**0.0389**
se(λ_w)	0.2450	0.2404	0.2636	0.2518	0.2652	0.1355	0.0062	0.0065	0.0063	0.1892
t-stat	*-2.06***	*-1.71**	*-1.10*	*-0.89*	*-1.94**	*-1.20*	*-2.48***	*-1.97***	*-1.10*	*0.21*
	(-1.99**)	(-1.67*)	(-1.09)	(-0.88)	(-1.88*)	(-1.18)	(-2.38**)	(-1.92*)	(-1.09)	(0.21)
$\overline{\lambda}_m$	**-0.0019**	**-0.0012**	**-0.0005**	**-0.0001**	**-0.0017**	**-0.0004**	**-0.0017**	**-0.0005**	**-0.0022**	**-0.0002**
se(λ_m)	0.0033	0.0033	0.0031	0.0032	0.0033	0.0037	0.0032	0.0032	0.0031	0.0034
t-stat	*-0.57*	*-0.36*	*-0.15*	*-0.04*	*-0.52*	*-0.10*	*-0.54*	*-0.16*	*-0.70*	*-0.05*
	(-0.57)	(-0.36)	(-0.15)	(-0.04)	(-0.52)	(-0.10)	(-0.54)	(-0.16)	(-0.70)	(-0.05)
$\overline{\alpha}_5$	**0.0146**	**0.0134**	**0.0123**	**0.0123**	**0.0136**	**0.0126**	**0.0154**	**0.0136**	**0.0133**	**0.0102**
se(α_5)	0.0028	0.0027	0.0025	0.0025	0.0026	0.0027	0.0026	0.0025	0.0026	0.0025
t-stat	*5.29****	*4.86****	*4.92****	*4.99****	*5.17****	*4.73****	*5.86****	*5.47****	*5.21****	*4.06****
$\overline{R}^2$	8.45%	8.43%	8.32%	8.32%	8.45%	9.40%	8.51%	8.19%	8.17%	8.32%

Note—* Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

Table 6.15: Coefficients estimated by firm-level regressions with $\hat{\beta}_w^-$

The firm-level cross-sectional regression, $R_{it} = \alpha_6 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}_{w,t-1}^- + u_6$, is rolling forward monthly from January 1985 to December 2009. Only firms that benefit from colder than expected weather are included in the sample. The table presents the averages of estimated coefficients over time, with their standard errors and *t*-statistics. The *t*-statistics are calculated both by the FM approach (in italic) and the Shanken's correction (in parentheses). The $\overline{R}^2$ is an average of R^2 of each monthly regression over 300 testing periods.

	W1	W2	W3	W4	W5	%W1	%W2	%W3	%W4	%W5
A. Tourism										
$\overline{\lambda}_w$	**-0.3736**	**-0.1469**	**-0.4738**	**0.0314**	**0.5645**	**-0.4745**	**0.0135**	**0.0178**	**0.0232**	**-0.4033**
se(λ_w)	0.4856	0.4656	0.5285	0.4523	0.6725	0.3335	0.0190	0.0208	0.0171	0.3178
t-stat	*-0.77*	*-0.32*	*-0.90*	*0.07*	*0.84*	*-1.42*	*0.71*	*0.85*	*1.36*	*-1.27*
	(-0.76)	(-0.31)	(-0.87)	(0.07)	(0.81)	(-1.28)	(0.69)	(0.81)	(1.21)	(-1.20)
$\overline{\lambda}_m$	**0.0023**	**0.0011**	**0.0002**	**-0.0007**	**0.0001**	**0.0027**	**0.0012**	**0.0009**	**0.0009**	**-0.0015**
se(λ_m)	0.0046	0.0045	0.0052	0.0053	0.0047	0.0049	0.0049	0.0052	0.0053	0.0051
t-stat	*0.50*	*0.25*	*0.05*	*-0.13*	*0.01*	*0.55*	*0.24*	*0.17*	*0.17*	*-0.29*
	(0.50)	(0.25)	(0.05)	(-0.13)	(0.01)	(0.55)	(0.24)	(0.16)	(0.17)	(-0.29)
$\overline{\alpha}_6$	**0.0054**	**0.0087**	**0.0074**	**0.0134**	**0.0151**	**-0.0002**	**0.0120**	**0.0143**	**0.0172**	**0.0092**
se(α_6)	0.0049	0.0050	0.0057	0.0057	0.0067	0.0063	0.0077	0.0078	0.0071	0.0063
t-stat	*1.09*	*1.75**	*1.30*	*2.33***	*2.24***	*-0.03*	*1.56*	*1.84**	*2.43***	*1.48*
$\overline{R}^2$	15.45%	15.19%	15.71%	16.05%	15.04%	15.95%	15.47%	15.90%	16.53%	17.20%
B. Utilities										
$\overline{\lambda}_w$	**0.2147**	**0.2361**	**0.1628**	**0.1395**	**0.0887**	**0.0651**	**0.0029**	**0.0002**	**0.0006**	**0.1331**
se(λ_w)	0.3226	0.3225	0.3279	0.2842	0.3772	0.1644	0.0081	0.0078	0.0074	0.2072
t-stat	*0.67*	*0.73*	*0.50*	*0.49*	*0.24*	*0.40*	*0.36*	*0.03*	*0.09*	*0.64*
	(0.66)	(0.73)	(0.49)	(0.49)	(0.23)	(0.40)	(0.36)	(0.03)	(0.09)	(0.64)
$\overline{\lambda}_m$	**0.0039**	**0.0039**	**0.0031**	**0.0028**	**0.0024**	**0.0022**	**0.0020**	**0.0007**	**0.0016**	**0.0021**
se(λ_m)	0.0034	0.0034	0.0035	0.0035	0.0035	0.0034	0.0036	0.0035	0.0035	0.0037
t-stat	*1.14*	*1.16*	*0.89*	*0.81*	*0.68*	*0.64*	*0.55*	*0.19*	*0.45*	*0.56*
	(1.14)	(1.16)	(0.89)	(0.81)	(0.68)	(0.64)	(0.55)	(0.19)	(0.45)	(0.56)
$\overline{\alpha}_6$	**0.0094**	**0.0095**	**0.0089**	**0.0088**	**0.0091**	**0.0092**	**0.0100**	**0.0098**	**0.0095**	**0.0102**
se(α_6)	0.0023	0.0023	0.0023	0.0024	0.0023	0.0023	0.0023	0.0023	0.0023	0.0024
t-stat	*4.11****	*4.18****	*3.82****	*3.74****	*3.89****	*3.95****	*4.39****	*4.34****	*4.14****	*4.26****
$\overline{R}^2$	13.54%	13.33%	13.63%	13.53%	13.53%	13.31%	13.39%	13.39%	13.33%	13.33%
C. All firms										
$\overline{\lambda}_w$	**-0.0001**	**0.0879**	**-0.0825**	**-0.0130**	**0.2390**	**-0.1298**	**0.0075**	**0.0103**	**0.0101**	**-0.1140**
se(λ_w)	0.2496	0.2386	0.2308	0.2243	0.2755	0.1866	0.0063	0.0076	0.0065	0.1931
t-stat	*0.00*	*0.37*	*-0.36*	*-0.06*	*0.87*	*-0.70*	*1.18*	*1.35*	*1.55*	*-0.59*
	(0.00)	(0.37)	(-0.36)	(-0.06)	(0.86)	(-0.69)	(1.17)	(1.32)	(1.51)	(-0.59)
$\overline{\lambda}_m$	**0.0019**	**0.0020**	**-0.0003**	**0.0002**	**0.0020**	**-0.0001**	**0.0023**	**0.0016**	**0.0030**	**-0.0004**
se(λ_m)	0.0031	0.0031	0.0033	0.0034	0.0031	0.0030	0.0032	0.0033	0.0034	0.0032
t-stat	*0.60*	*0.65*	*-0.09*	*0.06*	*0.64*	*-0.03*	*0.70*	*0.49*	*0.88*	*-0.13*
	(0.60)	(0.65)	(-0.09)	(0.06)	(0.64)	(-0.03)	(0.70)	(0.49)	(0.88)	(-0.13)
$\overline{\alpha}_6$	**0.0097**	**0.0105**	**0.0105**	**0.0106**	**0.0107**	**0.0095**	**0.0101**	**0.0112**	**0.0109**	**0.0101**
se(α_6)	0.0023	0.0023	0.0024	0.0025	0.0024	0.0024	0.0025	0.0026	0.0026	0.0024
t-stat	*4.24****	*4.60****	*4.40****	*4.20****	*4.44****	*4.01****	*3.99****	*4.23****	*4.25****	*4.28****
$\overline{R}^2$	8.71%	8.71%	8.62%	8.79%	8.68%	8.61%	8.68%	8.65%	8.83%	9.14%

Note—* Significant at the 10% level, ** Significant at the 5% level and *** Significant at 1% level.

Table 6.16: Serial correlations in time-series of weather risk premiums

The table summarizes the presence of serial correlations in the estimated weather premium time-series. Each row reveals findings of each model specification, while each column presents results in relation to the weather measure used for estimations of the premiums. The underlying process is assumed to be independent and the Ljung-Box statistic is used to test the null hypothesis that all *n* lags of the correlation coefficients are simultaneously equal to zero. The test is based on the asymptotic chi-square approximation. The numbers in the table represent the specific lags that can reject the null hypothesis of no autocorrelations at 5% level of significance.

Models	w1	w2	w3	w4	w5	%w1	%w2	%w3	%w4	%w5
A. $R_t^p = \alpha_1 + \lambda_m \hat{\beta}^p_{MR,t-1} + \lambda_w \hat{\beta}^p_{w,t-1} + u_1$				3-10				4-16	1-16	
B. $R_t^p = \alpha_2 + \lambda_m \hat{\beta}^p_{MR,t-1} + \lambda_w \hat{\beta}^p_{w,t-1} + u_2$	1, 2	8, 11-16			8-13	4	8-13	1	1-4, 7-16	
C. $R_{it} = \alpha_3 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}_{w,t-1} + u_3$				4-9				4-8	4-16	
D. $R_{it} = \alpha_4 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \left\lvert \hat{\beta} \right\rvert_{w,t-1} + u_4$				12-14						
E. $R_{it} = \alpha_5 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}^+_{w,t-1} + u_5$	1, 3 ,4			1-16	7	1, 7-11	1-16		1-8, 13-16	
F. $R_{it} = \alpha_6 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}^-_{w,t-1} + u_6$				1, 8, 10						

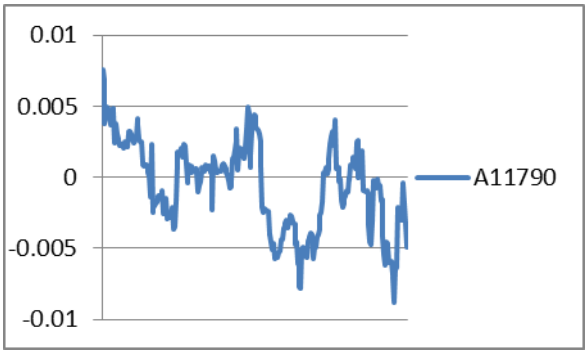
Figure 6.1: The instability of weather betas

The figures illustrate the movement of estimated weather betas of five random securities during 1985-2009. These securities are selected from stocks with full-period observations in each industry: 1 from agriculture, 2 from tourism and 2 from utilities. Each time-series graph plots each security's weather betas, β_w , estimated from

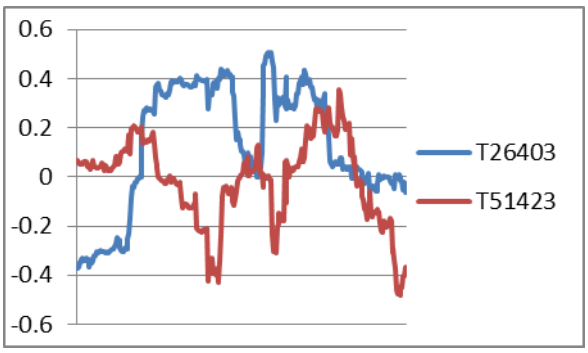
$$R_i = \alpha_i + \beta_{MR} MR + \beta_w W_j + \varepsilon_i$$

over the rolling five-year period. It should be noted that betas estimated from different weather measures are shown in each panel.

A: β_{w5} of an agricultural stock



B. $\beta_{\%w4}$ of tourism stocks



C. $\beta_{\%w3}$ of utilities stocks

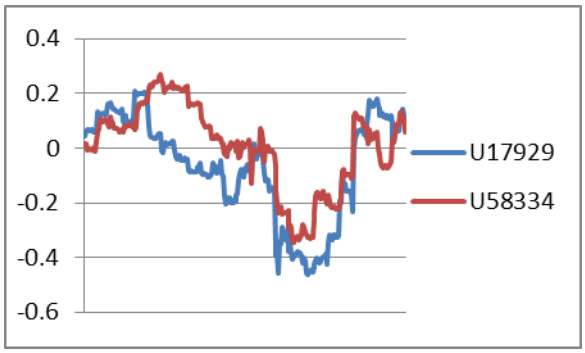
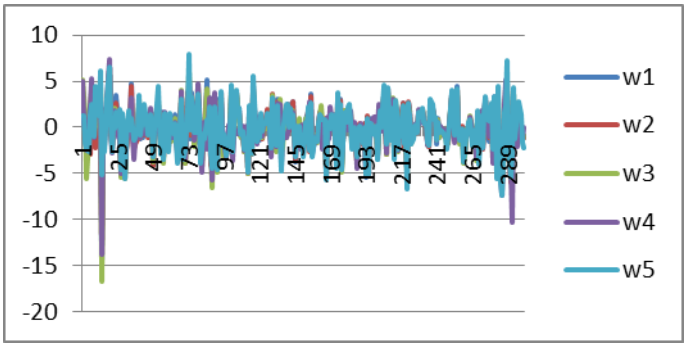


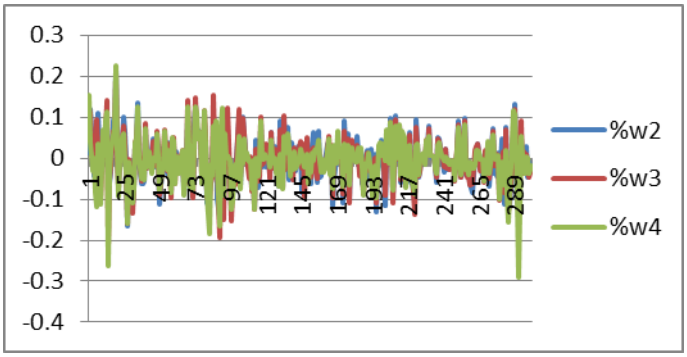
Figure 6.2: The movements of estimated weather risk premiums over 1985-2009

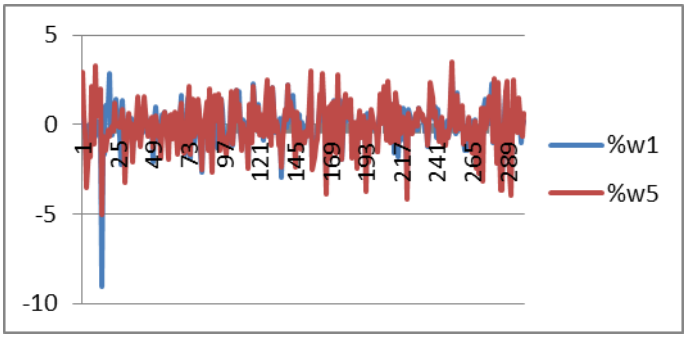
Based on the whole sample set, the estimated month-by-month weather risk premiums are displayed in the following figures. Panels A and B show the premiums obtained from the portfolio-based regressions, whilst C to F present those obtained from the firm-based regressions. Each header describes the OLS regression used to estimate these weather premiums.

Because the magnitudes of the estimated prices of weather risk are different to a great extent in relation to the weather measures, three figures are displayed within each panel. The first graph shows the time-series of weather risk premiums associated with the degree variables. The second figure depicts those of %W2-%W4, which usually estimate the smallest magnitudes of the premiums. The last one presents the premiums of the rest of the variables.

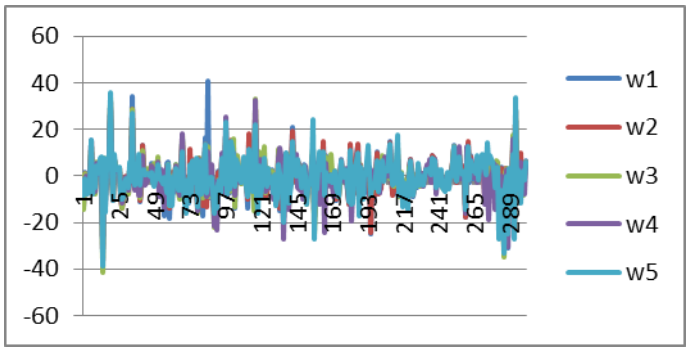
A: For portfolios ranked by the $\hat{\beta}_w^i$***:*** $R_t^p = \alpha_1 + \lambda_m \hat{\beta}_{MR,t-1}^p + \lambda_w \hat{\beta}_{w,t-1}^p + u_1$

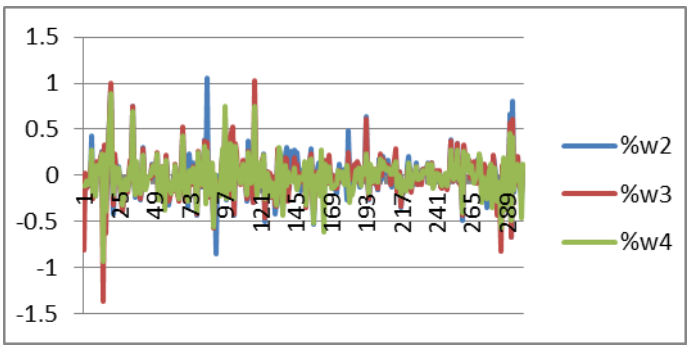


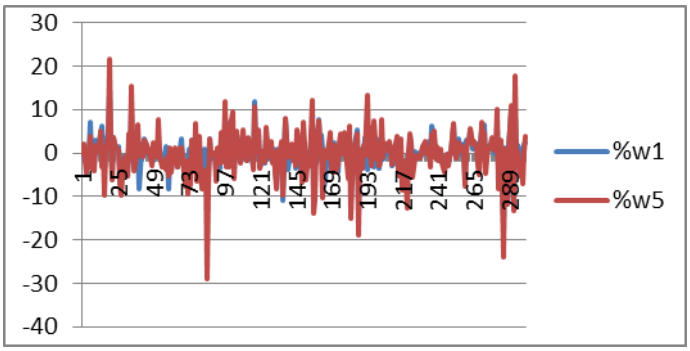




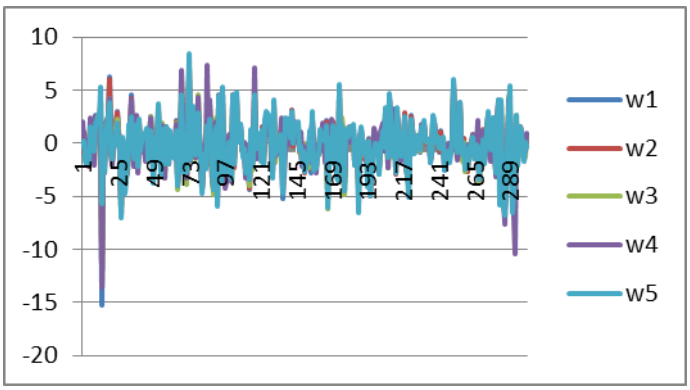
B: For portfolios ranked by the $\hat{\beta}^{i}_{MR}$ **:** $R^{p}_{t} = \alpha_2 + \lambda_m \hat{\beta}^{p}_{MR,t-1} + \lambda_w \hat{\beta}^{p}_{w,t-1} + u_2$

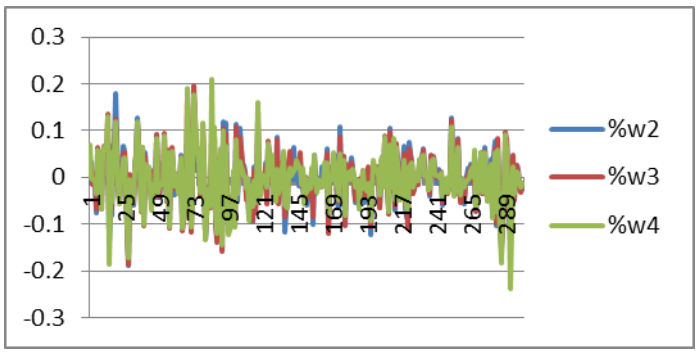


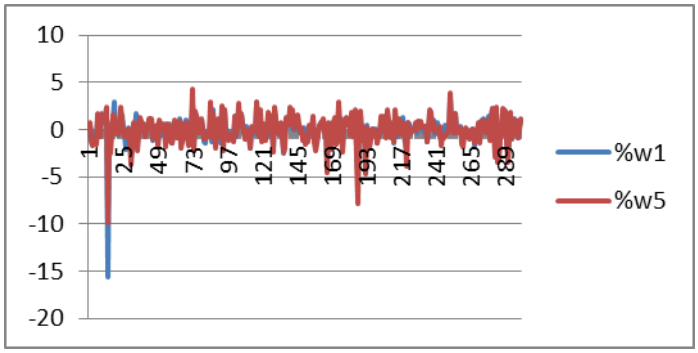




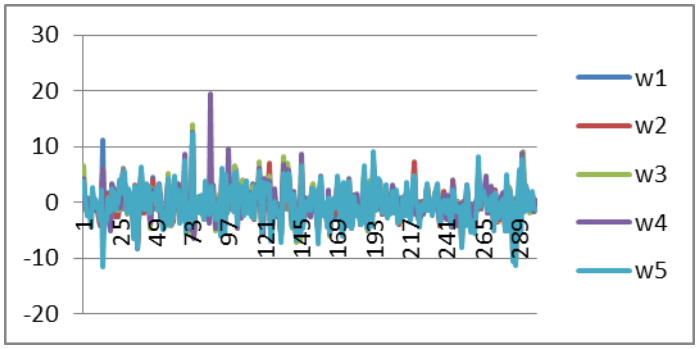
C. $R_{it} = \alpha_3 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}_{w,t-1} + u_3$

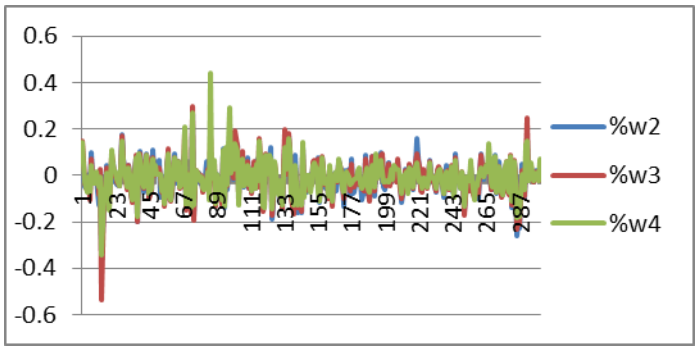


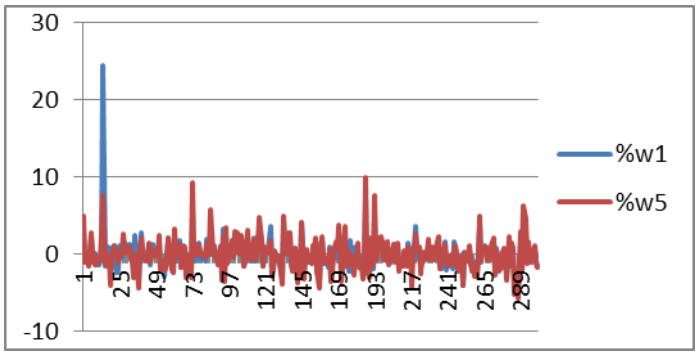




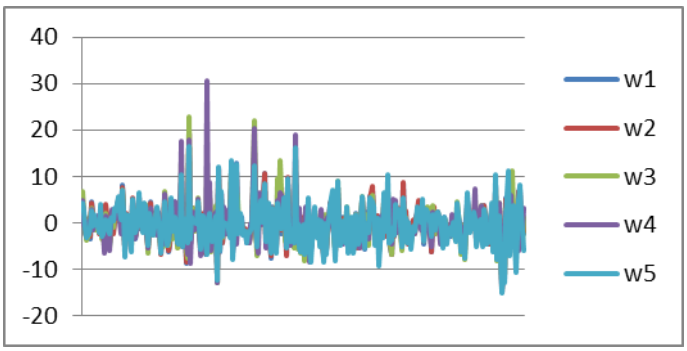
$$D.\ R_{it} = \alpha_4 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \left|\hat{\beta}\right|_{w,t-1} + u_4$$

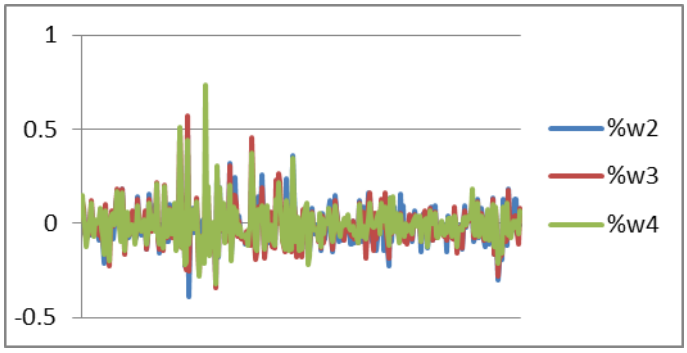


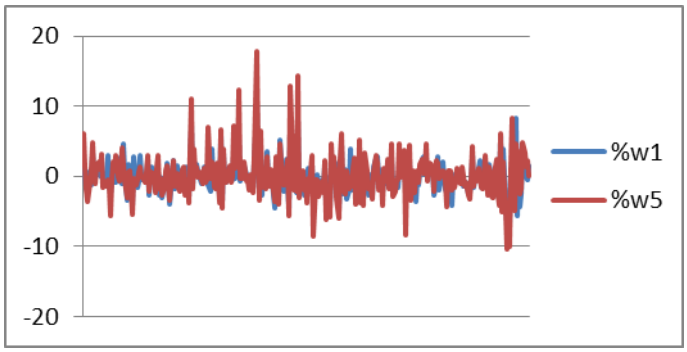




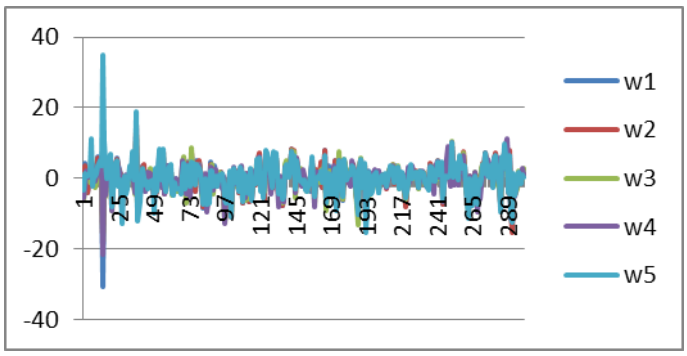
E. $R_{it} = \alpha_5 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}^{+}_{w,t-1} + u_5$

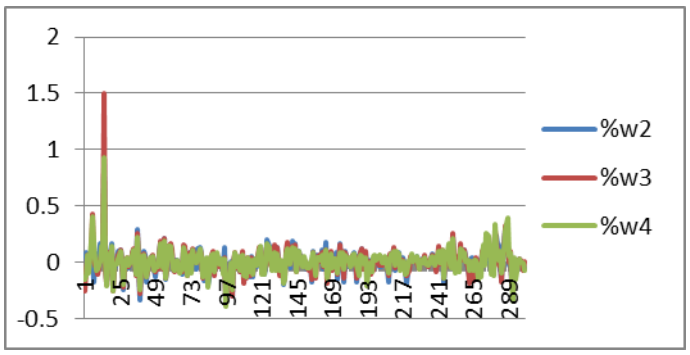


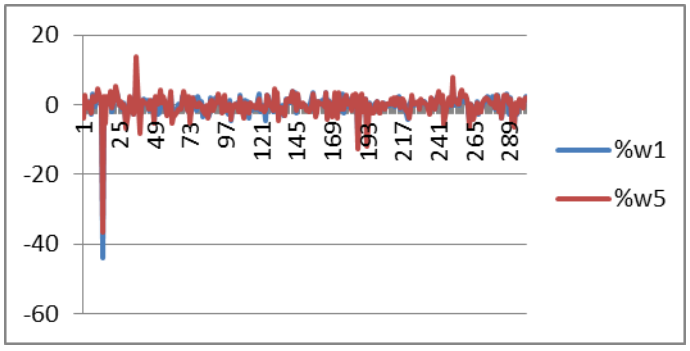




F. $R_{it} = \alpha_6 + \lambda_m \hat{\beta}_{MR,t-1} + \lambda_w \hat{\beta}^{-}_{w,t-1} + u_6$







Chapter 7

Conclusion

This thesis is designed to determine the financial effects of weather on stock returns and assess the compensation required by investors for not being perfectly hedged against weather. It has taken a new approach to estimate the weather exposure of a firm and the pricing of weather risk. In the context that stock returns are influenced by unanticipated events that cannot be fully diversified, the thesis has based its analysis upon the unpredictable element of weather. This study is the first to define and measure weather risk and its premium based on strong theoretical grounds. The methodology is parallel to the standard approach of the estimating of macroeconomic risks, and the proposed model is within the context of the well-established asset pricing theory.

As the study is the first of its kind, it has focused on the group of firms that are potentially most influenced by weather. There are 484 U.S. firms in the sample, from the agricultural, tourism and utilities industries. It should be noted that the study also includes dead stocks in the sample to avoid a survivorship bias. The sample period is between January 1980 to December 2009, which covers the time both before and after the invention of weather derivatives. This study opts for an intermediate record length of thirty years in order to provide extensive information whilst still capturing the recent climate pattern. The U.S. climate services usually define climate on a normal base period of this duration. The dependent variable in this thesis is a monthly stock return series of individual firms, while the independent variables are the market return series and the time-series of unexpected weather. The monthly frequency is used as it is considered long enough to explain the effects of persistent changes in day-to-day weather but also short enough not to eliminate these effects.

Although unexpected weather has rationally given an account of a firm's exposure to weather, as far as is known, the concept has never been implemented in literature. Thus, the study has initially developed the measurements of this unpredictable element. The following sections will summarise the advancement of unexpected weather variables in this study, the main findings of the research, the implications of the results, the limitations of the study and the recommended further research.

7.1 Measures of unexpected weather

The present study has sought to measure unforeseen weather by developing ten weather measures related to temperature. The research has centred on temperature because it has an impact on most businesses and a large proportion of weather derivatives in the market are still written in temperature indices (Dorfleitner and Wimmer, 2010). The continuous property of this parameter also avoids a measurement challenge in the research. Instead of using CDDs or HDDs, the study has directly applied the time-series of temperature for simplicity. This requires only one time estimate and is capable of handling results for any season.

An examination of 48 state-level temperature series has shown that the average monthly temperatures of the U.S. states are strongly correlated. Therefore, a principal component analysis (PCA) is applied to reduce the redundancy of information. The PCA results suggest keeping only one factor to explain monthly temperatures, and the equality of each state's component score coefficient leads to the use of the national temperature series in the research. Due to a strong seasonality in temperature, the ARIMA X-12 method is used to seasonally adjust the time-series.

This study discussed alternative measurements of unexpected temperatures based on different assumptions and statistical methodologies. It has gauged the variables either in the Fahrenheit scale or percentage terms, where the latter represents the percentage term of each choice in a degree measure. Mainly, this research has proposed five concepts and ten variables of unpredictable weather. To derive these factors, simple calculations to advanced ARMA processes have been applied to the temperature time-series. It is worth noting that all variables have been estimated using historical records because weather forecasts are basically changing when the timeframe is nearer. The proposed variables allow easy estimation as well as removing key features of temperature behaviour such as seasonal cycles. The constructed measures appear to be strongly correlated; however, the following analyses have continued to utilize these ten factors throughout the study.

7.2 The weather exposure

This research has focused on the relationships between unexpected temperature and stock returns and the economic importance of those relations. Given that a firm is exposed to unforeseeable weather rather than total weather conditions, the study has estimated the

weather exposure of each firm in the sample by regressing stock return on the market return and each of the unexpected weather measures developed earlier in the study. The market return is included in order to allow for the related macroeconomic factors that may correlate with weather measures. A weather exposure is a regression coefficient of equity return on the weather variable, and it is called a 'weather beta'.

By examining the distribution of weather betas in the sample, it is found that more than half of the estimates are grouped close to zero. This makes the sample distribution non-normal and it is true for all weather measures. The coefficients signs of estimated weather betas are reasonable for all three industries, although it is unclear in tourism. Most of the agricultural firms show positive weather betas, whereas a large amount of the utilities firms exhibit negative weather betas. Average means of weather betas are small in values, implying that unpredictable weather has a slight effect in explaining a variation of equity returns. However, they cannot be negligible because the number of firms that are significantly exposed to weather surprise is greater than what can be attributable to chance. This finding is especially substantial in utilities, consistent with the fact that the use of weather derivatives is more extensive in this industry than the others. Results are similar for all weather measures, but the magnitudes of weather betas for *%W2*, *%W3* and *%W4* are obviously larger than others.

The estimates of weather betas are re-assessed by considering their absolute values as weather risk depends on the magnitude of their sensitivity rather than the direction of surprise weather conditions (hotter or colder than prediction). Regardless of coefficient signs, the average weather coefficients in all industries are now larger. Tourism turns from the smallest weather beta to the largest in absolute terms compared with the other two industries, indicating that tourism firms are actually highly exposed to unexpected weather but the effects are more negligible at the industry level. This is not surprising because of the varied nature of businesses within this industry: some of which may benefit from colder than normal temperatures while the others may not. Nevertheless, the *t*-statistics are never significant.

The study has also examined if an emergence of weather derivatives in late 1997 brings a change in a weather beta of a firm. Due to different observation periods of each firm, the sample here is reduced to 172 firms. More than half of these firms have a weather beta with a different sign before and after 1998, and most of the changes are from positive to negative. Nevertheless, two-third of these changes is not significant at 5% level. Results of the ten weather measures are mostly consistent.

The deeper analysis of weather exposures into the summer and winter seasons reveal that a majority of the significant weather betas are found in winter. The winter effects are strong especially for utilities firms because gas and electricity demands are usually high in winter. However, even though evidence is more substantial in winter, there is less empirical support for the view that the weather betas of the sample firms in summer and winter are statistically different. Agricultural and utilities firms remain showing positive and negative means of weather betas, respectively, in both seasons. Signs of weather betas of tourism firms seem to be more clear than previously found, as more positive weather betas are shown in winter and *vice versa*. The seasonal analysis, to some extent, seems to be able to separate groups of tourism firms that rely on different seasons, yet the vulnerability within seasons is left unexamined. Generally, the seasonal dummy models provide clearer analyses of weather exposures than the general models, and the fitness of these models slightly improves.

In essence, this research has provided evidence that the number of firms that are exposed to weather surprise is greater than what might be expected by chance and evidence is more impressive in utilities. This finding is consistent with the prior assumptions that weather risk is pervasive and that stock returns are sensitive to unpredictable weather. However, the magnitudes of these weather betas seem to be small.

7.3 The market price of weather risk

The significance of weather risk has a direct implication in asset prices; therefore, the research has continued to investigate whether the pricing of weather risk is different from zero. This study has applied the breakthrough methodology of Fama and MacBeth (1973), enhanced with the Shanken's adjustment to correct the errors-in-variable problem. The research has focused on an unconditional estimate of the APT model, where the value-weighted stock index is the first state variable and each of the unexpected weather measures is the second.

The thesis has carried out various tests based on alternative samples, base assets, portfolio formations, model specifications, and the ten weather measures. The sample sets include tourism, utilities and all-firms. The base assets can be either portfolios or individual firms. For portfolio-level tests, ten portfolios are formed according to the estimated pre-ranking β^i_{MR} or β^i_w, and they are rebalanced monthly. This study has used pre-ranking portfolio betas

in the assessment because β_w^i estimated from the preceding five years of each security seem to be unstable over time. Consequently, portfolios' weather betas do not appropriately represent the spreading of betas if subsequent period data is used for the calculation. The use of pre-ranking portfolio betas increases the number of stocks within a portfolio in each observation period, which should bring more sampling variations. However, it is kept in mind that this procedure may also induce measurement errors and selection bias. At firm-level examinations, the study has explored the market price of weather risk further by using four variants of models: they are based on normal, absolute, positive and negative weather betas.

The estimates of weather risk premium at portfolio-level and firm-level regressions have shown a consistent result in that none of the estimated premiums are significant at 5% level. While there is no theoretical foundation for the sign of weather pricing, most results have exhibited negative prices. This indicates that stocks whose returns are inversely related to increases in unexpected temperatures are more profitable, *ceteris paribus*. The magnitudes of estimated weather premiums, although insignificant, are large. However, these do not lead to substantial returns of weather risk in economic terms because equity returns typically have little exposures to weather. This is the case for all weather variables, despite the fact that the degree-based variables have estimated comparatively larger weather premiums than those of the percentage variables. The different base asset and portfolio formation procedure has an impact on the magnitudes but not on the significance of the estimated coefficients. The sign of estimates are mostly consistent, yet several positive premiums have been revealed in estimates relative to the $\hat{\beta}_{MR}$-ranked portfolios. The average coefficients of determination (R^2) of portfolio-level regressions are higher than those of firm-level regressions to a great extent.

The study has further estimated the market price of weather risk by using absolute values of firm exposures to weather, which is more suitable for the nature of this risk. The weather premiums turn out to be statistically different from zero at 5% level of significance in several cases of both tourism and combined samples. These significant estimates remain negative. It may be interpreted that investors are not compensated for undertaking weather risk but experience losses in investment returns of approximately 1-3% per month for every unit of risk.

This research has also investigated the weather risk premiums in group of securities that benefit from hotter and colder weather than expected, by examining two alternative models of positive and negative weather betas. In firms only with positive betas, the pricing results of weather risk are significant at the 5% or 10% levels for half of the weather factors in the combined sample set. These estimates, again, are all negative. In contrast, the weather risk premiums estimated by negative weather betas are never significant. Some weather factors in specific samples have also experienced considerable alternation of the estimated weather pricings, compared with the findings of positive weather betas. The average R^2 obtained from these selective groups improve to nearly double from the whole sample.

In short, the results of this study indicate that there is little evidence that weather risk is priced in the U.S. stock market. The main pricing results of weather variables are robust to alternative sample sets, base assets, portfolio formations and weather measures, but only slightly affected by model specifications. The weather premiums are statistically different from zero in a few cases when positive values of weather betas are employed in cross-sectional regressions. These pricings, however, are negative, and this may suggest that assets exposed to weather need to be hedged against warmer than expected temperatures. The estimated weather premiums seem to vary over time and, in some cases, are auto-correlated. Nevertheless, the mixed results make the predictability of weather risk premiums unclear.

7.4 Suggested implications and the significance of the findings

The most obvious finding to emerge from this study is that whilst weather risk is found to be significant, it cannot explain the cross-sectional difference in expected stock returns of the U.S. weather-influenced equities. In other words, the weather risk premium is not different from zero and this implies that unpredictable weather is not one of the priced factors in the stock market. However, the empirical evidence found in this study does not necessarily mean that investors do not price weather risk, but rather the tests focus on specific sectors that may effectively hedge weather risk already. The results also depend largely on weather measures, of which this study has presented only a limited set. Therefore, the generalization of findings in the current study must be made with caution.

The empirical evidence in this thesis adds substantially to the knowledge of equity's exposure to unpredictable weather and weather risk-return trade-off. The results in Chapter 5 have confirmed the importance of weather risk, and provided the new evidence of weather

exposures in the U.S. stock market. The zero price of weather risk found in Chapter 6 has improved the understanding of the market price of weather risk, which is little seen in empirical studies at the moment. The information is central to weather derivative pricings that were the subject of a recent debate, and the present finding, to some extent, suggests the use of a risk-free rate in weather derivative valuations, consistent with the typical industrial norm.

Not only has this study provided empirical evidence that contributes to the body of knowledge, but it has also identified a reasonable approach to tackle the weather risk and pricing issues. In addition, the theoretical framework in Chapter 3 and the construction of unpredictable temperature in Chapter 4 can be considered as a theoretical contribution of this thesis, which may bridge the gap in literature.

7.5 Limitations and further research

Although the current study appears to be in the vanguard in this area, it is subject to a number of important limitations. Firstly, the study starts with limited choices of weather measure and model. This research only focuses on temperature and ignores other weather parameters. In fact, weather is rather interrelated system, and precipitation, for example, can also greatly influence returns of agricultural firms. However, most of the sample firms in this study are utilities, in which the demand depends largely on temperature. The solely use of temperature is rather convincing in this initial study, although an exploration of other parameters will be meaningful. This thesis is also based on a relatively small sample size, and all tests in the research are straightforward. Thus, findings are only initial estimates, and subsequent research ought to be worthwhile. Secondly, weather variables are not similar to other macroeconomic variables in that their scales are not returns. Therefore, caution must be applied with interpretation. Thirdly, the analyses of exposures in this study are conducted without knowledge of the hedging positions of firms in the sample. The estimated weather exposures may not be close to real exposure levels; however, the use of weather derivatives was not popular until late 1997 so a lack of hedging data seems not to be a great concern. Fourthly, the impact of weather on business activities should vary both geographically and seasonally, but this research fails to take account of location effects due to the lack of data on regional activities of companies. It has assumed the use of nationwide temperature data for the whole sample. However, this simplicity is supported by statistical results found in this

study and the finding of Lazo et al. (2011) that no one part of the U.S. is significantly more sensitive to weather than other in relative terms.

The present study considers only the contemporaneous weather effects, and assumes the linear and constant impacts. The current specification is to initially measure weather effects in the stock market by using such a simple framework, but further refinements of the data and model should have stronger explanatory power. A number of possible future studies using a similar approach would be very useful future projects. The study can be extended across sectors, weather parameters, models, space and time.

This research has also thrown up several questions in need of further investigation. If weather risk is important, it would be interesting to examine the determinants of this exposure. More information on the sources of differences in exposure would help researchers to establish a greater degree of accuracy in this matter. Additionally, the weather risk appears to be diversifiable and not priced in the market, so there must be other reasons to explain an increasing use of weather derivatives. Further investigation might explore whether the use of weather derivatives can increase a firm's value. Hopefully, this thesis will serve as a basis for future studies and encourage a growth in the literature on financial effects of weather and the price of weather risk in financial markets.

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