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Note

Stocks and the Weather: An Exercise in Data Mining or Yet Another Capital Market Anomaly?

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Abstract: We try to replicate the findings in Saunders (1993) that stock prices are "systematically affected by local weather". Using German data, we find that whether or not the null hypothesis of no relationship can be rejected depends mostly on the way the null hypothesis is phrased, and that no systematic relationship seems to exist.

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1 Weather and Human Behaviour

There are many well established capital market anomalies like seasonal effects, long-term autocorrelation, winner-looser overreaction, excess sensitivity to recent news (see Dimson 1989 for a survey), so it is certainly legitimate to ask: might not the weather provide yet another one?

It has been established by numerous authors that the weather does indeed affect behaviour: human performance in various mental and physical activities has been shown to correlate with humidity levels or hours of sunshine per day (Aucliemis 1972, Howarth and Hoffmann 1984, among others); calls to telephone support systems increase as the weathers worsens (Hribersek et al. 1987), and there is "a significant positive correlation between the time of attempted suicide and the weather parameters 'stable upslide, labile upslide, log, thunderstorm, worm air, upslide and weather drier on the 2 preceding days'" (Breuer et al. 1986). To the extent therefore that the weather also affects the mood of investors and security traders, one might hypothesize that

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security markets reflect such weather data as well, contrary to the tenets of financial theory that it is only economic information that determines prices.

According to Saunders (1993), this is indeed the case: Using cloud cover as a proxy for "weather" he finds that mean returns of Wall Street stocks are higher when the weather is better. For instance, the average daily change in the DJIA over the period 7/6/1962 to 12/31/1989 is 0.065 when cloud cover is below 20% as compared to −0.028 when cloud cover is 100% (Saunders 1993, Table 1), and similar significant effects, which according to Saunders are "robust with respect to time and not unduly influenced by infrequent, large daily changes," occur in other indices as well.

Below we show that there is at least one stock exchange where these results can not be replicated. Pairing daily data from 1/4/1960 to 12/28/1990 from the Frankfurt stock exchange with weather information from Frankfurt airport (about 11 miles away), we find that any weather effects are extremely nonrobust to the way that we classify the data, and that both a positive and a negative effect of weather can be established depending upon the test procedure used. We use the same indicator for the weather (cloud cover), but try other indicators such as humidity, atmospheric pressure and rainfall as well, with similar results: whether or not there is a "significant" causal link between weather and stock returns depends mostly on the test statistic used and the way that the weather variable is defined, as explored in section 2 below.

2 The Data and the Tests

We consider daily returns for the German stock index DAX, plus returns for various individual stocks from this index. During the period 1960–1990 which we use for our study the electronic IBIS trading system was not yet in place and about 75% of all trading in the stocks that compose the DAX took place on the Frankfurt stock exchange. Therefore, if there is a weather-effect at all, it is presumbly the Frankfurt weather which matters here[2]. Although dealers on the floor act mainly as agents, they are also allowed to exploit their own interests, and, by the same logic used in Saunders (1993), might in this capacity be subject to collective swings of mood that the triggered by the weather. In addition, market participants in Germany are much less geographically dispersed as compared to the US, so to the extent that the Frankfurt weather is a good proxy for the weather in Munich or Düsseldorf as well, or wherever

[2] Another reason why regional exchanges do not matter was recently provided by Hasbrouck (1995), who shows that even when a given stock is traded on several exchanges, it is mainly the largest exchange that determines prices, with the others following suit.

Table 1. Mean returns as a function of cloud cover

cloud cover	# days	DAX	BASF	BMW	DBK	KAR	SIE
0%	326	0.016	0.019	0.021	−0.019	0.008	0.017
0% ≤ 20%	504	0.053	0.064	0.121	0.075	0.122	0.082
20% ≤ 50%	1326	−0.003	−0.022	0.007	0.025	0.012	0.020
50% ≤ 80%	1833	0.011	0.028	0.043	0.014	0.030	0.014
80% < 100%	1884	0.014	−0.001	0.061	0.050	0.054	0.020
100%	1795	0.025	0.052	0.066	0.042	−0.015	0.060
p-value F-test		0.147	0.311	0.135	0.191	0.418	0.251

buy and sell decisions might be taken, weather conditions at Frankfurt airport might also effect agents outside the local trading floor. The weather variables are (i) cloud cover, (ii) relative humidity as measured in percent, and (iii) atmospheric pressure as measured in hPa, all taken daily at Frankfurt airport, which is about 11 miles from the Frankfurt stock exchange. Table 1 gives the mean returns of the DAX and some individual stocks for various degrees of cloud cover.

This table shows various things. First, there is no monotone relationship between the degree of cloud cover and mean returns, neither for the DAX nor for the individual stocks. In the case of e.g. DBK = Deutsche Bank, the worst performance occurs on sunny days, and among the stocks considered in the table only KAR = Karstadt fare worst when cloud cover is at a maximum. Second, these differences in average performance across cloud cover are not significant when subjected to a standard F-test (among the return-series studied, the smallest prob-value was 13.5% (BMW)), and these differences remain insignificant with a t-test as well: If we confine ourselves to the DAX and consider only the extreme cases of 100% cloud cover and no cloud cover at all, with 1795 and 326 trading days, respectively, the two sample t-test returns a value of 0.189, so the null hypothesis of no influence cannot be rejected. Third, this lack of monotonicity in the relationship between cloud cover and stock returns opens up a large potential for data mining, where various contradictory hypotheses are either all "significant", or can all not be rejected.

For instance, by a suitable redefinition of the variables, the null hypothesis of no influence can be rejected in favour of "*bad* weather = good returns": Defining "bad weather" as a combination of 100% cloud cover and relative humidity between 70% and 90% ("strichweise Regen"), "good weather" as the rest, the two sample t-test takes a value of 1.43, which is significant at less than 10% (the exact prob-value is 7.64%).

On the other hand, the same null hypothesis of no influence is rejected in favour of the alternative "*good* weather = good returns" if we define "good weather" as a combination of less than 20% cloud cover and relative humidity between 25% and 75% (neither too humid nor too dry) and "bad weather"

Table 2. Average DAX returns as a function of cloud cover and day of the week

cloud cover	Mo	Tu	Wed	Th	Fr	p-value F-test
0%	−0.165	−0.047	0.172	−0.057	0.157	0.340
0% ≤ 20%	−0.213	−0.060	0.142	0.216	0.144	0.446
20% ≤ 50%	−0.291	0.095	0.027	0.019	0.135	0.138
50% ≤ 80%	−0.172	−0.041	0.106	0.062	0.102	0.161
80% < 100%	−0.109	−0.031	0.072	0.018	0.119	0.179
100%	−0.121	−0.029	0.053	0.091	0.125	0.191
P-value F-test	0.485	0.427	0.177	0.391	0.141	

as the rest: The two sample t-test takes a significant value of 1.71, which can easily be increased to 2.17 if we restrict "good weather" to days where cloud cover is less than 20% and relative humidity between 25% and 50%.

Adding atmospheric pressure to the weather variables increases the range of hypotheses still further: For instance, adding the restrictions "atmospheric pressure falling" to the definition of "bad weather" and "atmospheric pressure rising" to "good weather", we obtain a two sample t-test value of 2.18, which is significant at less than 2%.

Following Saunders, one can also check returns separately for each day of the week, to disentangle the weather from weekday effects such as the well known negative Monday effect. Table 2 shows our results for the DAX – there are no significant effects, neither across days of the week nor across degrees of cloud cover (we attribute the lack of significance for the Monday effect, given cloud cover, to the sparseness of the data; not distinguishing between degrees of cloud cover, Monday returns are significantly negative).

However, the weather can be made significant for most days of the week, both in the sense of "good weather = good returns" and "bad weather = good returns", by appropriate definition of the weather variable. Table 3 gives the prob-values of the two sample t-test, separately for each day of the week, for two alternatives: no effect vs. bad weather = good returns, where bad weather is 100% cloud cover and relative humidity above 70%, and no effect vs. good weather = good returns, where good weather is cloud cover below 20% and relative humidity between 25% and 50%. The table shows that in both cases the null is rejected at 5% in favour of the alternatives for almost all days of the week.

As an alternative to a discrete categorization of the weather-variable, we also compared correlations between, on one hand, atmospheric pressure, humidity and cloud cover, plus selected summary statistics compiled from these, and stock returns on the other hand. Again, none of the correlations was significantly different from zero when no data mining was applied.

Table 3. p-values of the two sample t-test for DAX returns grouped by day of the week

	H_0: weather has no influence versus	
	$H_1^{(1)}$: bad weather = good returns	$H_1^{(2)}$: good weather = good returns
Mo	0.012	0.041
Tu	0.075	0.019
Wed	0.044	0.116
Th	0.129	0.036
Fr	0.037	0.021

3 Conclusion

We conclude that the data available to us are consistent with the hypothesis that short-term stock returns are not affected by the local weather. As always with statistical tests of significance, this does not mean that this hypothesis is true, only that the data do not force us to abandon it, and that any claims to the contrary such as in Saunders (1993) might well be due to a type I error in the statistical inference.

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