

R Event Study

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1 Introduction

The following script provides an application of an event study. The data and the script itself can be found here: <https://github.com/DavZim/Classes/tree/master/Advanced%20Corporate%20Finance/Event%20Study>

To run this notebook, make sure that you have at least RStudio version 1.0.44 installed and run R version 3.3.2.

The general outline for this document is to first load the data, merge the necessary data, inspect the data both visually and via tables, estimate a CMRM (constant-mean-return model), calculate the ARs (abnormal returns), and CARs (cumulative abnormal returns) and then test for significance using a t-test.

2 Preparation

2.1 Load libraries

```
library(dplyr)      # for data manipulation
library(ggplot2)    # for plotting
library(lubridate)  # for dates
library(readr)      # for data loading
library(scales)     # for plotting
library(tidyr)      # for tidy data
```

2.2 Load data

```
mar_wide <- read_csv("data/market.csv")
ret_wide <- read_csv("data/returns.csv")
events <- read_csv("data/events.csv")

# reshape returns and market to long format
returns <- gather(ret_wide, key = company,
                  value = ret, -date)
market <- gather(mar_wide, key = country,
                 value = mret, -date)

# date formatting
returns <- returns %>% mutate(date = dmy(date))
market <- market %>% mutate(date = dmy(date))
events <- events %>% mutate(event = dmy(event))
```

2.3 Inspect data

```
returns

## # A tibble: 26,604 x 3
##   date      company      ret
##   <date>    <chr>      <dbl>
## 1 1997-01-02 Chrysler  0.0341
## 2 1997-01-03 Chrysler  0.0146
## 3 1997-01-06 Chrysler  0.0289
```

```
## 4 1997-01-07 Chrysler 0
## 5 1997-01-08 Chrysler -0.00702
## 6 1997-01-09 Chrysler 0
## 7 1997-01-10 Chrysler 0.0106
## 8 1997-01-13 Chrysler -0.0210
## 9 1997-01-14 Chrysler 0.00714
## 10 1997-01-15 Chrysler 0
## # ... with 26,594 more rows
```

market

```
## # A tibble: 17,736 x 3
##   date      country      mret
##   <date>    <chr>      <dbl>
## 1 1997-01-02 us        -0.00751
## 2 1997-01-03 us         0.0149
## 3 1997-01-06 us         0.000372
## 4 1997-01-07 us         0.00791
## 5 1997-01-08 us        -0.00519
## 6 1997-01-09 us         0.00820
## 7 1997-01-10 us         0.00613
## 8 1997-01-13 us        -0.000457
## 9 1997-01-14 us         0.0122
## 10 1997-01-15 us        -0.00269
## # ... with 17,726 more rows
```

events

```
## # A tibble: 6 x 2
##   company      event
##   <chr>      <date>
## 1 Chrysler  1998-05-06
## 2 BellSouth 2006-03-06
## 3 Engelhard 2006-01-03
## 4 Norsk Hydro 2006-12-18
## 5 Pilkington 2005-10-31
## 6 INA        1999-09-14
```

2.4 Merge Data

```
comps <- c("Chrysler", "BellSouth", "Engelhard", "Norsk Hydro", "Pilkington", "INA")
counts <- c("us", "us", "us", "norway", "uk", "italy")
countries <- data_frame(company = comps, country = counts)

# merge into one dataset
merged <- left_join(returns, countries, by = "company")
merged <- left_join(merged, market, by = c("date", "country"))
merged <- left_join(merged, events, by = "company")
merged
```

```
## # A tibble: 26,604 x 6
##   date      company      ret country      mret event
##   <date>    <chr>      <dbl> <chr>      <dbl> <date>
## 1 1997-01-02 Chrysler  0.0341 us        -0.00751 1998-05-06
## 2 1997-01-03 Chrysler  0.0146 us         0.0149 1998-05-06
```

```
## 3 1997-01-06 Chrysler 0.0289 us 0.000372 1998-05-06
## 4 1997-01-07 Chrysler 0 us 0.00791 1998-05-06
## 5 1997-01-08 Chrysler -0.00702 us -0.00519 1998-05-06
## 6 1997-01-09 Chrysler 0 us 0.00820 1998-05-06
## 7 1997-01-10 Chrysler 0.0106 us 0.00613 1998-05-06
## 8 1997-01-13 Chrysler -0.0210 us -0.000457 1998-05-06
## 9 1997-01-14 Chrysler 0.00714 us 0.0122 1998-05-06
## 10 1997-01-15 Chrysler 0 us -0.00269 1998-05-06
## # ... with 26,594 more rows
```

2.5 Estimation and Events

```
# calculate the event-time as the difference in days to the event
merged <- merged %>% group_by(company) %>%
  mutate(date_index = 1:n(),
         event_index = max(ifelse(event == date, date_index, 0)),
         event_time = date_index - event_index)
```

```
merged
```

```
## # A tibble: 26,604 x 9
## # Groups:   company [6]
##   date      company      ret country      mret event      date_index
##   <date>      <chr>      <dbl> <chr>      <dbl> <date>      <int>
## 1 1997-01-02 Chrysler 0.0341 us -0.00751 1998-05-06      1
## 2 1997-01-03 Chrysler 0.0146 us 0.0149 1998-05-06      2
## 3 1997-01-06 Chrysler 0.0289 us 0.000372 1998-05-06      3
## 4 1997-01-07 Chrysler 0 us 0.00791 1998-05-06      4
## 5 1997-01-08 Chrysler -0.00702 us -0.00519 1998-05-06      5
## 6 1997-01-09 Chrysler 0 us 0.00820 1998-05-06      6
## 7 1997-01-10 Chrysler 0.0106 us 0.00613 1998-05-06      7
## 8 1997-01-13 Chrysler -0.0210 us -0.000457 1998-05-06      8
## 9 1997-01-14 Chrysler 0.00714 us 0.0122 1998-05-06      9
## 10 1997-01-15 Chrysler 0 us -0.00269 1998-05-06     10
## # ... with 26,594 more rows, and 2 more variables: event_index <dbl>,
## #   event_time <dbl>
```

Now we want to split our sample into estimation-sample ($[-230, -31]$) and event-sample ($[-30, +30]$). We also want to have a quick visualization of the return correlations to the market.

```
# windows
estimation_window <- c(-230, -31)
event_window <- c(-30, 30)

# filter returns
estimation <- merged %>% filter(event_time >= estimation_window[1] &
                              event_time <= estimation_window[2])

event <- merged %>% filter(event_time >= event_window[1] &
                          event_time <= event_window[2])

# have a look at the data
estimation
```

```
## # A tibble: 1,200 x 9
## # Groups:   company [6]
##   date      company      ret country      mret event      date_index
##   <date>     <chr>      <dbl> <chr>      <dbl> <date>      <int>
## 1 1997-06-18 Chrysler  0.00384 us      -0.00462 1998-05-06      120
## 2 1997-06-19 Chrysler -0.00382 us       0.00995 1998-05-06      121
## 3 1997-06-20 Chrysler  0        us       0.000297 1998-05-06      122
## 4 1997-06-23 Chrysler -0.0115 us      -0.0202 1998-05-06      123
## 5 1997-06-24 Chrysler  0.0234 us       0.0180 1998-05-06      124
## 6 1997-06-25 Chrysler -0.00381 us      -0.00757 1998-05-06      125
## 7 1997-06-26 Chrysler  0.0114 us      -0.00573 1998-05-06      126
## 8 1997-06-27 Chrysler -0.0113 us       0.00388 1998-05-06      127
## 9 1997-06-30 Chrysler  0.00382 us      -0.00263 1998-05-06      128
## 10 1997-07-01 Chrysler -0.00951 us       0.00659 1998-05-06      129
## # ... with 1,190 more rows, and 2 more variables: event_index <dbl>,
## #   event_time <dbl>
```

event

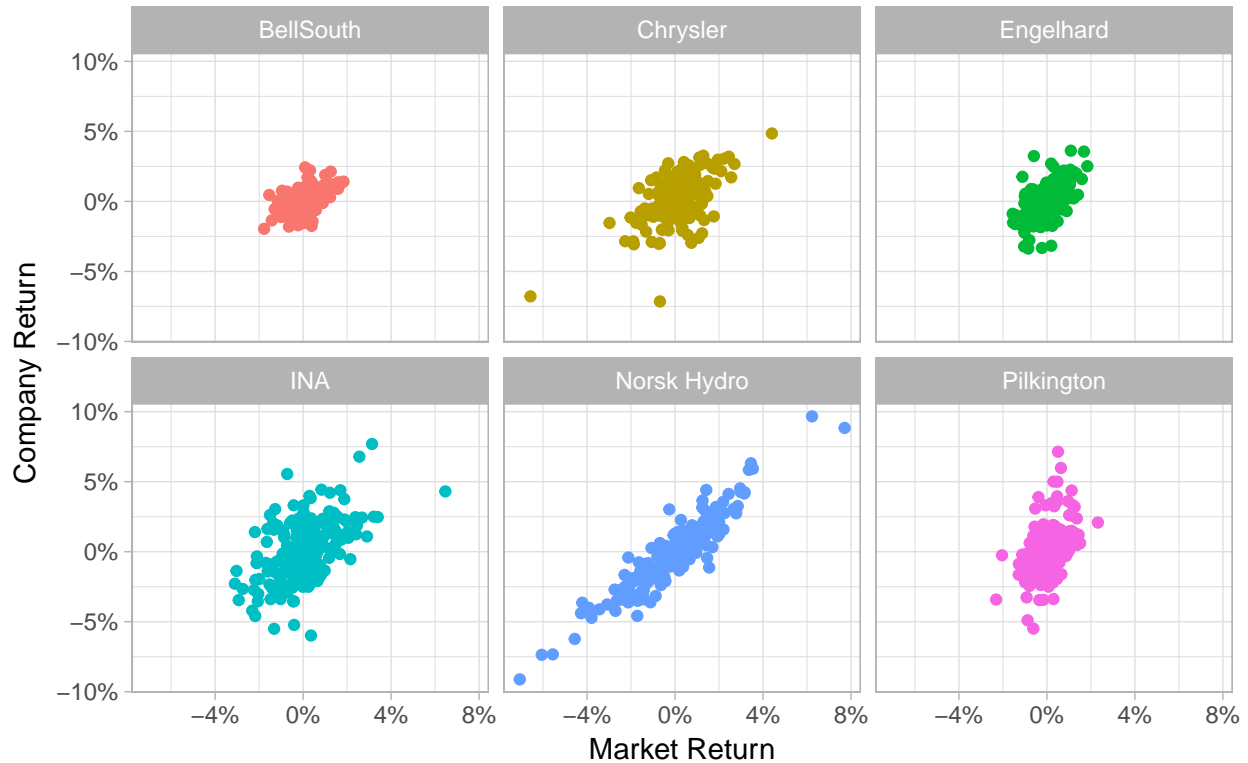
```
## # A tibble: 366 x 9
## # Groups:   company [6]
##   date      company      ret country      mret event      date_index
##   <date>     <chr>      <dbl> <chr>      <dbl> <date>      <int>
## 1 1998-03-25 Chrysler -0.0173 us      -0.00222 1998-05-06      320
## 2 1998-03-26 Chrysler -0.0132 us      -0.000497 1998-05-06      321
## 3 1998-03-27 Chrysler  0.00149 us      -0.00467 1998-05-06      322
## 4 1998-03-30 Chrysler -0.00593 us      -0.00151 1998-05-06      323
## 5 1998-03-31 Chrysler -0.00598 us       0.00787 1998-05-06      324
## 6 1998-04-01 Chrysler  0.00601 us       0.00625 1998-05-06      325
## 7 1998-04-02 Chrysler -0.0209 us       0.00974 1998-05-06      326
## 8 1998-04-03 Chrysler -0.00305 us       0.00218 1998-05-06      327
## 9 1998-04-06 Chrysler  0.0214 us      -0.00387 1998-05-06      328
## 10 1998-04-07 Chrysler  0.00300 us      -0.00971 1998-05-06      329
## # ... with 356 more rows, and 2 more variables: event_index <dbl>,
## #   event_time <dbl>
```

Graph data

```
theme_set(theme_light())
ggplot(estimation %>% filter(ret != 0), aes(x = mret, y = ret, color = company)) +
  geom_point() +
  facet_wrap(~company) +
  scale_x_continuous(labels = percent) +
  scale_y_continuous(labels = percent) +
  theme(legend.position = "none") +
  labs(title = "Correlations to Market Returns",
       subtitle = "The respective markets are USA, UK, Norway, and Italy",
       x = "Market Return", y = "Company Return")
```

Correlations to Market Returns

The respective markets are USA, UK, Norway, and Italy



3 Estimation

3.1 Calculate the CMRM

Although we have many options, this script uses the constant-mean-return model to calculate expected returns (for simplicity reasons mainly).

The expected return is given by

$$E[R_{i,t}|X_t]$$

using the CMRM (constant mean return model), we get

$$E[R_{i,t}|X_t] = \overline{R_{i,t}}$$

```
cmrm <- estimation %>% group_by(company) %>% summarise(cmrm = mean(ret))
cmrm
```

```
## # A tibble: 6 x 2
##   company      cmrm
##   <chr>      <dbl>
## 1 BellSouth  0.000395
## 2 Chrysler   0.00173
## 3 Engelhard -0.0000261
## 4 INA        0.000112
```

```
## 5 Norsk Hydro 0.000419
## 6 Pilkington 0.00147
```

3.2 CAPM

To calculate the capm we can use the simplified market-model (estimates the intercept (risk-free rate) instead of imposing it) which uses a linear regression of the form $return \sim marketreturn$, using the **broom**-library we can do the following:

```
capm <- estimation %>%
  group_by(company) %>%
  # "do" a regression using do() from the broom-package (tidyverse)
  # see https://github.com/tidyverse/broom
  do(fit = lm(ret ~ mret, data = .)) %>%
  # get the coefficients: intercept and slope (alpha and beta)
  # and discard the model itself (fit)
  mutate(alpha = coefficients(fit)[1],
          beta = coefficients(fit)[2],
          fit = NULL)
capm
```

```
## Source: local data frame [6 x 3]
## Groups: <by row>
##
## # A tibble: 6 x 3
##   company      alpha  beta
##   <chr>      <dbl> <dbl>
## 1 BellSouth -0.00000498 0.681
## 2 Chrysler  0.000699  0.851
## 3 Engelhard -0.000335  1.06
## 4 INA       -0.000117  0.870
## 5 Norsk Hydro -0.000616  1.27
## 6 Pilkington 0.000906  1.22
```

```
event_capm <- left_join(event, capm, by = "company") %>%
  # compute the expected return
  mutate(capm = alpha + mret * beta,
          alpha = NULL,
          beta = NULL)
event_capm
```

```
## # A tibble: 366 x 10
## # Groups:   company [6]
##   date      company      ret country      mret event      date_index
##   <date>    <chr>      <dbl> <chr>      <dbl> <date>      <int>
## 1 1998-03-25 Chrysler -0.0173 us      -0.00222 1998-05-06      320
## 2 1998-03-26 Chrysler -0.0132 us      -0.000497 1998-05-06      321
## 3 1998-03-27 Chrysler  0.00149 us      -0.00467 1998-05-06      322
## 4 1998-03-30 Chrysler -0.00593 us      -0.00151 1998-05-06      323
## 5 1998-03-31 Chrysler -0.00598 us       0.00787 1998-05-06      324
## 6 1998-04-01 Chrysler  0.00601 us       0.00625 1998-05-06      325
## 7 1998-04-02 Chrysler -0.0209 us       0.00974 1998-05-06      326
## 8 1998-04-03 Chrysler -0.00305 us       0.00218 1998-05-06      327
## 9 1998-04-06 Chrysler  0.0214 us      -0.00387 1998-05-06      328
## 10 1998-04-07 Chrysler  0.00300 us      -0.00971 1998-05-06      329
```

```
## # ... with 356 more rows, and 3 more variables: event_index <dbl>,
## #   event_time <dbl>, capm <dbl>
```

Nonetheless, we will continue the tests using the CMRM and leave the testing of the CAPM to the interested reader.

3.3 Merge Returns

Next, we want to merge the expected returns into the event-dataset to be able to calculate the next steps.

```
# select only necessary variables
event <- event %>% select(company, ret, event_time)
event <- left_join(event, cmrm, by = "company")
event
```

```
## # A tibble: 366 x 4
## # Groups:   company [?]
##   company      ret event_time    cmrm
##   <chr>      <dbl>      <dbl>    <dbl>
## 1 Chrysler -0.0173      -30.0 0.00173
## 2 Chrysler -0.0132      -29.0 0.00173
## 3 Chrysler  0.00149      -28.0 0.00173
## 4 Chrysler -0.00593      -27.0 0.00173
## 5 Chrysler -0.00598      -26.0 0.00173
## 6 Chrysler  0.00601      -25.0 0.00173
## 7 Chrysler -0.0209      -24.0 0.00173
## 8 Chrysler -0.00305      -23.0 0.00173
## 9 Chrysler  0.0214      -22.0 0.00173
## 10 Chrysler 0.00300      -21.0 0.00173
## # ... with 356 more rows
```

3.4 Calculate the Abnormal Returns

The abnormal return in period t for company i is given by

$$AR_{i,t} = R_{i,t} - E[R_{i,t}]$$

which we can calculate in R like this

```
event <- event %>% mutate(ar = ret - cmrm)
event
```

```
## # A tibble: 366 x 5
## # Groups:   company [6]
##   company      ret event_time    cmrm      ar
##   <chr>      <dbl>      <dbl>    <dbl>    <dbl>
## 1 Chrysler -0.0173      -30.0 0.00173 -0.0190
## 2 Chrysler -0.0132      -29.0 0.00173 -0.0149
## 3 Chrysler  0.00149      -28.0 0.00173 -0.000245
## 4 Chrysler -0.00593      -27.0 0.00173 -0.00766
## 5 Chrysler -0.00598      -26.0 0.00173 -0.00771
## 6 Chrysler  0.00601      -25.0 0.00173  0.00428
## 7 Chrysler -0.0209      -24.0 0.00173 -0.0226
## 8 Chrysler -0.00305      -23.0 0.00173 -0.00478
## 9 Chrysler  0.0214      -22.0 0.00173  0.0197
```



```
## 10 Chrysler 0.00300 -21.0 0.00173 0.00126
## # ... with 356 more rows
```

3.5 Calculate the Cumulative Abnormal Returns

The CARs are given by

$$CAR_{i,t} = \sum_{k=1}^t AR_{i,t-k}$$

with a known distribution of

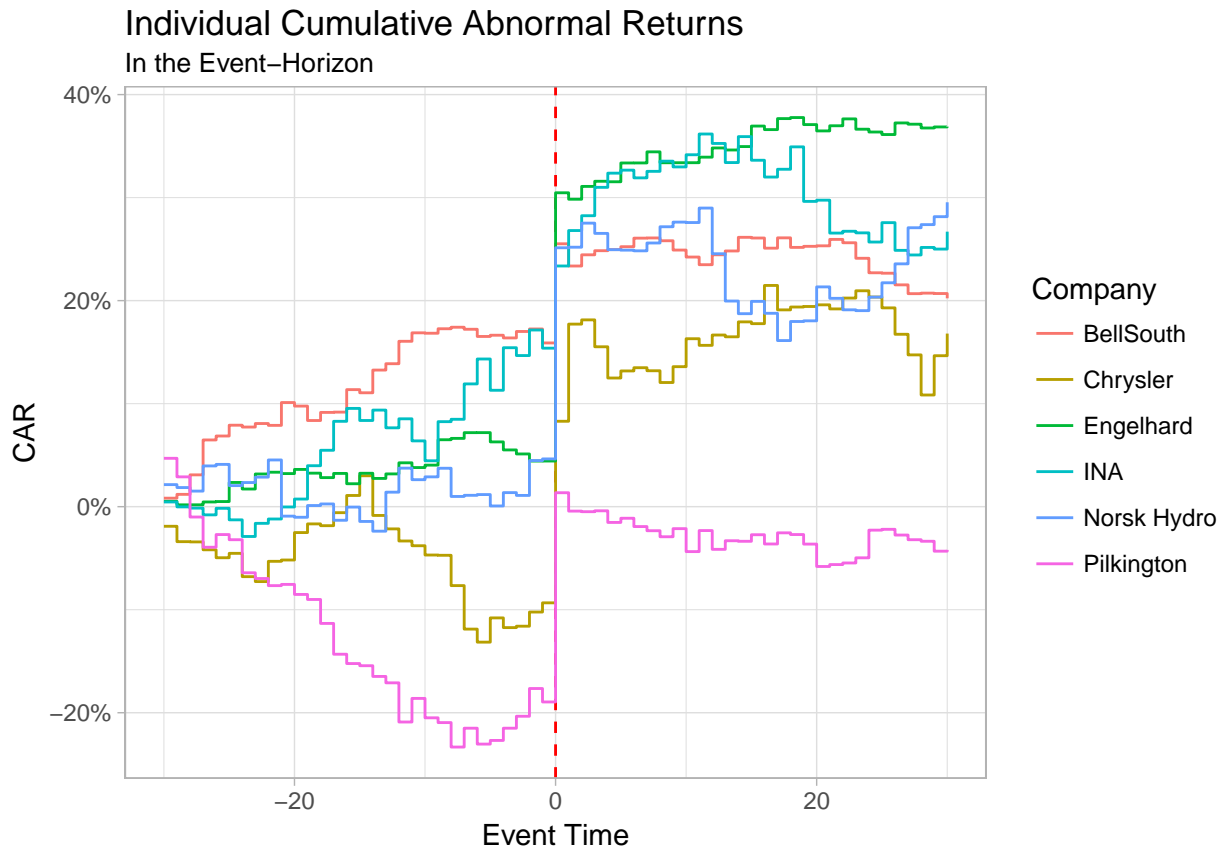
$$CAR_{i,t} \sim N(0, \sigma_{i,t}^2)$$

In R we can calculate the CARs like this

```
indiv_event <- event %>% group_by(company) %>% mutate(car = cumsum(ar))
indiv_event
```

```
## # A tibble: 366 x 6
## # Groups:   company [6]
##   company      ret event_time   cmrm      ar      car
##   <chr>      <dbl>      <dbl>   <dbl>   <dbl>   <dbl>
## 1 Chrysler -0.0173      -30.0 0.00173 -0.0190 -0.0190
## 2 Chrysler -0.0132      -29.0 0.00173 -0.0149 -0.0340
## 3 Chrysler 0.00149      -28.0 0.00173 -0.000245 -0.0342
## 4 Chrysler -0.00593      -27.0 0.00173 -0.00766 -0.0419
## 5 Chrysler -0.00598      -26.0 0.00173 -0.00771 -0.0496
## 6 Chrysler 0.00601      -25.0 0.00173 0.00428 -0.0453
## 7 Chrysler -0.0209      -24.0 0.00173 -0.0226 -0.0679
## 8 Chrysler -0.00305      -23.0 0.00173 -0.00478 -0.0727
## 9 Chrysler 0.0214      -22.0 0.00173 0.0197 -0.0530
## 10 Chrysler 0.00300      -21.0 0.00173 0.00126 -0.0518
## # ... with 356 more rows
```

```
ggplot(indiv_event, aes(x = event_time, y = car, color = company)) +
  geom_vline(xintercept = 0, color = "red", linetype = "dashed") +
  geom_step() +
  scale_y_continuous(labels = percent) +
  labs(title = "Individual Cumulative Abnormal Returns", subtitle = "In the Event-Horizon",
       x = "Event Time", y = "CAR", color = "Company")
```



We can also calculate aggregated values (*AAR* as the average abnormal return) per day, which is handy, for example for plotting

```
# aggregated
agg_event <- event %>% group_by(event_time) %>% summarise(aar = mean(ar))
agg_event <- agg_event %>% mutate(car = cumsum(aar))
agg_event
```

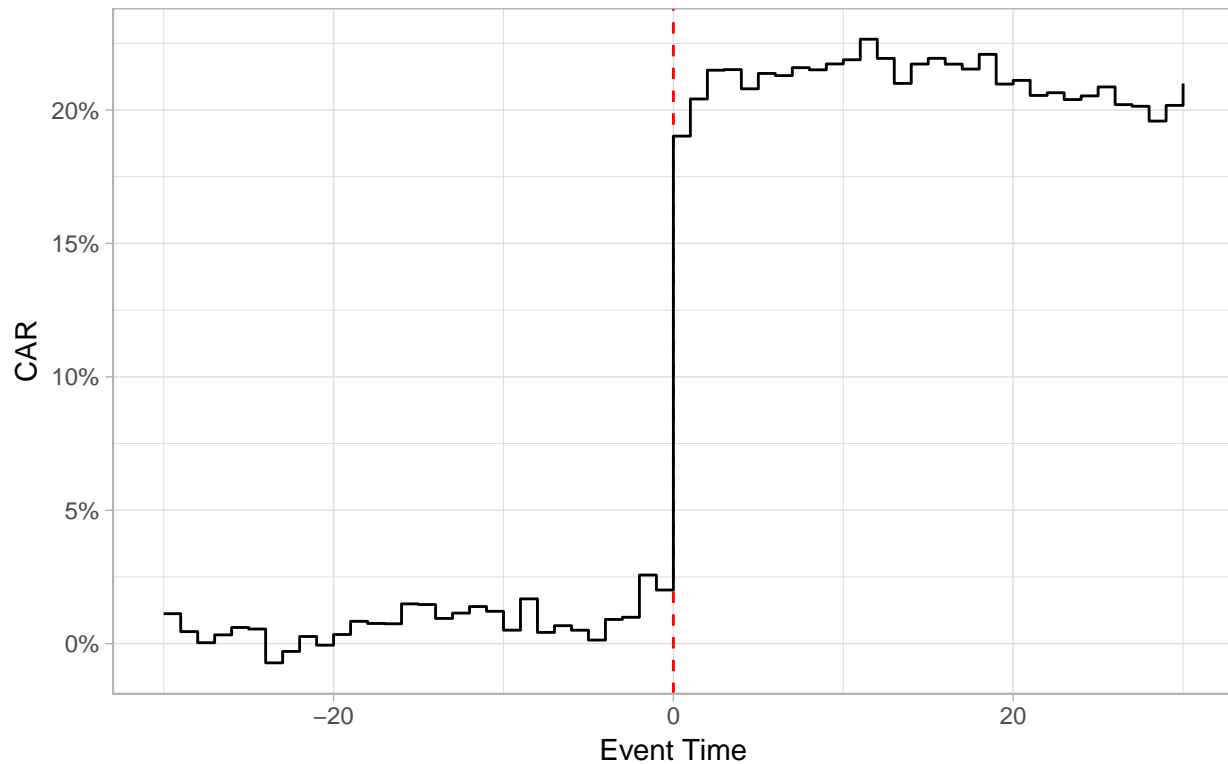
```
## # A tibble: 61 x 3
##   event_time    aar      car
##   <dbl>    <dbl>    <dbl>
## 1    -30.0  0.0112  0.0112
## 2    -29.0 -0.00671 0.00452
## 3    -28.0 -0.00415 0.000364
## 4    -27.0  0.00292 0.00329
## 5    -26.0  0.00278 0.00607
## 6    -25.0 -0.000583 0.00549
## 7    -24.0 -0.0127 -0.00719
## 8    -23.0  0.00429 -0.00291
## 9    -22.0  0.00559  0.00269
## 10   -21.0 -0.00326 -0.000577
## # ... with 51 more rows
```

```
ggplot(agg_event, aes(x = event_time, y = car)) +
  geom_vline(xintercept = 0, color = "red", linetype = "dashed") +
  geom_step() +
  scale_y_continuous(labels = percent) +
  labs(title = "Aggregated Cumulative Abnormal Returns", subtitle = "In the Event-Horizon",
```

```
x = "Event Time", y = "CAR")
```

Aggregated Cumulative Abnormal Returns

In the Event-Horizon



4 Testing

To test for significance, we mainly use t-test in this script, other tests include Boehmer et al. (1991) and Corrado (1989), among others.

The variance of the $CARs$, are known to be distributed with a variance of

$$\sigma_{i,t}^2 = \frac{1}{N(N-1)} \sum_{j=1}^N (CAR_{j,t} - \overline{CAR}_{j,t})^2$$

4.1 T-test

The first chunk uses a t-test to test the individual ARs (the question we are trying to answer: Is the abnormal return in time-period t different from zero?).

```
test1 <- indiv_event %>%
  group_by(event_time) %>%
  summarise(mean_ar = mean(ar),
            var_ar = 1/(n()*(n() - 1)) * sum((ar - mean_ar)^2),
            t_value = mean_ar / sqrt(var_ar),
            p_value = pt(abs(t_value), df = n(), lower.tail = F)*2)

test1
```

```
## # A tibble: 61 x 5
##   event_time mean_ar var_ar t_value p_value
##   <dbl>     <dbl>   <dbl>   <dbl>   <dbl>
## 1    -30.0  0.0112  0.0000795  1.26    0.255
## 2    -29.0 -0.00671  0.0000111 -2.01    0.0907
## 3    -28.0 -0.00415  0.0000596 -0.538   0.610
## 4    -27.0  0.00292  0.0000887  0.311   0.767
## 5    -26.0  0.00278  0.00000740 1.02    0.346
## 6    -25.0 -0.000583  0.0000349 -0.0988  0.924
## 7    -24.0 -0.0127  0.0000297 -2.33    0.0589
## 8    -23.0  0.00429  0.0000120  1.24    0.262
## 9    -22.0  0.00559  0.0000183  1.31    0.239
## 10   -21.0 -0.00326  0.000118  -0.301   0.774
## # ... with 51 more rows
```

The following chunk uses CARs to see if the price-development (which is represented by the CARs) is different from zero, instead of a snapshot of a single day as we did in the example above.

```
# test2 with CARs
stars <- function(p) {
  ifelse(p < 0.001, "***",
    ifelse(p < 0.01, "**",
      ifelse(p < 0.05, "*", " ")))
}

test2 <- indiv_event %>%
  group_by(event_time) %>%
  summarise(mean_car = mean(car),
    var_car = 1/(n()*(n() - 1)) * sum((car - mean_car)^2),
    t_value = mean_car / sqrt(var_car),
    p_value = pt(abs(t_value), df = n(), lower.tail = F)*2)

test2 %>% mutate(sign = stars(p_value),
  car = cumsum(mean_car)) %>%
  select(event_time, car, t_value, sign) %>%
  filter(event_time %in% -3:6) # look only at the frame [-3, 6], to have less output
```

```
## # A tibble: 10 x 4
##   event_time car t_value sign
##   <dbl> <dbl>   <dbl> <chr>
## 1    -3.00 0.184   0.165 " "
## 2    -2.00 0.210   0.444 " "
## 3    -1.00 0.230   0.357 " "
## 4     0    0.421   4.07  **
## 5     1.00 0.625   4.55  **
## 6     2.00 0.840   4.52  **
## 7     3.00 1.05    4.32  **
## 8     4.00 1.26    3.90  **
## 9     5.00 1.48    3.96  **
## 10    6.00 1.69    3.90  **
```

4.2 Testing over Aggregated Times

In the next step we want to look not at a single time-point, but at aggregated times, in this example, we want to see if the price in the time-horizon $[-3, +3]$ is different from zero.

```
time_window <- c(-3, 3)
test3 <- indiv_event %>% filter(event_time >= time_window[1] &
                               event_time <= time_window[2]) %>%

  select(company, ar) %>%
  group_by(company) %>% summarise(car = sum(ar))

# using the same logic as before
test3 %>% summarise(mean_car = mean(car),
                    var_car = 1/(n()*(n() - 1)) * sum((car - mean_car)^2),
                    t_value = mean_car / sqrt(var_car),
                    p_value = pt(abs(t_value), df = n(), lower.tail = F)*2,
                    sign = stars(p_value))
```

```
## # A tibble: 1 x 5
##   mean_car var_car t_value p_value sign
##   <dbl>    <dbl>   <dbl>   <dbl> <chr>
## 1    0.206 0.000893    6.89 0.000460 ***
```

So we can see, that we have detected highly significant returns in the time-period $[-3, +3]$. If we want to test multiple time-periods we can do it like this.

4.3 Multiple Time Windows

It may seem a bit more complicated, but we are essentially doing the same thing as before, but use a `lapply`-function to loop over the row-numbers and repeat the process.

```
time_windows <- data_frame(min = c(-1, 0, -1, -3),
                           max = c(0, 1, 1, 3))

list_events <- lapply(1:nrow(time_windows), function(i) {
  tmp <- indiv_event %>% filter(event_time >= time_windows$min[i] &
                               event_time <= time_windows$max[i]) %>%

    select(company, ar) %>%
    group_by(company) %>%
    summarise(car = sum(ar)) %>%
    summarise(mean_car = mean(car),
              var_car = 1/(n()*(n() - 1)) * sum((car - mean_car)^2),
              t_value = mean_car / sqrt(var_car),
              p_value = pt(abs(t_value), df = n(), lower.tail = F)*2,
              sign = stars(p_value)) %>%
    mutate(range = paste0("[", time_windows$min[i], ", ",
                          time_windows$max[i], "]" ))
  return(tmp %>% select(range, car = mean_car, t_value, p_value, sign))
})

# lapply returns a list of data_frames, to bind them into a single df, we use
# do.call in combination with rbind.
mult_events <- do.call(rbind, list_events)
mult_events
```

```
## # A tibble: 4 x 5
```

##	range	car	t_value	p_value	sign
##	<chr>	<dbl>	<dbl>	<dbl>	<chr>
## 1	[-1, 0]	0.164	5.27	0.00188	**
## 2	[0, 1]	0.184	5.85	0.00110	**
## 3	[-1, 1]	0.178	5.06	0.00231	**
## 4	[-3, 3]	0.206	6.89	0.000460	***