ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
MSc Economics & Business
Master Specialisation Financial Economics

Does investor sentiment shift along with the calendar?

Assessing the effect of the Seasonal Affective Disorder on the British stock market

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Finish date: October 2018

PREFACE AND ACKNOWLEDGEMENTS

I would like to thank everyone who supported me throughout the last chapter of my Master studies. A special thanks to my thesis supervisor Dr. Lemmen, who provided valuable feedback and guided me through the whole process. Finally, I would like to thank my family and friends who always supported me and stood by me throughout my academic career. I am very grateful for having you.

ABSTRACT

This study aims to examine the relationship between investor sentiment and the British stock market. The Seasonal Affective Disorder (SAD) is used as a mood-proxy to assess the influence of investor mood on both large-capitalization and small-capitalization indices in the UK. Daily index returns for the period of October 20th 1997 to January 8th 2018 are used, for both the FTSE 100 and the FTSE Small Cap. The descriptive statistics and Ordinary Least Squares regression estimates of the FTSE 100 index returns indicate no increased risk aversion in the fall and winter, and hence, no seasonal pattern is found in the returns of this index. However, the SAD effect appeared to be significantly present in the returns of the FTSE SmallCap, violating the Efficient Market Hypothesis. Thus, it can be concluded that investor sentiment has relatively more influence on small-capitalization stocks in the UK, which might be explained due to the relatively larger proportion of individual investors trading in small-capitalization stocks.

JEL Classification: G1, G14, G4 & G41

Keywords: British stock market, investor sentiment, Seasonal Affective Disorder, Efficient Market Hypothesis & market anomalies

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CHAPTER 1 Introduction

Most people wake up and take a look at the weather outside, in which especially the brightness of the sky and the presence of the sun play a major role in the mood of a person at the beginning of the day. Therefore, the mood of many people shifts along with the calendar, since it is darker in the fall and winter months and the number of hours of daylight are less. Hence, the shortening of the days affects the mood of many individuals during the day, which most likely will be visible in their behavior.

Contradicting the Efficient Market Hypothesis, a significant number of studies document that stock prices are affected by investor sentiment (Baker & Wurgler, 2007; Bollen, Mao & Zeng, 2011). Moreover, literature has shown that people are more optimistic and more risk-seeking when on a better mood (Grable & Roszkowski, 2008; Schwarz, 1990). Evidence has shown that an increase in the number of hours of daylight and sunshine positively affects the stock market returns due to investor sentiment, which has an influence on investors' behavior (Saunders, 1993; Hirshleifer & Shumway, 2003; Kamstra, Kramer & Levi, 2003).

The focus in this study is to capture a possible seasonality in the stock returns within the British stock market, possibly caused by mood swings of investors, through the prevalence of mental disorders. The main instrument for measuring mood in this study will be hours of daylight, which is a medically validated mood proxy (Keller, Fredrickson, Ybarra, Côté, Johnson, Mikels, Conway & Wager, 2005; Papadopoulos, Frangakis, Skalkidou, Petridou, Stevens & Trichopoulos, 2005). In particular, the Seasonal Affective Disorder (SAD) effect on the stock market returns, as documented by Kamstra et al. (2003), will be examined. SAD can be described as a type of depression from which individuals might suffer, when the days shorten in the fall and winter (Kamstra et al., 2003). Research has shown that depression, in turn, causes an increase in risk aversion (Eisenberg, Baron & Seligman, 1998). Related to these relationships, Kamstra et al. (2003) provided evidence that the stock market returns in some countries vary seasonally with the length of the day, which they call the SAD effect. Hence, this study intends to explore the relationship between investor sentiment and the British stock market, using SAD as a mood-proxy. The research question is formulated as follows:

Does investor mood, measured through Seasonal Affective Disorder, significantly affect the British stock market returns?

The Efficient Market Hypothesis (EMH) will be the underlying theory and the research in this study will focus on whether the SAD effect causes an anomaly regarding to the EMH. Thus, this study aims to examine the relationship between investor mood and the stock market and to question the EMH, as a traditional finance theory.

1.1 Seasonal Affective Disorder

The Seasonal Affective Disorder (SAD) is, as the name already suggests, a type of depression that occurs seasonal. Individuals who suffer from this mental disorder, experience the symptoms every year in the same period. The symptoms of this disorder usually occur at the beginning of the fall and continue until the end of the winter, this corresponds to the period in which the number of hours of daylight decreases per day. Usually, the symptoms get worse as this period progresses.

The specific causes of the presence of SAD are not entirely clear, but some factors are known that play a role in the appearance of this disorder. These include: change in biorhythm (decrease in sunlight disrupts body's internal clock); drop in serotonin levels (a brain chemical that affects mood) due to the reduction of sunlight; change in melatonin levels (affects sleep pattern and mood) due to the reduction of sunlight.

Furthermore, it is known that SAD is more often diagnosed in women relative to men and that younger adults suffer relatively more from SAD than older adults. There are several factors which increase the risk of suffering from SAD, these factors include: family history with SAD; suffering from depression or bipolar disorder; living far from the equator (due to the scarce number of hours of sunlight in countries far from the equator during fall and winter) [1].

1.2 The British stock market

The British stock market essentially consists of the London Stock Exchange (LSE), which is located in London. The history of the LSE goes back to 1801, which makes it one of the oldest exchanges in the world. Being the major stock exchange in the U.K. and the largest exchange in Europe, the LSE has a market capitalization of $4.38 trillion dollars[2]. The LSE consists of several indices, with the FTSE 100 as the large-capitalization (hereafter referred to as large-cap) index, consisting of the 100 companies with the highest market capitalization and the FTSE SmallCap as the index consisting of the companies with the lowest market capitalization. This study concerns these two indices as the main indices to test for a possible effect on the stock returns, hence, more in-depth information will be provided regarding these indices.

The FTSE 100 (Financial Times Stock Exchange 100) index is globally one of the most widely used stock indices. It originates from 1984, when it was established with a base level of 1000 points. As of January 2018, it had a level of over 7000 points. The FTSE 100 is the British blue-chip index and it

[1] https://www.mayoclinic.org/diseases-conditions/seasonal-affective-disorder/symptoms-causes/syc-20364651
[2] https://www.stockmarketclock.com/exchanges/lse

consists, as mentioned before, of the 100 British firms with the highest market capitalization. In particular, the index represents approximately 81% of the total market capitalization traded on the British stock market. Therefore, the FTSE 100 index is regarded as an indicator of the British economy as a whole and the British investors' sentiment[3].

The FTSE SmallCap index consists of the firms with the lowest capitalization listed on the LSE, these are the 351st-619th largest firms listed on the exchange. The index was founded in 1996, when it had a base value of over 2000 points. As of January 2018, the index has a level of over 5000 points. The FTSE SmallCap accounts for approximately 2% of the total British market capitalization[4].

1.3 Purpose and contribution of the study

The reason to conduct this research for the UK can be motivated as follows: Golder and Macy (2011) found that daylight, among various other mood-proxies, significantly influences the mood of individuals in the UK. Furthermore, Melrose (2015) found that 20% of the population in the UK experience winter blues[5] and 2% experience SAD. Hence, the significant prevalence of mood disorders in the UK should provide good insights in the relationship between investor sentiment and the stock market. Although the UK, among eight other countries, is included in the study of Kamstra et al. (2003), the magnitude of the impact of SAD in the UK, as well as a possible explanation, will be captured in this study. Furthermore, this study intends to extend the research to the most recent data, by using the time frame from October 20th 1997 to January 8th 2018. Where Kamstra et al. (2003) documented that stock market returns follow a seasonal pattern, which varies with the length of the day, this study will provide new evidence with the most recent results to support or contradict their findings.

Moreover, this study will provide new insights into this field of research, by testing the SAD effect for both large-cap and small-capitalization (hereafter referred to as small-cap) indices. The underlying rationale here is that small-cap stocks are more affected by investor sentiment, due to the large proportion of individual investors trading in small-cap stocks (Krivelyova & Robotti, 2003; Baker & Wurgler, 2006). Hence, the expectation is that the SAD effect is more present in the small-cap index.

The obtained findings might support the behavioral theory that SAD affects investors' mood and hence, investors become more risk averse in the fall and winter seasons. The possible increase in risk-aversion will be examined by testing for a decrease in the volatility of the index returns, which in turn might lead to lower returns. All in all, this study contributes to existing research in this field by providing a more contemporary view of the effect. Furthermore, existing literature is extended by testing for different

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[3] https://markets.businessinsider.com/index/ftse_100
[4] http://www.lse.co.uk/indices.asp?index=IDX:SMX&indexname=ftse_small_cap
[5] Winter Blues refers to a milder form of Seasonal Affective Disorder.

effects of investor mood between large- and small-cap indices, in a country where SAD is found to be significantly prevalent.

1.4 Outline

This study has the following structure: Firstly, the introduction is presented in Chapter 1. Following the introduction, Chapter 2 provides the theoretical framework of this study. An extensive literature review and the hypotheses development are presented in Chapter 3. The data and methodology section corresponds to Chapter 4 of this study. Chapter 5 will provide the results and analyses, after which the final conclusions are presented and discussed in Chapter 6.

CHAPTER 2 Theoretical Framework

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) was documented by Eugene Fama in 1970, when he provided strong evidence for the theory of market efficiency. In his paper, Fama (1970) defines an efficient market as a market in which asset prices fully reflect all available information. Hence, according to the EMH, it is impossible to 'beat the market' because the efficient markets already incorporate all the relevant information in the market prices. Since Roberts (1967), market efficiency is commonly distinguished in three levels of efficiency: the weak form; the semi-strong form and the strong form. These three levels of market efficiency will be briefly discussed in the following subsections.

2.1.1 Weak form efficiency

The weak form efficiency is the form in which the current prices fully reflect all historical available information relevant to the underlying assets. Hence, investors are not able to yield abnormal returns by implementing trading strategies based on technical analysis (analysis based on historical price patterns). This form of market efficiency is also linked to the 'Random Walk Hypothesis' (Malkiel, 1989).

2.1.2 Semi-strong form efficiency

According to the semi-strong form of market efficiency, stock prices reflect all information of historical prices and the public available information relevant for the firms' assets. If markets are efficient in the semi-strong form, investing strategies based on fundamental analysis (firms' public information) will not yield abnormal returns (Malkiel, 1989).

2.1.3 Strong form efficiency

If the market is efficient in the strong form, all information, both public and private, are fully reflected in the stock prices. Thus, not even investors with private information can yield abnormal profits by trading based on privileged information (Malkiel, 1989).

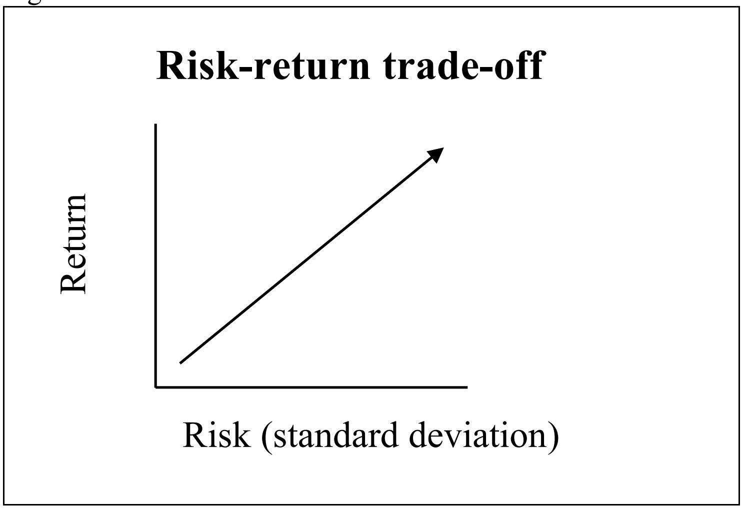
2.2 Risk and returns

In financial concepts, risk is essentially defined as the chance that the realized return of an asset deviates from the expected return. It is common to measure risk with the standard deviation of the asset (Fama & Macbeth, 1973). The standard deviation measures the dispersion around the mean of the return and is defined as follows (Senthilnathan, 2015):

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_i - \bar{R})^2}$$

A higher standard deviation indicates a higher level of risk and in turn, higher risk typically indicates higher expected returns. Hence, the risk-return trade-off refers to the phenomenon that stock returns tend to increase, along with the underlying stock risk. This trade-off is depicted in Figure 1.

Figure 1: Risk-return trade-off



2.3 Behavioural Finance

However, the time in which it was widely believed that conventional finance theories explain the behavior of the market successfully, are over. Academics started to detect certain behavior and anomalies in the financial markets, which could not be explained by conventional theories such as the EMH. In fact, these academics created a whole new field within finance called 'Behavioral Finance' and gained a large influence as time went on. Their purpose was to detect and explain market inefficiencies, which led to anomalies, and provide evidence that classic finance theories do not always hold. The presence of such anomalies led academics to introduce the concepts of investor psychology and investor sentiment, in order to explain the irrationality which is not accounted for in conventional finance theories. That is where behavioral finance differs from classic finance, it aims to explain the actions of the average investor, whereas conventional finance explains the market assuming that investors are fully rational 'homo economics'.

Several academics have made major contributions to the field of behavioral finance. Kahneman and Tversky are widely considered as 'the fathers' of behavioral finance, due to the fact that they published more or less 200 papers in this field. One of their major contributions to behavioral finance was made with their paper in which the Prospect Theory and the loss aversion concept were introduced (Kahneman & Tversky, 1979). Furthermore, Thaler is also widely considered as a major contributor to the field of behavioral finance. After he became aware of the shortcomings of conventional finance theories, he realized that psychological factors play a role in investors' behavior. As time went on, Thaler published many works, including collaborations with Kahneman and Tversky, and provided many new insights by combining financial economics with psychological elements. Concepts such as mental accounting and the endowment effect were the results of Thalers' work.

2.3.1 Investor sentiment

Investor sentiment is a concept in behavioral finance which refers to the general attitude of investors towards the financial market. This attitude is built upon by various factors such as fundamental, psychological and technical factors. Essentially, investor sentiment reflects the feelings and emotions of investors, which might have an influence on their decision making (Baker & Wurgler, 2007). There exists a variety of sources which influences investors' sentiment. A major source, which is also relevant for this study, consists of non-economic factors. These factors include non-economic events which influence the mood of the general population, such as the weather, sport events, holiday periods and so forth. A change in mood can, in turn, influence investors' risk aversion and trading behavior (Edmans, Garcia & Norli, 2007). It is common to measure investor sentiment by analyzing the trading activity and the direction of the prices of a market.

2.4 Financial Market Anomalies

Throughout the years, several articles provided empirical evidence for financial market anomalies. In the next subsections, some of the (major) anomalies, each relevant in its own manner for this study, are described.

2.4.1 The January Effect

Rozeff and Kinney (1976) were the first to provide empirical evidence of the January effect. This effect can be described as the empirical finding that the returns in the month of January systematically appears to be higher than in other months of the year. Consecutive research has confirmed these findings and has shown that this effect is especially present for smaller firms (Keim, 1983), for firms with low share prices (Branch & Chang, 1990) and firms that have underperformed in the past (De Bondt & Thaler, 1985).

Several explanations are provided in literature regarding the January effect. Wachtel (1942) documented the tax-loss selling hypothesis, which suggests that investors sell the underperforming stocks in their portfolio at the end of the year, to gain tax benefits. Subsequently, investors buy these stocks back at the beginning of the new year, which causes the returns to increase in January. The second most prominent explanation of the January effect is the window dressing hypothesis, as documented by Haugen and Lakonishok (1988). This theory suggests that investors sell certain stocks at the end of the year to make their portfolio seem more acceptable. Similar to the tax-loss selling hypothesis, investors buy these specific stocks back in the new year, leading to the higher returns in January.

In order to mitigate confounding effects in this study, a tax-loss dummy is included in the research model, which will be further elaborated upon in Chapter 4 of this study.

2.4.2 Day-of-the-Week

The day-of-the-week effect refers to the observation of stocks to exhibit relatively higher (or lower) returns on a particular day of the week. Cross (1973) was the first to document the Monday effect, when he provided evidence that the returns on Monday are, on average, lower relative to the returns of the previous trading day (usually Friday). The theory also suggests that the returns on Monday are driven by the closing prices of the stocks on the previous trading day. Lakonishok and Maberly (1990) relate the existence of this effect to the different trading strategies of institutions and individuals. Chen and Singal (2003) provide some evidence that short selling explains a part of the Monday effect. Consensus regarding explanations of this effect is not yet fully reached, causing the Monday effect to remain a largely debated topic. Similar to the tax-loss selling effect, the Monday effect overlaps with the SAD effect as well. Therefore, a Monday dummy is included in the research model to control for the Monday effect.

2.4.3 Size

The size effect, also called the “Small Firm Effect”, is a market anomaly that states that firms with smaller capitalization outperform firms with larger capitalization. That is, the effect refers to a negative relation between stock returns and the corresponding firm capitalization. Banz (1981) was the first to document this anomaly, whereas Fama and French (1993) included a size factor in their Three Factor Model, to capture the outperforming tendency of small-cap stocks.

Besides, this study aims to examine whether SAD is of greater influence on the returns of a small-cap index, relative to a large-cap index. The underlying rationale here is that investor sentiment is more present in small-cap stocks, as indicated by empirical evidence (Baker & Wurgler, 2006). Hence, this study contributes to the body of research in which a distinction has been made between the returns of small- and large-cap stocks.

CHAPTER 3 Literature Review and Hypotheses

3.1 Literature Review

Certain events can affect the mood of investors, which in turn can have an influence on their investing behavior. Johnson and Tversky (1983) and Wright and Bower (1992) found that mood affects the risk perception: individuals in a positive mood estimate the probability of an undesirable event to be lower than individuals in a negative mood. Furthermore, Schwarz (2002) found that people in a better mood are more optimistic when evaluating options and making decisions. Research also has shown that depressive symptoms are correlated with risk aversion (Eisenberg, Baron & Seligman, 1998).

Psychological studies have shown that the weather significantly affects mood. Howarth and Hoffman (1984) documented a significant relationship between various weather variables and mood. Following this finding, a variety of studies have used the weather as a proxy for mood, to measure the influence of investors' mood on stock returns. Saunders (1993) found a strong significant effect of the weather in New York City on the returns of major stock indices. In addition, Hirshleifer and Shumway (2003) document a positive correlation between good weather and stock returns for 26 international stock exchanges. In general, a significant number of studies have shown that the type of weather is of great influence on the mood of investors and hence, on stock returns.

Following the significant amount of research regarding the influence of the weather on investor sentiment, the effect of changing biorhythms on investor mood is also investigated. Kamstra, Kramer & Levi (2000) examined the influence of Daylight Saving Time Changes (DSTCs) on the stock markets in the US, Canada, the UK and Germany. The possible relation between the DSTCs and financial markets might come from investors who suffer from the change in their sleep patterns, which has several implications such as anxiety and decision making issues. They find that the returns on the Monday, after the DSTC, are significantly lower than expected in the US, Canada and the UK, which suggest that a "daylight-savings anomaly" indeed exists.

Kamstra, Kramer & Levi (2003) had another major contribution in this field of research, by examining the effect of the Seasonal Affective Disorder (SAD) on the stock market. SAD can be described as a mental disorder from which people might suffer from when the days begin to shorten, as happens in the fall and winter seasons. This implies that when the hours of daylight during the day decreases, investors are more likely to shun risky assets, due to the increase in their risk-aversion. The study sample contains four stock indices from the United States and stock indices from eight other countries, to capture the effect from countries across both hemispheres and different latitudes. SAD is measured by calculating the number of hours during the night. The findings provide evidence that the stock market returns in all countries but Australia, vary seasonally with the length of the day, which they call the SAD effect.

Garrett, Kamstra & Kramer (2005) re-study the SAD effect, by using an equilibrium asset pricing model, in an attempt to determine whether the SAD effect can be captured when using a conditional version of the CAPM. This way, the price of risk is allowed to vary over time, thus it is attempted to explain the seasonal variation in the stock returns due to SAD. Daily and monthly data is used for the indices of six countries. The findings show that a conditional version of the CAPM fully captures the SAD effect. This supports the findings of Kamstra et al. (2003), the SAD effect is caused by an increase in the risk aversion, which is due to the presence of the seasonal disorder.

Kamstra, Kramer, Levi & Wang (2009) aim to explore the seasonality of asset returns, which might arise due to SAD and time-varying risk preferences. They investigate an asset pricing model which is consumption based and can be in a state of low risk aversion or high risk aversion. They examine whether the asset pricing model can generate the empirical observed seasonality in the equity and Treasury returns. Their findings show that risky asset returns are more exposed to seasonality than risk-free asset returns and that the equity premiums are higher in the state of high risk aversion relative to the state of low risk aversion.

Kaplanski and Levy (2011) study the seasonality effect in real estate prices. They examine the price changes over a twenty-year period for the US, the UK and Australia. The findings show a significant and persistent seasonality in the real estate prices, where the lowest returns are documented in the fall. They conclude that this effect can be ascribed to both the decrease in the hours of daylight and the latitude of the examined areas. This is in line with the SAD effect, which confirms the change in risk perception and investment decisions due to seasonality.

Kaplanski, Levy, Veld & Veld-Merkoulova (2015) examine whether happy people forecast future risk and returns differently from unhappy people. They survey investors on a variety of aspects to acquire their market sentiment. These include sentiment developing factors; return- and risk expectations and investment plans. Their findings show that non-economic factors significantly affect returns- and risk expectations and investment plans. In particular, investors who suffer from SAD, expect returns to be lower in the fall than in other seasons, which is in line with the seasonality effect introduced by Kamstra et al. (2003).

However, not all published articles support the SAD effect. Jacobsen and Marquering (2008) test for a seasonal anomaly caused by mood changes of investors, in an attempt to re-examine the study by Kamstra et al. (2003). Their findings confirm the seasonality effect in stock returns: the stock returns tend to be relatively lower during the summer and fall seasons in many countries. However, they find that there is not enough evidence to ascribe this seasonality to the SAD effect. Moreover, they show that a dummy is simply enough to capture the seasonality effect and conclude that it is premature to state that weather-related variables affect stock returns trough mood swings of investors.

Furthermore, Kelly and Meschke (2010) aim to revisit the SAD anomaly as well. They replicate the original study of Kamstra et al. (2003) and extend the sample to 36 countries, consisting of 47 indices. Their findings, however, show no relation between the prevalence of SAD and stock returns. Moreover, they state that the methodology applied by Kamstra et al. (2003), mechanically induces the SAD effect to be significant. Their overall conclusion is that there is a lack of evidence to state that the SAD effect exists.

Kaustia and Rantapuska (2016) examine the effect of mood on trading behavior and include an investigation of the SAD effect in their study. They conduct this research for investors in Finland, as they argue that the circumstances in Finland are ideal to study whether mood affects investor behavior. They use account level stock trading data from all investors in Finland, which makes the data sample significantly large. However, their findings show little evidence of SAD influencing the buy versus sell tendency, whereas they do document a positive effect of SAD on the trading volume. They find that the clearest seasonal patterns in the trading data are linked to holiday seasons and the turn of the year.

The varying findings can be justified if one takes into account that the studies apply different methodologies for different countries in different periods. However, a significant number of studies have shown that the SAD effect exists and is present in some countries. Due to the interesting nature of this subject regarding the development of new trading strategies based on a SAD anomaly, it is a continuing discussion. Moreover, the lack of research on whether the SAD effect is (more) present in small-cap indices, makes this subject even more interesting to expand this area of research and extend the relevant literature.

3.2 Hypotheses

Following the discussion of relevant literature, several hypotheses can be developed. The first hypothesis tests whether the level of risk, as measured by the standard deviation of the returns, is lower in the fall and winter, due to a possible increase in the risk-aversion of investors in these seasons.

$$H_1: Index\ risk\ is\ lower\ during\ the\ fall\ and\ winter\ in\ the\ UK$$

The second hypothesis tests whether the returns of the FTSE SmallCap index are more affected by SAD than the returns of FTSE 100 index. This hypothesis is motivated by the findings of Krivelyova and Robotti (2003) and Baker and Wurgler (2006), who provided evidence that small-cap stocks are more affected by investor sentiment due to the large proportion of individual investors trading in small-cap stock. Hence, the second hypothesis is formulated as follows:

$$H_2\text{: }The\ FTSE\ SmallCap\ is\ more\ affected\ by\ SAD\ than\ the\ FTSE\ 100$$

The third hypothesis will test whether the SAD effect is symmetric between the fall and winter. This hypothesis is developed, motivated by the findings of Palinkas, Houseal & Rosenthal (1996) and Palinkas and Houseal (2000), in which evidence was provided for lower returns in the fall and higher returns in the winter.

$$H_3\text{: }The\ SAD\ effect\ in\ the\ UK\ is\ symmetric\ between\ the\ fall\ and\ winter$$

The fourth hypothesis addresses the main question of this study: it tests whether the EMH holds or if the SAD effect forms an anomaly for both a large-cap (FTSE 100) and small-cap (FTSE SmallCap) index in the British stock market.

$$H_4\text{: }The\ SAD\ effect\ does\ not\ affect\ the\ British\ stock\ market$$

CHAPTER 4 Data and Methodology

4.1 Data

Data necessary to conduct this research includes market returns data of the UK. In particular, the returns of both the FTSE 100 as well as the FTSE SmallCap indices are used, which are both value weighted (as measured by the capitalization) indices. The FTSE 100 is known as the index of the 100 companies listed on the London Stock Exchange, with the highest market capitalization. The FTSE 100 is therefore a strong indicator of the strength of the British economy and investor sentiment towards British equities. In addition, the FTSE SmallCap index, known as the index consisting of the firms with the lowest market capitalization in the UK, is used to conduct the research. Adjusted closing values are widely preferred over the closing values when analyzing historical returns, as it takes dividends, stock splits and new stock offerings into account, which is line with CRSP standards[6]. Hence, the daily adjusted closing values are used for the period of October 20th 1997 to January 8th 2018. This data is retrieved from the official website of the London Stock Exchange. The index returns are measured as the daily percentage change of returns. These daily percentage change of the returns are calculated by using the following calculation:

$$R_t = \ln(I_t) - \ln(I_{t-1})$$

Equation 1

4.2 Methodology

To measure a possible effect of the hours of daylight on the British index returns, the SAD effect introduced by Kamstra et al. (2003), is examined. Clinical evidence has shown that the shortening of days during the fall and winter has a significant and systematic effect on the mood of many individuals. The fall and winter is defined as the period from 21st of September until the 20th of March. Hence, the number of night hours during the fall and winter are used to capture the effect of SAD on the British stock market. The SAD variable is thus measured as proposed by Kamstra et al. (2003), which is as follows:

$$SAD_t = \begin{cases} H_t - 12, & trading\ days\ in\ the\ fall\ and\ winter \\ 0, & otherwise \end{cases}$$

Equation 2

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6 http://www.crsp.com/products/documentation/crsp-calculations

With H_t for the hours of night. To be able to calculate H_t at latitude δ[7], the sun's declination angle λ_t should be calculated first:

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

Equation 3

where $julian_t$ is a variable that can take the value ranging from 1 to 365 (366 in a leap year), which represents the number of the day in the year: it takes the value 1 for January 1st, 2 for January 2nd and so on. The hours of night H_t can then be calculated as follows[8]:

$$H_t = \begin{cases} 24 - 7.72 \times arcos\left[-tan\left(\frac{2\pi\delta}{360}\right)tan(\lambda_t\,)\right] & In\ the\ Northern\ Hemisphere \\ 7.72 \times arcos\left[-tan\left(\frac{2\pi\delta}{360}\right)tan(\lambda_t\,)\right] & In\ the\ Southern\ Hemisphere \end{cases}$$

Equation 4

where $arcos$ is the arc cosine

Findings of Palinkas, Houseal & Rosenthal (1996) and Palinkas and Houseal (2000) suggest that the SAD effect might be asymmetric around winter solstice. This implicates that the returns are relatively lower in the fall and higher in the winter. Hence, in line with Kamstra et al. (2003), to allow for the SAD effect to be asymmetric in the fall relative to the winter, a dummy variable for the days of the year in the fall season, is included in the research model:

$$D_t^{Fall} = \begin{cases} 1, & trading\ days\ in\ the\ fall \\ 0, & otherwise \end{cases}$$

Equation 5

[7] The latitude of London is used, which equals 51.50, derived from www.latlong.net.

[8] Because the UK is located in the Northern Hemisphere, the corresponding formula will be used to calculate H_t.

The trading days in the fall are defined as the period from 21nd September to 20th December of every year. This dummy variable allows the SAD effect to be asymmetric between fall and winter, but it is not required. If the dummy variable is statistically insignificant, this implicates that the SAD effect is symmetric between fall and winter.

To test for the impact of the SAD on the British investors and thus the stock market in the UK, a model inspired by Kamstra et al. (2003), is estimated using an Ordinary Least Squares (OLS) regression. Dummy variables for Monday and Tax will be added to mitigate confounding effects. The following model will be estimated:

$$R_t = \beta_0 + \beta_{1i}R_{t-1} + \beta_{2i}R_{t-2} + \beta_{3i}SAD_t + \beta_{4i}D_t^{Fall} + \beta_{5i}D_t^{Monday} + \beta_{6i}D_t^{Tax}$$

Equation 6

Where R_t is the daily return; β_0 is the regression intercept coefficient; R_{t-1} and R_{t-2} are the lagged index returns (included where necessary to account for first and second order serial correlation); SAD_t is the main variable to measure investor mood ; D_t^{Fall} is a dummy variable which equals one if the trading day is in the fall season and zero otherwise ; D_t^{Monday} is a dummy variable which equals one if the trading day is Monday and zero otherwise; D_t^{Tax} is a dummy variable which equals one, if the trading day is the last trading day or one of the five first trading days of the tax year[9] and zero otherwise.

[9] The tax year in the UK starts on 6 April and ends on 5 April.

CHAPTER 5 Results

This section of the paper provides and analyzes the research results. The descriptive statistics of the data sample are presented at first, after which the results of the regression analysis are provided.

5.1 Descriptive Statistics

Firstly, summary statistics for the whole sample period are presented. Table 1 presents the descriptive statistics of the daily index returns for both the FTSE 100 and the FTSE SmallCap, for the whole sample period. The sample consists of 5104 observations for both indices. As can be seen from the table, the daily mean return of the FTSE 100 index is 0.008% with a standard deviation of 1.20. However, it can be noticed that the FTSE SmallCap slightly outperforms the FTSE 100 index with a mean return of 0.018%. Furthermore, the FTSE SmallCap is less volatile than the FTSE 100, with a standard deviation of 0.71.

Table 1: Summary statistics of the daily index returns for both the FTSE 100 and the FTSE SmallCap for the whole sample period of 20-10-1997 to 08-01-2018

Index	N	Mean	Standard deviation	Min	Max	Skewness	Kurtosis
FTSE 100	5104	0.008	1.20	-9.27	9.38	-0.15	8.55
FTSE SmallCap	5104	0.018	0.71	-6.15	3.77	-1.15	10.49

More interesting and relevant for this study is to look at the summary statistics for the separate seasons. The fall and winter months are the months in which the hours of daylight decreases and, according to Kamstra et al. (2003), the stock returns also tend to decrease due to an increase in risk aversion. Hence, summary statistics for the separate seasons are derived to obtain insights regarding these relationships and examine the risk-return relationship. Table 2 presents the descriptive statistics of the daily returns for both indices in the fall and winter months over the whole sample period. Table 3 provides similar statistics for the spring and summer months. However, the statistics display results contrary to the findings of Kamstra et al. (2003). The mean returns for both indices are higher during the fall and winter months, where the FTSE 100 index returns are even negative in the spring and summer months. Hence, the results of the descriptive statistics do not indicate that the returns in the spring and summer are higher than in the fall and winter. Furthermore, this study aims to test whether index risk decreases during fall and winter. It can be seen from the tables that this is not the case; risk, as measured by the standard deviation of returns, is higher in the fall and winter for the FTSE 100 index and it is equal for the FTSE SmallCap for the separate seasons. Thus far, the summary statistics display results which are not in line with the theory of increased risk-aversion during the fall and winter. However, solely the descriptive statistics are not sufficient to make inferences concerning the index returns; regression analysis is necessary to obtain insights regarding the seasonality of returns.

Table 2: Summary statistics of the daily index returns for both the FTSE 100 and the FTSE SmallCap for the fall and winter in the sample period of 20-10-1997 to 08-01-2018

Index	N	Mean	Standard deviation	Min	Max	Skewness	Kurtosis
FTSE 100	2579	0.027	1.24	-9.27	9.38	-0.15	10.17
FTSE SmallCap	2579	0.026	0.71	-6.15	3.05	-1.33	11.39

Table 3: Summary statistics of the daily index returns for both the FTSE 100 and the FTSE SmallCap for the spring and summer months in the sample period of 20-10-1997 to 08-01-2018

Index	N	Mean	Standard deviation	Min	Max	Skewness	Kurtosis
FTSE 100	2525	-0.012	1.16	-5.89	8.47	-0.16	6.29
FTSE SmallCap	2525	0.010	0.71	-4.92	3.77	-0.98	9.62

5.2 Regression analysis

To be able to perform the regression analysis and obtain accurate and consistent estimates, various tests of the data are conducted first.

5.2.1 The Breusch-Godfrey test

Firstly, the Breusch-Godfrey test (Breusch & Godfrey, 1980) is conducted to test for serial correlation in the daily index returns. This test is preferred over the Durbin-Watson (DW) test for detecting autocorrelation due to various reasons. These reasons include: the DW test may give inconclusive reasons; the DW test cannot be applied when adding a lagged dependent variable to the model and the DW test cannot take into account higher orders of serial correlation (Asteriou & Hall, 2011). Hence, the Breusch-Godfrey test is performed, with the hypotheses of this test formulated as follows:

$$H_0\!: There\ is\ no\ serial\ correlation\ in\ the\ daily\ index\ returns$$
$$H_a\!: There\ is\ serial\ correlation\ in\ the\ daily\ index\ returns$$

The test is performed separately for the regression models, where the daily index returns of both the FTSE 100 and the FTSE SmallCap are defined as the dependent variables. Dependent lagged variables are added to the model to the degree where there is no more serial correlation, at the 5% significance level. The test statistics are provided in Table 4.

Table 4: The Breusch-Godfrey LM test for autocorrelation in the daily index returns for both the FTSE 100 and the FTSE SmallCap as dependent variables.

Daily index returns	$Lags$	χ^2	P-value
FTSE 100	-	2.440	0.1183
FTSE SmallCap	2	0.354	0.5516

The results show that the regression model with the daily index returns of the FTSE 100 as the dependent variable does not suffer from autocorrelation. No lagged dependent variables are required; thus, the alternative hypothesis is rejected. However, the results show that the regression model with the daily index returns of the FTSE SmallCap as the dependent variable does suffer from autocorrelation. Hence, dependent lagged variables up to two lags are added to this model to account for this issue.

5.2.2 The Augmented Dickey Fuller test

The Augmented Dickey Fuller (ADF) test is performed to test for stationarity of the data. The corresponding hypotheses of this test are defined as follows:

$$H_0\text{: } There\ is\ a\ unit\ root\ in\ the\ time\ series\ data$$
$$H_a\text{: } The\ time\ series\ data\ is\ stationary$$

As can be seen in Table 5, the output of the ADF tests shows t-statistics lower than the critical values for both the FTSE 100 and the FTSE SmallCap indices. Therefore, the null hypothesis can be rejected, which implies that the data is stationary. Hence, Ordinary Least Squares (OLS) regression can be adopted to perform the regression analysis (Mushtaq, 2011).

Table 5: Augmented Dickey Fuller (ADF) test for stationarity of the data of both the FTSE 100 and the FTSE SmallCap indices.

ADF Test	t-statistic	P-value
FTSE 100	-68.027	0.000
FTSE SmallCap	-53.142	0.000
Critical values		
1%	-3.430	-3.430
5%	-2.860	-2.860
10%	-2.570	-2.570

5.2.3 Modelling results

Ordinary Least Squares (OLS) regressions are conducted using the statistical software STATA. All regressions include robust standard errors. The first OLS regression is performed for the FTSE 100 index, the output of the modelling results is provided in Table 6.

Table 6: Ordinary Least Squares regression results for the FTSE 100 in the sample period of 20-10-1997 to 08-01-2018. Daily returns are regressed against the main variable of interest SAD and various control variables to capture confounding effects.

Panel A: Parameter Estimates Ordinary Least Squares Regression with Robust Standard Errors		
$\mathbf{R_t}$	**Coefficient**	**t-statistic**
Constant	-0.013	-0.58
$\boldsymbol{R_{t-1}}$		
$\boldsymbol{R_{t-2}}$		
SAD	0.014	1.18
Fall	-0.001	-0.02
Monday	0.003	0.07
Tax	0.107	1.22

Panel B: Model statistics			
N	5103	**P> F-statistic**	0.572
R^2	0.05%	**Durbin Watson statistic**	1.59
F-statistic	0.73	**Breusch-Godfrey statistic $\chi 2$**	2.44

*significant at 10% **significant at 5% ***significant at 1%

As can be seen from Table 6, all variables are insignificant. The results are quite interesting, because the main variable of interest, SAD, has a rather low coefficient and is insignificant at the same time. However, the sign of the coefficient is positive, in line with Kamstra et al. (2003), which indicates that the returns tend to increase as the level of risk-aversion decreases. Furthermore, the output shows an insignificant Fall dummy, with a magnitude of null. These findings indicate that the SAD effect is not present in the stock returns for the large-cap firms and there is no asymmetry between the SAD effect for fall and winter. Moreover, the Monday effect and tax-loss trading effects are neither present in the returns of the FTSE 100 index.

Following the regression results of the FTSE 100 index, the regression output for the FTSE SmallCap is presented in Table 7.

Table 7: Ordinary Least Squares regression results for the FTSE SmallCap in the sample period of 20-10-1997 to 08-01-2018. Daily returns are regressed against the main variable of interest SAD and various control variables to capture confounding effects.

Panel A: Parameter Estimates
Ordinary Least Squares Regression with Robust Standard Errors

$\mathbf{R_t}$	**Coefficient**	**t-statistic**
Constant	0.006	0.46
$\boldsymbol{R_{t-1}}$	0.200***	7.24
$\boldsymbol{R_{t-2}}$	0.064***	2.74
SAD	0.026***	4.08
Fall	-0.078***	-2.87
Monday	-0.053**	-1.96
Tax	0.154***	2.83

Panel B: Model statistics

N	5102	**P> F-statistic**	0.000
R^2	5.64%	**Durbin Watson statistic**	1.57
F-statistic	14.55	**Breusch-Godfrey statistic $\chi2$**	0.552

*significant at 10% **significant at 5% ***significant at 1%

The output of the regression provides some striking results. In contrast with the FTSE 100, all variables of this regression are statistically significant. SAD is even significant at 1%, which indicates significant presence of the SAD effect in the FTSE SmallCap. The positive sign of the SAD coefficient implies that the returns tend to increase as investors become less risk-averse when the days begin to lengthen, which is in line with the findings of Kamstra et al. (2003). Furthermore, the significant Fall dummy indicates that the SAD effect is asymmetrical between the fall and winter; the negative sign induces that the returns are lower in the fall relative to the winter. Moreover, the significant Monday and tax-loss trading dummies indicate that these anomalies are likewise present within the small-capitalization firms. All in all, it appears that the SAD effect is indeed present in the FTSE SmallCap, which indicates that the effect of mood on stock returns is more existing in the small-cap index.

CHAPTER 6 Conclusions

6.1 Discussion and conclusion

Clinical studies have shown that the presence of daylight is of significant influence on the mood of people. In turn, literature has found that mood affects the risk aversion of people. SAD is a mood proxy that has been shown to affect stock returns, which is known as the SAD effect, forming an anomaly on the classic finance theories. However, there is controversy about the existence of the SAD effect; relevant literature has not reached a consensus regarding the existence of this anomaly. Therefore, this study aimed to question the EMH and examine whether the SAD effect exists in the British stock market. Furthermore, it is attempted to provide new insights into whether this possible SAD effect differs between large- and small-cap indices. The main research question was defined as follows:

Does investor mood, measured through Seasonal Affective Disorder, significantly affect the British stock market returns?

To be able to answer the main question, the hypotheses of this study should be evaluated first. The first hypothesis was defined as follows:

$$H_1\text{: } Index\ risk\ is\ lower\ during\ the\ fall\ and\ winter\ in\ the\ UK$$

The first hypothesis tests whether index risk, which is essentially defined by the volatility of the returns, decreases during the fall and winter seasons. This hypothesis was motivated by findings which provided evidence that risk-aversion increases in the fall and winter, due to the prevalence of SAD. The standard deviation of the index returns as a risk measure showed however no decrease during the fall and winter, relative to the spring and summer seasons. Therefore, the null hypothesis is rejected for both the FTSE 100 as well as the FTSE SmallCap.

The second hypothesis was formulated as follows:

$$H_2\text{: } The\ FTSE\ Small\ Cap\ is\ more\ affected\ by\ SAD\ than\ the\ FTSE\ 100$$

This study aimed to add a new dimension to the existing literature concerning the SAD effect, by investigating whether this effect differs between large- and small-cap indices. After conducting the statistical tests, it can be documented that in the large-cap FTSE 100 index there is no SAD effect which influences the returns: the regression estimates show an insignificant SAD coefficient. However, the regression estimates of the FTSE SmallCap displayed a very significant SAD coefficient, which implicates that the SAD effect indeed exists in the returns of the FTSE SmallCap. Hence, the null hypothesis is not rejected.

The third hypothesis of this study was defined as follows:

$$H_3\text{: } The\ SAD\ effect\ in\ the\ UK\ is\ symmetric\ between\ the\ fall\ and\ winter$$

This hypothesis is tested for by adding a dummy variable for the days within the fall season, in the regression model. If this dummy is found statistically significant, it can be stated that the SAD effect is asymmetrical between fall and winter. However, the regression estimates provided an insignificant fall dummy for the FTSE 100 index. This implicates that, next to the insignificant SAD effect for the FTSE 100 index, the SAD effect is not asymmetrical between fall and winter. Hence, the null hypothesis cannot be rejected for the FTSE 100 index.

Analyzing the regression estimates for the FTSE SmallCap index, the Fall dummy appeared to be significant, which indicates that the SAD effect is asymmetric between fall and winter within this index. The negative sign of the dummy coefficient implicates that the returns are lower in the fall relative to the winter, which is in line with the days being the shortest in the fall season. Thus, the null hypothesis is rejected for the FTSE SmallCap.

The fourth hypothesis of this study was formulated as follows:

$$H_4\text{: } The\ SAD\ effect\ does\ not\ affect\ the\ British\ stock\ market$$

This hypothesis can be considered the main hypothesis of this study. The corresponding null hypothesis states that the EMH holds and no SAD effect exists in the British stock market. The results provided no evidence for a SAD effect in the large-cap FTSE 100 index, which is in line with the EMH. However, the modelling results showed that SAD significantly affects the FTSE SmallCap. Thus, the SAD effect is, to a certain extent, present in the British stock market. Hence, the null hypothesis is rejected.

After the evaluation of the hypotheses, it can be concluded that SAD has no influence on the returns of the FTSE 100 index. This is not in line with the findings of Kamstra et al. (2003), who documented a seasonal variation in the returns of large-cap indices in various countries including the UK, due to SAD. Hence, the results of this study provide no evidence to state that investors of the FTSE 100 index become more risk averse, as days begin to shorten, and change their investor behavior. This finding can possibly be explained by the large number of institutional investors who trade in large-cap stocks, who are less sensitive to investor sentiment (Krivelyova & Robotti, 2003). Moreover, the FTSE 100 index contains a large number of foreign investors, as it is a major index for Foreign Direct Investments[10]. These 'foreigners' suffer less from local factors which might influence investor sentiment, hence, their investor behavior might be less exposed to irrationality.

However, this study provides evidence for the presence of a SAD effect in the returns of the small-cap index, which indicates that investor mood does affect returns of firms with relatively low capitalization. This finding is thus in line with the findings of Kamstra et al. (2003): a seasonal variation exists in the stock returns due to SAD, where investors with this mental disorder are most risk averse in the fall season. After winter solstice, this increase in risk aversion appears to decline and the returns tend to increase again. This finding can be explained due to the large number of individual investors who trade in small-cap stocks. These individual investors are most likely more affected by investor sentiment, causing their investment decisions to be driven by mood and emotions (Krivelyova & Robotti, 2003).

Whether SAD actually affects investor sentiment in such a way that it forms an anomaly in the British stock market, remains after this study still somewhat ambiguous. The findings of this study do not provide evidence in favor of the existence of a SAD effect in the large-cap index of the British stock market. However, new insights are provided regarding the existence of this anomaly, by providing evidence of the effect for the small-cap index in the UK. Since SAD is significantly prevalent in the UK due to its circumstances, such as the climate and the location, the results of this study contribute to existing literature by providing new insights on the influence of investor sentiment on stock returns.

6.2 Limitations and recommendations

This study is however paired with some limitations. Firstly, it must be highlighted that mood, and hence investor sentiment, is difficult to measure. This study used SAD (mental disorder), which is caused by the change in hours of daylight, as a mood proxy. This can be justified by findings of psychological literature, which document that SAD is a medically validated mood proxy. However, it is still a proxy and, most likely, it cannot measure mood exactly. Hence, it is recommended for future research to develop models which measures the mood of investors more precisely, to test the relationship between investor sentiment and stock returns more accurately.

Moreover, as critics already questioned the existence of the SAD effect in the stock market, it is still the question whether solely SAD is the cause of a seasonal variation in the stock returns. It is possible that another factor, which is not addressed yet, has an influence on this seasonal anomaly. Thus, it is

[10] https://www.state.gov/e/eb/rls/othr/ics/investmentclimatestatements/index.htm#wrapper

important for future research to elaborate on this cause and look upon other factors which might play a role in the seasonal pattern of stock returns.

Furthermore, this study only used a large-cap and small-cap index to make inferences about the entire British economy. However, it might be that SAD has more influence in one sector within the British economy than another sector. It is certainly interesting for follow-up research to distinguish between the different sectors when testing for a SAD effect, by for example using fixed effects methods. This way, insights can be gained whether investor sentiment has a different influence between different sectors.

This study neither looked at possible changes in the liquidity of the index. It is possible that the prevalence of SAD also has some influence on the number of trades. Therefore, it is interesting for future research to examine the trading volume and to test whether investor sentiment affects the liquidity of an index.

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