The Oslo Stock Exchange and the Weather

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

Mark Twain

Introduction

This talk: Link the stock market and the weather.
How can the weather can directly influence the stock market?
When the weather influences the running of the stock exchange: Hurricane Sandy in October 2012. New York Stock Exchange was closed for two days.
Prices of stocks on the market: The weather can 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.

Behavioural finance:
Ask 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.

This talk
Empirical investigation:
Construct measure(s) of weather “quality”
Look for empirical link between measures of weather quality and stock prices.

Data is downloaded from eKlima, the web service of the Norwegian Meteorological Service

Data from Blindern, the met headquarters in Oslo.

The meteorological data

Weather	Code	Description
Clouds	NN	Cloud cover Total cloud cover, code 0 - 8 (0 = sky clear, 1-8 = octas of sky covered.)
Precipitation	RR_12	Precipitation (12 hours) – Amount of precipitation last 12 hours (mm)
Sunshine	OT_24	Sunshine last 24 hours – Number of hours with sunshine last 24 hours
Temperature	TA	Air temperature – Air temperature at time of observation (Degrees C)
Wind	FF	Wind Speed –in m/s measured 10 meters above ground

Source: `eklima.met.no`

Descriptive Statistics

	Temperature	Clouds	Sunshine	Rain	Wind
Period Start	1980	1980	1980	1980	1980
Period End	2018	2018	2005	2018	2018
Min	-20.90	0.00	0.00	0.00	0.00
Mean	8.82	5.40	4.52	2.26	3.09
Median	8.70	7.00	3.40	0.40	2.80
Max	32.40	8.00	16.00	58.90	13.00

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.

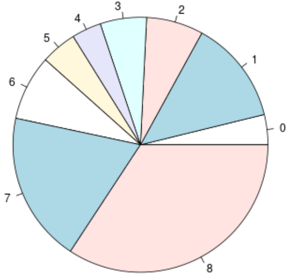
Descriptive Statistics - Correlations

Correlation Matrix

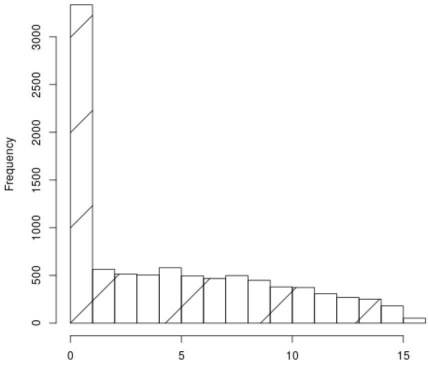
	Temperature	Clouds	Sunshine	Rain	Wind
Temperature	1	-0.009	-0.205	0.498	0.123
Clouds	-0.009	1	0.204	0.067	0.049
Sunshine	-0.205	0.204	1	-0.081	0.049
Rain	0.498	0.067	-0.081	1	0.151
Wind	0.123	0.049	0.049	0.151	1

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.

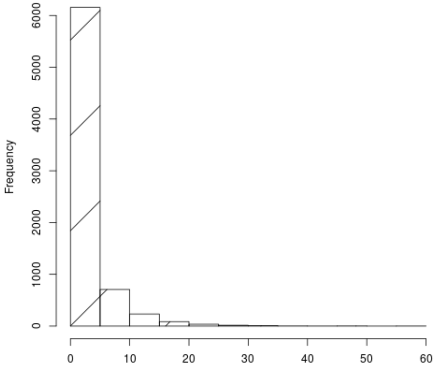
Cloud Coverage (NN)



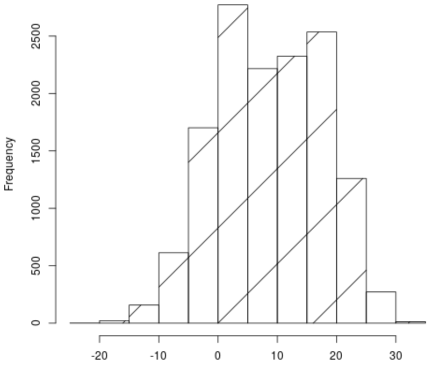
Hours sunshine (OT_24)



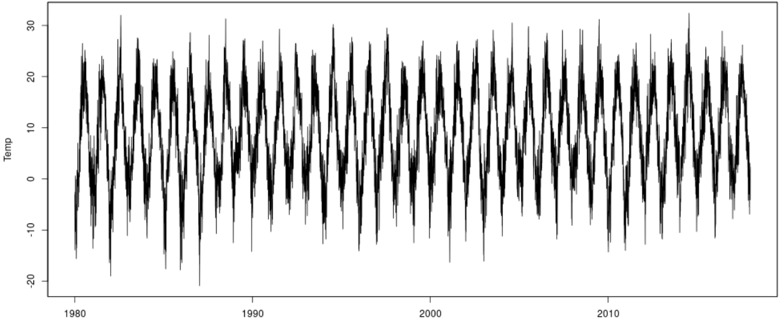
Precipitation (RR12)



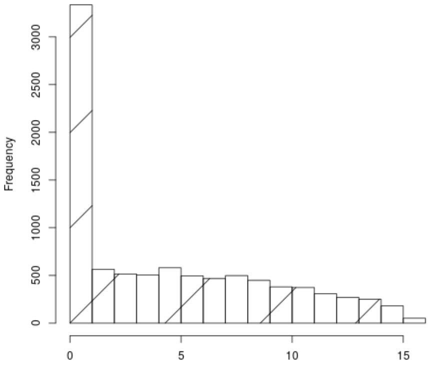
Temperature (TA)



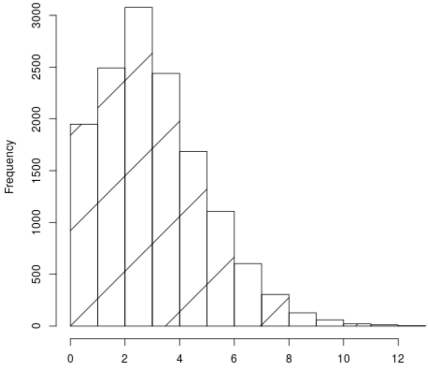
Temperature (TA)



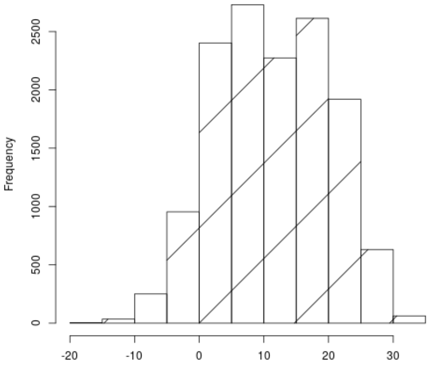
Hours sunshine(OT_24)



Wind



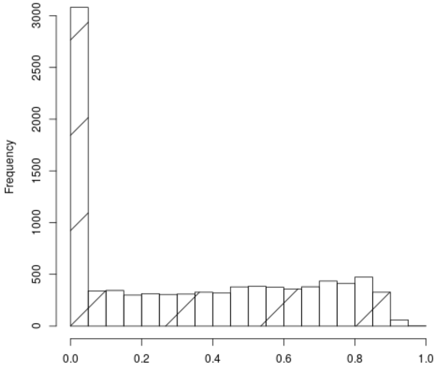
Windchill



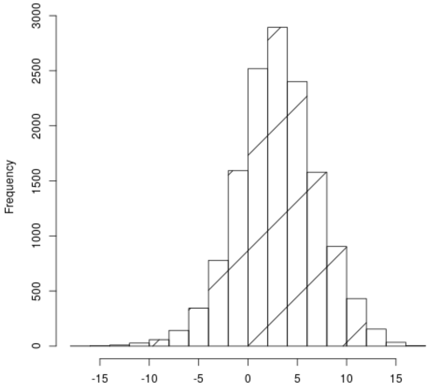
Constructed Weather Variables

Ask if weather "better" or "worse" than usual.
Need to correct for seasonality in temperature and hours of sunshine.
Sunshine: Correct for number of hours with sun: *Fraction of Day* with sun.
Temperature: See whether temperature above or below "normal temperature" for the time of year.

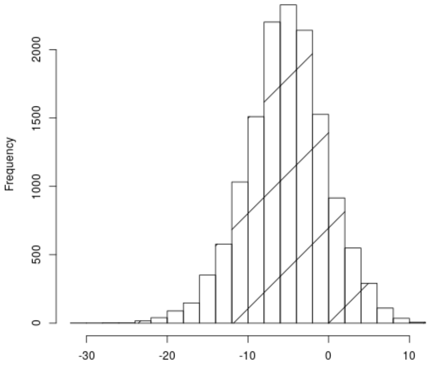
Fraction of day which is sunny



Temperature above "normal" temperature

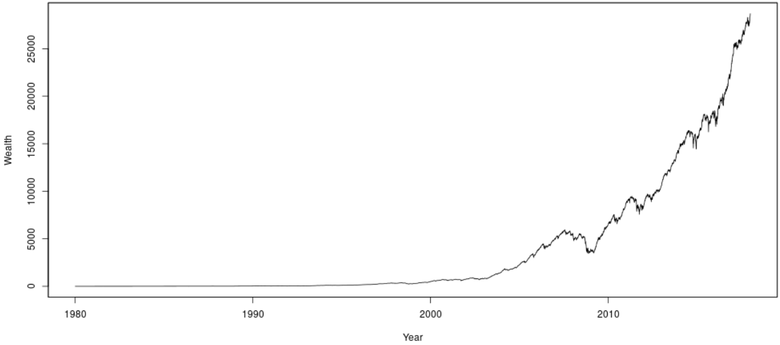


Windchill relative to “Normal” Windchill



Stock Market Data

Market-wide index stock returns.



Estimation Results

To investigate link between weather and stock returns,
Run the regression

$$R_{m,t} = a + bW_t + \varepsilon_t$$

where

- $R_{m,t}$ return on stock market
- W_t "weather" variable

	Dependent variable:				
	R_m^{EW}				
Temperature	-0.00001				
	(0.00002)				
Rain		-0.00004			
		(0.00003)			
Sunshine			0.0003		
			(0.0004)		
Cloud Coverage				-0.0001^{***}	
				(0.00003)	
WindChill					-0.0001^{***}
					(0.00002)
Constant	0.001^{***}	0.001^{***}	0.001^{***}	0.002^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Observations	9,527	4,983	6,325	9,197	9,527
Adjusted R^2	-0.0001	0.0002	-0.0001	0.001	0.001
Note:					*p<0.1; **p<0.05; ***p<0.01

Results for different regressions $R_{m,t} = a + bW_t + \varepsilon_t$ where R_{mt} 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"

Estimation Results

Significant relation between Stock Returns and:

- Cloud coverage
- Windchill

(Although very low R^2)

Discussion

So we find a correlation between weather *that day* and movement of the aggregate stock market.
What should we conclude from that?
Well, Saunders (1993) presents this as a choice between two alternative hypotheses.

- Efficient markets – if markets are efficient, New York (or Oslo) weather should not affect the prices of companies at the NYSE
- 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,
reject efficient markets, accept the alternative behavioral explanation

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

1. Usual statistical question: While we do find two (out of five) significant coefficients, 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?

Is it a statistical artifact?

Can never answer this completely.

Some tricks, though, that can be used in this context.

One possibility: *Placebo* regressions

– replacing the explanatory variable with some alternative variable *less* connected with the explanation.

How about weather in *Bergen* instead of *Oslo*?

In terms of behavioral explanations, Bergen weather less likely to affect *mood* in Oslo.

Lets look at the Bergen numbers

	Temperature	Clouds	Sunshine	Rain	Wind
Period Start	1980	1980	1980	1982	1980
Period End	2018	2018	2005	2018	2018
Min	-12.70	0.00	0.00	0.00	0.00
Mean	9.91	5.78	3.14	4.78	3.45
Median	9.50	7.00	0.90	1.80	3.10
Max	31.10	8.00	16.40	76.70	22.60

	Dependent variable:				
	R_m^{EW}				
Temperature	-0.0001^{**}				
	(0.00003)				
Rain		-0.00002			
		(0.00002)			
Sunshine			-0.0001		
			(0.0004)		
Cloud Coverage				-0.00003	
				(0.00004)	
WindChill					-0.00005
					(0.00004)
Constant	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Observations	9,523	6,091	6,396	9,446	4,223
Adjusted R^2	0.0005	0.0002	-0.0001	-0.0001	0.0001
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

What does a reasonable behavioral story look like?

Value of stock market index: Sum of prices of individual stocks.
How does a stock price change: Function of many trading decisions by individual traders.
Behavioral explanation: Some of these *traders* must change their behavior.
Categorization:

- Professsional `traders` – over time net position of zero
- "Buy side" – institutional / individual investors with a portfolio view of their asset holdings.

How are they likely to be affected by "mood"?
Professional traders – affecting quantity? – trading behavior?
Buy side – affecting portfolio composition?

Investigating professional traders?

If they change their trading behavior, affect

- market liquidity
- traded quantity

in the market.
Look at whether weather affects such variables.

	Dependent variable:				
	Turnover				
	(1)	(2)	(3)	(4)	(5)
Temperature	0.00002***				
	(0.00000)				
Rain		−0.00000			
		(0.00001)			
Sunshine			−0.0001		
			(0.0001)		
Cloud Coverage				0.00001	
				(0.00001)	
WindChill					−0.00002***
					(0.00000)
Constant	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.00002)	(0.00003)	(0.00004)	(0.00004)	(0.00003)
Observations	9,525	4,983	6,322	9,195	9,525
Adjusted R^2	0.002	−0.0001	−0.00005	0.0001	0.002
Note:					*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:				
	RelSpread				
	(1)	(2)	(3)	(4)	(5)
Temperature	-0.0001^{***}				
	(0.00003)				
Rain		0.0003^{***}			
		(0.00004)			
Sunshine			-0.0004		
			(0.0004)		
Cloud Coverage				-0.0001^{*}	
				(0.00004)	
WindChill					0.00003
					(0.00002)
Constant	0.033^{***}	0.030^{***}	0.036^{***}	0.033^{***}	0.033^{***}
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	9,525	4,983	6,322	9,195	9,525
Adjusted R^2	0.001	0.008	0.00003	0.0002	0.0001
Note:			*p<0.1; **p<0.05; ***p<0.01		

Basic variables related to action of professional traders does not seem affected by weather.
How about the buy side?
Would need to investigate actual portfolio decisions.
Not feasible with the data we use here, but e.g. Goetzmann and Zhu (2005) looks 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.

Left out variables?

Always a possibility that we are looking at a correlation coming from a joint relationship with some third variable.

Again, hard to empirically identify.

Typical method: Propose some relationship, find a proxy variable for the relationship of interest, see if it removes the relationship found in the first place.

For example, what about *seasonality*?

Seasonal component to stock returns, eg. january effect, holiday effect.

Show one example, dummying out the holiday, with a dummy for whether the date is july (the most common holiday month in Norway).

Monthly Returns

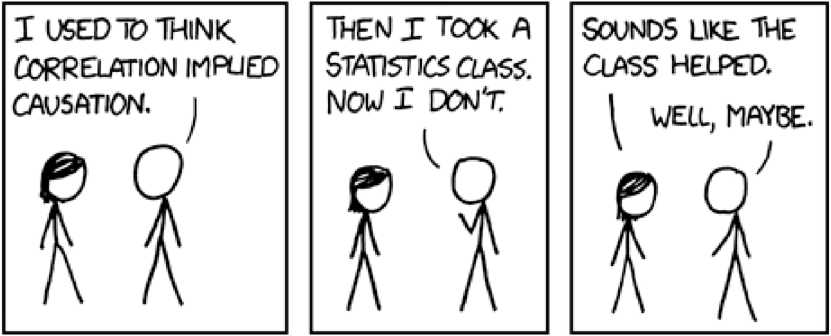
Month	EW	VW	TOT	OBX
Jan	5.3	3.7	2.9	1.5
Feb	2.9	2.1	1.8	2.1
Mar	2.2	1.8	2.1	2.2
Apr	3.2	4.3	3.5	2.7
May	1.5	2.2	1.6	1.1
Jun	-0.5	-0.2	-0.7	-0.5
Jul	2.7	3.1	2.3	2.4
Aug	0.1	0.7	-0.5	-1.1
Sep	-0.8	-0.4	-1.3	-2.0
Oct	0.9	1.8	0.6	0.4
Nov	0.4	0.3	-0.5	-0.5
Dec	2.3	3.2	2.8	2.9

The table shows percentage monthly returns split by month for four different stock market indices at the OSE.

	Dependent variable:				
	R_m^{EW}				
Temperature	-0.00001				
	(0.00002)				
Rain		-0.00004			
		(0.00003)			
Sunshine			-0.0005		
			(0.0004)		
Cloud Coverage				-0.0001^{***}	
				(0.00003)	
WindChill					-0.0001^{***}
					(0.00002)
July	0.0004	0.0004	0.001	0.0004	0.001^{**}
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Constant	0.001^{***}	0.001^{***}	0.001^{***}	0.002^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Observations	9,527	4,983	6,324	9,197	9,527
Adjusted R^2	-0.00001	0.0001	0.0002	0.001	0.001
Note:			*p<0.1; **p<0.05; ***p<0.01		

Conclusion

We investigate links between daily stock returns at the Oslo Stock Exchange and Oslo Weather. We find that cloudy days and cold, windy days are associated with lower returns.



XCD Webcomic

Using R to do analysis

Main challenge in using R in this context: The Weather Data

Gathering data on weather conditions at Blindern, the meterological station in Oslo, we download data with the following structure:

```
...
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
...
```

Reading this into R and creating time series

```
library(xts)

obs <- read.table("../../data/met_data_blindern/blindern_1980_20
                    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$TA,    order.by=dates))
OT24Blindern <- na.omit(xts(obs$OT_24,order.by=dates))
RR12Blindern <- na.omit(xts(obs$RR_12,order.by=dates))
RR12Blindern <- RR12Blindern[RR12Blindern>=0]
NNBlindern   <- na.omit(xts(obs$NN,    order.by=dates))
NNBlindern   <- NNBlindern[NNBlindern>=0]
```

Show an example of the resulting variables, `TempBlindern`

```
  > head(TempBlindern)
                       [,1]
1980-01-01 07:00:00 -3.2
1980-01-01 13:00:00 -3.1
1980-01-01 19:00:00 -4.5
1980-01-02 07:00:00 -6.4
1980-01-02 13:00:00 -5.2
1980-01-02 19:00:00 -6.8
```

Note that we have several observations each day, this is index with a *time* class; `POSIXct`.

Creating a time series of daily normals

```
norm <- read.table("../../data/met_data_blindern/blindern_air_te
                   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="-"
  ntemps <- c(ntemps,as.matrix(norm$X18700))
}
normtempsBlindern <- xts(ntemps,order.by=as.Date(ndates))
```

Resulting normals:

```
  > head(normtempsBlindern)
          [,1]
1980-01-01 -4.0
1980-01-02 -4.0
1980-01-03 -4.0
1980-01-04 -4.0
1980-01-05 -4.0
1980-01-06 -4.1
```

Picking one observation a day

```
            # temperature at midday, 13:00
TempBlindern <-
    TempBlindern[as.character(index(TempBlindern),"%H")=="13"]
           #  rainfall  at the end of the day
RR12Blindern <-
    RR12Blindern[as.character(index(RR12Blindern),"%H")=="19"]
          # cloud coverage observed in the morning
NNBlindern <-
    NNBlindern[as.character(index(NNBlindern),"%H")=="07"]

      # convert the posix dates to regular date classes
OT24Blindern <-
   xts(as.matrix(OT24Blindern),as.Date(index(OT24Blindern)))
RR12Blindern <-
   xts(as.matrix(RR12Blindern),as.Date(index(RR12Blindern)))
```

Constructing "mood" variables

Difference between actual temperature and “normal” temperature

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

Constructing "mood" variables

Fraction of day with sun

```
              # data on sun last 24 hours observed 7 in the
              # lag one day
OT24Blindern <- lag(OT24Blindern,-1)
              # then we construct the variable that measure
              # the fraction of the day with sunshine
length <- daylength(59,as.Date(index(OT24Blindern)))
             # Blindern is at 59 north
FracDaySunny <- OT24Blindern/length
```

Reading stock market data

```
library(zoo)
library(xts)
Rm <- read.zoo("../../data/data_stock_market/market_portfol
               sep=",",format="%Y%m%d",header=TRUE)
ew <- as.xts(100.0*Rm$EW)
ew <- na.omit(ew)
names(ew)[1]<-"ew"
```

Running regression

Show how the regression on cloud coverage is performed

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

William N Goetzmann and Ning Zhu. Rain or shine: Where is the weather effect? *European Financial Management*, 11(5):559–578, 2005.

Edward Saunders. Stock prices and Wall Street weather. *American Economic Review*, 83:1337–1346, 1993.