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# Spanish Stock Returns: Where is the Weather Effect?

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**Abstract**

*Psychological studies support the existence of an influence of weather on mood. Saunders (1993) and Hirshleifer and Shumway (2001) argue that the weather could affect the behaviour of market traders and, therefore, it should be reflected in the stock returns. This paper investigates the possible relation between weather and market index returns in the context of the Spanish market. In 1989, this market changed its open outcry trading system into a computerised and decentralised trading system. Therefore, it is possible to check the influence of weather variables (sunshine hours and humidity levels) on index returns in an open outcry trading system, and to compare it with a screen traded environment. The empirical evidence indicates that, independently of the trading system, there is no influence of weather on stock prices. Thus, these findings do not contest the notion of efficient markets.*

**Keywords:** *stock returns*; *weather*; *trading system.*

**JEL classification:** *G*12, *G*14, *D*84.

## 1. Introduction

There are a number of papers, mainly within the field of psychology, that have reported a significant impact of weather conditions on human behaviour. Howarth and Hoffman (1984), for instance, observed that positive human performance was negatively correlated with high humidity levels, but positively correlated with the number of hours of sunshine. These results lead immediately to the following question: could the weather have a direct impact on the financial markets by affecting the behaviour of the market traders?

Several works have tried to answer this question. By considering that people in a good mood make more optimistic choices and judgements, Saunders (1993) showed that the weather in New York City had a long history of significant correlation with

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the major US stock indices. More specifically, Saunders reported that the NYSE index returns tend to be negative on cloudy days. Starting from this paper, a branch of recent research has focused on the relationship between weather variables and asset prices. On one hand, Krämer and Runde (1997) replicated the findings in Saunders using German data, and concluded that short-term stock returns were not affected by local weather. On the other hand, Kamstra *et al*. (2000) found international evidence that the shift from daylight saving time had a significant and negative impact on asset prices. Also, Kamstra *et al*. (2002) studied the number of hours of potential daylight, lower in winter, and observed that it was significantly related to the return from international equity indices. Finally, Hirshleifer and Shumway (2001) detected a strong and positive correlation between morning sunshine at a country's leading stock exchange and market index stock returns at 26 countries.

All the above analyses present evidence concerning the most important stock exchanges, but none of them specify if the market analysed has a floor or a screen trading system. This is an important issue that should be taken into account, since these works rely on the assumption that weather in a location is representative of all the market in that location. This hypothesis makes sense if the trading is carried out physically at the market (as is the case in a floor trading system). On the contrary, if traders in one market can act remotely from other places, with different weather characteristics, then the weather should not affect the stock prices at all.

The objective of this paper is to check the possible relationship between weather and stock prices, taking into account if the stocks are floor or screen traded. In order to do that, the most representative Spanish Financial Market, the Madrid Stock Exchange (MSE) has been chosen, since it moved from a floor trading system to a computerised trading system in 1989, defining clearly two different periods. It is noteworthy that the Madrid Stock Exchange is one of the main European financial centres. In fact, its large trading volumes made it the fourth most active market in Europe and the seventh worldwide in 2000.

The remainder of the paper is organised as follows. Section 2 describes the financial and weather data used for the study. Section 3 contains a discussion on the methodology. In Section 4 the relationship between weather and stock price returns is examined taking into account if the market has an open outcry system or a computerised share trading system. The final Section summarises and presents the most relevant conclusions drawn from the analysis.

## 2. Financial and Weather Data

The financial data used in this study consist of daily closing values of the Madrid Stock Exchange Index (MSEI) from January 1981 through May 2000.[1] The Madrid Stock Exchange (MSE) was initially a call market, in which the trading was allowed only at specified times. When a security was 'called' the brokers who were interested in trading it were physically brought together.

The MSE began to use the Computer Assisted Trading System (CATS) on 24 April 1989. In this system the orders were entered electronically and continuously from brokering companies and routed to a computer file that displayed limited orders

[1] Both the financial and weather data used in this work are available from the authors upon request.

against which other investors might trade. Priority for matching an order was determined by price, but if prices turned out to be equal, then priority was given to the order with the oldest arrival time. In November 1995, CATS was replaced by the Sistema de Interconexión Bursátil Español (SIBE), which has similar characteristics to CATS, but it was fully developed at MSE.

Since 1989 both the call market and the electronic market have coexisted, but a given stock must only be traded in one of them at a time. It is worth highlighting that presently 99% of the total market turnover is traded at SIBE. Therefore, it can be considered that screen trading has fully replaced the floor trading system in Spain.

It is also important to note that there are several Spanish shares that are listed in US, Japanese, and German financial markets, as well as in Spain. Thus, specific price movements of several stocks could be due to arbitrage between markets. However, the small percentage of Spanish *blue-chips* that are traded in non-Spanish markets eliminates this problem.

The weather data have been collected from one of the weather stations of the Instituto Nacional de Meteorología in Madrid. Several variables are available at daily frequency that could be of interest for the analysis, namely air temperature, wind speed, relative humidity, rain precipitation, atmospheric pressure, and sunshine hours. The literature reviewed identifies sunshine (or the inverse variable, cloudiness) and relative humidity as the most relevant variables that affects human mood (Howarth and Hoffman, 1984), and thus that could influence the stock returns. Rain is highly correlated to high levels of humidity and cloudiness, and temperature, atmospheric pressure and wind speed have not been found in previous studies to influence mood. Therefore, sunshine hours and humidity levels have been selected as the variables to test their possible influence in the Spanish stock returns. The sunshine hours have been normalised by the theoretical length of each day, in order to obtain a measure of the time the sun has been actually shining. In consequence, a value of 0% of sunshine means that a day has been cloudy and a value of 100% means that it has been sunny all day. The relative humidity is given in percentages, where a 100% means that the air is saturated with water vapour, and low values characterise a dry atmosphere.

## 3. Methodology

The daily returns are calculated as $r_t = \log(P_t/P_{t-1})$ where $P_t$ and $P_{t-1}$ are closing values of MSEI on days $t$ and $t-1$, respectively. Statistical tests have been carried out for two different periods in order to test the possible relationship between weather and the stock prices, taking into account if the stocks are floor or screen traded. Thus, the data has been separated into two sub-periods. The first one spans from January 1981 through April 1989 and comprises the period when the MSE traded exclusively as an open outcry market. The second period covers from April 1989 to May 2000, when MSE used both floor and electronic trading systems. Obviously, if there is a weather effect, it should be stronger in the first period.

To investigate the effect of the weather on the stock prices, the daily returns have been separated into sunshine hours and relativity humidity quintiles. Thus, if sun matters to the stock price, the fifth quintile will present positive abnormal returns, considering that sunny days will produce an optimistic mood on the market traders. Similarly, if relativity humidity influences the stock price, the fifth quintile will present negative abnormal returns, taking into account that high humidity levels are related to negative performance of people.

The available data are given at daily frequency, that is, the total number of hours during which the sun has been shining, and the average humidity during the day. In principle, it could be more interesting to have hourly data, in order to consider the sunshine and humidity only during the period when trading is taking place in the market. Nevertheless, since we are interested in the highest quintiles of the data, i.e., in completely sunny days or very humid days, then the daily data are representative of the weather during the trading periods. For instance, if a day had 95% of sun, then it was likely sunny during the trading period; a day with an average humidity of 90% was probably also humid during the trading period. In addition, these extreme cases (sunny or humid) are predictable within 2 or 3 days, whereas intermediate values of sunshine or humidity are more difficult to predict. This feature might be important, since if there were an effect of weather on market returns, it could be exploited by adopting different trading strategies from one day to another.

Before testing the equality of mean returns across the quintiles, the equality of variances have been tested ($H_0$: $\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma_4^2 = \sigma_5^2$, where $\sigma_i$ is the standard deviation of the returns of the $i$th quintile), as the equality hypothesis of the former is based on that of the latter. It is well known that the equality variance of the $F$-test frequently rejects the null hypothesis of equal variances when the distributions being analysed present wider tails than those of normal distributions. Therefore, given that MSEI returns are leptokurtic on all the samples,[2] the equal variance tests have been studied using the Brown–Forsythe statistic (1974). This statistic is less sensitive to the absence of normality, and tests the null hypothesis that the variances in all the subgroups are equal against the alternative that at least one subgroup has a different variance. Under the null hypothesis of equal variance, this statistic is distributed as an F-Snedecor with $G-1$ numerator degrees of freedom and $N-G$ denominator degrees of freedom, where $G$ and $N$ are the number of subgroups and observations, respectively.

The hypothesis of equality of all the mean returns against the alternative that they are not equal has been tested with the parametric $F$-test ($H_0$: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$, where $\mu_i$ is the mean of the $i$th quintile). This test could be misspecified if the return variances are not constant across the different categories. For this reason, we also report the non-parametric Kruskal–Wallis statistic that makes no distributional assumptions on index returns ($H_0$: $m_1 = m_2 = m_3 = m_4 = m_5$, where $m$ is the median of the $i$th quintile).

In order to check that the returns belonging to the fifth quintile are random draws from the total number of observations, an additional non-parametric test has been performed. Thus, it has been calculated the $\chi^2$-statistic that tests the null hypothesis that the expected frequency of positive return days among the observations in the fifth quintile equals the realised frequency of positive return days among all the observations of the period. More specifically, the test statistic used is the square of the observed frequency ($O$) with respect to the estimated frequency ($E$), weighted by the estimated frequency:

$$\chi^2 = \sum \frac{(O-E)^2}{E}.$$

[2] The kurtosis coefficients, calculated as the ratio between the fourth order moment with respect to the mean and the fourth power of the standard deviation, reach values greater than 4.42 in all return series.

## 4. Empirical Results

Table 1 gives the standard deviations of returns of the MSEI for the two sample periods and for the different percentages of sunshine hours. For each period, the hypothesis of equality of variances across all the quintiles ($H_0$: $\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma_4^2 = \sigma_5^2$) cannot be rejected. Additionally, the highest quintile has been compared with the rest of the quintiles ($H_0$: $\sigma_{1-4}^2 = \sigma_5^2$). In this case, also, the equality of variances cannot be rejected, at the usual significance levels, between sunny and non-sunny days.

Table 2 collects the mean returns. First, it is important to note that mean returns in the first period (open outcry market) appear to follow an inverted U-shape, with the lowest mean returns in the first and fifth quintiles. Second, this shape changes in the second period (floor and electronic market) and the highest returns are observed in the extreme quintiles. Third, this lack of monotonicity has been formally tested with both the *F*-test and the Kruskal–Wallis statistics. In both periods, the results show that these differences in average performance are not significant, at the usual significance levels, across all the categories of sunshine hours ($H_0$: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ and $H_0$: $m_1 = m_2 = m_3 = m_4 = m_5$) and between sunny days and non-sunny days ($H_0$: $\mu_{1-4} = \mu_5$ and $H_0$: $m_{1-4} = m_5$).

Given that the hypothesis of mean equality cannot be rejected, it might be worth using another procedure for testing a possible effect of sunshine on stock prices.

Table 1

Standard deviations of MSEI returns as a function of the sunshine hours grouped into quintiles.

Sample period from January 1980 to May 2000. The first sample (2 January 1980 to 24 April 1989) comprises the period when the MSE traded exclusively as a call market. The second sample (24 April 1989 to 29 February 2000) makes reference to the period in which MSE used both floor and electronic trading systems. The Brown–Forsythe statistic tests the null hypothesis of equality of variances.

| | 2 January 1980 to 24 April 1989 | | 24 April 1989 to 29 February 2000 | |
|---|---|---|---|---|
| Sunshine hours (%) | Days | Standard deviation (%) | Days | Standard deviation (%) |
| 0 < = 28 | 368 | 1.154 | 530 | 1.122 |
| 28 < = 61 | 409 | 1.103 | 510 | 1.040 |
| 61 < = 78 | 409 | 1.036 | 476 | 1.215 |
| 78 < = 86 | 385 | 0.915 | 546 | 1.137 |
| 86 < = 100 | 312 | 1.045 | 514 | 1.156 |
| $H_0$: $\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma_4^2 = \sigma_5^2$ | | | | |
| Degrees of freedom | | (4, 1878) | | (4, 2571) |
| Brown–Forsythe | | 0.797 | | 1.172 |
| *p*-value | | 0.527 | | 0.321 |
| $H_0$: $\sigma_{1-4}^2 = \sigma_5^2$ | | | | |
| Degrees of freedom | | (1, 1881) | | (1, 2574) |
| Brown–Forsythe | | 0.432 | | 0.147 |
| *p*-value | | 0.511 | | 0.702 |

Table 2

Means of MSEI as a function of the sunshine hours grouped into quintiles.

Sample period from January 1980 to May 2000. The first sample (2 January 1980–24 April 1989) comprises the period when the MSE traded exclusively as a call market. The second sample (24 April 1989–29 February 2000) makes reference to the period in which MSE used both floor and electronic trading systems. The *F*-statistic tests the null hypothesis of equality of means. Kruskal–Wallis statistic (*K–W* test) is the non-parametric alternative for the *F*-statistic. *m* stands for the median of the *i*th quintile. The $\chi^2$ statistic tests for the equality of the positive return frequencies between *sunny* (fifth quintile) and normal days.

| | 2 January 1980 to 24 April 1989 | | 24 April 1989 to 29 February 2000 | |
|---|---|---|---|---|
| Sunshine hours (%) | Days | Mean (%) | Days | Mean (%) |
| $0 <= 28$ | 368 | 0.026 | 530 | 0.107 |
| $28 <= 61$ | 409 | 0.134 | 510 | 0.023 |
| $61 <= 78$ | 409 | 0.145 | 476 | −0.050 |
| $78 <= 86$ | 385 | 0.141 | 546 | 0.029 |
| $86 <= 100$ | 312 | 0.042 | 514 | 0.122 |
| $H_0$: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ | | | | |
| Degrees of freedom | | (4, 1878) | | (4, 2571) |
| *F*-test | | 1.122 | | 1.891 |
| *p*-value | | 0.344 | | 0.109 |
| $H_0$: $\mu_{1-4} = \mu_5$ | | | | |
| Degrees of freedom | | (1, 1881) | | (1, 2574) |
| *F*-test | | 1.200 | | 2.749 |
| *p*-value | | 0.273 | | 0.097 |
| $H_0$: $m_1 = m_2 = m_3 = m_4 = m_5$ | | | | |
| Degrees of freedom | | 4 | | 4 |
| Kruskal–Wallis | | 5.097 | | 6.839 |
| *p*-value | | 0.278 | | 0.145 |
| $H_0$: $m_{1-4} = m_5$ | | | | |
| Degrees of freedom | | 1 | | 1 |
| Kruskal–Wallis | | 2.612 | | 2.303 |
| *p*-value | | 0.106 | | 0.129 |
| $H_0$: $O_5 = E_5$ | | | | |
| Total $r_t > 0$ | | 53.21% | | 52.39% |
| $r_t > 0$ in the fifth quintile | | 47.44% | | 55.25% |
| Degrees of freedom | | 1 | | 1 |
| $\chi^2$ | | 1.341 | | 0.329 |
| *p*-value | | 0.247 | | 0.566 |

Specifically, it has been checked if the frequency of positive returns is the same on sunny and non-sunny days. If frequency of positive advances is higher on sunny days it could be established that sunshine affects stock prices positively. Therefore, the $\chi^2$-statistic that tests the null hypothesis that the expected frequency of positive returns on sunny days equals the realised frequency of positive returns days among all the observations has been calculated ($H_0$: $O_5 = E_5$). The two $\chi^2$-statistics return $p$-values of 24.7% and 56.6%, respectively, so the null hypothesis of equal frequency cannot be rejected in both sub-samples.

The same analysis has been addressed for relative humidity levels. So, if relative humidity influences stock prices, the fifth quintile will present negative abnormal returns in the floor trading period and no seasonality will be found during the computerised trading period.

The results in Table 3 show that the hypothesis of equality of return variances cannot be rejected in the second period when testing the volatility between humid and non-humid days (the $p$-value is 18.3%). However, the same hypothesis is rejected for the rest of samples and periods.

The above results lead us to test the equality of means by taking into account the non-parametric tests. Table 4 reports the mean returns and the resulting test. First, the mean returns present, again, an apparent inverted U-shape during the first period. Second, this shape changes drastically during the second period. Third, these differences in means across humidity levels are not significant in the first period when they are subjected to a non-parametric Kruskal–Wallis test (the exact $p$-value is 95.1%). Similar results are obtained when testing the equality between the mean of the highest quintile and the rest of them ($H_0$: $m_{1-4} = m_5$) in the same period.

Table 3

Standard deviations of MSEI returns as a function of the relative humidity grouped into quintiles.

Sample period from January 1980 to May 2000. The first sample (2 January 1980 to 24 April 1989) comprises the period when the MSE traded exclusively as a call market. The second sample (24 April 1989 to 29 February 2000) makes reference to the period in which MSE used both floor and electronic trading systems. The Brown–Forsythe statistic tests the null hypothesis of equality of variances.

| | 2 January 1980 to 24 April 1989 | | 24 April 1989 to 29 February 2000 | |
|---|---|---|---|---|
| Humidity (%) | Days | Standard deviation (%) | Days | Standard deviation (%) |
| 13 < = 40 | 517 | 0.895 | 448 | 1.123 |
| 40 < = 49 | 332 | 0.918 | 522 | 0.958 |
| 49 < = 60 | 374 | 1.075 | 546 | 1.203 |
| 60 < = 73 | 357 | 1.113 | 544 | 1.195 |
| 73 < = 99 | 303 | 1.315 | 594 | 1.147 |
| $H_0$: $\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma_4^2 = \sigma_5^2$ | | | | |
| Degrees of freedom | | (4, 1878) | | (4, 2649) |
| Brown–Forsythe | | 3.651 | | 3.932 |
| $p$-value | | 0.006 | | 0.004 |
| $H_0$: $\sigma_{1-4}^2 = \sigma_5^2$ | | | | |
| Degrees of freedom | | (1, 1881) | | (1, 2652) |
| Brown–Forsythe | | 5.751 | | 1.772 |
| $p$-value | | 0.017 | | 0.183 |

Table 4

Means of MSEI as a function of humidity grouped into quintiles.

Sample period from January 1980 to May 2000. The first sample (2 January 1980–24 April 1989) comprises the period when the MSE traded exclusively as a call market. The second sample (24 April 1989–29 February 2000) makes reference to the period in which MSE used both floor and electronic trading systems. The *F*-statistic tests the null hypothesis of equality of means. Kruskal–Wallis statistic (*K–W* test) is the non-parametric alternative for the *F*-statistic. *m* stands for the median of the *i*th quintile. The $\chi^2$ statistic tests for the equality of the positive return frequencies between *humid* (fifth quintile) and normal days.

| | 2 January 1980 to 24 April 1989 | | 24 April 1989 to 29 February 2000 | |
|---|---|---|---|---|
| Humidity (%) | Days | Mean (%) | Days | Mean (%) |
| $13 <= 40$ | 517 | 0.098 | 448 | 0.006 |
| $40 <= 49$ | 332 | 0.127 | 522 | 0.010 |
| $49 <= 60$ | 374 | 0.151 | 546 | −0.020 |
| $60 <= 73$ | 357 | 0.072 | 544 | 0.116 |
| $73 <= 99$ | 303 | 0.052 | 594 | 0.135 |
| $H_0$: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ | | | | |
| Degrees of freedom | | (4, 1878) | | (4, 2649) |
| *F*-test | | 0.492 | | 2.161 |
| *p*-value | | 0.742 | | 0.071 |
| $H_0$: $\mu_{1-4} = \mu_5$ | | | | |
| Degrees of freedom | | (1, 1881) | | (1, 2652) |
| *F*-test | | 0.794 | | 4.063 |
| *p*-value | | 0.373 | | 0.044 |
| $H_0$: $m_1 = m_2 = m_3 = m_4 = m_5$ | | | | |
| Degrees of freedom | | 4 | | 4 |
| Kruskal–Wallis | | 0.706 | | 9.436 |
| *p*-value | | 0.951 | | 0.051 |
| $H_0$: $m_{1-4} = m_5$ | | | | |
| Degrees of freedom | | 1 | | 1 |
| Kruskal–Wallis | | 0.038 | | 2.530 |
| *p*-value | | 0.845 | | 0.112 |
| $H_0$: $O_5 = E_5$ | | | | |
| Total $r_t > 0$ | | 53.21% | | 52.52% |
| $r_t > 0$ in the fifth quintile | | 56.44% | | 54.21% |
| Degrees of freedom | | 1 | | 1 |
| $\chi^2$ | | 0.417 | | 0.114 |
| *p*-value | | 0.518 | | 0.736 |

Different results are obtained when focusing on the second period. It can be observed that the mean return of the fifth quintile (0.135%) is higher than the mean return of the rest of quintiles. In fact, this mean is significant at less than 10% (the *p*-value is 5.1%). This result is, apparently, a contradiction since it would be expected to find low returns with high humidity levels. However, when testing the mean between the highest quintile and the rest of them ($H_0$: $m_{1-4} = m_5$), the Kruskal–Wallis statistic returns a $p$-value of 11.2%, so the null hypothesis of equality cannot be rejected at the usual probability levels.

Finally, the number of positive returns on humid days has been obtained. If there were a negative influence of humidity on returns, it would be expected to detect during the first period fewer positive returns on humid days than on non-humid days. To test this statement, the $\chi^2$-statistic that tests the null hypothesis that the expected frequency of positive returns on humid days equals the realised frequency of positive returns days among all the observations has been calculated ($H_0$: $O_5 = E_5$). The hypothesis of equal positive return frequencies between the two sub-samples cannot be rejected in any period.

## 5. Summary and Conclusions

It has been shown in psychological studies that some weather variables affect human performance and mood, in particular sunshine hours and air humidity levels. The market traders, as other professionals, can be affected by these weather conditions and some authors have suggested that markets could reflect that behaviour. Following this reasoning, on sunny days the market returns should be higher than usual due to optimistic judgements of the traders on the future evolution of the indices or stock prices related to their good mood and not to objective and rational arguments or observations. Similarly, high humidity levels would produce abnormal reduced returns in relation to the negative performance induced on the traders. In these conditions, weather could have a direct influence on the market returns through the mood of the traders, and not by physically influencing the production or demand of traded commodities (as could be electricity or other energy sources, etc).

Following these ideas, in this work the possible influence of sunshine and humidity has been tested using financial data from the Madrid Stock Exchange. Two different periods have been defined in order to analyse this influence under two different trading systems, the 'open outcry market' in which the trading is performed physically bringing together all the brokers to the market, and the computerised trading system that allows remote trading from places far from the market.

Different parametric and non-parametric tests have been used to check the equality of variances and mean returns corresponding to the highest sunshine and humidity quintiles, in relation to the rest of the quintiles in each case. The empirical evidence indicates that, independently of the trading system, there is no influence of sunshine hours or humidity levels on stock prices. Our findings are also consistent with those reported in Goetzmann and Zhu (2002) based on US data. The same results have been obtained when an alternative procedure, based on the expected and realised frequencies of positive returns, has been set up to test the influence of weather. The overall results obtained in this paper lead to the conclusion that Spanish stock returns are not influenced by weather, indicating a rational behaviour of the market.

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