Oslo Stock Exchange and the Weather

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Abstract

We investigate empirical links between the Oslo Stock Exchange and the weather, asking whether daily returns on the market, or market trading activity, seems to be related to the weather. We use this investigation to illustrate empirical methods and empirical thinking in financial economics.

∗University of Stavanger (UiS) and Norwegian School of Economics (NHH). This paper started as a set of exercises in a PhD class in empirical finance at NHH. The paper is a (somewhat expanded) solution to the same course exercises. My sympathy to generations of students suffering through the exercises. Reflecting this pedagogical purpose, an appendix lists computer code, and on my homepage you will find data and computer code that allows any reader to replicate the results in the paper.

Introduction

In this paper we link the stock market and the weather. There are some obvious ways in which the weather can directly influence the stock market. One is when the weather influences the running of the stock exchange, which we saw an example of after Hurricane Sandy in October 2012, where the New York Stock Exchange was closed for a record two days due to the flooding and power outtages in Manhattan.

If we instead talk about prices of stocks on the market, the weather can certainly influence stock prices through the cash flows of the firms on it. The same Hurricane Sandy resulted in large future losses to insurance companies, some of which are listed on the NYSE. So the weather can also influence the stock market that way.

In this paper we are not concerned with these direct influences from weather to the stock market, rather we refer to behavioral finance, where there is a long tradition for investigating a different link between the stock market and the weather, asking whether the weather influences the “mood” of participants on the exchange. If people trading on the exchange is facing a sunny spring day with wonderful weather, they may be more optimistic about the market than on one of those bleak, rainy fall days. The question we want to ask is whether we see a link between the weather faced by those people most likely to influence the stock prices in the market, which are those that live in the same city as the stock market is situated.

This was the argument in the first academic study of weather and the stock exchange, Saunders (1993), who found a negative correlation between weather in New York and returns on the exchange. The argument is that with “good” weather when they go to work, traders are more optimistic, and their trading behaviour results in higher prices when the weather is good than when it is bad. This is a recipe for an empirical investigation: Construct a measure of weather “quality,” and ask whether we see an empirical link between this measure of weather quality and measures of stock prices, such as stock returns.

We will in this paper look at some such empirical examples from the Oslo Stock Exchange. We construct measures of weather quality, and ask whether the weather being better or worse than usual is correlated with measures of stock market performance.

Everybody talks about the weather but nobody does anything about it.

Mark Twain
The structure of the paper is as follows. We first, in section 1 give some references to the behavioral finance literature. Section 2 presents the data we use. Section 3 investigates the link between weather and stock returns. After a discussion, section 5 concludes.

1 Literature

The idea is given in the before-mentioned paper by Saunders (1993), which is the starting point of the literature. Saunders makes the point that weather in New York should in general not affect the cash flows of firms on the exchange. The firms on the NYSE are claims on the cash flows of geographically diversified firms, few of which are directly exposed to New York weather. Stock returns on the NYSE should in a rational market therefore not be systematically related to New York weather. If over a very long time period (Saunders use the period 1927–1989) one observe a relationship between the observed weather in New York and the returns on the exchange, there is something wrong with the rational market hypothesis.

The argument made by Saunders is that what New York weather affects is the mood of traders on the stock exchange. The traders on the exchange are much more optimistic on a bright, sunny day than on a overcast or rainy day. This optimism translates into an higher view about the prospects for stock prices. Traders are more willing to buy on those optimistic days, driving prices up above the rational price. The result is a positive relationship between “good weather” and stock returns. But note that the psychological argument given by Saunders is an auxiliary hypothesis.

If we take as a starting point a hypothesized relationship between stock returns and weather, the empirical researcher’s sequence of actions should be to first ask

- Is the effect there?

This is a statistical question, where we need to investigate different ways of measuring weather, stock returns, and establish beyond reasonable doubt that this effect is there, and is not an artifact of the sample, or a result of data mining.

Having established that the effect seems to be there, we need to investigate alternative explanations.

- What can cause a correlation between weather variables and stock returns?

This is where we need to consider possible alternatives to the hypothesis proposed by Saunders (1993). He states his conclusion as follows

- “Rejection of the null hypothesis supports the view that security markets are systematically influenced by investor psychology”

But as empirical researchers we should know that we rejection of the null of “no correlation between weather and stock returns” can not lead to acceptance of an alternative hypothesis unless the alternative covers all possible alternatives to the null. In this case we are not there. The psychological explanation is one possible explanation consistent with a correlation between stock returns and the weather, but we need to consider alternative explanations.

Possible explanations we should investigate

- Psychological biases.
- The weather variable is related to some other variable with a (rational) causal effect on stock prices.
- Weather may directly affect the stock market, we just don’t understand the causal effect.

Once we bring in the other alternative here it is obvious that rejection of the null does not immediately lead to acceptance of the alternative of psychological biases, we need to at least make these alternative relationships less likely explanations before we end up accepting that the evidence points towards psychological biases.

The article by Saunders have spurred on other researchers to investigate the same relationships. The literature linking stock markets and meteorological observations is surprisingly extensive, but in this paper we will not give an extensive review, just give some highlights.¹

¹For a recent update on this literature, with a large number of references, see Lu and Chu (2012), and Novy-Marx (2014).
An early effort was Hirshleifer and Shumway (2003), which extends Saunders analysis to a large number of stock markets around the world (including Oslo), and find that the correlation between market returns and sunshine is a worldwide phenomena. Extending the sample, here from New York to the Stock Markets of the World, is the typical way of answering the “Is the effect there?” question. So the evidence is building up that there is a correlation between weather and stock returns.

Researchers have a harder time zeroing in on how any psychological mechanism plausibly work. For example, Goetzmann and Zhu (2005), looking at portfolio decisions of individual investors, find no effect from weather to these individual decisions. They instead point to the behaviour of market makers, the professionals “keeping the wheels of Wall Street turning.”

One comment on the research on the weather and the stock market is that this combines two of the most popular conversational gambits in the world. “Dreadful weather.” “How is the market doing?” This type of research will therefore have a separate entertainment value for many people. Another reason for why meteorological variable are popular is the “because it is there” argument. Meteorological data sets are very extensive, and also have long time series.

In the present paper we will use data for the Oslo Stock Exchange in Norway. We use various measures of “bad weather” and ask if they are related to changes in the return on the OSE.

2 Data

2.1 Meteorological Data

Data is provided by the Norwegian Meteorological Service, through their web service (eklima.met.no). The meteorological data available is extensive. We use data on precipitation, sunshine, cloud coverage and temperature. Table 1 gives details about daily observations available from the meteorological services.

<table>
<thead>
<tr>
<th>Weather</th>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clouds</td>
<td>NN</td>
<td>Cloud cover</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total cloud cover, code 0 - 8 (0 = sky clear, 1-8 = octas of sky covered.)</td>
</tr>
<tr>
<td>Precipitation</td>
<td>RR_12</td>
<td>Precipitation (12 hours)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Amount of precipitation last 12 hours (mm)</td>
</tr>
<tr>
<td>Sunshine</td>
<td>OT_24</td>
<td>Sunshine last 24 hours</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Number of hours with sunshine last 24 hours</td>
</tr>
<tr>
<td>Temperature</td>
<td>TA</td>
<td>Air temperature</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Air temperature at time of observation (Degrees C)</td>
</tr>
</tbody>
</table>

Source: eklima.met.no

If we are interested in the “mood” of traders at the Oslo Stock Exchange, we want to look at data relevant for the weather observed by local traders in Oslo. We therefore download weather observations from Blindern, the headquarters of the Norwegian Met office, which is situated at the University of Oslo, a few kilometers from the Oslo Stock Exchange. We will use stock market and meteorological data from 1980-2013.

Table 2 and Figure 1 give some descriptive statistics for the meteorological data. Note that observations of Sunshine (OT_24) stops in 2005, apparently the Met Office stopped recording this variable.

2.2 Proxies for “mood”

We want to create proxies that can be said to measure whether the weather conditions on a given day can be thought of as particularly bad (or good). Not all of the four weather variables can be used directly. Two of them, hours sunshine and air temperature, have a strong seasonal component. For example, five hours of sunshine in a day is pretty good in December, when that is most of the hours when the sun is above the horizon, but is not all that good in June, when the sun can stay above the horizon for sixteen hours. The same is true for temperature. We therefore correct for season the following ways. For sunshine we construct a proxy for “lots of sunshine” by calculating the fraction of the day with sunshine,
Table 2  Descriptive Statistics, Weather Observations
Panel A: Descriptive statistics for each time series

<table>
<thead>
<tr>
<th></th>
<th>Temperature</th>
<th>Clouds</th>
<th>Sunshine</th>
<th>Rain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>-20.90</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Mean</td>
<td>8.62</td>
<td>5.38</td>
<td>4.52</td>
<td>2.54</td>
</tr>
<tr>
<td>Median</td>
<td>8.50</td>
<td>7.00</td>
<td>3.40</td>
<td>0.60</td>
</tr>
<tr>
<td>Max</td>
<td>32.00</td>
<td>8.00</td>
<td>16.00</td>
<td>45.60</td>
</tr>
</tbody>
</table>

Panel B: Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>Temperature</th>
<th>Clouds</th>
<th>Sunshine</th>
<th>Rain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>1</td>
<td>-0.009</td>
<td>-0.205</td>
<td>0.497</td>
</tr>
<tr>
<td>Clouds</td>
<td>-0.009</td>
<td>1</td>
<td>0.167</td>
<td>0.103</td>
</tr>
<tr>
<td>Sunshine</td>
<td>-0.205</td>
<td>0.167</td>
<td>1</td>
<td>-0.074</td>
</tr>
<tr>
<td>Rain</td>
<td>0.497</td>
<td>0.103</td>
<td>-0.074</td>
<td>1</td>
</tr>
</tbody>
</table>

Descriptive statistics for four weather observations: TA Air Temperature (Degrees C), OT_24 Sunshine, Number of hours with sunshine last 24 hours, RR_12 Precipitation last 12 hours, NN Cloud cover (octals – 0-sky clear). Observations are once a day. TA: 1300, NN, OT_24: 0700, and RR_12: 1900.

Figure 1 Describing the various meteorological observations

Descriptive statistics for four weather observations: RR_12 Precipitation last 12 hours, NN Cloud cover (octals – 0-sky clear), OT_24 Sunshine, Number of hours with sunshine last 24 hours, TA Air Temperature (Degrees C). Observations are once a day. NN, OT_24: 0700, TA: 1300 and RR_12: 1900.
by dividing the number of hours of sunshine (OT_24) by the length of the day. For temperature we construct a “mood” variable by subtracting the observed temperature by the “normal temperature” that day.

Figure 2 Constructed meteorological "mood" variables

Distributions of constructed “mood” meteorological variables. The fraction of day which is sunny is calculated by diving the number of hours of sunshine (OT_24) with the length of the day. (Calculated using the R module geosphere.) Temperature above normal temperature is calculated by subtracting the temperature observation (TA) by the normal temperature also downloaded from eKlima.

Figure 2 illustrates the distributions of these two variables. Looking at the fraction of days with sun, one observes that Oslo is not California, most days the citizens of Oslo does not see the sun once. On the other hand, if we believe the psychological hypothesis, days with sunshine should give a very good mood.

2.3 Stock market variables

To proxy for the stock market we use an equally-weighted index of stocks on the OSE. Figure 3 shows the evolution of the market index in the period.

3 Linking weather and returns

To investigate the link between weather and stock returns we estimate the following regression

\[ R_{m,t} = a + b W_t + \epsilon_t \]  

where \( R_{m} \) is the daily return on the stock market, and \( W_t \) the value of the weather variable. We consider one market index, EW, and four weather variables measuring Temperature, Rain, Sunshine and Cloud coverage.

The estimation results are shown in table 3. There is one weather variable that significantly predicts the stock market, cloud coverage. The more clouds, the lower the return on the Oslo Stock Exchange. This is the same result as Saunders (1993) found for New York. However, even if the variable is statistically significant, note the \( \hat{R}^2 \) of all these regressions. They are all as very close to zero.

4 Discussion

We have found a significant relationship between one measure (of four possible) of the quality of weather that day and movement of the aggregate stock market. What should we conclude from that? Saunders (1993) presents this as a choice between two alternative hypotheses.

\(^2\)Downloaded from the web page of Bernt Arne Ødegaard. See Ødegaard (2014).

\(^3\)We have also done estimations using the Oslo Stock Exchange all-share index, the market-wide index calculated by the Oslo Stock Exchange. The index is constructed by splicing the current AllShare index with the earlier TOTX index. The results using this index is available on request.
Figure 3 Stock Market Index

Evolution of stock market value, constructed by aggregating the EW returns on the OSE.

Table 3 Estimating links between OSE market returns and weather variables

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_{EW} )</td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Rain</td>
<td>-0.006*</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Sunshine</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
</tr>
<tr>
<td>Cloud Coverage</td>
<td>-0.012***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.117***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
</tr>
<tr>
<td></td>
<td>0.114***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
</tr>
<tr>
<td></td>
<td>0.121***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
</tr>
<tr>
<td></td>
<td>0.180***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,523</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td>-0.0001</td>
</tr>
<tr>
<td></td>
<td>3.922</td>
</tr>
<tr>
<td></td>
<td>6,325</td>
</tr>
<tr>
<td></td>
<td>8,230</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Results for different regressions \( R_{mt} = a + bW_t + \varepsilon_t \), where \( R_{mt} \) is the return on the stock market (in percent), and \( W_t \) is a weather variable. The four weather variables are: Temperature: The difference between observed temperature and a “normal” temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN.
1. Efficient markets – if markets are efficient, New York (or Oslo) weather should not affect the prices of companies at the NYSE.

2. Behavioral explanations – The weather affects the mood of market participants, which again affect their view of where the market is going.

With this perspective, if we find a correlation between weather and stock returns, we would reject efficient markets, accept the alternative behavioral explanation.

However, there is a number of issues with this simplified statement of the problem.

1. The usual statistical question: While we do find one (out of four) significant coefficient, can we really say that the effect is there?

2. Can we really say that efficient markets rule out New York weather having effects on prices of companies listed at the NYSE?

   • Could there be direct cash flow effects?
   • Unobserved variable? – weather and stock returns connected through some unobserved third variable/relationship?

3. Need the behavioral explanation fleshed out and identified before we can justify a causal behavioral relationship.

4. While there may be a statistical relationship, is it an economically significant relationship?

4.1 Is the effect a statistical artifact?

One can of course never answer this completely, but there are some ways of gauging. One is to make the obvious observation that an effect that is observed both in New York and Oslo is less likely to be significant merely by chance.

Another way to look at this is to do a Placebo regression, replacing the explanatory variable with some alternative variable less connected with one of the explanations, and see whether we get significance. So how about weather in Bergen instead of Oslo? In terms of behavioral explanations, Bergen weather less likely to affect mood in Oslo. Some numbers for Bergen are given in table 4.

4.2 Behavioral explanations?

If we want to argue for a behavioral explanation, need some more specifics about how this explanation is supposed to work in terms of how trading on the exchange happens. The value of the stock market index is the sum of prices of individual stocks. Stock prices change as a result of many trading decisions by individual traders. If we want to argue for a behavioral explanation, some of these traders must change their behavior, in a way that pushes prices in a direction influenced by the weather.

If we think about traders on a stock exchange, one useful categorization in this context is

   • Professional traders. These are market professionals, which on average have zero net positions. One type of such a trader is a “market maker.”
   • “The buy side.” These are institutional / individual investors with a portfolio view of their asset holdings.

How are these traders likely to be affected by “mood”? If it affects professional traders, we may see effects on traded quantity, or trading behavior, which show up in the liquidity of the trading process on the exchange. For the “Buy Side” traders we should see changes in portfolio composition as a result of weather changes.

Let us take the case of professional traders. As said, if they change their trading behavior, it can affect

   • market liquidity
   • traded quantity in the market
### Table 4 Weather in Bergen

**Panel A: Descriptive Statistics**

<table>
<thead>
<tr>
<th></th>
<th>Temperature</th>
<th>Clouds</th>
<th>Sunshine</th>
<th>Rain</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Period End</strong></td>
<td>2014</td>
<td>2014</td>
<td>2005</td>
<td>2014</td>
</tr>
<tr>
<td><strong>Min</strong></td>
<td>-12.70</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td>9.77</td>
<td>5.76</td>
<td>3.14</td>
<td>4.95</td>
</tr>
<tr>
<td><strong>Median</strong></td>
<td>9.40</td>
<td>7.00</td>
<td>0.90</td>
<td>2.10</td>
</tr>
<tr>
<td><strong>Max</strong></td>
<td>31.10</td>
<td>8.00</td>
<td>16.40</td>
<td>76.70</td>
</tr>
</tbody>
</table>

**Panel B: Regression**

Dependent variable:

\[ R_{m,t}^{EW} = a + bW_t + \epsilon_t \]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>( p )-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>-0.007**</td>
<td>(0.003)</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Rain</td>
<td>-0.003</td>
<td>(0.002)</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Sunshine</td>
<td>-0.010</td>
<td>(0.042)</td>
<td>0.49</td>
</tr>
<tr>
<td>Cloud Coverage</td>
<td>-0.004</td>
<td>(0.004)</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Constant</td>
<td>0.139***</td>
<td>(0.013)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>0.130***</td>
<td>(0.016)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>0.133***</td>
<td>(0.015)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>0.135***</td>
<td>(0.025)</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

Observations: 8,519  5,086  6,396  8,443

Adjusted R\(^2\): 0.001  0.0002  -0.0001  -0.00002

**Note:** *p<0.1; **p<0.05; ***p<0.01

Panel A gives descriptive statistics for weather variables observed at the weather station in Florida, Bergen. Panel B shows results for different regressions \( R_{m,t}^{EW} = a + bW_t + \epsilon_t \) where \( R_{m,t} \) is the return on the stock market, and \( W_t \) is a weather variable, observed in Bergen. The four weather variables are: Temperature: The difference between observed temperature and a "normal" temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN.
Let us look at whether weather affects such variables. To investigate this, we, instead of returns, use measures of stock market liquidity as dependent variables:

\[ \text{Liq}_{m,t} = a + bW_t + \varepsilon_t \]  

(2)

where \( \text{Liq}_m \) is a measure of stock market liquidity, and \( W_t \) the value of the weather variable. We consider two liquidity measures, \textit{Relative Spread} and \textit{Turnover}, and four weather variables measuring Temperature, Rain, Sunshine and Cloud coverage.

Table 5 Estimating links between OSE market activity and weather variables

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Turnover</th>
<th>RelSpread</th>
<th>Turnover</th>
<th>RelSpread</th>
<th>Turnover</th>
<th>RelSpread</th>
<th>Turnover</th>
<th>RelSpread</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>0.003***</td>
<td>0.005*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.003)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rain</td>
<td>-0.001</td>
<td>0.005</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sunshine</td>
<td></td>
<td>-0.010</td>
<td>-0.031</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.008)</td>
<td>(0.039)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloud Coverage</td>
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<td>3.429***</td>
<td>0.282***</td>
<td>3.422***</td>
<td>0.277***</td>
<td>3.632***</td>
<td>0.278***</td>
<td>3.448***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.013)</td>
<td>(0.003)</td>
<td>(0.018)</td>
<td>(0.004)</td>
<td>(0.018)</td>
<td>(0.005)</td>
<td>(0.023)</td>
</tr>
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<td>0.001</td>
<td>0.001</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td></td>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
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</tr>
<tr>
<td>Observations</td>
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<td>3,922</td>
<td>6,323</td>
<td>6,323</td>
<td>8,228</td>
<td>8,228</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.004</td>
<td>0.0003</td>
<td>-0.00002</td>
<td>0.0003</td>
<td>0.0001</td>
<td>-0.0001</td>
<td>0.0002</td>
<td>-0.0001</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Results for different regressions \( \text{Liq}_{m,t} = a + bW_t + \varepsilon_t \) where \( \text{Liq}_{m,t} \) is a measure of stock market liquidity, and \( W_t \) is a weather variable. The four weather variables are: Temperature: The difference between observed temperature and a “normal” temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN.

The estimation results are shown in table 5. Here there is one variable that has a significant coefficient on turnover, the temperature. The interpretation of the positive coefficient is that days where the temperature is higher than normal are days when the activity, as measured by turnover, is higher. What we don’t see is a significant relationship with the same variable as the one correlated with returns, cloud coverage.

If we wanted to look at buy side traders, we would need to investigate actual portfolio decisions. This is not feasible with the data we use here, but e.g. Goetzmann and Zhu (2005), looking at individual traders, find no effect on portfolio compositions of weather.

So, once we dig into ways in which a behavioral explanation can give a causal relation, problems showing relation.

4.3 Left out variables?

So, we did find that some weather variables are significantly related to stock market variables. As mentioned, any empirical researcher should always be looking for alternative explanations for any observed empirical regularity. One possibility is that what we find is due to weather being related to some other variable affecting stock returns. One possibility is a well known effect in finance, seasonality, that there seems to be a regular variation in stock returns related to calendar month, which is illustrated in table 6, showing average returns by month for four different equity indices at OSE.

Let us illustrate how one can check if such effects may be behind the significant coefficients on the weather variables. We use the July effect of Hong and Yu (2009), that stock prices in July reflect the fact that many of the regular participants in the market is on holiday, which may affect the efficiency of pricing, as well as the activity (turnover). Tables 7 and 8 show the results. Adding the holiday dummy does not make us change our previous conclusions, it actually strengthens them.
Table 6 Monthly effects

<table>
<thead>
<tr>
<th>Month</th>
<th>EW</th>
<th>VW</th>
<th>AllShare</th>
<th>OBX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>5.9</td>
<td>4.2</td>
<td>3.5</td>
<td>2.0</td>
</tr>
<tr>
<td>Feb</td>
<td>3.0</td>
<td>2.0</td>
<td>1.7</td>
<td>2.1</td>
</tr>
<tr>
<td>Mar</td>
<td>2.3</td>
<td>1.9</td>
<td>2.3</td>
<td>2.5</td>
</tr>
<tr>
<td>Apr</td>
<td>3.2</td>
<td>4.4</td>
<td>3.5</td>
<td>2.7</td>
</tr>
<tr>
<td>May</td>
<td>1.4</td>
<td>2.1</td>
<td>1.5</td>
<td>1.0</td>
</tr>
<tr>
<td>Jun</td>
<td>-0.4</td>
<td>0.5</td>
<td>-0.7</td>
<td>-0.4</td>
</tr>
<tr>
<td>Jul</td>
<td>2.7</td>
<td>3.2</td>
<td>2.4</td>
<td>2.5</td>
</tr>
<tr>
<td>Aug</td>
<td>0.1</td>
<td>0.9</td>
<td>-0.4</td>
<td>-1.0</td>
</tr>
<tr>
<td>Sep</td>
<td>-1.1</td>
<td>-0.7</td>
<td>-1.7</td>
<td>-2.4</td>
</tr>
<tr>
<td>Oct</td>
<td>0.9</td>
<td>1.7</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>Nov</td>
<td>0.4</td>
<td>0.2</td>
<td>-0.5</td>
<td>-0.6</td>
</tr>
<tr>
<td>Dec</td>
<td>2.2</td>
<td>3.4</td>
<td>3.0</td>
<td>3.1</td>
</tr>
</tbody>
</table>

The table shows percentage monthly returns split by month for four different stock market indices at the OSE. Source Ødegaard (2014).

Table 7 Estimating links between OSE market returns and weather variables

<table>
<thead>
<tr>
<th>Dependent variable:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{EW}^{m,t}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Temperature</th>
<th>Rain</th>
<th>Sunshine</th>
<th>Cloud Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{m,t}$</td>
<td>$-0.0001$</td>
<td>$-0.006^*$</td>
<td>$-0.045$</td>
<td>$-0.012^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.038)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>July</td>
<td>0.046</td>
<td>0.033</td>
<td>0.058</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.052)</td>
<td>(0.042)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.113^{***}</td>
<td>0.111^{***}</td>
<td>0.139^{***}</td>
<td>0.176^{***}</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.018)</td>
<td>(0.017)</td>
<td>(0.022)</td>
</tr>
</tbody>
</table>

| Observations | 8,523   | 3,922   | 6,324   | 8,230   |
| Adjusted $R^2$| $-0.00004$ | 0.0003  | 0.0002  | 0.001   |

Note: *p<0.1; **p<0.05; ***p<0.01

Results for different regressions $R_{m,t} = a + bW_t + e_t$ where $R_{m,t}$ is the return on the stock market, and $W_t$ is a weather variable. The four weather variables are: Temperature: The difference between observed temperature and a “normal” temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN. In addition we include a dummy variable for July.
Table 8 Estimating links between OSE market activity and weather variables

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable: Turnover</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>0.003***</td>
<td>0.003***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>July</td>
<td></td>
<td></td>
<td>−0.091***</td>
<td>−0.081***</td>
<td>−0.087***</td>
<td>−0.089***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.007)</td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rain</td>
<td>−0.001</td>
<td>−0.0005</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sunshine</td>
<td>−0.007</td>
<td></td>
<td>0.002</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td></td>
<td>(0.008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloud Coverage</td>
<td>0.001</td>
<td>0.001*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.276***</td>
<td>0.283***</td>
<td>0.282***</td>
<td>0.289***</td>
<td>0.276***</td>
<td>0.280***</td>
<td>0.278***</td>
<td>0.286***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,524</td>
<td>8,524</td>
<td>3,922</td>
<td>3,922</td>
<td>6,325</td>
<td>6,325</td>
<td>8,231</td>
<td>8,231</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.004</td>
<td>0.021</td>
<td>−0.00002</td>
<td>0.016</td>
<td>−0.00004</td>
<td>0.015</td>
<td>0.00002</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Results for different regressions $Liq_{mt} = a + bW_t + \varepsilon_t$ where $Liq_{mt}$ is a measure of stock market liquidity, and $W_t$ is a weather variable. The four weather variables are: Temperature: The difference between observed temperature and a "normal" temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN.
5 Conclusion

We replicate the result in Saunders (1993) linking sunny days in New York with high returns at the NYSE using data from the Oslo Stock Exchange. We find that days with nice weather (little clouds) in the morning in Oslo are also days with higher returns on the Oslo stock market.
A Appendix: R code

In this appendix we show the computer code used to generate the results.

A.1 Reading the data

The structure of the data is illustrated by the first thirtyfive lines of the input file:

```plaintext
St.no;Year;Mnth;Date;Time(NMT);TA;OT_1;OT_24;RR_24;RR_12;WW;NN
18700;1980;1;1;7; -3.2; ;3.3; ;0.3;2;8
18700;1980;1;1;13; -3.1; ; ; ; ;2;6
18700;1980;1;1;19; -4.5; ; ; ;-1;1;2
18700;1980;1;2;7; -6.4; ;4.6; ;-1;2;1
18700;1980;1;2;13; -5.2; ; ; ; ;2;1
18700;1980;1;2;19; -6.8; ; ; ;-1;2;0
...```

R code for reading this file:

```r
library(xts)
obs <- read.table("./data/met_data_blindern/blindern_1980_2014.txt", skip=27, sep=";", header=TRUE, na.strings="x")
dates <- as.POSIXct(paste(obs$Year, obs$Mnth, obs$Date, obs$Time, sep="-"), format="%Y-%m-%d-%H")

TempBlindern <- na.omit(xts(obs$TA, order.by=dates))
head(TempBlindern)
OT24Blindern <- na.omit(xts(obs$OT_24, order.by=dates))
OT1Blindern <- na.omit(xts(obs$OT_1, order.by=dates))
RR12Blindern <- na.omit(xts(obs$RR_12, order.by=dates))
RR12Blindern[RR12Blindern>=0]

NNBlindern <- na.omit(xts(obs$NN, order.by=dates))
NNBlindern[NNBlindern>=0]

norm <- read.table("./data/met_data_blindern/blindern_air_temperature_daily_normals.txt", skip=11, sep=";");

ntemps <- NULL
ndates <- NULL
for (y in 1980:2013){
  ndates <- c(ndates, as.Date(paste(y, norm$Mnth, norm$Date, sep="-"), format="%Y-%m-%d"))
  ntemps <- c(ntemps, as.matrix(norm$X18700))
}
normtempsBlindern <- xts(ntemps, order.by=as.Date(ndates))
head(normtempsBlindern)
```

# daily normals is one observation for each data
# in a "normal year" Create a time series by adding years

```r
library(xts)

library(xts)
obs <- read.table("./data/met_data_blindern/blindern_1980_2014.txt",
                skip=27, sep=";", header=TRUE, na.strings="x")
dates <- as.POSIXct(paste(obs$Year, obs$Mnth, obs$Date, obs$Time, sep="-"),
                    format="%Y-%m-%d-%H")

TempBlindern <- na.omit(xts(obs$TA, order.by=dates))
head(TempBlindern)
OT24Blindern <- na.omit(xts(obs$OT_24, order.by=dates))
OT1Blindern <- na.omit(xts(obs$OT_1, order.by=dates))
RR12Blindern <- na.omit(xts(obs$RR_12, order.by=dates))
RR12Blindern[RR12Blindern>=0]

NNBlindern <- na.omit(xts(obs$NN, order.by=dates))
NNBlindern[NNBlindern>=0]

norm <- read.table("./data/met_data_blindern/blindern_air_temperature_daily_normals.txt",
                   skip=11, sep=";", header=TRUE)

ntemps <- NULL
ndates <- NULL
for (y in 1980:2013){
  ndates <- c(ndates, as.Date(paste(y, norm$Mnth, norm$Date, sep="-"), format="%Y-%m-%d"))
  ntemps <- c(ntemps, as.matrix(norm$X18700))
}
normtempsBlindern <- xts(ntemps, order.by=as.Date(ndates))
head(normtempsBlindern)
```
R code for transforming the data into what is necessary for analysis

```r
library(lubridate)
library(geosphere)

# for the temperature pick the observations at midday, 13:00
TempBlindern <- TempBlindern[as.character(index(TempBlindern), "%H") == "13"]

# pick the rainfall observed at the end of the day
RR12Blindern <- RR12Blindern[as.character(index(RR12Blindern), "%H") == "19"]

# pick the cloud coverage observed in the morning
NNBlindern <- NNBlindern[as.character(index(NNBlindern), "%H") == "07"]

# now convert the posix dates to regular date classes, so can do econometrics
OT24Blindern <- xts(as.matrix(OT24Blindern), as.Date(index(OT24Blindern)))
RR12Blindern <- xts(as.matrix(RR12Blindern), as.Date(index(RR12Blindern)))
NNBlindern <- xts(as.matrix(NNBlindern), as.Date(index(NNBlindern)))
TempBlindern <- xts(as.matrix(TempBlindern), as.Date(index(TempBlindern)))

DiffMeanTemp <- TempBlindern - normtempsBlindern
names(DiffMeanTemp)[1] = "DiffMean"

# the OT stuff needs to be converted a bit
# first we lag by one day, since the observation is at 7 in the morning
# the following day
OT24Blindern <- lag(OT24Blindern, -1)

# then we construct the variable that measures
# the fraction of the day with sunshine
length <- daylength(59, as.Date(index(OT24Blindern))) # Blindern is at 59 north
FracDaySunny <- OT24Blindern/length
```
A.2 Producing figures describing the data

# for the temperature pick the observations at midday, 13:00
filename <- paste0(outdir,"blindern_temperature_time_series.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
plot(TempBlindern)
dev.off()

filename <- paste0(outdir,"blindern_temperature_histogram.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
hist(as.matrix(TempBlindern), main="", density=TRUE, xlab="")
dev.off()

filename <- paste0(outdir,"blindern_OT24_time_series.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
plot(OT24Blindern, main="OT24, Blindern")
dev.off()

filename <- paste0(outdir,"blindern_OT24_histogram.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
hist(as.matrix(OT24Blindern), main="", density=TRUE, xlab="")
dev.off()

filename <- paste0(outdir,"blindern_RR12_time_series.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
plot(RR12Blindern, main="RR12, Blindern")
dev.off()

filename <- paste0(outdir,"blindern_RR12_histogram.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
hist(as.matrix(RR12Blindern), main="", density=TRUE, xlab="")
dev.off()

filename <- paste0(outdir,"blindern_normtemp_time_series.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
plot(normtempsBlindern, main="normtemp, Blindern", xlab="")
dev.off()

filename <- paste0(outdir,"blindern_normtemp_histogram.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
hist(as.matrix(normtempsBlindern), main="normtemp, Blindern", density=TRUE, xlab="")
dev.off()

filename <- paste0(outdir,"blindern_NN_time_series.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
plot(NNBlindern, main="NN, Blindern", xlab="")
dev.off()

cnt <- table(NNBlindern)
filename <- paste0(outdir,"blindern_NN_pie_chart.eps")
pie(cnt)
dev.off()

filename <- paste0(outdir,"blindern_NN_histogram.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
hist(as.matrix(NNBlindern), main="NN, Blindern", density=TRUE, xlab="")
dev.off()

filename <- paste0(outdir,"blindern_WW_time_series.eps")
postscript(filename, horizontal=FALSE, height=5, width=10)
plot(WWBlindern, main="WW, Blindern", xlab="")
dev.off()

cnt <- table(WWBlindern)
filename <- paste0(outdir,"blindern_WW_pie_chart.eps")
pie(cnt)
dev.off()
filename <- paste0(outdir,"blindern_WW_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(WWBlindern),main="WW, Blindern",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_diff_temp_normtemp_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(DiffMeanTemp),main="",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_diff_temp_normtemp_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(DiffMeanTemp,main="Difference mean and normtemp, Blindern",xlab="")
dev.off()

filename = paste0(outdir,"blindern_FracDaySunny_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(FracDaySunny, main="Fraction of Day with sun, Blindern")
dev.off()

filename = paste0(outdir,"blindern_FracDaySunny_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(FracDaySunny),main="",density=TRUE,xlab="")
dev.off()
A.3 Regression predicting returns

```r
# now do regressions
# temperature is observed the same day,
# so can use the return on the same day in regression

data <- merge(ew, DiffMeanTemp, all=FALSE)
head(data)
retew <- as.matrix(data$ew)
names(retew)[1] <- "ew"
diffmean <- as.matrix(data$DiffMean)
regr1 <- lm(retew ~ diffmean)

# use rainfall to predict.
# rain observed at the evening, so can use the same date

head(RR12Blindern)
names(RR12Blindern)[1] <- "RR12Blindern"
data <- merge(ew, RR12Blindern, all=FALSE)
head(data)
retew <- as.matrix(data$ew)
names(retew)[1] <- "ew"
regr2 <- lm(retew ~ rain)

# fraction of day with sun

data <- merge(ew, FracDaySunny, all=FALSE)
head(data)
FracSunny <- as.matrix(data$FracDaySunny)
names(FracSunny)[1] <- "FractionSunny"
regr3 <- lm(retew ~ FracSunny)

# use cloud cover, on the same date

data <- merge(ew, cloud, all=FALSE)
head(data)
retew <- as.matrix(data$ew)
names(retew)[1] <- "ew"
regr4 <- lm(retew ~ cloud)

tabl <- stargazer(regr1, regr2, regr3, regr4,
                   model.numbers=FALSE,
                   omit.stat=c("ser","f","rsq"),
                   float=FALSE,
                   dep.var.labels=c("$R_m^{EW}$","$R_m^{EW}$","$R_m^{EW}$","$R_m^{EW}$"),
                   covariate.labels=c("Temperature","Rain","Sunshine","Cloud Coverage","Constant"),
                   title="Explaining stock returns at the Oslo Stock Exchange with Oslo Weather")

filename <- paste0(outdir, "blindern_regr_returns_ew.tex")
cat(tabl, file=filename, sep="\n")
```
A.4 Regression predicting liquidity

data <- merge.xts(Turnover, RelSpread, DiffMeanTemp, all=FALSE)
head(data)

turnover <- as.matrix(data$Turnover)
names(Turnover)[1] <- "Turnover"
diffmean <- as.matrix(data$DiffMean)
lregr1 <- lm(turnover ~ diffmean)

relspread <- as.matrix(data$RelSpread)
names(relspread)[1] <- "RelSpread"
lregr2 <- lm(relspread ~ diffmean)

data <- merge(Turnover, RelSpread, RR12Blindern, all=FALSE)
head(data)
rain <- as.matrix(data$RR12Blindern)
names(rain)[1] <- "Rainfall"
turnover <- as.matrix(data$Turnover)
names(turnover)[1] <- "Turnover"
lregr3 <- lm(turnover ~ rain)

relspread <- as.matrix(data$RelSpread)
names(relspread)[1] <- "RelSpread"
lregr4 <- lm(relspread ~ rain)

data <- merge.xts(Turnover, RelSpread, FracDaySunny, all=FALSE)
head(data)

FracSunny <- as.matrix(data$FracDaySunny)
names(FracSunny)[1] <- "FractionSunny"
turnover <- as.matrix(data$Turnover)
names(turnover)[1] <- "Turnover"
lregr5 <- lm(turnover ~ FracSunny)

relspread <- as.matrix(data$RelSpread)
names(relspread)[1] <- "RelSpread"
lregr6 <- lm(relspread ~ FracSunny)

cloud <- NNBlindern

data <- merge.xts(Turnover, RelSpread, cloud, all=FALSE)
head(data)

cloud <- as.matrix(data$cloud)
names(cloud)[1] <- "Cloud"
turnover <- as.matrix(data$Turnover)
names(turnover)[1] <- "Turnover"
lregr7 <- lm(turnover ~ cloud)

relspread <- as.matrix(data$RelSpread)
names(relspread)[1] <- "RelSpread"
lregr8 <- lm(relspread ~ cloud)

tabl <- stargazer(lregr1, lregr2, lregr3, lregr4, lregr5, lregr6, lregr7, lregr8, 
omit.stat=c("ser", "f", "rsq"),
float=FALSE, 
dep.var.labels=c("Turnover", "RelSpread", "Turnover", "RelSpread", "Turnover", "RelSpread", "Turnover", "RelSpread"), 50 
covariate.labels=c("Temperature", "Rain", "Sunshine", "Cloud Coverage", "Constant"),
title="Explaining stock liquidity at the OSE with Oslo Weather")
filename <- paste0(outdir,"blindern_regr_liquidity.tex")
cat(tabl,file=filename,sep="\n")
References


