# Seasonality at The Oslo Stock Exchange 

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Seasonality concerns patterns in stock returns related to calendar time. Internationally, the best known such pattern is the january effect, where stock returns in january tend to be better than those for the rest of year.

In this lecture we look at the some such tests for the Oslo Stock Exchange, using various frequencies and tools.

### 0.1 Using Octave/Matlab

## Exercise 1.

January Effect Norway Matlab [3]
In finance one has identified various "calendar anomalies", that stock returns depend on calendar time in surprising ways. One of these is the "January effect," that stock returns seem to be higher in January.

Using returns for equally weighted index for the Norwegian stock market, test the hypothesis that the returns in January are different from other months.

In implementing this use a matlab type program, and use indicator variables in a regression framework.
We have collected the data into a data file with the returns in the second column, and a dummy for january in the third column, ie with a data structure like this:

```
date;EW;1;2;3;4;5;6;7;8;9;10;11;12
19800131;0.02166;1;0;0;0;0;0;0;0;0;0;0;0
19800229;0.055595;0;1;0;0;0;0;0;0;0;0;0;0
19800331;-0.053663;0;0;1;0;0;0;0;0;0;0;0;0
```


## Solution to Exercise 1.

January Effect Norway Matlab [3]
We ask whether returns in January are fundamentally different from the rest.
Regression to run

$$
r_{m}=E\left[r_{m}\right]+\beta D_{\text {january }}+e
$$

If january is different, $\beta \neq 0$.
The matlab code

```
EWRETS = dlmread("../data_stock_market/ew_monthly_w_month_indicators.txt");
n=rows(EWRETS)
rets = EWRETS(:,2);
# january is in column 3
y=rets;
X=[ones(n,1) EWRETS(:,3)];
bhat=ols(y,X)
e=y-X*bhat;
S2 = e'*e/(n-2)
V=S2*inv(X'*X);
stdevs = sqrt(diag(V))
tratios = bhat./stdevs
```

Gives results
$\mathrm{n}=492$
bhat $=$
0.013134
0.036350
$\mathrm{S} 2=2.7776 \mathrm{e}-03$
stdevs =
$2.4844 \mathrm{e}-03$
8.5032e-03
tratios $=$
5.2864
4.2748

We base the answer on the p-value for the dummy, which is significant. We therefore conclude that there is a January effect in the Norwegian stock market.

## Exercise 2.

Day of Week Oslo - Matlab [5]
In finance one has identified various "calendar anomalies", that stock returns depend on calendar time in surprising ways. One of these is the "Day of the week effect," that stock returns seem to be different across days of the week.

Using returns for equally weighted index for the Norwegian stock market, the period 1980-2006 test the hypothesis that the expected return is different across days of the week.

In implementing this use a matlab type program, and indicator variables in a regression framework. The data is available as a file with the index in the second column, and indicator variables for the weekdays as the other data, ie. the first few lines of data looks like:

```
date;EW;1;2;3;4;5;6;7
thu 19800103;-0.007849;0;0;0;1;0;0;0
thu 19800104;-0.002952;0;0;0;0;1;0;0
sun 19800107;0.000555;0;0;0;0;0;0;0
mon 19800108;-0.007474;1;1;0;0;0;0;0
tue 19800109;-0.004173;0;0;1;0;0;0;0
```


## Solution to Exercise 2.

Day of Week Oslo - Matlab [5]
The matlab code

```
EWRET = dlmread("../data_stock_market/ew_daily_w_day_indicators.txt");
n=rows(EWRET)
rets=EWRET(1:n,2);
monday=EWRET (1:n,3);
tuesday=EWRET(1:n,4);
wednesday=EWRET(1:n,5);
thursday=EWRET (1:n,6);
friday=EWRET (1:n,7);
means = ols(rets,[monday tuesday wednesday thursday friday])*100
X=[monday tuesday wednesday thursday friday];
y=rets;
bhat=ols(y,X)
e = y-X*bhat;
SSE_unrestr=e'*e
SSE_restr= (y-mean(y))'*(y-mean(y))
n=rows (y)
k=5
```

```
r=4
lr = ((SSE_restr-SSE_unrestr)/r)/(SSE_unrestr/(n-k))
pval = 1-chi2cdf(lr,r)
```

Gives results
$\mathrm{n}=10265$
means =
0.046689
0.068718
0.090080
0.103645
0.216978
bhat =
$4.6689 \mathrm{e}-04$
$6.8718 \mathrm{e}-04$
$9.0080 \mathrm{e}-04$
$1.0365 \mathrm{e}-03$
$2.1698 \mathrm{e}-03$
SSE_unrestr $=0.8666$
SSE_restr $=0.8699$
$\mathrm{n}=10265$
$\mathrm{k}=5$
$r=4$
lr = 9.8822
pval $=0.042460$

### 0.2 Using R

## Exercise 3.

January Effect OSE - R
The January effect in financial markets can very summarized as: The stock return in the month of january is higher than that in other months.

Using the monthly returns on an index for the Norwegian market, test whether January returns are different.
Do the analysis using $R$.
Solution to Exercise 3.
January Effect OSE - R
This can be formulated as a regression.

$$
r_{e w, t}=\mu+\alpha_{j a n} 1_{j a n, t}+\varepsilon_{t}
$$

where $1_{j a n, t}$ is a dummy variable equal to one if the month is january.
The proposed test is to test whether $\alpha_{j a n}=0$
In R it is simplest to just read in the dates and observations, and figure out the month from the date

```
library(zoo)
Rm <- read.zoo("../stock_market_data/market_portfolio_returns_monthly.txt",
                        header=TRUE,sep=";",format="%Y%m%d")
dates <- as.POSIXlt(index(Rm))
jan <- as.numeric(dates$mon==0)
reg1 <- lm(Rm$EW~jan)
summary(reg1)
    results in
lm(formula = Rm$EW ~ jan)
Residuals:
\begin{tabular}{rrrrr} 
Min & \(1 Q\) & Median & 3Q & Max \\
-0.197261 & -0.036369 & 0.003344 & 0.033067 & 0.140390
\end{tabular}
Coefficients:
            Estimate Std. Error t value Pr}(>|t|
(Intercept) 0.013987 0.003066 4.562 6.91e-06 ***
jan 0.047600 0.010622 4.481 9.90e-06 ***
--
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.05662 on 370 degrees of freedom
Multiple R-squared: 0.05148,Adjusted R-squared: 0.04892
F-statistic: 20.08 on 1 and 370 DF, p-value: 9.905e-06
```

Here look either at the coefficient on jan, or the F statistic, both give the same answer, january is different. Exercise 4.

Day of Week Effect OSE - R [5]
In finance one has identified various "calendar anomalies", that stock returns depend on calendar time. One of these is the "Day of the week effect," that stock returns seem to be different across days of the week.

Using returns for a market index for the Norwegian stock market, test the hypothesis that the expected return is different across days of the week.

In implementing this use indicator variables in a regression framework.

## Solution to Exercise 4.

Day of Week Effect OSE - R [5]
Using R we create indicator variables using the date library zoo

```
library(zoo)
Rm <- read.zoo("../../. ./data/norway/stock_market_indices/market_portfolio_returns_daily.txt",header=TRUE,sep
dates <- as.POSIXlt(index(Rm))
mon <- as.numeric(dates$wday==1)
```

```
> tue <- as.numeric(dates$wday==2)
> wed <- as.numeric(dates$wday==3)
> thu <- as.numeric(dates$wday==4)
> fri <- as.numeric(dates$wday==5)
```

This can be formulated (at least) two ways. One is a regression on the five dummies, without a constant

```
> reg1 <- lm(Rm$EW~}0+mon+tue+wed+thu+fri)
> summary(reg1)
Call:
lm(formula = Rm$EW ~ 0 + mon + tue + wed + thu + fri)
Residuals:
\begin{tabular}{rrrrr} 
Min & \(1 Q\) & Median & 3Q & Max \\
-0.147359 & -0.004338 & 0.000312 & 0.004559 & 0.114473
\end{tabular}
Coefficients:
    Estimate Std. Error t value Pr(>|t|)
mon 0.0007726 0.0002436 3.172 0.00152 *
tue 0.0006311 0.0002388 2.642 0.00825 **
wed 0.0010231 0.0002389 4.282 1.87e-05 ***
thu 0.0013983 0.0002437 5.739 9.90e-09 ***
fri 0.0022569 0.0002414 9.347 < 2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.009515 on 7772 degrees of freedom
Multiple R-squared: 0.01964,Adjusted R-squared: 0.01901
F-statistic: 31.14 on 5 and 7772 DF, p-value: < 2.2e-16
```

|  | Estimate | Std. Error | t value | $\operatorname{Pr}(>\|\mathrm{t}\|)$ |
| ---: | ---: | ---: | ---: | ---: |
| mon | 0.0006 | 0.0002 | 2.70 | 0.0069 |
| tue | 0.0006 | 0.0002 | 2.45 | 0.0144 |
| wed | 0.0010 | 0.0002 | 4.33 | 0.0000 |
| thu | 0.0013 | 0.0002 | 5.62 | 0.0000 |
| fri | 0.0022 | 0.0002 | 9.44 | 0.0000 |

One benefit of this formulation is that the coefficients are interpretable as the mean on each date. Another is to leave out one day, say monday. and use dummies for the other weekdays.

```
> reg2 <- lm(Rm$EW~ tue+wed+thu+fri)
> summary(reg2)
Call:
lm(formula = Rm$EW ~ tue + wed + thu + fri)
Residuals:
Min 1Q Median 3Q Max
-0.147359-0.004338 \(0.000312 \quad 0.004559 \quad 0.114473\)
Coefficients:
\begin{tabular}{|c|c|c|c|c|c|}
\hline \multicolumn{6}{|c|}{Estimate Std. Error t value \(\operatorname{Pr}(>|\mathrm{t}|)\)} \\
\hline (Intercept) & 0.0007726 & 0.0002436 & 3.172 & 0.00152 & ** \\
\hline tue & -0.0001415 & 0.0003411 & -0.415 & 0.67842 & \\
\hline wed & 0.0002505 & 0.0003412 & 0.734 & 0.46279 & \\
\hline thu & 0.0006257 & 0.0003445 & 1.816 & 0.06940 & \\
\hline fri & 0.0014843 & 0.0003430 & 4.328 & \(1.52 \mathrm{e}-05\) & *** \\
\hline Signif. code & s: \(0{ }^{(* * *}\) & \(0.001^{\prime * *}\) & 0.01 '* & , 0.05 & , 0.1 \\
\hline
\end{tabular}
```

Residual standard error: 0.009515 on 7772 degrees of freedom

Multiple R-squared: 0.003731,Adjusted R-squared: 0.003218
F-statistic: 7.276 on 4 and 7772 DF, p-value: $7.62 \mathrm{e}-06$
The second formulation has the benefit that it directly tests the desired hypothesis: The F test test for nonzero all coefficients except the intercept.

It rejects the hypothesis of equality of coefficients.
If we wanted to test the hypothesis of equality of coeffisients using the first formulation, we would need to write it as a linear hypothesis test, and test for equality of the coefficients against each other.

```
> #in this setting need to construct hypothesis tests for equality
```

$>C<-c(c(1,-1,0,0,0), c(0,1,-1,0,0), c(0,0,1,-1,0), c(0,0,0,1,-1))$
> $\mathrm{C}<-$ matrix (C, nrow=4, ncol=5, byrow=TRUE)
$>r<-c(0,0,0,0)$
> linearHypothesis(reg1,hypothesis.matrix=C,rhs=r)
Linear hypothesis test
Hypothesis:
mon - tue $=0$
tue - wed $=0$
wed - thu $=0$
thu - fri = 0
Model 1: restricted model
Model 2: ew ~ 0 + mon + tue + wed + thu + fri
Res.Df RSS Df Sum of $\mathrm{Sq} \quad \mathrm{F} \quad \operatorname{Pr}(>F)$
180290.72858
$280250.7256540 .00293448 .11291 .592 \mathrm{e}-06$ ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The test rejects the null of equality.

## Exercise 5.

There is a long literature in finance that investigates whether Friday the Thirteenth is a particularly unlucky day, by looking at the returns on those Fridays, and checking whether the return on those fridays is different from other fridays. Kolb and Rodriguez (1987) finds a lower than normal return on friday the thirteenth for the US, while Lucey (2000) shows the opposite for more recent, worldwide, data.

Choose a daily stock market index at the Oslo Stock Exchange, and investigate whether returns on OSE has been special on friday thirteenths, in the post 1980 period.

## Solution to Exercise 5.

Reading in the data and creating the dummy for friday thirteenth

```
Rm <- read.zoo("../../../data/norway/stock_market_indices/market_portfolio_returns_daily.txt",
+ header=TRUE,sep=";",format="%Y%m%d")
dates <- as.POSIXlt(index(Rm))
fri <- dates$wday==5
thirteenth <- dates$mday==13
dummy <- as.numeric(fri & thirteenth)
> sum(dummy)
[1] 52
```

The sum of the dummy variables is 52 , hence there are 52 friday the thirteenth in the period.
First doing this for the EW index.

```
Call:
lm(formula = as.matrix(Rm$EW) ~ dummy, na.action = na.omit)
Residuals:
\begin{tabular}{rrrrr} 
Min & \(1 Q\) & Median & 3Q & Max \\
-0.147880 & -0.004368 & 0.000408 & 0.004564 & 0.114344
\end{tabular}
```

Coefficients:
Estimate Std. Error $t$ value $\operatorname{Pr}(>|t|)$
(Intercept) $0.0011524 \quad 0.0001066 \quad 10.806 \quad<2 \mathrm{e}-16 * * *$
$\begin{array}{lllll}\text { dummy } & 0.0017194 & 0.0013253 & 1.297 & 0.195\end{array}$
Signif. codes: $0{ }^{\prime} * * *$ ' 0.001 ' $* *$ ' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.009526 on 8028 degrees of freedom
(1 observation deleted due to missingness)
Multiple R-squared: 0.0002096,Adjusted R-squared: 8.51e-05
F-statistic: 1.683 on 1 and 8028 DF, p-value: 0.1945

|  | Estimate | Std. Error | t value | $\operatorname{Pr}(>\|\mathrm{t}\|)$ |
| ---: | ---: | ---: | ---: | ---: |
| (Intercept) | 0.0012 | 0.0001 | 10.81 | 0.0000 |
| dummy | 0.0017 | 0.0013 | 1.30 | 0.1945 |

The VW index
Call:
$\operatorname{lm}($ formula $=$ as.matrix $($ Rm\$VW $) ~ \sim ~ d u m m y) ~$

Residuals:

| Min | 1Q | Median | 3Q | Max |
| ---: | ---: | ---: | ---: | ---: |
| -0.179138 | -0.006443 | 0.000236 | 0.006668 | 0.112676 |

Coefficients:
Estimate Std. Error $t$ value $\operatorname{Pr}(>|t|)$
(Intercept) $0.0010311 \quad 0.0001493 \quad 6.908 \quad 5.3 \mathrm{e}-12 * * *$
$\begin{array}{lllll}\text { dummy } & 0.0017401 & 0.0018549 & 0.938 & 0.348\end{array}$
---
Signif. codes: $0{ }^{\prime} * * *$ ' 0.001 ' $* *$ ' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01333 on 8028 degrees of freedom
(1 observation deleted due to missingness)
Multiple R-squared: 0.0001096,Adjusted R-squared: -1.494e-05
F-statistic: 0.8801 on 1 and 8028 DF, p-value: 0.3482

|  | Estimate | Std. Error | t value | $\operatorname{Pr}(>\|\mathrm{t}\|)$ |
| ---: | ---: | ---: | ---: | ---: |
| (Intercept) | 0.0010 | 0.0001 | 6.91 | 0.0000 |
| dummy | 0.0017 | 0.0019 | 0.94 | 0.3482 |

The Oslo Bors total index (TOTX) (spliced from the exchange's official indices)

```
> reg3 <- lm(as.matrix(Rm$TOTX)~ dummy)
> summary(reg3)
Call:
lm(formula = as.matrix(Rm$TOTX) ~ dummy)
```

Residuals:

| Min | $1 Q$ | Median | 3Q | Max |
| ---: | ---: | ---: | ---: | ---: |
| -0.191748 | -0.006212 | 0.000384 | 0.006877 | 0.109938 |

Coefficients:
Estimate Std. Error $t$ value $\operatorname{Pr}(>|t|)$
(Intercept) $0.00056060 .0001584 \quad 3.540 \quad 0.000402$ ***
$\begin{array}{llllll}\text { dummy } & 0.0025007 & 0.0019700 & 1.269 & 0.204339\end{array}$
Signif. codes: $0{ }^{\prime * * * '} 0.001$ '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01346 on 7272 degrees of freedom
(757 observations deleted due to missingness)

Multiple R-squared: 0.0002215,Adjusted R-squared: 8.405e-05
F-statistic: 1.611 on 1 and 7272 DF, p-value: 0.2043

|  | Estimate | Std. Error | t value | $\operatorname{Pr}(>\|\mathrm{t}\|)$ |
| ---: | ---: | ---: | ---: | ---: |
| (Intercept) | 0.0006 | 0.0002 | 3.54 | 0.0004 |
| dummy | 0.0025 | 0.0020 | 1.27 | 0.2043 |

The OBX index

```
> reg4 <- lm(as.matrix(Rm$OBX)~ dummy)
```

> summary (reg4)

Call:
$\operatorname{lm}($ formula $=$ as.matrix $(\mathrm{Rm} \$ O B X) \sim$ dummy)

Residuals:

| Min | $1 Q$ | Median | $3 Q$ | Max |
| ---: | ---: | ---: | ---: | ---: |
| -0.213672 | -0.007364 | 0.000332 | 0.007828 | 0.117099 |

Coefficients:
Estimate Std. Error $t$ value $\operatorname{Pr}(>|t|)$
(Intercept) 0.00042060 .00019992 .1040 .0354 *

| dummy | 0.0026268 | 0.0025040 | 1.049 | 0.2942 |
| :--- | :--- | :--- | :--- | :--- |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.01579 on 6275 degrees of freedom (1754 observations deleted due to missingness)
Multiple R-squared: 0.0001754,Adjusted R-squared: 1.602e-05
F-statistic: 1.101 on 1 and 6275 DF, p-value: 0.2942

|  | Estimate | Std. Error | t value | $\operatorname{Pr}(>\|\mathrm{t}\|)$ |
| ---: | ---: | ---: | ---: | ---: |
| (Intercept) | 0.0004 | 0.0002 | 2.10 | 0.0354 |
| dummy | 0.0026 | 0.0025 | 1.05 | 0.2942 |

The dummy is always very positive, but we can never reject the null that it is zero.

## References

Robert Kolb and Ricardo Rodriguez. Friday the thirteenth part VII: A note. Journal of Finance, 42:1385-1387, 1987.
Brian M Lucey. Friday the 13th and the philosophical basis of financial economics. Journal of Economics and Finance, 24 (3):294-301, 2000.

