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ABSTRACT: Multiple psychological studies support a relationship between weather and the mood of individuals. Furthermore, mood seems to influence the decision making process of individuals namely when those decisions are risky. Therefore, weather may have an indirect impact on market returns. We review the current evidence and investigate the relationship between four weather variables (Rain, Temperature, Sunshine and Wind speed) and the returns of a Portuguese stock market index between January 2000 and December 2009. In this research, based on "bin tests" and regression analysis, we detect the influence of temperature, especially, low temperatures, on the stock market (low temperatures being associated with higher returns) but we cannot rule out the possibility that weather effects are being confounded with simpler calendar patterns.

KEY WORDS: Stock market anomalies • Weather effects • Stock returns • Market efficiency

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1. INTRODUCTION

Can weather conditions influence stock markets? Certainly yes if the revenues or costs of the companies traded in the market are sensitive to weather conditions (such as with leisure, travel, agriculture, power generation companies, etc.). But can weather in a more subtle (and irrational) manner change investor's mood and thereby influence the markets? Psychology studies show that weather conditions influence the mood of individuals. In turn, the emotional state of the individuals, their good or bad mood, may influence their decision-making process. If their mood influences the perception or risk assessment of investments (or the pessimism regarding future investment prospects) this will impact investment decisions. A line of research that intends to detect the possible influence of weather on prices and returns of financial assets has grown in recent years, built upon this *weather*►*mood*►*investment decisions* causal chain.

There is plentiful evidence regarding the first link, documenting several types of weather effects on people's mood. For instance, violence and aggressiveness are associated with high temperatures (Bell & Baron 1976, Baron & Ransberger 1978, Palamarek & Rule 1979, Anderson 2001). Schneider et al. (1980) and Howarth & Hoffman (1984) argue that low temperatures may also increase aggressiveness and sunshine hours are inversely correlated with skepticism. Bell et al. (2003) state that extreme hot weather leads to more violence and that cold weather generates anxiety. Wyndham (1969) argues that extreme heat may lead to hysteria or apathy. As expected, human performance is affected in very high or low temperatures (Wyndham 1969, Allen & Fischer 1978). For Auliciems (1972) and Howarth & Hoffman (1984) there is a correlation between high humidity and sunshine hours with performance. Persinger (1975) and Cunningham (1979) concluded that sunshine hours are correlated with individual's mood self-assessment and McAndrew (1993) states that lack of sunshine generates melancholy or, according to Eagles (1994), even depression. Generosity is also affected and Rind (1996) relates tipping to sunshine hours while Cunningham (1979) concluded that people exhibit less helping behaviors when subject to extreme temperatures. Wind may also carry psychological and physiological consequences such as fatigue, headaches, migraines, irritability and sleepiness (Fletcher 1988, Rose et al. 1995, and Cooke et al. 2000). It was found that dramatic actions such as suicidal attempts are also correlated with weather conditions (Breuer et al. 1986, Tietjen & Kripke 1994). This is coherent with the findings of Wright & Bower (1992) and Bagozzi et al. (1999) that show that people in a good mood make more positive assessments of life satisfaction, past events, other people and consumer products.

In what concerns to the second link several studies document the impact of mood on the attitudes of individuals towards risk. However this relationship seems to be complex and two competing hypothesis are suggested. The affect infusion model (AIM) states that happy moods foster risk-prone behavior (Forgas 1995) and the mood-maintenance hypothesis (MMH) states that happy moods lead to risk-averse behavior in order to maximize the likelihood of individuals maintaining their mood (Isen & Patrick 1983). There is evidence supporting both theories, stronger for AIM, but finding the dominant effect may be hindered due to non-linearities in the relationship mood vs. risk aversion (Yuen & Lee 2003) and the mediating roles of factors such as age (Chow et al. 2007), gender (Fehr 2007) and how high are the stakes (Isen & Geva 1987, Michl et al. 2011).

In any case it seems plausible that weather conditions influence the mood of individuals which will condition investment decisions affecting stock markets.

This hypothesis has been investigated since 1993 for various markets and using different weather variables (mostly cloudiness or sunshine hours, temperature, wind speed, precipitation, humidity, barometric pressure and geomagnetic storms). In Table 1 we review the existing evidence that shows mixed results but where temperature stands out as the most robust weather effect.

Two multi-country studies comprising Portugal show that temperature (Dowling & Lucey 2008) and wind speed (Shu & Hung 2009) might have an impact on Portuguese stock market returns. If these effects are robust this could be a sign of inefficiency (irrationality) in the stock markets.

In this study we will conduct a more exhaustive analysis on the potential impact of four weather variables on the returns of the Portuguese stock market using a different weather database and a different sample period.

Table 1. Past research

Authors	Location/country, Period	Evidence
Weather variable: cloudiness (sunshine hours)		
Saunders (1993)	New York, 1927-1989	✓ Strong correlation with stock returns.
Trombley (1997)	New York, 1927-1992	× Weak evidence of correlation with stock returns. Saunders (1993) results are biased.
Kramer & Runde (1997)	Germany, 1960-1990	× Stock returns in Germany are not affected by cloudiness. Data-mining may affect these studies.
Hirshleifer & Shumway (2003)	26 countries, 1988-1997	✓ Strong correlation between cloudiness in the cities where stock exchanges are located and market indices.
Pardo & Valor (2003)	Spain, 1981-2000	× Cloudiness does not influence stock returns before or after the switch from floor trading to the computerized trading system in the Madrid Stock Exchange.
Loughran & Schultz (2004)	24 US cities, 1984-1997	× Cloudiness in cities where company headquarters are located does not influence stock returns; New York city cloud cover show some relation (non-significant) with stock returns.
Goetzmann & Zhu (2005)	Five US cities, 1990-1995	× Local weather does not have a significant impact in the investors' decision to trade stocks; ✓ The relation between liquidity (bid-ask spread) and cloud cover in New York is significant.
Dowling & Lucey (2005)	Ireland, 1988-2000	× The relation between cloudiness and the Irish stock market index is not statistically significant.
Limpaphayom et al. (2005)	Chicago, 1997-2001	✓ Some evidence of less could cover in Chicago being associated with larger income for traders.
Chang et al. (2006)	Taiwan, 1997-2003	✓ Extreme cloud cover conditions significantly impact the stock market.
Levy & Galili (2008)	Israel (Tel-Aviv), 1998-2002	× Average investor propensity to buy stocks is not affected by cloud cover.
Chang et al. (2008)	New York, 1994-2004	✓ Cloud cover impact is significant only during the opening of the market (15 minutes).
Yoon & Kang (2009)	Seoul, 1990-2006	× No significant relation in South Korea.
Goodfellow et al. (2010)	Germany, 2004-2005	✓ Cloud cover impacts liquidity in the Frankfurt Stock Exchange.
Fruehwirth & Sögner (2011)	US, 2002-2006	× Cloud cover is the most relevant weather variable influencing corporate bond spreads but only at the 10% level.
Akhtari (2011)	New York, 1948-2010	✓ Sunshine and daily market returns are positively correlated but the strength of the effect varies over time.
Weather variable: Temperature		
Keef & Roush (2002, 2005)	New Zealand, 1986-2002, 1980-2002	× Weak evidence for the impact of temperature on prices of bank bills, government bonds and stock indices.
Cao & Wei (2005a, 2005b)	a) 8 countries b) 27 countries	✓ Robust relation between temperature and stock returns (higher temperatures associated with lower returns).
Chang et al. (2006)	Taiwan, 1997-2003	✓ Extreme temperature (especially low) associated with low returns.
Keef & Roush (2007)	Australia, 1992-2003	✓ Strong negative impact of temperature on stock returns.
Gerlach (2007)	US, 1980-2003	× Extreme temperature associated with low returns but anomaly is explained by the release of relevant economic news during days with moderate temperature.
Shu (2008)	Taiwan, 1995-2004	✓ Temperature has a negative relation with stock returns. Evidence is found that temperature can influence proxies for investor sentiment.
Jacobsen & Marquering (2008)	48 countries, 1970-2004	× Higher temperatures are associated with lower returns but causality is questioned since seasonal dummies better explain the return differences.
Hu (2008)	25 countries, 1973-2008	✓ Negative correlation between temperature and returns.
Dowling & Lucey (2008)	37 countries, 1994-2004	✓ Negative correlation between temperature and returns mostly due to the impact of low temperatures; No relation with volatility or between deseasonalized temperature and stock returns.
Kang et al. (2009)	Shangai, 1996-2007	✓ Some evidence of temperature affecting stock returns and volatility; the effect is stronger when domestic investors are allowed to trade.

Yoon & Kang (2009)	Seoul, 1990-2006	✓ Temperature is the strongest weather effect diminishing after abolishing restrictions to foreign traders and the introduction of computerized trading systems.
Fruehwirth & Sögner (2011)	US, 2002-2006	× No evidence of influence over corporate bond spreads.
Weather variable: Wind Speed		
Keef & Roush (2002)	Wellington (New Zealand), 1986-2002	✓ Wind speed affects negatively stock returns (but not bank bills and government bonds).
Limpaphayom et al. (2005)	Chicago, 1997-2001	✓ Deseasonalized wind speed increases the bid-ask spread and lowers the propensity to buy. Wind speed by the morning is associated with more sell orders and less trader income by the afternoon.
Keef & Roush (2007)	Sydney (Australia), 1992-2003	× No relation between wind and index returns.
Dowling & Lucey (2008)	37 countries, 1994-2004	× No evidence of impact on stock returns, weak evidence of impact on volatility.
Shu & Hung (2009)	18 european countries, 1994-2004	✓ Some evidence of stronger winds being associated with lower returns across Europe.
Weather variable: Precipitation		
Goetzmann & Zhu (2005)	5 US cities, 1990-1995	× No evidence of any relation between annual and monthly precipitation and NYSE returns.
Dowling & Lucey (2005)	Ireland, 1988-2000	✓ Small but statistically significant effect (higher rainfall associated with lower market returns).
Gerlach (2007)	US, 1980-2003	× Rainy days are associated with lower returns but the effect disappears after considering the impact of economic news.
Dowling & Lucey (2008)	37 countries, 1994-2004	× No evidence of impact on stock returns, some evidence of impact on volatility.
Fruehwirth & Sögner (2011)	US, 2002-2006	× No evidence of influence over corporate bond spreads.
Weather variable: Humidity		
Pardo & Valor (2003)	Spain, 1981-2000	× Humidity does not explain stock returns regardless of the trading system in the Madrid Stock Exchange.
Dowling & Lucey (2005)	Ireland, 1988-2000	✓ Higher humidity associated with higher returns (contrary to expectations).
Chang et al. (2006)	Taiwan, 1997-2003	× No relation detected with stock returns.
Shu (2008)	Taiwan, 1995-2004	✓ Negative and significant relation between humidity and stock returns.
Kang et al. (2009)	Shangai, 1996-2007	× Humidity does not explain returns in the Shangai stock market.
Yoon & Kang (2009)	Seoul, 1990-2006	× No evidence of a humidity effect in stock returns.
Fruehwirth & Sögner (2011)	US, 2002-2006	× No evidence of influence over corporate bond spreads.
Weather variable: Geomagnetic storms		
Krivelyova & Robotti (2003)	9 countries, 1932-2002	✓ Strong empirical support for the relation between geomagnetic storms and stock market returns. World stock market returns are higher in absence of geomagnetic storms.
Dowling & Lucey (2005, 2008)	Ireland 1988-2000, 37 countries 1994-2004	× No relation with stock returns. At most there is a positive relation between geomagnetic storms and volatility.
Weather variable: Barometric Pressure		
Shu (2008)	Taiwan, 1995-2004	✓ Positive association with stock returns (uses barometric pressure as a proxy for sunshine).
Fruehwirth & Sögner (2011)	US, 2002-2006	× No relation with corporate bond spreads.

2. DATA AND METHODS

Daily weather information was obtained from the national *Instituto de Meteorologia* (previous studies covering Portugal used data from the U.S. National Climatic Data Center). The dataset covers the 10-year period between January, 2000, and December, 2009. Weather variables refer to the meteorological stations of *Gago Coutinho* (Lisbon) and *Pedras Rubras* (Oporto). The weather variables (Table 2) are the average Temperature (simple average of the daily maximum and minimum temperature) measured in degrees Celsius, average Wind speed (meters per second), total Sunshine hours and Precipitation (millimeters). The variable Wind speed is the most affected by missing data.

Table 2. Descriptive statistics for weather and financial variables. This table considers only the days when the stock market is open. The maximum number of observations is 2534. The differences correspond to missing observations. PSI stands for Portuguese Stock Index and SXW1E for STOXX Global 1800.

Variable	Obs.	Average	Max.	Min.	Standard Deviation
Temperature – Lisbon (ºC)	2530	17.4	33.3	3.9	5.1
Precipitation – Lisbon (mm)	2532	1.8	82	0	5.7
Sunshine – Lisbon (h)	2508	7.9	15.1	0	4.0
Wind – Lisbon (m s^{-1})	1848	3.3	9.4	0.8	1.2
Temperature – Oporto (ºC)	2447	15.1	31.2	1.3	4.4
Precipitation – Oporto (mm)	2492	3.1	80	0	7.6
Sunshine - Oporto (h)	2412	7.3	14.8	0	4.1
Wind – Oporto (m s^{-1})	2041	3.3	9.8	0.9	1.2
PSI-Geral (%)	2534	0.00	9.74	-10.65	1.06
SXW1E (%)	2534	-0.02	8.37	-6.81	1.19
Local PSI-Geral (%)	2534	0.02	5.79	-6.96	1.11

In our base method we use the returns of a version of the broad Portuguese Stock Index (PSI-Geral) intending to isolate the local component of the market index (local weather effects should impact only this element of market returns). Following Dowling & Lucey (2005) we simply subtract the return of a global market index (STOXX Global 1800) from the return of the Portuguese market index.

The STOXX Global 1800 (SXW1E) is a broad capitalization-weighted market index representative of developed markets and constituted by 1800 stocks (600 European, 600 American and 600 from Asia/Pacific). The series was collected from http://www.stoxx.com/. The PSI-Geral is a capitalization-weighted index representative of all stocks traded in the Euronext-Lisbon main market. The series was collected from the *Banco de Portugal*. Logarithmic returns were computed for both indices and the Local PSI-Geral return was given by:

$$r_{\text{Local PSI-Geral},\ t} = r_{\text{PSI-Geral},\ t} - r_{\text{SXW1E},\ t} \quad (1)$$

"Bin tests" and regression analysis will be used to discern a relation between weather variables and stock returns. The "bin test" methodology assigns each stock market return to a specific "bin" according to the weather conditions prevailing in the day. We defined three bins, a parsimonious choice guaranteeing that a reasonable number of daily returns would fall in each bin. Ideally, the bins should have similar amplitude so we defined:

$$\Delta = (Weather_{max} - Weather_{min}) / nr\ of\ bins \quad (2)$$

where *Weather* is the value (maximum or minimum) of each weather variable. Accordingly, the first bin corresponds to the interval $[Meteo_{min}; Meteo_{min} + \Delta]$, the second to the interval $]Meteo_{min} + \Delta; Meteo_{min} + 2\Delta]$ and the third is the interval $]Meteo_{min} + 2\Delta; Meteo_{max}]$. This procedure created the following bins:

- Temperature - bin 1 (3.9 ºC to 13.7 ºC), bin 2 (13.7 ºC to 23.5), bin 3 (23.5ºC to 33.3 ºC)
- Sunshine - bin 1 (0 h to 5.03 h), bin 2 (5.03 h to 10.07 h), bin 3 (10.07 h to 15.1 h)
- Wind - bin 1 (0.8 m s^{-1} to 3.67 m s^{-1}), bin 2 (3.67 m s^{-1} to 6.53 m s^{-1}), bin 3 (6.53 m s^{-1} to 9.4 m s^{-1})

This objective rule was adopted for all but one weather variable, Precipitation, where higher values must be considered outliers. Instead of removing the outliers we decided to create a bin for days without rain (1845 observations in Lisbon), a second bin for days with less than

2 mm of rain, leaving the third bin for days when the rainfall is above that level. Having established these limits we will average the returns falling in each bin and test if there are any differences between the first and the third bins with the T-test for independent samples and the non-parametric Wilcoxon-Mann-Whitney test. Additionally, we will calculate the proportion of negative returns in each bin (a measure not affected by outliers) and use the Z-test for differences in proportions between the extreme bins.

Obviously, the "bin test" has limitations and regression analysis will help overcome some of them. We will be able to analyze simultaneously the impact of the four weather variables, to include control variables and to quantify the relationship between dependent and independent variables. Following Dowling & Lucey (2005) we are going to estimate simple regressions, multiple regressions, regressions with dummies and regressions where some of the independent variables are combinations of different weather variables.

As a robustness test we will vary our regression approach using as the dependent variable the PSI-Geral (dropping the Local PSI-Geral) and adding as independent variable the STOXX Global 1800 index to capture the influence of international markets. An additional robustness test will be conducted applying the previous methodologies to combined weather data from Lisbon and Oporto, recognizing that not all local investors make their decisions under the influence of the weather in Lisbon.

3. RESULTS

We expected to find a positive relation, albeit small, between weather conditions that improve the mood of individuals and stock returns. After all, the better the mood the higher should stock prices be due to the increased optimism or decreasing risk-aversion. So, we would expect to find the variable sunshine hours to be positively related with stock prices. Wind speed and precipitation should be negatively related with stock prices. Temperature, however, has a more complex relation with mood. If low temperatures increase aggressiveness this would influence the risk-taking behavior of individuals with a positive impact on prices but high temperatures could, in principle, promote aggressiveness (with a positive impact on stock prices) or apathy (negative impact).

3.1. "Bin tests"

Table 3 shows that the average return in non-rainy days (bin 1) and in days with rainfall higher than 2 mm (bin 3) is very similar and, therefore, the difference is non-significant. The percentage of negative returns is higher in bin 3 but the difference is non-significant as well. The difference between colder (bin 1) and hotter days (bin 3) is higher, considering weather data from Lisbon only, but both tests reveal that the difference is non-significant such as the differences in the percentage of negative returns. The differences are not statistically significant between low wind days (bin 1) and windy days (bin 3). The apparently inconsistent results between the two datasets (Lisbon and Lisbon/Oporto) are, probably, driven by the small number of observations that fell in the third bin. Finally, cloudy days (bin 1) have better average returns than sunny days (bin 3) but the proportion of negative returns is similar. The differences are, again, non-significant.

3.2. Regression analysis

Table 4 shows the estimated OLS coefficients for different regressions and methodologies. The first methodology (model 1, third column) uses as dependent variable the Local PSI-Geral. The second methodology (model 2, fourth column) uses the original market index (PSI-Geral) as dependent variable and adds the returns on the STOXX Global 1800 as an additional independent variable (not shown in table). The estimated coefficients for this global market index (ranging from 0.45 to 0.51) are always statistically significant as expected. Model 3 is equal to model 2 applied to the combined weather data of the two major Portuguese cities (Lisbon and Oporto).

Table 3. "Bin tests". The T-test is an independent samples test comparing the average return between bin 1 and bin 3. The U-test is the non-parametric Wilcoxon-Mann-Whitney test for differences between the first and third bin. The Z-test tests the differences in the proportion of negative returns between the bin 1 and bin 3. For each weather variable the tests are applied with weather data from Lisbon and with data that combines weather observations in Lisbon and Oporto.

Weather variable	*Data*		*Bin 1*	*Bin 2*	*Bin 3*	*Test (Bin1, Bin3)*
Precipitation	Lisbon	Average return	0.017%	0.080%	0.011%	*T-test:* 0.100 | *U-test:* -0.364
		Nr. Observations	1845	294	393	
		% negative	48.0%	48.6%	51.1%	*Z-test:* -1.144
	Lisbon/ Oporto	Average return	0.034%	-0.022%	0.032%	*T-test:* 0.043 | *U-test:* -0.138
		Nr. Observations	1520	457	555	
		% negative	48.2%	47.5%	50.3%	*Z-test:* -0.826
Temperature	Lisbon	Average return	0.101%	-0.007%	-0.012%	*T-test:* 1.665 | *U-test:* -1.232
		Nr. Observations	712	1531	287	
		% negative	45.1%	50.3%	48.1%	*Z-test:* -0.861
	Lisbon/ Oporto	Average return	0.072%	-0.009%	0.067%	*T-test:* 0.060 | *U-test:* -0.116
		Nr. Observations	825	1533	172	
		% negative	45.8%	50.5%	44.8%	*Z-test:* 0.252
Wind	Lisbon	Average return	0.044%	0.006%	-0.095%	*T-test:* 0.707 | *U-test:* -0.054
		Nr. Observations	1206	612	30	
		% negative	48.2%	47.9%	50.0%	*Z-test:* -0.198
	Lisbon/ Oporto	Average return	0.033%	0.009%	0.459%	*T-test:* -1.720 | *U-test:* -1.864
		Nr. Observations	1178	535	19	
		% negative	48.7%	47.5%	36.8%	*Z-test:* 1.028
Sunshine	Lisbon	Average return	0.034%	0.067%	-0.036%	*T-test:* 1.195 | *U-test:* -0.990
		Nr. Observations	618	995	895	
		% negative	50.0%	46.7%	50.1%	*Z-test:* -0.021
	Lisbon/ Oporto	Average return	0.049%	0.015%	0.010%	*T-test:* 0.656 | *U-test:* -0.620
		Nr. Observations	651	1088	769	
		% negative	49.5%	48.1%	49.0%	*Z-test:* 0.164

This approach was also used by Cao & Wei (2005a). We computed a new daily value for each weather variable as a weighted-average of the observed weather data. The weighting factors (0.39 for Oporto and 0.61 for Lisbon) are proportional to the population estimates for the Great Lisbon and Oporto areas.

The first regression including simultaneously all weather variables shows no significant coefficients at a 5% level. The F-test (5% level) can not reject the possibility that all coefficients are simultaneously zero for any model. As the weather variables are correlated, multicollinearity could be affecting the estimation of the parameters. It appear not to be the case (all centered Variance Inflation Factors are below 2) but, similar to past studies, we will estimate a single regression for each variable (regressions 2 to 5).

The results do not change. The coefficients are not statistically significant but Temperature with a consistent negative sign is the most significant variable (p-values below 10%).

For the next set of equations we created two dummy variables, one variable for each extreme bin, with a value of 1 when the variable belongs to the bin or zero otherwise. For instance, the dummy High Precipitation has value 1 when rainfall is higher than 2 mm and zero otherwise.

Table 4. Regression analysis. Regression models:
1) $r_t = \beta_1 + \beta_2$ PRECIPITATION + β_3SUNSHINE + β_4 TEMPERATURE + β_5 WIND + ε_t, 2) $r_t = \beta_1 + \beta_2$ PRECIPITATION + ε_t, 3) $r_t = \beta_1 + \beta_2$ SUNSHINE + ε_t, 4) $r_t = \beta_1 + \beta_2$ TEMPERATURE + ε_t, 5) $r_t = \beta_1 + \beta_2$ WIND + ε_t,
6) $r_t = \beta_1 + \beta_2$ HIGH PRECIPITATION + β_3 ZERO PRECIPITATION + ε_t,
7) $r_t = \beta_1 + \beta_2$ HIGH TEMPERATURE + β_3 LOW TEMPERATURE + ε_t,
8) $r_t = \beta_1 + \beta_2$ INTENSE SUNSHINE + β_3 LOW SUNSHINE + ε_t, 9) $r_t = \beta_1 + \beta_2$ STRONG WIND + β_3 LOW WIND + ε_t,
10) $r_t = \beta_1 + \beta_2$ BAD WEATHER + β_3 GOOD WEATHER + ε_t,
11) $r_t = \beta_1 + \beta_2$ PERSISTENT BAD WEATHER + β_3 PERSISTENT GOOD WEATHER + ε_t,
12) $r_t = \beta_1 + \beta_2$ UNPLEASANT TEMP. $+\beta_3$ UNPLEASANT SUN. $+\beta_4$ UNPLEASANT PRECIP. + ε_t
The independent variable SXW1E is added in models 2 and 3 where the dependent variable becomes the PSI-Geral. The variable, omitted in this table, is always significant at the 1% level. Newey-West heteroskedasticity and autocorrelation consistent standard errors were used to compute t-statistics.* and ** indicate statistical significance at the 5% and 1% levels, respectively.

Regression	Independent variables	Model 1		Model 2		Model 3	
		Coefficient	*P-value*	*Coefficient*	*P-value*	*Coefficient*	*P-value*
1	*Precipitation*	-0.00005	0.19	-0.00006	0.05	-0.00008	0.07
	Sunshine	0.00000	0.96	-0.00002	0.75	0.00001	0.86
	Temperature	-0.00007	0.08	-0.00006	0.09	-0.00008	0.06
	Wind	-0.00018	0.39	-0.00009	0.60	0.00001	0.94
2	*Precipitation*	0.00000	0.90	-0.00001	0.81	-0.00003	0.29
3	*Sunshine*	-0.00007	0.20	-0.00006	0.20	-0.00003	0.57
4	*Temperature*	-0.00006	0.09	-0.00005	0.08	-0.00006	0.09
5	*Wind*	-0.00020	0.34	-0.00014	0.40	-0.00009	0.63
6	*High precipitation*	-0.00070	0.43	-0.00090	0.23	0.00026	0.66
	Zero precipitation	-0.00063	0.41	-0.00070	0.30	0.00062	0.26
7	*High temperature*	-0.00005	0.93	0.00013	0.78	0.00059	0.26
	Low temperature	**0.00107 ***	**0.01**	**0.00093 ***	**0.03**	0.00068	0.09
8	*Intense sunshine*	**-0.00103 ***	**0.03**	-0.00067	0.10	0.00007	0.86
	Low sunshine	-0.00033	0.58	-0.00027	0.55	0.00014	0.76
9	*Strong wind*	-0.00101	0.71	-0.00067	0.73	0.00069	0.68
	Low wind	0.00039	0.43	0.00026	0.49	0.00002	0.95
10	*Bad weather*	0.00067	0.15	0.00056	0.18	0.00017	0.70
	Good weather	-0.00038	0.51	-0.00046	0.30	-0.00041	0.39
11	*Persistent bad weather*	**0.00122 ** **	**0.01**	**0.00127 ** **	**0.00**	**0.00076 ***	**0.04**
	Persistent good weather	0.00070	0.20	0.00051	0.33	0.00025	0.66
12	*Unpleasant temperature*	0.00005	0.91	0.00022	0.59	0.00026	0.53
	Unpleasant sunshine	**0.00193 ***	**0.02**	0.00118	0.09	0.00071	0.33
	Unpleasant precipitation	**-0.00289 ** **	**0.01**	-0.00176	0.07	-0.00143	0.10

The Zero Precipitation dummy has value 1 in days without rain and zero otherwise. This approach allows us to estimate potential non-linear impacts of extreme weather (reg. 6 to 9).

Now, two variables show some significance: the dummy for Low Temperature (under 13.7 ºC) in Model 1 and Model 2 with a positive sign meaning that returns are positively affected by low temperatures (but not affected) by high temperatures; and the dummy for Intense Sunshine meaning that the occurrence of many sunshine hours impacts negatively the returns. In any case, this effect appears not to be robust and disappears in models 2 and

3. The positive coefficient for Low Temperature was expectable in the light of the psychological evidence and previous empirical studies (Cao & Wei 2005a, 2005b, Hu 2008, Keef & Roush 2007, Shu 2008, and Yoon & Kang 2009). The negative coefficient for the dummy Intense Sunshine is harder to understand. Psychological studies and previous weather research would not anticipate this relation. Only Dowling & Lucey (2005) were confronted with a positive coefficient for cloudiness.

The following equation (reg. 10) uses dummy variables to define good and bad weather conditions. A Bad Weather day was defined as a rainy, cold or cloudy day: i.e., a day with precipitation above 2 mm or average temperature below 13.7 ºC or absence of sunshine hours. A Good Weather day was defined as one with moderate temperature (between 18 and 25 ºC), no rain and at least 5 sunshine hours.

The parameters are not significant but we note that the signs (for all models) are negative for Good Weather and positive for Bad Weather.

Next, considering that a single day could be insufficient to affect the mood of an individual we defined two new dummy variables (Persistent Good and Persistent Bad Weather) that assume value 1 if the current day and the two previous days respect the criteria for being considered Good or Bad Weather day (reg. 11).

Estimation results show that both variables have positive signs but only the Persistent Bad Weather is statistically significant and robust to methodological changes and to the inclusion of the influence of Oporto weather. Although the result might seem a paradox, we have to bear in mind that Persistent Bad Weather occurs with continuing low temperatures or low sunshine hours, conditions that we concluded were positively associated with stock returns.

The last regression considers the impact of Precipitation, Temperature and Sunshine but only when their deseasonalized values are unpleasant. Individuals would only have their mood affected if bad weather was not expected. Unpleasant temperature will assume the value 1 during summer when daily temperatures are above their mean (or the deseasonalized value is greater than zero) or during winter when temperature is below its mean. Unpleasant Precipitation and Unpleasant Sunshine will be 1 when the deseasonalized value is greater than zero or lower than zero, respectively, but only during winter days. All deseasonalized values were computed as the difference between the recorded value and the average value for that calendar day during the ten-year period (reg. 12). Coefficients' signs are consistent across models but only significant (for Sunshine and Precipitation) in our base model. The Unpleasant Precipitation has the expected sign but Unpleasant Sunshine (lower than average sunshine hours in winter) has a positive sign contrary to expectations.

In this strand of literature, only Dowling & Lucey (2008) and Shu & Hung (2009) investigated the Portuguese stock market with data from the National Climatic Data Center. Dowling & Lucey (2008) studied 30 countries and included some results concerning the impact of temperature, wind and geomagnetic storms for Portugal. Their research covered the period 1994-2004 and, somehow consistent with our findings, they estimate a significant negative coefficient for the variable Temperature. In what concerns to wind and geomagnetic storms the coefficients are non-significant. Shu & Hung (2009) analyzed a similar period and, differently, found that among the 18 European countries Wind had the strongest (negative) impact in the Portuguese stock market. Their results (using both the "bin tests" and regression analysis) showed that wind is a significant variable at the 1% level for Portugal. Temperature, used as a control variable, was also negative and significant at the 5% level. We could not replicate these results but we acknowledge that our analysis regarding wind had limitations due to missing data from our weather source.

4. CONCLUSION

Our findings suggest that temperature in Lisbon, where the Portuguese stock market is located, seems to be associated with market returns. The "bin tests" showed some differences and in the regression analysis the variable shows consistent signs and low p-values robust to different model specifications. The regression with two dummies for low and high temperature days reveals that the strongest impact (and the only statistically significant) seems to come from cold days (average temperature below 13.7 ºC). This result is consistent with the psychological evidence and a previous study by Dowling & Lucey (2008) using different weather data and a non-coincident sample period.

The positive coefficient for our dummy variable that assumes a value of 1 after three days of successive cloudy, rainy or cold days (Persistent Bad Weather) seems to be robust and should be, at least partially, a consequence of the positive impact of low temperatures.

These results (and the negative impact of sunshine that surfaced on our base model) cannot, however, rule out the "simpler" explanation proposed by Jacobsen & Marquering (2008). Low temperatures and persistent bad weather are winter characteristics while long sunshine hours occur in the summer. Jacobsen & Marquering (2008) do not question the association between some weather variables and stock returns; they question the causality of the relation because seasonality or calendar patterns are a known feature of stock returns, also detectable in the Portuguese stock market where the highest returns occur between December and February (Silva 2010). The standard methodologies that we have applied (and most authors use) cannot, unfortunately, counter their criticism and, therefore, the focus of subsequent research should be on causality in order to ascertain if there is, indeed, a residual impact of weather on the mood of investors and thereby on stock market returns.

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