UNIVERSITY OF SOUTHAMPTON

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To what extent does weather influence individuals' financial decision-making behaviour? Evidence from the spread-trading market

by

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ABSTRACT

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TO WHAT EXTENT DOES WEATHER INFLUENCE INDIVIDUALS' FINANCIAL DECISION-MAKING BEHAVIOUR? EVIDENCE FROM THE SPREAD-TRADING MARKET

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This thesis, which is divided into 3 papers, investigates the relationship between weather and individuals' trading behaviour in the spread-trading market. The spread-trading market offers the opportunity of examining individuals' trading records, and thus enables the exploration of the impact of weather on individuals' financial decision-making behaviours. The first paper investigates the effect of a range of weather variables on individual spread traders' hourly trading volumes and their propensity to buy or sell (bullish/bearish trading sentiment). The findings suggest that a range of weather factors appear to influence the trading volume, but have less effect on trading sentiment. Importantly, the weather effects were different in the winter and the summer, and often in opposite directions. The neglect of this important seasonal effect could be why previous studies have produced ambiguous results concerning the effect of weather on trader behaviour.

The second paper examines the relationship between weather and the most widely reported behavioural bias in financial markets, the 'disposition effect' (DE); whereby, traders tend to sell positions which are in profit rather than those that are in loss. Previous research suggests that weather can influence individuals' mood. In addition, system 1 thinking is more associated with emotional rather than logical thought, whereby investors rely more on their intuition, rather than on rational analysis. Therefore, via its impact on mood, it is postulated in paper 2 that weather could influence the degree of system 1 thinking in which investors engage and that this in turn could influence the incidence of the DE. Indeed, the results reported in paper 2 indicate that weather does significantly influence individuals' DE. In addition, in line with the affect infusion model (AIM: Forgas, 1995), the biased decisions (i.e. DE) of less (cf. more) informed traders are more affected by weather factors. This study is the first to link weather conditions to the occurrence of the degree of the DE and, therefore, contributes to the literature exploring the origins of the DE.

The third paper tests the impact of weather *changes* on individuals' risk-taking decisions. Previous literature suggests that changes in weather can influence people's psychology and physiology. In addition, humans possess the ability to maintain thermal homeostasis via both biological mechanisms and behaviours. Therefore, sudden changes in weather may have a greater effect on mood and behaviour than the general weather conditions. It might, therefore, be expected that individuals' trading behaviour will be influenced not only by the current weather conditions, but also changes in those conditions. In addition, I control for current weather conditions and potential seasonal differences in the effects of weather factors. The results suggest that a range of weather changes that might be associated with greater relative personal discomfort (e.g. precipitation increases and air pressure decreases in winter and temperature increases in summer months) induce risk-taking behaviours. The results confirm the importance of taking account of weather changes when communicating risk-related messages and for those designing effective means of managing risk.

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Declaration of authorship

I, Shaosong Wang, declare that this thesis, and the work presented in it are my own and has been generated by me as the result of my own original research.

To what extent does weather influence individuals' financial decision-making behaviour? Evidence from the spread-trading market.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
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7. None of this work has been published before submission.

Signed: ....

Date: ....

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Introduction

Weather is an important environmental factor, which can affect the lives of human beings. In fact, previous studies have demonstrated that weather can significantly influence an individual's mood (Howarth and Hoffman, 1984; Denissen et al., 2008), which, in turn, can affect their decision-making (Simon, 1967; Wright and Bower, 1992; Mayer, 1992; Kauffman, 1999; Loewenstein et al., 2001) or risk-taking processes (Isen and Geva, 1987; Isen *et al*., 1998; Isen and Patrick, 1983; Hockey et al., 2000; Parker and Tavasolli, 2000). Therefore, it would not be surprising if the weather influenced individuals' financial decision-making behaviours, via its impact on mood.

The key aim of this thesis is to study the impact of a range of weather-related factors on individuals' trading behaviour in financial markets. In particular, this is the first study investigating the impact of weather on the decision-making of traders in the fast growing UK spread-trading market. In addition, it is the study to examine to what extent there are different effects of weather in summer and winter months.

Brady and Ramyar (2006) indicated that, of the £1.2 trillion traded annually on the London Stock Exchange (in 2006), 40 per cent was equity derivative related and 25 per cent of this related to spread trading (£120 billion). This figure almost certainly understates the current degree of rapidly expanding spread trading activity as the number of spread traders operating in the UK alone is predicted to rise from about half a million (in 2011) to reach one million by 2017 (Pryor, 2011). Many of traders in this market have little experience of financial market trading. Consequently, it is possible that spread traders may be swayed by factors, such as weather, which are unrelated to their investments' underlying economic fundamentals. The activities of spread traders also affect the underlying markets via the hedging activities of spread-trading companies. Consequently, if it found that spread traders' decisions are influenced by factors unrelated to an investment's underlying economic fundamentals (such as weather), this could have serious consequences for market efficiency. The unique spread-trading dataset employed in this thesis consists of the trading history of around 14,315 individual spread traders from 2005 to 2012.

The thesis is divided into 3 related but separate papers. The subject running through all three papers is the impact of weather on individuals' financial decision-making behaviour. Overall, the thesis offers an important contribution to the market efficiency literature. In particular, the results presented here demonstrate that traders' decision-making is swayed by weather factors and it is suggested that their failure to simply focus on underlying economic fundamentals may, potentially, lead to mis-pricing.

Chapter 1: **Mad dogs and Englishmen: Does weather really influence investors' behaviour.**

Most previous studies examining the impact of weather in the financial domain have examined the effect of weather on aggregate stock market returns (Hirshleifer and Shumway, 2003). There is only a limited literature exploring the impact of weather on individuals trading behaviour (e.g. Goetzmann and Zhu, 2005; Levy and Galili, 2008; Goetzmann et al., 2015). The few studies that do address individual decision-making in the financial domain present a confused picture of the impact of weather. This led to Jacobsen and Marquering's (2008) call for more direct and clearer evidence of weather impacts on investors' individual trading behaviour, rather than the impact of weather on aggregate stock return (which has been the main focus of the literature). I suspected that the some of the confusion in the individual trading literature may have resulted from previous studies failing to account for different effects of certain weather factors in winter and summer. Consequently, I investigated whether the impact of a range of different weather factors impacted on individuals' bullish/bearish trading sentiments (buy/sell) and trading volume, differently in different seasons. Specifically, the paper provides an improved methodology over that employed in the previous literature, and examines the trading activity of 14,315 individual traders between 2005 and 2012. The methodology adopted employs deseasonalized weather variables (Hirshleifer and Shumway, 2003; Goetzmann and Zhu, 2005) and examines their influence on individuals' trading sentiment and volume in different seasons. In order to ensure that results obtained account for other factors that might influence sentiment and trading volume, I control for Seasonal Affect Disorder (SAD), trading hours (a dummy value of 1 between normal trading times of 8am to 5pm during weekdays and zero at other times), the January effect (a dummy value of 1 in January and zero otherwise), the weekend effect (a dummy value of 1 for trading on Monday and zero otherwise) and a factor to capture the previously observed seasonal effect on stock returns (a Halloween dummy variable that takes the values 1 for trading taking place between May and October (summer) and zero otherwise (winter)).

The results of the analysis conducted in this paper lead to the conclusion that weather does indeed impact the behaviour of individual investors, but to a larger extent in terms of their trading volume than their buy/sell behaviour. Interestingly, I observe that the weather factors generally impact behaviour differently in different seasons and can have opposite effects. This, I suggest, can explain the confused picture which emerges from previous literature which has not taken into account this seasonal component.

Chapter 2: **To what extent does weather influence the degree to which individual investors display the disposition effect? Evidence from the UK spread-trading market**. This paper seeks to explore if there is a link between range of weather factors (with different effects in winter and summer) and one of the most frequently reported decision-making biases in financial trading, the disposition effect (DE). The DE is investors' tendency to sell positions which are in profit rather than those that are in loss. The majority of previous studies explain the DE in terms of prospect theory (Kahneman and Tversky, 1979). However, Barberis and Xiong's (2009) discovered that the degree of the DE was lower (i.e. sell a losing asset rather than winner) when the expected stock return is higher, as individuals' risk attitude changed to risk-seeking due to the higher expected stock return. However, this finding is *opposite* to prospect theory. Some experimental and theoretical evidence suggests that emotion plays a key role in the DE. In particular, some authors have pointed to mean reversion theory (Odean, 1998) and self-justification theory (Shefrin and Statman, 1985; Hirshleifer, 2001)) as possible explanations. It has, therefore, been argued that emotion might be a better explanation of the DE (Ackert and Deaves, 2009). If emotion plays a role in the DE then this might also be connected to a switch to System 1 thinking (Kahneman, 2011) which has been characterised as emotional, fast, automatic and instinctive thinking (i.e. lack of rational and careful thinking). System 1 thinking has been linked to biased behaviour, not unlike the sort of behaviour that might lead to the DE.

If emotion, which can be affected by mood, plays a role in the DE then I anticipated that weather, via its impact on mood, may influence the DE. The paper's first aim was to see if this is the case. The second aim of the paper is to examine whether different weather factors influence the DE in different ways in different seasons.

To achieve these objectives I employed multi-level mixed models. This allowed me to explore individual differences in the DE displayed by 9,101 individual traders in the period, 2005 to 2012. In order to help confirm that weather affected the DE via its impact on a trader's mood I also tested a hypothesis based on the Affect Infusion Model (AIM; Forgas, 1995). This model suggests that those engaged in more uncertain tasks are more likely to be influenced by mood when making judgments. I argue in the paper that the decision-making task for less (cf. more) informed traders are likely to involve more uncertainty. Consequently, I tested the hypothesis that weather factors are more likely to impact the DE of less informed traders.

The results from conducting the multi-level mixed models indicate that weather does influence the degree of the DE in both winter and summer months. Interestingly, I also find that the less informed traders are more prone to be influenced by weather than informed traders, which strongly supports the hypothesis based on the AIM model. These results suggest that investors often allow their decisions to be influenced by factors unrelated to fundamental news. Avoiding such reactions is likely to lead to better decisions and a more efficient market.

Chapter 3: **Risk-taking - come rain or shine: To what extent does weather changes influence risk-taking behaviour**.

The aim of this paper is to find the importance of weather *changes* for those involved in communicating risk-related messages and for those designing effective means of managing risk. Humans possess the ability to maintain thermal homeostasis via both biological mechanisms and behaviours. Therefore, the mood or behaviour might be more likely to be influenced by weather *changes* than the current weather condition. Consequently, it might be expected that individuals' trading behaviour and attitude will be affected not only by the current weather conditions, but also changes in those conditions. Therefore, in this paper, I proposed that weather changes might influence traders' risk-related messages. To achieve this, I employ multi-level mixed models as this allows the study to examine the individuals' trading/risking differences and preferences across traders. The study examines the trades of 4,368 individual traders from 2005 to 2012.

Previous literature has suggested weather changes can significantly influence people's psychology and physiology (e.g. blood pressure, Sato, *et al.,* 2001; chronic pain, Jamison, et al., 1995; rheumatic, Guedj and Weinberger, 1990; disease, Bierton *et al*., 2013) and extreme behaviours (e.g. violence, Hsiang, *et al*., 2013; suicide, Helama, *et al*., 2013). Therefore, it is not surprising to explore a relationship between weather changes and trading activities. Bassi et al., (2013) examined a direct link between weather and risk-taking for the first time, using laboratory experiments. However, to my best knowledge, the current study is the first to exam the effect of weather changes on risk-taking bases in a naturalistic setting. In particular, Anderson and Brown (1984) indicated that risk-taking (gambling) behaviour is significantly different in the real world from laboratory environments. Consequently, I believe this chapter makes a contribution towards the naturalistic study of risk taking.

The results of this analyse show that weather changes could significantly influence individuals' risk-taking activities. In particular, decreases of air pressure in winter and increases of temperature in summer lead to greater risk-taking behaviours. It is the first study to explore the relationship between weather changes and risk-taking based on naturalistic evidence. In addition, it is the first study examining these phenomena using multi-level mixed models, which produce robust results. As a result, the paper makes a significant contribution to the literature.

Chapter 1

Mad dogs and Englishmen: Does weather really influence investors' behaviour?

Abstract

We shed new light on the often contradictory 'weather-investor-behaviour' literature by examining hourly weather data linked to over 300,000 trades of 14,315 spread-traders. Our methodology manages issues which may be responsible for previous ambiguous/misleading results: seasonality in stock returns, the impact of multiple deseasonalized weather variables and different winter/summer weather-effects. We find that only wind speed (in winter) affects bullish/bearish behaviour but several weather factors affect trading volume. Importantly, many weather factors have different effects in winter and summer, suggesting that not accounting for winter/summer differences may be responsible for misleading conclusions concerning the influence of weather on investor behaviour.

1.1 Introduction

Psychological studies have demonstrated linkages between weather and mood (e.g., Keller et al., 2005; Denissen et al., 2008) and between mood and decision behaviour (e.g., Loewenstein et al., 2001). These links motivated Saunders' (1993) seminal weather-effects study, which found that cloud over New York had a strong negative effect on stock returns on the NYSE. This stimulated research examining the degree to which weather influences investor behaviour. However, a confused picture has emerged.

Several studies have purported to identify strong effects of weather variables, such as cloud cover/sunshine (e.g., Hirshleifer and Shumway, 2003) and temperature (e.g., Cao and Wei, 2005), on stock returns. Equally, it has been suggested that a medical condition influenced by a lack of sunshine (SAD: Seasonal Affect Disorder) may explain a seasonal pattern in stock returns (e.g., Kamstra, Kramer and Levi, 2009; 2012). However, some studies have found no effect of weather (e.g., Lu and Chou, 2012) or SAD on stock returns (Kelly and Meschke, 2010). Other studies identify different weather-effects through time (e.g., Saunders, 1993 *vs*. Loughran and Schultz, 2004): negative *vs*. insignificant effects of cloudiness on stock returns in New York) or contrasting effects of the same weather variable within the same country (e.g., Cao and Wei, 2005 vs. Floros, 2008): negative *vs*. insignificant effects of temperature on stock returns in the UK) or between countries (e.g., Pardo and Valor, 2003 *vs*. Saunders, 1993): insignificant vs. negative effects of cloudiness on stock returns in Spain vs. USA).

Early papers tended to find strong weather-effects, but these studies often employed raw weather variables (e.g., raw temperature). However, Yuksel and Yuksel (2009) demonstrate that a large proportion of the observed effect of temperature on stock prices is removed once the seasonal component of stock prices is controlled. Furthermore, they argue that the seasonal component may be explained by a range of factors unconnected to weather. Methodological concerns associated with the previous literature led Jacobsen and Marquering (2008) to question whether there is sufficient evidence to conclude that the weather really influences investor behaviour. They suggest that 'it would be more convincing if future research could establish a more direct link that weather influences investors buy and hold decisions' (p. 539). In other words, the authors suggest that a more useful approach would be to examine weather effects at the individual level or buying and selling securities rather than at the aggregate level of market returns. Our study aims to help establish if such a link exists.

We believe that there are several reasons for the complex, often contradictory 'weather-investor-behaviour' literature: (1) Many previous studies failed to account for seasonality in stock returns, perhaps leading to a false causality between weather factors and investor behaviour. (2) Some studies failed to examine weather variables *in the context of other weather variables*. This is important because the manner in which individuals react to stimuli is often influenced by the context (e.g., Loewenstein, et al., 2001; Yechiam, Druyan and Ert, 2008). For example, the effect of a particular temperature on mood may be modulated by whether it is raining. (3) Previous studies do not examine if investors' behaviour is differentially affected by weather in the winter and the summer, yet, for example, hotter than normal temperatures in the summer/winter may have a negative/positive impact on mood. (4) Most previous studies do not account for an important weather variable, namely, air pressure, a factor which has been demonstrated to effect human physiology and mood (e.g., Delyukov and Didyk, 1999; Radua, Pertusa and Cardoner, 2010). The limited focus on air pressure is surprising, since this is the one weather factor which is directly experienced indoors. (5) Most studies have employed aggregated stock return data and have used the weather at the location of the stock market (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003). However, to truly establish the influence of weather on investors' behaviour it is important to establish a more direct link between weather at a given location and individuals' buying/selling activity at that location (Jacobsen and Marquering, 2008). Most studies which have examined disaggregated data have failed to find evidence of weather-effects on investment decisions (Goetzmann and Zhu, 2005). However, this may have arisen as a result of a combination of issues 1-4 identified above or because most previous studies examined weather-effects on monthly or daily, rather than hourly, stock returns. The studies which employed disaggregated data did find significant effects of cloud cover on the institutional investors' propensity to sell stocks (Goetzmann, et al., 2015), the effect of weather on trading volume (Schmittmann et al., 2014; Kaustia and Rantapuska, 2012). However, these studies used *daily* trading and *average daily* weather data and did not examine weather effects in winter and summer with interactions. However, to discern if weather really affects the behaviour of investors we believe that differentiating seasonal effects and the combined influences of a range of weather variables is important. In addition, in a country such as the UK, where the weather can change significantly during the course of a day, it is, we believe, important to examine the extent to which weather in a given hour influences investors' choices in that hour.

Consequently, we respond to Jacobsen and Marquering's (2008) call for clearer evidence that weather factors can affect investor behaviour, by designing our study to address all the concerns indicated above. We show that weather does indeed influence the decisions of individual investors, particularly those decisions affecting trading volume and confirm that weather factors have significantly different effects in winter and summer. In addressing the methodological concerns discussed above, we believe the results presented here represent a clearer view of the real effects of weather on investor behaviour.

The remainder of the paper is organized as follows: Section 1.2 examines the relationships between weather, mood and trading behaviour and we use these to establish our hypotheses. Section 1.3 describes the data and methodology employed to test the hypotheses. The results and related discussion are presented in Section 1.4 and 1.5, and conclusions are drawn in Section 1.6.

1.2. Weather, Mood and Individual Trading Decisions

1.2.1 Weather-effects on mood and physiology

Extant literature suggests that weather can affect an individual's mood. For example, lack of exposure to sunshine causes imbalances in melatonin and cortisol hormone levels, resulting in low energy levels, decreased optimism and/or depression (Howarth and Hoffman, 1984). Similarly, sunlight and temperature affect the production of hormones and neurotransmitters, both of which can affect behaviour (Parker and Tavassoli, 2000). In particular, cooler temperatures can lead to more aggression (Schneider, Lesko and Garrett, 1980) and higher temperatures are correlated with a more positive mood and better memory (Keller et al., 2005). This may arise because in lower temperatures we expend more energy maintaining a regular body temperature, and this reduction in energy has a negative impact on mood (Denissen et al., 2008). Conversely, higher temperatures may be associated with negative moods in some individuals because they can aggravate certain medical conditions (e.g., rheumatoid arthritis (Guedj and Weinberger, 1990) and cardiovascular disease (Bierton, Cashman and Langlois, 2013)) and higher temperatures have been associated with extreme behaviours such as violence and suicide (Hsiang, Burke and Miguel, 2013).

Air pressure has been shown to impact blood pressure and mental activity (Delyukov and Didyk, 1999) and low air pressure have been linked to pain and headaches and more negative moods (e.g., Radua, Pertusa and Cardoner, 2010). Windy conditions have also been found to have a negative impact on mood (Denissen et al., 2008).

The broad conclusion to emerge is that good/bad weather (e.g., sunshine/cloud, high/low air pressure etc.) and positive/negative mood are correlated. Consequently, it is suspected that decisions are influenced by the weather via manipulation of mood.

1.2.2 Weather and decision-making

There is an extensive literature which demonstrates that mood has a strong impact on decision-making (e.g., Loewenstein et al., 2001). Consequently, it is not surprising that several studies have shown a link between weather and decision behaviour. For example, high temperatures have been shown to lead to apathy (Wyndham, 1969), whereas very cold temperatures can lead to aggression (Schneider, Lesko and Garrett, 1980). Extreme temperatures have also been shown to have a negative effect on the performance of memory tasks (Allen and Fisher, 1978) and negative moods induced by weather (e.g. rainy days) have been associated with greater decision accuracy (Forgas, Goldenberg and Unkelbach, 2009).

1.2.3 Weather and Financial Decision-making

1.2.3.1 Cloudiness/Sunlight

Saunders (1993) found a negative correlation between cloudiness and stock returns (using raw, daily, data) and several studies confirmed this relationship, even when deseasonalized cloudiness was examined (e.g., Hirshleifer and Shumway, 2003). Similarly, Goetzmann, et al. (2015) found that greater deseasonalized cloudiness increased perceptions of over-pricing amongst institutional investors and increased their propensity to sell. However, Chang et al. (2008) reported that cloudiness only had a negative impact on stock returns during the first 15 minutes of investors opening their transactions, but cloudiness was also associated with increased stock volatility and selling behaviour. In addition, some studies have found no significant relationship between cloudiness and stock returns (e.g., Pardo and Valor, 2003).

1.2.3.2 Temperature

Several studies have examined the link between temperature and stock returns. For example, Cao and Wei (2005) and Floros (2008) found a negative relationship between raw temperatures and daily stock returns. They suggested that this resulted from lower and higher temperatures increasing aggressive behaviour (e.g., Howarth and Hoffman, 1984) and apathy, respectively, these being associated with more risk-seeking and risk-averse behaviour (Wyndham, 1969).

These earlier studies could be criticized for not controlling for seasonality in stock returns, since the seasonality might have a cause unrelated to weather. Consequently, Jacobsen and Marquering (2008) and Yuksel and Yuksel (2009) controlled for seasonality and found that then raw/daily temperature had significantly less predictive value on stock returns.

1.2.3.3 Air pressure, rainfall and wind

The influence of air pressure on financial decisions has been examined in several studies. These find a positive relationship between raw/daily air pressure and investor sentiment and stock returns (Schneider (2013a, b)). A negative relationship between the strength of wind and stock prices has been found using daily raw and deseasonalized data (UK: Dowling and Lucey, 2008); 18 European markets: Shu and Hung, 2009). However, Lu and Chou (2012) found that wind levels did not affect the Shanghai order-driven stock market.

In summary, whilst a number of apparent effects of weather on stock returns have been identified, once weather variables are deseasonalized and account is taken of the seasonal stock returns, the variation in the reported results suggests that the impact of weather on investor behaviour remains in doubt (Jacobsen and Marquering (2008 and 2009)).

There is a concern that most previous studies only examine one weather variable in isolation. However, psychological studies have shown that the manner in which humans react to external stimuli is often influenced by the context (e.g., Yechiam, Druyan and Ert, 2008). Consequently, the effect on mood of a particular weather variable may be influenced by the state of other weather variables. For example, the effect of increased temperature may be modulated by the degree of cloud cover, the air pressure, whether it is raining, or the strength of wind. Therefore, a study simply examining the relationship between cloudiness or temperature and stock returns, without controlling for other weather factors, may not reveal the true causes of the observed effect.

1.2.4 Seasonal Component of Stock Prices and Weather-effects

The extent to which weather-effects are consistent throughout the year should also be considered, but it is important to control for the fact that stock returns have generally been shown to be higher in winter than summer (e.g., Jacobsen and Marquering, 2008). Clearly, there are many factors, other than weather, that could cause this seasonal effect (e.g., Hong and Yu, 2009).

Some models employed to examine the impact of weather on investor behaviour have included a Halloween dummy variable (i.e., taking a value of 1 for the months from May to October, and 0 otherwise) to control for seasonality in stock prices (e.g., Jacobsen and Marquering, 2008). Without the addition of this variable, any weather factor correlated with this seasonal effect (e.g., temperature) would be found to be significant in a model examining the impact on stock prices, whether or not it was causative.

It is also important, when examining a range of weather factors in combination to deseasonalize the weather data to avoid issues associated with multicollinearity between related variables (e.g., cloudiness and rainfall). This can be achieved by subtracting the respective calendar week or month mean value for each weather variable from each observation of that weather variable (Hirshleifer and Shumway, 2003; Yuksel and Yuksel, 2009).

The methodology described above will help determine the true effect of weather variables on stock prices if higher than monthly average values of these weather factors have the same effect in the winter and summer. However, this may not be the case. For example, higher than normal monthly temperatures in the winter/summer may have a positive/negative effect on mood. In fact, moods are generally more positive in warm weather (i.e., higher/lower than normal temperatures in winter/summer (Denissen et al., 2008). However, higher than normal summer temperatures may have a negative effect on mood as they aggravate certain medical conditions (Guedj and Weinberger, 1990) whereas extremely cold temperatures (e.g., lower than normal winter temperatures) have a negative effect on mood (Schneider, Lesko and Garrett, 1980).

Given that opposing effects may be observed in different seasons, important weather effects could be missed in regression models only employing deseasonalized weather variables, since the effects could net themselves out of significance. To capture the complexities associated with different mood effects in winter and summer, interaction terms between deseasonalized weather variables and the Halloween dummy are needed.

1.2.5 Weather and Individual Investors

The majority of existing studies exploring weather-effects on trading behaviour have employed aggregate market information (i.e., stock returns). Jacobsen and Marquering (2008) pointed out the difficulties of inferring a direct link between weather and investor behaviour using this approach and called for further studies that could provide a more direct link between weather and investors' buying and selling activity.

There are a limited number of studies examining weather-effects on the behaviour of individual investors, and, like the stock index studies discussed above, these produce contrasting conclusions. For example, Goetzmann and Zhu (2005) found that there was no significant difference in individuals' preference to buy or sell equities on cloudy, as opposed to sunny, days. However, Goetzmann, et al. (2015) found that on cloudy days, institutional investors perceived more over-pricing of securities and had a greater tendency to sell. Schneider (2013b) found that different levels of air pressure biased private but not institutional investors' expectations. Levy and Galili (2008) discovered that male, low income and young investors prefer to buy stocks on cloudy days whereas Limpaphayom, Locke and Sarajoti. (2005) found that floor traders prefer to buy on calm (less windy) days. However, these studies that have used individual trading data do not consider how *combinations* of weather factors impact on choices. Consequently, they may have mis-estimated the impact of weather or ascribed a causative relationship between trading behaviour and one weather variable, whereas others may be equally, or more, influential. In addition, none of the studies employing individual trading data controlled for seasonality in stock prices.

Schmittmann et al. (2014) analyse trading records of approximately 71,000 clients of one of the largest retail brokerages in Germany and find good weather can lead to more buying behaviours and trading volumes. Kaustia and Rantapuska (2012) employ a comprehensive dataset containing all trading records of all domestic investors in Finland during 1995-2002. Despite having 1.12 million investors, 444 municipalities and 13 million trades in their base data, they find that little of the day-to-day variation in trading is collectively explained by sunniness, temperature, or precipitation. However, neither of these two studies examining the sentiment of individuals or individual trading data, examined whether different weather factors have different impacts in winter and summer with interactions. In addition, they examined with daily data, which could be argued that daily weather cannot represent the frequently weather changes, particular in the country like the UK.

The few studies that have employed individual trading data do not differentiate between trades intended to close positions and those to establish short-selling positions.

The distinction between these two types of trade is important. First, an individual's decision to close a position by selling previously purchased stocks is associated with a reduction in risk exposure, whereas short-selling the market is associated with increased risk exposure. Second, the decision to close a position may be driven by a previously poor (or good) buying decision or for liquidity reasons (e.g., perhaps triggered automatically by a stop-loss) rather than necessarily stemming from a particular mood or from expectations about the future of the stock price. Consequently, focusing on decisions to open positions may provide a less ambiguous assessment of the aspects of trading behaviour which are influenced by weather factors.

In this study, we attempt to overcome all the limitations identified above by employing individual trader data, examining the effect of a range of deseasonalized weather factors, controlling for seasonality in stock prices, observing if different weather-effects exist in winter and summer and focusing on the decisions of traders when *opening* positions.

1.2.6 Hypotheses

In responding to Jacobsen and Marquering's (2008) call for clearer evidence that weather factors can affect investor behaviour, we test the following two related hypotheses:

H1. Traders' sentiment, as manifested in their propensity to exhibit bullish or bearish behaviour, is influenced by weather factors

H2. The decisions of individuals to engage in trading activity and the extent of that activity (in terms of the number of trades they initiate or the average investment per trade) are affected by weather factors.

1.3. Data and methodology

1.3.1 Data

We employ individual trading records of investors in the UK spread trading market. Spread trading is legal in many European countries, Australia, Hong Kong and Canada but not in USA. Spread traders open accounts in spread trading companies and undertake trading activates (Brady and Ramyar, 2006). Spread trading allows individuals to speculate on the movement of an underlying security. No ownership of the underlying security takes place, trades can be long or short and profits/losses are defined as the change in price of the underlying security (converted to points) multiplied by the investment size. Points are determined by the 'pip size', which is a scaling constant depending on the market being traded. The pip size for the FTSE 100, for example, is 1 and the pip size for the EUR/USD currency future is 0.0001. Points are calculated by dividing the price by the pip size. For example, a trader who 'buys' the FTSE100 with, say, a $50 investment per point, secures an unrealized profit/loss of $2500 if the FTSE100 rises/falls 50 points.

Spread trading has opened up speculation in financial markets to a wide cross section of the public (everyone can open an account), because, with few regulatory barriers (as little as £50), individuals can leverage a position worth thousands of pounds on an index future with a relatively small investment. The spread trading market is growing rapidly and Brady and Ramyar (2006) indicated that, of the £1.2 ($2.0) trillion traded annually on the LSE (in 2006), 40 per cent was equity derivative related and 25 per cent of this related to spread trading (£120 ($200) billion). This figure almost certainly under-states the current degree of spread trading activity as the number of spread traders operating in the UK alone is predicted to rise from about half a million (in 2011) to reach one million by 2017 (Pryor, 2011). Many types of instruments are available to trade in this market, such as currencies, stocks, indices etc. and the prices of these instruments (e.g. a stock) offered by the spread trading firms are based on and directly linked to the underlining market (Pryor, 2011). More importantly, the activities of spread traders have important implications for the underlying market because spread-trading companies, to control their risks, hedge into the underlying markets (Brady and Ramyar, 2006). More specifically, these companies have 'capital adequacy' requirements imposed on them by FCA via the ICAP rules. These rules determine how much capital the companies have to hold to cover risks. Depending on the company, this will force them to hedge some risks if their capital is not sufficiently large to cover their risks in line with the capital adequacy rules. In addition, even in the absence of these rules, these companies will have a certain risk appetite and if the risk they are running exceeds their risk tolerance, they will hedge the risk. Consequently, any biased trading behaviours by spread traders, caused by factors such as weather, are likely to impact conventional financial markets.

The dataset we employ is drawn from the detailed trading records of 14,315 individuals who held accounts with a large spread trading company between 1st January 2005 and 31st December 2012. To avoid inaccuracies in currency conversion associated with fluctuating exchange rates within a trading day, only trades executed in pounds sterling were examined. We used an hourly resolution in our analyses, whereby we examined the effect of weather during any given hour on trading during that hour. This was facilitated by the fact that spread traders tend to have higher trade frequencies than traditional longer-term speculators.

Studies have shown that the decision to close a position can be dramatically influenced by whether the position was in profit or loss, i.e. traders are often subject to the disposition effect (e.g., Barberis and Xiong, 2009). In order to eliminate the noise induced by the profit/loss status of an open position or from automated stop-losses, we examined *opening position* trades. In addition, the ease with which markets can be short-sold means that in spread trading long and short positions are both prevalent, unlike in equity markets in which short-selling is less commonplace. Accordingly, the opening position buy/sell trades provide a cleaner measure of the individual's bullish/bearish sentiment.

Previous studies exploring weather-effects tended to use weather from the location of the exchange. However individuals, via electronic trading, are increasingly more likely to place trades from the location where they base their daily activities. Employees of the spread trading company from whom we obtained the data, who deal with their customers on a regular basis, indicated that in their experience most traders place their trades from their home. The second largest group they believe place their trades from their place of work. Consequently, we examined weather data at the individual's notified trading location (i.e., normally their home address). Although they could make trades from other locations (e.g., at work), these are likely to be close to home (the average distance which individuals in the UK commute to work was 15 km in 2011) (Gower, 2014) and thus subject to similar weather conditions. Based on our data, the majority of trading (more than 85%) takes place during working hours (i.e. 8am-5pm). In addition, over 90% of spread trading occurs over the internet (Bardy and Ramyar, 2006).

We obtained hourly weather data from the British Atmospheric Data Centre at 554 UK locations. We matched traders' notified trading locations in the UK via postcode with the nearest weather station, trades were grouped by hour (e.g., to calculate the total net buy minus sell trades in a given hour at a given location) and trades in a given hour from a given location were matched with the weather conditions at that location. This resulted in 330,075 data points. This method of aggregating data enabled us to explore the extent to which weather in a given location and hour affects buying/selling in that location.

As indicated above, previous literature has tended to examine the relationship between weather and movements in financial indices. Those studies employing individual trading data have tended to only explore the impact on trading of a single or a very limited selection of weather variables. However, as indicated above, without controlling for a wide range of weather variables, we believe this could mask the weather factors that are truly driving the effect. Consequently, we examine the combined influence of cloud cover, rainfall, air temperature, air pressure and wind speed on individual trading behaviour. Second, we clearly distinguish between the deseasonalized effects of weather and the effects of seasons on prices (see Yuksel and Yuksel, 2009). Finally, we are the first to consider a homeostatic effect (weather and season interactions). We believe this is important because if the effects of deseasonalized weather factors are different in the summer and winter, then the true influence of weather may have been masked in previous studies.

1.3.2 Variables

1.3.2.1 Bullish/Bearish Sentiment and Trading Volume

We examine to what extent the weather affects two aspects of traders' behaviour, their bullish/bearish sentiment and their inclination to trade. The tendency of traders to buy or short-sell the market in a particular hour in a particular area is captured by a $NetBuySell_{ha}$ dependent variable (Goetzmann and Zhu, 2005), defined as the sum of investments (£) associated with 'buy' trades ($BuyStakes_{ha}$) minus that associated with 'sell' trades ($SellStakes_{ha}$) in hour *h* in geographical area *a*, as follows:

$$NetBuySell_{ha} = BuyStakes_{ha} - SellStakes_{ha} \tag{1.1}$$

The extent of investors' inclination to trade is defined as the sum of investments (£) associated with buy trades ($BuyStakes_{ha}$) plus that associated with sell trades ($SellStakes_{ha}$) in hour *h* in geographical area *a*, as follows:

$$TradeVolume_{ha} = BuyStakes_{ha} + SellStakes_{ha} \tag{1.2}$$

The degree of trading volume in a given hour and area captured in this manner involves three, potentially related, aspects of investors' inclination to trade, namely the number of investors who decide to trade ($No.Traders_{ha}$), the number of trades they decide to initiate ($No.Trades_{ha}$) and the degree to which they commit to those trades, measured by average investment per trade ($AverageStakeTrade_{ha}$). Having examined the degree to which weather affects the total trading volume we also explore the extent to which weather impacts these three related aspects of investment activity. Clearly, all the dependent variables may vary systematically by area (e.g. individuals in certain areas may have higher average investments per trade). To control for these potential systematic variations we include postcode as a random factor (see below).

1.3.2.2 Weather Variables

Cloudiness is the most frequently used variable in studies examining the weather's influence on trading activity. We employed a $cloud_{ha}$ variable, which measures the degree of cloud cover (on the oktas scale: 0-9) in UK location, *a*, during hour, *h*. Hourly cloud cover in any particular region in the UK is seasonal, with, for example, more cloudy days in winter than summer. To control for the seasonal effects, we deseasonalized *cloud*$_{ha}$ (named *Dcloud*$_{ha}$) by subtracting the monthly average *cloud*$_{ha}$ from the raw *cloud*$_{ha}$ (Goetzmann and Zhu, 2005). We followed this procedure for the other weather factors of interest: rainfall (*rain*), air temperature (*temp*), air pressure (*pres*), and wind speed (*wind*), measured in millimeters, degrees Centigrade, atmospheric pressure and knots, respectively. This resulted in the corresponding deseasonalized variables: *Drain*, *Dtemp*, *Dpres*, and *Dwind.* The variables are summarized in Table 1.1.

Table 1.1 List of explanatory and control variables employed in this study

Variable Type	Variable Name	Description	Raw Variable Units/Coding
Weather	*Dcloud*	Deseasonalized cloud cover	Oktas scale 0-9 (No cloud cover - sky obscured)
Weather	*Drain*	Deseasonalized rainfall	Millimeters (mm)
Weather	*Dtemp*	Deseasonalized air temperature	Degrees Centigrade (℃)
Weather	*Dpres*	Deseasonalized air pressure	Atmospheric pressure (hPA)
Weather	*Dwind*	Deseasonalized wind speed	Knots
Control	*Halloween*	Halloween dummy	1 = May to Oct.; 0 = Nov. to April
Control	*Hours*	Trading Hours dummy	1 = 8am to 5pm; 0 = 6pm to 7am
Control	*Monday*	Monday effect dummy	1 = Monday; 0 = Any other day
Control	*January*	January effect dummy	1 =January; 0 = Any other month

1.3.2.3 Control Variables

Seasonal affective disorder: SAD is an important environmental proxy that has been shown to impact individuals' mood in a systematic way (e.g., Kamstra, Kramer and Levi, (2009, 2012)). Consequently, we control for SAD to ensure that it does not subsume any observed weather effects. We calculate SAD in a similar manner to that employed by Kamstra, Kramer and Levi (2009, 2012).

Seasonality of stock returns: Stock returns contain a seasonal component (with higher returns often experienced in the winter months). Consequently, to avoid making spurious correlations between weather factors and trading behaviour in different seasons, we controlled for this effect. To achieve this, we followed Yuksel and Yuksel (2009), and included a dummy, *Halloween*, where 'summer' months (May to October) take the value one and the remaining 'winter' months take the value zero. When combined with the deseasonalized weather variables this ensures the effects of weather and season are accounted for, without suffering from multicollinearity issues (which exist when using the Halloween dummy with raw weather variables).

Trading hours: The majority of spread trading occurs when markets are open (8am to 5pm during weekdays), but a smaller amount continues outside these hours, based on futures' prices. To assess the true impact of weather factors on trading volume we controlled for the natural increase in trading volume when the underlying markets are open. Consequently, we employed an *Hours* dummy, taking the value one when markets are open and zero any other time.

Postcode: It is possible that trading may vary systematically across different areas. For example, the number of investors, the number of trades, the average investment per trade or the degree to which investors buy (*vs*. short sell) the market may generally be higher in certain areas. To control for this possibility we include postcode as a random variable. Bates (2010) distinguished the random and fixed in two ways: First he argued that the names of fixed and random are misleading, as the difference between them is more a property of the categorical level than an effect level. In particular, random factor is a categorical covariate that normally represents 'units'. In this study, the unit is the postcode, and it is a categorical variable, therefore, we control for postcode as a random variable in both simple regression models and multivariate regression. Second, Bates distinguished between the fixed factors which are parameters in a statistical model, and random factors which are not parameters. In our regression analysis, we do not compute any significance levels or coefficients for postcode, because it is a unit, a categorical, but not a parameter. However, we measure the F-test and significance for postcode in MANOVA test only, since the postcode represents a variable/parameter rather than unit/nonparameter. Therefore, we feel that the postcode factor is more likely a 'fixed' level than 'random' level factor in the MANOVA.

January and Monday effects: It has been widely reported that stock returns are generally higher in January and lower on Mondays (e.g., Cao and Wei, 2005). To control for the different behaviour which may influence returns at these times, we included two dummy variables: *Monday*, which takes the value one for Mondays and zero any other day, and *January* which takes the value one for days in January and zero otherwise.

1.3.2.4 Weather and Season Interaction Effects

We suspect that certain weather types may have different effects on mood in different seasons. To capture these effects we introduce interaction terms between the *Halloween* and the deseasonalized weather-variables: *Halloween*× *Dcloud*, *Halloween*× *Drain*, *Halloween*× *Dtemp*, *Halloween*× *Dpres and Halloween*× *Dwind*.

1.3.2.5 Lagged weather and trading variables

It is likely that the dependent variables (i.e. trading variables) and independent variables (i.e. weather variables) are trending and non-stationary. In addition, due to the high persistence in weather variables, any observed effects may be subsumed by their corresponding lagged variables. In order to explore the possibility that these time series are non-stationary, we employed the KPSS test (Kwiatkowski et al., 1992). The results suggested that the deseasonalized weather variables and dependent variables had significant autocorrelation (KPSS test results from calculating weighted mean of each variable and standard error over all locations (postcodes): $p < 0.05$). Consequently, we included the lagged value of the trading variables (i.e. *Dependent Variables* $_{(h\text{-}1)a}$), the lagged weather factors ($Dweather_{(h\text{-}1)a}$) and the seasonal interactions with lagged deseasonalized weather variables (i.e. *Halloween*× $Dweather_{(h\text{-}1)a}$). The residuals of the models reported below were tested for serial autocorrelation using Durbin-Watson statistics. These confirmed that the inclusion of lagged variables had resolved the non-stationary issue.

1.3.3 Models

We initially developed two multiple mixed linear regression models. The first, which aimed to test the effect of weather on traders' bullish/bearish trading sentiment, employs *NetBuySell* as the dependent variable, as follows:

$$NetBuySell_{ha} = \alpha_{ha} + \beta_1 SAD_{ha} + \beta_2 Hours_{ha} + \beta_3 Dcloud_{ha} + \beta_4 Drain_{ha} + \beta_5 Dtemp_{ha} + \beta_6 Dpres_{ha} + \beta_7 wind_{ha} + \beta_8 Dcloud_{(h-1)a} + \beta_9 Dcloud_{(h-1)a} + \beta_{10} Drain_{(h-1)a} + \beta_{11} Dtemp_{(h-1)a} + \beta_{12} Dpres_{(h-1)a} + \beta_{13} Dwind_{(h-1)a} + \beta_{14} Halloween + \beta_{15} January + \beta_{16} Monday + \beta_{17} Halloween \times Dcloud_{ha} + \beta_{18} Halloween \times Drain_{ha} + \beta_{19} Halloween \times Dtemp_{ha} + \beta_{20} Halloween \times Dpres_{ha} + \beta_{21} Halloween \times wind_{ha} + \beta_{22} Halloween \times Dcloud_{(h-1)a} + \beta_{23} Halloween \times Drain_{(h-1)a} + \beta_{24} Halloween \times Dtemp_{(h-1)a} + \beta_{25} Halloween \times Dpres_{(h-1)a} + \beta_{26} Halloween \times Dwind_{(h-1)a} + \gamma_1 Postcode_{ha} + \mathcal{E}_{ha} \quad (1.3)$$

where α_{ha} is the intercept of the model during hour h in area a, β_i are the coefficients for the fixed effects discussed above, γ_1 is the coefficient for the random effects for postcode and $\mathcal{E}_{ha}$ is the error term.

The second model, which aimed to assess the impact of weather on trading volume, takes the same form as eq.1.3, but employs $TradingVolume_{ha}$ as the dependent variable.

As indicated above, the degree of trading volume in a given hour and area, involves three aspects, namely the number of *traders*, the average number of *trades* placed by each trader and the degree to which they commit to those trades, measured by the average *stake per trade*. We found that these three variables are significantly correlated ($No.Trades_{ha}$ and $AverageStakeTrade_{ha}$, Pearson Correlation = 0.003, $p < 0.0001$; $No.Traders_{ha}$ and $AverageStakeTrade_{ha}$, Pearson Correlation = 0.028, $p < 0.0001$; $No.Traders_{ha}$ and $No.Trades_{ha}$, Pearson Correlation = 0.672, $p < 0.0001$). Although the effect sizes are small we accounted for the significant correlations whilst exploring the impact of weather on these different aspects of investment behaviour. To achieve this we conducted a multivariate multiple linear regression, which is to predict two or more dependent variables with a set of independent variables. This model is more efficient if the dependent variables are correlated than a simple regression which analyses dependent variables separately (Hartung and Knapp, 2014), as it allows each dependent variable (i.e. three trading volume variables) to have its own relationship with all independent variables (Krzanowski, 2005) at the same time. In addition, MANOVA enables us to combine all dependent variables as a whole to examine the significance of the mean differences of variables and control for Type 1 error (Warne, 2014). Therefore, we use this model to explain the three trading volume variables above and this, we believe, could provide a clear picture of the impact of weather on trading volume. This regression employed all three variables as joint dependent variables, with the same independent variables as those used in equation (1.3).

Having estimated the models associated with the *NetBuySell* and *TradingVolume*, we determined the impact of different weather factors on the dependent variables in winter by examining the sign and significance of the coefficients of the deseasonalized weather variables. In addition, to determine those weather factors which had a different effect on *NetBuySell* and *TradingVolume* in summer (*vs*. winter) we examined the significance of the coefficients of each variable in the summer by conducting a series of planned contrasts. For example, the coefficient for temperature in the summer would equal the coefficients for *Dtemp* and *Halloween* x *Dtemp* added together.

1.4 Results

1.4.1 Weather-effects and Bullish/Bearish Trading Sentiment

The results of estimating the *NetBuySell* model (1.3) are presented in Table 1.2. After controlling for SAD, lagged *NetBuySell*, trading hours, seasonality in stock prices, the January and Monday effects, lagged weather variables and postcode (as a random factor) we find evidence that there is a seasonal component to weather effects.[1] In particular, we find that greater wind speed in a given hour in the winter induces a greater inclination to buy in that hour.

Other than wind speed, we find that there are no significant impacts of other weather factors in a given hour in winter or summer (i.e., cloudiness (in line with Goetzmann and Zhu, 2005), rainfall, temperature and air pressure) on buying *vs*. selling behaviour in that hour. These results, therefore, give limited support for Hypothesis 1, that weather factors significantly influence individuals' bullish/bearish sentiment.

[1] We found that all the dependent variables in the models shown in the results section were subject to autocorrelation (i.e. in a minimum of 30 (44.8 percent) of the postcode areas the KPSS test was significant at $p<0.05$). Having introduced lagged values of the dependent variables and lagged weather variables the Durbin Watson statistics on the residuals indicate that the autocorrelation was removed for all the models estimated (DW value between 1.947 and 2.053).

Table 1.2 Estimated coefficients, standard errors and *t*-values for the linear regression model to determine the effect of a range of weather factors and control variables on the sum of investments (£) associated with 'buy' minus 'sell' trades in hour *h* in geographical area *a: NetBuySell*

Fixed Effects: Variables	Estimated Coefficients	Std. Error	*t*-value	
Constant	-24.2746	21.9846	-1.132	
Lagged NetBuySell	0.2943	0.0017	176.231	***
Hour	-0.1542	0.1964	-0.791	
SAD	-0.0359	0.0677	-0.532	
Dcloud	-0.0624	0.0581	-1.074	
Drain	-0.0072	0.1381	-0.053	
Dtemp	0.0642	0.0552	1.162	
Dpres	-0.0170	0.0231	-0.744	
Dwind	0.0714	0.0371	1.963	**
January	-0.1540	0.2742	-0.566	
Monday	-0.2490	0.1650	-1.525	
Lagged Dcloud	0.0743	0.0581	1.282	
Lagged Drain	0.0296	0.1280	0.231	
Lagged Dtemp	-0.0715	0.0490	-1.462	
Lagged Dpres	0.0247	0.0219	1.135	
Lagged Dwind	-0.0591	0.0359	-1.658	
Halloween	26.4900	17.4027	1.523	
Halloween× *Dcloud*	0.0915	0.0828	1.105	
Halloween× *Drain*	-0.0354	0.1818	-0.192	
Halloween× *Dtemp*	-0.0971	0.0696	-1.401	
Halloween× *Dpres*	0.0248	0.0225	1.104	
Halloween× *Dwind*	-0.0252	0.0512	-0.492	
Halloween× *Lagged Dcloud*	-0.1263	0.0823	-1.537	
Halloween× *Lagged Drain*	0.0019	0.1655	0.013	
Halloween× *Lagged Dtemp*	0.0413	0.0570	0.724	
Halloween× *Lagged Dpres*	-0.0260	0.0174	-1.502	
Halloween× *Lagged Dwind*	0.0354	0.0481	0.748	

Random effects: Variable	Variance	Standard Deviation
Postcode	2.765	1.663
Adjusted R^2	0.040	
Effect Size (Cohen's f^2)	0.042	

*** Significant at 1 percent level
** Significant at 5 percent level
* Significant at 10 percent level

1.4.2 Weather-effects and Trading Volume

The results of estimating the *TradingVolume* model are shown in Table 1.3. After controlling for SAD, the lagged trading volume, trading hours, the January and Monday effects, lagged weather variables and postcode (as a random factor) we find that several weather factors impact the trading volume. In addition, there appears to be a seasonal component to the weather-effects. Specifically, the results show that trading volumes are higher when deseasonalized rain is lower during both winter (coefficient: -0.2814, *t*-value: -1.825) and summer months (coefficient: -0.2814 − 0.0701 = -0.3515, *t*-value: -2.643), the effect being greatest in the summer. Lower deseasonalized air pressure significantly increases trading volume in the winter but there is no corresponding effect of air pressure in the summer. In addition, deseasonalized temperature only has a significant impact in the summer, with higher temperatures leading to lower trading volumes (coefficient: -0.0500 − 0.1014 = -0.1514, *t*-value = -2.698). Finally, more cloud cover in the summer leads to a marginally significant increase in trading volume (summer coefficient = 0.0180 + 0.0994 = 0.1174, *t*-value = 1.775).

Table 1.3 Estimated coefficients, standard errors and *t*-values for the linear regression model to determine the effect of a range of weather factors and control variables on the sum of investments (£) associated with buy trades plus that associated with sell trades in hour *h* in geographical area *a (TradeVolume)*

Fixed effects: Variables	Estimated Coefficients	Std. Error	*t*-value	
Constant	-63.7053	37.6770	-1.693	*
Lagged TradingVolume	0.4624	0.0015	300.732	***
Hour	3.4722	0.2204	15.752	***
SAD	0.1499	0.0847	1.771	
Dcloud	0.0180	0.0651	0.281	
Drain	-0.2814	0.1548	-1.825	*
Dtemp	-0.0500	0.0635	-0.793	
Dpres	-0.0795	0.0384	-2.071	**
Dwind	0.0294	0.0419	0.702	
January	0.2289	0.3132	0.733	
Monday	-0.5520	0.1849	-2.995	**
Lagged Dcloud	-0.0323	0.0652	-0.491	
Lagged Drain	-0.1626	0.1440	-1.134	
Lagged Dtemp	-0.0491	0.0569	-0.867	
Lagged Dpres	0.0661	0.0376	1.765	*
Lagged Dwind	0.0241	0.0407	0.592	
Halloween	82.4093	19.5866	4.214	***
Halloween× *Dcloud*	0.0994	0.0928	1.073	
Halloween× *Drain*	-0.0701	0.2038	-0.342	
Halloween× *Dtemp*	-0.1014	0.0782	-1.302	
Halloween× *Dpres*	0.1137	0.0253	4.414	***
Halloween× *Dwind*	-0.0258	0.0574	-0.459	
Halloween× *Lagged Dcloud*	-0.0438	0.0922	-0.475	
Halloween× *Lagged Drain*	-0.0274	0.1857	-0.157	
Halloween× *Lagged Dtemp*	0.0307	0.0643	0.485	
Halloween× *Lagged Dpres*	-0.0819	0.0196	-4.193	***
Halloween× *Lagged Dwind*	-0.0463	0.0540	-0.861	

Random effects: Variable	Variance	Standard Deviation
Postcode	19.58	4.425
Adjusted R^2	0.060	
Effect Size (Cohen's f^2)	0.064	

*** Significant at 1 percent level
** Significant at 5 percent level
* Significant at 10 percent level

In summary, these results demonstrate support for hypothesis 2, that weather influences retail spread traders' propensity to trade. They also indicate a strong seasonal component, with different weather factors having different effects in winter and summer. In addition, the results arguably suggest that those conditions associated with greater relative personal comfort, lower deseasonalized temperature and less deseasonalized rainfall (in the summer), lead to more desire to trade. The results which, appear not to fit with this 'personal comfort' explanation (e.g., higher trading volume associated with lower air pressure in winter), are addressed below in Section 1.5.4.

We further examined the impact of weather on the three aspects of trading behaviour which make up trading volume. To achieve this we estimated a multivariate multiple linear regression model with $No.Traders_{ha}$, $No.Trades_{ha}$, and $AverageStakeTrade_{ha}$ as joint dependent variables and the results are shown in Table 1.4. We found that, after controlling for SAD, trading hours, *Lagged* $No.Traders_{ha}$, *Lagged* $No.Trades_{ha}$, and *Lagged* $AverageStakeTrade_{ha}$, lagged weather variables, the January and Monday effects and postcode *all* the deseasonalized weather factors are significant in the overall model and there appears to be a strong seasonal component to the weather-effects, since all the Halloween-weather factor interactions are significant (suggesting that there are significant differences in the effects of the different weather variables in winter and summer)[2].

The estimated regression models for each separate outcome measure of individuals' inclination to invest, namely, $No.Traders_{ha}$, $No.Trades_{ha}$, and $AverageStakeTrade_{ha}$ reveal that a range of weather factors have a significant impact on each of these dependent variables (see Table 1.4).

The results relating to the impact of weather on the number of traders who decide to invest suggest that higher deseasonalized air pressure in the winter and summer months (summer coefficient: 0.0073 + 0.0031 = 0.0104, *t*-value: 7.681) are associated with a greater number of individuals investing. Higher than normal wind speed (coefficient: 0.0004 + 0.0038 = 0.0042, *t*-value: 3.538) and lower than normal rainfall (coefficient: -0.0020 − 0.0066 = -0.0086, *t*-value: -2.468) in the summer is associated with an increase in the numbers of traders who invest, but these effects are insignificant in winter. In addition, whereas more deseasonalized cloud cover and higher temperatures are associated with a larger number of individuals investing in the winter months, the effects are not significant in the summer.

[2] We estimated a separate model for summer months only, and the results confirmed that all weather factors in summer (i.e. *Halloween*× *Dweather* variables) are significant at 0.05.

Table 1.4 Estimated coefficients, Pillai, F- and *t*-values for the multivariate regression model to determine the effect of a range of weather factors and control variables on three jointly dependent variables: *No.Traders* (the number of investors who decide to trade), *No.Trades* (the number of trades they decide to initiate) and *AverageStakeTrade* (the degree to which they commit to those trades, measured by average investment per trade)

	MANOVA test		
Fixed Effects: Variables	*Pillai* value	Approximate *F*-value	
Hour	0.0088	981.1	***
Lagged No.Traders	0.2073	28772.2	***
Lagged No. Trades	0.1491	19278.1	***
Lagged AverageStakeTrade	0.2527	37193.3	***
SAD	0.0007	76.1	***
Dcloud	0.0001	4.2	***
Drain	0.0002	23.6	***
Dtemp	0.0031	337.5	***
Dpres	0.0001	5.6	***
Dwind	0.0002	23.6	***
January	0.0003	32.4	***
Monday	0.0001	11.7	***
Lagged Dcloud	0.0001	3.5	**
Lagged Drain	0.0005	58.5	***
Lagged Dtemp	0.0019	205.4	***
Lagged Dpres	0.0028	313.1	***
Lagged Dwind	0.0031	346.2	***
Halloween	0.0014	149.3	***
Halloween× Dcloud	0.0001	12.4	***
Halloween× Drain	0.0001	3.6	**
Halloween× Dtemp	0.0006	66.4	***
Halloween× Dpres	0.0003	35.5	***
Halloween× Dwind	0.0001	2.1	*
Halloween× Lagged Dcloud	0.0001	1.5	
Halloween× Lagged Drain	0.0001	9.5	***
Halloween× Lagged Dtemp	0.0004	41.7	***
Halloween× Lagged Dpres	0.0002	24.5	***
Halloween× Lagged Dwind	0.0001	3.6	*
Postcode	0.0836	141.1	***

Joint dependent variables test									
	No. Traders			No. Trades			AverageStakeTrade		
Fixed effects: Variables	Coefficient	*t*-value		Coefficient	*t*-value		Coefficient	*t*-value	
Constant	10.4665	8.481	***	12.1643	3.951	***	-28.3067	-3.191	***
Lagged dependent	0.3194	197.922	***	0.4092	261.411	***	0.4973	313.802	***
Hour	0.4336	73.363	***	0.6960	43.752	***	0.2475	4.992	***
SAD	-0.0722	-29.623	***	-0.0340	-5.333	***	0.0444	2.291	***
Dcloud	0.0088	5.125	***	0.0059	1.273		-0.0114	-0.775	
Drain	-0.0020	-0.504		-0.0578	-5.211	***	-0.0240	-0.691	
Dtemp	0.0124	7.238	***	-0.0021	-0.462		0.0261	1.822	*
Dpres	0.0073	5.819	***	0.0065	2.074	**	-0.0320	-3.542	**
Dwind	0.0004	0.353		0.0009	0.322		-0.0064	-0.673	
January	0.0617	7.345	**	0.0448	1.981	**	-0.0210	-0.304	
Monday	-0.0247	-5.067	***	-0.0725	-5.472	***	-0.0446	-1.077	
Lagged Dcloud	-0.0055	-3.214	**	-0.0048	-1.024		0.0043	0.298	
Lagged Drain	-0.0042	-1.103		-0.0286	-2.774	**	-0.0064	-0.203	
Lagged Dtemp	-0.0263	-17.005	***	-0.0122	-2.947	**	-0.0305	-2.375	**
Lagged Dpres	-0.0096	-7.787	***	-0.0112	-3.648	**	0.0300	3.394	**
Lagged Dwind	-0.0033	-3.081	**	0.0004	0.128		0.0192	2.101	**
Halloween	-1.5291	-2.953	**	-1.5998	-1.144		25.7524	5.842	***
Halloween× Dcloud	-0.0082	-3.366	**	-0.0086	-1.292		0.0389	1.866	*
Halloween× Drain	-0.0066	-1.236		0.0068	0.475		-0.0207	-0.451	
Halloween× Dtemp	-0.0110	-5.332	***	-0.0035	-0.624		-0.0713	-4.054	***
Halloween× Dpres	0.0031	4.714	***	0.0077	4.256	***	0.0253	4.452	***
Halloween× Dwind	0.0038	2.491	**	0.0019	0.473		0.0037	0.283	
Halloween× Lagged Dcloud	0.0045	1.853	*	0.0049	0.747		-0.0224	-1.086	
Halloween× Lagged Drain	-0.0098	-2.015	**	-0.0064	-0.482		-0.0372	-0.899	
Halloween× Lagged Dtemp	-0.0049	-2.877	**	-0.0368	-7.952	***	0.0945	6.528	***
Halloween× Lagged Dpres	0.0016	3.025	**	0.0019	1.364		-0.0265	-6.015	***
Halloween× Lagged Dwind	-0.0041	-2.903	**	-0.0037	-0.951		-0.0200	-1.644	
Random effects: Variable	Variance	Std. Dev.		Variance	Std. Dev.		Variance	Std. Dev.	
Postcode	0.1106	0.3326		0.2434	0.4934		1.287	1.134	
Adjusted R^2	0.080			0.070			0.070		
Effect Size (Cohen's f^2)	0.087			0.075			0.075		

*** Significant at 1 percent level
** Significant at 5 percent level
* Significant at 10 percent level

The reasons why different weather factors impact the number of traders remain a matter of speculation. However, the results may suggest that those conditions which are associated with greater personal comfort (warmer than normal temperatures, higher than normal air pressure in the winter) and lower than normal rainfall and higher than normal air pressure in the summer) induce a good mood which leads more individuals to engage in investment activity (Schneider, 2013b). However, we also find that higher than normal cloud cover in the winter leads more traders to invest. Consequently, it may also be the case that some conditions which deter individuals from undertaking outdoor activities (i.e.

higher than normal cloud cover in winter and greater than normal wind speed in the summer) may lead individuals to spend more time indoors, thus offering more opportunities for them to undertake trading activities. Whatever the reasons for the different effects observed in different seasons, the important finding, as we suspected, is that individuals appear to be differentially affected by the same deseasonalized weather factors in winter and summer.

The results relating to the number of trades also highlight interesting differences in the impact of weather factors in winter and summer. In particular, the results shown in Table 1.4 indicate that lower rainfall (summer coefficient: -0.0578 + 0.0068 = -0.0510, *t*-value = -5.337), and higher air pressure in the winter and summer (summer coefficient: 0.0065 + 0.0077 = 0.0142, *t*-value = 4.163) are associated with significantly more trades being initiated. The effects in summer are more significant. No other weather factors in winter or summer appear to significantly impact the number of trades. Clearly, whilst the same weather factors affect the number of trades initiated in both winter and summer their significance differs in the two seasons.

We also find that average investment per trade is affected by different weather factors. Specifically, the results presented in Table 1.4 show that deseasonalized temperature and air pressure significantly affect the levels of average investment per trade in the winter, with greater than normal temperature and air pressure having, respectively, positive and negative impacts on the average investment per trade. By contrast, in the summer, greater cloud cover (coefficient: -0.0114 + 0.0389 = 0.0275, *t*-value: 1.851) and higher than normal temperatures (coefficient: 0.0261 - 0.0713= -0.0452, *t*-value: -3.57) are associated with higher average investment per trade.

The average investment per trade may be regarded as a measure of risk-taking and previous studies have shown that conditions which induce a negative mood can lead to greater risk-taking behaviour (e.g., Raghunathan and Pham, 1999). In line with these findings, we observe that the average investment per trade increases in weather conditions which previous studies suggest induce negative mood: greater than normal cloud cover (e.g., Howarth and Hoffman, 1984) and lower temperatures (e.g., Denissen et al., 2008) in summer and when air pressure is lower (Radua, Pertusa and Cardoner, 2010) in winter. However, we also find that average investment per trade in a given hour in the winter increases when temperatures are higher, and these conditions have not been associated with inducing negative mood. Importantly, whilst the causal mechanisms for the impact of weather on the average investment per trade may be subject to speculation, we find that weather factors *do* influence this aspect of risk-taking and, that there are different effects in winter and summer.

In addition, we provide the R^2 and the Cohen's f^2 effect size (ES) values for each model. Effect size is a quantitative statistical method of the strength of a phenomenon. In particular, the effect size indicates the strength of the relationship, regardless of the data sample size (Kelley and Preacher, 2012). Furthermore, reporting the effect size is a good practice for empirical research (Wilkinson, 1999), particularly for large sample size data. Therefore, we report the effect size in this study, based on the measure of the Cohen's f^2 (Cohen, 1992). The R^2 values are fairly low. However, these values are similar to those obtaine din similar relative literature (e.g. R^2 = 0.01, 0.9% or even lower, see Goetzmann and Zhu, 2005; Goetzmann et al., 2015). Moreover, we are not expecting high R^2 values in our study, since individuals' trading activities and market returns are influenced by many important factors other weather, such as the real global, national, and local fundamental news (Hirshleifer and Shumway, 2003). Consequently, this suggests that the low R^2 values in the study are reasonable. In addition, according to Cohen (1992), the effect size of f^2 values of 0.02, 0.15 and 0.35 are termed as small, medium and large effect, respectively. Therefore, the results in this study can be classified as medium effect sizes (f^2) (i.e. range from 0.04 to 0.087), indicating our tests in the study are relative powerful. Reporting the effect size is important, since the significance test (i.e. *p*-value) is related to sample size, and *p*-values are not sufficient to examine the power of the results (Sullivan and Feinn, 2012).

Taken together, we believe that our findings of significant impacts of weather on individuals' trading behaviours are relatively powerful and that they provide a clear and convincing picture of the influence of weather on trading behaviour.

1.5 Discussion

1.5.1 Establishing link between weather and investment decisions

Jacobsen and Marquering's (2008) called for evidence to establish a more direct link between weather factors and individuals' investment decisions. The results presented here provide strong evidence of this link because the research was designed to overcome the limitations of some previous studies, thus allowing effects to be unearthed which may have been masked in earlier enquiries. In particular, we examine the impact of a *range* of deseasonalized weather variables, including barometric pressure (an important but under-researched weather variable), on traders' hourly buying/selling activity and on their hourly trading volume, whilst controlling for SAD, different weather impacts in summer and winter, seasonality in prices, lagged trading and weather factors and postcode. Overall, our results provide strong support for Hypothesis 2, that the decision of whether to trade and how much to stake will be affected by weather factors. The results also offer limited support for Hypothesis 1, that traders' propensity to exhibit bullish/bearish behaviour is influenced by the weather.

1.5.2 Establishing seasonal effects of weather

When testing each of our hypotheses we discover significantly different effects of specific weather factors in winter and summer. For example, we find significant differences between winter and summer concerning the effects of wind speed on traders' propensity to exhibit bullish behaviour and between winter and summer of the effects of cloud cover, air pressure, temperature and rain on the extent of trading behaviour. In particular, in terms of average investment per trade we find that temperature has the opposite effect in winter and summer and the degree of cloud cover and level of air pressure are only significant in summer and winter, respectively. Equally we observed seasonal differences in the weather factors affecting the number of individuals initiating trades and trading volume. The seasonal differences we observe may be because of the context in which individuals experience these different weather factors. For example, traders may spend more time indoors in the winter and as a result their trading behaviour may be less influenced by weather conditions. This is reinforced by the fact that air pressure is one of the weather factors which *does* appear to influence trading volume in the winter. This is the one weather factor which is *directly* experienced indoors and has been demonstrated to effect human physiology and mood (e.g., Delyukov and Didyk, 1999; Radua, Pertusa and Cardoner, 2010).

Our findings concerning different seasonal effects of weather are potentially important, as they may explain some of the null effects of weather previously observed in the literature which did not account for this phenomenon (e.g., Goetzmann and Zhu, 2005). Consequently, we believe that one of the reasons for the discrepancies between our findings and those of previous studies is that this is the first study, to our knowledge, to distinguish weather-effects in winter and summer.

1.5.3 Impact of weather on bullish/bearish behaviour

One of our more striking findings is that only wind speed (in winter) influences the degree of buying (vs. selling) behaviour among investors. This contrasts with a number of studies which suggest that stock returns are affected by the degree of cloudiness (e.g. Hirshleifer and Shumway, 2003; Goetzmann, et al., 2015) and temperature (Cao and Wei, 2005; Floros, 2008). We believe that the reasons for these discrepancies may be methodological. For example, it is interesting that Jacobsen and Marquering (2008) found no effect of temperature on stock returns when they controlled for seasonality. Our finding that increased wind speeds in winter increase the degree of bullish behaviour is at odds with most studies which have examined the effects of wind speed on stock returns (e.g., Dowling and Lucey, 2008; Shu and Hung, 2009). However, none of these studies distinguished seasonal weather effects and they did not examine wind speed in the context of a range of other weather variables. In addition, they used daily rather than hourly prices, some used raw rather than deseasonalized weather variables and none examined individual trading data.

1.5.4 Impact of weather on trading volume

Our results suggest that increased trading volume occurs in conditions associated with relative personal comfort in the summer (lower temperatures, less rainfall) and in the winter (less rainfall). These are the conditions likely to give rise to positive mood (e.g., Keller et al., 2005). However, by contrast, we find that lower air pressure conditions are correlated with greater trading volume. By unpicking the elements which make up trading volume we can discern some of the possible causal mechanisms associated with these apparently contradictory findings.

In particular, we speculate that a combination of weather conditions differentially affect three aspects of trading volume: factors which deter individuals from outdoor activities (thus providing them the opportunity to focus on trading activity), conditions that improve their personal comfort (associated with positive mood), thus inducing them to investment activity and conditions which induce a more negative mood, which previous research has associated with greater risk taking (i.e. higher average investment per trade). Specifically, we find that the *number of trades* is positively associated with weather conditions linked with greater personal comfort and positive mood in both winter and summer; namely higher air pressure (Radua, Pertusa and Cardoner, 2010) and decreased rainfall. These results are in line with studies which suggest that ‘good’ weather conditions improve people’s mood, which in turn leads to them making more investments (e.g., Limpaphayom, Locke and Sarajoti, 2005). The *number of traders* initiating investments increases in some weather conditions associated with positive mood (e.g., higher air pressure in winter and summer, higher temperature in winter, lower rainfall in summer: Keller et al., 2005) and in weather conditions which might deter individuals from engaging in outdoor activities (e.g., windy conditions in summer), thus providing them with more opportunity to focus on investment activities (Lee, Gino and Staats, 2014). Furthermore, we find, in line with the laboratory-based findings of Raghunathan and Pham, 1999) that *investors risk-taking* (i.e. average investment per trade) increases in weather conditions that previous studies link to negative mood (e.g., lower temperature and increased cloudiness in summer, lower air pressure in winter). Consequently, our results suggest that the main reason that trading volume in winter increases in periods when deseasonalized air pressure is lower and in summer in periods when deseasonalized cloud cover is greater and temperatures are lower, is because these weather conditions induce greater risk taking. However, we also find that average investment per trade in winter increases when deseasonalized temperatures are higher. Higher temperatures are generally associated with more positive moods (Denissen et al., 2008). This contrasting evidence confirms that the impact of weather on investment behaviour is not straightforward.

Taken together, the results relating to trading volume confirm a complex mixture of different weather effects in winter and summer affecting trading volume by differentially impacting on the *opportunity* and *desire* to engage in investment activity and on the level of associated risk-taking.

1.5.5 The impact of air pressure

An interesting finding of this study is that a weather factor which has not been employed in most previous studies, namely air pressure, appeared to have a significant effect on the number of individuals who engage in investment activity, the number of trades they initiated and on their average investment per trade. This finding is consistent with the limited number of studies which have examined the impact of air pressure on stock returns; although these studies do not distinguish between winter and summer effects (e.g., Schneider (2013a and 2013b)). Higher air pressure is generally associated with better weather, which may in turn improve individuals' mood (Keller *et al*., 2005). Consequently, the previous studies which did not include air pressure may have overlooked the root cause of the weather-effects observed. Interestingly, we find that on relatively low pressure days in the winter, trading volume and average investment per trade increases, suggesting that low pressure in the winter, which has been linked to negative mood (e.g., Radua, Pertusa and Cardoner, 2010), may increase traders' degree of risk taking. It is difficult to discern why this effect is only observed in the winter but this finding reinforces the view that it is vital to consider the context in which weather variables are experienced (e.g., examining the effect of a range of weather factors simultaneously and in different seasons). Failing to do this may lead to an under-estimation of the influence of weather factors and/or may lead to false attribution to the cause for traders' actions.

1.6 Conclusion

Previous studies have examined to what extent weather can affect individuals' trading behaviour in traditional stock markets (e.g., Goetzmann and Zhu, 2005; Levy and

Galili, 2008; Goetzmann et al., 2015). However, the evidence is mixed, some studies report strong effects of certain weather factors (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; Cao and Wei, 2005), others have failed to find any evidence that weather impacts trading behaviour (e.g., Pardo and Valor, 2003). Some studies find different effects of the same weather variable when examining different countries (Saunders, 1993 *vs*. Pardo and Valor, 2003) or even within the same country (Saunders, 1993 *vs*. Loughran, 2004). This confused picture may have arisen because of the range of methodologies employed (e.g., the use of raw *vs*. deseasonalized weather variables; controlling *vs*. not controlling for seasonal returns in stock prices or for other weather factors). This led Jacobsen and Marquering (2008) to question whether there is sufficient evidence to conclude that weather influences investor behaviour.

Our study attempts to establish if a direct link exists between trader behaviour and the weather by employing a methodology which draws on the best approaches employed in the previous literature. This approach stems from our belief that the methodology employed in some previous studies may have distorted the impact which weather has on trading behaviour.

Our results suggest that traders' decisions *are* influenced by the weather. In particular, our findings suggest that the number of individuals who initiate trades, the number of trades and the average investment per trade are all affected by a range of weather factors in different ways. Furthermore, we show that to some extent the propensity of traders to exhibit bullish or bearish behaviour is influenced by weather factors.

We believe that our results are robust since they offer important methodological advantages over previous studies. In particular, this is the first study, to our knowledge, which uses *individual* trading data (cf. aggregated stock returns information) to investigate the relationship between trading behaviours and *multiple* weather variables examined the context of others, including factors which many studies fail to incorporate (e.g. air pressure). This enables us to control for the interconnected effects of air pressure, rainfall, wind speed and temperature. In addition, we control for the seasonality in prices and different weather-effects in summer and winter. We employ disaggregated *hourly* weather data at the location where the individual trader makes their investment decision and we include the lagged value of each trading variable and weather factor as independent variables to overcome potential serial autocorrelation and to ensure that a deseasonalized weather variable in the current time interval had an *incremental* effect on traders' behaviour. In addition, we are able to restrict our analysis to trades undertaken to open positions. This we believe more accurately captures trading sentiment than analyses which also incorporate trades undertaken to close positions. Furthermore, unlike previous studies, our data enabled us to examine the impact of weather on three different aspects related to the degree of trading volume experienced in any given hour, namely the number of individuals who initiate trades, the number of trades initiated and the average investment per trade. Interestingly, we find that all three of these variables appear to be influenced by a variety of weather factors and that the effects of different weather factors vary depending upon the variable being examined. This suggests that the impact of weather on trading behaviour is more complicated and more widespread than previous studies have suggested. Moreover, a common cause of endogeneity is missing important variables from models (Brooks, 2008). Therefore, we make every effort to include all the key variables based on related literature to avoid the missing variables to reduce the potential issue of endogeneity.

The highly leveraged nature of spread trading means that this is a high risk activity and the Affect Infusion Model (Forgas, 1995), suggests that mood (which may be influenced by weather factors) is more likely to influence the actions of those engaged in high risk activities. This is valuable for the purposes of this study which seeks to establish a direct and clear link between weather factors and individuals' trading sentiment and volume. Whilst spread traders may not be representative of all investors in conventional financial markets, they are likely to share many similarities to retail investors, particularly those involved in options and futures trading. In addition, this is the first study, to our knowledge, to examine the effect of weather factors on spread traders. This is important because this is a rapidly growing market which has opened up speculation in financial markets to a wide cross section of the public. We unearth a significant influence of weather factors on trading behaviour amongst these investors. This is important because spread trading companies often hedge into the underlying markets and our results suggest that as spread trading markets expand the underlying markets are likely to become increasingly influenced by weather factors.

Our finding that a seasonal component is important in the weather-trading-behaviour relationship suggests that previous studies may not have appropriately assessed the influence of weather factors and this may explain why some studies have observed no significant weather-effects. Clearly, further research is required to verify the seasonal interactions we observe in traditional equity markets. However, the methodology employed here reveals that weather really does influence the behaviour of at least some investors.

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Chapter 2

To what extent does weather influence the degree to which individual investors display the disposition effect? Evidence from the UK spread-trading market

Abstract

Previous research has shown that investors are influenced by factors other than price fundamentals. The most widely reported behavioural bias, for example, is investors' tendency to sell positions which are in profit rather than those that are in loss (the 'disposition effect' (DE)). In addition, it has been shown that stock market returns are correlated with factors unrelated to price fundamentals, notably with certain types of weather. In this paper, we examine the relationship between weather and the DE. To achieve this, we investigate the behaviour of individual investors in the fast growing UK spread-trading market. In particular, we examine, using multi-level mixed models, the degree to which 9,101 individual UK spread traders who took positions on the FTSE and DAX between 2005 and 2012, were subject to the DE and to what extent their use of the DE was influenced by the weather. Our results demonstrate that weather does significantly influence individuals' DE. We also find evidence that suggests that mood plays a part in the DE. In particular, in line with the Affect Infusion Model (Forgas, 1995), we find that the biased decisions (i.e. DE) of less (cf. more) informed traders, who are more likely to be influenced by mood, are more affected by weather factors.

2.1 Introduction

The disposition effect (DE) is a phenomenon of human irrationality (Camerer, 2004) whereby investors tend to 'sell winners too early and ride losers too long' (Shefrin and Statman, 1985, p.777). It is one of the most important and widely documented anomalies reported in the behavioural finance literature, that traders have a higher probability of selling a profitable position than a losing position.

A number of traditional theories have been employed to explain the occurrence of the DE. The most widely used explanation is prospect theory (especially loss aversion), proposed by Kahneman and Tversky (1979). They argued that investors would be risk averse/seeking if the price of their asset was above/below their 'reference point'. Assuming that for most traders their reference point might be 'break even' then they would be likely to sell investments when in profits (to protect themselves from subsequent losses) and hold their assets in loss, hoping that they return to profit (e.g., Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998; Grinblatt and Han, 2005).

Mean reversion theory has also been used to explain the DE. This states that investors believe prices will return to the mean price. Consequently, they sell/hold assets when the price is higher/lower than the mean (e.g., Odean, 1998). In summary, the existing literature examining the origins of the DE has argued that it arises from investors' irrational use of a range of heuristics, such as having too optimistic/pessimistic an expectation of price (e.g., Mean reversion) when the price is low/high, and/or unwillingness to accept/realize a loss.

Some experimental and theoretical evidence suggests that emotion is another explanation for the DE. For example, self-justification theory implies that investors avoid admitting their poor decision-making, and thus avoid crystallizing losses (Shefrin and Statman, 1985; Hirshleifer, 2001). Summers and Duxbury (2007) found that prospect theory alone cannot explain the DE while emotions play a key role in the DE. In particular, they argued that emotions of regret or rejoicing when traders face a loss or gain, via responsibility and choice, could produce the DE. Arguably, rejoicing and regret are necessary to generate behaviour, such as the DE. If the incidence of the DE is influenced by emotion than it could be argued that is more likely to occur if the trader is adopting System 1 thinking (Kahneman, 2011), which is emotional, fast, automatic and instinctive and is characterized by the absence of rational and careful thinking.

It has been suggested that mood affects decision-making processes (e.g., Loewenstein et al., 2001; Kauffman, 1999; Simon, 1967; Wright and Bower, 1992; Mayer et al., 1992). For example, good mood has been demonstrated to increase reliance on heuristics, which, in turn, results in less careful and possibly more emotionally charged decision-making. Good mood has also been linked to system 1 thinking (Kahneman, 2011). On the other hand, it has been suggested that negative mood can subconsciously warn individuals that they are in a bad position, lead them to think more carefully think and avoiding relying on heuristics (e.g., Schwarz and Clore, 1983; Schwarz, 1990; Park and Banaji, 2000).

It has been shown in a considerable number of studies that weather, such as degree of sunshine (e.g., Howarth and Hoffman, 1984, 2008), temperature (Schneider et al., 1980; Goldstein, 1972), wind (e.g., Denissen et al., 2008), and air pressure (e.g., Keller et al., 2005), can influence an individual's mood. In particular, good weather conditions, such as sunshine/less cloudiness (Cunningham, 1979; Parrott and Sabini, 1990; Schwarz and Clore, 1983), higher air pressure (Keller et al., 2005), or calm conditions (less wind speed) (Denissen et al., 2008), leads to good mood. Therefore, it is not surprising that weather, via its impact on mood, influences individuals' decisions and, in particular, their financial decisions (e.g., stock trading decisions: Goetzmann and Zhu, 2005)).

In the light of the literature discussed above which links the DE to emotional and irrational thinking (Summers and Duxbury, 2007), we suspect that a relationship may exist between weather and the degree of the DE. If we observe such a relationship this will provide further evidence to support the fact that mood plays a role in the DE. Furthermore, if we identify that those individuals whose decisions are more likely to be influenced by mood have a stronger relationship between weather and the DE, this would provide further evidence of the role of mood in the DE.

To explore whether there is a significant relationship between weather and the DE, we explore the link between the DE and a range of weather factors, including, cloudiness, rainfall, temperature, air pressure and wind speed. To achieve this, we examine the behaviour of investors trading the FTSE 100 and DAX 30 in the UK spread-trading market. We calculate both the proportion of individuals' closing profitable positions and closing losing positions in 1−minute time intervals. We achieve this by linking our data concerning the actions of individual spread traders to tick data of the FTSE 100 and DAX 30. Studies of the DE in traditional financial markets have normally counted the number of paper/realized profit/loss in a day (e.g. Barberis and Xiong, 2009). However, most spread traders are intra-day traders and have considerably shorter time horizons and by using 1 minute intervals we were able to calculate the DE far more frequently, enabling us to focus on detailed market prices movements and trading activities.

Spread-trading markets are amongst the fastest growing markets in the UK, opening up financial market speculative opportunities to the wide cross section of the public. The number of spread traders is expected to reach 1 million in the UK alone by 2017 (Pryor, 2011). In addition, Brady and Ramyar (2006) indicate that about £1.2 trillion is traded in London Stock Exchange and about 10 percent of this the relates to spread trading (£120 billion). The spread trading companies must hedge into the underlining market to control their risks. Therefore, any biased behaviours in the spread trading market, which might be caused by environmental factors such as weather, might influence the traditional financial markets. Many traders in spread trading markets have little trading experience, and we suspect that they may be subject to at least the same degree of DE as that displayed in traditional financial markets.

The trading history of each individual in the most popular spread trading markets, the FTSE 100 and DAX 30, enables us to determine how long they hold a position in terms of minute intervals. To analyse the data we employ multi-level mixed models, as this allows us to identify trading differences between individual traders. In particular, in our study, we employ two-level mixed models, the first level being the DE in a particular hour for an individual trader and the second level being the DE by each client (Tabachnick and

Fidell, 2001; Luke, 2004; Denissen *et al.*, 2008).

Our data also allows us to examine whether there are differences in the degree to which weather influences the DE of different groups of investors; in particular, those whose overall trading performance suggests they are more/less informed. The use of the trading records of individual spread traders is particularly valuable in this respect, because at the time the trade is closed all uncertainty is resolved and the appropriateness of their decision (and their profitability) can be assessed. The AIM (Forgas, 1995) suggests that because all spread traders are engaged in a high risk activity, their decision making is likely to be affected by mood. However, the decision-making task for less informed traders is likely to involve more uncertainty and the AIM predicts that in these circumstances their decisions are likely to be more susceptible to mood effects. Consequently, if mood plays an important part in the incidence of the DE, we expect that weather (via its influence on mood) will have a bigger effect on the DE displayed by less informed spread traders.

Our results demonstrate that even when market-based variables (such as market return, volatility etc.) which have shown to be highly correlated with DE, are controlled, weather significantly influences individuals' DE. We also find that, in line with our expectations based on the AIM, the incidence of the DE amongst less informed traders is more affected by weather factors than is true for more informed traders.

In summary, we believe this study offers the following important contributions: It is the first study to explore the relationship between a range of weather conditions and the DE. Importantly we achieve this whilst controlling for market-related variables (e.g., market returns) that have been shown to be correlated with the DE. In addition, we account for the effects of multiple weather variables, allowing, via a seasonal dummy, for different effects in the winter and summer. Due to the nature of our data we are able to contrast the degree to which weather affects the degree of DE amongst more and less informed traders, thus allowing us to examine our expectations concerning the role played by mood in the DE. Finally, by employing multi-level mixed models, we are able to discern the extent to which the impact of weather on the DE varies between individual traders.

The reminder of the paper is organized as follows: In Section 2.2 we briefly review literatures related to the disposition effect, the effect of mood on decisions and the impact of weather on mood and weather on financial decisions. These literatures are used to establish our hypotheses. We describe the data and the methodology that are employed to examine our hypothesis in Section 2.3. In Section 2.4, we present and discuss our results. Finally, conclusions are drawn in Section 2.5.

2.2 Literature Review and Hypotheses

2.2.1 Disposition effect

The DE is one of the most widely reported behavioural biases observed amongst investors. Shefrin and Statman (1985, p. 777) were the first to document the tendency amongst investors to ‘sell winners too early and ride losers too long’. This effect has been observed in numerous subsequent studies and has become known as the DE (e.g., Ferris, *et al*., 1988; Weber and Camerer, 1998; Odean 1998; Grinblatt and Keloharju, 2001; Shapira and Venezia, 2001; Locke and Mann, 2005; Dhar and Zhu, 2006; Kumar, 2009; Kaustia, 2010; Jin and Scherbina, 2011). Clearly, such behaviour is irrational, as future performance of an asset is not associated with the price at which the investor purchased the asset (Camerer, 2004).

Numerous explanations for the DE have been proposed and the most popular of these relates to prospect theory (Kahneman and Tversky, 1979; Kahneman and Tversky, 1984). Prospect theory suggests that investors may use a reference point to judge the gains or losses they have made on an asset. When their asset price increases (above the reference point), investors may either hold the asset (risk seeking behaviour) in the expectation that the price will continue to increase or to sell the stock (risk averse behaviour) to secure some profit. Conversely, if the price falls, holding the asset shows a preference for the risky outcome (Payne et al. 1984), while selling the stock crystalizes the loss and shows a preference for the risk averse outcome. Prospect theory suggests that most investors are risk averse for gains (above the reference point) and risk preferring for losses, thus leading to a preference for selling/holding an asset if it increases above/falls below the reference point, as they are unwilling to accept the losses. This would lead to the DE.

Shefrin and Statman (1985) were the first to define the DE and to explain it in terms prospect theory and a number of other studies followed this lead (e.g., Odean, 1998; Grinblatt and Han, 2005). However, Barberis and Xiong (2009) argued that these studies had not linked prospect theory with the DE in formal terms. Therefore, they investigated the relationship between prospect theory and the DE in formal models and, surprisingly, found that the theory often predicted the opposite of the DE; i.e. investors were more inclined to sell losing (cf. profitable) positions, when the expected stock return is high. They argued that this may occur because the higher expected stock returns lead to investors wanting to take larger risks.

Odean (1998) suggested an alternative explanation for the DE. He argued that that an investor might not hold a losing asset because they are reluctant to realize a loss (as suggested by the prospect theory) but rather because they believe that today’s losers will outperform today's winners in the near future. Such a belief in 'mean reversion' would lead to the DE (Weber and Camerer, 1998).

Some experimental and some theoretical studies have suggested that emotion may be a better explanation for the DE. For example, it has been argued that self-justification, based on the theory of cognitive dissonance, could explain of DE. Cognitive dissonance refers to discomfort felt when holding two or more conflicting cognitions simultaneously (Festinger, 1962). In terms of the DE, investors would like to keep a positive mood and belief in their capability of making good investment decisions. As a result they are not keen to admit an investment error. Barber et al. (2007) support this theory and state that some investors would find it psychological painful to admit their mistakes. A related cause of the DE has been suggested by Shefrin and Statman (1985). They argue that the DE may stem from a tendency to avoid regret. In particular, they suggest that investors prefer to sell profitable positions to avoid the regret which would follow a fall in the price, no matter what the probability of the asset continuing to increase in value. Similarly, they suggest that investors will prefer to hold losing positions in order to avoid the regret arising from a mistaken decision. Similarly, Summers and Duxbury (2007) argue that anticipated rejoice and regret is a possible trigger of the DE. Their experiments led them to conclude that emotion is important driver for the DE.

In summary, the literature examining the 'rational' origins of the DE argues it is influenced by risk aversion in the region of losses from a reference point or from investors' optimistic/pessimistic expectation of price when the price is low/high(e.g., mean reversion), that leads to an unwillingness to realize losses. However, others explain the DE from the perspective of various aspects of emotions (e.g., self-justification, rejoice/regret etc.). If these later theories are correct then it is likely that some factors which lead to situational changes (Barberis and Xiong, 2009) and emotional thinking may drive the DE. In particular, changes which lead to the greater use of System 1 thinking (Kahneman, 2011), which is emotional, fast, automatic and instinctive (cf. rational, careful thought), are likely to lead to biased decision-making. In this paper, we seek to shed light on whether emotions/mood play an important role in the DE by trying to establish if there is a relationship of between weather factors and the DE. If we establish this link, it adds weight to the view that the linking mechanism at work is the mood of the investor.

2.2.2 Mood and decision-making

There is an extensive literature that indicates that mood has a strong impact on individuals' thoughts and expectations (Mayer et al., 1992), which can, in turn, influence their decision-making (e.g., Allen and Fisher, 1978; Schneider, et al., 1980; Loewenstein et al., 2001; Kauffman, 1999; Simon, 1967; Wright and Bower, 1992). For example, Forgas et al. (2009), in a study which explored the link between weather and shoppers' ability to recall memories, found that their recall of objects was better in bad (i.e. cloudy, rainy) weather conditions than in good (sunny) weather conditions. These might because good mood increases reliance on heuristics, which, in turn results in thinking less carefully before decision-making. On the other hand, negative mood could warn individuals that all is not well, leading them to be cautious, to think carefully and to avoid relying on heuristics (e.g. Schwarz, 1990; Park and Banaji, 2000). As a result, good mood might be a driver towards the use of heuristics.

2.2.3 Weather, season and mood, and decisions

There have been a considerable number of psychological studies exploring the relationship between weather and individuals' mood. For example, Rosenthal et al. (1984) discovered the seasonal affective disorder (SAD), which can make people feel unhappy, low in energy and/or depressed. He identified that this is caused by lack of sunshine, which is more likely in winter (Rosenthal, 1998). This phenomenon is highly seasonal, as the depression occurs in fall/winter with remission in spring/summer. Therefore, it has also been called 'Winter Depression'. Denissen et al. (2008) found that shortage of sunshine, windier conditions and lower temperatures had an impact on negative mood (e.g., led to increased anxiety or depression). It has been suggested that this occurs because Vitamin D3, which comes from a hormone generated by sunlight exploring the skin, changes serotonin levels in brain, and this in turn affects mood (Lansdowne and Provost, 1998). Similarly, Howarth and Hoffman (1984) found that individuals who experienced greater lengths of sunlight and higher temperatures displayed increased optimism and decreased anxiety, respectively. Some other studies, however, find a negative correlation between temperature and mood. For example, Goldstein (1972) established an experiment to investigate the relationship between weather and mood in 22 students attending a psychology course and found a significant positive mood in cooler conditions. A number of other weather phenomena, such as air pressure, have also been shown to influence individuals' moods. For example, Keller et al. (2005) demonstrated that in spring high air pressure helped to generate a positive mood. As high air pressure is normally associated with less cloud cover, this could be the underlying reason for the positive mood that is generated, while low air pressure is typically associated with cloudiness, or even rainfall (Ahrens et al., 2012). In summary, it has been suggested in the previous literature that good mood is induced by good weather, whilst bad weather conditions induce a negative mood.

2.2.4 Impact of weather on financial decisions

A number of studies have explored the relationship between weather and financial markets behaviour. For example, Saunders (1993), who was the first to examine the impact of weather on decisions in financial markets, discovered that returns on the New York stock exchange were lower on cloudy days. Some subsequent studies have confirmed this finding (Hirshleifer and Shumway, 2003; Akhtari 2011) and have suggested that this may arise because sunshine brings good mood, which could make individuals more optimistic in their evaluation of future prospects (i.e. stock price). However, other studies have found no significant correlation between stock returns and the degree of cloudiness or the amount of sunshine (Krämer and Runde, 1997; Trombley, 1997; Pardo and Valor, 2003; Loughran and Schultz, 2004).

A few studies have found a negative correlation between raw temperature (Cao and Wei, 2005), deseasonalized temperature (Yuksel and Yuksel, 2009) and stock returns. In particular, Chang et al. (2006), in investigating the Taiwan stock market, found that extreme high or low temperatures correlated with lower stock returns. A possible reason is because temperature could be negatively (Goldstein, 1972) correlated with mood, and low temperature increase aggressive behaviours (Schneider, et al., 1980; Howarth and Hoffman, 1984).

Other weather factors, such as wind and air pressure have also been linked with financial decisions. In particular, it has been found that greater wind has a negative impact on stock returns (Keef and Roush, 2005) and equity prices (Dowling and Lucey, 2008). This may arise because winder conditions could negatively affect mood (Denissen et al. 2008). Equally, a positive relationship between air pressure and stock returns was found by Shu (2008) and Schneider (2013). Once again this may arise because of the positive impact of high air pressure on mood (Keller et al., 2005).

Clearly, there might be factors other than weather that could influence the stock return seasonally. For example, the ‘gone fishin’ effect (Hong and Yu, 2009), suggest that activity on stock markets is lower in summer vacation period when traders are on holiday. In addition, cloudiness is highly seasonal (Hirshleifer and Shumway, 2003) and temperature is likely to be hotter on average in summer, suggesting that stock returns are likely to be lower in summer than winter (e.g. Cao and Wei, 2005). Consequently, to identify the real effect of cloudiness, temperature or other weather factors on stock returns it is first necessary to control for seasonal effects. For example, Jacobsen and Marquering (2008) included a ‘Halloween dummy’ (i.e. a dummy variable: 1 representing months from May to October, 0 otherwise) when examining the effect of raw temperature on stock returns using a GARCH model. Having controlled for seasonality they found very little correlation between temperature and stock returns, but that stock returns are generally higher in winter than summer months. However, Yuskel and Yuskel (2009) questioned the approach of Jacobsen and Marquering (2008), suggesting that because the Halloween dummy distinguishes summer and winter months, there may be a multicollinearity problem between raw temperature and the dummy. Consequently, they deseasonalized temperatures and controlled for the Halloween variable. As a result, they found that deseasonalized temperatures had a negative impact on stock returns, even though the significance was weaker than for results based on raw temperature.

An important omission in previous studies is the fact that different weather factors can be expected to have a different impact on mood in winter and summer. For example, hotter temperatures in the summer may cause individuals greater discomfort, which may have a depressing effect on mood. Whereas, warmer temperatures in the winter may cause an improvement in mood.

In summary, weather has been shown to influence mood, and this in turn can affect individuals' financial decisions. Consequently, since mood and emotion have been shown to play a key role of the degree of the DE (Shefrin and Statman, 1985; Summers and Duxbury, 2007) it seems sensible to explore to what extent weather might, via its effect on mood, affect the incidence of the DE.

2.2.5 More/Less Informed Individuals

A further question that has received only limited attention in the literature is to what extent there are differences in weather-effects between more and less informed investors. Studies have identified weather-effects amongst more informed traders. For example, Watson and Funck (2012) found that the trading activity of those who they regarded as more informed (short sellers: regarded as more informed due to the more technical nature of short selling: see Miller, 1997; Dechow et al. 2001; Geczy et al., 2002) was influenced by the degree of cloudiness. Goetzmann et al., (2015) found that institutional investors' (who are generally regarded as more informed) were affected by weather factors, being more inclined to sell stocks on cloudy days. In addition, Schneider (2013) showed, using survey data, that private investors' expectations are more biased by weather air pressure than institutional investors.

In general, less informed traders have been shown to be more susceptible to irrational biases. For example, it has been found that the DE is more pronounced amongst less informed traders (e.g., Odean 1999; Grinblatt and Keloharju, 2001). Consequently, it is interesting to investigate the manner in which the DE displayed by less and more informed traders is differentially affected by weather-factors.

Our belief that weather factors are likely to influence the DE displayed by less informed traders to a greater extent is based on the fact that biases are largely explained by the reliance on emotional (System 1) rather than on more rational (System 2) thinking (Kahneman, 2011), and we would expect that this is more likely to be the case for less informed traders. For example, it has been shown that less-informed traders are more likely to 'trade randomly on non-information news' (Frijns et al, 2008) and to be 'affected by their beliefs or sentiments that are not fully justified by fundamental news' (Shleifer and Summers, 1990, p.19). In addition, Forgas's (1995) Affect Infusion Model (AIM) predicts that those engaged in more uncertain tasks are more likely to be influenced by mood when making judgments. Clearly, those who have less valuable information on which to base a decision are facing a more uncertain task. Consequently, the AIM predicts that less informed investors, whose trading activity might be regarded as involving more uncertainty, are those most likely to allow weather-induced mood to influence their biased decisions, such as the DE.

A variety of means have been used to differentiate more and less informed traders but all of these have inferred their status as more or less informed. For example, some compare institutional vs. retail investors (Grullon and Wang, 2001; Dennis and Weston, 2001). However, a more direct means of distinguishing those that do and do not trade on relevant information may be to identify those that make the greatest long run profit from their trading activities. Our data enables us to distinguish traders in this way.

2.2.6 Hypothesis

As indicated above, it has been demonstrated that weather can affect individuals' mood, and, in turn, their decision-making (including that in the financial domain). Consequently, we expect that the DE displayed by a trader will be influenced by a range of weather factors.

It is also clear from the studies discussed above that mood and emotion can result in traders failing to think rationally, leading to increased reliance on heuristics. This in turn can lead to the DE. In addition, we suspect, as indicated above, that this is more likely to apply to less informed traders. Consequently, we test the following two hypotheses:

H1: The probability that a trader will hold losses longer than gains (i.e. display the DE) will be affected by range of weather conditions?

H2: The probability that a less (cf. more) informed trader will hold losses longer than gains (i.e. display the DE) will be more affected by range of weather conditions.

2.3. Data and methodology

2.3.1 Data

We employed individual trading records of spread traders in the UK market to calculate the DE. Spread-trading can be conducted on a huge number of financial markets around the world, and can be based on a range of financial instruments, including indices, shares, currencies, bonds, etc. Spread trading is a form of betting on the result of an event, with the return or payoff depending on the accuracy of the wager. Investors can buy/sell a position for any multiple of £1 per point (e.g. £10 per point), so that if the asset rises/falls in price by x points they gain x multiplied by their stake per point. Thus, if they buy the market at £10 per point and the market rises by 15 points then have secured a gain of £150. However, if the market moves in the opposite direction to their prediction (in this example falls by, say, 25 points) then they lose the stake per point multiplied by the number of points the market moves (£250).

A very important benefit of employing individual spread-trading data is that we can calculate the proportion of individuals' closing positions in profit and the proportion closing positions in loss in 1 minute intervals. This is achieved by matching the spread trading data to minute-by-minute tick data. The DE in traditional financial markets is normally explored by examining trades across a whole day (e.g. Barberis and Xiong, 2009). However spread traders operate on much shorter time scales, and the median time a trade is held for in our database is 11 minutes. We, therefore examine the DE across 1 minute intervals. This is important because spread traders are more likely to observe price changes at this level and, as a result, we are able to calculate the DE far more frequently than is the case in traditional financial market studies.

The spread-trading market is one of the fastest growing markets in the UK, opening up speculation opportunities to a wide cross section of the public. Spread trading requires only a very small margin (as little as £50 deposit to trade) meaning very low financial barriers to entry. In addition, the spread trading companies provide a service to the 'retail' sector rather than institutions, and so do not require any proof of experience or qualification to trade. Furthermore, it has been argued that one of the main reasons most spread traders lose money[3] is because they are amateurs (SpreadBettingBrokers, 2015). Therefore, we believe most traders in this market have little trading experience, leading, perhaps to a greater proportion of less informed traders operating in this market than in

[3] Based on our spread trading data, the historical average profits of more than 80% of traders are negative. This evidence is in line with the research of Brady and Ramyar from London Cass Business School (2006) that only 20% spread traders make profit.

traditional financial markets.

It is expected that there will be 1 million spread traders in the UK alone by 2017 (Pryor, 2011). In addition, Brady and Ramyar (2006) indicate that about £1.2 trillion is traded annually on the London Stock Exchange, 10 percent which relates to spread trading (£120 billion). The spread trading companies often hedge into the underlining market to control their risks. Therefore, any biased behaviour in the spread trading market, perhaps caused by environmental factors such as weather, might influence the traditional financial markets.

The individual trading data used to calculate the DE in this study is drawn from the period January 2005 to December 2012 and is based on trading in the two most popular indices, the FTSE 100 and DAX 30. As a result we examine the trading records of the 9,101 individual clients of a large spread trading company, who traded in these markets in this period. We link the individual trading records to the minute-by-minute tick data in these markets in order to calculate both the open positions and the closed positions in any given minute.

The weather data used in this study is provided by the British Atmospheric Data Centre (BADC), and this contains hourly descriptions of weather. Detailed records are obtained from 554 UK locations for the period January 2005 to December 2012. We establish a link between weather and trading data via the trading time and location indicated as the trading location of a given spread trader. This is achieved by matching the postcodes of the nearest weather observation station to the postcode of the home address of each spread trader.

2.3.2 Variables

2.3.2.1 Disposition Effect calculation

To calculate every single individual's DE, we link the tick data of FTSE 100 and DAX 30 with the trading records of each individual. For example, if trader Y opens a position on the FTSE 100 at 9:07 am on 4st January, 2010, with a 'buy' stake of £3 and the opening FTSE 100 price of 4000, we record this transaction as 'Open' during the seventh minute after 9.00 am. At 9:08am, if the price of the FTSE100 went up to, say, 4003, we then counted this minute (i.e. the eighth minute after 9am as one in which 'Paper Profits' are available). At 9:09, if the price of the FTSE 100 fell to 3098 and the client closed the transaction, we counted this minute as one in which a 'Realized Loss' (of £6) was made.

We then counted the number of 'Paper Profits', 'Paper Losses', 'Realized Profits' and 'Realized Losses' in a given hour for each trader (e.g. in the first hour after trading opened). This is the similar method to that employed by Odean (1998) and Dhar and Zhu

(2006), to calculate the DE, with the exception that we use 1-minute intervals rather than daily intervals. We then calculated the probability/proportion of closing a position in profit by a given spread trader in each hour (*ProbCloseProfit*) (see equation 2.1 below). Similarly, we calculated the probability/proportion of the same trader closing a losing position in that particular hour (*ProbCloseLoss*) (see equation 2.2 below). The DE for a given trader in a given hour is measured by the value of *ProbCloseProfit* minus the value of *ProbCloseLoss* for that trader in that particular hour. Consequently, we obtained the degree of the DE in each hour by each client.

We then linked the DE data for a given hour for a particular trader with the weather data for that hour at the notified trading location (i.e. postcode) of that trader. In this way, we were able to analyse the trading records of 9,101 traders spread across 70 UK cities/towns.

$$ProbCloseProfit_{it} = \frac{Number\ of\ Realized\ Profits_{it}}{Number\ of\ Realized\ Profits_{it} + Number\ of\ Paper\ Profits_{it}} \tag{2.1}$$

$$ProbCloseLoss_{it} = \frac{Number\ of\ Realized\ Losses_{it}}{Number\ of\ Realized\ Losses_{it} + Number\ of\ Paper\ Losses_{it}} \tag{2.2}$$

$$DispositionEffect_{it} = ProbCloseProfit_{it} - ProbCloseLoss_{it} \tag{2.3}$$

where *i* is client, *t* is hour

Note: the counts were made at 1 minute's intervals.

In order to test hypothesis 2, it was important that we could distinguish the trades of more and less informed traders. To make this possible, we restricted the analysis to those traders who had made at least 50 trades, so that we had a reasonable indication of their longer run performance.

2.3.2.2 Weather variables

The hourly weather variables used in this study are total cloudiness (*cloud*), rainfall (*rain*), temperature (*temp*), air pressure (*pres*) and wind speed (*wind*) and a full description of each is given in Table 2.1.

Table 2.1 List of explanatory and control variables employed in this study

Variable Type	Variable Name	Description	Raw Variable Units/Coding
Weather	*Dcloud*	Deseasonalized Cloud Cover	Oktas scale 0 = No cloud cover to 4 = Half cloud cover 8 = Total cloud cover 9 = Sky obscured from view
Weather	*Drain*	Deseasonalized Rainfall	Millimeters (mm)
Weather	*Dtemp*	Deseasonalized Air Temperature	Degrees Centigrade (℃)
Weather	*Dpres*	Deseasonalized Air Pressure	Atmospheric Pressure (hPA)
Weather	*Dwind*	Deseasonalized Wind Speed	Knots
Control Covariate	*LogMeanOpenPrice*	Logged mean open price	
Control Covariate	*MarketVolitility*	Volatility profit of the FTSE Future 100 market	
Control Covariate	*LogMarketReturn*	Logged mean return of the FTSE Future 100 market profit	
Control Covariate	*Halloween*	Halloween Dummy	1 = May to October 0 = November to April
Control Covariate	*Monday*	Monday Effect Dummy Variable	1 = Monday 0 = Any other day
Control Covariate	*January*	January Effect Dummy Variable	1 = January 0 = Any other month
Control Covariate	*SAD*	SAD Effect Continuous Variable	0 = Spring and Summer
Interaction	*Halloween*× *Dcloud*	Halloween and Deseasonalized cloudiness interaction	
Interaction	*Halloween*× *Drain*	Halloween and Deseasonalized rainfall interaction	
Interaction	*Halloween*× *Dtemp*	Halloween and Deseasonalized temperature interaction	
Interaction	*Halloween*× *Dpres*	Halloween and Deseasonalized air pressure interaction	
Interaction	*Halloween*× *Dwind*	Halloween and Deseasonalized wind speed interaction	

As discussed previously, a range of seasonal patterns exist, in terms of stock returns and likely effects of weather. For example, as indicated above, SAD is a condition far more prominent in winter months. In order to control for the seasonal patterns, we first include Halloween dummy in this study, which is defined as 1 if it is in summer months

(May to October), and 0 otherwise (November to April). Additionally, we seek to overcome the possible problem of multicollinearity identified by some earlier studies, if one uses both raw weather variables and Halloween dummy in a model (Yuskel and Yuskel, 2009). Consequently, we deseasonalized the raw weather variables employed in this studies and then control for Halloween. This is also the approach adopted by a number of existing studies (e.g., Hirshleifer and Shumway, 2003; Goetzmann and Zhu, 2005). For instance, we deseasonalize all the weather variables by subtracting the monthly average level of the variables from the observed value. As a result the raw variables *Cloud*, *rain*, *temp*, *pres*, and *wind*, were converted to deseasonalized variables, *Drain*, *Dtemp*, *Dpres* and *Dwind*. We examine these weather phenomena in combination rather than performing univariate analysis, as various weather conditions are related. In particular, Denissen *et al.* (2008) emphasise the importance of differentiating the different effects of weather phenomena since it is possible that the effect of temperature may change after controlling for the amount of sunshine.

2.3.2.3 Controlling variables

As discussed above, we have controlled for seasonality in stock returns via the use of the Halloween dummy. In addition, we include *Halloween* × *weather variable* interactions, as we suspect that certain weather factors might have different or even opposite impacts on mood, in different seasons; with resulting effects on behaviour. For example, hotter temperatures in summer might negatively influence mood, while warmer temperatures in winter may have appositive impact on mood. Consequently, we incorporate the following five deseasonalized *weather variable* × *Halloween dummy* interactions: *Halloween* × *Dcloud*, *Halloween* × *Drain*, *Halloween* × *Dtemp*, *Halloween* × *Dpres and Halloween* × *Dwind*.

Seasonal affective disorder (SAD) has been shown to be an important environmental factor that influences an individual's mood in a systematic manner (e.g., Kamstra, Kramer and Levi, (2003). Consequently, we control for SAD to ensure that any observed weather effects are not subsumed by SAD. We calculate SAD in a similar manner to that employed by Kamstra, Kramer and Levi, (2003), namely:

$$\mathrm{SAD} = \begin{cases} \mathrm{H_t} - 12 & \text{for trading from autumn equinox to spring equinox} \\ 0 & \text{otherwise} \end{cases} \tag{2.4}$$

Where: $\mathrm{H_t}$ as the time between sunset and sunrise (i.e. the number of hours of night)

H_t is determined by the latitude of a particular location and the sun's declination angle (i.e. λ_t):

$$\lambda_t = 0.1402 * \sin[\left(\frac{2\pi}{365}\right)(\text{julian}_t - 80.25)] \tag{2.5}$$

Where: julian_t is a number from 1 to 365, standing for the order of the day in a year. For example, julian_t equals 1 on 1st January, julian_t equals 32 on 1st February etc. We then calculate H_t as follows:

$$H_t = 24 - 7.72 * \text{arcos}[-\tan\left(\frac{2\pi\delta}{360}\right)\tan(\lambda_t)] \text{ in Northern Hemisphere} \tag{2.6}$$

Where: δ is the latitude of a particular location (e.g. $\delta \approx 51$ at London).

In this study, we also control for a number of market-related variables that could influence the DE displayed during a given trading period, including: the logged mean price of the market in that hour for a given trader ($LogMeanMarketPrice_{it}$), mean returns of the market in the hour that a given trader secures a profit or loss by closing a position ($MarketReturn_{it}$, see equation 2.7) volatility during the period of any trades opened by a given trader in that hour ($MarketVolatility_{it}$, see equation 2.8).

$$LogMeanMarketReturn_{it} = Log(\frac{MeanMarketPrice_{it}}{MeanMarketPrice_{i(t-1)}}) \tag{2.7}$$

$$MeanMarketVolitility_{it} = (LogMeanMarketReturn_{it})^2 \tag{2.8}$$

This importance of controlling for these variables is confirmed by Ben-David and Hirshleifer (2012). Consequently, by controlling for these variables we hope to truly measure the effect of the weather on the DE of a given trader. Clearly, individuals would prefer to buy when the price is low and sell when the price is high; therefore we control for the current mean price of the market as a factor ($LogMeanMarketPrice_{it}$). The volatility variables control for the possibility that traders may trade more actively in more speculative conditions (i.e. high volatility). The market return factors control for the obvious possibility that traders are more likely to close a position in profit or loss the greater the profit or loss, respectively. In addition, according to Barberis and Xiong (2009) there is a greater incidence of the DE when the expected stock returns are higher.

There are a number of other factors that could influence individuals' trading behaviour, including the Monday and January effects (e.g., Cao and Wei, 2005; Pardo and Valor 2003; Watson and Funck, 2012). In particular, it has been shown that returns/prices on Monday are lower and in January are higher than average. This could suggest that individuals' trading behaviour, and, in particular, the incidence of them displaying the DE, may differ when they trade on Mondays or in January. Consequently, we control for this by including a January dummy and a Monday variable that take the value 1 if the trading happens in January and Monday, respectively, 0 otherwise. Furthermore, we run the KPSS test (Kwiatkowski, et al., 1992) to explore whether a unit root exists. In particular, if a unit root exists in time series data it means that the series is not stationary and the regression might be spurious (Granger and Newbold, 1974). In fact, the results of KPSS tests indicate the data does not suffer this limitation (p-value > 0.09).

2.3.3 Models

2.3.3.1 Multi-level mixed model

The very few existing studies examining the relationship between weather and individual trading (e.g. stock return, trading volume etc.) largely use simple linear models (Goetzmann and Zhu, 2005) or logistic models (Levy and Galili, 2008). However, the preferences of each trader may well be different (e.g. the frequency of transactions). The data we employ, individual trading histories related to spread trades for the FTSE 100 and DAX 30, allows us to count the length of holding a position of every single trader by minute intervals. This in turn, enables us to calculate the DE value of each trader, during a given hour. Consequently, we are able to employ multi-level mixed models to capture the different levels in the data (Tabachnick and Fidell, 2001). In particular, they allow us to examine transactions (level 1 data) that are nested at the trader level (level 2 data) (Luke, 2004). As a result, we are able to examine the different weather impacts on individual traders.

The multi-level mixed model we employ has the following form (Laird and Ware, 1982):

$$\begin{aligned} y_{ij} = \beta_1 x_{1ij} + \beta_2 x_{2ij} + \cdots + \beta_p x_{pij} + \\ \gamma_{j1} z_{1ij} + \gamma_{j2} z_{2ij} + \cdots + \gamma_{jq} z_{qij} + \varepsilon_{ij} \end{aligned} \tag{2.9}$$

which can be written in a matrix form, as follows,

$$y = x\beta + z\gamma + \varepsilon \tag{2.10}$$

Where

j is the level one factor (trades in this study)

i is the level two factor (traders in this study)

y is the vector for the outcome variable (DE in this study)

x is the matrix for fixed effect factors (weather factors in this study)

β is the vector for fixed factors

z is the matrix for random effect regressors (ClientID/traderID in this study)

γ is the vector for random effect

Consequently, the specific model we employ to test the hypotheses concerning the impact of weather on the DE, takes the following form:

$$DispositionEffect_{it} = \alpha_{it} + \beta_1 LogMeanOpenPrice_{it} + \beta_2 MarketVolatility_{it} + \\ + \beta_3 MarketReturn_{it} + \beta_4 SAD_{it} + \beta_5 Dcloud_{it} + \beta_6 Drain_{it} + \beta_7 Dtemp_{it} + \\ \beta_8 Dpres_{it} + \beta_9 wind_{it} + \beta_{10} January + \beta_{11} Monday + \beta_{12} Halloween \times Dcloud_{it} + \\ \beta_{13} Halloween \times Drain_{it} + \beta_{14} Halloween \times Dtemp_{it} + \beta_{15} Halloween \times Dpres_{it} + \\ \beta_{16} Halloween \times wind_{it} + \gamma_0 ClientID_i + \varepsilon_{it} \tag{2.11}$$

Where

β is the vector of fixed factors (i.e. weather and controlling variables)

γ is the random coefficient on the *ClientID* random factor

i is the *trader*

t includes the whole transactions in the hour made by trader i

$ClientID_i$ is the unique number of traders (clients) in our spread-trading dataset, and it is also the means by which observations are nested

2.3.3.2 Differential Weather-effects for More and Less Informed Traders

Traders who most effectively employ available information are, ceteris paribus, more likely to achieve a higher average return per trade. Consequently, in order to test hypothesis 2, namely, that the degree of the DE of less (*vs*. more) informed individuals are more likely to be affected by weather, we ranked the traders in terms of their average return per trade and then split them into two groups: the top 25% (most profitable) *vs*. the bottom 25% (least profitable). Equation 2.11 was then estimated for each of these groups.

2.4. Results and discussions

2.4.1 Weather impact on the Disposition Effect

The results of estimating the relationship between weather factors (i.e. cloudiness, rainfall, temperature, air pressure and wind) and the DE (Model 2.11) are presented in Table 2.2. The market variables are significant, suggesting that the degree of DE increases under conditions of higher stock volatility, but decreases when the market price is higher. All weather factors in winter months significantly influence the degree of the DE. In particular, greater cloud cover (coefficient: 0.0006; *t*-value: 2.0909), decreased rainfall (coefficient: -0.0042; *t*-value: -3.8100), higher temperature (coefficient: 0.0013; *t*-value: 4.9641), lower air pressure (coefficient: -0.0001; *t*-value: -1.9651) and greater wind speed (coefficient: 0.0007; *t*-value: 3.7405) all increase the degree of an individuals' DE. However, planned contrasts suggest that these weather effects are less pronounced in summer months, with only higher deseasonalized temperature (coefficient: 0.0013 - 0.0001 = 0.0012; *t*-value: 3.959) and lower air pressure (coefficient: -0.0003; *t*-value: -2.307) increase the degree of the DE.

In summary, these results demonstrate support for Hypothesis 1, that the degree of DE is influenced by range of weather factors to a different degree and in a different manner in different seasons. In addition, the results, arguably, suggest that some of conditions which are related with greater personal comfort (less rainfall, and higher temperature (in winter)) induce a greater degree of the DE.

Table 2.2 Estimated coefficients, standard errors and t-value for the *Disposition Effect* model

Variable	Estimated Coefficients	Std. Error	*t*-value	
Intercept	0.6623	0.0477	13.8976	**
LogMeanOpenPrice	-0.0623	0.0056	-11.2285	**
MarketVolatility	14.4597	4.8941	2.9545	**
LogMarketReturn	0.1141	0.1182	0.9657	
SAD	0.0050	0.0006	9.1177	**
Dcloud	0.0006	0.0003	2.0909	*
Drain	-0.0042	0.0011	-3.8100	**
Dtemp	0.0013	0.0003	4.9641	**
Dpres	-0.0001	0.0001	-1.9651	*
Dwind	0.0007	0.0002	3.7405	**
January	-0.0035	0.0026	-1.3379	
Monday	-0.0031	0.0016	-1.9795	*
Halloween	0.0112	0.0017	6.5060	**
Halloween× *Dcloud*	0.0001	0.0005	0.0481	
Halloween× *Drain*	0.0032	0.0015	2.1187	*
Halloween× *Dtemp*	-0.0001	0.0004	-0.3104	
Halloween× *Dpres*	-0.0001	0.0001	-0.9607	
Halloween× *Dwind*	-0.0007	0.0003	-2.5989	**
Adjust R^2	0.0790			
Effect Size (Cohen's f^2)	0.0860			

* Significant at 0.05
** Significant at 0.01

2.4.2 Differential Weather-effects on More and Less Informed Traders

The results of estimating the extent to which weather factors differentially affect informed and less informed traders, defined in terms of the most and least profitable traders are shown in Table 2.3. The results suggest that weather factors, as hypothesized, have more impact on the incidence of the DE amongst the less informed traders.

Table 2.3. Estimated coefficients, standard errors and *t*-value for the *Disposition Effect* model fitted to the 25% most profitable and the 25% least profitable traders.

	Most profitable traders				Least profitable traders			
Variable	Estimated Coefficient	Std. Error	*t*-value		Estimated Coefficient	Std. Error	*t*-value	
Constant	0.6103	0.0911	6.6971	**	0.5256	0.0952	5.5215	**
LogMeanOpenPrice	-0.0568	0.0106	-5.3551	**	-0.0469	0.0111	-4.2336	**
MarketVolatility	30.3818	9.9528	3.0526	**	8.5681	8.7684	0.9772	
LogMarketReturn	0.0897	0.2218	0.4046		-0.2543	0.2319	-1.0969	
SAD	0.0063	0.0011	5.7415	**	0.0021	0.0011	1.8990	
Dcloud	0.0003	0.0006	0.5604		0.0015	0.0006	2.5261	*
Drain	-0.0032	0.0018	-1.8187		-0.0058	0.0024	-2.4147	*
Dtemp	0.0010	0.0005	1.8306		0.0009	0.0005	1.8038	
Dpres	-0.0001	0.0001	-0.5980		0.0001	0.0001	0.6140	
Dwind	0.0001	0.0004	2.4856	*	0.0010	0.0004	2.9026	**
January	-0.0084	0.0050	-1.6544		0.0009	0.0053	0.1745	
Monday	-0.0020	0.0032	-0.6274		0.0007	0.0031	0.2139	
Halloween	0.0122	0.0035	3.5396	**	0.0032	0.0034	0.9439	
Halloween× *Dcloud*	-0.0006	0.0009	-0.6250		-0.0012	0.0009	-1.2740	
Halloween× *Drain*	0.0005	0.0028	0.1829		0.0057	0.0031	1.8206	
Halloween× *Dtemp*	-0.0009	0.0008	-1.1224		0.0003	0.0008	0.4077	
Halloween× *Dpres*	0.0001	0.0003	0.2223		-0.0005	0.0003	-1.9874	*
Halloween× *Dwind*	-0.0011	0.0005	-2.0767	*	-0.0005	0.0006	-0.9246	
Adjusted R^2		0.075				0.083		
Effect Size (Cohen's f^2)		0.081				0.091		

* Significant at 0.05
** Significant at 0.01

Strikingly, for the more informed (25% most profitable) traders, the only weather factor which appears to affect the degree of the DE, is *Deseasonalized wind speed (Dwind)*; in winter months, suggesting that the degree of the DE is lower under calm conditions in winter months. However, no other weather factor in winter or summer (determined by planned contrast) significantly affects the degree of DE displayed by this group. By contrast, the *Deseasonalized cloudiness*, *rainfall* and *wind speed* are significant in the model estimating the degree of the DE of the less informed traders. Moreover, the planned contrasts indicate that lower air pressure (coefficient: 0.0001 - 0.0005 = -0.0004, *t*-value: -1.96) and higher temperatures (coefficient: 0.0009 + 0.0003 = 0.0012, *t*-value: 2.12) induce a greater degree of DE amongst less informed traders in summer. Furthermore, it is striking that the most of *t*-values of each of the weather factors in the models designed to explore the DE are considerably higher for the less informed than the more informed traders, again suggesting that the less informed traders decisions leading to the DE are more affected by weather factors.

Overall, these findings suggest that the DE displayed by less informed traders is far more affected by weather than is the case for the more informed traders. These results, therefore, provide support for hypothesis 2.

2.4.3 Discussion

The results provide evidence to support our hypothesis 1, that weather factors do influence the degree of DE displayed by traders. We make this assertion as we show correlation between the weather factors and the degree of the DE displayed and we know from existing literature (e.g., Ackert and Deaves, 2009), that the degree of the DE can be caused by emotions/mood, which are, in turn induced by weather phenomena. Specifically, we find that some of the weather factors which cause a decrease in DE in winter months are associated with inducing greater personal comfort (i.e. leading to more positive mood) conditions. The findings are in line with the chain that good mood, induced by good weather conditions, can increase reliance on heuristics and less careful thinking (Schwarz (1990) and Park and Banaji, (2000)). This, in turn, can lead to biased decision-making behaviours (Kahneman, 2011), which may be responsible for the DE. Taken together, the results indicate that most weather variables significantly influence the degree of the DE, which can support our Hypothesis 1.

Furthermore, the results also offer strong support for Hypothesis 2, that the incidence of the DE amongst less informed spread traders is more affected by weather factors than is case amongst more informed traders.

Importantly, we control for a number of market-related variables when we examine these hypotheses. In particular, market prices, and volatility are all highly related to individuals' buying or selling decisions, and as Ben-David and Hirshleifer (2012) suggested, these market variables are highly correlated with the DE. Failing to control for them would have led to a failure to reveal the real weather impact on the DE. Clearly, individuals prefer to sell/buy when the price is high/low. Moreover, traders may trade more actively in more speculative conditions (i.e. high volatility). Not surprisingly, the results demonstrated that the market variables are significantly associated with the degree of the DE. In particular, lower market price and higher market volatility increase the degree of the DE. However, we cannot argue whether the results are consistent with the previous literature, since this is the first study to examine spread trading markets and in these markets traders can buy or sell when they open a position. On the other hand, in traditional financial markets buying is investment behaviour whilst selling is a divestment activity.

Daniel Kahneman, the winner of the 2002 Nobel Prize in Economic Sciences, in his discussion of ‘System 1 and System 2’ thinking (Kahneman, 2011), argued that good mood can lead people tend to make decisions using System 1 (‘automatically and quickly’, p.20-21) rather than System 2 (‘allocates attention to the effortful mental activates’, p.20-21). This arises because System 1 thinking is associated with the use of heuristics. Specifically, ‘*System 1* operates automatically and quickly, with little or no effort and no sense of voluntary control’, while ‘*System 2’* allocates attention to the effortful mental activates that demand it, including complex computations’ (Kahneman, 2011, p.60). Therefore, he argues that when people are in a good mood they are in the state of cognitive ease, which could result in feeling good, true, familiar and effortless. This leads them to trust more in their intuitions, which are more associated with System 1 thinking. Schwarz (1990) and Park and Banaji, (2000) also argue that good mood increases reliance on heuristics, which, in turn results in thinking less carefully before decision-making (like System 1). Based on this literature, we know that good weather can induce good mood (e.g. Cunningham, 1979; Parrott and Sabini, 1990; Schwarz and Clore, 1983) and that this, in turn can lead to emotional, System 1 thinking. It is this which can lead to biased decision-making, and we suspect that this may be one of the factors increasing the incidence of the DE. In particular, less rainfall and higher temperatures cause improved personal comfort in winter months (Hsiang et al., 2013; Howarth and Hoffman, 1984)) and this can improve an individual’s mood. For example, (Hsiang et al., 2013) indicated that increases in precipitation can lead to a negative effect on individuals’ mood, resulting in aggressive behaviour. The fact that we observe greater DE under conditions of reduced rainfall and higher temperatures in winter months could thus be explained by this mood effect. However, it is more difficult to explain the effect of cloud, air pressure and wind, as meteorology these weather factors are complicated. In particular, according to Greets (2002) higher cloud cover can absorb long wavelength radiation from ground which leads to ‘net warming effect’ and this could keep temperatures warmer in winter months under conditions of lower air pressure. In addition, in the UK the prevailing wind is generally from the southwest (met office) in winter, which means warmer. Consequently, it is possible, in winter months that cloud, lower air pressure and wind could bring warmer condition, and in turn, lead to better mood and the higher degree of the DE.

By contrast, higher temperature and lower air pressure significantly increase the degree of the DE observed in summer months. These are weather conditions in summer which may lead to negative mood (Hsiang et al., 2013). Therefore, the summer results do not appear to be consistent with chain of good mood-higher degree of DE. A possible reason to explain this is that the temperature in the UK in summer months are not hot enough to cause discomfort (e.g. mean temperature is 14.4 ℃ between 1981 and 2010 (Met Office, 2013)), therefore, higher than average temperatures could improve individuals' mood, which in turn, increase the degree of the DE. Whatever the reasons are, the important finding is that the degree of the DE appears to be differentially affected by a range of weather effects between different seasons.

The results also demonstrate that the degrees of DE displayed by both more and less informed traders are affected by weather factors. However, we demonstrate, as expected, that the influence of weather effects on less informed traders appears to be greater. These results are consistent with the Affect Infusion Model (AIM) (Forgas, 1995), which predicts that the impact of mood on biased decision-making is greatest for those engaged in more uncertain tasks and we argue that less informed traders, by definition, hold less valuable information and consequently face a more uncertain trading 'task'.

It is possible that the measure we use for distinguishing informed and less informed traders based on their average return may lead to the issue of endogeneity. More specifically, one origin of long-term successful trades is from closing profitable positions, and this may also influence the analysis of the DE, as we count the closing profitable position to define the dependent variable. Therefore, both of the dependent variable of splitting traders group (Hypothesis 2) and original DE (Hypothesis 1) depends on the same factor (i.e. close profitable position), which may cause the issue of endogeneity. However, if endogeneity was a key concern then we would expect the results to show that informed traders are more likely to display the DE than less inform traders. However, our results indicate the opposite phenomenon. Consequently, whilst the issue of endogeneity may exist, it is unlikely to influence our results substantially.

Furthermore, we report the R^2 (range from 0.075 to 0.083) and effect size f^2 (from 0.081 to 0.091) (Cohen, 1992) in the study, and R^2 the values are reasonable compared to relative study (Hirshleifer and Shumway, 2003; Goetzmann et al., 2015), although these values are fairly low. In addition, the f^2 indicates a medium effect size and represents our tests are relative powerful.

We believe that the linking of a range of weather factors to the degree of the DE provide consistent evidence, in line with Summers and Duxbury (2007) that mood and emotion play a key role in the degree of the DE. In particular, this is the first study, to our knowledge, to establish that weather affects the DE, and is the first to identify that there are different effects in summer and winter.

One of the important methodological contributions of the current study is that we employed multilevel mixed models to explore the relationship between weather and the DE. This has enabled us to examine the extent to which the impact of weather on the DE varies between traders. Furthermore, the data we have collected from the spread-trading market enables us to calculate the degree of the DE in one-minute intervals, thus enabling us to explore the direct impact of weather at a particular time on decisions that lead to the DE. Previous studies have always calculated the degree of the DE on a daily basis (e.g. Odean, 1998), which arguably, cannot provide sufficient granularity to capture the factors which impact decisions associated with the frequently moving financial market price information. We therefore, believe that the methodology we employ is robust, as the approach does not suffer from this limitation. A further advantage of the methodology we employ is that by examining the trading records of individual traders we are able to distinguish more and less informed traders on the basis of a direct measure of their success over a long period, namely, their average profitability per trade. Overall, we believe that the methodology we employ in this study provides a clear point of view of the real impact of a range of weather factors on the degree of DE displayed by traders.

2.5 Conclusions

Previous studies have largely focused on explanations for the DE based on prospect theory and mean reversion (Kahneman and Tversky, 1979; Shefrin and Statman, 1985; Odean, 1998). However, it has been suggested by a few studies (e.g. Summers and Duxbury, 2007) that psychological phenomenon, such as mood and emotion can play an important role in determining the incidence of the DE. A large number of studies have found that weather can significantly influence individuals' mood (Howarth and Hoffman, 1984; Keller et al., 2005; Denissen et al., 2008), and that this, in turn, can affect their decision-making (Allen and Fisher, 1978; Schneider, et al., 1980; Loewenstein et al., 2001), financial behaviours (Goetzmann and Zhu, 2005). It has also been shown that weather can affect aggregated financial market returns (e.g., Saunders, 1993). Therefore, in this paper we try to link these two literatures by explore the link between weather the degree of the DE.

Using UK spread-trading data, we find that our results support the view encapsulated in hypothesis 1, namely that the incidence of the DE differs in different weather conditions, and this effect being particularly pronounced amongst less informed traders. These results could be explained by the fact that when people are in a good mood they are in the state of cognitive ease, which can result in them feeling good, familiar and that decision making is easy. Under such conditions, Kahneman (2011) suggests that individuals engage in System 1 thinking, which leads them to trust their intuition, and, that this in turn, results in a lack of rational thinking. This may then lead to biased decision-making which is likely to increase the incidence of the DE.

This is the first study to link weather and DE and the conclusions, we believe, are robust since the methodology employed offers important advantages over previous studies: it is the first study to use multi-level mixed models (Tabachnick and Fidell, 2001; Luke, 2004; Denissen et al., 2008) to test the hypothesis, which enables us to distinguish the trading differences and preferences across traders. Moreover, our data from spread-trading market enables me to calculate the minute- by- minute price movements. This, we believe, is the minimum interval needed to capture the influences on the decisions of spread traders associated with the frequent price movements of DAX and FTSE index (the methodology employed in previous studies examining weather impacts on decisions in financial markets have generally only used daily interval data (e.g. Odean, 1998)). Interestingly, our methodology of testing for different effects of the same weather factor in winter and summer has not been adopted in previous studies. We observe different and sometimes contradictory effects of the same weather factor in these two seasons and this may be the reason previous studies have under-estimated the true impact of weather on financial decision making behaviour.

Furthermore, we observe that the incidence of the DE amongst less informed traders is more strongly influenced by weather than that for more informed traders, providing a further confirmation of the less rational decision making of this group of traders. These results reported here make an important contribution to the market efficiency literature, as we demonstrate that traders' decisions are directly swayed by weather factors which are clearly not linked to the underlying economic fundamentals. Such behaviour therefore is likely to lead to mispricing. This, we believe, could mislead investors, as the prices would not reflect available information properly. More specifically, individual traders should be careful about allowing their (weather induced) emotional feelings affect their behaviours. Our results suggest that investors would probably be wise to consider selling losing positions and keeping profitable assets, particularly when they feel 'relatively comfortable', such as in warm conditions in winter. It is also recommended that traders, particularly less informed traders, should focus on the fundamental news rather than surrounding factors, such as weather. Future studies will need to examine whether the effects observed here are also present amongst traditional stock market investors, but the strength of the results reported here suggests that this will be the case. In addition, since we measure the minute interval spread-trading data to calculate the DE, we need minute level 'tick data'. Therefore, we focus on only two markets (i.e. FTSE 100 and

DAX 30) in this study, as we only had tick data for these two markets at the minute level. In addition, these two markets, based on our data, were the largest two futures markets (more than 60% trades covered by these two markets compared to all the markets). However, we still suffer a limitation of using only FTSE 100 and DAX 30, since we miss the trading activities from other markets. In addition, we also miss some evidence, for example, a trader may open a FTSE 100 or DAX 30 transaction, but close a position in other markets. Therefore, including more markets may provide a clearer picture of the impacts of weather on the degree of the DE. Consequently, it is recommended that future studies examine more markets (rather than FTSE and DAX) if data is available.

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Chapter 3

Risk-taking - come rain or shine: To what extent does weather changes influence risk-taking behaviour

Abstract

This paper is the first to examine to what extent *changes* in the weather throughout the impact individuals' risk-taking behaviour. To achieve this, we analyse 414,143 hourly individual trading records of 4,368 investors in the UK spread-trading market between 2005 and 2012. This is the first naturalistic study, using multi-level mixed models, to examine the impact of recent *changes* in a range of weather factors on the degree of risk-taking displayed by these traders. In addition, we control for current weather conditions and potential seasonal differences in the effects of weather factors. Our results suggest that the current weather has some effect on risk-taking but recent *changes* in various weather factors have a more noticeable effect, and these impacts vary between seasons. Specifically, we find that risk-taking increases following changes in weather which have been shown to induce poor mood (e.g. greater precipitation, lower air pressure and increases in temperature in the summer). We discuss the importance of these results for those involved in communicating risk-related messages and for those designing effective means of managing risk.

3.1 Introduction

Several studies have demonstrated a significant correlation between mood and weather factors such as cloudiness (Howarth and Hoffman, 1984; Rosenthal 1998), temperature (Goldstein, 1972), air pressure (Keller et al., 2005), rainfall, and wind speed (Denissen et al., 2008). The general finding is that 'good weather' (i.e., sunshine, higher air pressure, calm conditions) has a positive effect on individuals' mood whilst bad conditions (cloudiness, higher rainfall, low air pressure and high wind speed) have a negative effect on mood (Radua, Pertusa and Cardoner, 2010; Denissen et al., 2008).

A number of studies have also found a relationship between mood and decision-making (e.g. Kaufman, 1999; Loewenstein et al., 2001). In particular, Loewenstein et al (2001) showed that bad mood (such as anxiety) could increase risk-taking. In addition, a number of laboratory-based experiments have identified a link between an individual's mood and the degree to which they are prepared to take risks (Isen and Geva, 1987; Isen et al., 1988; Isen and Patrick, 1983; Hockey et al., 2000). The general finding of these studies is that individuals' risk-taking decreases when they are in a good mood. However, the results are odds to the study of Bassi et al., (2013) who examined a direct link between weather and risk-taking for the first time, bases on laboratory experiments, and found a positive relationship between good weather (leading to good mood) and risk-taking behaviour.

The research linking weather to mood and mood to decision-making resulted, not surprisingly, in several studies examining the impact of weather on decision-making (e.g. Wyndham, 1969; Schneider et al., 1980; Forgas et al., 2009). The majority of the literature examining the impact of weather and decision-making is lab-based. The few studies that have focused on this phenomenon in a real-world setting have examined indirectly the impact of only a limited range of weather factors on decision-making in financial markets (via the influence of these factors on stock returns). Some of these studies found a negative relationship between cloudiness and stock returns (Saunders, 1993; Hirshleifer and Shumway, 2003), whilst others found no such relationship (Pardo and Valor, 2003; Lu and Chou, 2012). Some studies have demonstrated that a negative relationship exists between temperature and stock returns (Howarth and Hoffman, 1984; Schneider et al., 1980). It has been suggested that the cause of this relationship may be that lower temperatures lead to aggressive behaviours, which some authors link to risk-taking (Howarth and Hoffman, 1984), while higher temperatures lead to apathy (risk aversion) (Wyndham, 1969). Such a causal mechanism is far from proven, however, since some studies have shown that *higher* temperatures lead to aggressive behaviours (Hsiang et al., 2013). It is also interesting that, given that air pressure induces positive mood (Keller et al., 2005), the relationship between air pressure and decision-making is relatively under-researched (rare exceptions being Schneider, 2013a and 2013b).

Environmental conditions can certainly affect mood and induce stress in individuals and such stressors can lead to increases in risk-taking (Porcelli and Delgado, 2009). One inescapable environmental factor is the current weather conditions. This is important since humans possess the ability to maintain thermal homeostasis via both biological mechanisms and behaviours. For example, we can maintain body temperature in cold conditions by regulating metabolism and by wearing more clothes and turning on office and home heating systems and spending less time outdoors. In warmer conditions we may wear fewer clothes, turn on air-conditioning systems and opt cold food. Therefore, we can act in ways that counteract the general weather conditions in a given period. Since we are able to adjust to weather conditions, it may be that sudden changes in weather may have a greater effect on mood and behaviour than the general weather conditions, since it may take time to adjust to these new environmental conditions. Indeed, a number of medical studies have explored the relationship between weather changes and various aspects of physiology and behaviour. For example, reductions in air pressure can lead to pain

(Funakubo et al., 2010) and headaches (Ray, 2013). Equally, increases in the amount of rainfall and temperature have been shown to lead to aggressive behaviours such as violence (Hsiang et al., 2013) and higher temperatures have even been linked to suicide (Helama, et al., 2013) and sudden death (Bierton et al., 2013). Therefore, we expect a risk-taking to be more strongly influenced by *changes* in weather than the general weather conditions. However, to our best knowledge, no study has examined the impact of weather *changes* on risk-taking.

In addition, many of the studies examining the impact of weather factors on decision-making in conventional financial markets suffer from a range of methodological problems: For example, some of the studies have used raw weather variables, which can be highly correlated, and it has been demonstrated that many of the effects are removed once account is taken of the seasonal component of stock returns (which may be unconnected to weather: e.g. Hong and Yu, 2009). Most previous studies have examined the impact of weather on stock market returns and have used weather at the location of the stock market (e.g. Saunders 1993; Hirshleifer and Sumway, 2003). These studies, therefore, fail to examine the weather at the location where the investor makes their decision and fail to examine the impact of the weather on the individual investor's risk-taking. In addition, most studies examine the impact of a single weather factor on stock returns and fail to examine the potentially combined effects of different weather factors in different seasons. As a result, there is a danger that important causal relationships are missed, since it has been demonstrated that the context often influences the manner in which stimuli impact an individual's decisions (e.g. Loewenstein at al., 2001; De Martino et al., 2006). For example, individuals may react differently to higher rainfall depending upon the temperature and wind speed and they may react to a greater degree of cloud differently in winter and summer. Importantly, the few studies which have explored the direct effect of weather on individual investors decisions have generally failed to find evidence of weather effects (e.g. Goetzmann and Zhu, 2005) and this may have resulted from a combination of the methodological reasons given above. The one study which did find direct effects of one weather variable (cloud) on individual investor behaviour did not examine the impact of cloud in the context of season or of other weather factors (Goetzmann et al., 2015).

Anderson and Brown (1984) have shown that gambling behaviour differs significantly between laboratory and naturalistic environments. In addition, Johnson and Bruce (2001) suggested that individuals can make outstanding subjective probability judgements in favourable environments. Consequently, in order to examine the impact of weather changes on the risk-taking, it is sensible to examine the behaviour of financial market traders, since their decisions really matter to them. The decisions are made in their ‘natural environment’ and familiarity with the conditions may aid effective decision making. In particular, the traders will be familiar with the environment in which they are making their decisions and they will receive regular feedback concerning the effectiveness of their decisions. These have been shown to be the circumstances most conducive to well calibrated decision making. Consequently, if we show that even under these conditions, where the decision makers are well motivated to make correct decisions and they have the environment to help them achieve this, that weather changes impact their risk taking, then this will provide convincing evidence that weather changes do indeed affect risk-taking behaviour. Importantly, we can be fairly certain that, unlike in laboratory-based enquiries, the effects we observe are not in influenced by the experimental design.

The main aim of the study is to investigate the true and direct impact of a range of weather *changes* on individuals’ financial risk-taking behaviours (rather than the indirect impact on stock returns), because we believe that weather changes can affect an individual’s physiology, mood or feelings, which, in turn, can influence their risk-taking.

To achieve our aims we examine the trading records of 4,368 individual traders from the UK spread-trading markets over an eight-year period and link this data to hourly weather data at their notified trading location. Spread trading involves speculating on the likely *direction* a particular index (e.g. FTSE100), currency, commodity or share price will move, the resulting profit/loss depending on the initial investment (per point) multiplied the number of points the asset price moves in/against the direction forecast. The UK spread-trading market is one of the fastest growing financial markets in the world. The number of traders in the UK alone expected to rise from 0.5 to 1 million traders by 2017 (Pryor, 2011). Even in 2006, Brady and Ramyar (2006) estimated that spread trading accounted for £120 billion in the UK (10 percent of all trading on the London Stock Exchange) and the fast rate of growth of this market suggests that this is now a considerable under-estimate. Spread traders usually make several trades in any given hour and this gives us the opportunity to examine to what extent weather changes in a given hour influence the degree of risk taken by an individual trader in that hour. We expect individual differences in the risk-taking responses to different weather changes and to cater for this we employ multi-level mixed models. This approach enables us to extract maximum information from the large sample of transactions (414,143 trades in this study). Importantly, the spread-trading data enables us to measure the level of risk-taking an individual trader in a variety of innovative ways, whereas the majority of the existing studies simply measure the level of risk-taking by whether individuals decide to trade. (e.g., Luke, 2004; Tabachnick and Fidell, 2001; Denissen et al., 2008).

Our results indicate that the current weather factors do influence an individual's risk-taking behaviour. However, we observe that weather *changes* have a greater effect and these effects are seasonal. In particular, changes in weather which are likely to induce greater discomfort such as an increase in rainfall and a decrease in air pressure in winter months and increases in temperature in the summer lead to greater risk-taking behaviour.

The reminder of the paper is organised as follows: In Section 3.2, we review the relative literature, including the effect of weather on mood and risk-taking and the impact of weather changes on physiology and psychology. This literature is employed to help develop our hypotheses. In Section 3.3, we discuss the data and methodology employed to test the hypotheses. The results are reported and discussed in Section 3.4. A conclusion is drawn in Section 3.5.

3.2 Literature

In this section, we briefly review the literature exploring the link between weather and mood and that between mood and risk-taking behaviour. We also discuss the literature examining the impact of weather changes on individuals' physiology and behaviour.

3.2.1 Weather and mood

It has been suggested that weather conditions, including sunshine/cloudiness, temperature, rainfall, air pressure, and wind, can influence an individual's mood. For example, the majority of studies suggest that individuals have a better mood on sunny days (e.g., Howarth and Hoffman, 1984; Denissen *et al*., 2008). Lack of sunshine can result in imbalances in cortisol and melatonin levels, leading to low energy levels (Howarth and Hoffman, 1984). In fact, lack of sunlight has been identified as the cause of Seasonal Affective Disorder (SAD), which can lead to depression (Rosenthal 1998). This may arise because changes in the hormone of sunshine, level of Vitamin D3 can change the serotonin levels in brain, which in turn, affect mood (Lansdowne and Provost, 1998). Hormones and neurotransmitters, which influence behaviour, are also affected by temperature (Parker and Tavassoli, 2000). In addition, it has been suggested that lower temperatures result in lower energy levels (as energy is required to maintain body temperature) and energy depletion leads to negative mood (Keller et al., 2005; Denissen, et al. 2008). In fact, cooler temperatures have also been shown to lead to aggressive behaviours (Howarth and Hoffman, 1984; Schneider et al., 1980). However, the relationship between temperature and mood is not straightforward, since it has been suggested that higher temperatures aggravate some medical conditions, which could result in negative mood for some individuals (e.g., cardiovascular disease: Bierton, Cashman and Langlois, 2013;

rheumatoid arthritis: Guedj and Weinberger, 1990). Delyukov and Didyk (1999) have demonstrated a relationship between air pressure and both mental activity and blood pressure and it has been found that higher air pressure is associated with good mood (Keller et al., 2005) whilst lower air pressure can cause headaches and negative moods (Radua, Pertusa and Cardoner, 2010; Ray 2013). Less research has been conducted on the impact of rainfall and wind on mood, but there is limited evidence that higher rainfall and greater wind speed decrease individuals' mood (Denissen et al., 2008).

In summary, the research linking weather conditions and mood suggests that, in general terms, good weather (sunshine, warmer temperatures, high air pressure etc.) is associated with good mood, and poor weather (e.g. cloudy conditions, low air pressure, stronger wind speed, rainfall) is associated with more negative mood.

3.2.2 Mood and risk-taking

The relationship between mood and risk-taking has been explored by some studies. Isen and her colleagues have undertaken a series of laboratory-based studies examining the impact of mood on risk-taking behaviour (Isen and Geva, 1987; Isen et al., 1998; Isen and Patrick, 1983). The general findings of these studies are that individuals, in gambling and lottery tasks, are more reluctant to take risks when they are in good mood. It has been suggested that this arises because individuals are keen to avoid outcomes which might destroy their good mood (Raghunathan and Pham, 1999). Conversely, individuals tend to be more risk seeking when they are in negative moods, particularly when facing fatigue (Hockey et al., 2000) and depression (Yuen and Lee, 2003). It is argued that this results from their belief that in these circumstances high-risk options can lead to outcomes that may change that mood (Raghunathan and Pham, 1999).

3.2.3 Weather and risk-taking

Laboratory studies

Given the established link between mood and risk-taking it is not surprising that a recent laboratory-based study examined the impact of weather on individuals' risk-taking. Bassi et al., (2013) conducted a series of experiments involving lottery pairs and weather impacts. Specifically, they defined weather conditions not only based on the real weather data, but also 'subjectively' judged weather. In particular, they asked participants a question 'How do you feel about the weather' and received the answers on a scale 1-7, where 1 means 'Terrible' and 7 means 'Awesome'. They found that good weather conditions (e.g. sunshine and subjectively judged good weather) were correlated with greater risk-taking and bad weather (e.g., cloudiness, rainfall and subjectively judged bad weather) appeared to lead to more risk averse behaviour. Bassi et al. (2013) argue that positive mood may increase individuals' confidence in their ability to evaluate their investments and to take risks (Kuhnen and Knutson, 2001). However, these results are not in line with the previous findings (in the laboratory) that positive mood induces risk averse behaviour (Isen and Geva, 1987; Isen et al., 1998; Isen and Patrick, 1983). This is clearly an area which requires further exploration.

Real-world studies

A number of studies have attempted to establish a link between weather and behaviour in financial markets. Saunders (1993), the first to examine the impact of weather on stock returns, found that more sunshine was correlated with increased returns on the New York stock market. A number of studies examining the link between various weather factors and stock returns followed, the general conclusion being that stock returns are higher in good weather conditions, such as more sunshine, higher air pressure, higher temperatures and lower wind speeds (e.g., Hirshleifer and Shumway 2003; Cao and Wei, 2005; Chang et al., 2006; Dowling and Lucey, 2008; Floros, 2008; Akhtari, 2011; Schneider, 2013a and 2013b). Based on the conclusions of Bassi et al. (2013), it might be argued that better weather results in investors being more confident to evaluate investments and take risks or to develop a more optimistic expectation of evaluating the fundamental prices, which, in turn, pushes stock prices higher. However, these studies do not directly examine the impact of weather on the risk-taking of individual investors and no direct link is established between greater risk-taking and higher stock prices. In addition, several studies have found no significant effect of weather factors on stock returns (Pardo and Valor, 2003; Loughran and Shultz, 2004; Floros, 2008).

A possible reason of the mixed findings in the studies discussed above is that they used different methodologies to examine the impact of weather. Specifically, some studies only examine one weather factor such as cloudiness (e.g., Saunders, 1993), while others control for the presence of other weather factors, such as rainfall (Hirshleifer and Shumway, 2003). In addition, some studies used deseasonalized weather factors (e.g., Hirshleifer and Shumway, 2003) while some employed raw weather variables (Cao and Wei, 2005). Perhaps most importantly, Jacobsen and Marquering (2008) observed that once the seasonality of stock returns (which can be affected by factors other than weather: Hong and Yu, 2009), is controlled, the effects of weather on stock prices is largely removed.

In summary, the results of studies examining the impact of weather on stock returns present a confusing picture, mainly due to the often inadequate methodologies employed.

In any case, these studies do not directly address our key concern, which is the effect of weather on individual risk-taking behaviour.

A limited number of studies have explored the impact of weather on individuals' trading activities, although none of these directly examines the effect on their risk-taking. Goetzmann and Zhu (2005) found deseasonalized weather factors significantly influenced individuals' propensity to buy or sell stocks. Other studies have found that more cloud cover can induce different groups of investors to either sell or buy stocks (e.g., buy- institutional investors: Goetzmann et al., 2015; sell- male, young and low-income level individuals: Levy and Galili, 2008) and to buy on calm days (floor traders: Limpaphayom et al., 2005). Moreover, some studies have found, via survey methods, that higher than normal air pressure has a positive impact on long-term private investors, but not on institutional investors (Schneider, 2013b). Once again these studies of individual investors present a confusing picture and fail to directly address to what extent individual's risk-taking is affected by weather.

3.2.4 Impact of Weather changes on physiology and behaviour

All the studies discussed above examine the effect of current weather on mood and/or aspects of risk-taking but none of them address the extent to which these are affected by weather *changes.* This is puzzling, because there is a considerable literature which indicates that weather changes impact individuals' physiology and behaviour. For example, Jamison et al., (1995) investigated the impact of weather changes on pain among 557 chronic pain patients in the US and found their pain was affected because of the weather changes. Moreover, Guedj and Weinberger (1990) found that weather changes can affect rheumatic symptoms from rheumatoid arthritis (RA), osteoarthritis (OA) and fibromyalgia. They found that pain increased: in RA when air pressure and temperature changes to high, in OA when air pressure, temperature and rainfall change to high, and in fibromyalgia when air pressure changes to high. However, a recent study from Japan (Funakubo et al., 2010) has found that falling air pressure could increase the pain-related behaviours. Changes in air pressure have been also linked with headaches. In particular, Ray (2013) indicated that air pressure changes can rapidly cause pain, as the middle ear equalizes the pressure with the surrounding atmosphere. Moreover, Sato et al. (2001) discovered that lowering barometric pressure could also cause pain in people who is suffering from arthritis. Additionally, increases in temperature can also lead to sudden death. According to the study by Bierton et al. (2013) using data between 2008 and 2009, increases in temperatures are associated with deaths from ischemic pulmonary thromboembolus, heart disease and cardiovascular disease. Moreover, weather changes have been shown to influence some extreme human behaviours, such as suicide, violence and warfare. Helama et al. (2013) examined the period from 1751 to 2008 in Finland, and revealed that in this country, which has the highest suicide rate in Europe, that suicide rate positively correlated with temperature changes. In fact, some studies found the similar result of a positive relationship between weather becoming warmer and suicide rate (Deisenhammer, 2003; Preti and Miotto, 2000). However, some studies have found the opposite relationship (Linkowski et al., 1992; Tietjen and Kripke, 1994). Hsiang et al. (2013) reviewed about 60 previous studies in the world and suggested that increases in rainfall and temperature could lead to more drastic personal and interpersonal behaviour such as human conflict, ranging from violence to political instability and battles. In summary, weather changes could influence individuals' physiology and behaviours. In particular, changes to 'worse' weather conditions, such as higher rainfall and lower air pressure, could increase bad physiological responses (e.g., increased pain) and can lead to extreme behaviour such as suicide and violence.

In summary, previous literature has established a clear link between weather and mood, the general conclusion being that good weather is correlated with more positive mood. The laboratory evidence linking mood and risk-taking suggests that individuals tend to take fewer/more risks when they are in positive/negative moods. The literature directly addressing the link between weather and risk-taking is a limited to one laboratory study which suggests that individuals take more risks in good weather conditions (Bassi et al., 2013). However, these findings are at odds with the previous literature which links good weather to positive mood and positive mood to reduced risk-taking. Financial market studies which indirectly address the impact of weather on risk-taking do so by and large by examining aggregate behaviour measured by stock returns. These studies paint a confused picture, probably as a result of a range of, often inadequate, methodologies having been adopted. If any conclusion can be drawn from these studies it is that good weather is more associated with increased stock returns. This may result from more optimistic assessment of returns/future prices, leading to more inclination to take risks (invest) on the part of traders. A few studies examine the impact of weather on the buying/selling activity of individual investors, and these suggest that some groups (excluding institutional investors) have a greater tendency to buy stocks in good weather conditions (higher air pressure, less cloud, less wind speed). One might surmise that the increased inclination to buy stocks might signal a greater intention to take risks. However, it may simply be that risks in these situations are considered smaller because the individual's expectation of future price increases is greater. Consequently, none of these studies directly address the degree to which weather affects the risk-taking activities of these individual traders. In addition, despite the clear evidence which demonstrates the impact of weather changes on physiology and mood. No previous paper has examined the impact of weather *changes* on risk-taking.

We attempt to fill the important gaps in the literature by exploring, in a real-world setting where the decisions of the individuals have real monetary implications to them, the extent to which *weather changes* impact the risk-taking behaviour of individuals. We suspect that weather changes will impact the risk-taking of individuals and we, thus, test the following hypothesis:

H_0: The degree of risk-taking undertaken by individuals is influenced by changes in a range of weather factors.

3.3 Data and methodology

3.3.1 Data

The majority of studies examining the link between mood and risk-taking and weather and risk-taking in the laboratory have employed gambling or lottery tasks (Isen et al., 1988). The vast majority of real-world studies examining the impact of weather on behaviour have focused on the impact of weather on stock returns (e.g. Saunders, 1993); Hirshleifer and Shumway, 2003; Cao and Wei, 2005). In an effort to make our findings compatible with these studies we elicit the behaviour of *individual* investors in a real-world market where their decisions are more akin to the gambling tasks employed in laboratory studies. In particular, we employed details of 414,143 individual trading records of 4,368 investors in the UK spread-trading market.

Spread trading is effectively betting on the movement of a particular asset (such as share index, a commodity, a currency or an individual share). When opening a position, investors can either buy (take a long position) or sell (take a short position) depending on whether they expect the market to rise or fall, respectively. The profit/loss they make equals their stake multiplied by the number of points the market rises/falls if they buy the market and by the number of points the market falls/rises if they sell the market. For example, an investor who opens a long position with a stake size of £10 per point in the FTSE100, which is currently trading at 7000, will secure an unrealized profit of £500 if the market rises to 7050 points and will have accumulated an unrealized loss of £500 if the market falls to 6050 points.

Spread trading is a very fast growing market, currently with well over 0.5 million traders in the UK alone, and expected to reach one million by 2017 (Pryor, 2011). These markets are important in their own right since the amount traded in the UK alone was estimated to be over £120 billion pa in 2006 (Brady and Ramyar, 2006) and the fast pace of growth of this market suggests that this is a considerable under-estimate of current trading activity. Importantly, for our study, spread trading has opened up speculation in financial markets to a very wide cross section of the public, as there are no barriers to entry. Consequently, examining the transactions of traders in these markets allows us a window on the impact of weather and weather changes on the risk-taking behaviour of a wide cross-section of the public. In addition, individuals generally trade frequently in these markets (an average of 2.5 transactions per person per hour). This allows us to examine the impact of risk-taking behaviour over short time intervals, which has the advantage that one can more readily isolate the influences on that behaviour. Having secured the co-operation of a large spread trading company in the UK we also have the advantage of being able to examine the transactions of a large number of individual traders (4,368) over a long time horizon (2005 to 2012).

To analyse the risk-taking behaviour of traders in the face of different weather factors and weather changes we obtained hourly weather data from the British Atmospheric Data Centre for 554 different UK locations for the period between 2005 and 2012. We then matched the transactions of a given individual in a given hour, via the postcode they notified as their normal trading location, with the weather observations for that hour and the preceding hour at the weather station.

It has been shown that traders may close positions for a range of motives unconnected to their propensity to take risk. For example, they may close for liquidity reasons (e.g., when they use automatic stop-losses orders) and it has been shown that traders often realize their gains more readily than their losses (Odean, 1998) - leading to the so called disposition effect (Kahneman and Tversky, 1979; Shefrin and Statman, 1985). Consequently, in order to develop a clearer view of the relationship between weather factors and risk-taking we restrict our analysis to transactions used to open positions, which are less likely to be affected by these non-risk behaviour factors.

A further advantage of our data is that profits from spread trading in the UK are tax-free. Consequently, unlike in more traditional markets, where investors may engage in transactions simply to minimize tax liabilities, we can be fairly certain that the traders are more likely to be motivated to maximize their returns in all trades.

3.3.2 Variables

3.3.2.1 Outcome variables

There are a number of reasons why some individuals may take more risks, including their risk attitude and their degree of wealth. However, we are interested in the extent to which changes in weather factors influence the degree of risk taken by these individuals relative to the normal levels to which they expose themselves. Our data allows us to calculate a number of variables to assess the relative degree of trading risk to which individuals expose themselves in a given hour.

The majority of the existing studies in financial markets measure risk-taking simply in terms of whether individuals decide to trade. However, our unique data enables us to measure the degree of their risk-taking using a variety of innovative measures. For example, the more positions an individual opens then, ceteris paribus, the greater the risk they are exposing themselves to in terms of the vagaries of the market. Consequently, we determine the 'absolute number of trades' (ANT_{it}) as the number of positions opened by client i in hour t (N_{it}). We also measure the 'relative number of trades' (RNT_{it}) as the number of positions opened by client i in hour t (N_{it}) relative to the mean number of positions they initiate per hour over their full trading history ($\overline{N}i$) as follows:

$$RNT_{it} = N_{it}/\overline{N}_i \tag{3.1}$$

Clearly, the greater the stakes committed in a given hour, irrespective of the number of transactions, then, ceteris paribus, the greater will be the profits or losses associated with those transactions. Consequently, we determine the 'absolute stake size' (ASS_{it}) of trader i in hour t in terms of the level of stakes they commit to their decisions in that hour (S_{it}); we also measure the 'relative stake size' (RSS_{it}) of trader i in hour t in terms of the level of stakes they commit to their decisions in that hour (S_{it}) compared to their mean stake size per hour over their trading history ($\bar{S}_i$), as follows:

$$RSS_{it} = S_{it}/\bar{S}_i \tag{3.2}$$

It is likely that trading data follows a trend and, thus, the dependent variables we construct are likely to suffer from autocorrelation. We checked for this possibility, by performing KPSS unit-root tests (Kwiatkowski et al., 1992) for each of the dependent variables. The results suggested that all the dependent variables did suffer from autocorrelation. The normal way to avoid this is to take the first difference of the dependent variable and use this as the revised dependent variable. Consequently, we took the first difference and re-tested for autocorrelation using the KPSS unit root test. The transformed dependent variables then showed no sign of autocorrelation (4,142, 4,143, 4,205, 4,204 clients from 4,368 are stationary for the dependent variables ΔANT_{it}, ΔRNT_{it}, ΔASS_{it}, ΔRSS_{it}, respectively). Consequently, throughout our analysis we employed four dependent variables, the change in their absolute and relative number of transactions and the change in their absolute and relative stake per transaction, for each trader i in hour t, defined as follows:

$$\Delta ANT_{it} = ANT_{it} - ANT_{it\text{-}1} \quad (3.3)$$

$$\Delta RNT_{it} = RNT_{it} - RNT_{it\text{-}1} \quad (3.4)$$

$$\Delta ASS_{it} = ASS_{it} - ASS_{it\text{-}1} \quad (3.5)$$

$$\Delta RSS_{it} = RSS_{it} - RSS_{it\text{-}1} \quad (3.6)$$

3.3.2.2 Weather variables

Some previous studies examining the impact of weather on behaviour in financial markets have examined the impact of a single weather factor such as degree of cloudiness (Loughran and Schultz, 2004). However, we are concerned that this may lead to false conclusions regarding the influence of weather factors on risk-taking behaviour as the context in which a particular weather factor is experienced is likely to impact the individual's mood (e.g., Kahneman and Tversky, 1979; Loewenstein, at al., 2001; De Martino, et al., 2006). For example, the effect of a decrease in temperature on mood on a sunny day may be different to that on a rainy day. Consequently, rather than simply examining the effect of changes in one weather variable we include in our model variables to capture recent changes in the degree of temperature, air pressure, rainfall, wind speed, and cloudiness, simultaneously.

Weather can change fairly frequently in the UK. However, it does not significantly change during every single hour. Therefore, we report results related to weather changes from two hours prior to the hour in which a transaction takes place. The change in temperature, air pressure, rainfall, wind speed and cloudiness associated with hour t ($\Delta temp_t$, $\Delta press_t$, $\Delta rain_t$, $\Delta wind_t$ and $\Delta cloud_t$) when a transaction is conducted by trader i are, therefore, determined as follows:

$$\Delta Weather_{it} = Weather_{it} - Weather_{i(t-2)} \quad (3.7)$$

It has been found, as discussed previously, that there are seasonal patterns in the behaviour of investors in financial markets, which may not be related to weather (Hong and Yu, 2009). Failing to account for these seasonal patterns could lead to false correlations and conclusions regarding the impact of weather on individuals' risk-taking behaviour. Consequently, to avoid this possibility we also include a Halloween dummy (*Halloween*), which takes a value of 1 in summer months (May to October) and 0 otherwise (Yuksel and Yuksel, 2009).

3.3.2.3 Control variables

Weather variables

As discussed above, there is some evidence from both the laboratory and real-world environments that risk-taking may be affected by current weather conditions (Bassi et al., 2013). When assessing the extent to which weather *changes* impact risk-taking it is, therefore, important to control for current weather conditions. However, it is likely that there will be severe multicollinearity between raw weather variables. For example, rainfall is usually strongly correlated with cloud cover and higher air pressure is generally associated with low cloud conditions (Ahrens et al., 2012). Consequently, rather than examining the weather variables in the current hour (i.e. $Weather_{it}$), we use the deseasonalized weather variables (e.g. Goetzmann and Zhu, 2005) in the current hour. These deseasonalized variables for temperature, air pressure, rainfall, wind speed and cloudiness in hour *t* ($Dtemp_t$, $Dpress_t$, $Drain_t$, $Dwind_t$ and $Dcloud_t$) are determined by subtracting from the raw weather variable the mean of that weather variable in that month.

We are also concerned that individuals may react to weather changes differently in winter and summer since it has been shown that the context often influences the manner in which stimuli impact an individual's decisions (e.g., Loewenstein, at al., 2001; De Martino, et al., 2006). For example, individuals may react differently in the winter and summer to rises in temperatures. We, therefore, include interactions between the Halloween dummy and the deseasonalized weather variables (*Halloween x Dcloud, Halloween x Drain, Halloween x Dtemp, Halloween x Dpres, Halloween x Dwind*) and between the Halloween dummy and the changes in deseasonalized weather variables *(Halloween x* Δ*cloud, Halloween x* Δ*rain, Halloween x* Δ*temp, Halloween x* Δ*pres, Halloween x* Δwind).

Trading Hours

The majority of trading occurs during the hours of 8am and 5pm on weekdays when the markets are open. A small number of transactions occur outside these times and we were concerned that these might have some special features. For example, one might trade outside the normal trading hours if one has suffered big losses during the day. Consequently, to avoid as far as possible increases in risk-taking arising from factors other than changes of weather factors, we control for the time that a transaction is conducted. We achieve this by incorporating a dummy variable, *Hours*, which takes the value 1 when transactions occur between 8am and 5pm on weekdays, and 0 otherwise.

The Monday and January effects

We also control for the fact that financial market traders appear to behave differently on Mondays and in January, because market prices are generally found to be lower on Mondays and higher in January (Pardo and Valor, 2003; Cao and Wei, 2005). To achieve this, we include two more dummy variables in our study: *January* and *Monday* which take the value 1 if a transaction occurs in January or on Monday, respectively, and 0 otherwise.

Seasonal affective disorder

It has been found that SAD, which is caused by a lack of sunlight, can affect an individual's mood (e.g., Kamstra, Kramer and Levi, 2003). To ensure that the effects of weather and weather changes we observe are not connected with SAD, we control for this condition by including in the model a *SAD* variable calculated in the manner recommended by Kamstra, Kramer and Levi (2003), as follows:

$$SAD = \begin{cases} H_t - 12 \; for\ trading\ from\ autumn\ equinox\ to\ spring\ equinox \\ 0 \quad otherwise \end{cases} \qquad (3.8)$$

where H_t as the number of hours between sunset and sunrise. This is determined by the latitude of a trading location and the sun's declination angle (i.e. λ_t):

$$\lambda_t = 0.1402 * \sin[\left(\frac{2\pi}{365}\right)(julian_t - 80.25)] \qquad (3.9)$$

where $julian_t$ is the order of the day in a year, from 1 to 365 (e.g., $julian_t$ equals 1 on 1st January). Finally, we calculate H_t as follows:

$$H_t = 24 - 7.72 * arcos[-tan\left(\frac{2\pi\delta}{360}\right)tan(\lambda_t)] \text{ in Northern Hemisphere} \qquad (3.10)$$

where δ is the latitude of a particular location.

A full list and outline description of each of the variables incorporated in our models is provided in Table 3.1.

Table 3.1 List of explanatory and control variables employed in this study

Variable Type	Variable Name	Description	Raw Variable Units/Coding
Weather	*Dcloud*	Deseasonalized Cloud Cover	Oktas scale 0 = No cloud cover to 4 = Half cloud cover 8 = Total cloud cover 9 = Sky obscured from view
Weather	*Drain*	Deseasonalized Rainfall	Millimeters (mm)
Weather	*Dtemp*	Deseasonalized Air Temperature	Degrees Centigrade (℃)
Weather	*Dpres*	Deseasonalized Air Pressure	Atmospheric Pressure (hPA)
Weather	*Dwind*	Deseasonalized Wind Speed	Knots
Weather	$\Delta cloud$	Changes in Cloudiness	Current cloudiness minus cloudiness value two hours ago
Weather	$\Delta rain$	Changes in Rainfall	Current rainfall minus rainfall value two hours ago
Weather	$\Delta temp$	Changes in Temperature	Current temperature minus temperature value two hours ago
Weather	$\Delta pres$	Changes in Air Pressure	Current air pressure minus air pressure value two hours ago
Weather	$\Delta wind$	Changes in Wind Speed	Current wind speed minus wind speed value two hours ago
Control Covariate	*Hours*	Trading Hours Dummy Variable	1 = 8am to 5pm 0 = 6pm to 7am
Control Covariate	*Halloween*	Halloween Dummy Dummy Variable	1 = May to October 0 = November to April
Control Covariate	*Monday*	Monday Effect Dummy Variable	1 = Monday 0 = Any other day
Control Covariate	*January*	January Effect Dummy Variable	1 = January 0 = Any other month
Control Covariate	*SAD*	SAD Effect Continuous Variable	1 = Autumn and Winter 0 = Spring and Summer
Interaction	$Halloween \times Dcloud$	Halloween and Deseasonalized cloudiness interaction	
Interaction	$Halloween \times Drain$	Halloween and Deseasonalized rainfall interaction	
Interaction	$Halloween \times Dtemp$	Halloween and Deseasonalized temperature interaction	
Interaction	$Halloween \times Dpres$	Halloween and Deseasonalized air pressure interaction	
Interaction	$Halloween \times Dwind$	Halloween and Deseasonalized wind speed interaction	
Interaction	$Halloween \times \Delta cloud$	Halloween and cloudiness changes interaction	

Interaction	$Halloween \times \Delta rain$	Halloween and rainfall changes interaction
Interaction	$Halloween \times \Delta temp$	Halloween and temperature changes interaction
Interaction	$Halloween \times \Delta pres$	Halloween and air pressure changes interaction
Interaction	$Halloween \times \Delta wind$	Halloween and wind speed changes interaction

3.3.3 Models – Multi-level mixed model

Previous studies that have examined the relationship between weather and stock returns, trading sentiment or trading volume have employed simple linear regression (e.g., Limpaphayom et al., 2005; Goetzmann and Zhu, 2005) or logistic models (Hirshleifer and Shumway, 2003; Levy and Galili, 2008) but these models do not account for differences in the behaviour of individual traders. By contrast, we capture the full richness of our data by accounting for individual differences in their reaction to weather and changes in weather by employing multi-level mixed models (Tabachnick and Fidell, 2001; Luck, 2004). We are, thus, able to examine the effect of weather and changes in weather on risk-taking whilst controlling for potential individual differences (Denissen *et al*., 2008). Consequently, the multi-level mixed model we estimate in order to examine the impact of weather and weather changes on the change in the absolute number of transactions in which an individual engages from one hour to the next is as follows:

$$\begin{aligned}\Delta ANT_{it} = \ & \alpha_{it} + \beta_1 Dcloud_{it} + \beta_2 DRain_{it} + \beta_3 DTemp_{it} + \beta_4 DPres_{it} + \beta_5 DWind_{it} + \\ & \beta_6 \Delta Cloud_{it} + \beta_7 \Delta Rain_{it} + \beta_8 \Delta Temp_{it} + \beta_9 \Delta Pres_{it} + \beta_{10} \Delta Wind_{it} + \beta_{11} Halloween + \\ & \beta_{12} Halloween \times DCloud_{it} + \beta_{13} Halloween \times DRain_{it} + \beta_{14} Halloween \times DTemp_{it} + \\ & \beta_{15} Halloween \times DPres_{it} + \beta_{16} Halloween \times DWind_{it} + \beta_{17} Halloween \times \Delta Cloud_{it} + \\ & \beta_{18} Halloween \times \Delta Rain_{it} + \beta_{19} Halloween \times \Delta Temp_{it} + \beta_{20} Halloween \times \Delta Pres_{it} + \\ & \beta_{21} Halloween \times \Delta Wind_{it} + \beta_{22} Hour_{it} + \beta_{23} January_{it} + \beta_{24} Monday_{it} + \beta_{25} SAD_{it} + \\ & + \gamma_0 ClientID_i + \varepsilon_{it} \end{aligned} \quad (3.11)$$

Where: β_i are the coefficients of fixed factors (i.e. weather and controlling variables), γ is the random coefficient on the *ClientID* random regressor, *i* is the trader, *t* refers to all the transactions made in the hour *t* made by trader *i*, and $ClientID_i$ is the unique identification number for trader *i*.

The models that were estimated to assess the effect of weather changes on changes in the relative number of transactions and in the absolute and relative stake size for trader *i* in hour t are of the same form as eq. 3.11, with ΔRNT_{it}, ΔASS_{it} and ΔRSS_{it} as dependent variables, respectively.

3.4 Results and discussions

3.4.1 Impact of weather changes on the absolute and relative number of trading transactions

The results of estimating the model to assess the impact of weather changes on the absolute and relative number of trading transactions undertaken by an individual in a given hour are presented in Table 3.2 and 3.3, respectively[4]. Strikingly, we find the current weather conditions of less deseasonalized rainfall in winter induced both absolute and relative risk taking in winter conditions. In addition, higher deseasonalized cloud cover and wind leads to relatively greater risk being taken. Furthermore, we find some current weather conditions significantly influence risk-taking in summer (e.g., greater cloudiness induces higher relative risk taking). After controlling for *SAD*, *Hours*, and the *January*, *Monday* and *Halloween* dummies and the current weather variables, we find that increasing temperatures and falling air pressure can both increase the absolute and relative number of trading transactions in winter months. Temperature increases also lead to a significant increase in the absolute and relative number of trading transactions in the summer (coefficients: 0.0311-0.0019 = 0.0292, *t*-value: 7.603; 0.0117-0.0008 = 0.0109, *t*-value: 7.887, respectively). In addition, increases in rainfall lead to an increase in the absolute and relative number of trading transactions in the winter and summer, respectively (coefficients: 0.0191, *t*-value: 1.997; coefficient: 0.0056+0.00001 = 0.0056, *t*-value: 1.827, respectively). The finding of risk-taking increasing when rainfall and temperature increases is consistent with Hsiang et al's (2013) finding that increases in rainfall and temperature may lead to aggressive behaviours. In addition, our results showing that falling air pressure in winter is associated with increases in risk taking (measured by the absolute and relative number of trading transactions). These findings are in line with the literature which shows that that good mood (induced by good weather) leads to lower risk-taking activities (e.g. Isen and Geva, 1987; Isen et al., 1988; Isen and Patrick, 1983). These results, in summary, provide support for our hypothesis, namely that weather changes influence individuals' risk-taking.

[4] We also estimate the ANT_{it} and models RNT_{it}, but employed the weather changes from one-hour prior (instead of two hours) to the current hour. This resulted in the same weather changes variables being significant, except the changes in rainfall in ANT_{it} *model*.

Table 3.2 Estimated coefficients, standard errors and *t*-value for the independent variables in the model to assess the impact of weather and weather changes on the absolute numbers of transactions of trader *i* in hour *t* (ANT_{it}), estimated on the basis of the transactions of 4,368 individual traders

Variable	Coefficient	Std. Error	*t*-value	
Intercept	0.0443	0.0142	3.112	***
Dcloud	0.0039	0.0022	1.791	
Drain	-0.0491	0.0115	-4.271	***
Dtemp	-0.0027	0.0017	-1.589	
Dpres	-0.0006	0.0005	-1.222	
Dwind	0.0022	0.0013	1.721	
$\Delta cloud$	0.0015	0.0028	0.540	
$\Delta rain$	0.0191	0.0096	1.997	**
$\Delta temp$	0.0311	0.0043	7.267	***
$\Delta pres$	-0.0179	0.0046	-3.867	***
$\Delta wind$	0.0038	0.0022	1.750	
Halloween	0.0003	0.0108	0.030	
Halloween×Dcloud	0.0004	0.0032	0.126	
Halloween×Drain	0.0051	0.0153	0.336	
Halloween×Dtemp	-0.0021	0.0025	-0.849	
Halloween×Dpres	-0.0002	0.0009	-0.217	
Halloween×Dwind	0.0006	0.0019	0.303	
$Halloween \times \Delta cloud$	-0.0008	0.0041	-0.196	
$Halloween \times \Delta rain$	-0.0069	0.0128	-0.541	
$Halloween \times \Delta temp$	-0.0019	0.0055	-0.349	
$Halloween \times \Delta pres$	0.0078	0.0079	0.989	
$Halloween \times \Delta wind$	0.0005	0.0032	0.160	
SAD	0.0052	0.0033	1.578	
Hours	-0.1307	0.0128	-10.248	***
January	-0.0076	0.0159	-0.478	
Monday	-0.0049	0.0101	-0.485	
Adjusted R^2	0.0300			
Effect Size (Cohen's f^2)	0.0310			

** significant at 0.05

*** significant at 0.01

Table 3.3 Estimated coefficients, standard errors and *t*-value for the independent variables in the model to assess the impact of weather and weather changes on the relative numbers of transactions of trader *i* in hour *t* (RNT_{it}), estimated on the basis of the transactions of 4,368 individual traders

Variable	Coefficient	Std. Error	*t*-value	
Intercept	0.0191	0.0051	3.718	***
Dcloud	0.0019	0.0008	2.352	**
Drain	-0.0176	0.0041	-4.260	***
Dtemp	-0.0011	0.0006	-1.851	
Dpres	-0.0001	0.0002	-0.914	
Dwind	0.0011	0.0005	2.499	**
$\Delta cloud$	0.0003	0.0010	0.290	
$\Delta rain$	0.0056	0.0034	1.613	
$\Delta temp$	0.0117	0.0015	7.609	***
$\Delta pres$	-0.0074	0.0017	-4.445	***
$\Delta wind$	0.0012	0.0008	1.582	
Halloween	-0.0008	0.0039	-0.195	
Halloween×Dcloud	0.0002	0.0012	0.159	
Halloween×Drain	-0.0002	0.0055	-0.040	
Halloween×Dtemp	-0.0003	0.0009	-0.282	
Halloween×Dpres	-0.0001	0.0003	-0.349	
Halloween×Dwind	-0.0001	0.0007	-0.089	
$Halloween \times \Delta cloud$	-0.0003	0.0015	-0.179	
$Halloween \times \Delta rain$	0.0000	0.0046	0.008	
$Halloween \times \Delta temp$	-0.0008	0.0020	-0.415	
$Halloween \times \Delta pres$	0.0045	0.0028	1.569	
$Halloween \times \Delta wind$	0.0001	0.0012	0.049	
SAD	0.0013	0.0012	1.091	
Hours	-0.0557	0.0046	-12.110	***
January	-0.0004	0.0057	-0.078	
Monday	-0.0008	0.0037	-0.228	
Adjusted R^2	0.0300			
Effect Size (Cohen's f^2)	0.0310			

** significant at 0.05
*** significant at 0.01

3.4.2 Impact of weather changes on absolute and relative investment sizes

The results of estimating the factors that influence the absolute and relative investment sizes chosen by traders are shown in Table 3.4 and 3.5[5], respectively. For the current deseasonalized weather conditions, the only factor can significantly influence the risk taking is the rainfall. In particular, less deseasonalized precipitation could induce risk-taking activities of relative staking size. We cannot find any significant current weather factors influence absolute risk-taking size in summer. After controlling for SAD, seasonal interaction terms and current deseasonalized weather conditions, we find that increase in temperature are associated with increases in an individual's absolute and relative risk-taking, measured by absolute and relative investment sizes, in both winter and summer (Absolute risk coefficients: winter: 0.2102, *t*-value 3.652; summer; 0.2102-0.0254 =

[5] We also estimate the ASS_{it} and models RSS_{it}, but employed the weather changes from one-hour prior (instead of two hours) to the current hour. This resulted in the same weather changes variables being significant.

0.1848, *t*-value: 3.582; Relative risk coefficients: winter: 0.0367, *t*-value 4.705; summer: 0.0367-0.0050 = 0.0317, *t*-value: 4.537) months. Moreover, we find that falling air pressure increases the size of individuals' absolute and relative investments (coefficients: -0.1628, *t*-value: -2.610 and -0.0178, *t*-value: -2.108, respectively) in winter. Overall, these findings are consistent with previous literature that increases in temperature lead to aggressive behaviours (Hsiang et al., 2013) and that weather changes that can induce discomfort (i.e. falling air pressure in winter) reduces individuals' mood (Ray, 2013), which, in turn, increases their risk-taking (Isen and Geva, 1987; Isen et al., 1988; Isen and Patrick, 1983). These results, therefore, demonstrate some more supports for the hypothesis, that weather changes influence investors' risk-taking behaviour.

Table 3.4 Estimated coefficients, standard errors and *t*-value for the independent variables in the model to assess the impact of weather and weather changes on the absolute stake size of trader *i* in hour *t* (ASS_{it}), estimated on the basis of the transactions of 4,368 individual traders

Variable	Coefficient	Std. Error	*t*-value	
Intercept	0.1379	0.1917	0.719	
Dcloud	-0.0097	0.0295	-0.327	
Drain	-0.2514	0.1548	-1.624	
Dtemp	-0.0245	0.0228	-1.074	
Dpres	0.0001	0.0061	0.024	
Dwind	0.0303	0.0171	1.765	
Δ*cloud*	-0.0004	0.0383	-0.011	
Δ*rain*	0.1818	0.1288	1.412	
Δ*temp*	0.2102	0.0576	3.652	***
Δ*pres*	-0.1628	0.0624	-2.610	**
Δ*wind*	-0.0456	0.0292	-1.561	
Halloween	-0.0173	0.1460	-0.119	
Halloween×Dcloud	0.0572	0.0435	1.315	
Halloween×Drain	0.1214	0.2061	0.589	
Halloween×Dtemp	0.0275	0.0338	0.813	
Halloween×Dpres	-0.0077	0.0118	-0.658	
Halloween×Dwind	-0.0239	0.0259	-0.923	
Halloween× Δ*cloud*	0.0317	0.0548	0.577	
Halloween× Δ*rain*	-0.0393	0.1723	-0.228	
Halloween× Δ*temp*	-0.0254	0.0747	-0.340	
Halloween× Δ*pres*	0.0741	0.1065	0.695	
Halloween× Δ*wind*	0.0670	0.0432	1.552	
SAD	0.0259	0.0440	0.589	
Hours	-0.3862	0.1716	-2.251	**
January	-0.3020	0.2145	-1.408	
Monday	0.0004	0.1366	0.003	
Adjusted R^2	0.0400			
Effect Size (Cohen's f^2)	0.0420			

** significant at 0.05
*** significant at 0.01

Table 3.5 Estimated coefficients, standard errors and *t*-value for the independent variables in the model to assess the impact of weather and weather changes on the relative stake size of trader *i* in hour *t* (RSS_{it}), estimated on the basis of the transactions of 4,368 individual traders

Variable	Coefficient	Std. Error	*t*-value	
Intercept	0.0513	0.0260	1.976	**
Dcloud	0.0015	0.0040	0.386	
Drain	-0.0428	0.0210	-2.038	**
Dtemp	-0.0041	0.0031	-1.314	
Dpres	-0.0002	0.0008	-0.292	
Dwind	0.0035	0.0023	1.499	
$\Delta cloud$	0.0013	0.0052	0.251	
$\Delta rain$	0.0151	0.0175	0.865	
$\Delta temp$	0.0367	0.0078	4.705	***
$\Delta pres$	-0.0178	0.0085	-2.108	**
$\Delta wind$	0.0013	0.0040	0.317	
Halloween	0.0176	0.0198	0.889	
Halloween×Dcloud	0.0073	0.0059	1.232	
Halloween×Drain	-0.0001	0.0279	-0.005	
Halloween×Dtemp	0.0001	0.0046	0.007	
Halloween×Dpres	-0.0014	0.0016	-0.854	
Halloween×Dwind	-0.0027	0.0035	-0.760	
Halloween× $\Delta cloud$	-0.0050	0.0074	-0.676	
Halloween× $\Delta rain$	-0.0082	0.0234	-0.352	
Halloween× $\Delta temp$	-0.0050	0.0101	-0.492	
Halloween× $\Delta pres$	0.0140	0.0144	0.967	
Halloween× $\Delta wind$	0.0070	0.0059	1.192	
SAD	0.0095	0.0060	1.588	
Hours	-0.1249	0.0233	-5.368	***
January	-0.0256	0.0291	-0.880	
Monday	0.0014	0.0040	0.317	
Adjusted R^2	0.1400			
Effect Size (Cohen's f^2)	0.1630			

** significant at 0.05
*** significant at 0.01

3.4.3 Discussion

The results provide evidence to support our hypothesis that weather changes influence individuals' risk-taking activities. This is an important finding, so no previous study has examined the impact of weather *changes* on risk taking. This is surprising, since humans possess the ability to maintain thermal homeostasis via both biological mechanisms and it seems likely that these, via changes in mood, are likely to influence behaviour.

Previous studies that have explored the impact of weather on behaviour using either raw weather data or deseasonalized weather data, leave some methodological issues unaddressed. Specifically, incorporating a range of raw weather variables in the same regression model is likely to cause multicollinearity, since weather factors are normally highly correlated with each other (Ahrens et al., 2012). We overcome this problem by using deseasonalized weather variables and, as a result, we are able to show that both the current weather conditions and weather changes impact individuals' risk-taking behaviour.

Importantly, when we examine the hypothesis, we control for deseasonalized current weather conditions, as most previous studies have explored the relationship between deseasonalized current weather and trading behaviour (e.g. Goetzmann and Zhu, 2005). In addition, as we believe that the same weather changes may have a different impact in different seasons (e.g., temperature increases could bring greater personal comfort in winter, but less personal comfort in summer), we control for seasonal interactions using the variables *Halloween*$\times$ Δ*weather*. We also control for SAD to ensure that our results are not subsumed by this phenomenon. Having controlled for all these variables we find some significant impacts of weather changes individuals' risk-taking activities.

We measure an individual's risk-taking in both absolute and relative terms, via the number of transactions and the size of investments in a given time period. In particular, the absolute levels of risk-taking are computed from the number of transactions and the size of investments placed by a trader. These are traditional methods for calculating risk-taking. However, we also employ relative levels of a trader's risk-taking by measuring the degree of risk they are taking at a particular time relative to the risk they have taken in the past. This we believe is an innovative measurement which captures a key feature of risk taking behaviour. For example, an absolute number of 10 transactions in a given hour might be regarded as high risk-taking compared to traders who on average only have 5 trades per hour. However, for a trader who averages 20 transactions per hour this would represent relatively low levels of risk taking if the average is 30 trades per hour. Consequently, we believe that our measures of risk taking enable us to capture the true impact of weather changes on the risks taken by traders.

Our results suggest that increasing temperatures (in winter and summer) and falling air pressure (in winter) can induce traders to take greater risks, using both absolute and relative risk, compared to their normal risk taking[6]. This effect was still observed after we control for current deseasonalized weather factors. This, we believe, makes our model and the findings concerning the impacts of weather changes more robust. The finding concerning the effect of temperature increases on risk taking is in line with Hsiang et al.,

[6] We also estimate the $ANT_{it,}$ RNT_{it}, ASS_{it} and models RSS_{it}, but employing the weather changes from one-hour prior (instead of two hours) to the current hour. This resulted in the same weather change variables being significant, except the changes in rainfall in ANT_{it} model._Consequently, the period over which we measure the weather changes does not appear to influence our main finding that weather changes do influence individuals' risk-taking activities, particularly for changes in temperature and air pressure.

(2013) who found that when temperatures increase, it can lead to aggressive behaviours. In addition, our finding that increases in rainfall in winter and summer increases risk-taking is in line with Hsiang et al., (2013) who found that that precipitation increases induce aggressive behaviours and risk-taking.

Taken together, our results suggest that a decrease in one's level of personal comfort, induced by weather changes (i.e. falling air pressure, increasing rainfall and rising temperatures (in summer)), can increase the risk an investor takes. This result may be explained by the fact previous research has found that a negative mood (perhaps induced by these weather changes) increases risk-taking (Funakubo et al, 2010; Ray, 2013; Denissen et al., 2008; Keller et al., 2005).

Our finding that changes in the degree of cloud cover do not influence traders' risk taking and that risk taking increases following increases in rainfall, are at odds with the findings of Bassi et al., (2013). They, in fact found that more sunshine and less rainfall (tested via dummy variables) could increase an individuals' risk-taking, and they explained their findings by suggesting that increased sunshine and less rainfall could induce good moods, this and increasing individuals' confidence when assessing their investments (Kuhnen and Knutson, 2001). However, our findings are consistent with previous studies that indicate that individuals are risk seeking when they are in a negative mood (perhaps induced by changes to 'poorer' weather) as they may believe that high-risk options could lead to outcomes that may reverse their mood (Raghunathan and Pham, 1999). Conversely, it has been suggested that individuals are reluctant to take risks when they are in a good mood, as this might lead to outcomes that destroy their mood (Isen and Geva, 1987; Isen et al., 1988; Isen and Patrick, 1983; Hockey et al., 2000; Parker and Tavassoli, 2000). It might appear that our results which show greater risk taking associated with a change to higher temperatures in winter (which one might associate with a change to a more positive mood), does not fit with this line of reasoning. However, factors other than mood may be playing a role and leading to the result we observe, In particular, is has been shown temperature increases can lead to aggressive behaviours (Hsiang, et al., 2013; Helama et al., 2013), and this might be displayed in terms of more trading or higher risk trading.

However, most previous studies have not distinguished different trading behaviour in summer and winter. These seasonal differences are potentially important, since the weather factors in summer and winter might cause completely opposite impacts on mood and feelings. Arguably, failing to examine these seasonal differences might lead to the underestimation of the impact of weather on mood and risk-taking. In fact, our results indicate that there are significant differences in the impact of a range of weather variables in summer and winter (e.g. air pressure and rainfall only influence risk-taking in one particular season).

Previous studies that have explored the individual level data and weather effects (Goetzmann and Zhu (2005); Levy and Galili (2008)) using univariate regression or logistic regression, have not distinguished the different risk-taking activities across traders. Our methodology, which employs multi-level mixed models, enables us to test the trading preferences of each trader and show how weather changes impact on their risk-taking across traders. We would argue that this is a more appropriate methodology to examine individuals level transactions (level 1) nested within individual traders (level 2) (Tabachnick and Fidell, 2001; Luck, 2004).

In summary, this is, to our best knowledge, the first study to examine the relationship between changes in weather variables and individuals' risk-taking behaviour. In addition, our individual level data enables us to explore, using a multi-level mixed model framework the impact of changes in weather in the trading behaviour of individuals. We believe this provides a more robust means of testing the effects of weather factors on individuals' risk-taking behaviour than that employed in previous studies, many of which have relied on aggregate stock market data. In addition, we restricted our analysis to an examination of trades to open positions (in contrast to existing studies which use trades to open and close positions (e.g., Goetzmann and Zhu (2005) and Levy and Galili (2008)). This is important because decisions associated with closing a position can be influenced by the paper profits or losses that have accumulated on that position (i.e. leading to the 'disposition effect' (Kahneman and Tversky (1979). In addition, we do not control for the relative market variables in our models, since this may raise the issue of endogeneity. More specifically, the endogeneity problem normally rises by the loop of causality between dependent and independent variables (Brooks, 2008). In this paper, the dependent variables (i.e. individuals' risk taking) may cause the market changes (e.g. market return). For example, the higher level of risk-taking could increase the expected return, which may cause the endogeneity. Therefore, we may increase the chance of endogeneity if we control for market variables as independent variables, since the dependent variables (i.e. risk-taking) could cause the changes of the market variables (i.e. independent variables) in regression models, which in turn, raise the potential issue of endogeneity. Consequently, we do not control for market variables as independent variables to avoid the possibility of endogeneity. Furthermore, we report the R^2 and Effect Size f^2, which indicate fairly low and medium values. Despite this, we believe these values are reasonable and powerful compared to relative literature (e.g. Hirshleifer and Shumway, 2003; Goetzmann et al., 2015). Consequently, we believe our methodology of testing the impact of weather changes on individuals' risk-taking is robust, enabling us to discover the true impacts of weather changes on risk taking behaviour.

3.5 Conclusion

Previous studies have demonstrated a relationship between weather changes and individuals' psychology and physiology (Sato, et al., 2001; Guedj and Weinberger, 1990; Bierton et al., 2013). It has also been found that weather could significantly influence decisions in the financial domain, including stock returns (Saunders, 1993; Cao and Wei, 2005) and individual trading behaviour (Goetzmann and Zhu (2005); Levy and Galili (2008); Goetzmann et al., 2015). Humans possess the ability to maintain thermal homeostasis via both biological mechanisms and behaviours; therefore, sudden changes in weather may have a greater effect on mood and behaviour than the general weather conditions. However, to our best knowledge, no study has examined the impact of weather *changes* on risk taking. We are, therefore, the first to provide a link between changes in weather variables and individuals' risk-taking behaviour. We achieve this using multi-level mixed model to capture the full richness of our individual level data and we identify the real impacts of weather changes by also accounting for the different effects which exist in winter and summer. Our findings suggest that when weather changes to a state providing relatively greater personal discomfort (increases in rainfall, falls in air pressure in winter and temperature increases in summer) this change appears to induce greater risk-taking behaviour.

We believe our results are robust, as they offer important methodological advantages over previous studies. In particular, to our best knowledge, this is the first study which explores the impact of *changes* in weather on individual's risk-taking behaviours based on the naturalistic data rather than laboratory. We employ *individual* (cf. aggregated stock returns) trading data to establish the relationship between changes in weather variables and individuals' risk-taking behaviour using multi-level mixed models. This enables us to distinguish the individual differences across traders (e.g. some have average stakes far greater than others) by allowing individual transactions (level 1) nested with individual traders (level 2) (Tabachnick and Fidell, 2001; Luck, 2004). We also control for SAD, trading hours, the Monday and January effects and seasonality in stock returns (via a Halloween dummy). Given the importance we find attaches to changes in weather factors on individual's risk-taking behaviour, and given the importance which financial markets attach to expectations, we believe that future studies could fruitfully explore the impact of expected weather on risk-taking behaviour.

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Conclusions

This section provides a summary of the findings and the contribution of each of the three papers in this thesis. It also examines the contribution of the thesis as a whole in providing a window on the effects of weather on individuals' financial decision-making. Finally, in this section I explore the implications, the limitations of this research and suggestions for future research.

The study presented in Chapter 1 is the first to examine the effects of weather on individuals' trading sentiment (bullish/bearish sentiments) and on trading volume in the fast growing spread-trading market. The results are obtained after controlling for seasonality in stock market prices and examine the combined effect of multiple deseasonalized weather factors. A multivariate regression model was employed to examine the effects of weather on three related volume variables (i.e. the number of investors who decide to trade, the number of trades they decide to initiate and the degree to which they commit to those trades, measured by average investment per trade). The findings of this paper suggested that weather significantly influences trading volume, but have less effect on trading sentiments. Most importantly, the findings of this paper indicate that there is an important seasonal component in the weather-trading-behaviour relationship and further research is required to verify the seasonal interactions I observe in traditional equity markets.

Chapter 2 was the first study to explore the relationship between weather factors and the incidence and degree of the well-documented decision bias, namely, disposition effect (DE). It was also the first study to use a short interval (minutes) to measure the value of the DE (most studies examine DE on daily level, e.g. Odean, 1998; Dhar and Zhu, 2006). A multi-level mixed model was employed to examine the impact of weather on the DE displayed by individual traders. These models were employed to identify the effects of weather factors on the DE displayed by individual traders and to examine whether different weather factors differentially impacted the DE in summer and winter. The results of this study indicated that weather does influence the degree of the DE. In particular, good weather conditions increase the degree of the DE in winter months. These results suggest that these weather conditions may induce a good mood, which is known to be more associated with system 1 thinking (Kahneman, 2011), leading investors to rely more on intuition than on rational analysis. This, I believe, is what leads to the biased decision-making which causes the DE. More importantly, the results demonstrated that less informed traders are more prone to be affected by weather than informed traders. This is a result in line with the Affect Infusion Model (Forgas, 1995), which predicts that those whose tasks involve more uncertainty (i.e. less informed traders) are likely to be more susceptible to mood effects.

Chapter 3 was the first study to demonstrate the relationship between hourly weather changes and the degree of an individuals' risk-taking. Using multi-level mixed models, this paper accounted for the trading/risk-taking differences and preferences across traders. In particular, this is the first study to explore this relationship based on the naturalistic data. The main conclusion to emerge was that a range of weather changes, particularly those in the direction of relatively greater personal discomfort induce the risk taking behaviours.

In summary, this thesis provides insights into the overall impact of a range of weather factors on financial decision-making behaviour. The data employed was obtained from the UK spread-trading market, but I suspect that the results may well apply across a broader set of markets. Overall, the results suggest that a range of weather factors and changes in these factors, probably via their influence on mood, affect individuals' financial decision-making. Importantly, the results suggest that effects of these weather factors are significantly different in summer and winter months. The study presented in Chapter 1 was the first to distinguish weather effects in summer and winter months and it was suggested that the failure of previous studies to control for this fact may be a key reason for the mixed findings that have been reported. Consequently, I controlled for this effect in studies reported in Chapters 2 and 3. In the study reported in Chapter 2, I found that weather factors significantly impact the degree of the DE displayed. This suggests that mood, which is known to influence the use of system 1 thinking and via this to influence the degree of biased decision making, may have a an important effect on the DE. Equally, I show that these effects are significantly different in summer and winter months. In Chapter 3, I explored to what extent weather changes impact risk taking behaviour. My reason for suspecting that this might be the case is that humans are known to possess the ability to maintain thermal homeostasis via both biological mechanisms and behaviours, therefore, sudden changes in weather may have a greater effect on mood and behaviour than the general weather conditions. The results suggested the weather changes do impact risk-taking and, once again I observed that these effects of changes in different weather factors are different in summer and winter seasons.

The overall finding of my research is that weather does influence individuals' trading behaviour and the effect varies seasonally. The trading information in the spread-trading market is connected to the conventional financial information. Therefore, if the biased decision behaviours are observed by the spread traders, they are likely to also exist in the wider financial markets. This is worrying because spread-trading companies often hedge into the underlying conventional stock markets and my results suggest that as spread-trading markets expand the underlying markets are likely to become increasingly influenced by weather factors. For market regulators, it is important that they are fully aware of the observed weather effects on mood and trading behaviours (e.g. good weather induces good mood and, it, in turn, increases the trading volume) in order to predict the upcoming trading activities. In terms of traders, they are also suggested to understand the weather effects on trading behaviours. In particular, those less-informed traders are strongly recommended to think carefully before making decisions, as they are more likely to be influenced by weather factors.

The results of this research make an important contribution to the market efficiency literature, as we demonstrate that traders' decision-making is swayed by weather factors, not the underlying economic fundamentals, leading, potentially to mis-pricing. Traders are suggested to focus on fundamental news, and more importantly, to avoid making decisions if their moods are unstable in different weather conditions. For example, a good trader should have a similar prediction of the market and trading activity, regardless of the weather conditions.

In sum, this thesis has made an important contribution to the existing literature of weather impacts on financial decision-making behaviours. Future researches are recommended to examine weather impacts seasonally. In addition, another weather variable, named humidity is worth to be included and tested if it is available. It has also been suggested by this research to investigate which groups of traders are more likely to be influenced by weather in the future studies.