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The weather effect – An analysis of individual and institutional investors on Dutch and Spanish markets

Bachelor Thesis – Bachelor Economics & Business Economics

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ABSTRACT

This study analyses the effect of weather variables on stock returns on Dutch and Spanish markets. Specifically, number of sunshine hours is examined. Data are collected from both small- and large capital indices per country, representing individual and institutional investors respectively. Using time series regressions, and controlling for different weather variables and seasonal anomalies, no significant relationship is found between number of sunshine hour and stock returns.

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1. Introduction

In the Netherlands, the average number of sunshine hours per month increases as the year progresses. From 61 hours in January, to 85 hours in February, 124 hours in March and 177 in April. Reaching a peak in May, only to start decreasing in the consequent months ("KNMI - Zonnig," n.d.). This illustrates a clear difference in the quantity of sunshine hours that can be expected throughout the year. Not only do variations in weather present themselves during the year, differences can also be observed amongst years. In the Netherlands, annual rainfall has increased by 18 percent since 1906 ("KNMI - Zware neerslag," n.d.). This has specially been caused by the inclusion of the winter and autumn seasons which have seen an increase of 26 percent each. These increases are largely due to warmer air being present in the atmosphere, a direct effect of climate change. And as it is expected that climate change will continue to affect weather conditions, weather becomes an interesting topic of research.

This is especially the case for the field of psychology. Psychologists have for a long time been interested in the effect of these weather changes on the mood of individuals and have done a considerable amount of research in this area. Cunningham (1979) found the amount of sunshine to be a strong indicator of an individual's willingness to partake in an interview. Furthermore, sunshine was also found to be a predictor of the size of a tip left at a restaurant. Schwarz and Clore (1983) elaborate on these findings by discovering that individuals use momentary affective states to judge the general level of happiness in their lives, and that these states can be induced by sunny weather in particular.

Mood and behaviour are also relevant topics in the field of finance. When observing equity premia obtained by investors, one fundamental point of debate remains the source. Here, literature is divided between the roles of risk and investor behaviour. Support for the 1st argument includes the works of Fama and French (see, e.g., Fama and French, (1992)). They argue that positive returns arise from differences in risk, with riskier stocks bearing higher returns than their lower risk counterparts. A different view is held by for example Lakonishok, Shleifer and Vishny, who argue that these positive returns are a result of investor behaviour (see, e.g., Lakonishok, Shleifer, and Vishny (1994)). This behavioural view has many implications regarding asset pricing models, the most prominent being that the behaviour of individuals determines their investment decisions.

As in countries like the Netherlands where the weather is continuously changing, an effect on the mood of individuals is of continuous relevance. Especially when this is combined with investor behaviour. This leads to the following research question;

"What is the effect of the weather on stock returns?"

As the existence of efficient markets was first hypothesized by Fama in 1970, an effect of weather on stock returns would clearly contest this. Furthermore, this would support the view that behavioural variables should be included in asset-pricing models.

Previous research in the field of weather effects on stock returns has indeed been conducted. Saunders (1993) finds the weather in New York City has a significant correlation with major stock exchanges located in the same city. Hirshleifer and Shumway (2003) support this finding by concluding that morning sunshine is significantly correlated with stock returns on 26 exchanges, including both Amsterdam and Madrid. After controlling for sunshine, they also found rain and snow to be insignificantly related to returns.

The purpose of this paper is to research the effect of weather on stock returns. The focus will lie on two countries, namely the Netherlands and Spain. These countries were chosen for their difference in climate. As both stock returns and weather observations are measured daily, time series data will be used to measure the possible effects and their significance.

In contrast to previous research, this paper will not solely focus on large capital indices. It is well documented across literature that individual investors may behave differently from institutional investors. Lakonishok and Maberly (1990) find that Mondays have the lowest number of institutional investors and highest number of individuals compared to other days of the week respectively. Furthermore, individual investors generally have higher degrees of ownership in smaller firms as opposed to larger firms (Lakonishok, Shleifer, and Vishny, 1992). For this reason, small capital indices will be included as a representative of individual investors, and large capital indices as a representative of institutional investors. A potential significant difference between these indices will be researched. In addition, when modelling the relationship between weather and stock returns, this research will control for the seasonal anomaly known as the Monday- or weekend effect. Lastly, this research will be conducted using data starting from the 1st of January 2000, until the 1st of January 2019. Essentially, using newer data to check if the effect found by Saunders in 1993 still persists.

The remainder of this paper is organised as follows. In section 2 the relevant literature and theory will be discussed. In this section, an introduction of the two hypotheses will be present. In the third section the data used for this research will be described and this will be followed by a discussion of the methodology used in the fourth section. Section 5 will present the results obtained and the final section will give a summary and interpretation of these results followed by a brief discussion and conclusion.

2. Theoretical Framework

2.1 Market efficiency and asset pricing

In 1970 Eugene Fama hypothesised the idea of efficient markets, later to be known as the Efficient Market Hypothesis (EMH). The EMH states that current prices contain all current information available (Malkiel & Fama, 1970). It further divides the hypothesis into three forms, these being the weak, semi-strong and strong. The weak form states that all past price information is reflected in the current market price. The semi-strong form argues that all publicly available information is reflected in the current market price. The strong form claims that all available information, this being both public and private information is reflected in the current market price. The result of the existence of the EMH is that no investor can obtain systematically abnormal returns by following any investment strategies. This is because any information obtained by an investor is immediately reflected on the market.

Risk

When attempting to explain the expected return on assets, William Sharpe developed the Capital Asset Pricing Model (CAPM) in 1964. The CAPM defines returns as compensation for bearing a certain amount of risk. It continues by dividing this risk into two components, the so-called systematic risk factor and the idiosyncratic risk factor. The systematic risk or market risk is the common risk factor shared by all stocks on the market. The idiosyncratic risk can be seen as unique to each firm. As the idiosyncratic factor is firm specific, a well-diversified portfolio leads to the elimination of this factor (Markowitz, 1952). As a result of this, the CAPM concentrates on the relationship between expected returns and the systematic risk factor, which is measured by the beta.

The Efficient Market Hypothesis and capital asset pricing model go hand in hand as the EMH acts as the framework in which the CAPM operates. These ideas however are no strangers to heavy criticism. Most notably for failing to explain certain phenomena exhibited by the markets.

Behaviour

When observing stock returns, literature distinguishes two main sources. The aforementioned CAPM model focuses on the first, namely risk. In this section, an elaboration will be made on the second source, investor behaviour. To gain an understanding of the role of behaviour, an introduction is first needed on the topic of value strategies. Value stocks are seen as having low prices relative to different measures of fundamental value such as earnings and dividends. Investors employing value strategies seek to make use of this bargain by buying these stocks and selling them in the future for a profit. The positive returns obtained by value strategies has been empirically confirmed by works such as Basu (1977).

The main question however remains the source of these returns. Lakonishok et al. (1994) argue that investor behaviour is the driver behind the returns generated by these so-called contrarian investment strategies. In their paper, they find investors to consistently overestimate the growth rate of stocks which have performed well in the past or 'glamour stocks' and underestimate the growth rate of value stocks. Furthermore, they find these value stocks to not be fundamentally riskier than glamour stocks, refuting the theory of returns being rewards for bearing risk. These results build upon the findings of De Bondt and Thaler (1985). In their research, they conclude that portfolios consisting of firms who performed poorly in the past outperform portfolios consisting of their well performing counterparts. In other words, investors indeed attach a large amount of weight to recent developments and neglect the application of Bayes' rule. This leads to investors exhibiting overreaction.

2.2 Market inefficiency

When the market displays signs of not being efficient, it becomes known as an inefficient market. This is the case when certain phenomena remain unexplained by conventional theories. For a lack of explanation these phenomena became known as anomalies. These anomalies later become known as seasonal anomalies when they are observed on a repeated calendar-based basis and are inexplicable by asset pricing models where returns are explained only by risk. Here, the argument arises to include investor behaviour as a determinant of returns in asset pricing models. Some examples include the January effect, where Rozeff and Kinney (1976) discovered that January exhibits significantly higher returns compared to the rest of the year. Also, and more relevant to this research, the weekend- or Monday effect. Cross (1973) set out to document examples of non-random movements on the market. After collecting a sample of 844 sets of Fridays and their subsequent Mondays from 1953 through 1970 on the S&P Composite Index, Monday returns were found to be significantly lower than that of other days of the week. Keim and Stambaugh (1984) investigated this effect further by extending the amount of time and stocks investigated. Finding significant negative Monday returns as early as 1928 for the S&P Composite Index. Furthermore, these results extend to Exchange-traded stocks of firms of all sizes and over-the-counter stocks.

French (1980) aimed at explaining the Monday effect through the examination of two hypotheses. The calendar time hypothesis states the return generating process to be continuous. Because of this Monday is seen as a 3-day investment (from Friday close to Monday close) meaning Monday returns are meant to be three times larger than the rest of the week. Under the trading time hypothesis however, returns are generated only when the market is actively traded upon. As a result, mean returns are equal for all weekdays. Results are obtained using the S&P Composite Index from 1953 to 1977. It is observed that Monday returns are significantly lower for all five-year subperiods used, rejecting both the calendar time- and trading time hypothesis. French continues by attempting to attribute the abnormal finding to markets being closed on weekends. This idea is tested by means of observing returns after the market has been closed due to holidays, and ultimately rejected. Hereafter, it is theorised that the low return on Monday is a result of information being released on the weekend, or the so called ‘bad news hypothesis’. The notion here is that in an effort to reduce ‘panic selling’, firms release unfavourable information over the weekend. Low Monday returns being a direct result. In theory, investors would start expecting this release of information and discount weekly stock prices accordingly. However, since the Monday effect is clearly present, its existence is in direct contrast with that of efficient markets.

Agrawal and Tandon (1994) prove that the Monday effect is an international phenomenon. In their sample including the Netherlands, Monday returns demonstrate to be the lowest or negative in 9 of the 18 countries tested.

In an attempt to explain the Monday effect, Abraham and Ikenberry (1994) study the relationship between the aforementioned effect and individual investors. The research is based on the arguments laid forth by Miller (1988) and Lakonishok and Maberly (1990). Here it is argued that individuals face high opportunity costs during weekdays and can only make investment decisions during the weekend. Furthermore, during the weekend often times it is sell decisions which are reached due to liquidity and rebalancing reasons.

2.3 Mood and decisions

Market inefficiency can also be extended to investor sentiment. Here, the current mood investors find themselves in is of influence on their investment decisions. Psychologists have done an ample amount of research in the field of decision making. Wright and Bower (1992) find mood to be a key variable influencing the decisions made by individuals, particularly their probability assessment. In their research, they induce two moods on their subjects namely 'happy' and 'sad'. People in happy moods are found to be more optimistic. Their reported probabilities for positive events and negative events increase and decrease respectively. The opposite is reported for people in bad moods. A so-called mood-state-dependant retrieval of information is implied.

Studies have also illustrated the effect of mood on analytical skills. Sinclair and Mark (1995) show that happy individuals tend to process information in a manner that is more passive, unsystematic and less critical. Whereas sad people have the tendency to do the opposite.

Much research has also been focused on the effect of weather variables on mood and behaviour. Howarth and Hoffman (1984) test eight weather variables and their effect on 10 different mood variables. Humidity, temperature and sunshine hours are found to have the greatest effect on mood. Sunshine can be said to have a positive effect on individuals' feelings of happiness and mood, and rain is said to decrease feelings of satisfaction with life (Schwarz & Clore, 1983). Mehra and Sah (2002) analyse stock prices when preferences are affected by mood. Their research shows that a significant change in the volatility of prices is caused by variations in preferences. Saunders (1993) also investigates this theory by researching the relationship between weather variables and stock returns in New York City. It is concluded that weather is significantly correlated with the major stock indices researched (Dow Jones Industrial Average, New York Stock Exchange). The aforementioned theories on mood and behaviour lead to the first hypothesis:

Hypothesis 1: Sunshine is positively correlated with stock returns - an increase in number of sunshine hours leads to increased returns.

Hirshleifer and Shumway (2003) support this finding by concluding that morning sunshine is significantly correlated with stock returns on 26 exchanges, including both Amsterdam and Madrid.

2.4 Institutional investors vs individual investors

When observing agents participating on financial markets a distinction can be made as to the type of investor. They can specifically be divided into institutional investors and individual investors. Institutional investors can be defined as “specialised financial institutions that manage savings collectively on behalf of small investors toward a specific objective in terms of acceptable risk, return maximisation and maturity of claims” (Davis & Steil, 2004). Conversely, individual investors can be seen as any investor which is not an institutional investor. Put differently, individual investors manage funds on their own behalf, whereas institutional investors manage funds which are not their own. Because of this, institutional investors are evaluated on their performance and thus need to justify their investment decisions. This leads to institutional investors gravitating towards easily justifiable firms with proven positive properties such as consistent earnings growth (Lakonishok, Shleifer, Vishny, Hart, & Perry, 1992). As a result, a difference in the behavioural patterns of individual and institutional investors can be expected.

Shapira and Venezia, (2001) investigate this further by analysing the investment patterns of a brokerage house. More specifically, the behaviour of clients making their own investment decisions are compared to that of professionally managed accounts. It is concluded that the disposition effect[1] is present for both types of investors. However, this effect is found to be

[1] Tendency to sell winning stocks faster than losing stocks

significantly weaker for professional investors than for individuals. This difference is attributed to the training received and experience gained by professional investors. These finding lead to the second hypothesis:

Hypothesis 2: Individuals react more strongly to weather – the effect of sunshine is more positive for individuals compared to institutional investors.

3. Data

3.1 Stock data

In this research, 4 stock indices will be used. These will represent institutional and individual investors in both the Netherlands and Spain. Using small and big capital indices as proxies for individual and institutional investors respectively is in accordance with the findings of Lee, Shleifer, and Thaler, (1991). Here it is concluded that small firms are mostly held by individuals whereas institutions mostly hold large firm stocks.

Starting with the Netherlands, the Amsterdam Exchange Index (AEX) is used to represent Dutch institutional investors. The AEX consists of 25 of the most frequently traded stocks on the Euronext Amsterdam exchange. The second Dutch index used is the Amsterdam Small Cap Index (AScX). This index consists of 25 stocks traded on the Euronext Index. These 25 stocks are ranked as the smallest in terms of capital valuation.

The Spanish indices of choice are the IBEX 35 and IBEX Small Cap Index. The IBEX 35 is a capital weighted index which consists of 35 highly liquid stocks traded on the Madrid Stock Exchange General Index. As such, the IBEX 35 is used as a representation of Spanish institutional investors. The IBEX Small Cap Index also a capital weighted index, designed to represent the performance of the small-sized securities traded on the Spanish Stock Market[2]. It is used as a representative of Spanish individual investors. Table 1 provides an overview of each index with its corresponding country and type of investor. Furthermore, descriptive statistics of each variable can be found.

All stock data are collected through Datastream. Daily closing prices are gathered starting January 1st, 2000 and ending on January 1st, 2019.

[2] http://www.bolsamadrid.es/docs/SBolsas/InformesSB/FS-SmallCap_ING.pdf

Table 1: Overview & descriptive statistics - Total observations, mean, minimum and maximum can be observed per variable.

Country	Type	Variable	Obs.	Mean	Min.	Max.
Netherlands	Individual	AScX	4828	558.32	219.73	1121.5
	Institution	AEX	4957	422.86	199.25	701.56
Spain	Individual	IBEX Small	4957	7040.47	3007.3	18198.9
	Institution	IBEX 35	4957	9812.47	5364.5	15945.7

It can be seen that the AScX index exhibits less observations than the remaining indices. This can be attributed to the fact that data for the AScX index was only found starting on the 30th of June 2000. It is also apparent that the maximum values for each index are significantly larger than the minimum values, displaying clear growth in market capitalisation over the course of the observed time period. Furthermore, the mean indicates the average value measured per index across the time span used.

The values of each index have been shown and elaborated upon. However, when researching the relation between weather and stock returns, it is apparent that daily returns will be used, rather than daily closing prices. For this reason, returns are acquired by means of computing the log difference. The following equation gives an illustration.

$$R_t = ln(Value_t) - ln(Value_{t-1})$$

Here R_t represents daily returns. The computation of these returns involves taking the natural logarithm for each daily closing price. Hereafter, the natural logarithm of day t_{-1} is subtracted from that of day t. Descriptive statistics of the computed returns can be found in table 2.

Table 2: Descriptive statistics daily returns - Total observations, mean, standard deviation, minimum and maximum can be observed per variable.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
AScX Return	4827	.0001079	.0097375	-.0822437	.0753505
AEX Return	4957	-.0000644	.0138991	-.0959033	.1002827
IBEX Small Return	4957	-8.22e-06	.0103985	-.0842089	.0712267
IBEX 35 Return	4957	-.0000625	.0144518	-.1318527	.1348364

3.2 Weather data

Weather data are collected from the national weather agencies of both countries. For the Netherlands this is the *Koninklijk Nederlands Meteorologisch Instituut* (Royal Netherlands Meteorological Institute) or KNMI for short. For Spain it is the *Agencia Estatal de Meteorología* (The State Meteorological Agency) or Aemet. As these are the national weather agencies of both countries, operating under their respective governments, the data provided can be considered of high quality.

In this research 3 weather variables are used. *Sunshine* is defined as the total number of sunshine hours on any given day. *Rain* is defined as the amount of total daily precipitation in millimetres, and *Temperature* is defined as the average daily temperature in degrees Celsius. In accordance with the stock data, weather data is also collected from the 1st of January 2000 until the 1st of January 2019. One crucial detail worth mentioning is the fact that the stock markets are closed on the weekends. For this reason, weekend weather observations are deleted in order to synchronise both stock and weather data. Table 3 displays descriptive statistics for each weather variable.

Table 3: Descriptive statistics weather variables - Sunshine is the average number of daily sunshine hours. Rain is the total daily precipitation in mm. Temperature is the average daily temperature in degrees Celsius. These variables can be observed per country.

Country	Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Netherlands	Sunshine Ams.	4957	4.91055	4.15102	0	15.5
	Rain Ams.	4957	2.32608	4.98607	-.1	67.2
	Temp. Ams.	4957	10.85794	6.11993	-7.7	29.5
Spain	Sunshine Madrid	4957	7.66394	4.26197	0	14.5
	Rain Madrid	4957	1.10938	3.67628	0	51
	Temp. Madrid	4957	15.21947	7.62771	-2.7	31.7

In accordance with the difference in climate, it can be seen that the average amount of sunshine hours in Spain exceed that in the Netherlands. The same can be said for the average Spanish temperature. Furthermore, the average amount of total rainfall in the Netherlands is more than the Spanish amount. Rain is marked as -.1 when the total amount of rainfall is less than 0.05 millimetres.

4. Methodology

4.1 Regression

This section will elaborate on the methods used to conduct this research. The relationship between weather and stock returns will be analysed by means of an Ordinary Least Squares (OLS) regression. More specifically, time series models will be used. In this model, daily stock returns are the dependent variable, and sunshine hours the independent variable. Furthermore, several control variables are included. The model looks as follows;

$$Y_t = \beta_0 + \beta_1 Sunshine + \beta_2 Y_{t-1} + \beta_3 Rain + \beta_4 Temp + \beta_5 Mon + \varepsilon$$

Here, Y_t will represent the daily returns per market index at time t. *Sunshine* represents the variable of interest, namely the number of sunshine hours.

As mentioned previously, several control variables are included in the used model. This is done to correct for possible omitted variable bias, thereby upholding internal validity. The first control variable included is Y_{t-1}. This represents the 1st lagged value of the dependent variable, namely daily stock returns. In other words, this variable represents the daily stock return of the previous day. This is done in accordance with the methodology employed by Cao and Wei (2005), to control for possible first order autocorrelations. The next control variable included is *Rain.* As the name suggest, this variable represents the amount of daily precipitation. Following this, is *Temp.* Cao and Wei (2005) identify temperature to be negatively correlated with stock returns. For this reason, this model will control for temperature. The last variable included is *Mon.* This variable is included as a control for the Monday effect. Moreover, it is a dummy variable, taking the value of 1 when the observed day is a Monday and 0 otherwise.

Regarding the testing of the hypotheses, the variable of interest, namely *Sunshine* will be observed. Here, a significance level of 5% will be used to test whether this variable is significantly different from zero. When testing the first hypothesis, the sign of the coefficients will be analysed. The second hypothesis will be tested by means of comparing the magnitude of small and large stock indices.

4.2 Stationarity

Time series regression assumes the data to be stationary. When this is not the case, the data is said to contain a trend or unit root. The presence of a unit root can lead to spurious regressions and therefore indicate misleading results. To avoid this, the data is tested. This is done by means of an augmented Dickey Fuller test. Here, under the null hypothesis, the variable is non-stationary. If the null is rejected, the variable can be considered stationary. To conduct this test, Dickey-Fuller critical values are used at a 5% significance level.

It can be argued that a stationarity test for stock returns is not needed, because returns are computed by taking the first difference of the daily closing prices and taking 1^{st} differences is actually considered a solution to non-stationarity. However, these tests are conducted purely to be certain that the data can indeed be regarded as stationary[3].

4.3 Homoskedasticity

Homoskedasticity particularly signifies a constant variance. When using OLS regressions, one assumption of the model is a constant variance of the residuals. If this is not the case, the data is said to be heteroskedastic. The homoskedasticity assumption is not needed in terms of assuring an unbiased and consistent model. However, a model containing heteroskedastic variances of the error term will be inefficient, meaning the existence of different models with better estimates. To correct for the potential presence of heteroskedasticity, Newey-West standard errors are used.

[3] Results of these tests can be found in table A1 in the appendix.

5. Results

A presentation of all obtained regression coefficients can be found in table 4. Here, the coefficients have been divided in 4 columns, one for each index used in this study. These indices subsequently represent the two countries observed. Moreover, the coefficients reported represent the computed effect on the dependent variable namely stock returns. Firstly, Hypothesis 1 is tested. This hypothesis states that *Sunshine is positively correlated with stock returns - an increase in number of sunshine hours leads to increased returns*. To test this hypothesis, the coefficient of the variable *Sunshine* is examined.

The first column displays the results obtained for the AEX index. The coefficient for the variable Sunshine displays a positive sign, in line with previous literature such as Hirshleifer and Shumway, (2003). However, this coefficient seems to be insignificant at all levels. For this reason, no conclusions can be drawn on the sign or magnitude of this coefficient. The second column displays results obtained for the AScX index. Here, similar results are observed as those of the AEX in terms of significance. An insignificant coefficient leading to no interpretation of said coefficient being allowed. With both indices representing the Netherlands exhibiting insignificant results, the null hypothesis that the coefficients are significantly different from zero cannot be rejected.

Next, the third column displays results for the IBEX 35 index. The coefficient obtained here is significant at a 10% level. Furthermore, this coefficient shows a positive sign. Multiplying the coefficient with the standard deviation of Sunshine in Madrid results in a value of .000417. When this is compared to the .0144518 standard deviation of IBEX 35 returns, the magnitude of the coefficient obtained can be interpreted as quite small. The last column displays the results obtained for the IBEX Small Cap. index. An insignificant coefficient is observed for the variable *Sunshine*.

The findings mentioned in the previous paragraphs show that of the four indices observed, only one exhibits a significant coefficient for the variable *Sunshine* at a 10% level. For the remaining three indices, this means the null hypothesis stating that the coefficient is significantly different from zero cannot be rejected. Based on these findings, Hypothesis 1, which states that *Sunshine is positively correlated with stock returns - an increase in number of sunshine hours leads to increased returns*, is rejected.

Table 4: Regression analysis output – AEX and AScX represent institutional and individual investors respectively on Dutch markets. IBEX 35 and IBEX Small represent institutional and individual investors respectively on Spanish markets[4].

	Country			
	Netherlands		Spain	
	AEX	AScX	IBEX35	IBEX Small
Constant	.0002917	.0007877	-.0000487	.0005177
	(.0004033)	(.000288)***	(.0005121)	(.0003656)
Sunshine	.0000839	.0000557	.0000979*	.000028
	(.0000536)	(.0000365)	(.0000595)	(.0000433)
1st Lag Return	-.006672	.1181962***	.0034984	.1325484***
	(.0234457)	(.0237776)	(.0216245)	(.0210213)
Rain	.0000205	.0000268	.0000529	.0000187
	(.000035)	(.0000267)	(.0000526)	(.000037)
Temperature	-.0000694**	-.0000981***	-.0000389**	-.0000557**
	(.0000352)	(.0000238)	(.0000316)	(.0000225)
Monday	-.0003211	.0002005	-.0011474	.0004277
	(.0005593)	(.0003903)	(.0005415)	(.0003964)
N	4,956	4,826	4,955	4,955
Newey-West standard errors between brackets				

**p* < 0.10, ***p* < 0.05, ****p* < 0.01

[4] R^2 has been omitted as it is not provided when using Newey-West standard errors. Furthermore, this measure of fit gives little information when modeling returns using OLS, as a straight line does not fit return data particularly well.

To test Hypothesis 2, which states that *Individuals react more strongly to weather – the effect of sunshine is more positive for individuals compared to institutional investors,* the same output from table 4 is used. Here, the magnitude of the coefficients for the variable *Sunshine* are compared. More specifically, the magnitude of the smaller index (AScX & IBEX Small) is compared to that of the bigger index (AEX & IBEX 35) per country.

It is noticeable that for both countries, the magnitude of the coefficient for the smaller index is less than that of the larger index, contesting the findings of Shapira and Venezia, (2001). However, as three of these four coefficients are insignificant at all levels, no conclusions can be drawn on their signs and values. In other words, the null hypothesis that these coefficients are significantly different from zero cannot be rejected. This leads to Hypothesis 2 being rejected.

When examining the control variables used, it is apparent that the coefficient obtained for the variable *Temperature* is significant at a 5% level for all indices, and at a 1% level for the AScX. Furthermore, the coefficients across all indices show a negative sign. These results are in line with those obtained by Cao and Wei, (2005). In their research they identify a negative correlation between stock returns and temperature. They continue to attribute this relationship to aggressive and risk-taking behaviour being caused by lower temperatures and apathy in higher temperatures. These moods subsequently lead to higher and lower returns respectively. The coefficient for the control variable *Mon* representing the Monday effect is also found to be insignificant at all levels for all indices used, signifying no presence of the Monday effect present on Dutch markets. This supports the findings of Marquering, Nisser, and Valla, (2006) where it is argued that the disappearance of calendar anomalies is a result of these anomalies becoming known to investors after their scientific publications. Because of this, investors eliminate these anomalies by trading on them.

It can also be seen that the coefficients for the 1^{st} lag of returns is significant at a 1% level for both smaller indices, indicating the presence of autocorrelation.

Robustness analysis

To check the robustness of the obtained results, a robustness analysis is performed. This analysis makes use of the same time-series model; however, a replacement variable is used for *Sunshine*. Instead of *Sunshine*, the variable *Coverage* is used. This variable represents the average amount of cloud coverage on a given day. Taking on a value of 0 when coverage is the least, and a value of 9 when coverage is the highest. This analysis is performed for the Dutch stock indices, as the *Coverage* variable is not available for Spain. When analysing the relationship between cloud coverage and stock returns, the opposite is expected compared to that of sunshine and stock returns. This is an intuitive deduction based on the following reasoning; an increase in cloud coverage leads to a decrease in sunshine, and a decrease in cloud coverage leads to an increase in sunshine. Additionally, the same control variables are included in this model. This leads to the following model;

$$Y_t = \beta_0 + \beta_1 Coverage + \beta_2 Y_{t-1} + \beta_3 Rain + \beta_4 Temp + \beta_5 Mo + \varepsilon$$

The results of this regression can be found in table 5. It can be seen that the coefficients for the variable *Coverage* is negative for both indices. However, these coefficients are insignificant at all levels resulting in no conclusions being drawn from their sign or magnitude. The insignificance of these coefficients does however indicate the robustness of the results obtained on the *Sunshine* variable. As the null hypothesis stating that the coefficients are significantly different from zero cannot be rejected, Hypothesis 1 which states that *Sunshine is positively correlated with stock returns - an increase in number of sunshine hours leads to increased returns,* and indirectly stating that *an increase in cloud coverage leads to a decrease in stock returns*, is rejected.

To test the robustness of Hypothesis 2 which states that *Individuals react more strongly to weather – the effect of sunshine is more positive for individuals compared to institutional investors,* the magnitude of the coefficients for the variable *Coverage* are analysed. As these coefficients are insignificant, the null hypothesis stating that the coefficients are significantly different from zero cannot be rejected. This leads to a rejection of Hypothesis 2. Indicating a robustness of the results obtained on the variable *Sunshine*.

Furthermore, it can be seen in table 5 that the coefficients of the variable *Temperature* remain significant at a 10% level for both indices, and that of the AScX index at a 1% level as well.

Table 5: Robustness analysis - AEX and AScX represent institutional and individual investors respectively on the Dutch market[5].

	Netherlands	
	AEX	AScX
Constant	.0011261	.001437
	(.0006992)	(.0004573)***
Coverage	-.0001076	-.0000878
	(.0000917)	(.0000615)
1st Lag Return	-.0069284	.1181266***
	(.0246719)	(.025639)
Rain	.0000156	.0000258
	(.0000347)	(.0000265)
Temperature	-.000054*	-.0000891***
	(.0000317)	(.0000217)
Monday	-.0003128	.0002051
	(.0005541)	(.0003885)
N	4,955	4,827

**p < 0.10, **p < 0.05, ***p < 0.01*

[5] R^2 has been omitted for the same reasons mentioned in footnote 4.

6. Discussion & Conclusion

This paper analyses the relationship between the weather and stock returns. Moreover, data were gathered for two countries, namely the Netherlands and Spain, and two indices per country were observed. These data span from the 1st of January 2000 until the 1st of January 2019.

Based on the findings elaborated upon in the results section, Hypothesis 1 which states that *Sunshine is positively correlated with stock returns - an increase in number of sunshine hours leads to increased returns* is ultimately rejected. This means an increase in the number of sunshine hours does not lead to an increase in stock returns. These results are in contrast to the findings of Saunders, (1993) and Hirshleifer and Shumway, (2003). The results are however in line with the findings of Pardo and Valor, (2003) where no significant relationship is found between sunshine and stock returns. In their study, the transition from an open outcry system to a decentralised computer-based system is researched. It is hypothesised that this transition can lead to a disappearance of the weather effect, as there is no need for investors to be physically present in the location of the exchange. They find no effect prior nor post the transition to a decentralised system, however. Indicating no initial presence of a weather effect.

Hypothesis 2, which states that *Individuals react more strongly to weather – the effect of sunshine is more positive for individuals compared to institutional investors,* is also ultimately rejected. As elaborated on in the results section, due to the coefficients being insignificant, no conclusions can be drawn from their sign or magnitude. For this reason, nothing can be said about the magnitude of an effect of sunshine on individuals compared to institutional investors.

These results do support the Efficient Market Hypothesis which argues that the market reflects all current available information and that external stimuli such as weather conditions should have no influence on market prices.

Using the aforementioned results, the research question posed in this study can be answered namely;

"What is the effect of the weather on stock returns?"

When attempting to answer this question, it is important to specify the definition of weather. In this study, weather was particularly defined as the daily number of sunshine hours. And when observing this particular variable, no significant relationship was found. In other words, the weather has no effect on stock returns. However, if weather were to be defined differently, particularly as the average daily temperature, then indeed significant results were found, and it can be said that the weather has an effect on stock returns. Moreover, temperature seems to have a negative effect on stock returns, with an increase in temperature leading to a decrease in stock returns, and a decrease in temperature leading to an increase in stock returns. This result presents an opposing view on the Efficient Market Hypothesis and supports the inclusion of behavioural variables in asset-pricing models.

Based on the results of this study, an investment strategy which would be reliant on weather forecasts, specifically sunshine and cloud coverage, will yield no significant abnormal returns. However, it is worth mentioning that this study only observes the Dutch and Spanish markets. For this reason, the results cannot be extrapolated to all markets as this would not be an externally valid approach. It is therefore recommended to replicate this study with a dataset consisting of more countries. This will result in a similar study as that conducted by Hirshleifer and Shumway in 2003, however, a newer study will make use of more recent data thereby making it academically relevant.

Furthermore, as cloud coverage data were only available for the Netherlands, this presented a limitation for this study. It is recommended that further research be done including this variable as well.

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Appendix

Table A1: Results Augmented Dickey-Fuller test – variable names are displayed in the first column. Test statistics and p-values are displayed in the second and third columns respectively. All variables are stationary.

	Test statistic	p-value
AEX Returns	-70.179	0.0000
AScX Returns	-61.545	0.0000
IBEX 35 Returns	-70.179	0.0000
IBEX Small Returns	-61.526	0.0000
Sunshine Ams.	-43.202	0.0000
Rain Ams.	-56.399	0.0000
Temp. Ams.	-13.158	0.0000
Coverage Ams.	-43.533	0.0000
Sunshine Madrid	-34.955	0.0000
Rain Madrid	-55.203	0.0000
Temp. Madrid	-10.317	0.0000