Practicum 1

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Econometrics A

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The first two parts of this assignment were completed on my iPad and their screenshots are on pages 2-5. This includes questions 1 and 2 from the main document. Page 6 marks the start of the code portion of this assignment, starting with question 3 where I calculate the Least Squares estimate of β.

1 Bookwork

2 Alternative Representations of $\hat{\beta}_2$

$\boxed{\text{Assignment 1}}$

$\boxed{\text{Bookwork}}$ Ch.2: 2, 7, 9, 13

② $y = \beta_0 + \beta_1 x + u \quad E(u) \neq \emptyset \quad a_0 = E(u)$

If the expected value of the error of a model is not $\emptyset$, it implies that the model is a poor fit for the data.

Supposing $\alpha_0 = E(u) \rightarrow z = u - \alpha_0$ so $E(z) = E(u - \alpha_0) = E(u) - \alpha_0 = \emptyset$

So $\longrightarrow y = \beta_0 + \beta_1 x + (\alpha_0 + z)$

↪ Combine $\beta_0 + \alpha_0$ since they are both constants; new intercept of α_0

↪ $y = \alpha_0 + \beta_1 x + z$ where $E(z) = \emptyset$

⑦ ⓘ $sav = \beta_0 + \beta_1 inc + u \quad u = \sqrt{inc} \cdot e$

e is a random variable with $E(e) = \emptyset$ and $Var(e) = \sigma^2$

Show that $E(u|inc) = \emptyset$:

$E(u|inc) = \emptyset,\ u = \sqrt{inc} \cdot e \rightarrow E(\sqrt{inc}\, e \mid inc) = \emptyset ? \rightarrow \sqrt{inc}\, E(e|inc) = ?$

$\longrightarrow \sqrt{inc} \cdot \emptyset = \emptyset ? \longrightarrow \emptyset = \emptyset$ ✓

• zero conditional mean assumption states that $E(u|x) = \emptyset$ or the error does not vary across x_i after controlling for them, and since inc is the independent variable in this regression, it is saying that $E(u|\sqrt{inc}) = \emptyset$ so it is satisfied.

ⓘⓘ Show that $Var(u|inc) = \sigma^2 inc$ (homoskedasticity assumption violation)

AKA, Var of sav increases with inc...

$Var(\sqrt{inc} \cdot e \mid inc) = \sigma^2 inc$

$\sqrt{inc}\ Var(e \mid inc) = \sigma^2 inc$

$\underline{\sqrt{inc}\ Var(\sigma^2 \mid inc) = \sigma^2 inc} \longleftarrow \boxed{\text{Violation}}$

(iii) I think this makes sense intuitively since on the lower end of the earnings spectrum, it is likely more challenging for individuals to put away money to save because it has a higher opportunity cost (like affording essentials). Similarly, the more you have the more you will likely save due to limited time and interest. once youve bought everything, what happens to your additional earnings?

(9) (i) $\hat{\beta}_0\ \hat{\beta}_1 \longrightarrow y_i\ x_i \rightarrow n$ obs $\longrightarrow c_1 c_2 \neq \emptyset$

$$y_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$$
$$c_1 y_i = \tilde{\beta}_0 + \tilde{\beta}_1 c_2 x_i$$

} Show that $\tilde{\beta}_1 = \left(\frac{c_1}{c_2}\right)\hat{\beta}_0$ and $\tilde{\beta}_0 = c_1\hat{\beta}_0$

Say we scale the regression x_i on y_i by c_2 and c_1 respectively.

$$y^* = c_1 y \Rightarrow y = \frac{y^*}{c_1}$$
$$x^* = c_2 x \Rightarrow x = \frac{x^*}{c_2}$$
$$\longrightarrow \frac{y^*}{c_1} = \hat{\beta}_0 + \hat{\beta}_1\left(\frac{x^*}{c_2}\right)$$

$$\Rightarrow \underline{y^* = \boxed{\hat{\beta}_0 c_1} + \boxed{\hat{\beta}_1 \frac{c_1}{c_2}} x^*}$$

(ii) $(c_1 + y_i) = \tilde{\beta}_0 + \underline{\tilde{\beta}_1}(c_2 + x_i) \Rightarrow y_i = \underline{\hat{\beta}_0 - \hat{\beta}_1 c_2 + c_1} + \underline{\hat{\beta}_1 x_i}$

(iii) $\log(y_i) = \hat{\beta}_0 + \hat{\beta}_1 x_i$ where $y_i > 0$

$$\log(c_1 y_i) = \hat{\beta}_0 + \hat{\beta}_1 x_i \Rightarrow \log(c_1) + \log(y_i) = \hat{\beta}_0 + \hat{\beta}_1 x_i$$
$$\log(y_i) = \hat{\beta}_0 + \hat{\beta}_1 x_i - \log(c_1)$$
$$\log(y_i) = \underbrace{\hat{\beta}_0 + \log(c_1)}_{\tilde{\beta}_0} + \underbrace{\hat{\beta}_1 x_i}_{\tilde{\beta}_1}$$

(iv) $y_i = \tilde{\beta}_0 + \tilde{\beta}_1 \log(x_i c_2)$

$$\underbrace{\tilde{\beta}_0 + \log(c_2)}_{\text{adds } \log(c_2)} \quad \underbrace{\tilde{\beta}_1 \log(x)}_{\text{Same as}}$$

(13) (i) $\bar{y} = \frac{1}{n}\sum y_i$ We can write $n_0 = \sum_{i=1}^{n}(1-x_i), n_1 = \sum_{i=1}^{n} x_i$

This is because you are summing up every instance where $X_i = \emptyset$, in which case the binary indicator for n_0 would trigger, equaling 1 and if X_i is not zero it would not trigger, equaling $\emptyset$. Similarly, for n_1 the X_i value either triggers at 1 or doesnt at $\emptyset$

$\bar{X}_n$ would be the portion of the time X_i is triggered as being equal to 1 and similarly, $(1-\bar{X}) = n_0/n$ is the portion where X_i is triggered as $\emptyset$

(ii) $\bar{y}_0 = n_0^{-1}\sum(1-x_i)y_i$ and $\bar{y}_1 = n_1^{-1}\sum x_i y_i$

This is, ineffect, saying that the average of y_i when $X_i = \emptyset$ equals the sum of the product of all triggered y_i values divided by the total number of times n_0 was triggered. Similarly, the average of y_i when $X_i = 1$ is the sum of all triggered values of y_i given that $X_i = 1$ divided by the number of times n_1 was triggered.

(iii) $y_i = (1-x_i)y_i + x_i y_i$ so the average of y_i, $\bar{y}$ would be equal to the weighted average of triggered y_0 values and y_1 values summed, where X_i is the indicator variable.

(iv) When X_i is binary $n^{-1}\sum x_i^2 - (\bar{x})^2 = \bar{x}(1-\bar{x})$ because the when X_i is binary, its squared value is the same value (e.g. $1^2 = 1$, $\emptyset^2 = \emptyset$). In both cases, we are talking about subtracting weighted averages from eachother: $n^{-1}\sum x_i^2 = \frac{1}{n}\sum x_i^2 = \bar{x}_i - \bar{x}^2 = \emptyset$

(v) Similar to the previous equation, $n^{-1}\sum x_i y_i = \frac{1}{n}\sum x_i y_i = \bar{x}\bar{y}$ and that minus $\bar{x}\bar{y} = \emptyset$ while on the right

$\bar{x}(\bar{y}_1 - \bar{y}_0 - \bar{x}\bar{y}_1 - \bar{x}\bar{y}_0) = \bar{x}\bar{y}_1 - \bar{x}\bar{y}_0 + \bar{x}\bar{y}_1 - \bar{x}\bar{y}_0 = \emptyset$

(vi) use (iv) and (v) to obtain (2.74): $\hat{\beta}_1 = \bar{y}_1 - \bar{y}_0$

$$\hat{\beta}_1 = \bar{y}_1 - \bar{y}_0 \longrightarrow \text{avg } y_i | x=1 - \text{avg } y_i | x=0 \Rightarrow$$

$$= n_1^{-1} \sum x_i y_i - n^{-1} \sum (1-x_i) y_i = \bar{y}_1 - \bar{y}_0 = \hat{\beta}_1$$

* slope here equals the difference in average y_i (binary)

(vii) Derrive (2.73): $\hat{\beta}_0 = \bar{y}_0$

$$\hat{\beta}_0 = \bar{y}_1 - \bar{y}_0 \longrightarrow \bar{y}_1 - \bar{y}_0 = (\bar{y}_0 + \bar{y}_1) - \bar{y}_0 = \bar{y}_0$$

So $\hat{\beta}_0 = \bar{y}_0$ The intercept estimate is just the weighted average of the sum of all triggered y_i values given that $x_i = 1$, since its binary

Other Stuff

(2) $\hat{\beta}_2 = \dfrac{\sum x_i y_i - n\bar{x}\bar{y}}{\sum x_i^2 - n\bar{x}^2}$ = $\dfrac{\text{summed product of observed x and y variables minus the product of the the xy means and } n}{\text{sum of all x values squared minus the sum of } n \text{ and the average x value squared}}$

Expanded to shifted mean form $\longrightarrow$ $\hat{\beta}_2 = \dfrac{\sum x_i (y_i - \bar{y})}{\sum x_i (x_i - \bar{x})}$ (Partial centering form)

These say that $\hat{\beta}_2$ is the quotient of the product of the sum of all differences between observed and mean xy values divided by the sum of all squared differences between x and its mean.

$$\hat{\beta}_2 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$ (centered form)

They are equivalent to each other and the first equation in that they all find the same bit of information just in slightly different ways and equal $\frac{\text{cov } xy}{\text{var } x}$.

$$\sum x_i (x_i - \bar{x}) = \sum (x_i^2 - x_i \bar{x}) = \sum x_i^2 - n\bar{x}^2$$

3 Lease Squares Estimate of β

4 Is January Different?

5 COVID Lockdown: Event Studies

practicum_1

Kieran Douglas

3) Least Squares Estimates of

A)

```r
# Load data and packages
library(tidyquant)
```

```
Registered S3 method overwritten by 'quantmod':
  method            from
  as.zoo.data.frame zoo
```

```
-- Attaching core tidyquant packages ----------------------- tidyquant 1.0.11 --
v PerformanceAnalytics 2.0.8      v TTR                  0.24.4
v quantmod             0.4.28     v xts                  0.14.1
-- Conflicts ------------------------------------------ tidyquant_conflicts() --
x zoo::as.Date()                 masks base::as.Date()
x zoo::as.Date.numeric()         masks base::as.Date.numeric()
x PerformanceAnalytics::legend() masks graphics::legend()
x quantmod::summary()            masks base::summary()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

```r
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.4     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
```

```
x dplyr::filter() masks stats::filter()
x dplyr::first()  masks xts::first()
x dplyr::lag()    masks stats::lag()
x dplyr::last()   masks xts::last()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

```r
library(data.table)
```

```


Attaching package: 'data.table'

The following objects are masked from 'package:lubridate':

    hour, isoweek, mday, minute, month, quarter, second, wday, week,
    yday, year

The following objects are masked from 'package:dplyr':

    between, first, last

The following object is masked from 'package:purrr':

    transpose

The following objects are masked from 'package:xts':

    first, last

The following objects are masked from 'package:zoo':

    yearmon, yearqtr
```

```r
library(car)
```

```

Loading required package: carData

Attaching package: 'car'

The following object is masked from 'package:dplyr':

    recode
```

```
The following object is masked from 'package:purrr':

    some
```

```
stock <- tq_get(
  c("XOM", "BAC", "^GSPC", "^IRX"),
  get = "stock.prices",
  from = "2010-01-01",
  to = "2019-12-31",
  naa.rm = TRUE
)

# group data by date
stock_clean <- stock %>%
  select(date, symbol, adjusted, volume, open, high, low, close) %>%
  pivot_wider(
    names_from = symbol,
    values_from = c(adjusted, volume, open, high, low, close)
  ) %>%
  na.omit()

# My expectation is that Bank of America will be a riskier asset
# than Exxon since banks would probably be more prone
#  to exposure to broader shifts in  the economy
# We are using US treasury yield as the risk free rate,
# s&p500 index as the market rate, EXXON as the risky rate and BAC as the safe rate
# calculate returns
stock_clean$irx_return <-
  (stock_clean$`close_^IRX` - lag(stock_clean$`close_^IRX`)) /lag(stock_clean$`close_^IRX`)
stock_clean$xom_return <-
  (stock_clean$close_XOM - lag(stock_clean$close_XOM)) /lag(stock_clean$close_XOM)
stock_clean$bac_return <-
  (stock_clean$close_BAC - lag(stock_clean$close_BAC)) /lag(stock_clean$close_BAC)
stock_clean$gspc_return <-
  (stock_clean$`close_^GSPC` - lag(stock_clean$`close_^GSPC`)) /lag(stock_clean$`close_^GSPC

#Divide your sample in two, the first half spanning January 2010-December 2014,
#  and the second half covering January 2015-December 2019.
# I want to work with the data from 2010-2014
from2010to2014 <- stock_clean %>%
  filter(date >= as.Date("2010-01-01") & date <= as.Date("2014-12-31"))
```

```r
from2015to2019 <- stock_clean %>%
  filter(date>= as.Date("2015-01-01") & date<= as.Date("2019-12-31"))
```

B)

```r
# Estimating the CAPM model
# start by calculating market-riskfree dif and firm-riskfree dif for xom
from2010to2014$excessreturn_xom <- from2010to2014$xom_return-from2010to2014$irx_return
from2010to2014$mrpremium <- from2010to2014$gspc_return-from2010to2014$irx_return

from2015to2019$excessreturn_xom <- from2015to2019$xom_return-from2015to2019$irx_return
from2015to2019$mrpremium <- from2015to2019$gspc_return-from2015to2019$irx_return

# run xom model for each year bundle
xom_model1 <- lm(data = from2010to2014, excessreturn_xom~mrpremium)
summary(xom_model1)
```

```
Call:
lm(formula = excessreturn_xom ~ mrpremium, data = from2010to2014)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.038727 -0.003741  0.000118  0.004001  0.031858 

Coefficients:
              Estimate Std. Error  t value Pr(>|t|)    
(Intercept) -0.0002530  0.0001966   -1.287    0.198    
mrpremium    0.9996397  0.0003828 2611.634   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.006914 on 1254 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.9998,	Adjusted R-squared:  0.9998 
F-statistic: 6.821e+06 on 1 and 1254 DF,  p-value: < 2.2e-16
```

```r
xom_model2 <- lm(data = from2015to2019, excessreturn_xom~mrpremium)
summary(xom_model2)
```

```
Call:
lm(formula = excessreturn_xom ~ mrpremium, data = from2015to2019)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.042968 -0.005099 -0.000308  0.005190  0.047702 

Coefficients:
              Estimate Std. Error  t value Pr(>|t|)    
(Intercept) -0.0005414  0.0002638   -2.053   0.0403 *  
mrpremium    1.0001004  0.0005262 1900.636   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0093 on 1254 degrees of freedom
Multiple R-squared:  0.9997,    Adjusted R-squared:  0.9997 
F-statistic: 3.612e+06 on 1 and 1254 DF,  p-value: < 2.2e-16
```

```r
# now by calculating market-riskfree dif and firm-riskfree dif for bac
from2010to2014$excessreturn_bac <- from2010to2014$bac_return-from2010to2014$irx_return
from2010to2014$mrpremium <- from2010to2014$gspc_return-from2010to2014$irx_return

from2015to2019$excessreturn_bac <- from2015to2019$bac_return-from2015to2019$irx_return
from2015to2019$mrpremium <- from2015to2019$gspc_return-from2015to2019$irx_return

bac_model1 <- lm(data = from2010to2014, excessreturn_bac~mrpremium)
summary(bac_model1)
```

```
Call:
lm(formula = excessreturn_bac ~ mrpremium, data = from2010to2014)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.135995 -0.008491 -0.000793  0.007794  0.120903 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -7.878e-05  5.149e-04  -0.153    0.878    
mrpremium    1.001e+00  1.002e-03 998.475   <2e-16 ***
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01811 on 1254 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.9987,    Adjusted R-squared:  0.9987
F-statistic: 9.97e+05 on 1 and 1254 DF,  p-value: < 2.2e-16
```

```
bac_model2 <- lm(data = from2015to2019, excessreturn_bac~mrpremium)
summary(bac_model2)
```

```

Call:
lm(formula = excessreturn_bac ~ mrpremium, data = from2015to2019)

Residuals:
      Min        1Q    Median        3Q       Max
-0.056393 -0.006984 -0.000624  0.006376  0.071586

Coefficients:
             Estimate Std. Error  t value Pr(>|t|)
(Intercept) 0.0002645  0.0003413    0.775    0.439
mrpremium   0.9997472  0.0006809 1468.311   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01203 on 1254 degrees of freedom
Multiple R-squared:  0.9994,    Adjusted R-squared:  0.9994
F-statistic: 2.156e+06 on 1 and 1254 DF,  p-value: < 2.2e-16
```

```
# It seems like all of my regressions came back with beta coefficients close
#  to what would be expected if the individual stock just followed market trends.
#  I dont see any meaningful deviation from this in the data.
#  The only weirdness is in the alphas, where we rarely have statistical significance.
#  This is not super surprising though, an.
#  all alpha values are close to zero suggesting a very low excess of the stocks
#  return being explained by more than just the beta coeficient.
# These are not ststistically significant though (might have to do with outliers?)
```

C)

It kind of seems like some of the major dips in premium for the Bank of America happen right around election cycles. I see that pre 2012 and pre 2016 there are some of the larger dips, but they are few and far between.

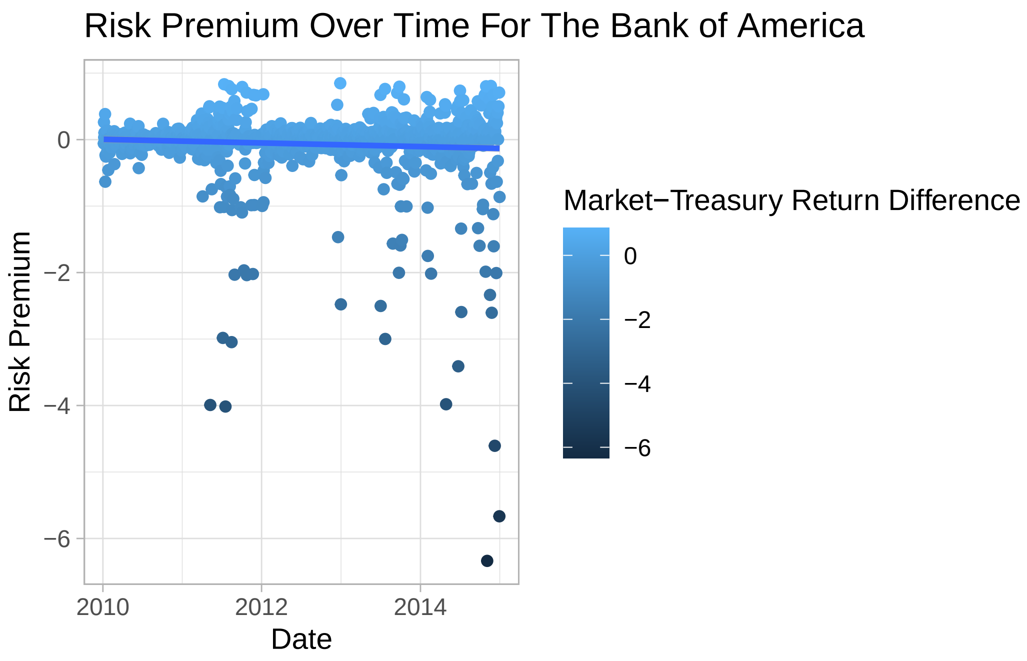
```r
ggplot(data = from2010to2014, mapping = aes(x = date, y = excessreturn_bac, color = mrpremiu
  geom_point() +
  geom_smooth(method = lm) +
  theme_light() +
  labs(title = "Risk Premium Over Time For The Bank of America",
  x = "Date", y = "Risk Premium", color = "Market-Treasury Return Difference")
```

```
`geom_smooth()` using formula = 'y ~ x'
```

```
Warning: Removed 1 row containing non-finite outside the scale range
(`stat_smooth()`).
```

```
Warning: The following aesthetics were dropped during statistical transformation:
colour.
i This can happen when ggplot fails to infer the correct grouping structure in
  the data.
i Did you forget to specify a `group` aesthetic or to convert a numerical
  variable into a factor?
```

```
Warning: Removed 1 row containing missing values or values outside the scale range
(`geom_point()`).
```



D)E)

Hypothesis testing! In each of these hypothesis tests there is insufficient evidence to conclude that for D) the intercept differs from 0 and for E) the premium coefficient differs from 1. This is to be expected when firms have returns that are in line with market trends.

```
# hpoothesis test that a=0
linearHypothesis(bac_model1, "(Intercept) = 0")
```

```
Linear hypothesis test:
(Intercept) = 0

Model 1: restricted model
Model 2: excessreturn_bac ~ mrpremium

  Res.Df     RSS Df  Sum of Sq      F Pr(>F)
1   1255 0.41107
2   1254 0.41107  1 7.6731e-06 0.0234 0.8784
```

```r
linearHypothesis(xom_model1, "(Intercept) = 0")
```

```
Linear hypothesis test:
(Intercept) = 0

Model 1: restricted model
Model 2: excessreturn_xom ~ mrpremium

  Res.Df      RSS Df  Sum of Sq      F Pr(>F)
1   1255 0.060020
2   1254 0.059941  1 7.9118e-05 1.6552 0.1985
```

```r
# the f stat being effectively 0 with a relatively
#  high p value indicates that we cannot reject the null hypothesis.
# I think that a rejection out the null in this case
#  would probably invalidate the results, as a nonzero alpha indicates
#  that the market risk does not fully explain the abnormal returns.

# Using the li
linearHypothesis(bac_model1, "mrpremium = 1")
```

```
Linear hypothesis test:
mrpremium = 1

Model 1: restricted model
Model 2: excessreturn_bac ~ mrpremium

  Res.Df     RSS Df  Sum of Sq      F Pr(>F)
1   1255 0.41129
2   1254 0.41107  1 0.00022808 0.6958 0.4044
```

```r
linearHypothesis(xom_model1, "mrpremium = 1")
```

```
Linear hypothesis test:
mrpremium = 1

Model 1: restricted model
Model 2: excessreturn_xom ~ mrpremium

  Res.Df      RSS Df Sum of Sq      F Pr(>F)
1   1255 0.059983
2   1254 0.059941  1 4.236e-05 0.8862 0.3467
```

```
# from this I find that the null hypothesis can only be rejected
#  for the more volatile industry, the Bank of America.
# For the bank I dont find this surprising since it was
# shown to not follow market trends.
# For Exxon I also dont find the nonrejection
# surprising since it was fairly normal in paramaters.
```

F)

The output I received showing proportional market risk makes lots of sense and confirms that the stocks I chose are normal market movers. The market risk proportion is close to 1 for both indicating that almost all of the risk and excess returns from each company can be explained by the more systematic market risk. The market movements explain the volatility.

```
# bank of america prop risk
beta <- coef(bac_model1)
market_var <- var(from2010to2014$mrpremium, na.rm = TRUE)

asset_var_bac <- var(from2010to2014$excessreturn_bac, na.rm = TRUE)

# Proportion of risk attributable to market
proportion_market_risk_bac <- (beta^2 * market_var) / asset_var_bac
print(proportion_market_risk_bac)
```

```
 (Intercept)    mrpremium
6.188243e-09 9.987437e-01
```

```
# exxon prop risk
beta <- coef(xom_model1)
market_var <- var(from2010to2014$mrpremium, na.rm = TRUE)

asset_var_xom <- var(from2010to2014$excessreturn_xom, na.rm = TRUE)

# Proportion of risk attributable to market
proportion_market_risk_xom <- (beta^2 * market_var) / asset_var_xom
print(proportion_market_risk_xom)
```

```
 (Intercept)    mrpremium
6.402889e-08 9.998162e-01
```

G)

In my sample, large estimates of $\beta$ definitely correspond with higher R^2 values.

This makes sense given what we have learned about the two stocks in question being pretty highly linked in behavior to broader market moves. I would not expect this to always be the case though. We could imagine a case where a stock has a very small (negative) beta value but a high R^2. In this scenario, maybe the beta value implies effectively opposite movements to the broader market. This can still be well explained by the model, it just operates in the opposite way that we would a typical "market-tracking" stock to.^

4) Is January Different?

A)

The market risk premium would be unaffected in this case because there would be no change in compensation for risk to speak of since everything is scaling up. Adding or subtracting the same amount from both of them would leave their difference unchanged. In the case that the risk free and market are affected by the same amount, using CAPM wouldn't make sense because the excess return relation would remain unchanged as stated before. It would probably make more sens to interpret January is different as something that applies to only riskier assets for it to be reasonable to test with the CAPM framework. This is due to the fact that CAPM prices excess returns while in this scenario, the risk premium would be no different than other times of the year, fuzzing any real effect.

B)

In this case I think it is clear that the market risk premium would be higher by j_m because it is specified that only the risk free is not being affected. If a and $\beta$ were constant we would have $r_p' = r_f + \beta(r_m - r_f) + \beta_{jm} = r_p + \beta_{jm}$which absent β_{jm} is just $rf + \beta(rm - rf) = rp$ which is just the same equation as in the typical non-January months. I think this would indicate that unable to individually identify j_m CAPM wouldn't allow you to distinguish January from the rest of the months.

C)D)

```r
# download monthly price data for the companies of interest:
#  Apple, Exxon, and Chase (3 different industries).
library(ggthemes)
library(tidyquant)
library(tidyverse)
library(car)

# Define tickers and date range
tickers <- c("AAPL", "BAC", "XOM")
start_date <- "2010-01-01"
end_date <- "2019-12-31"

# Download monthly prices for each ticker
prices_monthly <- tq_get(
  tickers,
  from = start_date,
  to = end_date,
  get = "stock.prices",
  periodicity = "monthly"
)

prices_monthly <- prices_monthly %>%
  mutate(jan_dummy = ifelse(month(date) == 1, 1, 0)) %>%
  group_by(symbol) %>%
  arrange(date) %>%
  mutate(rp = (adjusted / lag(adjusted)) - 1) %>%
  ungroup()

# Get S&P 500 data and calculate market returns
sp500 <- tq_get("^GSPC", from = start_date, to = end_date, get = "stock.prices", periodicity
  arrange(date) %>%
  mutate(rm = (adjusted / lag(adjusted)) - 1)

# Merge stock and market returns
prices_monthly_joined <- prices_monthly %>%
  left_join(sp500 %>% select(date, rm), by = "date")

# Filter out rows with NA in rp or rm before running regressions
run_model <- function(symbol) {
  data <- prices_monthly_joined %>%
    filter(symbol == symbol, !is.na(rp), !is.na(rm))
  model <- lm(rp ~ rm + jan_dummy, data = data)
  summary(model)
}

# Run and print summaries for each company
cat("AAPL:\n")
```

```
AAPL:
```

```r
print(run_model("AAPL"))
```

```

Call:
lm(formula = rp ~ rm + jan_dummy, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.207901 -0.034834 -0.004002  0.038635  0.236591 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.002307   0.003450   0.669    0.504    
rm           1.206637   0.090195  13.378   <2e-16 ***
jan_dummy   -0.009112   0.012181  -0.748    0.455    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06076 on 354 degrees of freedom
Multiple R-squared:  0.3358,	Adjusted R-squared:  0.332 
F-statistic: 89.49 on 2 and 354 DF,  p-value: < 2.2e-16
```

```r
cat("\nXOM:\n")
```

```

XOM:
```

```r
print(run_model("XOM"))
```

```

Call:
```

```
lm(formula = rp ~ rm + jan_dummy, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.207901 -0.034834 -0.004002  0.038635  0.236591 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.002307   0.003450   0.669    0.504    
rm           1.206637   0.090195  13.378   <2e-16 ***
jan_dummy   -0.009112   0.012181  -0.748    0.455    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06076 on 354 degrees of freedom
Multiple R-squared:  0.3358,	Adjusted R-squared:  0.332 
F-statistic: 89.49 on 2 and 354 DF,  p-value: < 2.2e-16
```

```
cat("\nBAC:\n")
```

```
BAC:
```

```
print(run_model("BAC"))
```

```
Call:
lm(formula = rp ~ rm + jan_dummy, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.207901 -0.034834 -0.004002  0.038635  0.236591 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.002307   0.003450   0.669    0.504    
rm           1.206637   0.090195  13.378   <2e-16 ***
jan_dummy   -0.009112   0.012181  -0.748    0.455    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.06076 on 354 degrees of freedom
Multiple R-squared:  0.3358,    Adjusted R-squared:  0.332
F-statistic: 89.49 on 2 and 354 DF,  p-value: < 2.2e-16
```

```r
# In this case the market premium definitely matters
# but January still does not!
```

E)

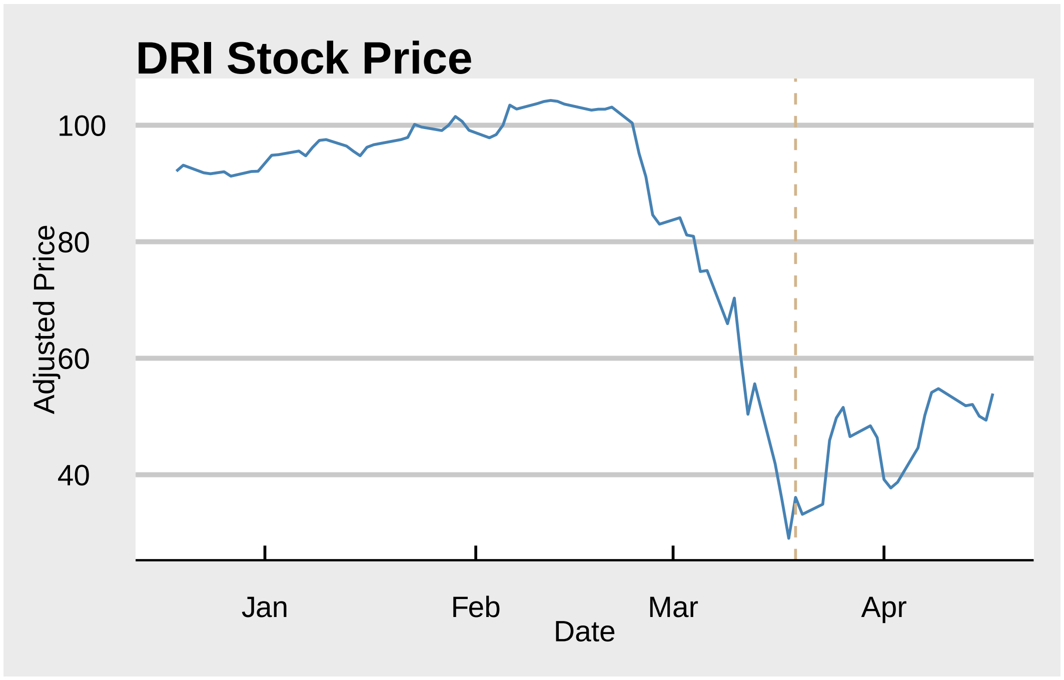
From my analysis I can conclude that for the companies I looked at and in the time frame of interest, January was not in fact different than the other months of the year. I tested this hypothesis in various ways including a simple jan dummy in addition to running a CAPM with a separate January intercept, none of which turned up results that were statistically significant. January is NOT different.

5) COVID Lockdown - Event Studies

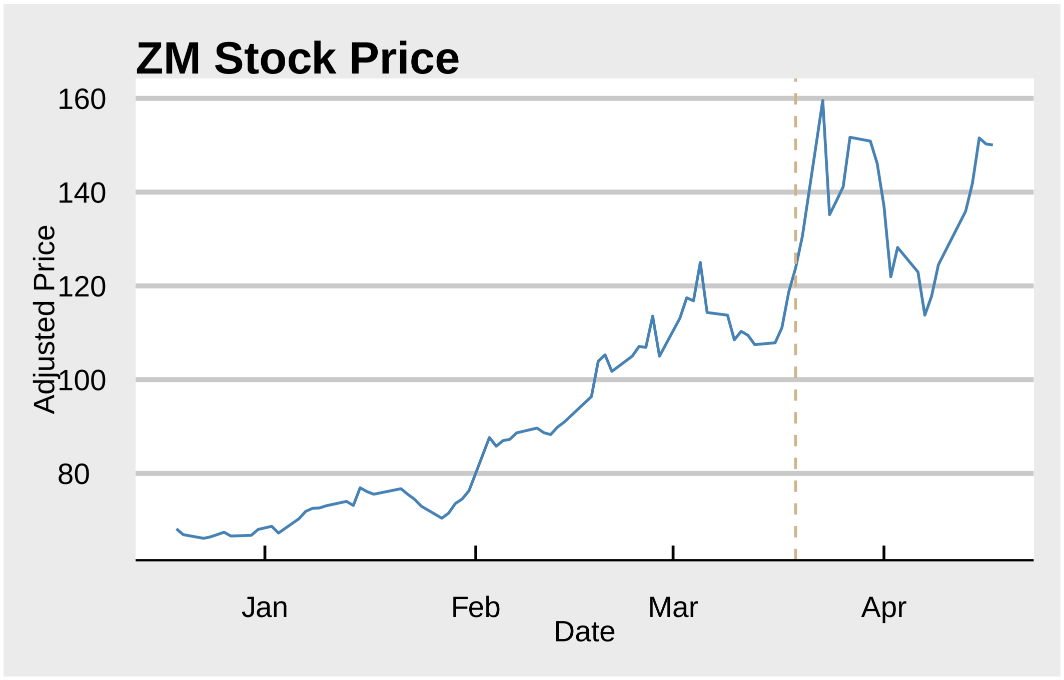
A)

```r
library(tidyquant)
library(lubridate)
library(tidyverse)
# Define tickers and date range
tickers <- c("DRI", "ZM", "PTON", "COST", "WMT", "^GSPC")
start_date <- "2019-09-19"
end_date <- "2022-09-18"

# Download daily stock prices for each ticker
prices_daily <- tq_get(
  tickers,
  from = start_date,
  to = end_date,
  get = "stock.prices",
  periodicity = "daily"
)

# defining date:
event_date <- as.Date("2020-03-19")

prices_daily <- prices_daily %>%
  mutate(event_day = as.numeric(date - event_date))
```

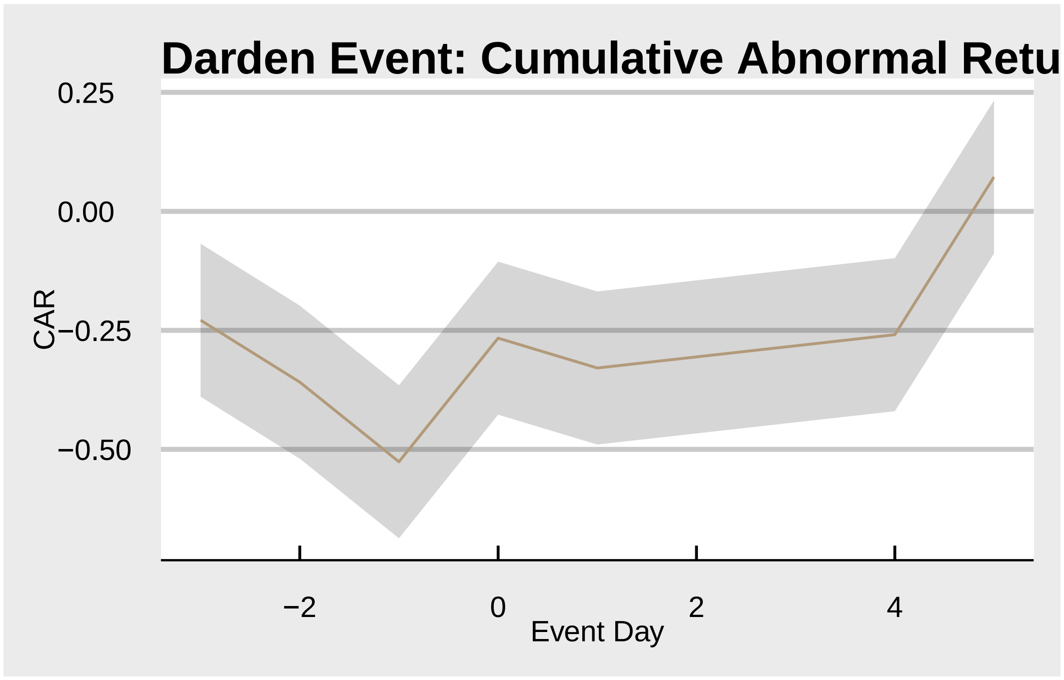
```r
# calculate % change in prices before and after the event_date
before <- prices_daily %>%
  filter(event_day == -30 | event_day == -1) %>%
  group_by(symbol) %>%
  arrange(date) %>%
  summarise(change = last(adjusted) / first(adjusted) - 1)
after <- prices_daily %>%
  filter(event_day == 0 | event_day == 30) %>%
  group_by(symbol) %>%
  arrange(date) %>%
  summarise(change = last(adjusted) / first(adjusted) - 1)

# make df for the plot
to_plot <- prices_daily %>%
  filter(date >= event_date %m-% months(3), date <= event_date %m+% months(1))

# plotting darden adjusted over time
to_plot %>% filter(symbol == "DRI") %>%
  ggplot(aes(x = date, y = adjusted)) +
  geom_line(color = "steelblue") +
  geom_vline(xintercept = as.numeric(event_date), linetype = "dashed", color = "tan") +
  labs(title = "DRI Stock Price",
       x = "Date", y = "Adjusted Price") +
        theme_economist_white()
```



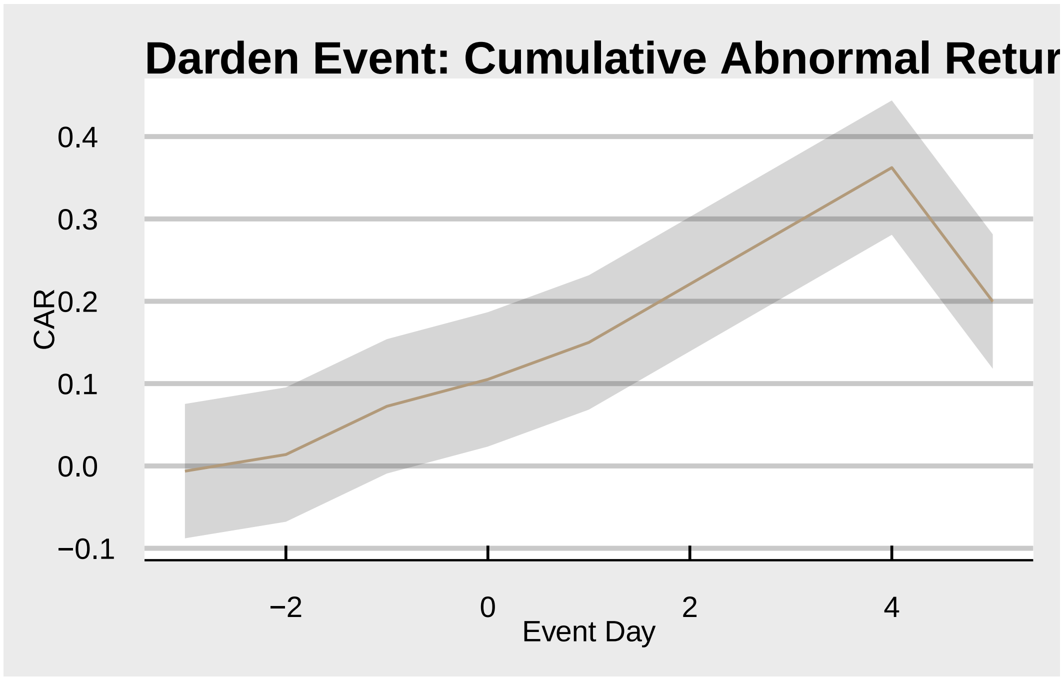
```
to_plot %>% filter(symbol == "ZM") %>%
  ggplot(aes(x = date, y = adjusted)) +
  geom_line(color = "steelblue") +
  geom_vline(xintercept = as.numeric(event_date), linetype = "dashed", color = "tan") +
  labs(title = "ZM Stock Price",
       x = "Date", y = "Adjusted Price") +
        theme_economist_white()
```



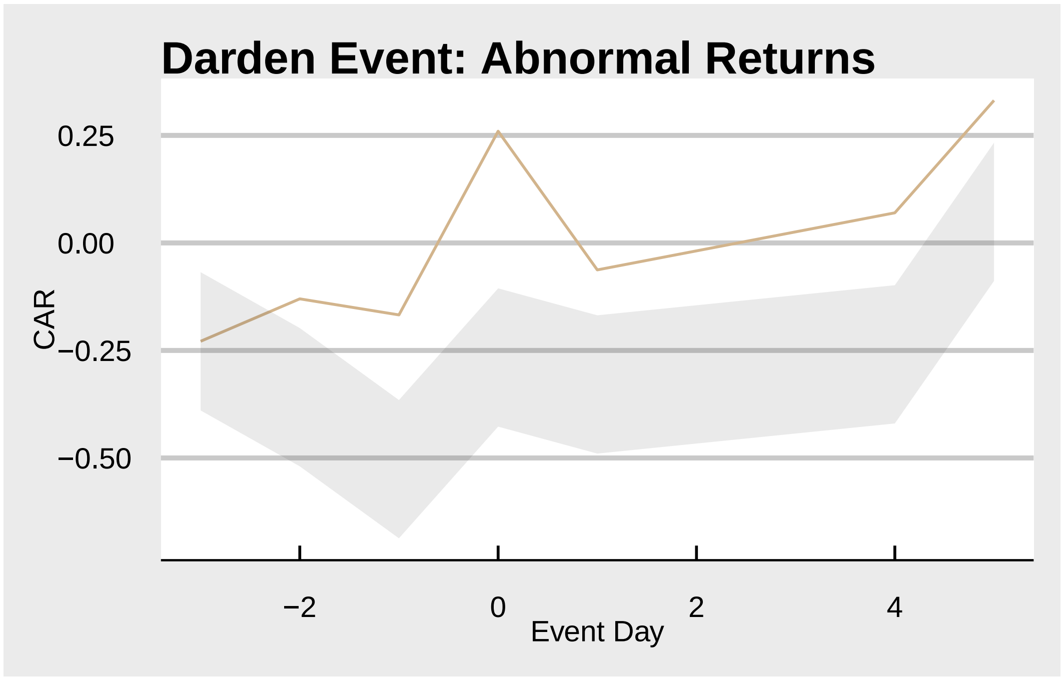
```r
#daily returns
daily_returns <- prices_daily %>%
  group_by(symbol) %>%
  arrange(date) %>%
  mutate(return = (adjusted / lag(adjusted)) - 1)

est_start <- event_date %m-% months(3)
est_end <- event_date - 1

darden <- daily_returns %>% filter(symbol == "DRI")
zoom <- daily_returns %>% filter(symbol == "ZM")

# Mean return for each
dr_mean <- darden %>%
  filter(date >= est_start, date <= est_end) %>%
  summarise(mu = mean(return, na.rm = TRUE)) %>% pull(mu)
zm_mean <- zoom %>%
  filter(date >= est_start, date <= est_end) %>%
  summarise(mu = mean(return, na.rm = TRUE)) %>% pull(mu)

# Event window (e.g., -5 to +5 days around event)
darden_event <- darden %>%
  filter(event_day >= -5, event_day <= 5) %>%
  mutate(abnormal = return - dr_mean)
zoom_event <- zoom %>%
  filter(event_day >= -5, event_day <= 5) %>%
  mutate(abnormal = return - zm_mean)

calc_dar <- function(darden_event) {
  darden_event %>%
    mutate(CAR = cumsum(abnormal)) %>%
    mutate(se = sd(abnormal, na.rm=TRUE)/sqrt(n()),
           lower = CAR - 1.96*se, upper = CAR + 1.96*se)
}

calc_zoo <- function(zoom_event) {
  zoom_event %>%
    mutate(CAR = cumsum(abnormal)) %>%
    mutate(se = sd(abnormal, na.rm=TRUE)/sqrt(n()),
           lower = CAR - 1.96*se, upper = CAR + 1.96*se)
}
darden_event <- calc_dar(darden_event)
zoom_event   <- calc_zoo(zoom_event)


# Plots for both darden and zoom for Cumulative Abnormal Returns
ggplot(darden_event, aes(x = event_day, y = CAR)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.2) +
  labs(title="Darden Event: Cumulative Abnormal Returns",
       x = "Event Day", y = "CAR") +
        theme_economist_white()
```



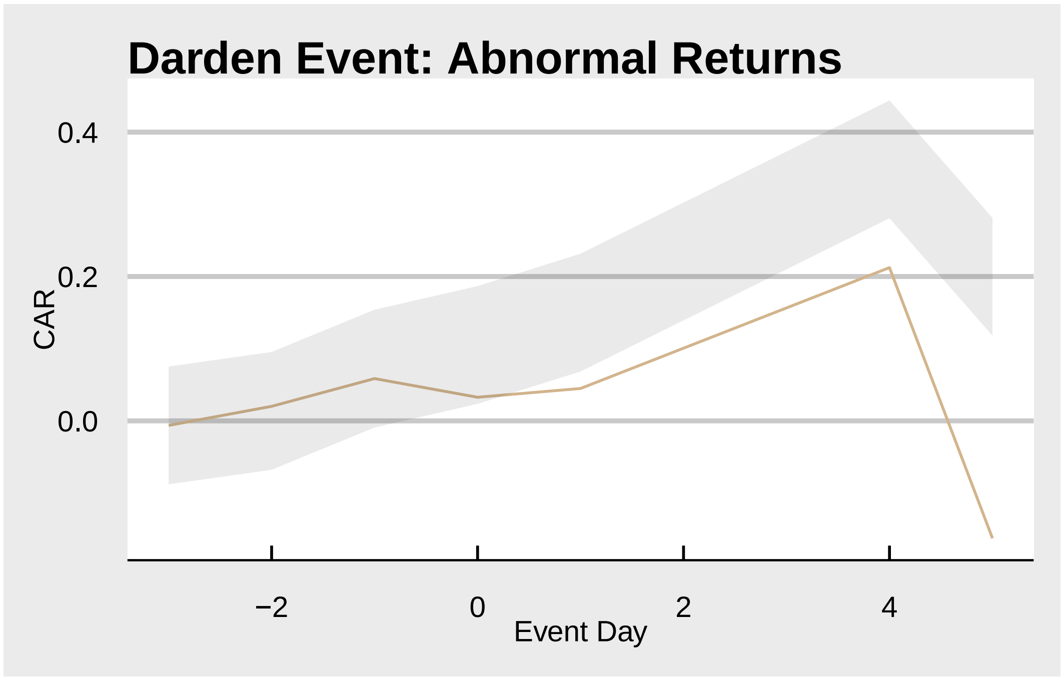
```
ggplot(zoom_event, aes(x = event_day, y = CAR)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.2) +
  labs(title="Darden Event: Cumulative Abnormal Returns",
       x = "Event Day", y = "CAR") +
        theme_economist_white()
```



```
ggplot(darden_event, aes(x = event_day, y = abnormal)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.1) +
  labs(title="Darden Event: Abnormal Returns",
       x = "Event Day", y = "CAR") +
        theme_economist_white()
```



```
ggplot(zoom_event, aes(x = event_day, y = abnormal)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.1) +
  labs(title="Darden Event: Abnormal Returns",
       x = "Event Day", y = "CAR") +
        theme_economist_white()
```



Before the lockdown, prices changes by change COST -4.52% DRI -72.65% PTON -4.76% WMT +2.47% ZM +23.16% ^GSPC -28.85%

The daily return for Darden during the event window was -24.66%, -14.79%, -18.53%, +24.18%, -8%, +5%, and +31.34% while for Zoom it was +0.36%, +3%, +6.89%, +4.26%, +5.48%, +22.22%, and -15.28%.

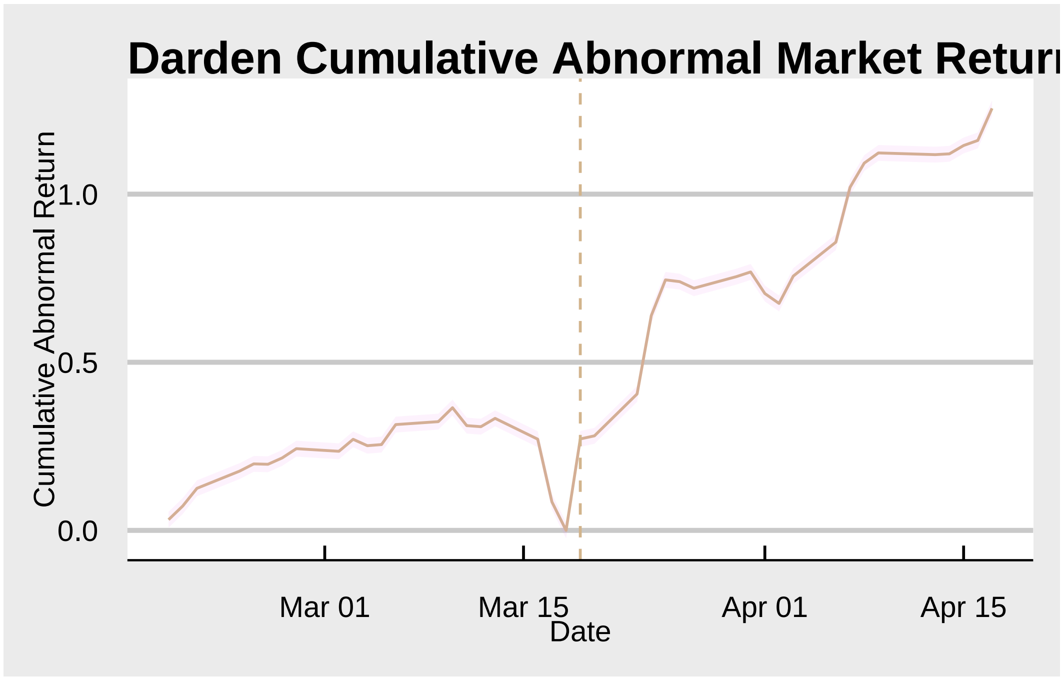
B)C)

```
gspc_df <- daily_returns %>% filter(symbol == "^GSPC") %>% select(date, sp500_return = retur
```

```
Adding missing grouping variables: `symbol`
```

```
dri <- daily_returns %>% filter(symbol == "DRI") %>% left_join(gspc_df, by = "date")

# Generate the window prior to event
event_date <- as.Date("2020-03-19")
est_start <- event_date %m-% months(1)
est_end   <- event_date - 1

dri_est <- dri %>% filter(date >= est_start, date <= est_end)
```

```r
# run the market model similar to before
mod <- lm(return ~ sp500_return, data = dri_est)
alpha <- coef(mod)[1]
beta  <- coef(mod)[2]
# a=-0.036 and b= 1.24055

# define window (1 month before/after)
window <- dri %>% filter(date >= event_date %m-% months(1), date <= event_date %m+% months(1
window <- window %>% mutate(abnormal = return - (alpha + beta * sp500_return))

# grab cumulative abnormal returns
window <- window %>%
  mutate(CAR = cumsum(abnormal))

# generate CI around the cumulative abnormal returns
ar_sd <- sd(window$abnormal, na.rm = TRUE)
n <- nrow(window)
window <- window %>%
  mutate(lower = CAR - 1.96 * ar_sd / sqrt(n),
         upper = CAR + 1.96 * ar_sd / sqrt(n))

# create a graphic of cumulative abnormal returns for the market
ggplot(window, aes(x = date, y = CAR)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.1, fill = "violet") +
  geom_vline(xintercept = as.numeric(event_date), linetype = "dashed", color = "tan") +
  labs(title = "Darden Cumulative Abnormal Market Returns)", x = "Date", y = "Cumulative Abn
  theme_economist_white()
```

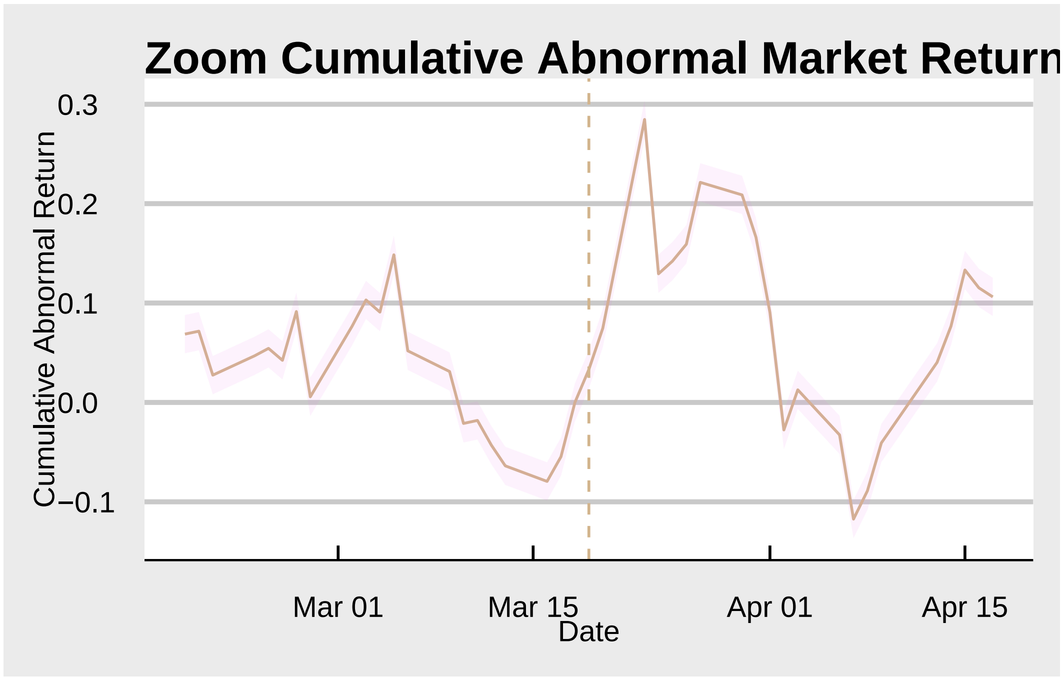


```r
### For "ZM", "PTON", "COST", and "WMT"
### ZM
gspc_df <- daily_returns %>% filter(symbol == "^GSPC") %>% select(date, sp500_return = retur
```

```
Adding missing grouping variables: `symbol`
```

```r
zm <- daily_returns %>% filter(symbol == "ZM") %>% left_join(gspc_df, by = "date")

# Generate the window prior to event
event_date <- as.Date("2020-03-19")
est_start <- event_date %m-% months(1)
est_end   <- event_date - 1

zm_est <- zm %>% filter(date >= est_start, date <= est_end)

# run the market model similar to before
mod <- lm(return ~ sp500_return, data = zm_est)
alpha <- coef(mod)[1]
beta  <- coef(mod)[2]
# a=0.00986 and b= -0.0784

# define window (1 month before/after)
```

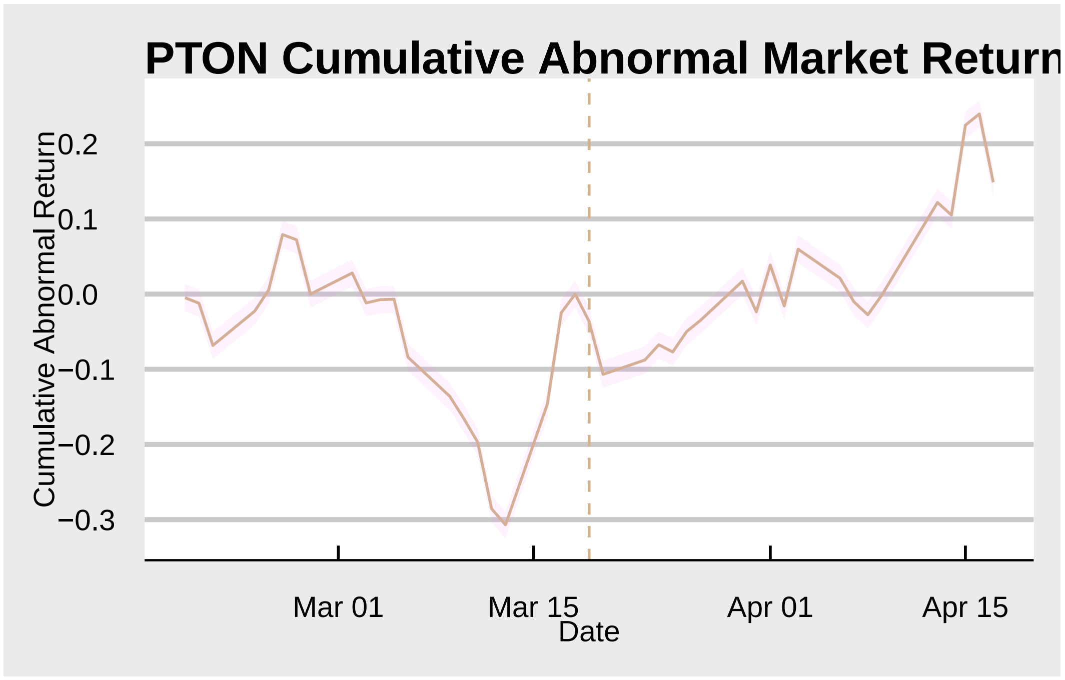
```
window <- zm %>% filter(date >= event_date %m-% months(1), date <= event_date %m+% months(1)
window <- window %>% mutate(abnormal = return - (alpha + beta * sp500_return))

# grab cumulative abnormal returns
window <- window %>%
  mutate(CAR = cumsum(abnormal))

# generate CI around the cumulative abnormal returns
ar_sd <- sd(window$abnormal, na.rm = TRUE)
n <- nrow(window)
window <- window %>%
  mutate(lower = CAR - 1.96 * ar_sd / sqrt(n),
         upper = CAR + 1.96 * ar_sd / sqrt(n))

# create a graphic of cumulative abnormal returns for the market
ggplot(window, aes(x = date, y = CAR)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.1, fill = "violet") +
  geom_vline(xintercept = as.numeric(event_date), linetype = "dashed", color = "tan") +
  labs(title = "Zoom Cumulative Abnormal Market Returns)", x = "Date", y = "Cumulative Abnor
  theme_economist_white()
```



```
### PTON
gspc_df <- daily_returns %>% filter(symbol == "^GSPC") %>% select(date, sp500_return = retur
```

```
Adding missing grouping variables: `symbol`
```

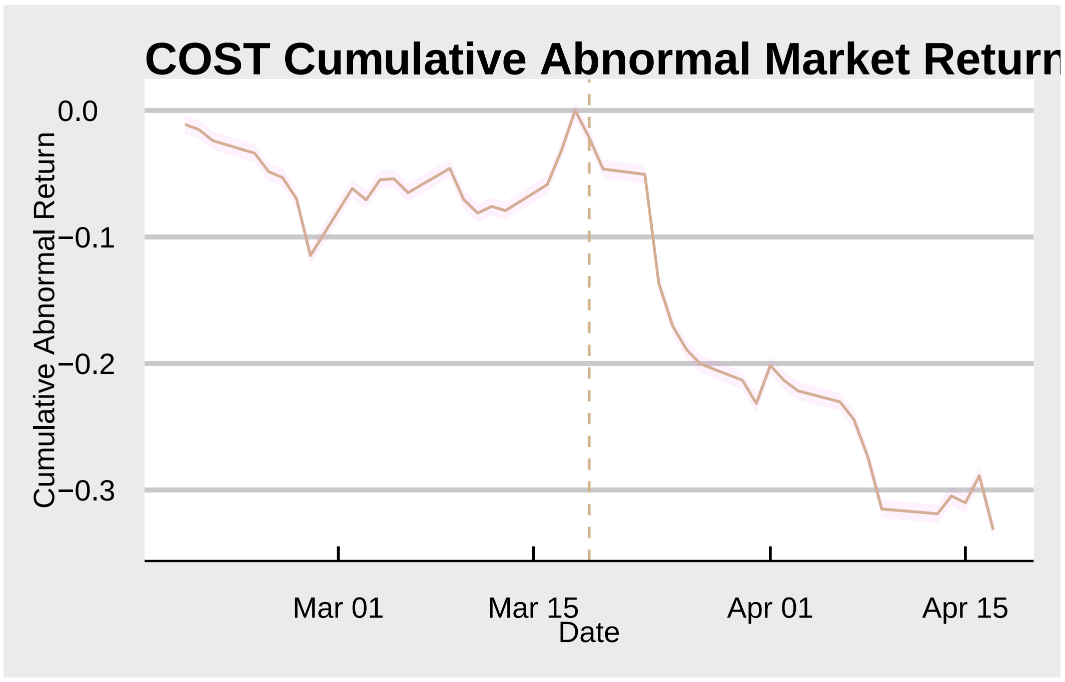
```
pton <- daily_returns %>% filter(symbol == "PTON") %>% left_join(gspc_df, by = "date")

# Generate the window prior to event
event_date <- as.Date("2020-03-19")
est_start <- event_date %m-% months(1)
est_end   <- event_date - 1

pton_est <- pton %>% filter(date >= est_start, date <= est_end)

# run the market model similar to before
mod <- lm(return ~ sp500_return, data = pton_est)
alpha <- coef(mod)[1]
beta  <- coef(mod)[2]
# a=0.0041 and b= 0.302

# define window (1 month before/after)
window <- pton %>% filter(date >= event_date %m-% months(1), date <= event_date %m+% months(
window <- window %>% mutate(abnormal = return - (alpha + beta * sp500_return))

# grab cumulative abnormal returns
window <- window %>%
  mutate(CAR = cumsum(abnormal))

# generate CI around the cumulative abnormal returns
ar_sd <- sd(window$abnormal, na.rm = TRUE)
n <- nrow(window)
window <- window %>%
  mutate(lower = CAR - 1.96 * ar_sd / sqrt(n),
         upper = CAR + 1.96 * ar_sd / sqrt(n))

# create a graphic of cumulative abnormal returns for the market
ggplot(window, aes(x = date, y = CAR)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.1, fill = "violet") +
  geom_vline(xintercept = as.numeric(event_date), linetype = "dashed", color = "tan") +
  labs(title = "PTON Cumulative Abnormal Market Returns)", x = "Date", y = "Cumulative Abnor
  theme_economist_white()
```



```
### COST
gspc_df <- daily_returns %>% filter(symbol == "^GSPC") %>% select(date, sp500_return = retur
```

```
Adding missing grouping variables: `symbol`
```

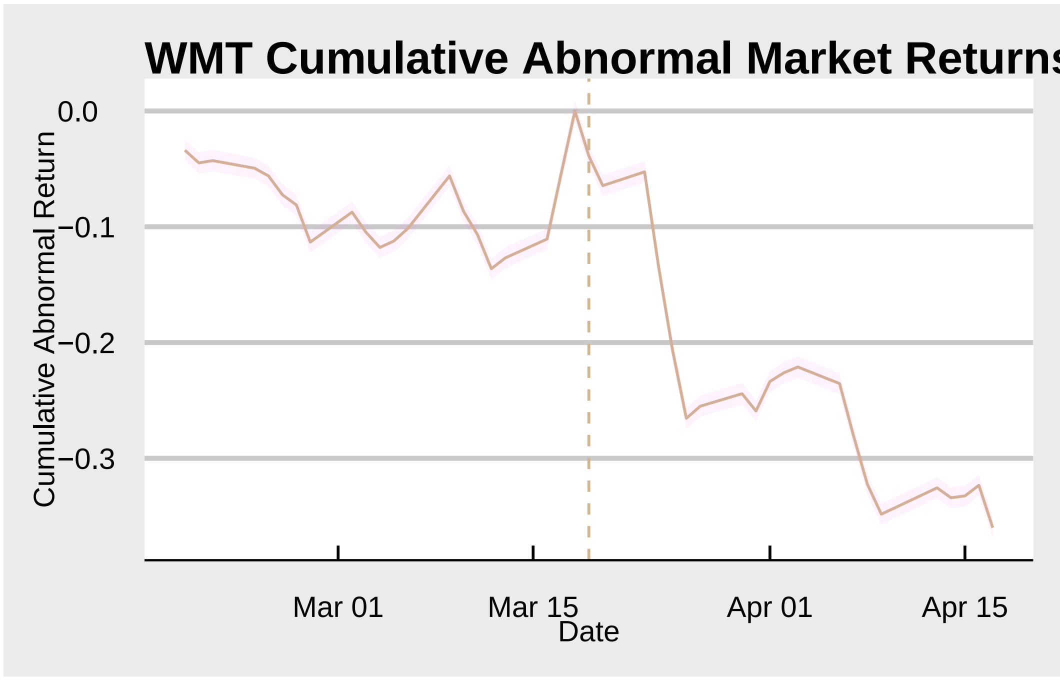
```
cost <- daily_returns %>% filter(symbol == "COST") %>% left_join(gspc_df, by = "date")

# Generate the window prior to event
event_date <- as.Date("2020-03-19")
est_start <- event_date %m-% months(1)
est_end   <- event_date - 1

cost_est <- cost %>% filter(date >= est_start, date <= est_end)

# run the market model similar to before
mod <- lm(return ~ sp500_return, data = cost_est)
alpha <- coef(mod)[1]
beta  <- coef(mod)[2]
# a=0.01039 and b= 0.7857

# define window (1 month before/after)
window <- cost %>% filter(date >= event_date %m-% months(1), date <= event_date %m+% months(
window <- window %>% mutate(abnormal = return - (alpha + beta * sp500_return))

# grab cumulative abnormal returns
window <- window %>%
  mutate(CAR = cumsum(abnormal))

# generate CI around the cumulative abnormal returns
ar_sd <- sd(window$abnormal, na.rm = TRUE)
n <- nrow(window)
window <- window %>%
  mutate(lower = CAR - 1.96 * ar_sd / sqrt(n),
         upper = CAR + 1.96 * ar_sd / sqrt(n))

# create a graphic of cumulative abnormal returns for the market
ggplot(window, aes(x = date, y = CAR)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.1, fill = "violet") +
  geom_vline(xintercept = as.numeric(event_date), linetype = "dashed", color = "tan") +
  labs(title = "COST Cumulative Abnormal Market Returns)", x = "Date", y = "Cumulative Abnor
  theme_economist_white()
```



```
### WMT
gspc_df <- daily_returns %>% filter(symbol == "^GSPC") %>% select(date, sp500_return = return
```

```
Adding missing grouping variables: `symbol`
```

```
wmt <- daily_returns %>% filter(symbol == "WMT") %>% left_join(gspc_df, by = "date")

# Generate the window prior to event
event_date <- as.Date("2020-03-19")
est_start <- event_date %m-% months(1)
est_end   <- event_date - 1

wmt_est <- wmt %>% filter(date >= est_start, date <= est_end)

# run the market model similar to before
mod <- lm(return ~ sp500_return, data = wmt_est)
alpha <- coef(mod)[1]
beta  <- coef(mod)[2]
# a=0.0139 and b= 0.7895

# define window (1 month before/after)
window <- wmt %>% filter(date >= event_date %m-% months(1), date <= event_date %m+% months(1
window <- window %>% mutate(abnormal = return - (alpha + beta * sp500_return))

# grab cumulative abnormal returns
window <- window %>%
  mutate(CAR = cumsum(abnormal))

# generate CI around the cumulative abnormal returns
ar_sd <- sd(window$abnormal, na.rm = TRUE)
n <- nrow(window)
window <- window %>%
  mutate(lower = CAR - 1.96 * ar_sd / sqrt(n),
         upper = CAR + 1.96 * ar_sd / sqrt(n))

# create a graphic of cumulative abnormal returns for the market
ggplot(window, aes(x = date, y = CAR)) +
  geom_line(color = 'tan') +
  geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.1, fill = "violet") +
  geom_vline(xintercept = as.numeric(event_date), linetype = "dashed", color = "tan") +
  labs(title = "WMT Cumulative Abnormal Market Returns)", x = "Date", y = "Cumulative Abnorma
  theme_economist_white()
```



I have successfully computed and plotted all of the CAR using a market model for each stock over the specified event window. SUrprisingly, Darden spiked a bit in a period where, given that it's industry, would be unexpected. After using the market model rather than just price changes, the outcome does change and the event seems to have a significant impact on Darden. This effect however, is positive??? This is odd.

It seems like whether the market sees the lockdown as a good or a bad thing depends on the industry. WTM and COST have decreasing returns on average during the post lockdown period, suggesting that grocery stores see a decrease. This feels counterintuitive to me as since more people are staying home I would expect them to eat out less. Perhaps it could be that people are ordering more food now rather than going to buy things to avoid going out. Darden and Peloton see positive returns on average in the post period, which in some ways backs my arguement of people ordering takeout more often rather than going to grocery stores. I think the PTON could be explained by the fact that they focus on "connective fitness" which is largely remote (makes sense if people stay home). THe "Zoom Boom" makes a lot of sense intuitively, as people would now be more likely to meet remotely since they arent leaving their homes. I think the market viewed the effect of lockdowns on different industries differently because different industries could benefit more or less from peoples tendency to leave their homes.