Are UK Financial Markets SAD? A Behavioural Finance Analysis

by

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Abstract

Behavioural finance argues that some market anomalies can be explained by assuming investors are not always fully rational. This thesis contributes a greater understanding of the relationship between investor mood and financial markets, through exploring the effect of seasonal affective disorder (SAD) on UK financial markets .

Chapter 2, the first empirical chapter, investigates the SAD effect on UK stock portfolio returns, by employing daily returns of all stocks traded on the London Stock Exchange (LSE) from 1988 to 2011. The chapter constructs SAD variables and six stock portfolios to examine the SAD effect in different stock portfolios, with some well-known market anomalies and weather factors are considered. The estimation result supports the existence of the SAD effect in UK stock portfolio returns, and the SAD effect is more pronounced in small size stock portfolios.

Chapter 3, explores the SAD effect on UK stock trading activities, by applying a variety of econometric techniques to ascertain whether SAD affects stock portfolio turnover. The analysis indicates the more people suffer from SAD, the less stock turnover, and the SAD effect is more influential on small size stock turnover.

Chapter 4 turns to bond markets, aiming to ascertain the SAD effect on UK government bond returns. We study the relationship between SAD indicators and eight government bond returns, and a positive correlation between SAD indicators and government bond returns are uncovered. The result suggests that investors prefer investing in government bonds when suffering from SAD.

Overall, this thesis demonstrates a clear and significant relationship between investor mood and UK financial markets, through exploring the SAD effect on stock and government bond markets. This thesis concludes that the onset of SAD leads to lower stock returns and turnover, and higher government bond returns; and that recovery from SAD leads to higher stock returns and turnover, and lower government bond returns.

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Chapter 1 Introduction

1.1 Aim and Motivation

The existence of seasonality in financial markets has a dramatic impact on variety of traditional economic and finance theories. The famous efficient market hypothesis (EMH) was introduced by Fama (1965) and documented that stock prices incorporate all public available information if the market is efficient. The EMH is based on the notion that investors behave rationally and understand the trade-off between risks and returns in financial markets, maximising their expected utility by analysing all public available information. In an efficient stock market, stock prices are expected to follow a 'random walk' and future prices are not predictable. Fama (1965) argued that, since all information related to past stock prices is reflected in current stock prices instantaneously, it is insignificant to use past prices to analyse future prices. The random walk hypothesis also rejects the existence of any price patterns in financial markets. However, a number of recent studies in financial markets have amassed the existence of seasonality, which demonstrates the inefficiency of markets. The implication of seasonality in financial markets is a challenge to the efficient market hypothesis and has generated a great deal of attention to investigate calendar anomalies in financial markets.

Researchers have identified a number of calendar anomalies in asset returns, suck as: the January effect, the Monday effect, the Halloween effect, and so on. Rozeff and Kinney

(1976) first documented that average stock returns in January were higher than in the remaining months of the year. Keim (1983) and Reinganum (1983) further confirmed the existence of the January effect and argued that it was more significant in small firm stocks. Clayton et al. (1989) and Chang and Huang (1990) pointed out that the January effect was also present in the bond markets. After Cross (1973) documented significant abnormal stock returns over weekends, the Monday effect were found in various financial markets in various countries (Flannery and Protopapadakis, 1988; French, 1980; Gibbons and Hess, 1981; Griffiths and Winters, 1995; Lakonishok and Levi, 1982). The Halloween effect, also known as the famous 'Sell in May and go away' investment strategy, is based on the discovery that the period from November to April inclusive has significantly higher returns on average than the other months on stock markets. Bouman and Jacobsen (2002) showed that the Halloween effect did indeed exist in 36 out of 37 countries they examined, thus they argued that the seasonal pattern in stock returns can not be explained by risk factors, interest rates, trading volume, correlation between markets or the January effect.

Numerous explanations have been developed to rationalize the puzzling discovery of calendar anomalies in financial markets. In recent years, psychologists have identified that people do no always behave rationally in financial markets and can systematically make suboptimal decisions. Behavioural finance enriches economic understanding by incorporating cognitive psychology into financial models and providing potential explanations for the market anomalies. Belsky and Gilovich (1999) suggested that people occasionally make seemingly irrational or illogical investment decisions. Prospect theory introduced by Kahneman and Tversky (1979) and developed by Tversky and Kahneman (1992) stated that people use their own heuristics to evaluate the potential value of gains and losses rather than the final outcome, when they making decisions. This theory incorporate psychology factors into investors decision-making processes. Specifically, Odean (1998) pointed out that overconfident investors often trade too frequently, offsetting potential gains and leading to excessive trading volumes in financial markets. Lakonishok and Maberly (1990) found individual investors tended to increase the number of sell transactions relative to buy transactions on Mondays, and argued that the individual investors noisy trading behaviour might partly explain this phenomenon. Ritter (1988) found that individual investors have below average transactions in late December and above average translations in early January, combining the argument that individual investors disproportionately invest in small capitalisation stocks. Ritter (1988) implemented the individual investors trading patterns to explain why small stocks exhibit a strong January effect. In general, the concepts of irrational individual investor behaviour has received considerable attention from finance researcher who have attempted to explain market anomalies.

In addition, since psychologists have proven that people are sensitive to the surrounding environment, where changes can lead to concomitant changes in human emotional status. In the field of behavioural finance, research has documented evidence of mood misattribution influencing investors' risk perception, which in turn affected investor decision-making, that is, investors trading behaviour is subject to their moods. Consequently, the environment have a great impact on the investors trading behaviour, and subsequently, asset returns and trading activities. Recent studies has confirmed the hypothesis by employing environmental factors as mood-proxies variables to test the relationship between these mood-proxy variables and asset returns and trading activities, and seasonal and daily patterns in financial markets have been uncovered. Saunders (1993) and Hirshleifer and Shumway (2003) found significant a relationship between cloud cover and stock returns; Cao and Wei (2005) suggested low temperatures were related to high stock returns;

Kamstra et al. (2003, 2012, 2014) proved the influence of seasonal depression symptoms caused by seasonal affective disorder (SAD) on both stock and government bond returns; Lu and Chou (2012) argued that weather variables and SAD also affect trading activities. Behavioural finance researchers have documented the influence of mood-proxy variables in global financial markets.

Among all the mood-proxy variables, some researchers have argued that biorhythm disorders, such as SAD, have more pronounced effects on mood than daily weather. Denissen et al. (2008) investigated the effect of six weather variables on mood and found the daily weather effect on mood was small. The result was in line with findings by Keller et al. (2005) and Watson (2000a), who also indicated that weather did not significantly affects mood valence. Added to this, Denissen et al. (2008) suggested some individuals experience seasonal depression due to the shortening of daylight time, falling prey to SAD. Molin et al. (1996), Rastad et al. (2005) and Beck and Beamesderfer (1974) also concluded that there is a strong SAD effect on mood. Moreover, SAD is also claimed to be the the most significant mood-proxy variable affecting financial markets. Dowling and Lucey (2008) tested the relationship between seven mood-proxies and international stock prices and found SAD showed the greatest impact on equity pricing. Kamstra et al. (2003, 2012, 2014) further confirmed the SAD effect in international financial markets. In this thesis, we target the SAD effect in UK financial markets in order to provide potential explanations for seasonal anomalies.

However, to the best of my knowledge, most researchers who have investigated the relationship between mood-proxies and financial markets have focused on US financial markets, with little attention paid to UK financial markets. Within the studies about UK financial markets, stock indices data are mostly adopted, which motivated us to take a deeper look into seasonality in UK financial markets, by investigating the SAD effect in UK stock and bond markets. Specificity, since Dowling and Lucey (2008) found a stronger SAD effect on small capitalisation stocks, we constructed six stock portfolios, based on the characteristics of stocks to test whether the SAD effect varies across different stocks. Kamstra et al. (2014) argued that short-term Treasury bills exhibit small seasonal movements, hence we grouped eight government bonds into two groups, based on their maturities, to analyse whether the SAD effect is different between long-term bonds and short-term bonds. Moreover, it is important for individual investors to understand the relationship between mood and financial decision-making, so they can overcome mood bias and earn higher profit, while a diminishing of mood effect in financial markets can improve market efficiency.

The empirical analysis presented in this thesis investigates seasonality in UK financial markets and aims to contribute to the existing literature in several ways. The second chapter aims to investigate the SAD effect on UK stock portfolio returns. The third chapter explores the relationship between SAD and UK stock portfolio turnover. The analysis in the second and third chapter includes all the stocks traded on the London Stock Exchange (LSE), involving the construction of six stock portfolios. The SAD effect is tested across portfolios to test whether different portfolios yield different results. The final chapter focuses on seasonal patterns in UK government bond returns and SAD is used as a proxy for variation in investor risk perception. Eight government bonds with maturities ranging from 2-year to 30-year are analysed, and the bonds are grouped into groups, based on their maturities, in order to account for potentially different seasonal patterns in bond returns with different maturities.

1.2 Structure of Thesis

The thesis is organized as follows: Chapters 2, 3 and 4 present the empirical analysis of this thesis, the three chapters investigate seasonality in UK financial markets, Chapter 5 conclude the thesis.

1.2.1 Chapter 2

Chapter 2 presents analysis of the determinants of seasonality in UK stock returns by exploring all stocks in the LSE from 1988 to 2011. The analysis presents the hypothesis that environmental factors have a profound effect on investors' moods, and in turn mood is proven to be related to individual investors' risk perception and decision-making. Consequently, there is a significant relationship between environmental factors and stock returns.

Following Kamstra et al. (2012), who constructed SAD variables as mood proxies and found a significant SAD effect on international stock indices returns, SAD variables were constructed based on the length of day or changes in the proportion of SAD sufferers. In addition, six stock portfolios were constructed based on characteristics of the stocks to test the argument of Dowling and Lucey (2008), who found a more pronounced SAD effect on small capitalisation indices. We followed Kamstra et al. (2012) including some market anomalies and weather factors to control for well-known anomalies, and performed regressions to investigate the relationship between SAD variables and stock portfolio returns.

In the existing literature, the most common econometric techniques employed to analyse the effect of weather on stock markets are the Ordinary Least Square (OLS) method and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method. By performing the Lagrange multiplier (LM) test for residual autocorrelation, ARCH effects are found in five stock portfolio returns. That lead us to adopt GARCH method for the five portfolio returns, to account for the time-varying variance in the estimation and OLS specifications for the other portfolio. In addition, seemingly unrelated regression (SUR) was run, in order to take account of the inter-portfolio correlations, and joint tests on the coefficients SAD variables were performed to further investigate whether SAD affected different stocks differently.

In line with Kamstra et al. (2003, 2012), the estimation result of the chapter indicates that there is a statistically significant SAD effect in the UK stock portfolio returns which is more significant for small size stock portfolios. Ng and Wu (2006) indicated individual investors prefer small size stocks, hence the stronger SAD effect in this area indicates that individual investors who suffer from SAD are pessimistic in relation to their pricing of stock. There is also an indication of a significant relationship between SAD variables and return variance. Our result provides support for the SAD hypothesis that when investors suffer from SAD and become depressive in the fall, they tend to avoid risk in favour of risk-free assets; when investors recover from SAD, as days get longer, they resume their risk perception and rebalance their risky investments. The SAD hypothesis potentially anticipates seasonality in the UK stock market by suggesting lower returns in the fall and higher returns in the winter, especially for small size stocks.

1.2.2 Chapter 3

The third chapter explores the relationship between SAD variables and the UK stock portfolio turnover, in order to investigate seasonality in the stock portfolio turnover. In psychological studies, human activities are found to be affected by the surrounding environment which has a great impact on people's moods and decision-making processes, such as their investment activities. For example, Lu and Chou (2012) found trading activities of investors were affected by SAD and some weather factors. Therefore, to examine the SAD affect on stock portfolio turnover and eliminate the other market anomalies, we followed Kamstra et al. (2012) including some well-known market anomalies and weather factors in our regression model, so as to estimate to the coefficients of SAD variables.

The stock turnover data consists of daily trading volumes of all stock in the LSE and Six constructed portfolios based on the nature of the stocks, to capture the SAD effect on different stock portfolio turnover. Portfolio turnover is calculated using the mean daily trade volume of each stock in the portfolio, divided by the shares outstanding for all the stocks within the Portfolio. The LM test results indicate ARCH effects are presented in five portfolios, thus we employ GARCH model to estimate the SAD effect in them, and apply an OLS model to the other portfolio. To examine the SAD effect across different size portfolios, SUR and joint tests on the coefficients SAD variables were performed.

The results reveal that, the SAD variable that measures the change in proportions of SAD sufferers (OR) is the most significant variable examined in relation to the SAD effect in stock portfolio turnover. The analysis indicates a negative correlation between OR and stock portfolio turnover and the SAD effect is more significant on small size portfolios.

Our result suggests that the stock turnover is more volatile when more investors experience SAD symptoms, especially for small size stocks which are favoured by individual investors. Our result is consistent with the SAD hypothesis introduced by (Kamstra et al., 2003), individual investors suffering from SAD tend to avoid risk and reduce risky investments.

1.2.3 Chapter 4

Chapter 4 investigates seasonal pattern in the UK government bond returns. According to our findings in Chapter 2 and 3, investors tend to invest in risk-free assets when they suffer from SAD, so we expect a reversed seasonal pattern in bond returns compared to that of stock returns. In the existing literature, a number of studies have documented seasonal patterns in bond returns. For example, Athanassakos (2008) found strong seasonality in Canadian bond market and indicated the seasonal pattern to be opposite in direction from that of the stock market. Kamstra et al. (2014) also documented a seasonal treasury return pattern and argued that it was correlated with the mood proxy that measures investor risk aversion across the seasons. We follow Kamstra et al. (2014) and use four different seasonal indicators to examine seasonal patterns in UK government bond returns.

The four seasonality indicators were constructed to match the timing of the onset of SAD and recovery from SAD. The bond data adopted in this chapter consists of monthly returns of eight government bonds, with maturities ranging from 2-year to 30-year over the period from 1980 to 2014. The bonds were allocated into two groups based on their maturities. The seasonality test was performed by estimating the model using Generalized Method of Moments (GMM) which controls the potential endogeneity arising from the explanatory variables and controls for possible explanatory variable. We also performed $\tilde{\chi}^2$ tests to examine whether the seasonality indicators were jointly different from zero in the two groups.

In line with the findings of Kamstra et al. (2014), Ogden (2003) and Athanassakos (2008), the result of this chapter provides support for the existence of a seasonal pattern in government bond returns, and the seasonal bond return pattern is opposite in direction to the seasonal pattern in stock return, which means higher bond returns when the investors experience SAD and becoming risk averse in the fall and winter. The result, in accordance with the analysis presented in Chapter 2, further confirmed the SAD hypothesis that investors suffering from SAD become more risk averse, tending to sell stocks in favour of safe assets; when they recover from SAD, their risk perception will return normal and they will rebalance their investment portfolios. Therefore, seasonally varying investor risk aversion due to SAD leads to lower stock returns and higher bond returns when days begin to shorten in the fall.

Chapter 2 The SAD effect on UK Stock Portfolio Returns

2.1 Introduction

In classic finance theory, market efficiency ensures that asset prices are determined by market fundamentals, such as: firm-specific and economy-wide factors. According to the efficient market hypothesis (EMH), stocks always trade at prices which reflect all public available information. Moreover, Markowitz (1952) introduced modern portfolio theory (MPT), it assumes that individual investors construct investment portfolios for risky assets under the trade-offs between risks and returns; hence it is expected that investors understand the relationship between risks and returns and treat high risk high return portfolios with the same level of satisfaction as low risk low return portfolios. Sharpe (1964) introduced the Capital Asset Pricing Model (CAPM) which extends MPT by defining the positive relationship between risk and return. In the CAPM framework, investors rationally choose to obtain higher return by taking greater risks. Both MPT and CAPM assume that investment portfolios are built on the assumption of investors willingness to take risks (Mayo, 2013). With the supports of this assumption, investors are economically rational when making trade-offs between risk and return.

Many studies have been carried out to test the validity of equity market efficiency theories. Reviewing all the reference in literature, Avramov et al. (2012) argued that the global asset pricing models have failed to capture the cross-section of country equity returns. Moreover, behavioural finance has emerged with a new theory that provide us an alternative view of financial markets. One important aspect in behavioural finance is that investors are all always fully rational, but sometimes behave under the influence of mood. Simon (1965) came up with the idea of Bounded rationality, in which individual decision making is limited by personal information, cognitive limitations, and time constraints, and thus not all investors are fully rational. Barberis and Thaler (2003) showed that various cognitive biases limit humans' ability to act as fully rationally. Kahneman (2003) furthered these ideas, and proposed bounded rationality as a model to solve some limitations of the rational-agent models in economic literature. Moreover, the paradigm of modern finance that all derives from investor rationality has altered, recently given the wide evidence of anomalies in global stock markets (Shefrin, 2010). Market anomalies are stock price distortion on financial markets that contradict the efficient-market hypothesis. For example, Cross (1973) and French (1980) uncovered evidence of the Day-of-the-Week effect on stock markets, which refers to a bias toward negative market performance on Mondays. Banz (1981) and Reinganum (1981) demonstrated the small-cap effect in stock markets by showing that on average small capitalization stocks experience returns significantly higher than those of large capitalization stocks. Literature in this field supports the conclusion in behavioural finance that investors make irrational decisions, and so justify the use of models that incorporate investor irrationality.

In the field of behavioural finance, investors irrationality is mainly studied under the idea that individual investors are subject to mood. Loewenstein et al. (2001) stated that individual' emotional states have a great impact on their decision-marking process. Under this hypothesis, for individual investors, their investment decisions are not all based on public fundamental information, sometimes their mood can cause bias. A number of studies focus on mood-proxy variables effect on equity returns. These mood-proxy variables include: weather conditions, seasonal affective disorder (SAD) and sporting event results. The results show that financial markets are greatly affected by these mood-proxy variables, specifically, investors tend to hold optimistic opinions on their risky investments when they are in a good mood, and investors tend to avoid risk when they experience depression (e.g. Daniel et al., 1998; Hirshleifer, 2001; Kamstra et al., 2003).

However, there is no universal agreement about how to measure investors' moods. Weather and seasonal factors have been shown to have a significant effect on human mood in many psychological studies (Howarth and Hoffman (1984); Cunningham (1979)). Therefore, These environmental factors are considered to be good proxies to measure investor mood, and so are widely used in literature. These factors include weather indicators such as temperature and wind speed; and the biorhythm indicators such as lunar phases and SAD. Financial studies have shown the significant relationship between mood-proxy variables and stock market returns. An early paper by Saunders (1993) indicated a negative correlation between cloud cover levels in New York and New York Stock Exchange stock returns. Cao and Wei (2005) found low temperatures lead to higher stock returns. Kamstra et al. (2003) constructed a variable based on the length of daytime to measure SAD, and found a significant relationship between the SAD variable and stock prices. They argued that investors are less tolerant of risk when they experience SAD and feel depressive, thus seasonal depression induced by SAD leads to lower stock prices.

Rather than simply concentrating on the SAD effect on UK stock indices, in this chapter, on key contribution we have made is to construct six stock portfolios and analyse the SAD effect on different portfolios. The portfolios are built according to the size and book-to-market values of all the stocks traded on LSE. Portfolios 1 to 3 are small size portfolios, which contain stocks with size is lower that the average size of all the stocks; Portfolios 4 to 5 are large size portfolios, which contain stocks with size is higher than the average size of all the stocks. Portfolios 1 and 4 contain stocks with low book-to-market values; Portfolios 2 and 5 contain stocks with medium book-to-market values; Portfolio 3 and 6 contain stocks with high book-to-market values. Different types of investor s have tendency to hold different types of stocks and different types of investors are expected to be affected by SAD in a different levels. For instance, as Keim (1983) suggested individual investors prefer to invest on small size stocks and Dowling and Lucey (2008) argued that individual investors are more likely to be influenced by mood. Therefore, when investors are suffered from SAD, individual investors are expected to experience greater level of influence of mood than institutional investors, and the returns of small size stocks that mostly held by individual investors are more violate than usual. We expect that the returns of small portfolios are more affected when people are suffered from SAD.

The aim of this chapter is to test whether UK stock portfolio returns are influenced by SAD, with some weather and market anomalies factors are considered. In addition, we also examine whether the SAD effect varies across different types of stocks. This chapter makes the following contributions to the existing literature: firstly, daily stock returns of all stocks traded on the London Stock Exchange(LSE) were collected from 1988 to 2011. Six portfolio have been constructed, based on the size and book-to-market values of the stocks. This chapter in order to isolate whether SAD affects different stock portfolios differently. Secondly, numbers of well-known market anomalies and weather variables are controlled in the specifications in order to investigate the SAD effect on stock portfolio returns. The market anomalies include the Monday effect and the Tax-Loss Selling effect; the weather variables are temperature, visibility and wind speed. The SAD variables are constructed as a measure of the reduction of daylight in the fall. This chapter tests the null hypotheses that seasonal depression as measured by SAD, does not affect UK stock portfolio returns against the alternative hypotheses that there is a SAD effect on UK stocks portfolio returns and the SAD effect on small size stock portfolios are more pronounced.

The findings of this chapter demonstrate that there is a significant SAD effect on UK stock portfolio returns, even after a number of well-known market anomalies and weather variables are controlled. In addition, we also find that the SAD effect is more pronounced on small size stocks. We observe that stock portfolio returns are lower when the investors suffer from SAD, and returns are higher when they recovery from SAD. Also this chapter show a significant relationship between some mood-proxy variables and variance of portfolio returns. Through this analysis, we provide solid evidence to support the SAD effect hypothesis that investors are depressed and more risk averse when they suffer from SAD, these investors tend to avoid risk and in favour of safe assets. When investors recover from SAD, their risk perception back to normal and they will resume their investment portfolio.

The outline of the chapter is as follows. Section 2 reviews the relevant literature. Section 3 provides a data description and methodology. Test results are analysed in Section 4. Section 5 offers some conclusions and discussions.

2.2 Literature Review

This section will provide comprehensive review of some key findings of the previous literature that links environment factors, mood and stock returns. Initially, we first look at the theoretical psychology literature that links weather and human emotion. We then explore the relationship between investor emotion and their decision-making. Finally, we explore literature that has implemented environmental factors as mood proxies to study seasonality in stock returns.

2.2.1 SAD, Weather and Mood

The theory of how mood influence people's mood draws on findings in the field of psychology, clinical studies and behavioural finance. People's mood is considered to be greatly affected by daily weather. Researches have begun to investigate how various environmental factors influence individuals' moods for a long time. In clinical studies, the various senses of humans responds to different climatic factors stimuli of the skin and mucous membrane, respiratory tract, vision and pressure receptor in the ears (Faller and Schünke, 2004). Human beings perceive and understand the world through the senses, the weather is a key factor that influences those senses and affects people's mindset. A sudden change of weather can lead to biological rhythm disorder and changes in human emotion. The information is generated in from the surrounding environment and transmitted into people's mind. Thus, changes in weather have a great impact on human emotion and behaviour directly or indirectly through psychological or physical influence. The physical influences can be exposure to strong winds limited outdoor activities and feeling hot when the temperature is relatively high. The psychological involves people's moods and their attitude toward their own surroundings and the wider climatic context(Bell et al., 2001). Therefore, It can be assumed that human beings are largely influenced by surrounding environmental factors, such as: temperature, wind speed and barometric pressure.

The relationship between human mood and weather changes is one of the most frequent studies in biometeorology and psychology studies. For example, Baron and Bell (1976) employed sixty-four undergraduate male students as subjects to test the relationship between negative affect and aggression levels. Participations were assigned into eight groups and exposed to different levels of negative affect, including: cool and hot ambient temperatures; positive and negative personal evaluations from another person; and similar and dissimilar attitudes to this person. The study found a significant curvilinear relationship between negative affect and aggression levels, they argued that the negative affect serves as a mediator in the relationship between high ambient temperatures and aggression levels. The impact of ambient temperature upon aggression depends on the levels of discomfort that subjects experience at a particular moment. If subjects experience low levels of discomfort, it was proven that a high ambient temperature enhances overt aggression. The finding shows that extreme high temperature makes subjects become aggressive and weather has a direct influence over human emotions.

More other studies have explicitly analysed the relationship between mood and weather. Goldstein (1972) adopted 6 weather variables, including temperature humidity, barometric pressure, clearness, temperature deviation from normal for the date, and wind speed, to explore the relationship between weather and mood. [1] The experimental results indicated that self-reported mood scores correlated with weather variables. More specifically, subjects tended to report high mood scores in low humidity, high barometric pressure and cooler and normal days, people feel better when they experience comfort weather conditions. Furthermore, Repetti (1993) measured the subjective well-being and perceived

[1] 22 college students were asked to report emotion states on scales representing the semantic differential factors of evaluation, potency, and activity for 11 consecutive Tuesdays and Thursdays.

job conditions of air-traffic controllers on 3 consecutive days and found low visibility had a negative impact on mood. Cooke et al. (2000) examined headache data of 75 patient diaries from the University of Calgary Headache Research Clinic. They employed individual and multiple logistic regression models to determine relationships between weather and the probability of migraine onset. They realised a significant negative relationship between wind speed and mood scores. Howarth and Hoffman (1984) went on to consider the relationship between weather and multiple mood dimensions. In addition to previous studies, they included a full range of weather variables in the study in order to deal with the inter-correlation between weather variables. They used the Howarth Multiple Adjective check List (Howarth (1977, 1979)) as the mood instrument to record 10 mood dimensions of the subjects. The results showed that humidity, temperature and hours of sunshine had the most significant influence on subject mood. More precisely, high levels of humidity lower mood scores on concentration; rising temperatures led to anxiety and scepticism mood scores and the amount sunshine is significantly positive correlate to optimism mood scores.

Persinger (1975) found that weather even have a lag effect on mood, they aimed to ascertain the relationship between self-evaluated mood reports and the weather in the previous two days.[2] Multiple regression results indicated that there was a two-day weather lag effect on the subjects' mood scores. The mood scores positively correlated to the amount of sunshine and negatively correlated to humidity levels.

More recent studies also concurred with the idea that there is a relationship between

[2] Ten university students were selected as subjects and asked to rate their mood using the Doorland mood rating scale (Dorland and Brinker, 1973). The weather variables they investigated included: barometric pressure, wind speed, number of sunshine hours, temperature, humidity and a variable that related to daily global geomagnetic activity.

weather and mood. Page et al. (2007) denoted temperature to be negatively correlative with mood in summer months in the UK. In detail, they showed that, when the temperature is above 18 degree Celsius, a one degree increase in temperature increase suicide rate by 3.8%. Nastos and Matzarakis (2012) tested the temperature effect on mood using the daily mortality of Athens, Greece from 1992 to 2001. The results revealed that there was a clear influence of the temperature on the daily mortality in Athens. Moreover, different temperatures affected mortality differently, it was found that a cold temperature had a 3-day lag effect on mortality, against warn temperatures only had 1-day lag effect on mortality.

However, a number of psychological studies have found no evidence to support a significant relationship between weather and mood. Bauer et al. (2009) examined the mood of 360 patients daily from different continents who were receiving treatment as usual. The results indicated climate variables are not associated with mood by season or month. Watson (2000a) carried out one of the largest test of the weather-mood hypothesis by collecting daily mood reports from 478 undergraduate students during the fall or the spring for a total of 20818 observations. It was pointed out that no significant correlations between mood and any of the assessed weather variables were found. The weather variables that have been tested includes: hours of sunshine, barometric pressure, temperature and precipitation. Therefore, whether daily weather has a direct effect on mood is still a controversial topic.

Comparing to daily weather, some other researchers argued that biorhythm disorders, such as seasonal affective disorder (SAD) and lunar phase, have more pronounced effects on mood than daily weather. Denissen et al. (2008) carried out an experiment of 1233 participants and examined whether day-to-day weather affects people's moods. The experimental results revealed sunlight has a main effect on tiredness and wind had more of a negative effect on mood in spring and summer than in fall and winter. Especially, they speculated that people are more likely to experience depression when the days get shorter, especially for those people at higher risk of SAD, as known as Winter Blues, which is a psychological condition where a reduction in the number of daylight hours is correlated with the onset of depressive symptoms, thus the reduction of daylight hours leads to depression for SAD suffers. Some symptoms of SAD in winter can be difficulty waking up in morning, a lack of energy and lack of concentration. In spring and summer, symptoms of SAD include insomnia, anxiety, irritability, social withdrawal and reduced appetite. Thus, patients who suffer from SAD tend to feel depressed during the seasons of reduced total daylight hours(Rosenthal (2012)).

To summarise, the literature showed that weather had a determinant and significant influence on human emotions. The majority of people feel pleasant and optimistic on days with long hours of sunshine; and on days with comfortable wind speed, temperature and humidity. Strong winds, extreme temperatures, high levels of humidity and cloudy days lead to negative effects on individual mood. However, a number of evidences showed that there is no significant relationship between daily weather and mood. Some other researchers argued that biorhythm disorders such as SAD had more pronounced effect on mood than daily weather. They found that SAD have a direct impact on mood, and it is one of major reasons that causes people feel depressed in the winter.

2.2.2 Mood, Decision-Making and Risk Perceptions

Psychological researches have established a link between weather, mood and risk-taking decisions. Mood serves as a mediator in the relationship between surrounding environmental factors and individual decision-making. A growing body of research has targeted the role that mood plays in decision-making processes under conditions of risk. The results show that mood can profoundly influence decision-making in risky situations and ultimately affects investment decisions (Johnson and Tversky, 1983; Slovic, 2010).

Some psychologists have built some solid theoretical background for the importances of mood in decision-making process. Schwarz (1990) developed the feelings-as-information theory to evaluate the influence of happy and sad moods in decision-making. He found that individuals frequently used their emotional state when making choices of processing strategies. In detail, the author stated that people in a negative mood tend to think their current situation is problematic and need longer time than usual to foster analytical processing strategies, whereas people in a positive mood usually made decisions much more quickly. Loewenstein et al. (2001) carried on and introduced the risk-as-feelings hypothesis and built a risk-as-feelings model that incorporated the role of mood experienced at the moment of decision-making. The risk-as-feeling model was developed based on a meta-analysis from clinical and physiological studies. The study concluded that emotional reactions to risky situations often diverge from cognitive assessments of those risks. When such divergence occurs, mood plays a vital role in risky decision-making process. The implication of the the risk-as-feelings hypothesis is that financial research should make it a routine to include investors' mood information in models, together with probabilities and outcomes, to analyse financial decision-making.

Other psychologists tried to use experiments to prove that mood have a significant effect on decision-making process. Damasio (2008) aimed to investigate the relationship between mood and optimal decision-making. The findings revealed that people with an impaired ability to experience emotion have difficulty in making optimal decisions. Johnson and Tversky (1983) showed that moods induced by reading a newspaper article influenced subsequent risk judgements by testing two groups of people with different moods to sort some risk-relative factors which could cause death. The first group read some negative news that might lead to depression, the second group did not read the news. The results revealed the group of subjects which read negative news were less optimistic about the risk factors cause death than subjects did not read negative news, and they therefore concluded that people in negative moods are more pessimistic and tend to overestimated risky outcomes.

Williams et al. (2003) used a risk-assessment instrument to test 149 managers from a variety of industries and companies in the US. The test results showed that managers with positive emotions tended to view risk-related uncertainty more optimistically, but were not more willing to seek risks. Managers with negative emotions viewed risky choices pessimistically and were also significantly more likely to avoid risk-taking behaviour. The results is consistent with studies from Deldin and Levin (1986); Yuen and Lee (2003) that people with negative emotions manifested less risk-taking behaviour. Jorgensen (1998) explained that people with negative emotions are more likely to perceive the threat of risky decisions and thus tend to avoid risky options. On the other hard, Nygren et al. (1996) denoted that people with positive moods can result in optimistic behaviour, hence positive outcomes become increasingly overestimated and negative outcomes become increasingly underestimated. The experiment carried out by Eisenberg et al. (1998) enhances the argument. In the experiment, participants with different degrees of depression were asked to choose some options at different risk levels. The findings showed that anxiety is positively correlated with risk aversion, as were depressive symptoms. Therefore, people who were anxious and depressive were more risk averse than people with neutral moods, which is expressed by less risk-taking and more favouring safe options.

In recent years, increasing attention has been paid to investigate the symptoms and behaviour of SAD sufferers. SAD is a condition that affects people during the seasons of reducing hours of daylight. Mersch et al. (1999) aimed to assess the prevalence of SAD in The Netherlands by randomly selecting 5356 subjects, the result showed that subjects who met winter SAD criteria were significantly more depressed than other subjects.[3] Magnusson (2000) carried on and found seasonal variations in mood in 19 out of 20 SAD related retrospective studies and he argued that depressive symptoms usually peaking in winter and appeared to be a relatively common disorder which the prevalence varied across ethnic groups. Kramer and Weber (2012) extended the SAD symptoms to risk-assessment process by studying 5000 on-line financial risk self-assessment survey results which were sent to university staff in 2008. They found that SAD sufferers exhibited stronger seasonal variations in aversion to financial risk than people who do not suffer from SAD. Therefore, in financial markets, investors who suffer SAD have lower return expectations in the fall than in other seasons, tending to shun risk, and refocus on rebalancing their investment portfolios and turn to relatively safe assets at this point in the year. These studies have documented that SAD sufferers experience depression in the fall when days become shorter and the depressive symptoms made they become more risk averse.

[3] The subjects were asked to complete the Seasonal Pattern Assessment Questionnaire and the Centre for Epidemiological Studies Depression Scale over a period of 13 months.

Generally, the literature stated that people with negative moods tended to make more pessimistic judgements than when in neutral moods. Risk perceptions of people with positive moods are still a controversial topic, some made optimistic estimations and become less risk aversion; however, some other people with positive moods were afraid of loss and tended to avoid risks. Therefore, it is expected that SAD sufferers were more depressed and risk averse than normal people.

2.2.3 SAD Effect on Stock Returns

The findings of previous studies suggested that weather and SAD had a significant influence on mood, and mood has been repeatedly shown to affect individuals' decision-making process (Denissen et al., 2008; Schwarz, 1990). Especially, people with negative moods are usually more pessimistic and tend to avoid risks. Thus, we hypothesize that, investors' expectations are largely influenced by moods, investors with negative moods generally expect lower market returns than those with positive or neutral moods. Both weather and SAD have been proven to have a great influence on mood. However, SAD sufferers have been proven to be directly associated with depressive symptoms and more risk averse. Therefore, SAD can be used as mood-proxy to investigate mood effect on stock returns. (Dowling and Lucey, 2008; Kamstra et al., 2012).

Previous literature has established the relationship between daily weather and stock returns. Seminar paper from Saunders (1993) employed the cloud coverage ratio of the Central Park area of New York City as the mood proxy to analyse the weather effect on New York stock returns. The result showed that on sunny days stock returns are higher than on cloudy days. Specifically, stock returns were below average on 100 percent cloud cover days, while they were higher than average on 0-20 percent cloud cover days. Thus the cloud cover ratios negatively correlate with stock returns. Hirshleifer and Shumway (2003) extended his study and used stock returns data from 26 stock exchanges from 1982 to 1997 to show the relationship between sunshine and international stock returns. The amount of sunshine is affected by cloud cover, hence these two weather variables are correlated. Their findings revealed that sunshine was significantly correlated with international daily stock returns. After controlling for sunshine, other weather proxies, such as rain and snow, showed no correlation with daily stock returns. They also argued the possibility of improving the Sharpe ratio of the investment portfolios if the sunshine effect is considered. However, they all suggested that the sunshine effect was still not enough to account for a risk-free arbitrage opportunity in international stock markets.

Instead of focusing on sunshine or cloudiness, Cao and Wei (2005) used nine international stock indices data across the period from 1962 to 2001 to investigate the influence of temperature on stock market returns. They employed a semi-parametric “bin test”, an OLS regression and a seemingly unrelated regression test to analyse the correlation between temperature and stock returns. The analysis pointed out a statistically significant and negative correlation between temperature and stock returns. This finding is confirmed by Keef and Roush (2007) who also concluded that stock index is negatively related to temperatures. Wind speed has also been proven to correlate with stock returns. Shu and Hung (2009) considered the the relationship between wind speed and daily stock market returns in 18 European countries from 1994 to 2004 and found evidence of a pervasive wind speed effect on stock returns across countries.

Simultaneously, Dowling and Lucey (2008) aimed to conduct a comprehensive analyses on the influence of mood-proxy variables on stock prices. The relationship between seven mood-proxy variables and global equity price were investigated. The mood-proxy variables they adopted in their study included: precipitation, temperature, wind, geomagnetic storms, seasonal affective disorder (SAD), daylight savings time changes and lunar phases. They employed the GARCH specifications to test the relationship between daily stock returns for 37 country indices and the mood-proxy variables. They found a strong SAD effect on both equity returns and variance and the SAD effect was more significant for small capitalisation indices than for main ones. They argued that individual investors are more likely to be affected by SAD in the pricing of small capitalisation stocks. Among all the mood-proxy variables, they claimed that SAD is the most significant variable and the influence of SAD on stock markets increased with latitude.

Studies about SAD effect in international stock market returns began decades ago. A study by Kamstra et al. (2003) aimed to find evidence to support the argument that SAD explained seasonal variations in global stock returns. They argued that investors become depressive and more risk averse when the days become shorter in the fall. Thus, increasingly negative returns were observed as the length of daytime decreased from fall to winter, while from winter to spring, increasingly positive stock returns were found as the amount of daytime increased. The paper exploited four indices from the US and indices from eight other countries. As SAD symptoms are related to the latitudes and hemispheres of locations, the paper included the Sweden index, the largest exchange among the far northerly markets, and the Australia index, the largest exchange in the Southern Hemisphere, to account for the global SAD effect. Single regressions were conducted for each country to account for the different SAD effects in different countries. Two lagged returns were considered, in order to address the issue of autocorrelation and White (1980) standard errors are employed to control for heteroskedasticity. The regression results provide strong support for the SAD hypothesis that seasonal depression caused by SAD leads to higher risk aversion, and lower international stock market returns. The SAD effect is consistent, even after controlling for some well-known market seasonal variations and weather variables. The SAD hypothesis provides explanations for the seasonal variations in global stock returns and the effect is greater in counties with higher latitudes. Kamstra et al. (2012) employed modern statistical methods and further confirmed the existing of SAD effect in international stock markets.

Some other literature also stated the impact SAD has on financial markets. Dolvin et al. (2009) found that stock analysts also exhibited SAD biases by identifying that analysts are less optimistic in their forecasts during SAD months. Furthermore, the relation is more pronounced for analysts located in northern states, who should be the ones more influence by SAD. Kliger et al. (2012) documented SAD also substantially influences initial public offering (IPO) performance. They examined IPO first trading days and indicated that in the short run stocks earn lower returns when days were getting shorter. They claimed that the impact of seasonal affective disorder on investors' mood decrease the demand for IPOs. all found evidence consistent with the influence of SAD on investors' mood and therefore, stock markets performance.

2.2.4 Other Well-known Anomalies in Stock Returns

A growing amount of literature has attempted to investigate seasonal anomalies in the stock market. For example, a well-known market abnormality is the Monday effect, also known as the day of the week effect, which is a tendency for stock market returns to be relatively lower, or even negative, on Mondays rather than on any other day of the week.

An early attempt by French (1980) found that the average daily returns of the Standard and Poor's composite portfolio from 1953 to 1977 were significantly negative on Mondays, while the average daily returns for the other days of the week were positive. Later studies by Gibbons and Hess (1981), Lakonishok and Smidt (1988) also attested to the presence of the Monday effect. Mehdian and Perry (2001) further studied the Monday effect on the five major US stock market indexes, by using daily returns from three large-cap indices and two small-cap indices from 1964 to 1998. The results showed that the Monday effect in large-cap indices is different from that of small-cap indices. Specifically, Monday returns were significantly negative in all five US stock indexes before 1987, which is consistent with previous literature. However, significant positive Monday returns in the large-cap indices are found after 1987, meaning that the Monday effect is reversed with large-cap indices. They suggested that the Monday seasonal pattern is size determined.

The January effect, also known as the turn-of-the-year effect, is another famous seasonal pattern which refers to abnormal high stock returns in January. Rozeff and Kinney (1976) analysed monthly stocks returns on the New York Stock Exchange from 1904 to 1974 and found large January returns, which is statistically significantly different to the remaining eleven months. Keim (1983) and Reinganum (1983) offered the tax-loss selling behaviour as a partial explanation of the January effect. They argued that it centred on the idea that individual investors, who disproportionately held small-cap stocks, sought to sell stocks at the end of the tax year to offset capital gains, and bought them back in January. Gultekin and Gultekin (1983) found significant evidence to support the existing tax-loss selling effect in the stock returns in most industrial countries. The study presented significantly positive returns occurring at the turn of the tax-year. For countries with a tax year ending in December, general increase in stock prices are observed in December; disproportionately large April returns were expected in UK stock market, whose tax year ends in April. Starks et al. (2006) provided recent evidence supporting the tax-loss selling hypothesis by analysing turn-of-the-year return and volume patterns for municipal bond closed-end funds, which are majority owned by tax-sensitive individual investors.

Some researchers claim that the mood effects do not apply equally to all stocks, price of stock with different characteristics may react quite differently, even if the investor sentiment is the same. Baker and Wurgler (2007) documented that investor sentiment has significant effected on cross-sectional stock prices, as investor sentiment influences stocks with different characteristics, displaying strong conditional patterns. The small, youth, growth and high volatility stocks generate high returns when sentiment is low. When sentiment is high, the large and value stocks earn relatively high subsequent returns. Kumar and Lee (2006) provided additional evidence by examining stock transactions of more than 1.85 million individual investor from 1991 to 1996, and found that individual investors, whose portfolios are concentrated on the small-cap and lower-priced stocks, tend to buy and sell stocks in concert. Forgas (1995) suggested that investment decisions are more complex for individual investors than for institutional investors, since individuals investors general exhibited greater reliance on mood and feeling in risky decision-making, hence the small-cap and growth stocks owned mostly by individual investors are more likely to be affected by a change of mood than large-cap and stock mainly owned by institutional investors. Therefore, the mood effects on these small-cap and lower-priced stocks are greater than the large-cap and higher-priced stocks.

Thus, as stated earlier, psychological studies indicate that weather and SAD affect people's mood and mood has a great influence on people's decision-making and risk perceptions. Additionally, the strength of the mood effect on stock markets varies with the characteristic of the stocks, small-cap stocks, being mainly owned by individual investors, are more likely to be influenced by mood. However, local London weather only affects a proportion of investors who live in London and invest on the LSE, SAD is a type of depression symptom that affects people across countries, hence SAD is expected to affect a majority of investors who invest on the LSE. Hence, we expect a solid linkage between SAD and UK stock market returns. Given the literature evidence reviewed above, we hypothesize that lower stock market returns are associated with SAD, which are occurred in the fall when the days become shorter. In this chapter, six stock portfolios and SAD instrument variables are constructed to investigate the SAD effect in UK stock market returns and the strength of the SAD effect on different portfolios, some well-known market anomalies and weather factors are considered.

2.3 Data and Methodology

The empirical analysis presented in this chapter draws on time series data from the London Stock Exchange (LSE). Six portfolios are constructed, based on the ratio of book equity to market equity (BE/ME) and size (market equity, ME) of the stocks. Three mood-proxy weather variables and two market anomaly variables are controlled in the regressions to capture the SAD effect on the portfolio returns.

2.3.1 Equity Data and Portfolios

Our equity data consists of all the stocks on the London stocks exchange (LSE), within the period from 1 February 1988 to 30 December 2011. For each stocks the daily closing prices, market equity and the ratios of book equity to market equity are collected. The daily total market index during the same period are also recorded. The daily stock returns are calculate using the log difference between the closing price today and the closing price of the previous trading day. All the equity data are obtained from DataStream.

Six stock portfolios were constructed based on the characteristics of the stocks following, the Fama and French (1993) benchmark size and book-to-market portfolios. The portfolios are the intersections of 2 portfolios formed on the market equity (size) and 3 portfolios formed from the ratio of book equity to market equity (book-to-market value). The breakpoint for the market equity (size) portfolios was the mean market equity value of all stocks at the end of June, the two breakpoints for the ratio of book equity to market equity (book-to-market value) were the 30th and 70th of book-to-market value of all stocks percentiles at the end of December. The portfolios were reconstructed each year for the period 1988 to 2011 as the size and book-to-market values of each stocks varied over time.

Table 2.1 show the structure of the portfolios. Portfolios 1-3 contains small size stocks, while large size stocks are in Portfolios 4-6. Portfolios 1 and 4 contain stocks with a low book-to-market ratio, which are also known as growth stocks. Portfolios 2 and 5 contain neutral stocks, value stocks are in Portfolios 3 and 6. Growth stocks refer to companies which are expected to grow at a faster rate than average companies in the same industry, and these companies tend to reinvest retained earnings and pay small or no dividends. Value stocks refer to companies' trading prices which are believed to be lower than their fundamental value prices. Investors buy value stocks in the hope that the stock prices will eventually increase when the market recognizes their full potential value. Generally, growth stocks are considered overvalued, while value stocks are considered undervalued by the market. Investing on growth stocks and value stocks are two different types of investment habits. Individual investors are claimed to concentrate on small size stocks (Keim, 1983).

2.3.2 Mood-proxy Data

The literature reviewed above has established the relationship between mood and weather variables, including temperature, visibility and wind speed (Allen and Fischer, 1978; Cooke et al., 2000; Repetti, 1993). The relationship between stock returns and these weather variables are also proven in the literature (Keef and Roush, 2007; Saunders, 1993; Shu and Hung, 2009).[4]

Therefore, the daily mean temperature, mean visibility and mean wind speed are selected as weather indicators for mood proxies. The implementation of weather factors to analyse stocks returns is common in behaviour finance studies. The daily weather condition is completely exogenous, as Roll (1992) argued, weather is unambiguously and exogenous observable. Thus there is no endogeneity issue when using weather data to investigate stock returns. The weather data was obtained from the National Oceanic and Atmospheric Administration (NOAA) website[5], within the global summary of the day (GSOD) database. We extracted the London city station (station ID 03768399999) from the database within the period 1 February 1988 to 30 December 2011.

The daily UK SAD variable was calculated as the normalized length of night variable

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[4] The London city cloud cover data is not available and visibility should influence stock returns in the same manner as cloud cover, hence we adopted visibility instead.

[5] See: http://www.noaa.gov/

using formulas from the paper Kamstra et al. (2003) by applying the London latitude. The formulas are based on the hours of night in the day in the fall and winter, as clinical studies show that reduction in the amount of daylight in the fall and winter has a systematic effect on human emotions. The SAD variable was calculated as in following steps:

Firstly, SAD is defined as

$$SAD_t = \begin{cases} H_t - 12 & \text{For days in the fall and winter} \\ 0 & \text{Otherwise} \end{cases}$$

where H_t stands for the time from sunset to sunrise.

$$H_t = \begin{cases} 24 - 7.72 * \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right) tan(\lambda_t)\right] & \text{in the Northern Hemisphere} \\ 7.72 * \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right) tan(\lambda_t)\right] & \text{in the Southern Hemisphere} \end{cases}$$

And

$$\lambda_t = 0.4102 * \sin\left[\left(\frac{2\pi}{365}\right)(julian_t - 80.25)\right]$$

Kamstra et al. (2003) argued that, by deducting H_t by 12, SAD_t reflects the difference between the length of light time in the fall and winter and the average length of light time during the entire year[6]. δ is the latitude of the location[7] and λ represents the sun's

[6] The average length of night time all year round is assumed to be 12 hours.

[7] In this chapter we use 51°N for London.

declination angle. $julian_t$ presents the number of the day in the year, its value takes from 1 to 365(366 in a leap year).

In order to capture the possible asynchronous effect of SAD between the fall and winter, two dummy variables were generated, based on the fall and winter seasons[8], which are $FallSAD_t$ and $WinterSAD_t$.

$$FallSAD_t = \begin{cases} SAD_t & \text{For days in the fall} \\ 0 & \text{Otherwise} \end{cases}$$

$$WinterSAD_t = \begin{cases} SAD_t & \text{For days in the winter} \\ 0 & \text{Otherwise} \end{cases}$$

However, the SAD variable only takes value in the fall and winter, when the length of a day changes. Kamstra et al. (2014) introduced a new measure to capture the effect of SAD, Onset/Recovery (OR), which is linked to the clinically observed onset and recovery of SAD symptoms in the population. OR represents change in the proportion of SAD sufferers during the entire year. Thus, we include OR in our specifications to capture the non-linear changes of mood of SAD sufferers. OR is constructed base on the oneset of SAD symptoms and recovery from SAD symptoms from Lam (1998) and Young et al. (1997). They introduced a monthly SAD incidence variable that denotes the difference between the cumulative proportions of people suffering SAD symptoms and the cumu-

[8] In this chapter, the Autumn Equinox and Winter Solstice dates are adopted to mark the beginning and end of the seasons, so that the fall begins on September 21st and the winter on December 21st, and ends on March 20st.

lative proportion of people recovery from SAD within the same month. By applying an interpolation function to this incidence variable, the monthly data was transformed to a daily date. Finally, a logistic regression ($\frac{1}{1+e^{(}\alpha+\beta day_t)}$) was performed by substituting the daily incidence variable and the length of daytime of the location to achieve the fitted value (ranges from 0% to 100%.) of the non-linear function. The fitted value is the OR variable[9]. Khaled and Keef (2013) suggested the following way to convert the New York OR to an OR for other cities as Kamstra et al. (2003) claimed that the amplitude of SAD is positively correlated to latitude.

$$\gamma^j = \frac{Latitude^{City_i}}{Latitude^{NewYork}} \tag{2.1}$$

$$OR^{City_i} = \gamma^j * OR^{NewYork} \tag{2.2}$$

Therefore, the OR variable we adopted in this chapter can be obtained by substituting the latitude of London and the latitude of New York in the equations above[10].

Figure 4.1 shows OR variable reaches peak around the fall equinox and reaches bottom near the spring equinox, the equinoxes are the points of inflection in the annual daylight cycle. OR is negative in the winter and spring and positive in the summer and fall.

The FallWinter dummy variable equals 1 in the fall and winter, and 0 in the spring and summer. The FallWinter dummy variable can capture the material difference between the

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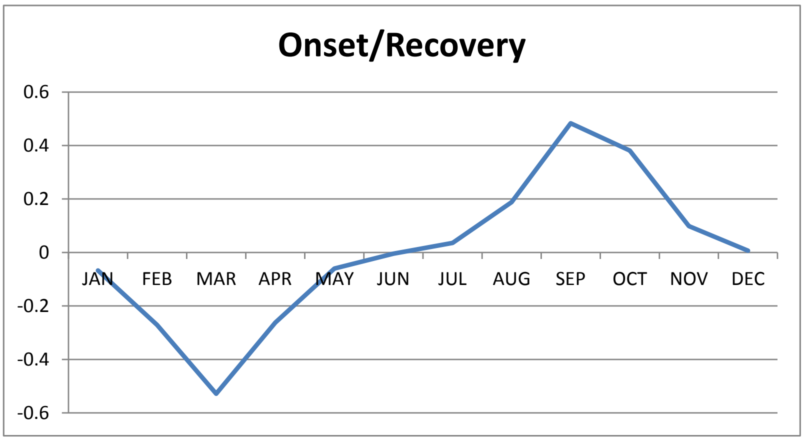
[9] The New York Onset/Recovery (OR) variable is available from www.lisakramer.com/data.html

[10] The latitude of London is 51°N and New York is 41°N.

Figure 2.1: **Onset/Recovery (OR)**



length of night effect and fall and winter seasonal effect. The Fall dummy variable equals 1 in the fall, 0 in other seasons. Including a Fall dummy variable in the specifications enables us to distinguish the SAD effect difference between fall and winter. Noticeable the previous literature, investors who suffer SAD become more risk averse when the days become shorter in the fall, so the stock prices are under-valued. When investors recovery from SAD and return to normal risk aversion levels, the stock prices increase and return to normal in the winter. The implication is that stock returns are lower in the fall and higher in the winter. Therefore, the asymmetric effect of SAD in the fall and winter is reflected by the coefficient of the Fall dummy variable and its significance level.

2.3.3 Other Controlled Variables

A number of works in the literature have documented the tax-loss selling effect in the stock market (Brown et al., 1983; Tinic and West, 1984). In order to control this effect, the tax dummy variable is included in the specifications. The tax year in the UK ends on

April 5, thus Tax_t is equals one for the last trading day before April 5 and the first five trading days begin with April 5.

The Monday effect also known as the Day-of-the-Week effect in stock markets has alos been proven by a large amount of literature (Gibbons and Hess, 1981; Lakonishok and Levi, 1982; Mehdian and Perry, 2001), therefore, the Monday dummy variable was adopted to control for the Monday effect in stock returns. $Monday_t$ equals to one when the trading day is Monday, and equals zero otherwise.

2.3.4 Descriptive Statistics

In this section, the summary statistics of both equity data and mood-proxy data are presented and discussed. Table 2.2 shows the summary statistics for each stock portfolio used in this chapter. The first column of the summary statistics plots the daily percentage mean returns across the six portfolios. The mean daily returns range from -0.19 percent to 0.029 percent. Standard deviation of the returns varies across portfolios, with portfolio 6, which of large size and value stocks, the most volatile at 2.392 percent; and portfolio 2, the least volatile at 0.512 percent. Portfolio 3 has the maximum single day return increase, at 33.64 percent, and portfolio 6 has the maximum single day return drop at 36.43 percent. The returns of portfolio 1 and 3 were strongly skewed to positive returns, while the returns of the remaining portfolios were negatively skewed. All the portfolio returns display high kurtosis, which is typical in stock markets. Therefore, the summary statistics indicate that the portfolio returns are not normally distributed, which are also typical in international stock market data.

2.3.5 Methodology

The aim of this chapter is to examine the SAD effect on the UK stock portfolio returns. This research adopts specifications similar to that employed by Kamstra et al. (2012). They employ these specifications to analyse SAD effect on international stock indices.

$$\begin{aligned} Return_{i,t} = &\beta_{i,Tax}Tax_{i,t} + \beta_{i,Monday}Mondayi,t + \beta_{i,Fall}Falli,t + \beta_{i,FallWinter}FallWinteri,t \\ &+ \beta_{i,Temp}Tempi,t + \beta_{i,Wdsp}Wdspi,t + \beta_{i,Visib}Visibi,t + \sigma_{i,t} \end{aligned} \tag{2.3}$$

$$\begin{aligned} Return_{i,t} = &\beta_{i,Tax}Tax_{i,t} + \beta_{i,Monday}Mondayi,t + \beta_{i,Fall}Falli,t + \beta_{i,SAD}SADi,t \\ &+ \beta_{i,Temp}Tempi,t + \beta_{i,Wdsp}Wdspi,t + \beta_{i,Visib}Visibi,t + \sigma_{i,t} \end{aligned} \tag{2.4}$$

$$\begin{aligned} Return_{i,t} = &\beta_{i,Tax}Tax_{i,t} + \beta_{i,Monday}Mondayi,t + \beta_{i,Fall}Falli,t + \beta_{i,FallSAD}FallSADi,t \\ &+ \beta_{i,WinterSAD}WinterSADi,t + \beta_{i,Temp}Tempi,t + \beta_{i,Wdsp}Wdspi,t + \beta_{i,Visib}Visibi,t + \sigma_{i,t} \end{aligned} \tag{2.5}$$

$$\begin{aligned} Return_{i,t} = &\beta_{i,Tax}Tax_{i,t} + \beta_{i,Monday}Mondayi,t + +\beta_{i,OR}ORi,t \\ &+ \beta_{i,Temp}Tempi,t + \beta_{i,Wdsp}Wdspi,t + \beta_{i,Visib}Visibi,t + \sigma_{i,t} \end{aligned} \tag{2.6}$$

where $Return_{i,t}$ is the return to portfolio i at time t; $Tax_{i,t}$ is a dummy variable equals 1 on the first five trading days and the last trading day of the UK fiscal year and zero otherwise; $Monday_{i,t}$ is a dummy variable for trading days on Mondays; $FallWinter_{i,t}$ is a dummy variable equal to one between September 21st and March 20th and zero otherwise; $Fall_{i,t}$ is a dummy variable equal to one between September 21st and December 20th and zero otherwise; $SAD_{i,t}$ is the normalized length of night variable for the UK; $OR_{i,t}$ reflects the change in the proportion of SAD sufferers. $Temp_{i,t}$, $Cloud_{i,t}$, and $Rain_{i,t}$ are daily weather variables.

Equation 2.3 tests the argument claimed by Kelly and Meschke (2010) that the SAD variables are not materially different from a simple fall-winter dummy. Equation 2.4 tests the SAD effect on stock portfolio returns. By splitting the SAD variable into FallSAD and Winter SAD in Equation 2.5, whether the overlap of SAD and Fall variables drives away the significant results on the Fall dummy is investigated. OR reflects the change in the number of SAD sufferers. It can capture the timing of depressive symptoms of SAD sufferers, which directly related to stock returns.

Following Kelly and Meschke (2010) and Kamstra et al. (2003), Firstly, we aim to test whether the coefficients of the SAD-related variables are statistically different from zero for each portfolio. The null hypothesis is that there is no SAD effect in the UK stock portfolio returns, against the alternative hypothesis that SAD drives seasonal pattern in UK stock returns. The Ordinary least squares (OLS) method has been widely used in literature to investigate the weather effect on stock returns. Thus, single OLS regression is conducted separately for each portfolio and returns are regressed on two lagged returns to control the autocorrelation in the daily returns. The MacKinnon and White (1985) heteroskedasticity-consistent standard errors are employed in the OLS regressions.

The OLS regression assumes the variance of the error term over time to be constant. Engle (2001) argued financial data is known to exhibit time varying variance as stock risks are not constant over time. The Auto Regressive Conditional Heteroscedastic (ARCH) model introduced by Engle (1982), which takes account of Heteroscedasticity, has become a famous econometric technique in behaviour finance studies. Heteroscedasticity refers to time varying variance. ARCH is a mechanism by which considers the future variances are not isolated from past variances. The General-ARCH (GARCH) model is an extension of ARCH which is mostly employed in analysing time series data. The GARCH model enables us to accurately estimate variances and covariances of stock returns through its ability to model time varying conditional variances (Bollerslev, 1986). Engle's Lagrange Multiplier (LM) test for the presence of autoregressive conditional heteroskedasticity are preformed using five lags. The LM test results[11] lead to a diagnosis of ARCH effects in portfolio returns except portfolio 1, hence the OLS model may result in inefficient estimates for Portfolios 2 to 6, as OLS regression assumes that the variance of the error term is constant over time. Consequently, we consider the changing variance in the estimation and the GARCH (1,1) model introduced by Bollerslev (1986) is employed to take into account the conditional mean and volatility.

The mean equations of the GARCH models are in Equation 2.3 to 2.6. The variance equations are as follows:

[11] In table 3.14

$$h_t = \eta_i + \mu_i h_{t-1} + \tau_i \sigma_{t-1}^2 + \theta_{i,Visib} Visib_t + \theta_{i,Wdsp} Wdsp_t + \theta_{i,Temp} Temp_t + \theta_{i,Fallwinter} Fallwinter_t \tag{2.7}$$

$$h_t = \eta_i + \mu_i h_{t-1} + \tau_i \sigma_{t-1}^2 + + \theta_{i,Visib} Visib_t + \theta_{i,Wdsp} Wdsp_t + \theta_{i,Temp} Temp_t + \theta_{i,SAD} SAD_t \tag{2.8}$$

$$\begin{aligned} h_t = & \eta_i + \mu_i h_{t-1} + \tau_i \sigma_{t-1}^2 + + \theta_{i,Visib} Visib_t + \theta_{i,Wdsp} Wdsp_t + \theta_{i,Temp} Temp_t \\ & + \theta_{i,FallSAD} FallSAD_t + \theta_{i,WinSAD} WinSAD_t \end{aligned} \tag{2.9}$$

$$h_t = \eta_i + \mu_i h_{t-1} + \tau_i \sigma_{t-1}^2 + \theta_{i,Visib} Visib_t + \theta_{i,Wdsp} Wdsp_t + \theta_{i,Temp} Temp_t + \theta_{i,OR} OR_t \tag{2.10}$$

Where h_t represents the variance of the residual (error term) derived from mean equations respectively, σ_{t-1}^2 is the previous trading day square residual derived from mean equations. h_{t-1} is the GARCH term and $\sigma_{t-1}^2$is the ARCH term in our models. $Visib_t$, $Wdsp_t$, $Temp_t$, $Fall_t$, $Fallwinter_t$ SAD_t ,$FallSAD_{t-1}$,$WinSAD_{t-1}$ and OR_t are the mood-proxy variables (variance regressors) that contribute in the volatility of stock portfolio turnover.

In addition, all stocks in our sample were traded on the LSE, so the inter-market correlations need to be considered. For instance, investors with fixed amounts of capital available at each point in time wanting to invest in stocks in Portfolio 1 may have needed to sell some stock holding in other portfolios to gain funds; on the other hand, the increasing prices of stocks in one portfolio may have attracted public attention and results in capital shifting from other portfolios to that specific portfolio. Therefore, in order to account for the cross-section correlation across portfolios and to perform joint tests on the SAD coefficients, seemingly unrelated regression (SUR) estimation with two lagged returns were carried out. And joint tests were conducted to test whether the coefficients of SAD indicator variables jointly differed from zero [12]. The joint test results enable us to investigate whether the SAD coefficients are jointly significant after controlling for inter-market correlations.

2.4 Results

In this section, The regression results are presented and discussed. The OLS regression results are in Tables 2.3, A1, A2 A3 and A4. The Engle's Lagrange multiplier test results are shown in Table 2.4. The GARCH regression results are in Tables 2.5, 2.6, 2.7 and 2.8. Finally, Tables 3.10,3.11 ,2.11 and 3.13 report the SUR estimation results. The joint test results are demonstrated in Table 3.14.

2.4.1 Expectation of the SAD variables

In this section, the expectation of the SAD variables coefficients are discussed. The literature showed that SAD-influenced investors are depressed and more risk averse, they

[12] The joint tests are performed based on the size of portfolios.

tend to sell stocks and turn to safe assets when the days are getting shorter during the fall. When the days are getting longer after winter solstice in late December, they recover from SAD and return to stock markets, which will boost the stock prices. Therefore, in our regressions, we have the Fall dummy as a controlled variable, we expect the SAD coefficients to be positive and the coefficient of Fall to be negative. The positive stock return due to recovery of SAD combined with the negative return due to the Fall dummy suggests that on balance the seasonal asymmetric effects of SAD are transforming the stock returns from the fall to the winter.

In order to further test the significant of the SAD variables, we followed Kelly and Meschke (2010) and Kamstra et al. (2012) to test whether the overlap of the SAD and Fall variables drives the significant results on the Fall dummy by splitting the SAD to FallSAD and WinterSAD. If the regression 2.4 is correctly specified, decomposing the SAD into FallSAD and WinterSAD should not affect the results. Otherwise, decomposing the SAD would eliminate the significance of the Fall variable. Thus, we expect the coefficients of Fall still to be negative and coefficients of WinterSAD to be positive. The OR variable stands for the proportion of people who suffer from SAD, more people suffer from SAD means lower stock market participation rate, thus, we expect its coefficient to be negative.

2.4.2 OLS Regression and LM test Results

We first performed the OLS regressions for the UK total market returns. Table 2.3 reports the results. For brevity, only coefficients estimated for the variables of interest related to the SAD hypothesis are presented. In the table, it is noticeable that none of the coefficients are statistically significant at the 10% level. The results indicate that there was no SAD effect on UK total market returns, which is consistent with our hypothesis that the strength of the SAD effect varies across portfolios. We assumed that the small size portfolios, which are disproportionately held by individual investors, are more likely to be affected by changes of mood. Our result is also in line with the findings of Kamstra et al. (2012), who found no correlation between the SAD variables and the UK FTSE100 index returns. The result also further confirmed the findings of Dowling and Lucey (2008) that there is a more pronounced relationship between SAD variables and small capitalisation indices. Therefore, it is expected that there will be significant SAD effect on the small size portfolio returns.

Tables A1 to A4 show the OLS regression results for the six portfolios in Equations 2.3 to 2.6, respectively.[13] The null hypothesis is that the coefficients of the SAD variables are not statistically significant against the alternative hypothesis that the coefficients of the SAD variables are statistically significantly different from zero.

Table 2.4 reports the Engle's Lagrange Multiplier test results for the equations. The results suggest that with all the ARCH effects presented in all the equations for Portfolios 2 to 6, there are time varying volatility in the portfolio returns, hence the OLS estimators are no longer BLUE[14]. Since the diagnosis of ARCH effects, the GARCH (1,1) models are adopted to account for the changing volatility in the estimations. The AR terms and GARCH(1,1) terms are included in the regressions to analyse the relationship between portfolio returns and SAD variables.[15] No ARCH effect are detected in portfolio 1, the OLS regression results are still efficient, they are included in the tables below and dis-

[13] The OLS regression results are shown in Appendix.

[14] Best linear unbiased estimator

[15] For Portfolios 2 to 6.

cussed together with the GARCH model results.

2.4.3 GARCH Model Returns

Tables 2.5, 2.6, 2.7 and 2.8 demonstrate the GARCH (1,1) model results for Portfolios 2 to 6 in equations 2.3, 2.4, 2.5 and 2.6, respectively. The mean equation results are displayed in panel A, panel B contains the variance equation results, and ARCH and GARCH terms are in panel C. The OLS results for Portfolio 1 are also included in Column 1 in the tables .

Across the tables, the coefficient of the Monday variable in the mean equations is significantly positive at the 5% significance level for Portfolio 3 and is significantly negative at the 1% level for all large size portfolios. The result indicates the Monday return of small size value stocks portfolio is 2.5% higher than the other days of the week, and the Monday returns of all the large size portfolios are lower than the other days of the week. In other words, all the large size stocks generate relatively lower returns on Mondays than those on the other days of the week and the large size value stocks are the most influential. There is a reversal of the Monday effect between small size stocks and large size stock. The result is consistent with the findings of Mehdian and Perry (2001), who found a reversal Monday effect between small size and large size indices and suggested that the Monday seasonal pattern is size determined. The tax coefficients estimate is statistically significant and negative for Portfolio 2 and positive for Portfolio 4. The result reveals that the tax-loss selling effect is negatively related to small neutral portfolio returns and positively related to large neutral portfolio returns. Our findings further confirm the argument of Keim (1983) and Reinganum (1983) that individual investors who hold a large proportion of small size stocks tend to sell stocks before the end of the tax year to offset capital gains and suggests these individual investors will shift their fund to large size and neutral stocks. The visibility coefficient from regressions is statistically significant and negative for all small size portfolios, expect Portfolio 1. Therefore, in terms of statistical significance, visibility is negatively correlated with small size portfolio returns. It suggests that the higher the visibility lower the small portfolio returns.

Table 2.5 shows the coefficient of Fall dummy variable is statistically significant at 1% for Portfolios 1, 2, 3, 5, 6, and at 10% significance level for Portfolio 4. The coefficient of Fallwinter dummy variable is statistically positive for portfolios 2, 4, 5 and 6. The negative coefficient of Fall dummy, combined with the positive coefficient of Fallwinter dummy suggest that portfolio returns are lower than average in the fall and higher than average in the winter for Portfolio 2, 4, 5 and 6. The results of Fall and Fallwinter variables indicate that the portfolio returns are negative in the fall and positive in the winter for Portfolios 2, 4, 5 and 6. In Table 2.6, the Fall coefficient estimate is uniformly statistically significant and negative in all portfolios except Portfolio 4. The SAD coefficient estimate is uniformly statistically significant and positive in all portfolios except Portfolio 2 and 6. The result provides support for the idea of SAD effect in UK stock portfolio returns, and that SAD suffered investors experience seasonal depression and become more risk averse when the days become shorter in the fall; when they recover from SAD, their risk perceptions return to normal in the winter when the days become longer. However, we can not conclude any size pattern based on the results, as these two models fail to capture the different SAD effect in different portfolios.

By splitting the SAD variable into FallSAD and WinterSAD, The results in Table 2.7 exhibit a comprehensive picture of the SAD effect in UK stock portfolio returns. The Fall coefficient remains negative, but it is only statistically significant for small size portfolios. In the table, the WinterSAD coefficient is positive and significant at the 1% level for all small size portfolios. The negative coefficient of the Fall variable means the small portfolio returns were negative in the fall, and the positive coefficient of the WinterSAD variable indicates small portfolio returns were positive in the winter. The result provides strong evidence to support the SAD hypothesis that investors suffering from SAD begin shunning risk and adjust their portfolios in favour of safe assets other than stocks in the fall, the investors recover from SAD and resume their normal investment portfolios when the days become longer after spring equinox. Moreover, The significance of the SAD effect is related to size, only the small size portfolios which individual investors disproportionately hold, exhibit a strong SAD effect, as individual investors are more likely to be affected by mood changes. The result in consistent with the findings of Kamstra et al. (2012) and Dowling and Lucey (2008).

Table 2.8 shows the regression results for Equation 2.6, in which the OR variables is included in the model. The value of OR variable reflects the changes of SAD sufferers. From Figure 4.1, OR is negative in the winter and summer and its lowest value is during the Spring Equinox; and it is positive in the summer and fall, reacheing its peak during the autumn Equinox. The coefficient of OR is statistically significant and negative for all portfolios except Portfolio 4. The negative sign of OR variable indicates that more people suffering from SAD is associated with lower stock portfolio returns and more people recovering from SAD is associated with higher stock portfolio returns. Our findings support the SAD hypothesis that people suffer from SAD are more risk averse, they prefer safe assets other than stocks. This result provides strong support to reject the null hypothesis that there is no SAD effect in UK portfolio returns.

Turning to the variance equation results of the GARCH (1,1) regressions, the wind speed and temperature variables are significantly correlated with volatility of the Portfolio 2 returns. The visibility and temperature variables are significantly correlated with the volatility of portfolio 5 returns. The Fallwinter dummy variable had a significant influence on the volatility of Portfolio 2 3 and 5 returns. Both SAD, FallSAD and WinterSAD variables had significant impact on the volatility of Portfolio 5 returns, while the OR variable affected the volatility of Portfolio 6 returns. Both ARCH and GARCH terms in the tables are statistically significant at 1% for all portfolios which means that both previous day return and volatility of return affected today's portfolio return for all portfolios. The variance equation results indicate a significant relationship between mood-proxy variables[16] and the volatility of the portfolio returns in portfolios 2 and 5, which are neutral stocks. The results further confirm the findings of Dowling and Lucey (2008), who also found some indication of a relationship between SAD variables and the variance of stock returns.

It is clear from the regression results that the null hypothesis of no SAD effect in UK stock portfolio returns are strongly rejected. The significant positive coefficients of SAD variables combined with the significantly negative coefficients of fall variables, which suggest that, on balance the seasonal asymmetric effects of SAD shift portfolio returns from the fall to the winter. Concluding the results from all equations, strong evidence were found to support the SAD hypothesis that seasonal depression measured by SAD led to lower small size portfolio returns in the fall, higher small size portfolio returns in the winter. Individual investors who owned mostly small size stocks, suffered SAD and experience seasonal depression symptoms when the days become shorter after autumn equinox be-

[16] Weather and SAD.

came more risk averse and avoided risky investments, hence the stock returns decreased in the fall; when investors recovered from SAD as the increment of daytime after spring equinox, their risk perceptions return to normal, and the stock returns increased. This argument is consistent with the findings of Kamstra et al. (2003, 2012).

2.4.4 SUR Model Returns

In this section the results of seemingly unrelated regression (SUR) model are discussed. In the OLS and GARCH model above, each portfolio is estimated separately. As mentioned above, stock returns usually exhibit inter-market correlations, for example, the returns of Portfolios 1 might correlate to the returns of other portfolios. Moreover, the GARCH model results indicate that the SAD effect was size determined. To further investigate the SAD effect in different size portfolios, we performed joint tests on coefficients of SAD variables to examine whether SAD affected different size portfolios differently, since Dowling and Lucey (2008) argued that the SAD effect is more significant in relation to small size stocks. Therefore, in order to account for the inter-market correlations between portfolios and perform joint tests on SAD variable coefficients, we employed SUR method.

Tables 3.10, 3.11, 2.11 and 3.13 contain SUR estimation results for equations 2.3, 2.4, 2.5 and 2.6, respectively. The joint tests on the coefficients of length of night related variables results is shown in Table 3.14.

The SUR individual coefficient significance results in Tables 3.10, to 3.13 are similar to the GARCH estimation results. The SAD, FAllSAD and WinterSAD variables exhibit a statistically significant influence on small size portfolio returns. The OR variable is negatively related to all portfolio returns except Portfolio 4, which means more people suffering from SAD leads to lower stock returns for all stocks but large size and growth stocks. More importantly, The p-values of joint tests are shown in Table 3.14, the joint test results indicate the coefficients of Fallwinter, SAD, FallSAD, WinterSAD and OR all jointly differed from zero for all small size portfolios, while only the coefficient of OR variable is jointly differed from zero at a 1% significance level for the large size portfolios. The joint test of no SAD effect on small size portfolios is strongly rejected at a 1% significance level. Therefore, in terms of statistical significance, the SAD variables exhibits a strong effect on all small size stock portfolio returns, and the large size portfolio returns were only affected by OR.

The SUR results provide further evidence to support for existence of the SAD effect on stock portfolio returns, especially on the small size portfolio returns, and the results are consistent with the findings of Kamstra et al. (2012) and Dowling and Lucey (2008), the seasonal depression measured by SAD has a great influence on individual investor financial risk perception and changes in investors risk perception result seasonal variation in portfolio stock returns and mood-proxy variables have more pronounced effects on small size stocks. The OR variable significantly affects both small size and large size portfolios, together with the significant and negative coefficient of OR in Table 3.13, the result indicates that the more people suffer from SAD, the lower the stock returns. Moreover, the SAD effect is more pronounced in small size portfolio returns as p-values of all SAD variables are significantly at 1%. This is exactly what we expected for the mood effect on stock returns, since individual investors are more likely to be affected by mood, and those investors tend to focus on investing small size stocks. Our results prove supportive evidence for the argument from Gompers and Metrick (1998), who suggested that the mood-proxy variables have a greater impact on individual investors than institutional investors in pricing small size stocks.

2.5 Conclusion

Behavioural finance suggests that anomalies in asset prices can be explained by investor psychology. The literatures shows that investors are not always fully rational, they can be influenced by mood, emotions and sentiments. This chapter has analysed the seasonal affective disorder (SAD) effect in the stock returns of six portfolios, using data for all stock traded on the LSE between 1988 and 2011. The portfolios were formed based on the size and book-to-market value of the stocks. Following Kamstra et al. (2012), four regression and three models were employed to analyse the SAD effect in portfolio returns. SAD symptoms are caused by reduction in light time in the fall, SAD variables are constructed which reflect the nominal length of night.

In clinical and psychological studies, human emotions have proven to have a substantial influence on the decision-marking process. SAD is a recognized clinical diagnosis, which is caused by reduction in daylight in the fall. SAD symptoms sufferers generally experience seasonal depression in the fall and become more risk averse. When the days begin to draw out after the winter solstice, they become less risk averse. The relationship between risk aversion levels of investors and stock returns are found by past financial studies. Therefore, through the changes in the risk aversion level of investors caused by seasonal depression, SAD has a significant effect on stock market returns, as proven in many behavioural finance studies.

The first model used in this chapter is the single-equation ordinary least squares model with MacKinnon and White (1985) standard errors and two lagged returns are included, which is adopted by Kelly and Meschke (2010). The ARCH effect is presented in the OLS estimation results, thus Bollerslev (1986) GARCH (1,1) model is the second model used in this chapter. Finally, in order to account for cross-sectional correlations in portfolio returns, SUR model is performed to analyse the joint significance of the coefficients.

The regression results provide evidence that the null hypothesis is strongly rejected, there is a significant relationship between SAD and stock portfolio returns. Specifically, when the influence of other well-known market seasonal and weather factors are controlled, a large and significant SAD effect still exists. Further, evidence suggests the impact of SAD is more pronounced for small size portfolios. These results are generally consistent with the findings in the previous literature.

Our findings indicate that the SAD effect on the UK stock market should not be ignored.For individual investors, understanding the SAD effect enable them to overcome their possible seasonal variation in their risk aversion, thus their investment could be more efficient and unbiased. For institutional investors, understanding the the SAD effect in the stock market enable them to generate a better trading strategy and earn higher potential profits. In summary, awareness of the SAD effect in the stock market promote an more efficient market.

It is important to acknowledge the shortcomings of the empirical analysis presented in this chapter. This study could be improved by using hourly mood tracks for the same investors over time and their investment portfolios. Despite the fact that SAD are proven to cause seasonal depression, it is arguably limited, as the SAD effect is long-standing, it could not account for short-term mood changes. For example, Lu and Chou (2012) use hourly weather observations of Shanghai as mood-proxies to analyse the association between hourly weather-related mood factors and hourly trading intervals of stock returns.

Table 2.1: Stock Portfolios Structure

	Low Book-to-Market Ratio (Growth Stocks)	Medium Book-to-Market Ratio (Neutral Stocks)	High book-to-Market Ratio (Value Stocks)
Small Size	Portfolio 1	Portfolio 2	Portfolio 3
large Size	Portfolio 4	Portfolio 5	Portfolio 6

Notes: This table shows the structure of the stock portfolios. Portfolio 1 to 3 are small size stock portfolios, and Portfolio 4 to 6 are large size stock portfolios. Portfolio 1 and 4 contain growth stocks which book-to market ratios are low. Portfolio 2 and 5 contain medium stocks which book-to-market ratios are medium. Portfolio 4 and 6 contain value stocks which book-to-market ratios are high.

Table 2.2: Summary Statistics For Each Portfolio

Portfolios	Mean	Stand deviation	Maximum	Minimum	Skewness	Kurtosis
Portfolio 1 (Small Growth Stocks)	0.031	0.788	25.81	-10.05	9.11	294.79
Portfolio 2 (Small Neutral Stocks)	-0.057	0.512	3.70	-10.05	-3.20	45.73
Portfolio 3 (Small Value Stocks)	-0.190	0.783	33.64	-9.65	12.71	594.92
Portfolio 4 (large Growth Stocks)	0.029	0.999	7.44	-7.90	-0.34	9.84
Portfolio 5 (large Neutral Stocks)	-0.034	1.294	11.63	-16.39	-1.25	23.35
Portfolio 6 (large Value Stocks)	-0.140	2.392	26.66	-36.43	-1.08	40.19

Table 2.3: OLS Results for the UK Total Market

SAD Variables	FallWinter	SAD	FallSAD	WinSAD	OR
Coefficients	-0.0024	0.0049	0.0107	0.0027	0.0119
	(0.0436)	(0.0116)	(0.0217)	(0.0123)	(0.0802)

Notes: This table provides the coefficients for the OLS regressions results involving the UK total market index and different SAD variables. The P-values show that the UK total market index return is not correlated to all the SAD variables. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.4: LM test results

Portfolios	1	2	3	4	5	6
EQ 2.1	0.2543	**0.0000**	**0.0878**	**0.0000**	**0.0000**	**0.0000**
EQ 2.2	0.2691	**0.0000**	**0.0826**	**0.0000**	**0.0000**	**0.0000**
EQ 2.3	0.2702	**0.0000**	**0.0803**	**0.0000**	**0.0000**	**0.0000**
EQ 2.4	0.2438	**0.0000**	**0.0761**	**0.0000**	**0.0000**	**0.0000**

Notes: The table shows p-value for the Lagrange Multiplier test using five lags, the p-values in bold indicate the ARCH effect is presented in the models. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small and growth stocks; Portfolio 2 contains small and neutral stocks; Portfolio 3 contains small value stocks; Portfolio 4 contains large and growth stocks; Portfolio 5 contains large and neutral stocks; Portfolio 6 contains large size and value stocks.

Table 2.5: Equation 2.3 regression results

Portfolios	1	2	3	4	5	6
Panel A: Mean Equation						
Fall	-0.0850***	-0.0802***	-0.0712***	-0.0436*	-0.0968***	-0.1332***
	(0.022)	(0.0106)	(0.0139)	(0.0263)	(0.0299)	(0.0416)
Fallwinter	0.0215	0.0293**	-0.0014	0.0577**	0.0880**	0.0822*
	(0.032)	(0.0125)	(0.0155)	(0.0289)	(0.0356)	(0.0445)
Monday	-0.0195	0.0074	0.0247**	-0.0722***	-0.0904***	-0.0902***
	(0.023)	(0.0088)	(0.0111)	(0.0218)	(0.0254)	(0.0333)
Tax	-0.0686	-0.0704***	-0.0587*	0.1679***	0.1135	0.1246
	(0.070)	(0.0263)	(0.0302)	(0.0580)	(0.0722)	(0.1008)
Visib	-0.0073	-0.0062*	-0.0125***	-0.0042	-0.0010	-0.0062
	(0.009)	(0.0035)	(0.0041)	(0.0079)	(0.0096)	(0.0112)
Wdsp	-0.0002	-0.0001	0.0001	-0.0001	-0.0003	0.0001
	(0.005)	(0.0003)	(0.0007)	(0.0009)	(0.0012)	(0.0014)
Temp	-0.0023*	-0.0000	-0.0009	0.0008	0.0001	-0.0013
	(0.001)	(0.0005)	(0.0006)	(0.0012)	(0.0014)	(0.0018)
Constant	0.2104**	0.0432	0.0557	0.0398	0.0351	0.0774
	(0.085)	(0.0362)	(0.0429)	(0.0817)	(0.0989)	(0.1199)
Panel B: Variance Equation						
Fallwinter		-0.2321**	0.4972*	0.1028	-0.7398***	0.0979
		(0.1166)	(0.2569)	(0.2139)	(0.0988)	(0.3838)
Visib		-0.0126	0.1722	0.3604	-0.1787**	0.4262
		(0.0708)	(0.1826)	(0.2662)	(0.0866)	(0.4428)
Wdsp		-0.0414*	-0.0250	-0.1022	0.0007	-0.0634
		(0.0249)	(0.0471)	(0.0699)	(0.0096)	(0.1210)
Temp		-0.0211***	0.0175	0.0020	-0.0336***	0.0209
		(0.0071)	(0.0135)	(0.0123)	(0.0072)	(0.0148)
Constant		-3.1459***	-6.5555***	-5.9283***	-0.3247	-7.9854**
		(0.4436)	(1.2233)	(1.6157)	(0.3569)	(3.4336)
Panel C: ARCH and GARCH Terms						
ARCH		0.2883***	0.2697***	0.0999***	0.1350***	0.0682***
		(0.0115)	(0.0211)	(0.0080)	(0.0083)	(0.0051)
GARCH		0.7090***	0.7606***	0.8861***	0.8431***	0.9287***
		(0.0067)	(0.0125)	(0.0088)	(0.0075)	(0.0044)
Observations	6,075	6,056	5,967	5,949	5,939	5,181

Notes: This table reports coefficient estimates from running the regressions for each of the six portfolios. Column 1 refers to OLS regression results for portfolio 1, Columns 2 to 6 refer to GARCH (1,1) regression results for portfolio 2 to 6, respectively. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.6: Equation 2.4 Regression Results

Portfolios	1	2	3	4	5	6
Panel A: Mean Equation						
Fall	-0.1077***	-0.0715***	-0.0830***	-0.0399	-0.0792***	-0.1069***
	(0.023)	(0.0099)	(0.0127)	(0.0243)	(0.0281)	(0.0394)
SAD	0.0241***	0.0044	0.0093**	0.0178**	0.0181*	0.0106
	(0.008)	(0.0033)	(0.0044)	(0.0081)	(0.0096)	(0.0130)
Monday	-0.0193	0.0081	0.0252**	-0.0732***	-0.0903***	-0.0883***
	(0.023)	(0.0088)	(0.0110)	(0.0218)	(0.0256)	(0.0331)
Tax	-0.0461	-0.0782***	-0.0490	0.1624***	0.0946	0.0973
	(0.069)	(0.0249)	(0.0320)	(0.0597)	(0.0698)	(0.1013)
Visib	-0.0067	-0.0063*	-0.0116***	-0.0037	-0.0010	-0.0062
	(0.009)	(0.0035)	(0.0041)	(0.0079)	(0.0097)	(0.0112)
Wdsp	-0.0002	-0.0001	0.0001	-0.0001	-0.0003	0.0001
	(0.005)	(0.0004)	(0.0007)	(0.0009)	(0.0013)	(0.0015)
Temp	-0.0007	-0.0004	-0.0001	0.0009	-0.0007	-0.0026
	(0.001)	(0.0005)	(0.0006)	(0.0012)	(0.0014)	(0.0017)
Constant	0.1030	0.0698**	-0.0056	0.0387	0.0926	0.1678
	(0.075)	(0.0348)	(0.0418)	(0.0784)	(0.0957)	(0.1138)
Panel B: Variance Equation						
SAD		-0.0375	0.0049	-0.0781	-0.1690***	-0.1248
		(0.0347)	(0.0735)	(0.0666)	(0.0268)	(0.1661)
Visib		0.0062	0.1198	0.3225	-0.1775**	0.3542
		(0.0717)	(0.1707)	(0.2607)	(0.0848)	(0.4365)
Wdsp		-0.0420*	-0.0168	-0.1116	0.0003	-0.0581
		(0.0245)	(0.0469)	(0.0729)	(0.0128)	(0.1272)
Temp		-0.0182**	0.0005	-0.0105	-0.0261***	0.0101
		(0.0076)	(0.0131)	(0.0118)	(0.0072)	(0.0143)
Constant		-3.4548***	-5.1524***	-4.8326***	-0.8253**	-6.8952**
		(0.4945)	(1.1502)	(1.6022)	(0.3820)	(3.3669)
Panel C: ARCH and GARCH Terms						
ARCH		0.2875***	0.2708***	0.0990***	0.1344***	0.0681***
		(0.0117)	(0.0211)	(0.0080)	(0.0084)	(0.0050)
GARCH		0.7085***	0.7602***	0.8874***	0.8426***	0.9294***
		(0.0070)	(0.0126)	(0.0087)	(0.0075)	(0.0043)
Observations	6,075	6,056	5,967	5,949	5,939	5,181

Notes: This table reports coefficient estimates from running the regressions for each of the six portfolios. Column 1 refers to OLS regression results for portfolio 1, Columns 2 to 6 refer to GARCH (1,1) regression results for portfolio 2 to 6, respectively. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.7: Equation 2.5 Regression Results

Portfolios	1	2	3	4	5	6
Panel A: Mean Equation						
Fall	-0.0928**	-0.0368**	-0.0489**	-0.0494	-0.0696	-0.0441
	(0.040)	(0.0175)	(0.0209)	(0.0402)	(0.0464)	(0.0658)
FallSAD	0.0193*	-0.0061	-0.0010	0.0208	0.0153	-0.0096
	(0.011)	(0.0057)	(0.0068)	(0.0131)	(0.0152)	(0.0216)
WinterSAD	0.0262***	0.0089**	0.0133***	0.0168*	0.0194*	0.0170
	(0.009)	(0.0039)	(0.0049)	(0.0089)	(0.0106)	(0.0146)
Monday	-0.0192	0.0074	0.0255**	-0.0732***	-0.0910***	-0.0881***
	(0.023)	(0.0088)	(0.0111)	(0.0218)	(0.0254)	(0.0331)
Tax	-0.0442	-0.0747***	-0.0455	0.1617***	0.0963	0.1029
	(0.069)	(0.0245)	(0.0321)	(0.0595)	(0.0719)	(0.1018)
Visib	-0.0067	-0.0062*	-0.0121***	-0.0035	-0.0025	-0.0064
	(0.009)	(0.0035)	(0.0041)	(0.0079)	(0.0099)	(0.0112)
Wdsp	-0.0002	-0.0001	0.0001	-0.0001	-0.0003	0.0001
	(0.005)	(0.0004)	(0.0006)	(0.0009)	(0.0013)	(0.0015)
Temp	-0.0006	-0.0003	0.0000	0.0009	-0.0006	-0.0025
	(0.001)	(0.0005)	(0.0006)	(0.0012)	(0.0014)	(0.0017)
Constant	0.0994	0.0601*	-0.0122	0.0390	0.0937	0.1596
	(0.075)	(0.0351)	(0.0419)	(0.0786)	(0.0965)	(0.1136)
Panel B: Variance Equation						
FallSAD		-0.0510	0.0138	-0.0961	-0.1288***	0.0033
		(0.0364)	(0.0764)	(0.0731)	(0.0293)	(0.1374)
WinterSAD		0.0341	-0.0108	-0.0302	-0.3571***	-0.4895
		(0.0374)	(0.1011)	(0.0916)	(0.0718)	(0.4084)
Visib		0.0116	0.1299	0.3403	-0.2585***	0.3652
		(0.0734)	(0.1726)	(0.2682)	(0.0795)	(0.3984)
Wdsp		-0.0459*	-0.0137	-0.1167	0.0008	-0.0606
		(0.0238)	(0.0472)	(0.0740)	(0.0091)	(0.1291)
Temp		-0.0135*	-0.0001	-0.0082	-0.0309***	-0.0017
		(0.0074)	(0.0135)	(0.0119)	(0.0077)	(0.0145)
Constant		-3.7291***	-5.2035***	-5.0485***	-0.1096	-6.2098**
		(0.4866)	(1.1703)	(1.6438)	(0.3408)	(3.0422)
Panel C: ARCH and GARCH Terms						
ARCH		0.2851***	0.2701***	0.0988***	0.1325***	0.0691***
		(0.0115)	(0.0211)	(0.0079)	(0.0082)	(0.0051)
GARCH		0.7092***	0.7607***	0.8876***	0.8466***	0.9282***
		(0.0069)	(0.0126)	(0.0087)	(0.0073)	(0.0044)
Observations	6,075	6,056	5,967	5,949	5,939	5,181

Notes: This table reports coefficient estimates from running the regressions for each of the six portfolios. Column 1 refers to OLS regression results for portfolio 1, Columns 2 to 6 refer to GARCH (1,1) regression results for portfolio 2 to 6, respectively. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.8: Equation 2.6 Regression Results

Portfolios	1	2	3	4	5	6
Panel A: Mean Equation						
OR	-0.0915*	-0.0817***	-0.0628**	-0.0379	-0.1241**	-0.2308***
	(0.047)	(0.0191)	(0.0249)	(0.0471)	(0.0556)	(0.0718)
Monday	-0.0202	0.0079	0.0246**	-0.0736***	-0.0920***	-0.0897***
	(0.023)	(0.0088)	(0.0111)	(0.0217)	(0.0258)	(0.0333)
Tax	-0.0835	-0.0867***	-0.0608*	0.1308**	0.0478	0.0470
	(0.070)	(0.0267)	(0.0330)	(0.0603)	(0.0692)	(0.0948)
Visib	-0.0064	-0.0044	-0.0105**	-0.0042	-0.0032	-0.0062
	(0.009)	(0.0034)	(0.0042)	(0.0079)	(0.0094)	(0.0112)
Wdsp	-0.0002	-0.0001	0.0001	-0.0001	-0.0003	0.0001
	(0.004)	(0.0004)	(0.0007)	(0.0010)	(0.0014)	(0.0015)
Temp	-0.0015	0.0005	0.0002	-0.0004	-0.0009	-0.0008
	(0.001)	(0.0004)	(0.0005)	(0.0010)	(0.0011)	(0.0015)
Constant	0.1515**	-0.0024	-0.0371	0.1219*	0.1228*	0.0563
	(0.066)	(0.0263)	(0.0331)	(0.0637)	(0.0731)	(0.0917)
Panel B: Variance Equation						
OR		-0.3228	-0.4585	-0.5161	-0.1872	1.9032***
		(0.2105)	(0.4547)	(0.3994)	(0.2192)	(0.6656)
Visib		0.0013	0.1056	0.3284	-0.1470*	0.5809
		(0.0714)	(0.1669)	(0.2557)	(0.0883)	(0.4571)
Wdsp		-0.0473*	-0.0274	-0.1114	0.0003	-0.0349
		(0.0261)	(0.0475)	(0.0713)	(0.0127)	(0.1056)
Temp		-0.0101*	0.0047	0.0036	-0.0071	0.0006
		(0.0058)	(0.0106)	(0.0101)	(0.0059)	(0.0175)
Constant		-3.8599***	-5.1867***	-5.6979***	-2.1756***	-8.1090**
		(0.3043)	(0.9371)	(1.3875)	(0.3508)	(3.1551)
Panel C: ARCH and GARCH Terms						
ARCH		0.2917***	0.2766***	0.0994***	0.1342***	0.0665***
		(0.0114)	(0.0214)	(0.0080)	(0.0082)	(0.0050)
GARCH		0.7058***	0.7568***	0.8865***	0.8409***	0.9301***
		(0.0067)	(0.0126)	(0.0087)	(0.0074)	(0.0043)
Observations	6,075	6,056	5,967	5,949	5,939	5,181

Notes: This table reports coefficient estimates from running the regressions for each of the six portfolios. Column 1 refers to OLS regression results for portfolio 1, Columns 2 to 6 refer to GARCH (1,1) regression results for portfolio 2 to 6, respectively. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.9: Equation 2.3 SUR model results

Portfolios	1	2	3	4	5	6
Fall	-0.0965***	-0.0982***	-0.1129***	-0.0485	-0.0903*	-0.2398**
	(0.023)	(0.020)	(0.025)	(0.042)	(0.052)	(0.098)
Fallwinter	0.0481*	0.0112	-0.0149	0.0209	0.0036	0.0131
	(0.026)	(0.022)	(0.028)	(0.048)	(0.060)	(0.112)
$Return_{t-1}$	0.0746***	0.1332***	0.1495***	-0.0487***	0.0041	0.0304***
	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)
$Return_{t-2}$	0.0442***	0.0790***	0.1328***	-0.0296***	0.0005	-0.0244**
	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)
Monday	-0.0005	-0.0064	0.0119	-0.1095***	-0.1329***	-0.2476***
	(0.020)	(0.017)	(0.021)	(0.036)	(0.045)	(0.084)
Tax	-0.0270	-0.0464	-0.0428	0.1561	0.1693	0.5222**
	(0.057)	(0.049)	(0.061)	(0.104)	(0.130)	(0.243)
Temp	-0.0029***	-0.0031***	-0.0039***	-0.0041**	-0.0055**	-0.0088*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)
Wdsp	-0.0001	-0.0002	0.0001	-0.0004	-0.0006	-0.0007
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Visib	-0.0159**	-0.0240***	-0.0256***	-0.0155	-0.0200	-0.0338
	(0.007)	(0.006)	(0.007)	(0.013)	(0.016)	(0.029)
Constant	0.2581***	0.2851***	0.2504***	0.3628***	0.4236**	0.6329**
	(0.073)	(0.062)	(0.078)	(0.133)	(0.166)	(0.310)
Observations	5,167	5,167	5,167	5,167	5,167	5,167
R-squared	0.060	0.114	0.139	-0.006	0.006	0.012

Notes: This table reports coefficient estimates from running the SUR regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.10: Equation 2.4 SUR model results

Portfolios	1	2	3	4	5	6
Fall	-0.1089***	-0.1105***	-0.1271***	-0.0451	-0.0823*	-0.2062**
	(0.021)	(0.018)	(0.022)	(0.038)	(0.048)	(0.089)
SAD	0.0268***	0.0128**	0.0043	0.0055	-0.0042	-0.0186
	(0.007)	(0.006)	(0.008)	(0.014)	(0.017)	(0.031)
$Return_{t-1}$	0.0740***	0.1328***	0.1494***	-0.0489***	0.0039	0.0303***
	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)
$Return_{t-2}$	0.0436***	0.0786***	0.1326***	-0.0298***	0.0004	-0.0245**
	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)
Monday	-0.0004	-0.0065	0.0116	-0.1093***	-0.1327***	-0.2470***
	(0.020)	(0.017)	(0.021)	(0.036)	(0.045)	(0.084)
Tax	-0.0136	-0.0341	-0.0293	0.1534	0.1615	0.4894**
	(0.056)	(0.048)	(0.060)	(0.103)	(0.129)	(0.241)
Temp	-0.0017	-0.0022**	-0.0031***	-0.0042**	-0.0060**	-0.0109**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Wdsp	-0.0001	-0.0002	0.0001	-0.0004	-0.0006	-0.0006
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Visib	-0.0151**	-0.0236***	-0.0254***	-0.0154	-0.0202	-0.0346
	(0.007)	(0.006)	(0.007)	(0.013)	(0.016)	(0.029)
Constant	0.1835***	0.2279***	0.1969***	0.3676***	0.4561***	0.7704**
	(0.071)	(0.060)	(0.075)	(0.129)	(0.161)	(0.301)
Observations	5,167	5,167	5,167	5,167	5,167	5,167
R-squared	0.061	0.115	0.139	-0.007	0.006	0.012

Notes: This table reports coefficient estimates from running the SUR regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.11: Equation 2.5 SUR model results

Portfolios	1	2	3	4	5	6
Fall	-0.0793**	-0.0900***	-0.0842**	-0.0653	-0.0859	-0.2050
	(0.033)	(0.028)	(0.035)	(0.061)	(0.076)	(0.142)
FallSAD	0.0173	0.0062	-0.0095	0.0120	-0.0031	-0.0190
	(0.011)	(0.009)	(0.012)	(0.020)	(0.025)	(0.047)
WinterSAD	0.0312***	0.0159**	0.0107	0.0025	-0.0048	-0.0184
	(0.008)	(0.007)	(0.009)	(0.015)	(0.019)	(0.035)
$Return_{t-1}$	0.0739***	0.1328***	0.1492***	-0.0489***	0.0039	0.0303***
	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)
$Return_{t-2}$	0.0436***	0.0786***	0.1324***	-0.0297***	0.0004	-0.0245**
	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)
Monday	-0.0005	-0.0065	0.0115	-0.1093***	-0.1327***	-0.2470***
	(0.020)	(0.017)	(0.021)	(0.036)	(0.045)	(0.084)
Tax	-0.0096	-0.0313	-0.0234	0.1507	0.1610	0.4896**
	(0.057)	(0.048)	(0.060)	(0.104)	(0.129)	(0.241)
Temp	-0.0016	-0.0022**	-0.0029***	-0.0042**	-0.0060**	-0.0109**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)
Wdsp	-0.0001	-0.0002	0.0001	-0.0004	-0.0006	-0.0006
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Visib	-0.0152**	-0.0237***	-0.0255***	-0.0153	-0.0202	-0.0346
	(0.007)	(0.006)	(0.007)	(0.013)	(0.016)	(0.029)
Constant	0.1752**	0.2222***	0.1849**	0.3733***	0.4571***	0.7701**
	(0.071)	(0.061)	(0.076)	(0.130)	(0.162)	(0.303)
Observations	5,167	5,167	5,167	5,167	5,167	5,167
R-squared	0.062	0.115	0.139	-0.007	0.006	0.012

Notes: This table reports coefficient estimates from running the SUR regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.12: Equation 2.6 SUR model results

Portfolios	1	2	3	4	5	6
OR	-0.1098***	-0.1407***	-0.1883***	-0.1151	-0.2485***	-0.6282***
	(0.040)	(0.034)	(0.043)	(0.073)	(0.092)	(0.171)
$Return_{t-1}$	0.0752***	0.1348***	0.1516***	-0.0484***	0.0041	0.0301***
	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)
$Return_{t-2}$	0.0447***	0.0802***	0.1345***	-0.0293***	0.0005	-0.0248**
	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)
Monday	-0.0010	-0.0078	0.0095	-0.1099***	-0.1343***	-0.2512***
	(0.020)	(0.017)	(0.021)	(0.036)	(0.045)	(0.084)
Tax	-0.0608	-0.0636	-0.0518	0.1238	0.1229	0.4064*
	(0.057)	(0.048)	(0.060)	(0.103)	(0.129)	(0.241)
Temp	-0.0026***	-0.0014*	-0.0008	-0.0034**	-0.0027	-0.0018
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Wdsp	-0.0001	-0.0002	0.0001	-0.0004	-0.0006	-0.0008
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Visib	-0.0155**	-0.0233***	-0.0245***	-0.0156	-0.0199	-0.0335
	(0.007)	(0.006)	(0.007)	(0.013)	(0.016)	(0.029)
Constant	0.2421***	0.1707***	0.0450	0.3225***	0.2546**	0.2054
	(0.055)	(0.047)	(0.059)	(0.101)	(0.126)	(0.234)
Observations	5,167	5,167	5,167	5,167	5,167	5,167
R-squared	0.058	0.112	0.137	-0.006	0.007	0.013

Notes: This table reports coefficient estimates from running the SUR regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 2.13: Joint test results for SUR model

Portfolios	FallWinter	SAD	FallSAD	WinterSAD	OR
Small Size Portfolios	0.0111**	0.0001***	0.0264**	0.0002***	0.0000***
large Size Portfolios	0.8842	0.5332	0.4934	0.8092	0.0008***

Notes: This table reports p-values of the joint tests. The null hypothesis is the estimated coefficients are jointly equal to zero. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level

2.6 Appendix To Chapter 2

Table A1: Fallwinter OLS model results

Portfolios	1	2	3	4	5	6
Fall	-0.0850***	-0.0713***	-0.1283***	-0.0331	-0.0567	-0.2244**
	(0.022)	(0.017)	(0.036)	(0.039)	(0.050)	(0.103)
Fallwinter	0.0215	0.0124	0.0142	0.0207	0.0125	0.0138
	(0.032)	(0.020)	(0.046)	(0.042)	(0.055)	(0.103)
$Return_{t-1}$	0.1334***	0.2867***	0.1993**	0.0784***	0.0900***	0.1034**
	(0.047)	(0.058)	(0.095)	(0.022)	(0.029)	(0.044)
$Return_{t-2}$	0.0895***	0.1257***	0.1312*	-0.0008	0.0125	-0.0290
	(0.028)	(0.032)	(0.069)	(0.024)	(0.022)	(0.033)
Tax	-0.0686	-0.0182	-0.0561	0.2418**	0.2262**	0.4821
	(0.070)	(0.053)	(0.065)	(0.103)	(0.113)	(0.311)
Monday	-0.0195	-0.0179	-0.0016	-0.1022***	-0.1371***	-0.2467***
	(0.023)	(0.017)	(0.023)	(0.035)	(0.047)	(0.082)
Temp	-0.0023*	-0.0019**	-0.0023*	-0.0028	-0.0026	-0.0081**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Visib	-0.0073	-0.0157**	-0.0243**	-0.0098	-0.0165	-0.0297
	(0.009)	(0.007)	(0.010)	(0.014)	(0.016)	(0.037)
Wdsp	-0.0002	-0.0003	0.0002	-0.0004	-0.0005	-0.0006
	(0.005)	(0.004)	(0.001)	(0.007)	(0.006)	(0.015)
Constant	0.2104**	0.1847***	0.1728	0.2511**	0.2434	0.5778**
	(0.085)	(0.056)	(0.116)	(0.118)	(0.155)	(0.293)
Observations	6,075	6,056	5,967	5,949	5,939	5,181
R-squared	0.034	0.135	0.082	0.011	0.012	0.017

Notes: This table reports coefficient estimates from running the OLS regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table A2: SAD OLS model results

Portfolios	1	2	3	4	5	6
Fall	-0.1077***	-0.0829***	-0.1495***	-0.0325	-0.0493	-0.1933**
	(0.023)	(0.018)	(0.038)	(0.038)	(0.049)	(0.097)
SAD	0.0241***	0.0128**	0.0200	0.0074	-0.0005	-0.0165
	(0.008)	(0.005)	(0.017)	(0.011)	(0.015)	(0.029)
$Return_{t-1}$	0.1323***	0.2858***	0.1986**	0.0783***	0.0900***	0.1034**
	(0.047)	(0.058)	(0.095)	(0.022)	(0.029)	(0.044)
$Return_{t-2}$	0.0885***	0.1249***	0.1304*	-0.0009	0.0126	-0.0290
	(0.028)	(0.032)	(0.070)	(0.024)	(0.022)	(0.033)
Tax	-0.0461	-0.0068	-0.0352	0.2419**	0.2194**	0.4520
	(0.069)	(0.053)	(0.064)	(0.101)	(0.111)	(0.310)
Monday	-0.0193	-0.0177	-0.0016	-0.1021***	-0.1370***	-0.2462***
	(0.023)	(0.017)	(0.023)	(0.035)	(0.047)	(0.082)
Temp	-0.0007	-0.0011	-0.0009	-0.0027*	-0.0030	-0.0100***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)
Visib	-0.0067	-0.0154**	-0.0238**	-0.0097	-0.0166	-0.0304
	(0.009)	(0.007)	(0.011)	(0.014)	(0.016)	(0.036)
Wdsp	-0.0002	-0.0003	0.0002	-0.0004	-0.0005	-0.0006
	(0.005)	(0.004)	(0.001)	(0.007)	(0.006)	(0.014)
Constant	0.1030	0.1300**	0.0784	0.2442**	0.2690*	0.7033***
	(0.075)	(0.052)	(0.127)	(0.110)	(0.138)	(0.262)
Observations	6,075	6,056	5,967	5,949	5,939	5,181
R-squared	0.035	0.135	0.083	0.011	0.012	0.017

Notes: This table reports coefficient estimates from running the OLS regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table A3: **FallSAD/WinterSAD OLS model results**

Portfolios	1	2	3	4	5	6
Fall	-0.0928**	-0.0677**	-0.0946**	-0.0613	-0.0942	-0.1947
	(0.040)	(0.033)	(0.044)	(0.066)	(0.077)	(0.152)
FallSAD	0.0193*	0.0078	0.0023	0.0167	0.0140	-0.0161
	(0.011)	(0.009)	(0.014)	(0.020)	(0.024)	(0.050)
WinterSAD	0.0262***	0.0149***	0.0281	0.0032	-0.0071	-0.0167
	(0.009)	(0.006)	(0.021)	(0.012)	(0.018)	(0.031)
$Return_{t-1}$	0.1323***	0.2857***	0.1981**	0.0783***	0.0900***	0.1034**
	(0.047)	(0.058)	(0.095)	(0.022)	(0.029)	(0.044)
$Return_{t-2}$	0.0884***	0.1248***	0.1300*	-0.0008	0.0126	-0.0290
	(0.028)	(0.032)	(0.070)	(0.024)	(0.022)	(0.033)
Tax	-0.0442	-0.0049	-0.0279	0.2380**	0.2133*	0.4518
	(0.069)	(0.053)	(0.065)	(0.102)	(0.112)	(0.310)
Monday	-0.0192	-0.0177	-0.0015	-0.1021***	-0.1370***	-0.2462***
	(0.023)	(0.017)	(0.023)	(0.035)	(0.047)	(0.082)
Temp	-0.0006	-0.0010	-0.0007	-0.0028*	-0.0031	-0.0100***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)
Visib	-0.0067	-0.0155**	-0.0241**	-0.0095	-0.0163	-0.0304
	(0.009)	(0.007)	(0.011)	(0.014)	(0.016)	(0.036)
Wdsp	-0.0002	-0.0003	0.0002	-0.0004	-0.0005	-0.0006
	(0.005)	(0.004)	(0.001)	(0.007)	(0.006)	(0.014)
Constant	0.0994	0.1263**	0.0639	0.2518**	0.2811**	0.7037***
	(0.075)	(0.052)	(0.134)	(0.110)	(0.138)	(0.261)
Observations	6,075	6,056	5,967	5,949	5,939	5,181
R-squared	0.035	0.136	0.083	0.011	0.012	0.017

Notes: This table reports coefficient estimates from running the OLS regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table A4: OR OLS model results

Portfolios	1	2	3	4	5	6
OR	-0.0915*	-0.0903**	-0.1679***	-0.0705	-0.2010**	-0.5795***
	(0.047)	(0.036)	(0.054)	(0.075)	(0.092)	(0.182)
$Return_{t-1}$	0.1347***	0.2887***	0.2027**	0.0783***	0.0892***	0.1028**
	(0.047)	(0.058)	(0.096)	(0.022)	(0.029)	(0.044)
$Return_{t-2}$	0.0908***	0.1275***	0.1343*	-0.0010	0.0116	-0.0298
	(0.028)	(0.032)	(0.070)	(0.024)	(0.022)	(0.033)
Tax	-0.0835	-0.0306	-0.0739	0.2178**	0.1768	0.3754
	(0.070)	(0.053)	(0.064)	(0.101)	(0.110)	(0.307)
Monday	-0.0202	-0.0187	-0.0034	-0.1023***	-0.1377***	-0.2498***
	(0.023)	(0.017)	(0.023)	(0.035)	(0.047)	(0.082)
Temp	-0.0015	-0.0010	-0.0003	-0.0026*	-0.0008	-0.0017
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Visib	-0.0064	-0.0149**	-0.0227**	-0.0098	-0.0165	-0.0294
	(0.009)	(0.007)	(0.010)	(0.014)	(0.016)	(0.038)
Wdsp	-0.0002	-0.0003	0.0002	-0.0004	-0.0006	-0.0007
	(0.004)	(0.004)	(0.001)	(0.007)	(0.007)	(0.016)
Constant	0.1515**	0.1161***	0.0279	0.2411***	0.1403	0.1848
	(0.066)	(0.040)	(0.060)	(0.089)	(0.120)	(0.238)
Observations	6,075	6,056	5,967	5,949	5,939	5,181
R-squared	0.033	0.133	0.079	0.011	0.013	0.018

Notes: This table reports coefficient estimates from running the OLS regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Chapter 3 The SAD effect on UK Stock Portfolio Turnover

3.1 Introduction

Over the past decades individual investors influence on financial markets have received an increased level of interest in economics and financial studies, whilst also capturing the attention of the public, including economists and investors. A large body of psychological research has shown that individual emotion has a detrimental impact on the decision-making process (Finucane et al., 2000; Schwarz, 2000). Researchers have found evidence to support the idea that psychological factors have a tremendously effective impact on the investors decision-making process in financial markets. Schwarz (2000) discussed multiple links between emotion, cognitive ability and decision-making process, and argued that emotions can bias the decision-making process. Slovic et al. (2005) studied the affect heuristic on smokers, using surveys to trace the heuristic impacts on how people perceived and evaluated risks, and ultimately how the heuristic influences people's decision-making processes. The result revealed that the affect heuristic can lead to biases in the decision-making processes. Literature also states that emotional reactions are able to mislead people and people might make wrong judgements about their risk-taking behaviour (Finucane et al., 2000; Loewenstein et al., 2001). These studies suggested that the risk aversion level of people is related to their emotions at that moment. Therefore, investors' mood directly affects their risk perceptions, and hence ultimately influences their financial decision-making, which is proposed to have a great impact on financial markets. At the forefront of this research area is behavioural finance, combining the disciplines of economics, finance and psychology.

Psychological literature has documented the relationship between weather and mood. It has been proven that an individual's mood status is largely affected by the surrounding environment, such as temperature, humidity and sunshine levels. Keller et al. (2005) analysed the contingent effects of the weather on mood and concluded that pleasant weather improves mood and broadens cognitive ability. In particular, pleasant levels of humidity (Sanders and Brizzolara, 1982), warm temperatures (Howarth and Hoffman, 1984) and high levels of sunshine (Schwarz and Clore, 1983), all have been proven to be associated with pleasant moods, and vice versa. Despite these findings, some researchers argued that the relationship between human emotions and weather factors is still a controversial area. Watson (2000b) carried out an experiment involving a total of 478 students over a long period, in order to test the weather effect hypothesis. He found no significant evidence to support the relationship between mood and weather variables. Hardt and Gerbershagen (1999) studied around 3000 chronic pain patients over a 5-year period. The questionnaire result showed that these patients' depression levels did not correlate with the time of the year, nor the amount of sunshine hours.

Combining these subject areas, researchers have begun to investigate the relationship between weather factors and financial markets. Most of the existing studies have focused on the relationship between stock markets and weather, especially stock returns. Saunders (1993) showed a significant correlation between New York city cloud cover and major stock indices to support the hypotheses that investor psychology influences asset prices. Hirshleifer and Shumway (2003) extended his research and investigated stock exchange data for 26 counties, concluding a negative correlation exists between cloud cover and international stock returns. Meanwhile, some studies have pointed out that weather factors can also influence the stock trading behaviour of individual investors. Chang et al. (2008) found that weather affects not only stock returns, but also investors' intra-day trading behaviour, such as turnover. Moreover, some other researchers have argued that biorhythms such as Seasonal Affective Disorder (SAD), play an more important role in affecting financial markets other than the daily weather aspect. Kamstra et al. (2003) documented a significant SAD effect in stock returns, based on their analysis of 37 countries' stock indices. Dowling and Lucey (2008) supported their argument and stated that SAD has a stronger relationship with stock markets than weather factors. By extending these studies, in order to capture the mood effects on trading behaviours, this chapter investigates the SAD effect in the UK stock turnover, and some weather and market anomalies are considered.

This chapter makes the following contributions to the existing literature. Firstly, previous literature mostly analyses the link between weather and investors' decision-making by focusing on the relationship between weather and stock returns (Chang et al., 2008; Saunders, 1993). However, it is expected that mood not only affects stock prices but also trading behaviour such as the trading volume. In this chapter, the daily turnover of all stocks traded on the London Stock Exchange (LSE) are collected as proxy variable for trading behaviour, in order to examine the influence of SAD on investors' trading behaviour.

Secondly, some studies, like Saunders (1993) and Cao and Wei (2005), only investigate limited weather variables (cloud cover and temperature). Empirical studies have shown that mood-proxy variables ranging from temperature, wind speed, visibility, to SAD are all related to stock market activities. In addition, London local daily weather conditions only affect people living around London, while SAD is a universal symptom that everyone in the world might experience in the fall, when days begin to shorten. Hence, three important weather variables are controlled in the specifications, in order to analyse the SAD effect in the UK stock market daily turnover.

Finally, past studies mainly examine the impact of weather variables on stock market indices or overall market turnover (Kamstra et al., 2003; Lu and Chou, 2012; Saunders, 1993). To the best of my knowledge, this is the first article that focuses on the SAD effect on turnover of different UK stock portfolios. In particular, by extending the prior studies, six stock portfolios were constructed, based on the characteristics of the stocks to exploit the SAD effect on different portfolios. Krivelyova and Robotti (2003) found a more pronounced effect of geomagnetic storms on small capitalization stocks. They argued that individual investor, who usually hold more small cap stocks than large cap stocks, are more likely to be affected by the change of mood, compared to institutional investors, hence they find stronger weather effects on small cap stocks. Our results also indicates that the SAD effect on small size stock portfolios are more pronounced than large size stock portfolios, which means that when individual investors suffer from SAD and become depressive, they tend to adjust their investment portfolios.

This chapter studies the relationship between mood and investor trading behaviour by testing the SAD effect on stock portfolios turnover. The sample data of this chapter consists of all stocks traded on the London Stock Exchange (LSE) on a daily basis from January 1988 to December 2011. The null hypothesis is the LSE stock portfolio turnover not being systematically affected by SAD, against the alternative hypothesis that stock turnover was systematically affected by SAD, and that SAD affects different portfolios differently. The underlying assumption is that weather and some other mood-proxy variables affect investor mood, and the change of mood influences the investor decision-making process, hence trading behaviour is associated with these mood-proxy variables. The regression results of this chapter shows that when investors suffer from SAD, the volatility of turnover will be increased and the SAD effect is more pronounced on small size portfolios. Among all the SAD related variables, OR is the most appropriate variable that describe the SAD effect on investor trading behaviour. This chapter demonstrates the impact of SAD on the UK stock portfolio turnover and how SAD affects different stock portfolios differently.

This chapter is structured as follows. Section 2.2 reviews the previous literature and Section 2.3 discusses the data and portfolios. Section 2.4 discusses the research methodology and results. Finally, Section 2.5 concludes the exploration of this issue.

3.2 Literature Review

This section will provide a comprehensive review of past studies that consider the relationship between mood and trading behaviour. Initially, environmental factors that influence human emotion are considered, then the literature is presented, showing how mood plays a crucial role in decision-making processes. Finally, by linking these studies, the relationship between environmental factors and trading activities are explored.

3.2.1 SAD, Weather and Mood

The exploration of the determinants of mood has long been of interest to clinical psychologist. People are sensitive to the surrounding environment and weather is considered as an important factor that influences daily human feelings. Any significant change in weather, such as sudden heavy rain, might affect people both psychologically and physically. Once weather changes greatly excess our expectations, psychological discomfort is often felt immediately. The result of psychological discomfort is a change of mood.

Human beings are gifted with amazing sensor systems that work with the brain to process and interpret data from the surrounding environment. Eyes, there are have two different types of light sensors which sense light intensity and colour, and enable us to feel the stimuli of visibility and the levels of sunshine. Sensors in our ears enable us to detect orientation in the gravitational field and air pressure. In skin, there are at least four different types of nerve endings: heat sensitive; cold sensitive; pain sensitive; and pressure sensitive. These cells provide humans with the sense of touch, of temperature and of air pressure. Thus, skin makes us feel the stimuli of temperature, wind, sunshine and humidity. The human sensory system is constantly taking in information from the surrounding environment without any judgement. The brain processes and interprets information that is accessed via the nervous system. Therefore, all these various senses are capable of responding to the the change in the weather immediately. After the brain receives and processes this weather information, mood is affected (Damasio, 2000; Edelman, 2006).

A number of psychological studies have found there is a significant relationship between weather and mood. Page et al. (2007) studied the relationship between daily temperature and daily suicide counts in England and Wales between 1 January 1993 and 31 December 2003, and the result concluded there is an increased risk of suicide in summer when the temperature is above 18 degrees Celsius. Pleasant weather conditions such as, warm temperature and lots of sunshine, are claimed to be in favour of positive social relationships and improving mood. Guéguen (2013) proposed that there is a high chance that women to agree to their confederate's courtship on sunny days rather than on bad weather days and he believes that positive mood induction on sunny days may explain such results. Cunningham (1979) did two experimental case studies, both of which proved that the increasing amount of sunshine and higher temperatures could significantly help to improve participants' moods. Howarth and Hoffman (1984) assessed the relationship between mood and weather by tracking 24 male university students over 11 consecutive days. The third version of the Howarth Multiple Adjective Check List (HMACL-3) was used as the instrument to evaluable mood. The HMACL-3 reports were collected under different weather conditions, weather variables included: precipitation, temperature, wind, hours of sunshine, humidity and barometric pressure. They found a significant effect on mood correlated with the weather variables, especially with regards to humidity, temperature and amounts of sunshine.

However, some other researchers have argued that weather have little or indirect effect on mood. Denissen et al. (2008) tested the effects of six weather parameters (temperature, wind power, sunlight, precipitation, photoperiod, and air pressure) on mood and concluded that the correlation between mood and weather is very limited. Keller et al.

(2005)) examined 605 participants responses in three separate studies to examine the effect of temperature and barometric pressure on mood and cognition. They found no consistent evidence to support the hypothesis that pleasant weather improves mood all year round. They also argued that the relationship between weather and mood only observed during spring is consistent with the impact of seasonal affective disorder (SAD), people recover from SAD in the spring and their moods are improved. Rastad et al. (2005) also found a strong SAD effect on mood, They sent the Seasonal Pattern Assessment Questionnaire (SPAQ) to a random sample of 2500 persons between 18 and 64 years old. The survey results indicated a total of 19.3% people were negatively affected by winter depression in everyday life and they argued that SAD sufferers experience depressive symptoms is common in the population .

Seasonal affective disorder (SAD) is clinically known as a kind of depressive disorder, it is caused by the reduction of total daylight time in the fall. Variation in the hours of daylight leads to variation in mood, and SAD is a type of seasonal depression that occurs mostly during fall and winter when days get shorter (Rosenthal, 1998). The type of depression could sap people's energy and make people feel moody. As study by Molin et al. (1996) further confirmed the SAD symptoms, they investigated the results of 13 item Beck Depression Inventory (Beck and Beamesderfer, 1974) from 126 patients who suffered from seasonal depression and found the length of the day was strongly correlated with seasonal depression.

Therefore, among these mood-proxy variables, SAD are found to be closely related to mood, and individuals with SAD report a strong seasonal depression (Denissen et al., 2008). In this chapter, SAD variables are constructed to investigate the mood effect on investors trading activities, while some weather factors are considered as controlled variables.

3.2.2 Mood and Decision-Making

Traditional psychology and economic theories hypothesized that people evaluate their desirability, and potential outcomes and combine all related information through an unbiased expectation calculus to make final decisions. Mood, as an emotional state and a transient state of feeling, has no impact on decision-making process. However, some psychology and behaviour finance research has attempted to dispute this conclusion and argued that mood plays a significant role in the decision-making processes (Damasio, 2008; Loewenstein et al., 2001). Emotional reactions to decision-making choices often diverge from usual cognitive assessments of those choices, emotional reactions often drive decision-making. The seminal work of Damasio (2008) demonstrated that emotions can violate or motivate rational thoughts by studying decision-making processes of people with impaired ability to experience emotions. Mayer et al. (1992) invented the term mood congruency in judgements to describe situations in which mood affects an individual's thoughts, and influences that individual's decisions through three sample studies. According to their research, people with pleasant moods are more likely than those people with unpleasant to expect nice weather for outdoor activities, because their pleasant mood brings them optimistic expectation. McFarland et al. (2003) proposed that people with pleasant moods tend to judge those around them to be more blissful compared to those in an unpleasant mood, who tend to judge surroundings less favourably. Simple put, some recent literature has demonstrated that the emotional states of people have a great impact on their decision-making process. We have provided some more details about how mood influences decision-making process in chapter 2, therefore, in this section we focus on how mood impacts trading decisions and ultimately stock turnover.

In finance markets, investors hold different risk perceptions and their investment decisions are mostly based on their risk preferences. Decision-making under risk and uncertainty is an very active research topic. Recent work has proposed that mood has a complex influence on risk preferences and decisions involving risk-taking. An experiment carried out by Isen et al. (1988) focused on the relationship between induced positive affect and decision-making. They provided candy as reward to half of the participants in order to induce a positive mood, then these participants were asked to anticipate a decision-making gamble game with poker chips representing their risk perception. On each trial, participants were required to indicate their choices for either a gamble that had both outcomes fixed at a particular amount of points (for example: the same points were rewarded or deducted depending on the occurrence of an event) and another gamble that had one fixed outcome and one variable outcome (the reward and punishment points were different). They found that participants with a pleasant mood demonstrated an increased preference for avoiding losses. The experiment concluded that individuals in a pleasant mood were more risk averse than individuals in neutral or bad moods. The argued that individuals in bad moods would image themselves having nothing much to lose, so being desperate and willing to select choices that offer the possibility of a substantial return, thus they tended to choose high risk and reward options. This experiment showed that people' risk preferences are subjected to their mood, people in bad mood are more willing to engage in risk-taking activities, thus mood have a great impact on investors' decision-making process.

An alternative view is that people tend to evaluate the future optimistically when they are in a pleasant mood. Wright and Bower (1992) showed that happy people tend to be optimistic and, in contrast, sad people tend to be pessimistic. According to their study, investors with pleasant mood would expect a bull market and increase their buying activities, anxious or depressed people tend to avoid risk and leave the market. Experiments performed by Eisenberg et al. (1998) further confirmed the argument. In the experiments, the subjects were college students in an abnormal psychology class at the University of Pennsylvania. They were asked to completed a questionnaire related to what they would choose in hypothetical decision-making scenarios, when choosing between a risky option and a relatively safe option. The results of the two experiments were replicated, both showed depressive symptoms correlated with anxiety and risk-aversion is correlated with both depression and anxiety.

In summary, the psychological studies cited above concluded that people' risk preferences are associated with their emotion status, and mood has a significant effect on the decision-making process. Investors are believed to be significantly affected by their emotion statues when engaging in stock market activities. For example, when investors are in a pleasant mood, they could be optimistic and expect a bull market, these investors are more willing to buy stocks; on the other hand, depressed investors tend to be pessimistic and leave the market. In this last section, we recognized that SAD is directly associated with mood, SAD sufferers are known to be seasonal depressed. Therefore, investors who suffer from SAD sufferers are depressed and pessimistic, they are more likely to adjust their investment portfolios.

3.2.3 SAD and Trading Behaviour

Studies on the relationship between weather and trading behaviour have proven the presence of such a relationship. Goetzmann and Zhu (2005) studied the weather effect on US stock markets trading activities. They applied a large panel database of individual trading accounts in five major cities to test whether the local weather affected individual trading activities. The result outlined that the average daily bid-ask spread (liquidity) widened on cloudy days and narrowed on sunny days in NYSE, hence they showed that cloudiness had a tremendous effect on investor trading behaviour. Chang et al. (2008) also focused on NYSE, finding that, although cloud cover impacted on stock returns, it was only significant during the first 15-min of the opening of the stock market, when it had a significantly positive effect on return volatility and a negative effect on market depth[1] over the entire day. Studies on international stock markets also support the association between cloud cover and trading activities. Goodfellow et al. (2010) concluded that could cover impacted on liquidity in the Frankfurt Stock Exchange and Lu and Chou (2012) found that trading activities were significantly reduced on cloudy days in the Shanghai Stock Exchange. These results provide solid evidence to support the hypothesis that investors are optimistic on sunny days and pessimistic on cloudy days. The optimistic mood makes investors more likely to engage in stock market activities and a pessimistic mood makes investors more likely to avoid risks. Therefore, these studies suggested that cloud cover has a significant impact on investor trading behaviour. Overall, the literature suggests that cloudiness and pessimistic mood may be responsible for distorting investors' trading behaviour.

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[1] The average quote size at the best bid and ask prices

A large body of studies have attempted to confirm the relationship between weather and trading behaviour by using some other weather variables. Limpaphayom et al.(2005) employed an in depth analysis on the Chicago Mercantile Exchange(CME) to test the relation between local weather conditions and floor traders of S&P500 index futures contracts trading behaviour. The result indicated that the effective bid-ask widens on windy days in CME and morning high wind speed leads to both lower trader order and trader income in the afternoon. They provided a possible explanation, explaining that morning wind affects the daily floor trader sentiment through the ion imbalance and results in traders exhibiting a quoted imbalance on windy days. Keef and Roush (2007) investigated the wind effect on returns of three New Zealand stock indices. They documented a negative correlation between wind speed and stock returns and suggested the fresh winds of Wellington led to a mood of growing pessimism among investors. Krivelyova and Robotti (2003) tested the relationship between geomagnetic storms(GMS) and international equity returns. Their results provided evidence that GMS leads to a lower global equity returns. They argued that geomagnetic storms have a profound effect on investor sentiment, which in turn affects their risk perception. Severe geomagnetic storms makes investors more risk averse, hence the stock returns will decrease. The widespread explanation of the observed weather effect on the stock market is that weather has a significant influence on mood, then investor' mood is associated with investors risk perceptions, which in turn affects their trading behaviour.

Some other studies have argued that human body biorhythms, such as SAD and the lunar phase, have a more significant effect on mood and trading behaviour, rather that daily weather conditions. Research paper from Kamstra et al. (2003) hypothesise SAD, a mental depression symptom with seasonal patterns which is caused by the lack of sunlight in the fall, is associated with lower stock returns in the fall and higher stock returns in the winter. They explained that SAD-suffering investors tend to avoid risks when days get shorter in the fall and resume risk perceptions when days get longer after the winter solstice. Kamstra et al. (2003) constructed variables to measure SAD and controlled some weather variables (cloud cover, precipitation and temperature) and some well-known market anomaly variables (the Monday effect and the tax-loss selling effect) to investigate whether there is a relationship between SAD and numerous stock exchange returns. They applied ordinary least squares estimation and found supportive evidence of a significant SAD effect in most of international stock markets and demonstrated a clear link between weather, mood and trading behaviour. Kamstra et al. (2012) employed modern statistical methods, such as system-of-equations generalized method of moments (GMM) estimation and OLS-based time-series estimation account for cross-sectional correlation (SUR), to further test the influence of SAD on global equity markets. Their findings confirmed the SAD effect on international stock markets.

Lu and Chou (2012) investigated the hourly turnover of the Shanghai Composite Index and found that SAD affects trading behaviour, as investors are less willingness to trade when they suffer from SAD. Dowling and Lucey (2008) grouped 37 countries according to the distances between the equator and the counties to analyse the SAD effect in different stock markets. They employed the GARCH method and showed the existence of the SAD effect on international stock markets and the significance of the SAD effect was greater for stock markets located far away from the equator. Added to this, Dowling and Lucey (2008) also found a more pronounced SAD effect in riskier small capitalization indices and argued that individual investors are more likely to be affected by mood in the pricing of small capitalisation indices. Kliger and Levy (2008) studied the influence of SAD on investors' provability weighting functions(PWFs)and showed that SAD led investors to systematically distort their PWFs.

Thus, empirical studies cited above overall provided supportive evidence of mood-proxy variables significantly influencing investor trading activities. Specifically, pleasant mood is associated with greater willing to trade and pessimistic mood leads reluctant to trade. Among all the proxies for mood influences on investor trading behaviour, SAD is found to be the most important and significant mood-proxy variable. We hypothesize that SAD-influenced investors tend to have pessimistic market expectations and leave the market, which decreases the stock turnover in the fall; when they recover from SAD, the stock turnover would back to normal.

3.2.4 Other Anomaly Effects

The literature has also documented some well-known market anomalies, based on trading activities, especially the trading amount. Osborne (1962) argued that individual investors have more time to make financial decisions over the weekend, thus they are more active in the financial markets on Mondays. However, institutional investors are less active in financial markets on Mondays as they usually have meeting and planning sessions on Mondays. His argument is supported by Lakonishok and Maberly (1990), which documented that NYSE trading volumes on Mondays is lower than on the others days of the week, and that there is a tendency for normal investors to increase trading activities on Mondays. The reduction in trading volume on Mondays implies less trading activities by institutional investors. Therefore, in order to analyse the SAD effect on stock turnover, the Monday effect is controlled in our models.

Rozeff and Kinney (1976) observed a seasonal pattern on the New York Stock Exchange namely that stock returns on January were significantly higher than the remaining eleven months. Brown et al. (1983) clarified their research further by pointing out that this phenomenon is related to the abnormally high returns on small firm stocks. He documented a significant portion of the small firms' higher risk-adjusted returns occur in the first trading week of January. Roll (1983) argued that this 'January effect" is due to the tax-loss selling at the end of the tax year. He also provided supporting evidence that small size stocks are affected more by the tax-loss selling than the large size stocks. Reinganum (1983) also reported similar findings. The tax-loss selling is an irrational behaviour by investors. These investors are mainly tax-sensitive individual investors who disproportionately buy small size stocks, and they tend to sell stocks before the tax year ends, in order to offset capital gains. Ng and Wu (2006) confirmed the systematic stock preferences of individual investors for small capitalisation stocks.

The UK tax year starts in April, thus for the UK stock market under the tax-loss selling hypothesis, there is an April effect. This chapter aims to analyse the SAD affect in different stock portfolio turnover. The studies cited above suggest that the tax-loss selling effect has a great influence on stock markets. Therefore the tax-loss selling effect is controlled in our models.

3.3 Data and Portfolios

3.3.1 Weather Data

This chapter investigated the SAD effect on the LSE stock portfolio turnover. London locate weather data are controlled in the specifications. The London weather data is obtained on a daily basis from the the National Oceanic and Atmospheric Administration (NOAA)[2], an agency which provides daily weather observations through local weather stations in the world's major cities. The weather data in London was extracted from the London city station(Station ID: 03768399999)within the global summary of the day (GSOD) database from January 1988 to December 2011.

The weather data adopted in this chapter are daily mean temperature (in Fahrenheit), daily mean wind speed (in knots) and daily mean visibility(in miles). We also constructed the daily UK specific SAD and Onset/Recovery (OR) variables, in order to capture the SAD effect on mood. Following Kamstra et al. (2003)) the $SAD_{i,t}$ variable is constructed in the same way as in Chapter 1, which stands for the normalized length of the night in London. In the Northern Hemisphere, $SAD_{i,t}$ equals to $H_t - 12$ for trading days in fall and winter, equals to zero otherwise. And $H_t = 24 - 7.72 * \arccos(-\tan(\frac{2\pi\delta}{360}\tan(\lambda_t)$, where δ represents the latitude of London and λ represents the sun's declination angle, $\lambda = 0.4102 * \sin(\frac{2\pi}{360})(x_t - 80.25)$, x_t represents the number of the day in the year. The Onset/Recovery(OR)[3] variable was introduced by Kamstra et al. (2012), which reflects the changes in the proportion of SAD symptoms sufferers. They claimed OR was an

[2] See Website: http://www.noaa.gov/

[3] Data is available from Website: http://www.markkamstra.com/data.html.

improved SAD measure as it closely captured the timing of depression symptoms experienced by SAD sufferers. Kamstra et al. (2003) stated that the amplitude of SAD is positively correlated to latitude, and Khaled and Keef (2013) suggested the following equations to convert the New York OR to OR for other cities.

$$\gamma^j = \frac{Latitude^{City_i}}{Latitude^{NewYork}} \tag{3.1}$$

$$OR^{City_i} = \gamma^j * OR^{NewYork} \tag{3.2}$$

Therefore, The London OR can be obtained by substituting the latitudes of London and of New York in the equations above[4].

3.3.2 Equity Data and Portfolios

The sample data consists of daily turnover by volume, the market equity value and the ratio of book equity to market equity of all stocks traded on the London stock exchange (LSE) , within the period January 1988 to December 2011. All our equity data were obtained from DataStream. Turnover was calculated to be separated within each Portfolio, by averaging daily trade volume of each stock in the Portfolio over the shares outstanding for all the stocks within the Portfolio.

The table 3.1 shows the construction of the portfolios. Six portfolios were constructed

[4] Latitude of London is 51°N and latitude of New York is 41°N.

based on the characteristics of the stocks. The six portfolios were the intersections of 2 portfolios formed on market equity(size) and 3 portfolios formed on the ratio of book equity to market equity (BM ratio). The breakpoint for market equity(size) portfolios was the median value of LSE market equity, so we had large size and small size portfolios. The breakpoints for BM ratio portfolios are the 30^{th} and 70^{th} LSE BM ratio percentiles. We named these portfolios growth, neutral and value portfolios[5], respectively. Due to both the size and the BM ratio of the stocks not being constant within the whole time period, the portfolios are reconstructed on a yearly basis.

The small size stocks refer to stocks with a relatively small market capitalization. With respect to large size stocks, small size stocks are not as financially stable, which leads to high volatility, and it is also associated with high risks for investors. The BM ratio is the ratio of a stock's book value to its market value. The BM ratio is a comparison of a company's net asset value per share to its share price. It is an important ratio in financial markets which reflects the market prices of a company relative to its actual worth. A high BM ratio indicates undervalued stock, which a low BM ratio refers to overvalued stock. Low BM ratio stocks are also known as growth stocks, which means earnings for these companies are expected to grow faster than average growth rate of the companies in the same industry. High BM ratio stocks are also known as value stocks, and are considered to be trading at a lower price relative to it's fundamentals. Institutional investors generally seek out stocks with high BM ratios for their investment portfolios, in order to gain constant profits. However, investing in small size and growth stocks is the opportunity for individual investors to outperform institutional investors. Because institutional investors

[5] Growth portfolio include stocks within 0^{th} to 30^{th} LSE BM ratio percentiles, neutral portfolio include stocks within 30^{th} to 70^{th} LSE BM ratio percentiles and value portfolio include stocks within 70^{th} to 100^{th}LSE BM ratio percentiles.

have restrictions that limit them from buying large portions of single stocks or investing in financially unstable stocks, individual investors are more flexible in investing small size and growth stocks, which are able to increase their profits at a faster speed than large size stocks, and have the potential to deliver greater capital appreciation for investors. Therefore, individual investors generally pay more attention to small size and growth stocks than institutional investors.

3.3.3 Descriptive Statistics

The descriptive statistics of the weather and equity data is presented in this section. Table 3.2 shows descriptive statistics of the equity data. The mean turnover of small size stocks is lower than mean turnover of large size stocks, the mean turnover of small size stock portfolios is around 0.3% while the mean turnover of large size portfolios is around 0.5%. Portfolio 1 has the highest maximum turnover standard deviation among all the portfolios, which means the small size and growth stock are most volatile stocks. Portfolio 6 has the second highest turnover standard deviation, the turnover standard deviation of Portfolio 2-5 do not have many differences. Small size portfolios exhibit a higher average skewness than large size portfolios, and all portfolios are positively skewed. All the portfolio turnover displays high kurtosis, which is common in stock markets.

Table 3.3 shows summary statistic of weather variables for all portfolios. The daily mean temperature is 53.41 in Fahrenheit, with standard deviation of 10.22. The daily mean wind speed is 8.495 knots, with the highest standard deviation of 13.32 among all weather variables. The daily mean visibility is 6.101 miles, with the lowest standard deviation of 1.1140. The maximum wind speed value is 999.9 knots, which is much higher than the mean and medium of wind speed, indicating extreme weather conditions, such as typhoons and storms. The minimum visibility is 0 miles, which means people can hardly see during the periods. Temperature and wind speed are positively skewed, while visibility is skewed to negative. All the weather variables demonstrate high kurtosis, as expected.

3.4 Methodology and Results

3.4.1 OLS and LM Test

A large number of studies have investigated the weather effect in financial markets useing the Ordinary least square (OLS) method or generalized autoregressive conditional heteroskedasticity (GARCH) method to estimate the correlation between weather variables and equity data. Initially, the OLS model regressions are adopted.

Firstly, two variable are defined as follows:

$$\Phi = \beta_{tax,i} Tax_{i,t} + \beta_{Mon,i} Mon_{i,t} \tag{3.3}$$

$$\Gamma = \rho_{1,Temp} Temp_{i,t} + \rho_{1,Wdsp} Wdsp_{i,t} + \rho_{1,Visib} Visib_{i,t} \tag{3.4}$$

These two variables are well-know market anomaly factors and weather variables that influence stock market activities, respectively. Where ϕ stands for the Tax-Loss Selling effect and the Monday effect. Tax_t is a dummy variable equals to one on the first five trading days. the last trading day of Britain fiscal year, equals to zero otherwise; Mon_t is a dummy variable equals to 1 when the trading day is Monday, equals to 0 otherwise. Γ serves as control for the daily weather effect in the UK stock market. $Temp_t$ is the mean temperature of the trading day; $Wdsp$ is the mean wind speed of the trading day; $Visib_t$ is the mean visibility of the trading day.

Following Kamstra et al. (2012), the OLS model regressions[6] employed in this chapter are as follows:

$$Tur_t = \alpha_i + \rho_{1,i} Tur_{i,t-1} + \rho_{2,i} Tur_{i,t-2} + \Phi + \beta_{i,Fall} Fall_{i,t} + \beta_{i,Fallwinter} Fallwinter_{i,t} + \Gamma + \sigma_{i,t} \tag{3.5}$$

$$Tur_t = \alpha_i + \rho_{1,i} Tur_{i,t-1} + \rho_{2,i} Tur_{i,t-2} + \Phi + \beta_{i,Fall} Fall_{i,t} + \beta_{i,SAD} SAD_{i,t} + \Gamma + \sigma_{i,t} \tag{3.6}$$

$$\begin{aligned} Tur_t = &\alpha_i + \rho_{1,i} Tur_{i,t-1} + \rho_{2,i} Tur_{i,t-2} + \Phi + \beta_{i,Fall} Fall_{i,t} \\ &+ \beta_{i,FallSAD} FallSAD_{i,t} + \beta_{i,WinSAD} WinSAD_{i,t} + \Gamma + \sigma_{i,t} \end{aligned} \tag{3.7}$$

$$Tur_t = \alpha_i + \rho_{1,i} Tur_{i,t-1} + \rho_{2,i} Tur_{i,t-2} + \Phi + \beta_{i,OR} OR_{i,t} + \Gamma + \sigma_{i,t} \tag{3.8}$$

[6] We employ MacKinnon and White (1985) heteroskedasticity-consistent errors.

where,

$$\sigma_{i,t} \sim N(0, h_t) \tag{3.9}$$

Where Tur_t is the daily turnover of the portfolios, $Tur_t - 1$ and $Tur_t - 2$ are the first and second lags of the daily turnover. The two lagged turnover is adopted as explanatory variables so the conditional mean part of the model is appropriately specified. $Fall_t$ is a dummy variable with a value of 1 in the fall, zero otherwise; $Fallwinter_{i,t}$ is a dummy variable with a value of 1 in the fall and winter, zero otherwise; $SAD_{i,t}$ is the normalized length of night variable for UK; $FallSAD_{i,t}$ only takes value of the $SAD_{i,t}$ in the fall, zero otherwise; $WinSAD_{i,t}$ only takes value of the $SAD_{i,t}$ in the winter, zero otherwise. In order to capture the change caused by the SAD effect during the entire year, providing that SAD only takes value in the fall and winter, $OR_{i,t}$ is included in the specifications. OR presents changes in the proportion of SAD sufferers,based directly on the diagnoses of depression (Lam, 1998).

Tables A5 to A8 show OLS regression results are in appendix[7]. However, The OLS estimation ignores the time-varying volatility of turnover, which is the ARCH effect. In this chapter, the presence of ARCH effects were detected in the data by using Engle's Lagrange Multiplier (LM) test. The LM test results are shown in Table 3.4, where the ARCH effect is presented in Portfolio 2-6 in all estimations, as the P-values are significant at 1% level, thus the GARCH (1,1) model is more appropriate than OLS estimation to examine the correlation between turnover and SAD variables for Portfolios 2 to 6, as it

[7] The estimated coefficients are very small in all methods, which are typical in the literature related to stock data, especially turnover

takes account of the time varying conditional variance of the data. The p-values of Portfolio 1 are 0.9901, hence the null hypothesis is accepted and there is no serial correlation in residuals, which means there is no ARCH effect in Portfolio 1. The OLS model results are still efficient for Portfolio 1. Therefore, we applied the GARCH (1,1) model to analyse the relationship between SAD variables and turnover for Portfolio 2-6 and the OLS model for Portfolio 1.

3.4.2 GARCH Model and Result

The GARCH model developed by Bollerslev (1986) was generalized from the seminar paper of Engle (1982) that introduced the ARCH model. Chang et al.(2006) argue that the GARCH model might be a better model for estimation, as stock market data generally exhibits heteroscedasticity. Hence the GARCH model is more appropriate as it takes the time-varying turnover volatility into account. Thus the Bollerslev (1986) GARCH (1,1) model is employed in this chapter. We follow Kamstra et al. (2012) in constructing regression models for this chapter to investigate the SAD effect on the UK stock portfolio turnover.

The GARCH(1,1) regressions which are employed in this study are as follows:

$$Tur_t = \alpha_i + \Phi + \beta_{i,Fall} Fall_{i,t} + \beta_{i,Fallwinter} Fallwinter_{i,t} + \Gamma + \sigma_{i,t} \tag{3.10}$$

$$Tur_t = \alpha_i + \Phi + \beta_{i,Fall} Fall_{i,t} + \beta_{i,SAD} SAD_{i,t} + \Gamma + \sigma_{i,t} \tag{3.11}$$

$$Tur_t = \alpha_i + \Phi + \beta_{i,Fall} Fall_{i,t} + \beta_{i,FallSAD} FallSAD_{i,t} + \beta_{i,WinSAD} WinSAD_{i,t} + \Gamma + \sigma_{i,t} \tag{3.12}$$

$$Tur_t = \alpha_i + \Phi + \beta_{i,OR} OR_{i,t} + \Gamma + \sigma_{i,t} \tag{3.13}$$

where,

$$\sigma_{i,t} \sim N(0, h_t) \tag{3.14}$$

These four equations above are the mean equations for the GARCH(1,1) model. The variance equations are as follows, respectively:

$$h_t = \eta_i + \mu_i h_{t-1} + \tau_i \sigma_{t-1}^2 + \theta_{i,Fall} Fall_t + \theta_{i,Fallwinter} Fallwinter_t + \Gamma \tag{3.15}$$

$$h_t = \eta_i + \mu_i h_{t-1} + \tau_i \sigma_{t-1}^2 + \theta_{i,Fall} Fall_t + \theta_{i,SAD} SAD_t + \Gamma \tag{3.16}$$

$$h_t = \eta_i + \mu_i h_{t-1} + \tau_i \sigma_{t-1}^2 + \theta_{i,Fall} Fall_t + \theta_{i,FallSAD} FallSAD_t + \theta_{i,WinSAD} WinSAD_t + \Gamma \tag{3.17}$$

$$h_t = \eta_i + \mu_i h_{t-1} + \tau_i \sigma_{t-1}^2 + \theta_{i,OR} OR_t + \Gamma \tag{3.18}$$

Where h_t represents variance of the residual (error term) derived from the mean equations respectively,σ_{t-1}^2 is the previous trading day's square residual derived from mean equations. h_{t-1} is the GARCH term and $\sigma_{t-1}^2$is the ARCH term for our model. Γ, $Fall_t$,$Fallwinter_t$ SAD_t ,$FallSAD_{t-1}$,$WinSAD_{t-1}$ and OR_t are the predetermined variables (variance regressors) that contribute to the volatility of stock portfolio turnover.

Each mean and variance set for Portfolios 2 to 5 were run respectively, and the results are shown in Tables 3.5 to 3.8. Across the tables, the coefficients of Monday variable are statistically significant at 1% and negative for all six portfolios except Portfolio 1. The result indicates a strong Monday effect in the UK stock portfolio turnover, and shows Monday turnover is significantly lower than the other days of the week in these portfolios. The result supports the argument from Osborne (1962) and Lakonishok and Maberly (1990) that stock trading volume is lower on Mondays than other days of the week, meaning that there is a day-of the-week-effect in UK portfolio turnover. One possible explanation is that Monday tends to be a day of strategic planning for institutional investors, thus their trading activities are reduced on Monday.

The Tax variable presented in the Tables, in line with prior expectations, indicates that some tax-sensitive investors seek to sell stock before the end of the tax year and buy them back afterwards to offset tax gains. The portfolio turnover is positively related to the tax variable for Portfolio 2 and 4, which means that the turnover of small neutral stocks and growth stocks are higher than normal in the first five days and the last trading day of the UK tax year. The tax-loss selling effect influenced turnover in Portfolios 2 and 4.

Among all the weather variables in the mean equation results, temperature has the strongest influence on daily turnover. The result shows temperature is negatively related to most stock portfolio turnover, which indicates that the lower the temperature in London, the higher the daily stock turnover in the LSE. The finding is consistent with the analysis present in Cao and Wei (2005), who argued a lower temperature leads to aggressive risk-taking for investors, and so daily stock market trading activities increase when the temperature decreases. Moreover, Portfolio 3 and 6 are more likely to be affected by weather variables.[8] From the mean equation results, visibility is positively related to Portfolio 3 turnover and wind speed is negatively related to turnover. However, the visibility and wind speed effect on Portfolio 6 is reverse, visibility is negatively correlated with turnover, while wind speed is positively correlated with turnover. These results are different from the findings of Lu and Chou(2012), who found that both temperature and wind had positive effect on turnover and the Monday effect did not exist. However, the sample studied by Lu and Chou (2012) was of the Chinese Shanghai Composite Index. The climate of China and the UK is quite different, and the Chinese stock market is order driven market and LSE is quote driven market, so the impact of weather on turnover is not necessarily the same.

From Table 3.5, the coefficient of the Fall variable in the mean equation is statistically significant and negative for all portfolios except Portfolio 1. The negative sign of the Fall variable means that daily mean turnover of these portfolios tends to reduce in the Fall. The statistically significant and positive coefficient of the Fallwinter variable on the mean equation estimation for Portfolios 2 to 5 indicates that the turnover of these portfolios in the fall and winter are higher than during the rest of the year. Combining

[8] Portfolio 3 contains small size and neutral stocks and portfolio 6 contains large size and value stocks

the Fall and Fallwinter estimation results in Table 3.5, it is clear that the daily turnover of Portfolio 2 to 5 reduces in the fall and increases in the winter, which is in line with the SAD hypothesis proposed by Kamstra et al. (2003) that investors become more risk averse when they experience seasonal depression cased by SAD in the fall, and recover from SAD symptoms and resume their risk perception when the days get longer in the winter. When investors become more risk averse in the fall, they tend to favour safe assets; when investors' risk perception return normal, they resume their normal risky holdings. Therefore, the portfolio turnover are lower in the fall and higher in the winter.

Table 3.6 reveals that, the SAD variable exhibits a strong effect on turnover for Portfolio 2 and 3, given that the t-values are significant at the 1% level for Portfolio 2 and at 5% for Portfolio 3. The SAD coefficient is negative for Portfolio 3 and positive for Portfolio 2, it indicates that investors who suffer from SAD are reluctant to trade small size and value stocks but are willing to trade small size neutral stocks. By splitting SAD in FallSAD and WinSAD, the estimation results in table 3.7 show that FallSAD is positively correlated to turnover for Portfolios 2, 5 and 6, and negatively correlated to Portfolio 3 turnover; the WinSAD coefficient is significantly positive for Portfolio 3 and negative for Portfolio 6. Estimation results in Tables 3.6 and 3.7 suggest there is a SAD effect in the portfolio turnover in the LSE, however, both models fail to capture the uniform relationship between turnover and the SAD related variables.

In Table 3.8, by introducing the OR variable, the OR coefficient is statistically significant and negative for Portfolio 2, 4, 5 and 6 in the mean equation. Thus, the change of proportion of people suffering from SAD is negatively correlated with turnover in these portfolios, which indicates that investors tend to reduce their trading amount when they suffer from SAD. This is consistent with the findings of Lu and Chou (2012), who found the coefficient of OR is significantly negative in estimating turnover in the Shanghai Stock Exchange. Among all the SAD related variables, obviously, OR is the most appropriate SAD variable to investigate the SAD effect on the LSE stock portfolio turnover.

Turning to the results of variance equations, all the SAD related variables significantly correlated with the volatility of most portfolio turnover. The weather variables also exhibit a great impact on the volatility of turnover. Moreover, all coefficients of the ARCH and GARCH terms in every portfolio are statistically significant at 1%. This reveals that both the previous day portfolio turnover and volatility of portfolio turnover affect volatility of today's portfolio turnover.

In summary, The GARCH models results suggest there is a SAD effect on daily stock portfolio turnover. This offers significant explanatory power for daily turnover in LSE, as when investors experience SAD symptoms in the fall, they are reluctant to trade and turnover of the LSE decreases; while investors recover from SAD symptoms after the winter solstice, their trading behaviour return normal and turnover of LSE rises. The weather factors are also found to affect the LSE turnover, especially temperature. The variance equations suggest evidence of a relationship between the mood-proxy variables and volatility of stock portfolio turnover. However, it needs to be pointed out that the GARCH estimation results fail to conclude a pattern in the relationship between SAD related variables and portfolio turnover, since the SAD effect seems to have the same effect on different stock portfolios.

3.4.3 SUR model and Result

A number of studies have documented that the mood-proxy variables effect on stocks are size determined. For example, Dowling and Lucey (2008) and Krivelyova and Robotti (2003) found a more pronounced SAD and geomagnetic storms effect on small capitalisation stocks, respectively.

In order to further investigate on whether SAD affects different portfolio differently, the portfolios are grouped in to two groups based on their size as shown in Table 3.9. The seemingly unrelated regression (SUR) is adopted and joint tests are conducted to investigate the SAD effect on different size portfolios. The SUR model is an OLS-based time-series estimation, but it accounts for cross-sectional correlation between portfolios. More importantly, the joint test results enable us to distinguish the SAD effect in different size portfolios. The specifications are the same as in Equations3.5 to 3.8, with two lags of turnover included to account for potential autocorrelation in our daily turnover.

The SUR results are shown in Tables 3.10 to 3.13. The joint test on the coefficients of SAD related variables is Table 3.14. The individual coefficient significance results in the tables are close to the OLS estimation results in Tables 3.5 to 3.8. Only Fallwinter and OR variables exhibit influence on the portfolio turnover. Focusing on the joint test results in Table 3.14, these indicate that the coefficient of Fallwinter and OR are significantly different from zero all the small size portfolios. For large size portfolios, the coefficient of Fallwinter is significantly different from zero at 1% significance level.

The SUR results show the turnover in the fall and winter are significantly different from that in the remaining seasons of the year for both small and large size portfolios. The significant coefficient of OR variables for small size portfolio indicates the turnover for such portfolios are affected by SAD, which means investors suffering from SAD are less active in trading small size stocks. From the SUR results, there is some indication that the SAD effect on portfolio turnover is size determined, as small size portfolio turnover is more likely to be affected by SAD.

3.5 Conclusion

It is well established in the literature that mood affect investors' decision-making processes and mood is affected by the surrounding environment, such as weather and biorhythm disorders. A body of psychological literature has shown that SAD is one of the most important factors that affects people's mood globally (Denissen et al., 2008; Rosenthal, 1998). Empirical evidence suggests that some people experience a serious mood change when the seasons change, SAD is caused by the reduction of daytime in the fall, SAD sufferers generally feel a lack of energy and are depressed. Damasio (2008) argued that people in depression are more pessimistic, thus it is natural to conjecture that investors suffering from SAD become pessimistic and tend to avoid risky investments, SAD thus causes investors to alter their trading activities.

The aim of this chapter is to explore the relationship between SAD and stock portfolio turnover, meanwhile some weather and well-known market anomaly factors are controlled. The analysis is implemented by including the daily turnover of all the stocks on LSE. The variables adopted to measure SAD are constructed based on the length of the nights and the changes in the proportion of SAD sufferers. Since some studies suggested that the relationship between the SAD effect and stock market activities is more significant for small capitalisation indices (Dowling and Lucey, 2008), six portfolios are constructed in this chapter based on the size and book-to-market values of the stocks. The hypothesis is the SAD leads to lower stock turnover due to investor's defensive risk-taking when they experience depression in the fall, and the SAD effect is stronger in small size portfolios, as individual investors own mostly small size stocks and are more likely to be affected by mood.

Initially, the single-equation ordinary least squares (OLS) model with MacKinnon and White (1985) standard error are employed. Since the ARCH effect is detected in the data of Portfolio 2 to 5. The GARCH (1,1) model is performed to test the SAD effect in these portfolios. Finally, the SUR model is carried out to determine whether SAD affects different portfolio differently.

After examining all the SAD related variables we had constructed, OR indeed is the most appropriate variable to investigate the SAD effect on investor trading activities. The analysis presented in this chapter reveals a negative correlation between SAD and stock portfolio turnover, while the SAD effect is more significant on small size portfolios. Our results also suggest a relationship between SAD, weather factors and variance of turnover. The stock turnover are more volatile in relation to changes in investor mood. The findings of this chapter are reconcilable with the findings in the existing literature.

Table 3.1: The structure of the portfolios

small size and growth stock portfolio (Portfolio 1)	large size and growth stock portfolio (Portfolio 4)
small size and neutral stock portfolio (Portfolio 2)	large size and neutral stock portfolio (Portfolio 5)
small size and value stock portfolio (Portfolio 3)	large size and value stock portfolio (Portfolio 6)

Table 3.2: Summary statistics of turnover for each Portfolio

Portfolios	Mean	Medium	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis
Portfolio 1	0.003	0.02	2.446	$2.61e^{-6}$	0.032	76.45	5899
Portfolio 2	0.002	0.002	0.101	$3.26e-6$	0.003	17.18	417.2
Portfolio 3	0.003	0.002	0.078	$2.92e^{-6}$	0.003	9.111	152.2
Portfolio 4	0.005	0.004	0.023	$4.09e^{-6}$	0.002	1.202	5.828
Portfolio 5	0.004	0.004	0.074	0.000	0.002	6.091	140.3
Portfolio 6	0.006	0.003	0.167	$1.52e^{-7}$	0.008	7.003	99.41

Notes: Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks.

Table 3.3: Summary statistics of weather variables

Variables	Temperature	Wind Speed	Visibility
Mean	53.41	8.495	6.101
Medium	53.30	7.900	6.500
Maximum	85.00	999.9	10.10
Minimum	22.30	0.100	0.000
Std.Dev.	10.22	13.32	1.140
Skewness	0.015	68.47	-2.089
Kurtosis	2.363	5094	7.620

Table 3.4: LM Test Results for Autoregressive Conditional Heteroskedasticity

Equations	Equation 3.5	Equation 3.6	Equation 3.6	Equation 3.8
Portfolio 1	0.9901	0.9901	0.9901	0.9901
Portfolio 2	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Portfolio 3	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Portfolio 4	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Portfolio 5	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Portfolio 6	**0.0000**	**0.0000**	**0.0000**	**0.0000**

Notes: The table shows p-value for the Lagrange Multiplier test using five lags, the p-values in bold indicate the ARCH effect is presented in the models. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small and growth stocks; Portfolio 2 contains small and neutral stocks; Portfolio 3 contains small value stocks; Portfolio 4 contains large and growth stocks; Portfolio 5 contains large and neutral stocks; Portfolio 6 contains large size and value stocks. level.

Table 3.5: Fallwinter Esitmation of GARCH Model

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mean Equation						
Fall	0.0004	0.0000*	-0.0003***	-0.0002***	-0.0004***	0.0003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fallwinter	-0.0022	0.0001**	0.0002***	0.0003***	0.0002***	-0.0000
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tax	-0.0012	0.0003***	0.0003**	0.0006***	0.0001	-0.0002
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mon	0.0018	-0.0003***	-0.0003***	-0.0008***	-0.0009***	-0.0007***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0001	$-5.10e^{-6}$***	0.0000	$-5.17e^{-6}$**	$-6.64e^{-6}$***	$-5.59e^{-6}$*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0002	0.0000	$3.46e^{-5}$**	-0.0000	-0.0000	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0080	0.0024***	0.0017***	0.0042***	0.0043***	0.0040***
	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Variance Equation						
Fall		1.3246***	-1.6968***	0.2237***	-0.4455***	0.0754
		(0.156)	(0.051)	(0.085)	(0.132)	(0.142)
Fallwinter		-0.7811***	2.4445***	-0.3404***	-0.4588***	0.5422***
		(0.184)	(0.067)	(0.078)	(0.133)	(0.194)
Temp		-0.0077	0.0544***	-0.0142***	0.0017	0.0302***
		(0.007)	(0.004)	(0.004)	(0.005)	(0.007)
Visib		-0.2485***	0.6116***	-0.3502***	-0.1436***	-0.2182**
		(0.068)	(0.052)	(0.034)	(0.028)	(0.087)
Wdsp		0.0037	0.0044***	-0.0033	-0.0883***	-0.0511*
		(0.036)	(0.002)	(0.013)	(0.015)	(0.028)
Constant		-15.5270***	-22.2219***	-12.4493***	-13.0621***	-15.4612***
		(0.430)	(0.365)	(0.209)	(0.291)	(0.472)
Panel C: ARCH and GARCH Terms						
ARCH		0.2082***	0.3603***	0.3857***	0.4599***	0.2976***
		(0.003)	(0.013)	(0.014)	(0.028)	(0.011)
GARCH		0.8138***	0.6260***	0.5739***	0.5384***	0.7370***
		(0.002)	(0.008)	(0.012)	(0.020)	(0.004)
Observation	6,018	6,021	5,877	6,044	6,045	5,790

Notes: This table reports coefficient estimates from running the regressions for each of the six portfolios. Column 1 refers to OLS regression results for portfolio 1, Columns 2 to 6 refer to GARCH (1,1) regression results for portfolio 2 to 6, respectively. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 3.6: SAD Esitmation of GARCH Model

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mean Equation						
Fall	-0.0001	0.0000*	0.0003***	-0.0000	-0.0003***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SAD	-0.0005	0.0000**	-0.0001***	-0.0000	0.0000*	-0.0000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tax	-0.0008	0.0003***	0.0001	0.0005***	0.0000	-0.0002
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mon	0.0018	-0.0003***	-0.0003***	-0.0008***	-0.0009***	-0.0007***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0001	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0002	0.0000	0.0001***	-0.0000	-0.0000	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	-0.0000***	-0.0000	-0.0000	0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0069*	0.0024***	0.0024***	0.0048***	0.0044***	0.0039***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Variance Equation						
Fall		0.5970***	-1.1827***	0.2710***	-0.8485***	0.0916
		(0.146)	(0.081)	(0.081)	(0.115)	(0.122)
SAD		0.1082*	0.3933***	-0.1168***	0.0682*	0.3052***
		(0.055)	(0.018)	(0.025)	(0.035)	(0.054)
Temp		0.0217***	0.0111**	-0.0149***	0.0183***	0.0472***
		(0.008)	(0.004)	(0.004)	(0.004)	(0.006)
Visib		-0.1979***	0.5674***	-0.3443***	-0.1219***	-0.2181**
		(0.073)	(0.055)	(0.034)	(0.031)	(0.093)
Wdsp		-0.0048	0.0051*	-0.0033	-0.0853***	-0.0482*
		(0.035)	(0.003)	(0.013)	(0.015)	(0.026)
Constant		-17.5893***	-19.0316***	-12.4749***	-14.2910***	-16.5768***
		(0.455)	(0.351)	(0.216)	(0.283)	(0.542)
Panel C: ARCH and GARCH Terms						
ARCH		0.2111***	0.5511***	0.3899***	0.4626***	0.2853***
		(0.004)	(0.015)	(0.014)	(0.028)	(0.010)
GARCH		0.8107***	0.5486***	0.5706***	0.5364***	0.7448***
		(0.002)	(0.007)	(0.012)	(0.020)	(0.004)
Observation	6,018	6,021	5,877	6,044	6,045	5,790

Notes: This table reports coefficient estimates from running the regressions for each of the six portfolios. Column 1 refers to OLS regression results for portfolio 1, Columns 2 to 6 refer to GARCH (1,1) regression results for portfolio 2 to 6, respectively. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 3.7: FallSAD and WinSAD Esitmations of GARCH Model

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mean Equation						
Fall	-0.0006	-0.0000	0.0001	0.0000	-0.0005***	-0.0002**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FallSAD	-0.0003	0.0000***	-0.0001***	-0.0000	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WinSAD	-0.0005	0.0000	0.0001***	0.0000	0.0000	-0.0001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tax	-0.0009	0.0002***	0.0002**	0.0005***	-0.0000	-0.0002
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mon	0.0018	-0.0003***	-0.0003***	-0.0008***	-0.0009***	-0.0007***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0001	-0.0000***	-0.0000*	-0.0000***	-0.0000***	-0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0002	0.0000	0.0000***	-0.0000	-0.0000	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	-0.0000*	-0.0000	-0.0000	0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0070	0.0024***	0.0020***	0.0048***	0.0045***	0.0041***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Variance Equation						
Fall		-0.2500	1.0986***	0.1796	-1.5109***	-0.3297**
		(0.250)	(0.077)	(0.148)	(0.223)	(0.162)
FallSAD		0.3130***	-0.3312***	-0.0914**	0.2638***	0.4022***
		(0.080)	(0.038)	(0.045)	(0.069)	(0.062)
WinSAD		-0.2164**	0.5919***	-0.1340***	-0.0096	0.1645**
		(0.088)	(0.014)	(0.027)	(0.044)	(0.074)
Temp		0.0101	0.0247***	-0.0153***	0.0159***	0.0414***
		(0.008)	(0.004)	(0.004)	(0.004)	(0.006)
Visib		-0.1905**	0.5251***	-0.3483***	-0.1263***	-0.2081**
		(0.075)	(0.052)	(0.034)	(0.033)	(0.095)
Wdsp		-0.0166	0.0047*	-0.0037	-0.0900***	-0.0226
		(0.038)	(0.003)	(0.013)	(0.016)	(0.025)
Constant		-16.7716***	-19.6426***	-12.4244***	-14.1023***	-16.4098***
		(0.494)	(0.351)	(0.217)	(0.293)	(0.541)
Panel C: ARCH and GARCH Terms						
ARCH		0.2125***	0.4599***	0.3890***	0.4478***	0.2860***
		(0.004)	(0.015)	(0.014)	(0.027)	(0.011)
GARCH		0.8113***	0.5662***	0.5723***	0.5524***	0.7442***
		(0.002)	(0.009)	(0.012)	(0.019)	(0.004)
Observation	6,018	6,021	5,877	6,044	6,045	5,790

Notes: This table reports coefficient estimates from running the regressions for each of the six portfolios. Column 1 refers to OLS regression results for portfolio 1, Columns 2 to 6 refer to GARCH (1,1) regression results for portfolio 2 to 6, respectively. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 3.8: OR Esitmation of GARCH Model

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mean Equation						
OR	-0.0004	-0.0001***	-0.0001	-0.0006***	-0.0010***	-0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tax	-0.0000	0.0002***	0.0002	0.0003***	-0.0002	-0.0004**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mon	0.0018	-0.0003***	-0.0004***	-0.0008***	-0.0009***	-0.0007***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0000	-0.0000***	-0.0000***	-0.0000***	0.0000	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0003	0.0000	0.0000***	-0.0000	-0.0000	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	-0.0000	-0.0000	-0.0000*	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0031**	0.0025***	0.0020***	0.0045***	0.0039***	0.0040***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Variance Equation						
OR		0.8950***	0.5225***	0.1297	-1.1717***	0.2756*
		(0.188)	(0.063)	(0.082)	(0.149)	(0.151)
Temp		-0.0158***	-0.0300***	-0.0069**	0.0310***	0.0049
		(0.004)	(0.002)	(0.003)	(0.004)	(0.004)
Visib		-0.1348*	0.6620***	-0.3075***	-0.1527***	-0.2779***
		(0.070)	(0.060)	(0.033)	(0.031)	(0.072)
Wdsp		-0.0016	0.0047	-0.0074	-0.0759***	-0.0272
		(0.030)	(0.003)	(0.013)	(0.016)	(0.024)
Constant		-15.5897***	-17.0489***	-13.0782***	-15.1132***	-13.6146***
		(0.315)	(0.419)	(0.159)	(0.190)	(0.238)
Panel C: ARCH and GARCH Terms						
ARCH		0.2153***	0.5864***	0.3801***	0.4359***	0.3011***
		(0.003)	(0.014)	(0.013)	(0.026)	(0.011)
GARCH		0.8057***	0.5240***	0.5697***	0.5660***	0.7335***
		(0.002)	(0.007)	(0.011)	(0.019)	(0.004)
Observation	6,018	6,021	5,877	6,044	6,045	5,790

Notes: This table reports coefficient estimates from running the regressions for each of the six portfolios. Column 1 refers to OLS regression results for portfolio 1, Columns 2 to 6 refer to GARCH (1,1) regression results for portfolio 2 to 6, respectively. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 3.9: Two Groups of Portfolios

Portfolios			
Small Size Portfolios	Portfolio 1	Portfolio 2	Portfolio 3
large Size Portfolios	Portfolio 4	Portfolio 5	Portfolio 6

Notes: Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks.

Table 3.10: Fallwinter SUR model results

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Fall	0.0005	0.0000	-0.0004***	-0.0001*	-0.0001**	0.0000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fallwinter	-0.0024	-0.0000	0.0003**	0.0001**	0.0003***	-0.0001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T1	0.0025	0.2342***	0.2591***	0.5329***	0.4210***	0.4807***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
T2	0.0023	0.0806***	0.1658***	0.2784***	0.2490***	0.2501***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
Tax	-0.0014	0.0002	0.0001	0.0001	0.0000	-0.0005
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mon	0.0019*	-0.0003***	-0.0005***	-0.0012***	-0.0011***	-0.0013***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0001**	-0.0000	0.0000	0.0000	0.0000**	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0003	-0.0000	0.0001*	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0083**	0.0022***	0.0011***	0.0008***	0.0009***	0.0016**
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Observation	5,790	5,790	5,790	5,790	5,790	5,790

Notes: This table reports coefficient estimates from running the SUR regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 3.11: SAD SUR model results

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Fall	-0.0001	0.0000	-0.0003***	-0.0000	-0.0000	-0.0000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SAD	-0.0005	-0.0000	0.0000	0.0000	0.0000	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T1	0.0027	0.2342***	0.2599***	0.5337***	0.4231***	0.4808***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
T2	0.0024	0.0806***	0.1666***	0.2796***	0.2507***	0.2501***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
Tax	-0.0009	0.0002	-0.0000	-0.0000	-0.0001	-0.0004
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mon	0.0018*	-0.0003***	-0.0005***	-0.0012***	-0.0011***	-0.0014***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0001*	-0.0000	-0.0000	-0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0002	-0.0000	0.0001	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0070*	0.0023***	0.0014***	0.0011***	0.0013***	0.0014**
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Observation	5,790	5,790	5,790	5,790	5,790	5,790

Notes: This table reports coefficient estimates from running the SUR regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 3.12: FallSAD and WinSAD SUR model results

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Fall	-0.0005	-0.0002	-0.0002	-0.0000	-0.0000	-0.0003
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FallSAD	-0.0004	0.0001	-0.0000	0.0000	0.0000	0.0001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WinSAD	-0.0005	-0.0000	0.0000	0.0000	0.0000	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T1	0.0027	0.2336***	0.2598***	0.5337***	0.4231***	0.4806***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
T2	0.0024	0.0804***	0.1665***	0.2796***	0.2507***	0.2501***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
Tax	-0.0010	0.0001	0.0000	-0.0000	-0.0001	-0.0004
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mon	0.0018*	-0.0003***	-0.0005***	-0.0012***	-0.0011***	-0.0013***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0001*	-0.0000	-0.0000	-0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0002	-0.0000	0.0001	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0071*	0.0023***	0.0014***	0.0011***	0.0013***	0.0015**
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Observation	5,790	5,790	5,790	5,790	5,790	5,790

Notes: This table reports coefficient estimates from running the SUR regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 3.13: OR SUR model results

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
OR	-0.0002	0.0000	-0.0005***	-0.0001	-0.0002**	-0.0002
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T1	0.0030	0.2342***	0.2596***	0.5335***	0.4222***	0.4806***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
T2	0.0026	0.0806***	0.1661***	0.2794***	0.2497***	0.2501***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
Tax	-0.0001	0.0002	-0.0002	-0.0000	-0.0002	-0.0004
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mon	0.0018*	-0.0003***	-0.0005***	-0.0012***	-0.0011***	-0.0014***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0003	-0.0000	0.0001	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0032	0.0022***	0.0011***	0.0011***	0.0013***	0.0012**
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Observation	5,790	5,790	5,790	5,790	5,790	5,790

Notes: This table reports coefficient estimates from running the SUR regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 3.14: Joint test results for SUR model

Portfolios	Fallwinter	SAD	FallSAD	WinSAD	OR
Small Size Portfolios	0.0741*	0.4939	0.6386	0.2635	0.0166**
Big Size Portfolios	0.0004***	0.7503	0.8700	0.6977	0.1572

Notes: This table reports p-values of the joint tests. The null hypothesis is the estimated coefficients are jointly equal to zero. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

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Table A5: **Fallwinter OLS Regression Results**

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Fall	0.0004	0.0000	-0.0004***	-0.0001	-0.0001*	0.0000
	(0.0007)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
Fallwinter	-0.0022	-0.0000	0.0003*	0.0001*	0.0003**	-0.0001
	(0.0026)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Tur_{t-1}	0.0024	0.2351***	0.2610***	0.5587***	0.4344***	0.4837***
	(0.3155)	(0.0669)	(0.0525)	(0.0262)	(0.1437)	(0.0756)
Tur_{t-2}	0.0026	0.0806**	0.1676***	0.2751***	0.2656**	0.2540***
	(0.2821)	(0.0386)	(0.0381)	(0.0249)	(0.1128)	(0.0626)
Tax	-0.0012	0.0001	0.0001	0.0000	0.0000	-0.0005
	(0.0021)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0003)
Mon	0.0018	-0.0003***	-0.0005***	-0.0012***	-0.0010***	-0.0013***
	(0.0022)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
Temp	-0.0001	$-7.19e^{-6}$	$2.22e^{-6}$	$2.11e^{-6}$	$7.08e^{-6}$**	$3.10e^{-6}$
	(0.0001)	$(5.01e^{-6})$	$(4.20e^{-6})$	$(2.08e^{-6})$	$(3.56e^{-6})$	$(9.51e^{-6})$
Visib	0.0002	-0.0000	0.0001*	0.0000	0.0000	$9.95e^{-6}$
	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Wdsp	$7.90e^{-6}$	$-9.93e^{-7}$	$5.09e^{-7}$	$-7.07e^{-7}$	$-1.78e^{-6}$	$6.47e^{-6}$***
	(0.0001)	$(4.26e^{-6})$	$(1.46e^{-6})$	$(8.54e^{-6})$	$(8.77e^{-6})$	$(1.25e^{-6})$
Cons	0.0080	0.0023***	0.0011***	0.0008***	0.0008***	0.0015**
	(0.0055)	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0007)
Observations	6018	6021	5877	6044	6045	5790

Notes: This table reports coefficient estimates from running the OLS regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table A6: **SAD OLS Regression Results**

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Fall	-0.0001	0.0000	-0.0003***	$-6.28e^{-7}$	-0.0000	0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
SAD	-0.0005	-0.0000	0.0000	$-2.51e^{-7}$	0.0000	-0.0000
	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Tur_{t-1}	0.0025	0.2350***	0.2618***	0.5593***	0.4360***	0.4837***
	(0.3124)	(0.0669)	(0.0526)	(0.0262)	(0.1441)	(0.0756)
Tur_{t-2}	0.0027	0.0806**	0.1684***	0.2759***	0.2670**	0.2540***
	(0.2796)	(0.0386)	(0.0381)	(0.0249)	(0.1136)	(0.0626)
Tax	-0.0008	0.0001	$-4.10e^{-6}$	-0.0000	-0.0001	-0.0004
	(0.0016)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0003)
Mon	0.0018	-0.0003***	-0.0005***	-0.0012***	-0.0010***	-0.0013***
	(0.0022)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
Temp	-0.0001	$-7.66e^{-6}$	$-2.24e^{-6}$	$-1.11e^{-6}$	$2.05e^{-6}$	$4.87e^{-6}$
	(0.0001)	$(5.41e^{-6})$	$(4.27e^{-6})$	$(2.01e^{-6})$	$(2.86e^{-6})$	$(9.56e^{-6})$
Visib	0.0002	-0.0000	0.0001*	0.0000	0.0000	$9.85e^{-6}$
	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Wdsp	$7.26e^{-6}$	$-9.91e^{-7}$	$6.18e^{-7}$	$-6.37e^{-7}$	$-1.65e^{-6}$	$6.42e^{-6}$***
	(0.0001)	$(4.24e^{-6})$	$(9.30e^{-7})$	$(7.31e^{-6})$	$(6.60e^{-6})$	$(1.21e^{-6})$
Cons	0.0069*	0.0023***	0.0014***	0.0010***	0.0012***	0.0014**
	(0.0042)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0007)
Observations	6018	6021	5877	6044	6045	5790

Notes: This table reports coefficient estimates from running the OLS regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table A7: FallSAD/WinterSAD OLS Regression Results

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
Fall	-0.0006	-0.0002**	-0.0002*	$-8.06e^{-6}$	$2.58e^{-7}$	-0.0002
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
FallSAD	-0.0003	0.0001	$1.92e^{-6}$	$-1.93e^{-6}$	0.0000	0.0001
	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
WinSAD	-0.0005	-0.0000	0.0000	$-2.76e^{-6}$	0.0000	-0.0000
	(0.0007)	(0.000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Tur_{t-1}	0.0025	0.2345***	0.2617***	0.5594***	0.4360***	0.4836***
	(0.3132)	(0.0669)	(0.0560)	(0.0261)	(0.1441)	(0.0756)
Tur_{t-2}	0.0027	0.0803**	0.1683***	0.2759***	0.2670**	0.2540***
	(0.2802)	(0.0385)	(0.0382)	(0.0249)	(0.1136)	(0.0626)
Tax	-0.0009	0.0001	$7.32e^{-6}$	-0.0000	-0.0001	-0.0004
	(0.0017)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0003)
Mon	0.0018	-0.0003***	-0.0005***	-0.0012***	-0.0010***	-0.0013***
	(0.0022)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
Temp	-0.0001	$-8.39e^{-6}$	$-1.96e^{-6}$	$-1.11e^{-6}$	$2.09e^{-6}$	$4.23e^{-6}$
	(0.0001)	$(5.48e^{-6})$	$(4.30e^{-6})$	$(2.03e^{-6})$	$(2.88e^{-6})$	$(9.57e^{-6})$
Visib	0.0002	-0.0000	0.0001*	0.0000	0.0000	0.0000
	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Wdsp	$7.31e^{-6}$	$-9.53e^{-7}$	$6.11e^{-7}$	$-6.37e^{-7}$	$-1.65e^{-6}$	$6.45e^{-6}$***
	(0.0001)	$(4.80e^{-6})$	$(8.10e^{-7})$	$(7.31e^{-6})$	$(6.65e^{-6})$	$(1.18e^{-6})$
Cons	0.0070	0.0023***	0.0014***	0.0010***	0.0012***	0.0014**
	(0.0043)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0007)
Observations	6018	6021	5877	6044	6045	5790

Notes: This table reports coefficient estimates from running the OLS regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table A8: OR OLS Regression Resultd

Portfolios	(1)	(2)	(3)	(4)	(5)	(6)
OR	-0.0004	-0.0000	-0.0006***	-0.0000	-0.0002*	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tur_{t-1}	0.0028	0.2351***	0.2614***	0.5592***	0.4353***	0.4836***
	(0.307)	(0.067)	(0.052)	(0.026)	(0.144)	(0.076)
Tur_{t-2}	0.0029	0.0806**	0.1678***	0.2757***	0.2662**	0.2539***
	(0.276)	(0.039)	(0.038)	(0.025)	(0.113)	(0.063)
Mon	0.0018	-0.0003***	-0.0005***	-0.0012***	-0.0010***	-0.0013***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tax	-0.0000	0.0002	-0.0002	-0.0000	-0.0002	-0.0005
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temp	-0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visib	0.0003	-0.0000	0.0001**	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wdsp	0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0031**	0.0022***	0.0011***	0.0010***	0.0012***	0.0012**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6,018	6,021	5,877	6,044	6,045	5,790

Notes: This table reports coefficient estimates from running the OLS regressions for the six portfolios. Portfolios 1 to 3 refer to small size portfolios and Portfolios 4 to 6 refer to large size portfolios. Portfolio 1 contains small size and growth stocks; Portfolio 2 contains small size and neutral stocks; Portfolio 3 contains small size and value stocks; Portfolio 4 contains large size and growth stocks; Portfolio 5 contains large size and neutral stocks; Portfolio 6 contains large size and value stocks. Standard errors in parentheses, *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Chapter 4 The SAD effect on UK Government Bond Returns

4.1 Introduction

Traditional economics and finance theory holds that there is hardly any bond-specific or private information regarding government bonds. A number of studies have documented that returns of government bonds are related to macroeconomic variables such as inflation and interest rates, and the fiscal and monetary policy the country conducts (Barr and Campbell, 1997; Christiansen, 2000; Litterman and Scheinkman, 1991). However, over the past two decades, empirical studies on government bond returns have acknowledged a number of seasonal patterns in government bond returns. Kamstra et al. (2014) found a seasonal variation in the US government bond returns and argued that the seasonal pattern is not caused by seasonality in macroeconomics or risk factors. Athanassakos (2008) also documented a seasonal pattern in Canadian government bond returns by indicating that bond returns are higher from May to October than in the rest of the year. Much less attention has been paid to seasonality in UK government bond returns. In this chapter, we examine seasonality in UK government bonds. We test whether there is a relationship between SAD indicators and the UK government bond returns. Our findings provide supportive evidence of seasonality in government bond returns is caused by seasonal variation in investor risk perception. In addition, it is also found that the seasonal patterns vary across bond return series, depending on their maturities.

A number of empirical studies have proven the existence of return patterns in equity returns. Fields (1931) first discovered that the returns of US stock market tended to be low on Mondays and higher on Fridays. The day-of-the-week effect received increasing attention during the 1980's and developed by a number of researchers (Agrawal and Tandon, 1994; French, 1980; Gibbons and Hess, 1981; Jaffe and Westerfield, 1985; Lakonishok and Levi, 1982). The January effect was first identified by Rozeff and Kinney (1976), who found that the stock returns were higher in January than the other months of the year and the effect is also existed in international stock markets. Not only stock returns but also international government bond returns exhibited evidence of the January effect. In contrast to stock returns, Clayton et al. (1989) argued that the long-term US Treasury returns were lower in January than in any other month of the year. Fridson (2000) extended their study and indicated that the returns on 10-year US treasury bills were higher from June to November. Kamstra et al. (2014) found seasonal variation in US treasury returns, the returns are related to the mood proxies that stood for variation in investor risk aversion.

The findings of the previous two chapters demonstrate that investors become more risk averse when they suffer from SAD and the seasonally varying investor risk aversion leads to seasonality in stock markets. SAD-influenced investors tend to shun risk and turn to safe assets. Compared to institutional investors, individual investors are more rely on emotion status when they are making investment decisions. There is a high probability that SAD-influenced individual investors would reduce investment in risky assets and shift to safe assets, such as government bonds. Therefore, we hypothesize that seasonally varying investor risk aversion levels will also lead to seasonality in government bond markets, as investors are expected to turn to bond markets when they experience SAD and become more risk averse.

In general, researchers have established the fact that there are seasonal patterns in government bond returns, the government bond returns are not simply reflected in public available information. This chapter purports to investigate seasonal pattern in UK government bond returns for the following reasons: firstly, for all individual investors, understanding seasonal patterns in bond returns plays a substantial role in their investment portfolio, especially for those who experience seasonal variation in their risk perception. Investors could adjust their investments in equity market at the right time to achieve a better return. However, the “arbitrage” opportunity will diminish when awareness of seasonality increases. Secondly, from the government and companies view, understanding seasonality in bond markets would help them to select the right time to issue new debts and fulfil their financial needs. Finally, governments and central banks could take seasonality in bond markets into consideration when they carrying fiscal and monetary policy to maximise the function of the policies.

The aim and motivations of this chapter is to fulfil the gap in the existing literature on seasonal patterns in the UK government bond returns in the following ways. Firstly, a large amount of research has focused exclusively on seasonality in US government returns, to the best of my knowledge only a few studies attempt to address seasonality in the UK government bond market. Smith (2002) investigated international government bond markets and revealed a January effect in the UK government bond market. Clare and Thomas (1992) introduced a market risk variable and found that the beginning of March is best timing in investing in UK government bonds. They argued that this may be explained by the UK’s tax year ends at the beginning of April. In this chapter we examine seasonality in the UK government bond market, where eight government bonds with different maturities are analysed. According to the seasonal affective disorder (SAD) hypothesis in chapter 2 and 3, we hypothesise that seasonal variation in investor risk perception caused by SAD also stimulates seasonality in bond returns.

Secondly, since the mood-proxy effect on stock returns are size determined , in order to test whether the SAD effect on bond returns vary across maturities, two government bond return series are constructed, based on the maturities of the bonds. Joint tests were performed to investigate the existence of seasonal patterns in different bond return series.

Finally, past literature has identified a number of macroeconomic and risk factors are related to bond returns. Ang and Piazzesi (2003) used a term structure model with economic growth factors to investigate bond prince and yield curves, their result suggested that macro variables could explain up to 85% of the variation in bond returns. De Bondt and Bange (1992) and Brandt and Wang (2003) both documented that inflation surprises significantly affected government bond returns. Fama and French (1989) stated that the term structure of interest rates is important in predicting bond returns. Added to that, macroeconomic factors are confounding factors to government bond returns, only considering the association between mood-proxy variables and bond returns can not measure the precise correlation. Thus, we included macroeconomics and risk factors in the models in order to provide several potential alternative explanations to the seasonality in UK government bond returns. Therefore, in this chapter, we consider both macroeconomics and risk factors, and construct four models to examine seasonality in UK government bond returns.

Kamstra et al. (2014) focused on the medium-to-long term government bonds, as they mentioned short-term government bonds are not respond freely to market forces. However, we believe that short-term government bonds are more likely to be affected by investor emotions. Therefore, we incorporated eight UK government bonds with maturities ranging from 2-year to 30-year for the UK from 1988 to 2014 in this chapter. In addition, we divided the eight bonds into two groups according to their maturities and ran seemingly unrelated regressions (SUR) to test which group is more likely to be affected by emotions. In this chapter we provides evidence in support of seasonality in the UK government bond returns. The system equation of Generalized method of moments (GMM) specifications and heteroscedasticity-consistent (HAC) standard errors are employed in this chapter to control for cross-section covariance between different bond returns, heteroskedasticity and autocorrelation in bond returns. The instruments for the GMM regressions are explanatory variables.[1] The macroeconomics and risk factors in different models are considered endogenous to models of bond returns determination. The null hypothesis of this chapter is that there is no seasonal pattern in UK government bond returns, against the alternative hypothesis that seasonal variation in investor risk perception caused by SAD simulates seasonal variation in UK government bond returns and the seasonal pattern varies across bonds with different maturities.

The remainder of the chapter is organized as follows. Section 2 reviews the literature on seasonality in equity market returns. Section 3 presents the data and methodology which are adopted for this chapter. Section 4 overviews the empirical results. Finally, this chapter is concluded and discussed in Section 5.

[1] For example, the instruments for model 1 are seasonality indicators, term spread, inflation, default spread and industrial production rate.

4.2 Literature Review

In this section a review of the previous literature is presented. Initially, empirical literature relating to seasonality in risky asset returns and bond returns are explored, respectively. This section will then present the importance of mood effect in risk perception and links between mood-proxies and asset returns. This review finally provides some key empirical findings of other factors related to bond returns.

4.2.1 Seasonality in Risky Asset Returns

An extensive of literature have documented seasonal patterns in risky asset returns. The existence of these anomalies has strong implications against the efficient market hypothesis. Examples of the patterns include: the Sell in May principle, the Monday effect, the January effect, the Weekend effect, the SAD effect and the Turn-of-the-month effect.

Starting with the Monday effect, it refers a tendency of stock market returns to be relatively lower, and often negative on average, on Mondays rather than the other days of the week. This theory also states that lower returns on Monday are driven by the closing performance of stocks on the previous Friday. This effect has been observed in international financial markets. Market practitioners identified the Monday effect as early as the 1920s. Kelly (1930) investigated a three-year US stock market data and identified Mondays are the worst days to buy stocks. He ascribed weekend decisions of individual investors to be the cause of lower returns on Mondays. Cross (1973) studied 844 sets of Fridays and the following Mondays price changes in the Standard & Poor's Composite Stock Index from January 2, 1953 to December 21, 1970 and reported Fridays outperformed Mondays in terms of both mean percentage change and the percentage of times the Index advanced during the whole eighteen years period. Jaffe and Westerfield (1985) used six distinct samples, including American, Canadian, British, Japanese and Australian equity markets and reported the existence of the Monday effect in international stock markets. Evidence from some emerging markets also supported the Monday effect. Basher and Sadorsky (2006) considered daily closing prices on 21 emerging stock markets and the Morgan Stanley Capital International (MSCI) World index across the period 31 December 1992 and 31 October 2003. Analysing a total number of of 2827 observations and used five different models to examine the day-of-the-week effect. Their estimation results indicate strong day-of-the-week effects in some emerging stock markets even after controlling conditional market risk.

The May principle or the popular expression 'Sell in May and Go Away' is another well-known seasonal pattern. It refers to the trading strategy of investors to sell their stock holdings in May and return to the stock market in November to avoid the typically volatile May-October period, also known as the seasonal decline in stock markets. Bouman and Jacobsen (2002) documented that the famous Sell in May effect in stock return was presented in 36 of the 37 countries in their sample, and this effect goes as far back as 1964 in the UK stock market. However, they found no explanations for the seasonal pattern. Maberly et al. (2004) argued that the average negative return patterns in stock markets can be explained by two outliers, namely the 1987 Black Monday crash in world financial markets and the bailout of the Long Term Capital Management hedge fund in 1998.

The Turn-of-the-Month (TOM) effect is a tendency of asset returns to increase during the last two days and the first three days of each month. This tendency is supported by extensive academic research, including Barone (1990) who discovered the turn of the month effect in Italy, Ziemba (1991) in Japan, Cadsby and Ratner (1992) in Australia, Canada, Germany and Switzerland, Hensel and Ziemba (1994) in the U.K. and Martikainen et al. (1995) in Finland. In addition, Kunkel et al. (2003) studied 2153 months of daily stock closing prices from 19 countries from 1988 to 2000, and employed parametric and non-parametric tests to search for evidence of the TOM effect. Their result showed that the TOM effect was presented throughout the 1990s in 16 of 19 countries. Their models supported a significant TOM pattern in stock markets that is independent of any other calendar-related patterns, which can not be explained by outlier observations.

The January effect refers to an increase in stock prices in January along with a drop in stock price at the end of December. The January effect was first brought to the attention of modern finance by Rozeff and Kinney (1976), who calculated the average return on NYSE index from 1904 to 1974 , they found this to be more than eight times higher in January than in any other months. Dyl (1977) and Branch (1977) also confirmed the existence of the January effect in US stock markets. Gultekin and Gultekin (1983) found the January effect also influenced international stock markets. Subsequent research by Reinganum (1983) and Keim (1983) indicated that the January effect in more pronounced on small capitalisation stocks. Chu and TUNG LIU (2004) provided additional evidence of the January effect is size determined , they employed the Markov-switching model to explore the monthly stock returns from 1926 to 1992 and found a significant January effect in small capitalisation stocks only. Branch (1977) introduced the Tax-loss selling hypothesis to explain the January effect, which indicates investors tend to sell stock holdings before the end of tax year to reduce tax payments, and resume stock holdings at the beginning of January.

The seasonal patterns in risky assets cited above have been uncovered and analysed for decades. Recent behaviour finance studies reported a seasonal pattern in equity returns named the SAD effect. The SAD effect also known as Winter Blues, refers to the principle that stock returns are significantly related to the amount of daylight through the fall and winter. In clinical studies, SAD is a medical symptom where sufferers feel depressive when the days become shorter after the autumn equinox, and experimental psychologists have documented that depression led to higher risk aversion, hence stock return are lower when investors suffer from SAD. Kamstra et al. (2003) documented the SAD effect by providing international evidence that stock market returns vary seasonally, according to the length of the daytime in the fall and winter. Their result indicated that the SAD effect persists in the seasonal cycle of stock returns, even after controlling for some well-known market anomalies and weather factors. They ascribed the cause of the SAD effect to the change of daylight, which has a more pronounced effect on people's mood than weather factors and mood is related to investor risk perception. Dowling and Lucey (2008) extended the SAD hypothesis research in international stock markets. They grouped countries into those close to the equator against those distance from it, amd by employing the GARCH model, they found a large proportion of SAD coefficients were significant and with the expected sign to support the SAD hypothesis. Moreover, Dowling and Lucey (2008) further provided two key pieces of evidence for the SAD effect. Firstly, they documented a more pronounced SAD effect for those countries further away from the equator, just as SAD is caused by the reduction of daytime in the fall and winter, it is expected that more investors will suffer from SAD in those countries which are far away from the equator. Secondly, they also found a more significant SAD effect in small capitalisation equities, held mostly by individuals, which is an indication of stronger SAD effect on individual investors, given that individual investors are more likely to be affected by the change of mood (Yuan et al., 2006). Kamstra et al. (2012) adopted more statistical methods to support the existence of the SAD effect in international stock markets. The methods include: ordinary least square (OLS) and the seeming unrelated regression (SUR) with MacKinnon and White (1985) standard errors, and a system of equations general method of moments (GMM) with heteroskedasticity and autocorrelation consistent (HAC)standard errors.

4.2.2 Seasonality in Bond Returns

While the seasonality in risky equity markets has received extensive coverage in existing literature as cited above, much less focus has been paid to seasonality in risk-free equity returns. However, arguably, investors who expect seasonality in risky asset returns might shift their investment portfolio to risk-free assets to avoid potential loss. Therefore, we expect reverse seasonal patterns in bond returns compared to seasonality in stock returns.

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Several studies have shown the days of the week effect also exists in risk-free asset market. Gibbons and Hess (1981) found a pattern in Treasury bill returns similar to those in risky equity. They investigated Treasury Bills for the period of December 1962 to December 1968 and observed Treasury bill returns on Mondays are lower than average. Flannery and Protopapadakis (1988) analysed seven Treasury Bills maturities ranging from one month to thirty years and overnight repurchase agreements. Their study showed that Monday Treasury returns and underlying maturity is negatively correlated. Johnston et al. (1991), Singleton and Wingender (1994),and Griffiths and Winters (1995)) further confirmed the existence of the days of the week effect in a types of debts, including federal funds and mortgage-backed securities. The Monday effect is consistent in both stock and bond markets, our findings of Chapter 3 suggested that trading activities on Mondays are lower than the other days of the week, as Monday tends to be a day of strategic planning for institutional investors. Thus, it is expected that returns of both stock and bond market are lower on Mondays.

The May principle refers to negative or below average returns in stock markets from May to October. When a growing number of investors are expecting the May principle in stock markets, then it is expected that the returns of government bonds will also be affected during this period, as investors who sell their stocks in May may turn to the bond market. Athanassakos (2008) considered stock and government bond data from 1957 to 2003 and employed time series dummy GMM regressions to test for seasonality in the Canadian financial market. He documented significant seasonal patterns in both risky and risk-free markets in Canada. In addition, he also revealed the seasonality effect on stock market was in the opposite direction to that of bond markets, which is as expected. In detail, the average bond returns from November to April is higher than that from May to October, stock returns from November to April is lower than that from May to October.

The January effect has also been proven in the literature. Chang and Huang (1990) demonstrated the January effect in US long-term corporate bonds by studying the pricing of equally weighted long-term corporate bond portfolios in six different ratings. Their sample consists of Moody's classifications from Aaa-rated to B-rated bonds. Wilson and Jones (1990) also presented the January effect on corporate bonds and commercial paper returns . They examined a 131-year period of data for both series, and applied a procedure that provides consistent estimates of the variance-covariance matrix. Their result suggested that the January effect persists for both corporate bond and commercial paper during the entire period. Clayton et al. (1989) documented that the long-term government bonds had significantly lower returns in January than in the remaining year and argued the tax-loss selling in the equity markets together with investors investing their December sales proceeds in January provide a potential explanation for the January effect. Smith (2002) extended the study of the January effect to international government bond markets and provided evidence of the January effect in US, France, Germany, UK and Canada. He stated that the results provided considerable diversification opportunities for investors. However, the January effect in US treasury markets were challenged by the studies of Schneeweis and Woolridge (1979), Smirlock (1985) and Chang and Pinegar (1986), who suggested that the January effect is not consistent over time. Clayton et al. (1989) questioned the findings of these three papers and argued that the datasets and methodologies they employed were not favourable for discovering the January effect in bond markets.

Literature is also available regarding the SAD effect in risk-free asset returns. Kamstra et al. (2014) examined 4 medium-to-long term US treasury returns and documented a seasonal pattern in US treasury returns. They performed seasonality tests by estimating Hansen (1982) generalized method of moments tests with Newey and West (1987, 1994) heteroskedasticity and autocorrelation consistent stand error to control for heteroskedasticity and autocorrelation in treasury returns. The result indicated the seasonal variation result an average 80 basis points swing in treasury returns from October to April. They included the SAD effect in their study on bond returns and provided evidence of a fall-winter and a OR bond return patterns. In the fall-winter pattern, bond returns are higher during September to November and lower in February to April. The OR variable, introduced by Kamstra et al. (2014), represents changes in the proportion of SAD symptoms sufferers, it is negative in winter and spring and positive in summer and fall. Including OR variable could constitute an improved version that links the bond returns to the clinical evidence of SAD symptoms as SAD variables are only related to the length of daytime. A positive relationship between OR and US treasury returns discerned, this means a higher proportion of SAD sufferers in the population leads to higher treasury returns, which is opposite to the SAD effect on stock returns. They considered 11 alternative models with macroeconomic and risk factors are controlled, and showed that seasonality in these macroeconomic and risk factors does not respond to the seasonal Treasury return pattern. It is thus suggested that SAD, causing seasonally varying investor risk perception, is the most important factor behind seasonal variations in financial markets. Investors suffer from SAD symptoms and become more risk averse, they tend to avoid risk and turn to bond markets, leading higher bond returns in the fall and winter; when investors recover from SAD symptoms, they rebalance their portfolios and increase investment in risky assets.

4.2.3 Mood and Risk Perception

The literature review above provides supportive evidence for seasonality in both risky and risk-free markets, and several papers have considered how investor behaviour can contribute to explain seasonal variation in financial markets. For example, Kamstra et al. (2003, 2014) found seasonal patterns in both stock and government bond markets in relation to the SAD hypothesis that seasonal variation in investor risk perception is due to seasonally varying investor mood, changes in investor risk perception leads to seasonal pattern in both stock and bond returns. They constructed SAD variables elated to the length of daytime to measure investor mood. More precisely, Kamstra et al. (2003, 2014) found the seasonal pattern in stock returns was opposite to the seasonal pattern in bond returns and they argued that was due to investors becoming more risk averse when experiencing SAD and shifting their funds from stock markets to bond markets. Therefore, in this section, we review the literature which examine the relationship between investor mood and risk perception.

Numerous clinical studies have documented that moods, as transient states of feeling, are effected by the surrounding environment. Kamstra et al. (2003) found that people's mood is related to their risk perceptions, the weather conditions and the surrounding environment, all of which have a significant influence on human emotion, and in turns affect asset returns. Especially, when investors experience SAD and feel depressive in the fall, they become more risk averse and shift their investment portfolios from risky assets to risk-free assets like government bonds. Experimental results from Eisenberg et al. (1998) also confirmed the relationship between depressive symptoms and risk aversion levels. In their experiment, subjects with different depression level were asked to make some risky or risk-less choices. The result indicates high depression level subjects are more likely to choose safe choices than low depression level subjects.

SAD caused seasonal depression in the fall when days become shorter is found in many recent studies. Young et al. (1997) investigated 190 Chicago residents who experienced seasonal depression and the results indicated that most of them began to experience depression symptoms in the fall. Lam (1998) studied 454 Vancouver residents that experienced seasonal depression and discovered that the onset of depression symptoms start in the fall, too. These clinical studies argued that the cause of these depression symptoms is the reduction of daytime in the fall and winter, in other word, SAD is responsible for these depression symptoms.

Kramer and Weber (2012) tested the how seasonal variation in individual' risk perception influences financial market seasonality based on the survey data from faculty and staff in a large North American university. Participants were asked to complete a seasonal pattern assessment questionnaire (SPAQ; Rosenthal et al. (1987)), a diagnostic measure of SAD and their risk perceptions were measured in different seasons. The results showed that SAD sufferers had significantly stronger preferences for risk-free investments during the winter than those do not experienced SAD, they suggested the effect of SAD on risk aversion in the winter is mediated by seasonal depression.

Therefore, seasonal variation in moods can change investors' risk perception. Specifically, if investors experience SAD, they become more risk averse in the fall and winter, and tend to avoid risks and prefer risk-free assets. When the seasonal depression diminishes after the spring equinox as the days become longer, investor's risk aversion rebounds and hence they resume their investment in risky assets. The SAD effect hypothesis on the mood of investors provides a possible explanation for the following observed seasonal patterns in asset returns. It is expected that seasonal patterns in risk-free asset returns will be converse of seasonal patterns in risky asset returns, as documented in Chapter 2.

4.2.4 Other Factors Influence Bond Returns

Ownership of a bond is the ownership of a stream of future cash payments. These future cash flows are related to time-varying risks and macroeconomics factors. For instance, interest rate risks and inflation risks affect the value of future payments, and GDP explains part of cross-sectional variation in asset returns. The literature has explored factors affecting risk-free equity returns.

Large amount of literature has documented the link between asset returns and macroeconomic factors. Boudoukh and Richardson (1993) studied the link between interest rate and inflation and consumption growth, with time-varying volatility. They pointed out that time-varying macroeconomic factors like inflation and consumption growth affect the time series properties of the risk premia implicit in bond prices. Baele et al. (2010) implemented a dynamic factor model to study bond return movements. They concluded that the macro factors, like interest rates, inflation and the output gap play a prominent role in fitting bond return volatility.

Studies of bond yield also provided evidence that time-varying risks have a great impact on bond returns and predicting future bond returns. A seminar paper from Fama and Bliss (1987) studied the bonds with annual maturities up to 5 years and demonstrated that the expected bond returns across maturities changes through time, which implies changes in risks across bond maturities. Recent work by Cochrane and Piazzesi (2005) futher studied the time-varying risk premia impact on the term structure of interest rates and suggested a linear combination of yields capture variation in one-year excess returns for bonds ranging from one year to five years maturities.

In recent years, some research has focus on behavioural explanations of risk-free asset returns. Baker et al. (2008) focused the link between bond and bond-like stock. Their work provided strong evidence to support the idea that behavioural factors like investor sentiment affect bond returns. Fleming et al. (2005) argued that market participants frequently bid at inefficient rates in weekly offerings of four-week Treasury bill auctions. Fleming and Garbade (2007) carried on their research on deal behaviour by investigating dealer behaviour in the specials market for US Treasury securities. They analysed the reports from Federal Reserves securities loan auctions from 1999 to 2002 and found suboptimal dealer behaviour in non-competitive Treasury bill auctions, where dealers tended to give up arbitrage, leading to a loss of opportunities and frequently overpaid for borrowing. The literature mentioned provides strong evidence that, even in the modern market, dominated by many professional market participants, investor behaviour can still causes inefficiency and influence asset returns.

In summary, from reviewing the existing literature, it is apparent that the empirical analysis presented in this chapter contributes to a strong support for seasonal variation in asset returns. The SAD hypothesis introduced by Kamstra et al. (2003) provided a possible explanation for the seasonality in asset returns, suggesting that investors experiencing SAD tend to shun risk and turn to the bond market; and that when they recover from SAD, they resume their risk perception and invest more on risky assets. Therefore, to investigate seasonality in UK government bond returns, we focus on the SAD effect on bond returns.

4.3 Data and Methodology

4.3.1 Government Bond Data

In this chapter, UK government bond return series are analysed. The UK government bonds are also known as gilts, which are marketable sterling bonds issued by the UK Debt Management Office on behalf of the UK government as part of its debt management responsibilities and they are listed on the London Stock Exchange. The United Kingdom benchmark government bond clean price index series data is collected from Datastream on a monthly basis, ranging from 2-year to 30-year UK benchmark government bonds. There are in total of eight bond series studied in this chapter from January 1980 to December 2014. The bond return series is generated by calculating the log-return of the corresponding bond price index series separately. Kamstra et al. (2014) argued that the shorter end of the bond market, the smaller seasonal effect is expected, and when the bond is about to mature, the smaller seasonal effect is expected. Thus they mainly focused on searching for seasonality in the medium-to-long end bonds and their results indicate much stronger seasonality in the medium-to-long term bond returns than in the short term bond returns. Gibson (1970) suggested that the Federal Reserve system tries to remove seasonal fluctuations from interest rates by issuing short end bonds. Therefore, in this chapter the bond return series are analysed in two separate groups, based on their maturities: a short-term bond returns group and a long-term bond returns group, in order to capture the different seasonal movements between the two groups. The details of the construction of the groups are shown in the Table 4.1.

Table 4.1: Two Government Bond Groups

Short-term bonds	**Medium-to-long term bonds**
2-year government Bond	10-year government Bond
3-year government Bond	15-year government Bond
5-year government Bond	20-year government Bond
7-year government Bond	30-year government Bond

4.3.2 Seasonal Indicators

In order to examine the SAD effect in UK government bond returns, the seasonality indicators adopted in this chapter follow Kamstra et al. (2014) and comprise Fall/Winter (indicator variable represents the difference between fall and winter), SEP/MAR (indicator variable represents the difference between September and March), APR/OCT (indicator variable represents the difference between April and October) and Onset/Recovery(OR)

[2]. The Oct/Apr and Sep/Mar indicators are closest to match the timing of investors suffer from SAD and recover from SAD, when the days become shorter after the autumnal equinox and become longer after the spring equinox, respectively. And the Fall/Winter variable presents the average SAD impact during the two seasons. Onset/Recovery (OR) was introduced by Kamstra et al. (2014), as another proxy for SAD, which represents changes in he proportion of the total number of SAD symptoms sufferers in the population. The monthly Onset/Recovery variable (OR) is obtained from their website,[3] Kelly and Meschke (2010) and Khaled and Keef (2013) showed that OR is correlated with a country's latitude. Thus, London latitude is applied to convert North American OR to UK OR.[4] The convert equation and monthly OR chart are displayed in figure 4.1 as follow.

$$OR_{London} = \left(\frac{Latitude_{London}}{Latitude_{NewYork}} \right) OR_{NewYork} \tag{4.1}$$

Unlike the SAD variables in Chapter 2 and 3, which are constructed based on the length of day, only have observations for fall and winter, OR takes observations during the entire year [5]. From Figure 4.1, we can see that OR is negative in winter and spring, and positive in summer and fall, which means that more people suffer from SAD when the days are about to get shorter, and, conversely, more people recover from SAD when the days are about to get longer.

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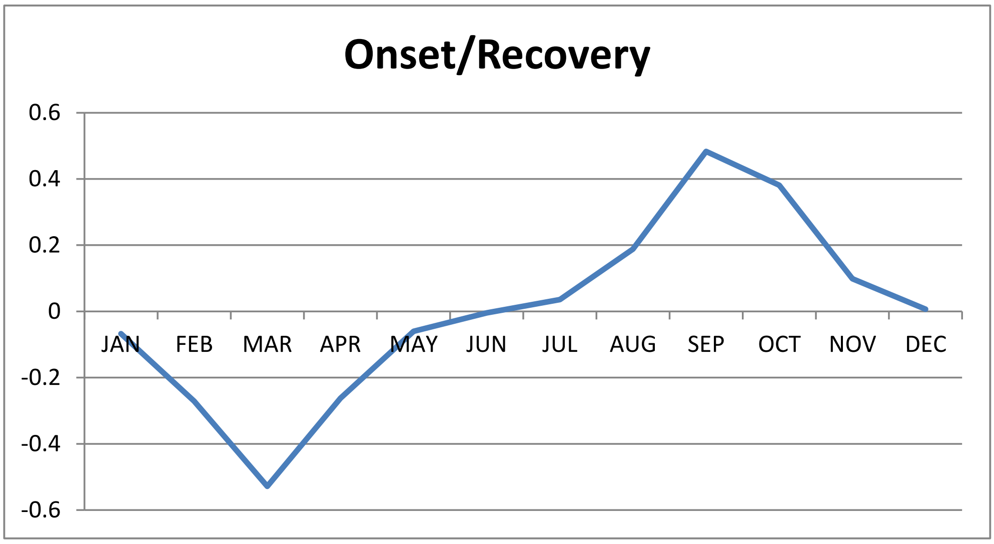
[2] $D_{t,Fall/Winter}$ is equal to one in the fall(October, November, and December), and equal to minus one in the winter(January, February and March), $D_{t,Sep/Mar}$ is equal to one in in September, equal to minus one in March and equal to zero in other months, $D_{t,Oct/Apr}$ is equal to one in October, equal to minus one in April and equal to zero otherwise

[3] http://www.lisakramer.com/data.html

[4] OR data obtained from the website is based on the length of day time in New York City

[5] Onset/Recovery(OR) is constructed following monthly incidence variable data for SAD from Lam (1998) and Young et al. (1997). The monthly incidence represents the difference between the proportion of SAD sufferers and the proportion of these who recover within the same month.

Figure 4.1: **Onset/Recovery chart**



Therefore, all the seasonal indicators specification come closest to match the timing of investors' seasonal decline in mood and their recovery in mood. Our null hypotheses is that there is no seasonal deference in UK government bond returns, against the alternative hypothesis that the seasonal indicators should have significant coefficients.

4.3.3 Seasonality in Government Bond Returns

In this section, seasonal patterns in government bond returns are discussed. Monthly returns to hold short-term government bond returns (2-year, 3-year, 5-year, 7-year) and long-term government bond returns (10-year, 15-year, 20-year, 30-year) are analysed.

Figures 4.2 and 4.3 contain plots of the monthly average UK government bond returns. Figure 4.2 depicts the short-term bond return series, where the monthly average returns reach their lowest point during March and April. Starting from September till October, the bond returns climb to their highest return point. The difference between the peak and trough is about 100 basis points. Figure 4.3 describes the long-term bond return series, which declines from March and reaches its lowest returns in April; the bond returns increase from September and peak in October. Both Figure 4.2 and 4.3 show the same return movement patterns for short-term and long-term bond returns. It is noticeable from the figures that the bond returns are shifted from fall to winter seasons. The the seasonal anomaly in bond returns is strong and persistent in the UK. Therefore, four estimations are applied to analyse seasonal variations in UK government bond returns.

These seasonal indicator variables include: Fall/Winter, Sep/Mar, Oct/Apr and Onset/Recovery(OR). The Oct/Apr and Sep/Mar seasonal indicators capture the timing of the SAD sufferers seasonal depression and recovery in mood, as documented in the literature above. They also match the turning points of bond returns in Figure 4.2 and 4.3. The Fall/Winter variable picks up the overall impact of SAD during fall and winter seasons, this is also noticeable from the figures that the hugh difference in returns between fall and winter seasons. The OR variable represents the change in the proportion of SAD sufferers, it is positive in the fall and negative in the winter, and reaches a maximum at the autumn equinox and minimum at the spring equinox, which is monotonic in relation to bond returns.

4.3.4 Methodology and Seasonality Test

Our null hypothesis is that there is no seasonal variation in UK government bond returns. The alternative hypothesis is the seasonal indicators described above capturing seasonal patterns in bond returns, where there is a SAD effect in UK government bond returns.

Figure 4.2: Short-term bond returns

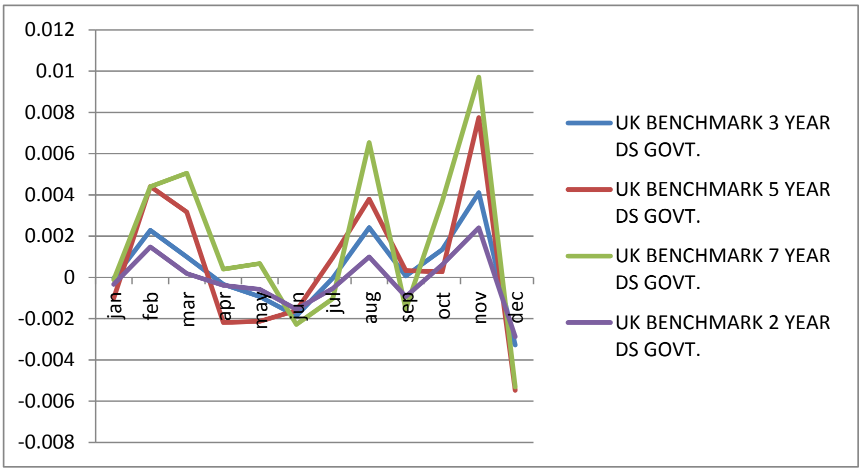
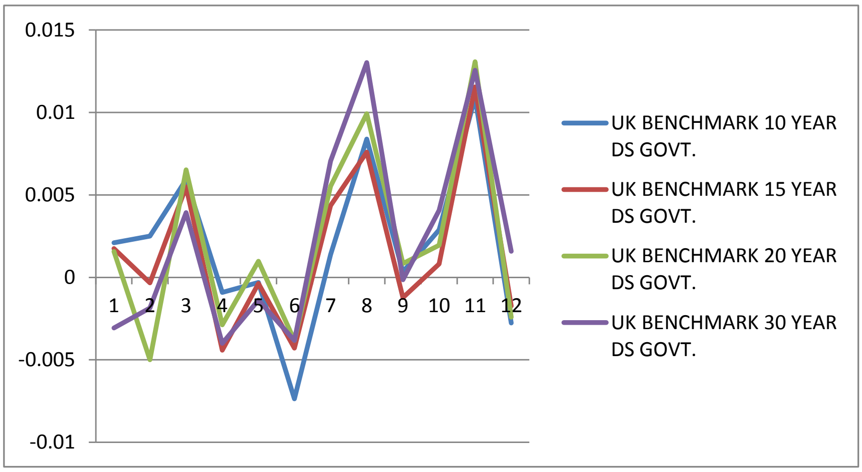


Figure 4.3: Long-term bond returns



Four simple models are constructed to test whether the seasonal indicator variables could capture seasonality in bond returns alone.

$$r_{i,t} = \alpha_i + \beta_{OR} OR_t + \sigma_{i,t} \tag{4.2}$$

$$r_{i,t} = \alpha_i + \beta_{Fallwinter} Fallwinter_t + \sigma_{i,t} \tag{4.3}$$

$$r_{i,t} = \alpha_i + \beta_{SepMar} SepMar_t + \sigma_{i,t} \tag{4.4}$$

$$r_{i,t} = \alpha_i + \beta_{OctApr} OctApr_t + \sigma_{i,t} \tag{4.5}$$

The dependent variable is the UK government bond return series, i indexes of differing maturity bonds returns. The independent variables are seasonal indicators to estimate various seasonality patterns.

To deal with potential endogenous issues in the bond returns we follow Kamstra et al. (2014), each seasonality test is regressed by estimating the Hansen (1982) generalized method of moments (GMM), Newey and West (1987, 1994) heteroskedasticity and autocorrelation consistent (HAC)[6] standard errors are applied in the GMM estimations. The HAC standard errors are adopted to control heteroskedasticity and autocorrelation effects

[6] HAC standard errors based on Bartlett kernel with Lags chosen by Newey-West method automatically.

in government bond returns. The explanatory variables and constants are used as instruments.

The GMM method has a number of important advantages that make it an intuitive and logical choice for estimating the SAD effect on government bond returns. Firstly, the GMM approach does not require that the distribution of bond returns changes be normal; secondly, the GMM estimators and their standard error are consistent even if the disturbances are conditionally heteroskedastic; thirdly, System GMM controls for the potential endogeneity arising from the explanatory variables in the model; finally, the system GMM technique has also been used in other empirical studies of bond markets, such as Gibbons and Ramaswamy (1988), Harvey (1988) and Kamstra et al. (2014).

4.3.5 Macroeconomic Data and Models

In many previous studies, macroeconomic variables are considered to play an important role in determining the prices of Treasury returns. Evans and Marshall (1998) used vector autoregressive (VAR) model to search how exogenous impulses in monetary policy affect treasury yields. Their results indicate that monetary policy shocks affect short-term treasury yields, with a diminishing effect on long-term yields.

Ang and Piazzesi (2003) improved their model by using a term structure model with latent factor variables to analyse how macroeconomic variables impact on bond return , it enables them to capture the behaviour of the entire yield curve during macro shocks. Their results show macroeconomic factors can explain up to 85% of the variation in bond yields. Fama and French (1993) studied the common risk factors that influence equity returns, they found stock returns impact on bond returns through some specific stock market factors. Therefore, macroeconomic variables and stock market factors are included in three different models to analyse the potential alternative explanations for seasonality in bond returns.

4.3.6 Model 1

The first model follow the study of Chen et al. (1986). Based on efficient market theory and rational expectations inter-temporal asset pricing theory from Cox et al.(1985), they argued that asset prices should be determined by their exposures to macroeconomic factors. They examined a set of economic state variables as systematic impacts on the asset pricing market and found a set of economic variables which significantly affected asset prices. Based on their research, the economic factors included in the first model are the growth in industrial production (IP), unanticipated inflation (CPIs) and expected inflation (CPIp), return differences in a long-term bond and a short-term bond (Termspread) and the spread between Baa bond and Aaa bond (Defaultspread).

Default-spread is included in order to capture unexpected changes in risk premia. Risk premia is the return in excess of the return of risk-free investment, it represents the willingness to accept compensation for risks. In this chapter, Default-spread is constructed using the monthly yield difference between Moody's Seasoned Aaa Corporate bond yield and Moody's Seasoned Baa Corporate bond yield, the data is collected from Datastream. Default-spread variable reflects much of the unanticipated movement in the degree of risk aversion.

The data used to construct Termspread is the monthly return difference between 30-year government bond and 2-year government bond from Datastream, with one period lagged.

Term is included in the model in order to capture the shape of the term structure effect, it can also represents the unanticipated return on long-term bonds.

The monthly consumer price index, seasonally adjusted, is collected from the Office for National Statistics (ONS [7]). ONS is the largest independent UK official statistics producer and publishing comprehensive UK economics statistics. Monthly inflation rate is the log difference of the Consumer Price Index (CPI). Based on the actual inflation data, an ARMA(1,1) model is adopted to generate the predicted inflation (Inf) and surprise inflation (InfSurp) variables.

Monthly industrial production growth rate(IP) is the log-difference of the Industrial Production Index (IP), IP is included as the equity market is related to changes in industrial productivity in the long term. IP is collected from ONS[8].Thus, the equation for Model 1 is estimated as follows:

Model 1:

$$\begin{aligned} r_{i,t} =& \alpha_i + \beta_{i,Termspread} Termspread_{t-1} + \beta_{i,CPIp} CPIp_t + \beta_{i,CPIs} CPIs_t + \beta_{i,IP} IP_t \\ &+ \beta_{i,Defaultspread} Defaultspread_t + \sigma_{i,t} \end{aligned} \tag{4.6}$$

4.3.7 Model 2

The second model adopted in this study is constructed following Kamstra, Kramer and Levi (2014) using another set of macroeconomic variables which include the following: GDP growth rate (GDP), percentage change in the producer price index (PPI), industrial

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7 http://www.ons.gov.uk/

8 Index of Production - Output of the production industries, seasonally adjusted.

production growth rate (IP), unemployment growth rate (U), and percentage change in the consumer price index (CPI). All macroeconomic data are on a monthly basis, except for GDP. The GDP growth rate is on a quarterly basis, then we applied linearly interpolation and transformed the data to monthly basis. The macroeconomic variables employed in model 1 are all deseasonalized, as predictable seasonality on these variables does not impact on bond returns. Kamstra et al. (2014) argued that even though predictable seasonality does not affect bond returns, there is a possibility that it could influence seasonality in bond returns. Therefore, macroeconomic variables employed in this model are all seasonally unadjusted.

Industrial production growth rate (IP), seasonally unadjusted, is calculated based on the industrial production index from IMF (International Financial Statistics[9]) through Datastream. The percentage change in the CPI, seasonlly unadjusted, is calculated using UK CPI INDEX from ONS. The quarterly GDP growth rate is also collected from ONS, and linearly interpolated to the monthly frequency. Unexpectedly high GDP growth is perceived to be potentially inflationary if the economy is at full capacity and causes bond returns to drop and yields to rise. On the other hand, lower than expected GDP growth makes risk averse investors shift their investments to bond market to avoid excess risk, which in turns, increases the bond returns.

The UK monthly percentage change in the producer price index (PPI) is collected from Datastream. PPI measures prices at the producer level before they are passed along to consumers and are considered as a precursor of the consumer price index. If prices that producers receive rise, then retailers will attempt to pass those costs to consumers. Bond

[9] http://www.imf.org/

prices fall when PPI is higher than expected, and therefore lower returns are generated. The bond market would rallies when the PPI decreases or the increment is lower than expected.

The UK monthly unemployment growth rate (U) is the log-difference of unemployment rate, unemployment rate is obtained from OECD,[10] through Datastream. The unemployment rate is a lagging indicator of the economic situation, as it increases or falls following a change in economy activity. Unexpectedly low unemployment may causes the Bank of England to increase interest rates in order to curb a possibly overheating economy, and vice-versa. Therefore, a negative unemployment growth rate could causes yields to rise and bond returns to drop, while a positive unemployment growth rate could increase bond returns.

Thus, the following regression model is estimated :

Model 2:

$$r_{i,t} = \alpha_i + \beta_{i,GDP} GDP_{SU,t} + \beta_{i,PPI} PPI_{SU,t} + \beta_{i,IP} IP_{SU,t} + \beta_{i,U} U_{SU,t} + \beta_{i,CPI} CPI_{SU,t} + \sigma_{i,t} \tag{4.7}$$

4.3.8 Model 3

The set of macroeconomic factors in Model 1 and Model 2 are separately able to explain bond returns, there is a possibility that the combination of all these macroeconomic factors could improve capability of explaining bond returns. Thus, Model 3 is the combination of Models 1 and 2, and it is estimated as follows:

[10] http://www.oecd.org/

Model 3:

$$
\begin{aligned}
r_{i,t} = &\alpha_i + \beta_{i,Termspread} Termspread_{t-1} + \beta_{i,CPIp} CPIp_t + \beta_{i,CPIs} CPIst + \beta_{i,IP} IP_t \\
&+ \beta_{i,Defaultspread} Defaultspread_t + \beta_{i,GDP} GDP_{SU,t} + \beta_{i,PPI} PPI_{SU,t} + \beta_{i,IP} IP_{SU,t} \\
&+ \beta_{i,U} U_{SU,t} + \beta_{i,CPI} CPI_{SU,t} + \sigma_{i,t}
\end{aligned}
\tag{4.8}
$$

4.3.9 Model 4

Fama and French (1993) studied the common risk factors in stock and bond returns, they investigated whether these risk factors were capable of explaining the cross-section of equity returns. They identified three stock-market factors which can capture variation in stock returns and two bond return factors. Even though these stock-market factors have little influence on government bond returns, together with the two bond returns factors, these five factors are capable of linking stock and bond markets. The stock-market factors indicated were the excess return on the overall market(RmRf); the difference between the returns on small and large stock portfolios, with about the same weighted-average book-to-market equity (SMB); the return difference between high and low book-to-market equity portfolios with about the same weighted-average size (HML). The two bond returns factors are the term spread (Term) and the default spread (Default). These two factors are defined in the above model. Fama and French (1993) showed that the stock returns factors affect bond returns through the excess market return, and excess market return is related to bond returns. Thus, the five Fama-French risk factors are included in the regression below to test the seasonal cycle in government bond returns. The UK Fama-French Factors data are from Xfi Centre for Finance and Investment[11].

[11] website: http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/

Model 4:

$$r_{i,t} = \alpha_i + \beta_{i,SMB}SMBt + \beta_{i,HML}HML_t + \beta_{i,RmRf}RmRf_t + \beta_{i,Default}Default_t + \beta_{i,Term}Term_t + \sigma_{i,t} \tag{4.9}$$

4.3.10 Descriptive Statistics

The descriptive statistics of the bond return series are presented in Table 4.2. From the table, the average returns of the short-term bond series is much lower than that of the long-term bond series, within the 418 observations from 1980 to 2014. The 2-year mean government bond return is -0.016 percent, which is the only negative average monthly return within all bond returns. The 30-year mean government bond return is 0.258 percent, which is the highest among all government bonds. The bond returns in the table indicate a positive relationship between bond returns and maturities, which means the longer the maturity of the bond, the higher the mean bond returns. Thus, the positive term structure of interest rates indicates that investors seek a higher rate of return for taking the higher risk of lending their money to governments for a longer time period, it also shows that investors are confident about the future economic growth rate.

The mean and standard deviations of the bond returns increase monotonically with maturity, except the 15-year bond monthly mean return, which is roughly 0.03 percent lower than the 10-year bond monthly mean return. The standard deviation of all bond returns are quite small, meaning that the risk of investing in governments are small, as expected. The differences between the minimum and maximum bond return series are larger as maturity increases. All the bond return series are leptokurtic, and the kurtosis values fall as maturity rises. All the bond return series are skewed toward positive returns except 5-year bond return, whose skewness is -0.214. The statistic means that generally all bond returns are stable, specially, the long-term bond returns are more stable than short-term bond returns, which is exactly what we expected.

Table 4.3 shows descriptive statistics of the macroeconomic variables adopted in Models 1 to 4, respectively.

In model 1, the macroeconomic variables are seasonally adjusted. The average monthly Industrial production growth rate is 0.034 percent with 1.03 standard deviation, the highest IP is 3.33 percent, while the lowest is -4.82 percent. The average monthly expected inflation growth rate is almost zero with 0.418 standard deviation, the highest Inf is 3.07 percent, while the lowest is -1.13 percent. The monthly average surprise inflation growth rate is 0.228 percent with 0.035 standard deviation. InfSurp has a maximum of 0.483 percent and minimum of 0.134 percent. The mean Defaultspread and TermSpread are 1.11 percent and -0.003 respectively. Industrial production growth rates exhibit a fair amount of negative skewness (-0.459), while all other variables in Model 1 are positively skewed. All macroeconomics variables in Model 1 are leptokurtic, which means these historical macroeconomics variables have clustered around the mean values.

The macroeconomic variables presented in Model 2 are seasonally unadjusted. The monthly average GDP growth rate is 0.177 percent with a small standard deviation (0.177), which indicates that the UK GDP has steadily grown in the last decade. The mean CPI monthly growth rate is only 0.002 percent with 0.004 standard deviation and mean PPI at 0.205 percent, which indicates steady prices in the market. The UK seasonally unadjusted industrial production growth rate is only available on a year-over-year basis, thus IP in model 2 is largely different from IP in Model 1 and its standard deviation is a fairy large value. The mean unemployment growth rate is negative, at 0.002 percent, which indicates that labour unemployed level has fallen during the last decade.

In Model 4, the mean and standard deviation of all three Fama and French factor variables are small. The mean value of SMB, HML and RmRf is 0.01, 0.03 and 0.05 respectively. SMB is positively skewed, HML and RmRf exhibit a large mount of negative skewness. All three Fama and French factor variables are leptokurtic, which is common in equity data.

4.4 Results

In this section the various results relating to seasonal variation in bond returns analysed in this chapter are discussed. Initially, the results for direct seasonality in bond returns are presented, and the results for various of macroeconomics models are subsequently considered. For each model, the results relating to whether macroeconomics models help explain seasonal variation in government bond returns are discussed. The estimation periods are different in different models as data availability is limited in some datasets. In each model, the dependent variables are UK government bond returns and the independent variables are the seasonal indicators, macroeconomic and risk factors.

4.4.1 Seasonality in Government Bond Returns

Initially, the estimation results of Equations 4.2 to 4.5 are presented. Table 4.4 and 4.5 contain the results for seasonality test for short-term bond returns and long-term bond returns respectively. The seasonality tests are estimated using the system-equation of GMM and HAC(1987,1994) standard errors. In each cell of the bond returns, the coefficient and standard error (in parentheses) of the variables are provided. The p-values for joint tests test whether the coefficients of each SAD indicator jointly differ from zero using Chi-Square test. Our null hypothesis is that there is no seasonal pattern caused by SAD in UK government bond returns.

Table 4.4 shows the results of the seasonality test based on the short-term bond return series against the four seasonal indicators. The short-term bond return series contains 2-year, 3-year, 5-year and 7-year monthly bond returns. All short-term bond returns exhibit no seasonality, with the p-values of the coefficients of the SAD indicators statistically insignificant at 10 percent level. The p-values for coefficients joint test are only statistically significant for the Sep/Mar test at 5 the percent level, which means that returns of short-term bond series are different between September and March. The GMM test of overidentification restrictions proves the instruments are valid and not correlated with the errors.

Table 4.5 shows the results for seasonality test based on the long-term bond return series against four seasonal indicators. All coefficients of the indicator variables are statistically insignificant at the 10 percent level. The p-values for coefficients joint tests different from zero is statistically significant for the Fall/Winter test at the 5 percent level and is statistically significant for the OR test at the 10 percent level. The results show no seasonal variation in each bond return separately. The joint test shows the long-term bond series returns are different between fall and winter and are impacted by OR (Onset/Recovery). The result of the GMM test of overidentification restrictions indicates that the instruments are not correlated with the errors.

The results in Table 4.4 and 4.5 indicate that we can not reject the null hypothesis that there is no seasonality in single UK government bond returns. However, the join tests results show some indication of seasonality in bond series returns. The returns of short-term bond series are different between September and March, while returns of long-term bond series are affected by Fall/Winter and OR. Therefore, in order to further analyse the SAD effect in UK government bond returns, we follow Kamstra et al. (2014) and constructed four alternative models to determine whether UK government bond returns are affect by SAD.**?**

4.4.2 Model 1

The estimation results of Model 1 are displayed in Table 4.6 to Table 4.13. The default-spread variable is positively related to short-term bond returns and predict CPI is negatively related to long-term bond returns across Tables 4.6 to 4.13. The significantly positive coefficient of default-spread (Defaultspread) shows that the larger the difference between monthly Moody's seasoned Aaa corporate bond yield and Moody's seasoned baa corporate bond yield ,the higher the short-term bond monthly returns. The significantly negative coefficient of expected inflation (CPIp) indicates expected inflation is negatively correlated to long-term bond returns. High inflation prediction would decrease long-term bond returns. The results are consistent to the findings of Kamstra et al. (2014) and Chen et al. (1986), they also suggested default-spread is positively related to short-term bond returns and expected inflation is negatively related to long-term bond returns.

It is clear from Tables 4.6 and 4.7, the Sep/Mar seasonal indicator is statistically insignificant in both shot-term and long-term bond returns, which means that the bond returns are not different between September and March individually. The positive and significant coefficients of Oct/Apr indicator variables in Table 4.8 and 4.9 show that both short-term and long-term bond returns were higher in October and lower in April, as the Oct/Apr dummy variable equals to 1 in October and -1 in April. Similarly, From Table 4.10 to 4.13, Fall/Winter and OR indicator variables had statistically significant impact on short-term and long-term bond returns. The significantly positive coefficients of Fall/Winter denote that UK government bond returns were higher in rhe fall and lower in the winter. The significantly positive relationship between bond returns and OR implies the more people suffer from SAD the higher bond returns. It has been found in the existing literature that investors become more risk averse when they suffer from SAD, hence they tend to shift their investment from risky assets to low risk assets. Increments of people suffering from SAD leads to greater investment in government bonds, and eventually increases bond returns.

Furthermore, it is clear from tables 4.10 and 4.11 that the seasonality in the long-term bonds is more pronounced than in the short-term bonds. The results is consistent with the finding of Kamstra et al. (2014), who found evidence of seasonality in the short-term bonds is weaker than that of in the long-term bonds. Gibson (1970) suggested that aim of government policies is try to reduce the seasonal fluctuations in government bond, especially short-term bonds. Therefore, returns of short-term government bonds might not fully respond freely to market activities, this helps in explaining why seasonal fluctuations in the long-term bonds are more pronounced than in the short-term bonds.

Finally, Table 4.14 demonstrates the p-values of whether the coefficients of seasonal indicators jointly differ from zero. The null hypothesis is there is no seasonal effect in bond return series. From the second column of Table 4.14 only the OR variable fails to exhibit joint seasonal effect, so the short-term bond return series are not affected by OR. The short-term bond return series shows p-values below 5 percent for the Sep/Mar and Oct/Apr joint test, and a p-value below 10 percent for the Fall/Winter joint test. The long-term bond return series exhibit strong seasonality, as p-values of Oct/Apr, Fall/Winter and OR are all below 1 percent. The results in Table 4.14 show returns of the short-term bond series are different between September and March, between October and April, and between Fall and Winter seasons. Returns of long-term bond series are different between October and April, Fall and Winter seasons. OR is also found to have a significant influence on long-term bond returns series.

4.4.3 Model 2

In this section, seasonally unadjusted macroeconomic data are adopted to analyse the seasonal pattern in the UK government bond returns. Tables 4.15 to 4.22 represent Model 2 estimation results of seasonality test on UK government bond returns. Across the tables, GDP growth rate (GDP) is significantly negative related to all UK government bond returns except 30-year bond return and Industrial production growth rate (IP) has significantly negative impact upon the 2-year and 3-year bond returns. The results suggest that when GDP and industrial production are growing at high speed, investors tend to reduce their investments on government bonds, thus resulting in lower government bond returns.

The null hypothesis of the seasonality test, which is that there is no seasonal variation in UK government bond returns. Models 2 results display evidence of a Sep/Mar seasonal effect only on 3-year bond returns at 10% significance level, an Oct/Apr seasonal effect on 3-year and 5-year bond returns at 1% significance level. The positive coefficients of

Sep/Mar and Oct/Apr variable denote the corresponding bond returns as being higher in September and October, and lower in March and April. All the bond returns demonstrate strong Fall/winter and OR seasonal effect. The significantly positive coefficients of OR and Fall/Winter indicator variables denote that UK government bond returns are higher in the fall season than in the winter season, as the OR variable is positive in the fall and negative in the winter, and Fall/Winter equals to 1 in the fall, -1 in the winter.

Table 4.23 contains joint test results on the all seasonal indicators across the two bond return series. The null hypothesis is that the coefficients of the seasonal indicators are jointly zero. The null hypothesis is rejected since the Sep/Mar, Fall/Winter and OR coefficients are jointly different from zero for short-term bond return series, with p-value below 3% for Sep/Mar, and p-values below 10% for Fall/Winter and OR. The p-values indicate strong seasonality for long-term bond return series, as all seasonal indicators are jointly differ from zero, except Sep/Mar.

4.4.4 Model 3

Tables 4.24 to 4.31 report Model 3 estimation results. Model 3 combines the seasonally adjusted macroeconomic variables in Model 1 and the seasonally unadjusted macroeconomic variables in Model 2, in order to examine the seasonal variation in the UK government bond returns. GDP coefficients are negative and statistically significant for all bond returns; while CPIsu coefficients are negative and statistically significant for long-term bond returns only; CPIs coefficients are significantly negative for 2-year, 3-year and 5-year bond returns.

Tables 4.24 to 4.31 present a full set of GMM estimation results. Sep/Mar and Oct/Mar variables show no impact on the individual UK government bond returns, except that the Sep/Mar variable is statistically significant for 3-year bond returns only at the 10 percent level of significance. Fall/Winter and OR indicator variables exhibit a strong impact on all bond returns as their coefficients are significantly positive.

Table 4.32 reports the p-values for joint tests. The null hypothesis is the coefficients of the seasonal indicators are jointly zero within the corresponding bond return series. The coefficients of Sep/Mar variables are jointly significantly different from zero at 1 a percent level of significance for the shot-term bond return series only. Again, long-term bond returns series exhibits strong seasonality, as Oct/Apr, Fall/Winter and Or are all jointly differ from zero. Thus the results indicate that returns on short-term bond series are different between September and March. Returns from long-term bond series are different between October and April, and different between fall and winter seasons.

4.4.5 Model 4

In this section, the Fama-French model factors are included to test seasonality in UK government bond returns. The explanatory variables employed in model 4 are the three Fama-French equity return factors, Term-spread Default-spread and seasonal indicators. The estimation results are in Tables 4.33 to 4.40. Defaultspread is significantly positively related to bond returns, which is the same as it affects bond returns in Model 1. Among the Fama-French factors, SMB and RmRf have a statistically significant influence on all UK government bond returns. The negative coefficients of SMB indicate that bond returns decrease when the average return difference between small portfolios and large portfolios increase. The positive coefficient of RmRf shows that the UK government bond returns are positively correlated to the risk premium, which is in line with the findings of Fama and French (1993).

Across tables, the coefficients of seasonality indicator variables are all statistically insignificant, which indicates no seasonal pattern in individual bond returns. Table 4.41 reports the summary joint seasonality tests results for long-term and short-term bond return series. For the short-term bond return series, the null hypothesis is rejected at a 10% level of significance, where the coefficients of Sep/Mar variable are jointly differ from zero. The resuslt indicates returns of short-term bond series are significantly different between September and March. For the long-term bond return series, the p-value of the Fall/Winter join test is statistically significant at a 5% level of significance, which means the long-term bond series returns are different between the fall and winter.

4.4.6 Results Discussion

Initially, the government bond returns exhibit no seasonal patters when only seasonal indicators are considered in the regressions. We then constructed four alternative models, which included macroeconomic and risk factors that have been proven in the literature that are related to bond returns, to further investigate seasonality in bond returns.

The regression results from the four model indicate striking seasonal patterns in UK government bond returns and the seasonal patterns vary across bonds. More precisely, short-term government bond returns are higher than average in October and lower in April; long-term government bond returns are higher than average in the fall and lower in the winter. The long-term government bond returns are also affected by OR, which means long-term government bond returns are higher when more people suffer from SAD.

Since the Oct/Apr seasonal indicator matches the timing of investors suffer from SAD and recover from SAD, Fall/Winter presents the average SAD impact during the two seasons and OR reflects the changes in proportion of SAD sufferers. The results of this chapter provide supportive evidence for the existence of SAD effect on UK government bond returns. Moreover, in line withKamstra et al. (2014), we found that, overall, long-term government bond returns exhibit stronger SAD effect than short-term bond returns. We can conclude that seasonal variation in UK government bonds returns is driven by seasonally varying investor risk perception, which is affected by SAD. Add to this, the seasonal pattern in bond returns we found in this chapter is opposite in direction to the seasonal pattern in stock return, which further confirmed the SAD hypothesise, investors suffer from SAD tend to avoid risks, they will increase investment in safe assets such as government bonds, thus bond returns are higher and stock returns are lower in the fall.

4.5 Discussion and Conclusion

This chapter has analysed seasonal variations that influence UK government bond returns between 1980 and 2013. The UK government bond return series contains monthly average bond returns across the 2,3,5,7,10,15,20 and 30-year maturities. In line with Kamstra et al.(2014), this chapter adopted four models in order to capture the seasonality in bond returns, which were constructed as two groups, based on their maturities. These were the short-term bond return series containing bonds with 2-year to 7-year maturities, while the long-term bond return series containing bonds with 10-year to 30-year maturities. The seasonal indicators adopted in this chapter are Sep/Mar, Oct/Apr, Fall/Winter dummy variables and OR (Onset/Recovery).

The empirical analysis presented in this chapter aims to develop the literature in several distinct ways. Initially, this chapter explores the seasonal variation in UK government bond returns. Previously, Kamstra et al. (2014), focused on US bond market, and Athanassakos (2008), considered only the Canadian financial market. Secondly, some other studies such as Smith (2002), tested government bond market seasonality using only one index for each country. This chapter studies the UK government bond returns with maturities ranging from 2-year to 30-year. Moreover, the bond returns were tested in 2 groups based on their maturities, the result indicates that the seasonal effect in different groups were different. Finally, this chapter adopted several macroeconomics and risk factors variables that previous studies have proven that they are related to bond returns. Four models were constructed using these bond return related variables to test whether these variables in favour of uncovering seasonal patterns in UK government bond returns.

The first model includes seasonally adjusted macroeconomics variables which Chen et al. (1986) proved are significantly related to equity returns. The second model is constructed following the study of Kamstra et al. (2014), who argued there is a possibility that seasonally unadjusted component of macroeconomic risk factors could help to explain seasonality in bond returns. The third model is the combination of Model 1 and Model 2. Fama and French (1993) identified three equity and two bond return factors which can explain average returns on stocks and bonds. In Model 4, the Fama-French five factors are employed to analyse the seasonal pattern in UK government bond returns.

The seasonal pattern in UK government bond returns was presented where the monthly average bond returns were statistically and economically significantly different, as shown through the seasonal indicators. The bond returns failed to exhibit strong seasonal pattern by simply regressing bond returns against different seasonal indicators. By considering several macroeconomics and risk factor variables and forming four alternative models, the bond returns show significant seasonal patterns. The macroeconomic variables include inflation, the growth in industrial production, GDP growth rate, the producer price index growth rate, unemployment growth rate and percentage change in the consumer price index. The risk factors include return difference between a long-term and short-term bond (Termspread), yield spread between high-grade and low grade bonds (Defaultspread), risk premium (RmRf), returns difference between small and big size portfolios (SMB), and returns difference between low- and high- book-to-market value portfolios.

Consistent with the findings of Kamstra et al. (2014), Ogden (2003) and Athanassakos (2008), the result of this chapter provides support for there is a seasonal pattern in UK government bond returns. The UK government bond returns exhibit strong seasonality. From the bond return series joint seasonality tests tables, the Sep/Mar joint tests are statistically significant for the short-term bond return series in all four models, the Fall/Winter join tests are statistically significant for the long-term bond return series in all four models. The results show significant seasonal patterns in bond series, with a significant returns difference between September and March for short-term bond series, and a significant returns difference between the fall and the winter for long-term bond series. The seasonal pattern of bond returns presented in this chapter is consistent with the findings of Chapter 2, which showed that investors suffer from SAD and become more risk averse when the days become shorter in the fall, these investors tend to avoid risks and turn to safe assets, thus stock returns are lower in the fall, while bond returns are higher.

This chapter's finding could be useful to individual investors. This is of particular importance to investors who are likely be affect by SAD and experience seasonal varied risk aversion. These investors tend to wrongly shift their investments by seasons and ultimately earn lower than average returns. Understanding the seasonal variation in bond returns will help these investors to secure their returns all year round. Moreover,the findings of this chapter identified a behavioural factor that should not be ignored in modelling seasonal patterns in UK equity markets.

Table 4.2: **Descriptive statistics of bond returns**

Series	N	Mean	Std	Min	Max	Skew	Kurt
Short-Term Bond Returns							
2-year	418	-.016%	.008	-.028	.046	.951	7.46
3-year	418	.040%	.011	-.039	.063	.850	7.41
5-year	418	.073%	.017	-.075	.080	-.214	6.99
7-year	418	.172%	.021	-.086	.096	.167	5.72
Long-Term Bond Returns							
10-year	418	.205%	.024	-.114	.115	.088	5.74
15-year	418	.177%	.027	-.097	.099	.219	3.94
20-year	418	.237%	.030	-.108	.108	.007	4.13
30-year	418	.258%	.032	-.117	.114	.047	3.98

Notes: This table contains summary statistics for all bond return series adopted in this chapter. For each bond return the number of observations (N), mean, standard deviation (Std), minimum (Min), skewness (Skew), and kurtosis (Kurt) are presented.

Table 4.3: **Descriptive statistics of macroeconomic variables**

Variables	N	Mean	Std	Min	Max	Skew	Kurt
Model 1/3: CRR Macro Factors Model							
Industrial Production Growth (IP)	418	.034	1.03	-4.82	3.33	-.459	4.68
Expected Inflation (Inf)	322	-.000	.418	-1.13	3.07	.999	12.0
Surprise Inflation (InfSurp)	322	.228	.035	.134	.483	1.01	12.1
Default Spread (Default)	418	1.11	.485	.550	3.38	1.75	6.67
Term Spread (Term)	417	-.003	.028	-.105	.117	.131	4.25
Model 2/3: KKL Macro Factors Model							
GDP Growth (GDP)	416	.177	.236	-.733	.800	-1.12	5.98
Consumer Price Index Growth (CPI)	322	.002	.004	-.010	.034	1.04	12.2
Industrial Production Growth (IP)	417	.342	4.16	-14.2	10.1	-.599	3.68
Producer Price Index Growth (PPI)	286	.205	.991	-3.00	3.90	.353	4.29
Unemployment Growth (U)	297	-.002	.032	-.071	.128	.958	4.50
Model 4: Fama and French Model							
Size (SMB)	408	.001	.031	-.115	.156	.114	5.21
Book-to-Market (HML)	408	.003	.032	-.186	.123	-.554	9.43
Excess Return (RmRf)	408	.005	.045	-.271	.133	-.991	6.62

Notes: This table contains summary statistics for all macroeconomics variables adopted in this chapter. For each variables the number of observations (N), mean, standard deviation (Std), minimum (Min), skewness (Skew), kurtosis (Kurt) are presented.

Table 4.4: Seasonality in short-term bond returns

Short-term Bond Return Series	**Sep/Mar** Coeff. (S.D.)	**Oct/Apr** Coeff. (S.D.)	**Fall/Winter** Coeff. (S.D.)	**OR** Coeff. (S.D.)
2-year	-0.0005	0.0005	-0.0002	-0.0001
	(0.0010)	(0.0011)	(0.0005)	(0.0024)
3-year	-0.0004	0.0010	-0.0001	0.0009
	(0.0015)	(0.0015)	(0.0008)	(0.0033)
5-year	-0.0014	0.0014	-0.0006	-0.0003
	(0.0024)	(0.0022)	(0.0015)	(0.0053)
7-year	-0.0033	0.0019	-0.0001	-0.0015
	(0.0031)	(0.0025)	(0.0014)	(0.0061)
P-values for Joint Tests	0.0169**	0.8166	0.8396	0.3432
Overidentification Restrictions	1	1	1	1
Observations	418	418	418	418

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.5: Seasonality in long-term bond returns

Long-term Bond Return Series	**Sep/Mar** Coeff. (S.D.)	**Oct/Apr** Coeff. (S.D.)	**Fall/Winter** Coeff. (S.D.)	**OR** Coeff. (S.D.)
10-year	-0.0029	0.0023	0.0002	0.0008
	(0.0035)	(0.0027)	(0.0020)	(0.0072)
15-year	-0.0035	0.0031	0.0007	0.0014
	(0.0042)	(0.0033)	(0.0023)	(0.0076)
20-year	-0.0031	0.0030	0.0017	0.0047
	(0.0046)	(0.0032)	(0.0026)	(0.0087)
30-year	-0.0025	0.0049	0.0033	0.0080
	(0.0051)	(0.0034)	(0.0025)	(0.0093)
P-values for Joint Tests	0.7662	0.2901	0.0340**	0.0751*
Overidentification Restrictions	1	1	1	1
Observations	418	418	418	418

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.6: **Model 1: Sep/Mar seasonality test in short-term bond returns**

Seasonality indicator variables	**2-year** Coeff. (S.D.)	**3-year** Coeff. (S.D.)	**5-year** Coeff. (S.D.)	**7-year** Coeff. (S.D.)
Sep/Mar	0.0009	0.0018	0.0021	0.0014
	(0.0008)	(0.0012)	(0.0020)	(0.0025)
termspread	0.0060	0.0049	-0.0049	0.0047
	(0.0161)	(0.0208)	(0.0307)	(0.0327)
CPIp	-0.0010	-0.0015*	-0.0021	-0.0033*
	(0.0006)	(0.0008)	(0.0013)	(0.0018)
CPIs	-0.0086	-0.0180	-0.0289	-0.0332
	(0.0133)	(0.0169)	(0.0217)	(0.0221)
IP	-0.0004	-0.0003	-0.0005	-0.0002
	(0.0003)	(0.0004)	(0.0005)	(0.0007)
defaultspread	0.0020***	0.0026***	0.0025**	0.0037**
	(0.0008)	(0.0009)	(0.0012)	(0.0016)
Observations	322	322	322	322

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.7: **Model 1: Sep/Mar seasonality test in long-term bond returns**

Seasonality indicator variables	**10-year** Coeff. (S.D.)	**15-year** Coeff. (S.D.)	**20-year** Coeff. (S.D.)	**30-year** Coeff. (S.D.)
Sep/Mar	0.0020	0.0030	0.0032	0.0053
	(0.0032)	(0.0038)	(0.0042)	(0.0044)
termspread	0.0239	0.0209	0.0423	0.1076
	(0.0389)	(0.0420)	(0.0489)	(0.0712)
CPIp	-0.0051**	-0.0060**	-0.0075***	-0.0085***
	(0.0025)	(0.0027)	(0.0027)	(0.0029)
CPIs	-0.0364	-0.0382	-0.0355	-0.0600
	(0.0268)	(0.0301)	(0.0334)	(0.0381)
IP	0.0000	-0.0003	-0.0002	0.0009
	(0.0009)	(0.0013)	(0.0017)	(0.0019)
defaultspread	0.0037*	0.0025	0.0019	0.0002
	(0.0021)	(0.0024)	(0.0027)	(0.0032)
Observations	322	322	322	322

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.8: Model 1: Oct/Apr seasonality test in short-term bond returns

Seasonality indicator variables	2-year Coeff. (S.D.)	3-year Coeff. (S.D.)	5-year Coeff. (S.D.)	7-year Coeff. (S.D.)
Oct/Apr	0.0016*	0.0023**	0.0033**	0.0034*
	(0.0009)	(0.0011)	(0.0014)	(0.0018)
termspread	0.0043	0.0015	-0.0088	0.0024
	(0.0151)	(0.0194)	(0.0284)	(0.0312)
CPIp	-0.0005	-0.0009	-0.0011	-0.0023
	(0.0006)	(0.0009)	(0.0013)	(0.0017)
CPIs	-0.0087	-0.0180	-0.0290	-0.0333
	(0.0128)	(0.0163)	(0.0208)	(0.0213)
IP	-0.0004	-0.0003	-0.0004	-0.0002
	(0.0003)	(0.0004)	(0.0005)	(0.0007)
defaultspread	0.0020***	0.0025***	0.0025**	0.0037**
	(0.0008)	(0.0009)	(0.0012)	(0.0016)
Observations	322	322	322	322

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.9: Model 1: Oct/Apr seasonality test in long-term bond returns

Seasonality indicator variables	10-year Coeff. (S.D.)	15-year Coeff. (S.D.)	20-year Coeff. (S.D.)	30-year Coeff. (S.D.)
Oct/Apr	0.0037**	0.0039*	0.0054**	0.0071**
	(0.0018)	(0.0022)	(0.0025)	(0.0030)
termspread	0.0111	0.0113	0.0341	0.0937
	(0.0342)	(0.0384)	(0.0459)	(0.0663)
CPIp	-0.0037	-0.0044*	-0.0057**	-0.0063**
	(0.0023)	(0.0024)	(0.0024)	(0.0027)
CPIs	-0.0499**	-0.0521**	-0.0512**	-0.0775***
	(0.0204)	(0.0228)	(0.0249)	(0.0282)
IP	0.0001	0.0000	0.0003	0.0012
	(0.0008)	(0.0012)	(0.0015)	(0.0018)
defaultspread	0.0030	0.0018	0.0012	-0.0006
	(0.0020)	(0.0022)	(0.0025)	(0.0030)
Observations	322	322	322	322

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.10: Model 1: Fall/Winter seasonality test in short-term bond returns

Seasonality indicator variables	2-year Coeff. (S.D.)	3-year Coeff. (S.D.)	5-year Coeff. (S.D.)	7-year Coeff. (S.D.)
Fall/Winter	0.0007**	0.0012***	0.0020***	0.0025***
	(0.0003)	(0.0005)	(0.0008)	(0.0009)
termspread	0.0054	0.0037	-0.0051	0.0073
	(0.0156)	(0.0196)	(0.0282)	(0.0298)
CPIp	-0.0010	-0.0016*	-0.0022*	-0.0035**
	(0.0007)	(0.0009)	(0.0013)	(0.0017)
CPIs	-0.0098	-0.0201	-0.0324	-0.0377*
	(0.0136)	(0.0172)	(0.0219)	(0.0218)
IP	-0.0004	-0.0004	-0.0005	-0.0003
	(0.0003)	(0.0004)	(0.0005)	(0.0006)
defaultspread	0.0020***	0.0025***	0.0024**	0.0035**
	(0.0008)	(0.0009)	(0.0011)	(0.0015)
Observations	322	322	322	322

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.11: Model 1: Fall/Winter seasonality test in long-term bond returns

Seasonality indicator variables	10-year Coeff. (S.D.)	15-year Coeff. (S.D.)	20-year Coeff. (S.D.)	30-year Coeff. (S.D.)
Fall/Winter	0.0038***	0.0047***	0.0058***	0.0082***
	(0.0011)	(0.0013)	(0.0014)	(0.0015)
termspread	0.0282	0.0250	0.0485	0.1147*
	(0.0349)	(0.0368)	(0.0448)	(0.0684)
CPIp	-0.0053**	-0.0063**	-0.0080***	-0.0090***
	(0.0025)	(0.0027)	(0.0027)	(0.0030)
CPIs	-0.0432	-0.0465	-0.0458	-0.0746**
	(0.0266)	(0.0299)	(0.0332)	(0.0379)
IP	-0.0001	-0.0004	-0.0003	0.0007
	(0.0008)	(0.0012)	(0.0016)	(0.0018)
defaultspread	0.0035*	0.0023	0.0015	-0.0003
	(0.0020)	(0.0023)	(0.0026)	(0.0030)
Observations	322	322	322	322

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.12: Model 1: OR seasonality test in short-term bond returns

Seasonality indicator variables	2-year Coeff. (S.D.)	3-year Coeff. (S.D.)	5-year Coeff. (S.D.)	7-year Coeff. (S.D.)
OR	0.0031*	0.0053**	0.0074**	0.0074*
	(0.0016)	(0.0024)	(0.0035)	(0.0038)
termspread	0.0075	0.0072	-0.0008	0.0103
	(0.0165)	(0.0212)	(0.0310)	(0.0332)
CPIp	-0.0008	-0.0012	-0.0016	-0.0028
	(0.0006)	(0.0008)	(0.0013)	(0.0017)
CPIs	-0.0091	-0.0188	-0.0301	-0.0344
	(0.0132)	(0.0167)	(0.0214)	(0.0217)
IP	-0.0004	-0.0003	-0.0005	-0.0002
	(0.0003)	(0.0004)	(0.0005)	(0.0007)
defaultspread	0.0020***	0.0026***	0.0025**	0.0037**
	(0.0008)	(0.0009)	(0.0012)	(0.0016)
Observations	322	322	322	322

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.13: Model 1: OR seasonality test in long-term bond returns

Seasonality indicator variables	10-year Coeff. (S.D.)	15-year Coeff. (S.D.)	20-year Coeff. (S.D.)	30-year Coeff. (S.D.)
OR	0.0100**	0.0123***	0.0159***	0.0225***
	(0.0043)	(0.0045)	(0.0048)	(0.0058)
termspread	0.0312	0.0288	0.0540	0.1224*
	(0.0386)	(0.0407)	(0.0476)	(0.0715)
CPIp	-0.0044*	-0.0051*	-0.0065**	-0.0069**
	(0.0024)	(0.0027)	(0.0027)	(0.0029)
CPIs	-0.0380	-0.0402	-0.0381	-0.0636*
	(0.0263)	(0.0296)	(0.0328)	(0.0375)
IP	0.0000	-0.0003	-0.0002	0.0008
	(0.0008)	(0.0013)	(0.0016)	(0.0019)
defaultspread	0.0038*	0.0026	0.0020	0.0003
	(0.0021)	(0.0023)	(0.0026)	(0.0031)
Observations	322	322	322	322

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.14: Model 1: Joint seasonality test

	short-term bond return series	long-term bond return series
Sep/Mar joint test	0.0383**	0.3023
Oct/Apr joint test	0.0405**	0.0026***
Fall/Winter joint test	0.0604*	0.0000***
OR joint test	0.1949	0.0005***

Notes: This table reports p-values of the joint tests. The null hypothesis is the estimated coefficients are jointly equal to zero. The short-term bond return series contains bond returns with maturities from 2-year to 7-year. The long-term bond returns contains bond returns with maturities from 10-year to 30-year. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 4.15: Model 2: Sep/Mar seasonality test in short-term bond returns

Seasonality indicator variables	2-year Coeff. (S.D.)	3-year Coeff. (S.D.)	5-year Coeff. (S.D.)	7-year Coeff. (S.D.)
Sep/Mar	0.0012	0.0021*	0.0026	0.0017
	(0.0008)	(0.0012)	(0.0019)	(0.0025)
GDP	-0.0043***	-0.0060***	-0.0078**	-0.0107***
	(0.0013)	(0.0019)	(0.0034)	(0.0038)
PPIsu	-0.0004	-0.0002	-0.0002	-0.0004
	(0.0004)	(0.0006)	(0.0010)	(0.0011)
IPsu	-0.0002**	-0.0002**	-0.0002	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Usu	0.0103	0.0153	0.0231	0.0296
	(0.0090)	(0.0138)	(0.0199)	(0.0256)
CPIsu	-0.1116	-0.1673*	-0.2115	-0.2487
	(0.0710)	(0.0923)	(0.1509)	(0.1938)
Observations	284	284	284	322

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.16: Model 2: Sep/Mar seasonality test in long-term bond returns

Seasonality indicator variables	10-year Coeff. (S.D.)	15-year Coeff. (S.D.)	20-year Coeff. (S.D.)	30-year Coeff. (S.D.)
Sep/Mar	0.0019	0.0028	0.0029	0.0043
	(0.0031)	(0.0036)	(0.0040)	(0.0046)
GDP	-0.0124**	-0.0130*	-0.0144*	-0.0115
	(0.0055)	(0.0068)	(0.0075)	(0.0076)
PPIsu	-0.0004	-0.0002	0.0003	0.0004
	(0.0016)	(0.0018)	(0.0020)	(0.0022)
IPsu	0.0001	0.0003	0.0003	0.0004
	(0.0003)	(0.0004)	(0.0004)	(0.0005)
Usu	0.0345	0.0310	0.0278	0.0084
	(0.0340)	(0.0383)	(0.0406)	(0.0410)
CPIsu	-0.3572	-0.4208	-0.5880*	-0.6962*
	(0.2727)	(0.2877)	(0.3127)	(0.3781)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.17: Model 2: Oct/Apr seasonality test in short-term bond returns

Seasonality indicator variables	2-year Coeff. (S.D.)	3-year Coeff. (S.D.)	5-year Coeff. (S.D.)	7-year Coeff. (S.D.)
Oct/Apr	0.0017	0.0023*	0.0030*	0.0029
	(0.0010)	(0.0013)	(0.0017)	(0.0020)
GDP	-0.0038***	-0.0053***	-0.0068**	-0.0098***
	(0.0013)	(0.0019)	(0.0035)	(0.0037)
PPIsu	-0.0004	-0.0003	-0.0003	-0.0005
	(0.0004)	(0.0006)	(0.0010)	(0.0012)
IPsu	-0.0002**	-0.0002**	-0.0002	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Usu	0.0139	0.0200	0.0294	0.0361
	(0.0087)	(0.0135)	(0.0205)	(0.0254)
CPIsu	-0.0515	-0.0872	-0.1061	-0.1432
	(0.0687)	(0.0926)	(0.1568)	(0.1903)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.18: **Model 2: Oct/Apr seasonality test in long-term bond returns**

Seasonality indicator variables	**10-year** Coeff. (S.D.)	**15-year** Coeff. (S.D.)	**20-year** Coeff. (S.D.)	**30-year** Coeff. (S.D.)
Oct/Apr	0.0025	0.0016	0.0028	0.0038
	(0.0026)	(0.0035)	(0.0039)	(0.0047)
GDP	-0.0116**	-0.0124*	-0.0135*	-0.0103
	(0.0056)	(0.0068)	(0.0075)	(0.0078)
PPIsu	-0.0006	-0.0003	0.0001	0.0002
	(0.0017)	(0.0019)	(0.0021)	(0.0023)
IPsu	0.0001	0.0003	0.0003	0.0004
	(0.0003)	(0.0004)	(0.0004)	(0.0005)
Usu	0.0399	0.0338	0.0337	0.0162
	(0.0339)	(0.0389)	(0.0420)	(0.0426)
CPIsu	-0.2675	-0.3666	-0.4879	-0.5614
	(0.2803)	(0.3072)	(0.3327)	(0.4178)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.19: **Model 2: Fall/Winter seasonality test in short-term bond returns**

Seasonality indicator variables	**2-year** Coeff. (S.D.)	**3-year** Coeff. (S.D.)	**5-year** Coeff. (S.D.)	**7-year** Coeff. (S.D.)
Fall/Winter	0.0009*	0.0014**	0.0024**	0.0028***
	(0.0004)	(0.0006)	(0.0010)	(0.0010)
GDP	-0.0037***	-0.0051**	-0.0061*	-0.0088***
	(0.0013)	(0.0020)	(0.0035)	(0.0034)
PPIsu	-0.0005	-0.0004	-0.0005	-0.0008
	(0.0004)	(0.0006)	(0.0009)	(0.0009)
IPsu	-0.0002**	-0.0002**	-0.0002	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Usu	0.0158	0.0243*	0.0386*	0.0486*
	(0.0097)	(0.0147)	(0.0229)	(0.0265)
CPIsu	-0.1035	-0.1544*	-0.1880	-0.2182
	(0.0672)	(0.0881)	(0.1489)	(0.1892)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.20: Model 2: Fall/Winter seasonality test in long-term bond returns

Seasonality indicator variables	10-year Coeff. (S.D.)	15-year Coeff. (S.D.)	20-year Coeff. (S.D.)	30-year Coeff. (S.D.)
Fall/Winter	0.0042***	0.0049***	0.0060***	0.0085***
	(0.0013)	(0.0014)	(0.0015)	(0.0018)
GDP	-0.0096**	-0.0096*	-0.0103*	-0.0058
	(0.0046)	(0.0053)	(0.0060)	(0.0069)
PPIsu	-0.0011	-0.0010	-0.0007	-0.0010
	(0.0014)	(0.0016)	(0.0017)	(0.0019)
IPsu	0.0001	0.0003	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Usu	0.0628*	0.0643*	0.0686*	0.0655*
	(0.0342)	(0.0350)	(0.0373)	(0.0388)
CPIsu	-0.3111	-0.3670	-0.5215*	-0.6037*
	(0.2576)	(0.2629)	(0.2756)	(0.3414)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.21: Model 2: OR seasonality test in short-term bond returns

Seasonality indicator variables	2-year Coeff. (S.D.)	3-year Coeff. (S.D.)	5-year Coeff. (S.D.)	7-year Coeff. (S.D.)
OR	0.0034*	0.0058**	0.0082**	0.0079**
	(0.0018)	(0.0024)	(0.0035)	(0.0038)
GDP	-0.0039***	-0.0055***	-0.0070**	-0.0099***
	(0.0013)	(0.0020)	(0.0035)	(0.0038)
PPIsu	-0.0004	-0.0003	-0.0004	-0.0006
	(0.0004)	(0.0005)	(0.0009)	(0.0010)
IPsu	-0.0002**	-0.0002**	-0.0002	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Usu	0.0141	0.0217	0.0323	0.0387
	(0.0093)	(0.0142)	(0.0213)	(0.0261)
CPIsu	-0.0741	-0.1039	-0.1209	-0.1604
	(0.0709)	(0.0922)	(0.1493)	(0.1850)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.22: Model 2: OR seasonality test in long-term bond returns

Seasonality indicator variables	10-year Coeff. (S.D.)	15-year Coeff. (S.D.)	20-year Coeff. (S.D.)	30-year Coeff. (S.D.)
OR	0.0100**	0.0124***	0.0157***	0.0206***
	(0.0043)	(0.0045)	(0.0048)	(0.0061)
GDP	-0.0114**	-0.0118*	-0.0129*	-0.0096
	(0.0052)	(0.0063)	(0.0070)	(0.0075)
PPIsu	-0.0007	-0.0006	-0.0002	-0.0002
	(0.0015)	(0.0017)	(0.0019)	(0.0021)
IPsu	0.0001	0.0003	0.0004	0.0004
	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Usu	0.0462	0.0453	0.0461	0.0322
	(0.0330)	(0.0365)	(0.0395)	(0.0417)
CPIsu	-0.2445	-0.2817	-0.4114	-0.4649
	(0.2549)	(0.2600)	(0.2722)	(0.3421)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.23: Model 2: Joint seasonality test

	short-term bond return series	long-term bond return series
Sep/Mar joint test	0.0203**	0.4220
Oct/Apr joint test	0.2714	0.0890*
Fall/Winter joint test	0.0875*	0.0000***
OR joint test	0.0772*	0.0007***

Notes: This table reports p-values of the joint tests. The null hypothesis is the estimated coefficients are jointly equal to zero. The short-term bond return series contains bond returns with maturities from 2-year to 7-year. The long-term bond returns contains bond returns with maturities from 10-year to 30-year. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 4.24: Model 3 Sep/Mar seasonality test in short-term bond returns

Seasonality indicator variables	**2-year** Coeff. (S.D.)	**3-year** Coeff. (S.D.)	**5-year** Coeff. (S.D.)	**7-year** Coeff. (S.D.)
Sep/Mar	0.0012	0.0021*	0.0025	0.0018
	(0.0008)	(0.0012)	(0.0021)	(0.0027)
Termspread	0.0071	0.0047	-0.0063	0.0041
	(0.0174)	(0.0230)	(0.0349)	(0.0380)
CPIp	0.0022	0.0019	0.0097	0.0142
	(0.0032)	(0.0043)	(0.0067)	(0.0089)
CPIs	-0.0133*	-0.0250**	-0.0320**	-0.0298
	(0.0080)	(0.0113)	(0.0162)	(0.0210)
IP	0.0000	0.0003	0.0003	0.0005
	(0.0004)	(0.0005)	(0.0007)	(0.0010)
Defaultspread	-0.0014	-0.0021*	-0.0035	-0.0029
	(0.0009)	(0.0012)	(0.0023)	(0.0029)
GDP	-0.0062***	-0.0092***	-0.0128***	-0.0152**
	(0.0019)	(0.0026)	(0.0043)	(0.0061)
PPIsu	-0.0003	-0.0001	-0.0001	-0.0004
	(0.0004)	(0.0005)	(0.0009)	(0.0011)
IPsu	-0.0003**	-0.0003**	-0.0003	-0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0003)
Usu	0.0087	0.0115	0.0184	0.0230
	(0.0098)	(0.0138)	(0.0203)	(0.0270)
CPIsu	-0.3454	-0.3798	-1.1917*	-1.6767*
	(0.3428)	(0.4377)	(0.7224)	(0.9203)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.25: Model 3 Sep/Mar seasonality test in long-term bond returns

Seasonality indicator variables	**10-year** Coeff. (S.D.)	**15-year** Coeff. (S.D.)	**20-year** Coeff. (S.D.)	**30-year** Coeff. (S.D.)
Sep/Mar	0.0023	0.0032	0.0036	0.0059
	(0.0032)	(0.0037)	(0.0041)	(0.0048)
Termspread	0.0215	0.0134	0.0350	0.1045
	(0.0441)	(0.0462)	(0.0520)	(0.0752)
CPIp	0.0259	0.0327*	0.0391*	0.0513**
	(0.0160)	(0.0188)	(0.0203)	(0.0220)
CPIs	-0.0237	-0.0188	-0.0093	-0.0212
	(0.0352)	(0.0423)	(0.0457)	(0.0518)
IP	0.0008	0.0004	0.0006	0.0018
	(0.0013)	(0.0018)	(0.0022)	(0.0024)
Defaultspread	-0.0035	-0.0042	-0.0056	-0.0070
	(0.0038)	(0.0043)	(0.0049)	(0.0054)
GDP	-0.0179**	-0.0189**	-0.0215**	-0.0212*
	(0.0078)	(0.0091)	(0.0103)	(0.0110)
PPIsu	-0.0005	-0.0003	0.0001	0.0002
	(0.0016)	(0.0018)	(0.0020)	(0.0022)
IPsu	-0.0001	0.0001	0.0001	0.0000
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Usu	0.0281	0.0263	0.0272	0.0029
	(0.0372)	(0.0426)	(0.0445)	(0.0438)
CPIsu	-2.9475*	-3.6711**	-4.4718**	-5.8334***
	(1.5705)	(1.8334)	(1.9561)	(2.1155)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.26: Model 3: Oct/Apr seasonality test in short-term bond returns

Seasonality indicator variables	**2-year** Coeff. (S.D.)	**3-year** Coeff. (S.D.)	**5-year** Coeff. (S.D.)	**7-year** Coeff. (S.D.)
Oct/Apr	0.0016	0.0021	0.0026	0.0025
	(0.0010)	(0.0013)	(0.0016)	(0.0019)
Termspread	0.0048	0.0002	-0.0115	0.0008
	(0.0163)	(0.0212)	(0.0317)	(0.0355)
CPIp	0.0007	-0.0004	0.0069	0.0119
	(0.0035)	(0.0050)	(0.0074)	(0.0091)
CPIs	-0.0140*	-0.0263**	-0.0335**	-0.0306
	(0.0079)	(0.0117)	(0.0170)	(0.0212)
IP	0.0000	0.0003	0.0003	0.0005
	(0.0004)	(0.0005)	(0.0007)	(0.0010)
Defaultspread	-0.0014	-0.0020*	-0.0034	-0.0028
	(0.0009)	(0.0012)	(0.0023)	(0.0028)
GDP	-0.0056***	-0.0085***	-0.0119***	-0.0144**
	(0.0017)	(0.0025)	(0.0042)	(0.0059)
PPIsu	-0.0004	-0.0002	-0.0002	-0.0005
	(0.0004)	(0.0006)	(0.0009)	(0.0011)
IPsu	-0.0002**	-0.0003**	-0.0003	-0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0003)
Usu	0.0121	0.0158	0.0237	0.0286
	(0.0092)	(0.0130)	(0.0202)	(0.0263)
CPIsu	-0.1405	-0.0812	-0.8274	-1.3639
	(0.3745)	(0.5211)	(0.7973)	(0.9513)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.27: **Model 3: Oct/Apr seasonality test in long-term bond returns**

Seasonality indicator variables	**10-year** Coeff. (S.D.)	**15-year** Coeff. (S.D.)	**20-year** Coeff. (S.D.)	**30-year** Coeff. (S.D.)
Oct/Apr	0.0020	0.0010	0.0022	0.0031
	(0.0024)	(0.0032)	(0.0035)	(0.0041)
Termspread	0.0166	0.0054	0.0266	0.0902
	(0.0421)	(0.0445)	(0.0511)	(0.0749)
CPIp	0.0236	0.0302*	0.0358*	0.0460**
	(0.0158)	(0.0183)	(0.0196)	(0.0212)
CPIs	-0.0252	-0.0212	-0.0119	-0.0255
	(0.0350)	(0.0423)	(0.0457)	(0.0516)
IP	0.0008	0.0004	0.0006	0.0018
	(0.0013)	(0.0018)	(0.0022)	(0.0024)
Defaultspread	-0.0035	-0.0041	-0.0055	-0.0068
	(0.0037)	(0.0043)	(0.0048)	(0.0054)
GDP	-0.0171**	-0.0185**	-0.0206**	-0.0201*
	(0.0079)	(0.0092)	(0.0102)	(0.0111)
PPIsu	-0.0006	-0.0003	0.0001	0.0001
	(0.0017)	(0.0019)	(0.0021)	(0.0023)
IPsu	-0.0001	0.0001	0.0001	0.0000
	(0.0004)	(0.0005)	(0.0006)	(0.0006)
Usu	0.0320	0.0272	0.0311	0.0078
	(0.0372)	(0.0436)	(0.0462)	(0.0447)
CPIsu	-2.6464*	-3.3928*	-4.0670**	-5.2125**
	(1.5621)	(1.7904)	(1.8987)	(2.0647)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.28: Model 3: Fall/Winter seasonality test in short-term bond returns

Seasonality indicator variables	**2-year** Coeff. (S.D.)	**3-year** Coeff. (S.D.)	**5-year** Coeff. (S.D.)	**7-year** Coeff. (S.D.)
Fall/Winter	0.0009*	0.0014**	0.0024**	0.0028***
	(0.0005)	(0.0007)	(0.0011)	(0.0011)
Termspread	0.0063	0.0029	-0.0065	0.0071
	(0.0166)	(0.0214)	(0.0315)	(0.0338)
CPIp	0.0009	-0.0003	0.0067	0.0114
	(0.0033)	(0.0045)	(0.0067)	(0.0086)
CPIs	-0.0149*	-0.0276**	-0.0354**	-0.0329
	(0.0080)	(0.0117)	(0.0163)	(0.0200)
IP	-0.0000	0.0003	0.0003	0.0004
	(0.0004)	(0.0005)	(0.0007)	(0.0009)
Defaultspread	-0.0015*	-0.0023*	-0.0038	-0.0033
	(0.0009)	(0.0013)	(0.0024)	(0.0029)
GDP	-0.0057***	-0.0084***	-0.0115***	-0.0137**
	(0.0017)	(0.0023)	(0.0039)	(0.0054)
PPIsu	-0.0005	-0.0003	-0.0005	-0.0008
	(0.0004)	(0.0005)	(0.0008)	(0.0009)
IPsu	-0.0003**	-0.0003**	-0.0003	-0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0003)
Usu	0.0147	0.0209	0.0343	0.0427
	(0.0102)	(0.0145)	(0.0237)	(0.0283)
CPIsu	-0.2076	-0.1526	-0.8774	-1.3776
	(0.3437)	(0.4536)	(0.7178)	(0.8872)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.29: Model 3: Fall/Winter seasonality test in long-term bond returns

Seasonality indicator variables	10-year Coeff. (S.D.)	15-year Coeff. (S.D.)	20-year Coeff. (S.D.)	30-year Coeff. (S.D.)
Fall/Winter	0.0042***	0.0050***	0.0062***	0.0088***
	(0.0016)	(0.0017)	(0.0019)	(0.0025)
Termspread	0.0270	0.0185	0.0423	0.1127*
	(0.0396)	(0.0401)	(0.0463)	(0.0685)
CPIp	0.0220	0.0278	0.0332*	0.0423**
	(0.0156)	(0.0181)	(0.0196)	(0.0216)
CPIs	-0.0281	-0.0243	-0.0159	-0.0312
	(0.0334)	(0.0403)	(0.0432)	(0.0474)
IP	0.0007	0.0003	0.0004	0.0015
	(0.0013)	(0.0017)	(0.0020)	(0.0022)
Defaultspread	-0.0042	-0.0049	-0.0065	-0.0083
	(0.0037)	(0.0042)	(0.0047)	(0.0052)
GDP	-0.0155**	-0.0161*	-0.0180*	-0.0164*
	(0.0071)	(0.0084)	(0.0093)	(0.0097)
PPIsu	-0.0012	-0.0011	-0.0008	-0.0012
	(0.0014)	(0.0016)	(0.0017)	(0.0019)
IPsu	-0.0001	0.0001	0.0001	-0.0000
	(0.0004)	(0.0005)	(0.0006)	(0.0006)
Usu	0.0576	0.0610	0.0704	0.0640
	(0.0426)	(0.0453)	(0.0472)	(0.0466)
CPIsu	-2.5238	-3.1384*	-3.8338**	-4.8728**
	(1.5429)	(1.7797)	(1.8999)	(2.1002)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.30: Model 3: OR seasonality test in short-term bond returns

Seasonality indicator variables	2-year Coeff. (S.D.)	3-year Coeff. (S.D.)	5-year Coeff. (S.D.)	7-year Coeff. (S.D.)
OR	0.0036*	0.0058**	0.0080**	0.0080*
	(0.0019)	(0.0026)	(0.0038)	(0.0042)
Termspread	0.0088	0.0071	-0.0018	0.0106
	(0.0178)	(0.0233)	(0.0351)	(0.0381)
CPIp	0.0017	0.0010	0.0087	0.0138
	(0.0032)	(0.0043)	(0.0066)	(0.0085)
CPIs	-0.0136*	-0.0255**	-0.0324**	-0.0295
	(0.0078)	(0.0110)	(0.0156)	(0.0198)
IP	0.0000	0.0003	0.0003	0.0004
	(0.0004)	(0.0005)	(0.0007)	(0.0010)
Defaultspread	-0.0014	-0.0021*	-0.0035	-0.0029
	(0.0009)	(0.0012)	(0.0022)	(0.0028)
GDP	-0.0058***	-0.0086***	-0.0120***	-0.0144**
	(0.0018)	(0.0025)	(0.0043)	(0.0059)
PPIsu	-0.0004	-0.0003	-0.0003	-0.0006
	(0.0004)	(0.0005)	(0.0009)	(0.0010)
IPsu	-0.0003**	-0.0003**	-0.0003	-0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0003)
Usu	0.0126	0.0179	0.0274	0.0323
	(0.0098)	(0.0137)	(0.0215)	(0.0275)
CPIsu	-0.2603	-0.2346	-1.0168	-1.5483*
	(0.3448)	(0.4376)	(0.7085)	(0.8737)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.31: Model 3: OR seasonality test in long-term bond returns

Seasonality indicator variables	10-year Coeff. (S.D.)	15-year Coeff. (S.D.)	20-year Coeff. (S.D.)	30-year Coeff. (S.D.)
OR	0.0106**	0.0129**	0.0168**	0.0233***
	(0.0053)	(0.0062)	(0.0070)	(0.0085)
Termspread	0.0303	0.0230	0.0490	0.1214*
	(0.0396)	(0.0427)	(0.0479)	(0.0632)
CPIp	0.0254	0.0318	0.0383	0.0495*
	(0.0181)	(0.0228)	(0.0258)	(0.0278)
CPIs	-0.0234	-0.0187	-0.0088	-0.0212
	(0.0358)	(0.0445)	(0.0501)	(0.0522)
IP	0.0008	0.0004	0.0005	0.0017
	(0.0013)	(0.0017)	(0.0020)	(0.0023)
Defaultspread	-0.0036	-0.0042	-0.0057	-0.0071
	(0.0042)	(0.0049)	(0.0055)	(0.0063)
GDP	-0.0168**	-0.0176**	-0.0198**	-0.0189*
	(0.0072)	(0.0087)	(0.0097)	(0.0101)
PPIsu	-0.0008	-0.0007	-0.0004	-0.0005
	(0.0014)	(0.0016)	(0.0017)	(0.0019)
IPsu	-0.0001	0.0001	0.0001	0.0000
	(0.0004)	(0.0005)	(0.0006)	(0.0006)
Usu	0.0406	0.0413	0.0470	0.0299
	(0.0407)	(0.0475)	(0.0509)	(0.0539)
CPIsu	-2.7811	-3.4420	-4.2084*	-5.4079**
	(1.7719)	(2.2333)	(2.5245)	(2.6900)
Observations	284	284	284	284

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.32: Model 3: Joint seasonality test

	short-term bond return series	long-term bond return series
Sep/Mar joint test	0.0095***	0.5099
Oct/Apr joint test	0.4602	0.0693*
Fall/Winter joint test	0.1116	0.0035***
OR joint test	0.1100	0.0334**

Notes: This table reports p-values of the joint tests. The null hypothesis is the estimated coefficients are jointly equal to zero. The short-term bond return series contains bond returns with maturities from 2-year to 7-year. The long-term bond returns contains bond returns with maturities from 10-year to 30-year. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 4.33: Model 4: Sep/Mar seasonality test in short-term bond returns

Seasonality indicator variables	**2-year** Coeff. (S.D.)	**3-year** Coeff. (S.D.)	**5-year** Coeff. (S.D.)	**7-year** Coeff. (S.D.)
Sep/Mar	-0.0003	-0.0003	-0.0015	-0.0032
	(0.0011)	(0.0016)	(0.0027)	(0.0035)
Termspread	-0.0031	-0.0196	-0.0295	-0.0293
	(0.0137)	(0.0194)	(0.0248)	(0.0345)
SMB	-0.0319***	-0.0396***	-0.0639***	-0.0712***
	(0.0077)	(0.0098)	(0.0178)	(0.0202)
HML	-0.0009	-0.0020	-0.0190	-0.0048
	(0.0096)	(0.0139)	(0.0264)	(0.0221)
RmRf	0.0278**	0.0380**	0.0729***	0.0658**
	(0.0124)	(0.0164)	(0.0261)	(0.0285)
Defaultspread	0.0026***	0.0030***	0.0011	0.0050***
	(0.0007)	(0.0009)	(0.0018)	(0.0018)
Observations	408	408	408	408

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.34: Model 4: Sep/Mar seasonality test in long-term bond returns

Seasonality indicator variables	**10-year** Coeff. (S.D.)	**15-year** Coeff. (S.D.)	**20-year** Coeff. (S.D.)	**30-year** Coeff. (S.D.)
Sep/Mar	-0.0021	-0.0028	-0.0024	-0.0008
	(0.0039)	(0.0047)	(0.0052)	(0.0054)
Termspread	-0.0161	0.0291	-0.0130	0.0719
	(0.0340)	(0.0439)	(0.0475)	(0.0557)
SMB	-0.0831***	-0.0970**	-0.1057**	-0.1161*
	(0.0302)	(0.0391)	(0.0461)	(0.0607)
HML	-0.0081	-0.0190	-0.0335	-0.0520
	(0.0355)	(0.0335)	(0.0384)	(0.0472)
RmRf	0.1114***	0.1054***	0.1412***	0.1739***
	(0.0397)	(0.0393)	(0.0477)	(0.0609)
Defaultspread	0.0042*	0.0037	0.0037	0.0023
	(0.0022)	(0.0024)	(0.0024)	(0.0029)
Observations	408	408	408	408

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.35: **Model 4: Oct/Apr seasonality test in short-term bond returns**

Seasonality indicator variables	**2-year** Coeff. (S.D.)	**3-year** Coeff. (S.D.)	**5-year** Coeff. (S.D.)	**7-year** Coeff. (S.D.)
Oct/Apr	0.0008	0.0011	0.0016	0.0024
	(0.0011)	(0.0014)	(0.0022)	(0.0025)
Termspread	-0.0028	-0.0195	-0.0278	-0.0251
	(0.0128)	(0.0180)	(0.0233)	(0.0329)
SMB	-0.0308***	-0.0380***	-0.0612***	-0.0670***
	(0.0072)	(0.0091)	(0.0177)	(0.0197)
HML	-0.0002	-0.0011	-0.0174	-0.0022
	(0.0099)	(0.0144)	(0.0264)	(0.0232)
RmRf	0.0285**	0.0390**	0.0753***	0.0704**
	(0.0123)	(0.0163)	(0.0260)	(0.0280)
Defaultspread	0.0026***	0.0030***	0.0011	0.0050***
	(0.0007)	(0.0009)	(0.0018)	(0.0018)
Observations	408	408	408	408

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.36: **Model 4: Oct/Apr seasonality test in long-term bond returns**

Seasonality indicator variables	**10-year** Coeff. (S.D.)	**15-year** Coeff. (S.D.)	**20-year** Coeff. (S.D.)	**30-year** Coeff. (S.D.)
Oct/Apr	0.0029	0.0033	0.0033	0.0049
	(0.0028)	(0.0035)	(0.0033)	(0.0036)
Termspread	-0.0138	0.0323	-0.0105	0.0711
	(0.0321)	(0.0429)	(0.0445)	(0.0535)
SMB	-0.0787***	-0.0918**	-0.1006**	-0.1097*
	(0.0297)	(0.0389)	(0.0464)	(0.0612)
HML	-0.0054	-0.0158	-0.0304	-0.0481
	(0.0369)	(0.0348)	(0.0390)	(0.0480)
RmRf	0.1152***	0.1101***	0.1454***	0.1773***
	(0.0393)	(0.0386)	(0.0471)	(0.0612)
Defaultspread	0.0042*	0.0037	0.0037	0.0022
	(0.0022)	(0.0025)	(0.0024)	(0.0029)
Observations	408	408	408	408

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.37: Model 4: Fall/Winter seasonality test in short-term bond returns

Seasonality indicator variables	2-year Coeff. (S.D.)	3-year Coeff. (S.D.)	5-year Coeff. (S.D.)	7-year Coeff. (S.D.)
Fall/Winter	-0.0006	-0.0007	-0.0015	-0.0011
	(0.0005)	(0.0008)	(0.0016)	(0.0014)
Termspread	-0.0033	-0.0200	-0.0293	-0.0257
	(0.0132)	(0.0187)	(0.0244)	(0.0331)
SMB	-0.0346***	-0.0429***	-0.0705***	-0.0752***
	(0.0084)	(0.0114)	(0.0218)	(0.0218)
HML	-0.0008	-0.0019	-0.0186	-0.0039
	(0.0096)	(0.0138)	(0.0263)	(0.0225)
RmRf	0.0283**	0.0385**	0.0748***	0.0693**
	(0.0122)	(0.0161)	(0.0259)	(0.0275)
Defaultspread	0.0027***	0.0030***	0.0012	0.0050***
	(0.0007)	(0.0009)	(0.0018)	(0.0018)
Observations	408	408	408	408

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.38: Model 4: Fall/Winter seasonality test in long-term bond returns

Seasonality indicator variables	**10-year** Coeff. (S.D.)	**15-year** Coeff. (S.D.)	**20-year** Coeff. (S.D.)	**30-year** Coeff. (S.D.)
Fall/Winter	-0.0011	-0.0006	-0.0002	0.0019
	(0.0019)	(0.0024)	(0.0027)	(0.0026)
Termspread	-0.0142	0.0328	-0.0094	0.0759
	(0.0329)	(0.0430)	(0.0450)	(0.0544)
SMB	-0.0875***	-0.0988**	-0.1056**	-0.1066*
	(0.0317)	(0.0424)	(0.0513)	(0.0642)
HML	-0.0076	-0.0182	-0.0328	-0.0518
	(0.0359)	(0.0339)	(0.0385)	(0.0464)
RmRf	0.1139***	0.1085***	0.1437***	0.1742***
	(0.0390)	(0.0382)	(0.0472)	(0.0614)
Defaultspread	0.0042*	0.0037	0.0038	0.0022
	(0.0022)	(0.0025)	(0.0024)	(0.0030)
Observations	408	408	408	408

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.39: Model 4: OR seasonality test in short-term bond returns

Seasonality indicator variables	**2-year** Coeff. (S.D.)	**3-year** Coeff. (S.D.)	**5-year** Coeff. (S.D.)	**7-year** Coeff. (S.D.)
OR	0.0000	0.0006	-0.0009	-0.0015
	(0.0025)	(0.0034)	(0.0054)	(0.0063)
Termspread	-0.0025	-0.0186	-0.0278	-0.0252
	(0.0140)	(0.0195)	(0.0252)	(0.0342)
SMB	-0.0317***	-0.0389***	-0.0640***	-0.0713***
	(0.0074)	(0.0098)	(0.0188)	(0.0208)
HML	-0.0008	-0.0018	-0.0187	-0.0042
	(0.0097)	(0.0141)	(0.0263)	(0.0224)
RmRf	0.0281**	0.0387**	0.0740***	0.0683**
	(0.0123)	(0.0165)	(0.0262)	(0.0286)
Defaultspread	0.0026***	0.0030***	0.0011	0.0050***
	(0.0007)	(0.0009)	(0.0018)	(0.0018)
Observations	408	408	408	408

Notes: Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.40: Model 4: OR seasonality test in long-term bond returns

Seasonality indicator variables	**10-year** Coeff. (S.D.)	**15-year** Coeff. (S.D.)	**20-year** Coeff. (S.D.)	**30-year** Coeff. (S.D.)
OR	0.0014	0.0016	0.0044	0.0098
	(0.0073)	(0.0080)	(0.0089)	(0.0098)
Termspread	-0.0116	0.0350	-0.0059	0.0804
	(0.0341)	(0.0446)	(0.0472)	(0.0563)
SMB	-0.0810***	-0.0944**	-0.1007**	-0.1069*
	(0.0302)	(0.0396)	(0.0468)	(0.0613)
HML	-0.0074	-0.0180	-0.0321	-0.0502
	(0.0359)	(0.0337)	(0.0382)	(0.0471)
RmRf	0.1144***	0.1092***	0.1459***	0.1798***
	(0.0397)	(0.0391)	(0.0474)	(0.0608)
Defaultspread	0.0042*	0.0037	0.0038	0.0023
	(0.0022)	(0.0025)	(0.0024)	(0.0029)
Observations	408	408	408	408

Notes: Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 4.41: Model 4: Joint seasonality test

	short-term bond return series	**long-term bond return series**
Sep/Mar joint test	0.0571*	0.7440
Oct/Apr joint test	0.8823	0.4504
Fall/Winter joint test	0.7520	0.0127**
OR joint test	0.5436	0.1070

Notes: This table reports p-values of the joint tests. The null hypothesis is the estimated coefficients are jointly equal to zero. The short-term bond return series contains bond returns with maturities from 2-year to 7-year. The long-term bond returns contains bond returns with maturities from 10-year to 30-year. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Chapter 5 Conclusions

The overall aim of this thesis is to contribute to the existing literature relating to issue of seasonality in financial markets and provide a potential explanation for certain patterns. Over the past decades, seasonal anomalies in financial markets have attracted increasing attention, and researcher have documented a number of seasonal patterns in international equity markets, including the Monday effect (Cross, 1973; Gibbons and Hess, 1981; Mehdian and Perry, 2001), the January effect (Clayton et al., 1989; Reinganum, 1983; Starks et al., 2006), the May principle (Athanassakos, 2008; Bouman and Jacobsen, 2002; Maberly et al., 2004), the SAD effect (Dowling and Lucey, 2008; Kamstra et al., 2003, 2014) and so on. In the literature of behaviour finance, research has attempted to implement investor irrational behaviour to explain the seasonal anomalies in financial markets, that is investors allowing moods to influence their financial decision-making, and ultimately affect financial markets. The approach is adopted by analysing the relationship between mood-proxies and financial markets. Weather conditions, seasonal affective disorder (SAD), sport results have all been used as mood-proxies and proven to be associated with equity returns and trading activities (e.g. Edmans et al., 2007; Kamstra et al., 2003; Lu and Chou, 2012; Saunders, 1993). Among these mood-proxies, SAD was found to be closely related to government bond returns, stock returns and trading activities (Kamstra et al., 2003, 2014; Lu and Chou, 2012). In addition, since local weather conditions only influence investors who live in a certain area and sport results only influence a proportion of investors who care about the results, SAD, which is related to the length of daytime, has been said to have considerable world-wide influence. As a consequence, The analysis presented in this thesis explores the SAD effect in UK financial markets.

Chapter 2 explores the SAD effect on UK stock market. The study analyses daily returns of all stocks traded on the London Stock Exchange (LSE) from 1988 to 2011. In accordance with Kamstra et al. (2003, 2014), SAD variables were constructed related to the length of daytime or changes in the proportion of SAD sufferers. In order to determine the SAD effect for different stocks, six stock portfolios were constructed, based on the size and book-to-market ratio of the stocks. Some well-known market anomalies and weather factors are considered in the specifications.

In the existing literature, the majority of studies use either ordinary least squares (OLS) or generalized autoregressive conditional heteroskedasticity (GARCH) methods to analyse the relationship between mood-proxy variables and stock returns (e.g. Cao and Wei, 2005; Dowling and Lucey, 2008; Kamstra et al., 2003). Initially, the OLS method is employed to test the SAD effect in different stock portfolio returns. However, the ARCH effect is detected by implementing the Lagrange multiplier (LM) test in five portfolio returns, and the GARCH method is then adopted to account the time-varying variance in these portfolio returns. Finally, in order to account for the inter-market correlation between the portfolios, and to determine whether SAD affects large size and small size stock portfolios differently, seemingly unrelated regression (SUR) is carried out and joint tests on the SAD coefficients are performed.

The findings of the estimation results indicate the existence of SAD effect in the UK stock market. Specifically, we show that a reduction in the length of the daytime as measure by SAD leads to a significant reduction in stock portfolio returns. This tendency for a reduction in returns is more pronounced for small size portfolios. Moreover, Chapter 2 also shows that the higher the proportion of people suffering from SAD in the population, the lower the stock portfolio returns, and this relationship existed in all six portfolios. Finally, there is some indication of a significant relationship between variance of neutral stock portfolio returns and both SAD and weather variables. Overall, the findings in this chapter strongly support the SAD hypothesis that seasonal depression, brought on by SAD, leads to lower stock returns when days get shorter in the fall, since individual investors sometimes make investment decisions which are subject to their moods.

The analysis presented in Chapter 3 examines the impact of SAD variables on investor trading activities. Extending the conclusion in Chapter 2, which states that seasonal variation in investor risk perception drives seasonal variation in stock returns, we seek to figure out whether changes in investor risk perception also influences the trading activities. The empirical data for this chapter consists of daily trading volumes of all stocks traded on the LSE for the period 1988-2011. We constructed six stock portfolios based on the financial nature of the stocks, and the stock portfolio turnover was calculated following Lu and Chou (2012), which is based on the daily trading volume of each stocks and the total share outstanding for all stocks within the portfolio.

The methodology adopted in Chapter 3 is similar to Chapter 2, where OLS method and GARCH method were employed to examine the SAD effect in individual portfolio turnover separately, and the SUR method was adopted to consider the SAD effect in different size portfolio turnover. The estimation result shows that the SAD variables are negatively correlated with the portfolio turnover, especially, the SAD effect, is more significant on the small size portfolio turnover. This result is consistent with the findings of Lu and Chou (2012), who found investors trade less when they suffer from SAD. We further show that the weather and SAD variables are significantly related to the variance of the turnover, the result indicating that changes in investor mood lead to change in stock turnover. Moreover, the findings of negative coefficients of Monday variable and positive coefficients of Tax variable are in line with predictions from the literature. The literature on the Monday effect emphasizes that Mondays are the days of strategy planning for institutional investors, hence they are less active in trading (Osborne, 1962). The literature on the Tax effect emphasizes that tax-incentive investors seek to sell stocks before the end of tax year to offset capital gains, and buy them back at the beginning of next tax year, thus trading activities increase around the end of tax year (Reinganum, 1983).

Overall, our empirical findings in Chapter 3 provide further support for the SAD effect on UK stock market, supporting the SAD effect hypothesis that SAD sufferers tend to shun risk and adjust their investment portfolio in favour or safe assets, therefore, we expected more seller-initiated trades on the LSE just after the autumn equinox, when the days start to get shorter, but after that the total turnover should decrease as SAD sufferers become more risk averse and less willing to engage in stock markets.

The last empirical study of this thesis, Chapter 4, investigates the SAD effect on UK monthly government bond returns from 1980 to 2014, in contrast to the previous empirical studies that examined the SAD effect on UK stock market, this chapter turns to UK bond market. The sample data consists of monthly returns of eight UK government bonds with maturities ranging from 2-year to 30-year. The hypothesis of Chapter 4 is that since investors who suffer from SAD become more risk averse and favour safe assets, seasonal variation in investor risk perception will also drive seasonal variation in government bond returns, so seasonal patterns in bond returns are expected to have the opposite pattern to seasonal patterns in stock returns.

We conducted system GMM estimation to examine the effect of SAD variables on UK government bond. In line with Kamstra et al. (2014) The findings showed a statistically significant relationship between SAD variables and government bond returns, and the SAD effect was more significant for the long-term bond returns. Specifically, UK government bond returns were higher when investors suffered from SAD, and lower when investors recovered. We uncovered a significant reversal of the SAD effect in the bond market related to the stock market. In addition, the SAD effect in bond returns can not be dismissed, even if some macroeconomic and risk factors are controlled. The result in Chapter 4 provide further evidence in support of the SAD effect hypothesis that investors prefer safe assets when they suffering from SAD, hence we observed higher government bond returns during the onset of SAD.

The empirical studies presented in this thesis explored the SAD effect in UK financial markets in three dimensions. Chapter 2 investigates the SAD effect in stock returns; Chapter 3 studies the SAD effect in stock trading activities; in Chapter 4 , we turn to the bond market and analyse the SAD effect in government bond returns. The findings of the empirical studies provide convincing evidence for the existence of SAD effect on UK financial markets. Specifically, investors suffering from SAD become more risk averse, then they are less likely to take risks, and that leads to lower stock returns and turnover. As SAD-affected investors become more risk averse, they tend to adjust their portfolios in favour of safe assets, which leads to higher bond returns. Therefore, stock returns and turnover are lower and government bond returns are higher in the fall, during the onset of SAD.

Our findings could contribute to public awareness in several distinct ways. Firstly, understanding the mood effect on their financial decision-marking will help individual investors overcome mood-biased decisions and secure higher returns. Secondly, for institutional investors, considering the SAD effect in their investment strategies will enable them gain higher returns. Thirdly, being aware of the SAD effect in bond markets helps central banks to select the best timing to issue government bonds and fulfil financial needs. Finally, market efficiency can be improved if all market participants aware the SAD effect on financial markets when they are trading.

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