Investments Strategy

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0. Assumption

We suppose that the market is not efficient in practice.

Search out mispriced securities.

(follow Active investment strategy)

Ⅰ. Our objective

※ Our objective : to maximize the utility

- considered not just the profit, but the risk of securities.

So we attempted to

1. find underpriced stocks.
2. make an optimal portfolio by using these stocks.

II. Security Selection

✓ The way we chose stocks we want

※ Criteria for judging 'underpriced'

The stocks have ··· 1. positive alpha value ?

2. low price ratio ?

+) We also considered

3. low beta value ?

4. low correlation ?

we obtained the values by doing Data analysis.

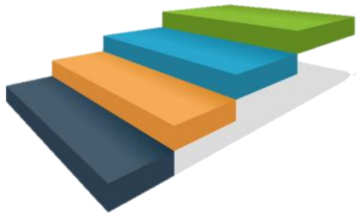
Ⅱ. Security Selection

✓ The data we used for analysis

- Market Index : KOSPI 200 TIGER ETF
- CD rates (risk-free asset)
- Time period (2017.10.31 ~ 2019.10.31)
- Analysis Tool : Excel & R (statistical program)

Ⅱ. Security Selection

✓ The Steps of analysis



1. Induce SML of CAPM.
   → pick the stocks which have positive 'alpha'(otherwise drop)

2. Among them, find low price-ratio and low beta stocks.

3. Identify the correlation between stocks.
   → finally pick stocks of which correlation is low.

4. Form Tangent Portfolio.

Ⅱ. Security Selection

※ Before analysis, we collected and cleaned the data.

✓ Data crawling

1. Crawled the data of all listed stocks on KRX.

- data : stock name, adjusted stock price, etc. (based on last business day)
- except for preferred stocks, funds.
- total : 2075 stocks
- reference : https://www.krx.co.kr

2. Crawled the data of financial statement of each stock.

- To calculate the price ratio of each stock, extracted the value of ROE, EPS, Sales.
- reference : https://comp.fnguide.com

Raw data

	market	code number	stock name	industry	closing price	change	capital stock
1	KOSPI	5930	Samsung electronics	electrical electronics	50400	-700	3.01E+14
2	KOSPI	660	SK Hynix	electrical electronics	81500	-1500	5.93E+13
3	KOSPI	207940	Samsung BioLogics	medication	397000	-3500	2.63E+13
4	KOSPI	68270	Celltrion	medication	204000	-1500	2.62E+13
5	KOSPI	5380	Hyundai Motor Company	transportation equipment	122500	0	2.62E+13
⋮							
2070	KOSDAQ	69330	UID	IT H/W	1060	-15	12601059520
2071	KOSDAQ	192410	Gammanu	IT H/W	408	0	9969806400
2072	KOSDAQ	83470	KJpretech	IT H/W	387	0	9560730123
2073	KOSDAQ	222810	HanryuAI Center	IT S/W & SVC	386	0	8486706396
2074	KOSDAQ	30270	S-Mark	textile fabrics, clothing	998	0	7547575598
2075	KOSDAQ	149940	Moda	IT H/W	155	0	3279863395

Raw data

	PER	PBR	PCR	PSR	code number
2062	NA	1.548443	19.44156	2.430196	96870
2063	NA	0.757953	NA	0.180313	113810
2064	NA	9.90286	NA	1.438877	123260
2065	NA	3.06806	NA	0.427391	106080
2066	NA	0.696826	NA	0.283086	28040
2067	NA	0.724225	4.762325	0.111617	53060
2068	0.892909	0.208345	NA	0.310302	194510
2069	NA	0.405177	NA	0.889138	33790
2070	NA	0.443699	NA	2.571645	69330
2071	NA	0.216485	NA	0.294551	192410
2072	NA	0.831368	2.276364	0.17904	83470
2073	NA	0.459315	NA	0.704513	222810
2074	NA	0.281626	NA	0.531519	30270
2075	NA	0.053857	NA	0.029898	149940

Ⅱ. Security Selection

※ Before analysis, we collected and cleaned the data.

✓ Data crawling

3. Crawled the data of CD rates.

- reference : http://ecos.bok.or.kr
- raw data

Date	Daily rates
2017-01-01	
2017-01-02	1.52
2017-01-03	1.52
2017-01-04	1.51
2017-01-05	1.51
2017-01-06	1.49

～

Date	Daily rates
2019-11-04	1.46
2019-11-05	1.49
2019-11-06	1.5
2019-11-07	1.52
2019-11-08	1.52

II. Security Selection

※ Before analysis, we collected and cleaned the data.

✓ Data preprocessing

we wanted each stock's monthly return
monthly market return
monthly CD rates.

```r
KOR_price = read.csv('data/KOR_price.csv',
                     stringsAsFactors = FALSE)
dim(KOR_price) # daily return for 2076 stocks
colnames(KOR_price)[1] <- 'date'
KOR_price <-  # process to make montly return
  KOR_price %>%
  separate(date, into = c('year', 'month', 'day'), sep = '-') %>%
  unite(year_month, year, month, sep = '-') %>%
  group_by(year_month) %>%
  filter(day == max(day)) %>%   # only take monthly return
  separate(year_month, into = c('year', 'month'), sep = '-') %>%   # preprocess y-m-d form
  unite(date, year, month, day, sep = '-') %>%
  column_to_rownames(var = 'date')
KOR_price <- KOR_price[-dim(KOR_price)[1], ]  # last row is 2019-11-01, so remove

# make monthly return matrix
return_mat = Return.calculate(KOR_price)
return_mat <- return_mat[-1, ] # first row NA generate
write.csv(return_mat, 'data/return_matrix_2076stocks.csv') # make excel file
```

<R code>

So **firstly,**

we arranged the data of each stock's closing price (daily → monthly) and calculated the monthly return.

※ Time period : 2017.10.31 ~ 2019.10.31

Preprocess the data

2017-10-30	54040	79800	374000
2017-10-31	55080	82200	384000
2017-11-01	57220	85300	406000
2017-11-02	57060	83400	392500
2017-11-03	56380	84400	395500
2017-11-06	56380	83500	394500
2017-11-07	56100	82400	389000
2017-11-08	56760	83200	387000

⋮

2019-10-22	51200	79100	344000
2019-10-23	51200	77700	372500
2019-10-24	50700	80000	378000
2019-10-25	50900	82900	383500
2019-10-28	51300	82900	398000
2019-10-29	51100	83000	400500
2019-10-30	50400	81500	397000
2019-10-31	50400	82000	398500

2075 stock's closing price

	X005930	X000660	X207940
2017-11-30	-0.0777	-0.0657	-0.1081
2017-12-28	0.00315	-0.0039	0.08321
2018-01-31	-0.0208	-0.0392	0.18194
2018-02-28	-0.0569	0.0449	0.02623
2018-03-30	0.0459	0.05859	0.08222
2018-04-30	0.0768	0.03936	0.00205
2018-05-31	-0.0434	0.10533	-0.1086
2018-06-29	-0.0799	-0.0824	-0.0414
2018-07-31	-0.0086	0.007	-0.1055
2018-08-31	0.04757	-0.0382	0.24129
2018-09-28	-0.0413	-0.1193	0.15335
2018-10-31	-0.0872	-0.067	-0.2743
2018-11-30	-0.013	0.02053	-0.1368
2018-12-28	-0.0753	-0.1307	0.15546
2019-01-31	0.19251	0.22149	0.03234
2019-02-28	-0.0228	-0.0528	-0.0576
2019-03-29	-0.01	0.06	-0.1503
2019-04-30	0.02688	0.06469	0.06416
2019-05-31	-0.0731	-0.1734	-0.1176
2019-06-28	0.10588	0.06432	0.06667
2019-07-31	-0.0351	0.10647	-0.125
2019-08-30	-0.0298	0.0065	-0.0393
2019-09-30	0.11477	0.06202	0.14312
2019-10-31	0.02752	-0.0024	0.29593

…

X060380	X035200	X023790
-0.0064	0.05754	0.00126
0.00648	-0.0097	-0.0528
0.12882	0.03136	0.12483
-0.0742	0.4222	-0.039
0.03698	-0.2316	-0.0332
0.211	-0.0924	-0.0241
-0.0994	0.06737	0.34375
0.0218	-0.0841	-0.1618
-0.1067	-0.003	0.00462
0.0791	-0.0147	-0.0449
-0.0429	-0.0179	0.0253
-0.1676	-0.2658	-0.215
0.02604	0.02521	0.18713
0.00846	0.06715	-0.0303
0.12584	0.09306	0.19376
-0.0238	-0.0297	-0.0305
-0.058	-0.1281	-0.0528
0.02917	0.03994	0.09964
-0.0236	-0.0323	0.137
-0.0065	0.14762	0.0759
-0.0714	-0.1895	-0.2813
-0.0175	0.09556	-0.0773
0.03915	-0.0405	0.11037
0.00171	-0.0373	-0.0515

2075 stock's monthly return

Ⅱ. Security Selection

Secondly, the same process was applied to the market return.

```r
symbols = c('102110.KS')  # take kospi 200 ETF
getSymbols(symbols)
market_prices = do.call(cbind,
                 lapply(symbols, function(x)Cl(get(x)))) # make price data frame
market_prices <- market_prices['2017-10::2019-10'] # required period
colnames(market_prices) <- 'Kospi200_ETF' # change column name
market_prices <- market_prices[complete.cases(market_prices)] # remove NA
market_prices <- as.data.frame(market_prices)

market_prices <-
  market_prices %>%
  mutate(date = row.names(market_prices)) %>%
  separate(date, into = c('year', 'month', 'day'), sep = '-') %>%   # i want to select ends
  unite(year_month, year, month, sep = '-') %>%
  group_by(year_month) %>%
  filter(day == max(day)) %>%   # closing prices of ends of month
  separate(year_month, into = c('year', 'month'), sep = '-') %>%   #preprocessing as y-m-d
  unite(date, year, month, day, sep = '-') %>%
  column_to_rownames(var = 'date')

market_return <- Return.calculate(market_prices) # calculate returns
market_return <- market_return[-1, ] # first row is NA, so remove it
mean(market_return)
names(market_return) <- rownames(return_mat)

write.csv(market_return, 'data/market_return.csv')
```

<R code>

2017-11-30	-0.0266
2017-12-28	0.0097
2018-01-31	0.0256
2018-02-28	-0.0602
2018-03-30	0.0092
2018-04-30	0.0097
2018-05-31	-0.0352
2018-06-29	-0.0342
2018-07-31	-0.0093
2018-08-31	0.0057
2018-09-28	0.006
2018-10-31	-0.1251
2018-11-30	0.03
2018-12-28	-0.0212
2019-01-31	0.0888
2019-02-28	-0.0055
2019-03-29	-0.0219
2019-04-30	0.0126
2019-05-31	-0.0754
2019-06-28	0.0567
2019-07-31	-0.042
2019-08-30	-0.029
2019-09-30	0.0589
2019-10-31	0.0084

<monthly market return>

※ market : KOSPI 200 TIGER ETF

Ⅱ. Security Selection

Thirdly, the same process was applied to the CD rates.

```
# make CD values for monthly return
CD = read.csv('data/CD_Monthly.csv', row.names = 1) %>% as.vector
CD
monthly_CD <- CD / 12
monthly_CD
```

<R code>

	CD
2017-11-30	0.0014
2017-12-29	0.0014
2018-01-31	0.0014
2018-02-28	0.0014
2018-03-30	0.0014
2018-04-30	0.0014
2018-05-31	0.0014
2018-06-29	0.0014
2018-07-31	0.0014
2018-08-31	0.0014
2018-09-28	0.0014
2018-10-31	0.0014
2018-11-30	0.0016
2018-12-31	0.0016
2019-01-31	0.0016
2019-02-28	0.0016
2019-03-29	0.0016
2019-04-30	0.0015
2019-05-31	0.0015
2019-06-28	0.0015
2019-07-31	0.0013
2019-08-30	0.0012
2019-09-30	0.0013
2019-10-31	0.0012

<monthly CD rates>

Ⅱ. Security Selection

Lastly, we calculated the value of market risk premium & each stock’s risk premium.

In this process, 145 stocks were excepted. → 1930 stocks remain
(∵ they has at least more than one monthly return of NA)

	X005930	X000660	X207940	X068270	X005380	X035420	X012330	X051910	X055550	X051900	X017670	X028260	X005490	X034730	X105560
2017-11-30	-0.0791	-0.0671	-0.1094	0.15461	0.02037	-0.1065	0.0249	0.03333	-0.0372	-0.0048	-0.0014	-0.1095	0.02782	0.00727	0.02432
2017-12-28	0.00177	-0.0053	0.08183	0.12552	-0.0531	0.08612	-0.0398	-0.0313	0.01928	0.01226	0.00998	-0.0468	-0.0088	-0.0322	0.05705
2018-01-31	-0.0222	-0.0406	0.18057	0.42649	0.03709	0.04461	-0.0603	0.06529	0.07757	-0.0115	-0.007	0.12561	0.14299	0.12407	0.06014
2018-02-28	-0.0583	0.04352	0.02485	0.09716	-0.0045	-0.119	-0.0802	-0.1148	-0.1121	-0.0668	-0.0974	-0.0964	-0.0513	-0.1081	-0.0504
2018-03-30	0.04452	0.05722	0.08085	-0.1246	-0.1128	-0.0151	0.04906	0.00515	-0.0372	0.09681	-0.0285	0.08812	-0.101	0.03905	-0.0529
2018-04-30	0.07542	0.03799	0.00068	-0.1258	0.11361	-0.0973	0.03412	-0.0675	0.04129	0.13273	-0.0228	-0.0014	0.14302	-0.0081	0.00686
2018-05-31	-0.0448	0.10395	-0.11	-0.0217	-0.1326	-0.067	-0.1223	-0.0611	-0.0832	-0.0211	-0.0298	-0.1049	-0.09	-0.0592	-0.155
2018-06-29	-0.0813	-0.0838	-0.0428	0.14175	-0.0985	0.13914	-0.0289	-0.0161	-0.0117	0.03809	0.04817	-0.0731	-0.0323	-0.0664	0.01793
2018-07-31	-0.0099	0.00563	-0.1069	-0.1068	0.0305	-0.063	0.0741	0.12306	0.0044	-0.1346	0.07373	0.05871	0.00318	0.016	0.01378
2018-08-31	0.04619	-0.0396	0.23991	-0.0069	-0.0361	0.04891	-0.0189	-0.0254	-0.0002	0.04408	0.04653	-0.0054	-0.0135	-0.0033	-0.0368
2018-09-28	-0.0427	-0.1207	0.15197	0.09862	0.03463	-0.0493	0.01648	-0.0027	0.03074	0.00732	0.07291	0.05147	-0.0994	0.08988	0.04698
2018-10-31	-0.0886	-0.0684	-0.2758	-0.2691	-0.179	-0.203	-0.1681	-0.052	-0.0559	-0.1832	-0.0511	-0.1636	-0.1254	-0.0903	-0.1269
2018-11-30	-0.0146	0.01894	-0.1384	0.09957	0.00311	0.10322	-0.0516	-0.0059	-0.0333	0.10953	0.07864	-0.0569	-0.0423	0.0749	-0.0058
2018-12-28	-0.0769	-0.1324	0.15385	-0.056	0.10587	-0.0372	0.05102	0.00273	-0.0404	-0.0525	-0.0707	0.02766	-0.0198	-0.078	-0.0164
2019-01-31	0.19096	0.21994	0.03079	-0.0173	0.09128	0.1132	0.18266	0.05897	0.08936	0.14741	-0.0442	0.13589	0.12602	0.01191	0.03178
2019-02-28	-0.0243	-0.0543	-0.0592	-0.0678	-0.0247	-0.0236	-0.0216	0.05957	0.00884	-0.0166	0.00811	-0.0391	-0.0417	0.03258	-0.0786
2019-03-29	-0.0116	0.05842	-0.1518	-0.1165	-0.0569	-0.0693	-0.056	-0.0643	-0.0394	0.13566	-0.0361	-0.0752	-0.0396	-0.0089	-0.058
2019-04-30	0.02534	0.06316	0.06263	0.16974	0.15746	-0.0378	0.11357	-0.0152	0.04847	0.002	-0.0174	-0.0436	0.00637	-0.0533	0.10241
2019-05-31	-0.0746	-0.175	-0.1192	-0.1053	-0.0304	-0.0685	-0.0682	-0.0791	0.0064	-0.1028	0.01059	-0.101	-0.0702	-0.099	-0.0535
2019-06-28	0.1044	0.06284	0.06518	0.0801	0.03941	0.02094	0.08377	0.06308	0.00864	0.0259	0.03245	0.03535	0.02799	0.00068	0.04532
2019-07-31	-0.0364	0.10522	-0.1263	-0.1716	-0.0977	0.20928	0.0221	-0.0492	-0.0324	-0.0439	-0.0418	-0.043	-0.079	-0.0487	-0.0547
2019-08-30	-0.031	0.00526	-0.0405	-0.0804	0.01457	0.06035	0.02988	-0.022	-0.0645	-0.0633	-0.0375	-0.059	-0.0655	-0.0963	-0.0865
2019-09-30	0.11348	0.06072	0.14183	0.04329	0.04151	0.07038	0.01279	-0.0951	0.02448	0.10727	0.00706	0.0369	0.07454	0.01871	0.07428
2019-10-31	0.02632	-0.0036	0.29473	0.21831	-0.0908	0.04339	-0.0568	0.02551	0.01555	-0.0364	-0.0198	0.11363	-0.0695	0.26596	-0.0188

<each stock’s risk premium>

	market return	CD rates	market premium
2017-11-30	-0.026622794	0.0164	-0.043022794
2017-12-28	0.009680393	0.0166	-0.006919607
2018-01-31	0.025566885	0.0165	0.009066885
2018-02-28	-0.060246327	0.0165	-0.076746327
2018-03-30	0.009158377	0.0165	-0.007341623
2018-04-30	0.009701142	0.0165	-0.006798858
2018-05-31	-0.035177437	0.0165	-0.051677437
2018-06-29	-0.034211372	0.0165	-0.050711372
2018-07-31	-0.009313155	0.0165	-0.025813155
2018-08-31	0.005707571	0.0165	-0.010792429
2018-09-28	0.006009014	0.0165	-0.010490986
2018-10-31	-0.1251037	0.017	-0.1421037
2018-11-30	0.029963967	0.019	0.010963967
2018-12-28	-0.021174738	0.0193	-0.040474738
2019-01-31	0.088788563	0.0186	0.070188563
2019-02-28	-0.00552868	0.0189	-0.02442868
2019-03-29	-0.021890202	0.019	-0.040890202
2019-04-30	0.012611012	0.0184	-0.005788988
2019-05-31	-0.075425364	0.0184	-0.093825364
2019-06-28	0.056725479	0.0178	0.038925479
2019-07-31	-0.042010772	0.015	-0.057010772
2019-08-30	-0.029047976	0.0149	-0.043947976
2019-09-30	0.058868944	0.0155	0.043368944
2019-10-31	0.00838498	0.0144	-0.00601502

<market risk premium>

Ⅲ. Security Analysis

✓ **We've learned the meaning of 'alpha' through this class.**

CAPM (2)

✦ Interpretation of alpha

$$E(r_i) - r_f = \alpha_i + \beta_i\{E(r_m) - r_f\}$$

- Suppose that the CAPM is correct. What does a non-zero alpha indicate?

	Underpriced / Overpriced
$\alpha_i > 0$	underpriced
$\alpha_i < 0$	overpriced

So, we picked the stocks which have positive 'alpha'(otherwise drop)
(among 1930 stocks)

We doubted whether …

1. the stock of which the alpha very close to zero can be said 'underpriced'
2. SML we induced is appropriate

So we examined the F-test & t-test

(Doubt 1) t-test

→ Ho : $\alpha=0$ vs H1: $\alpha\neq0$

(Doubt 2) F-test

→ Ho : $\alpha=\beta=0$ vs H1: at least one is not zero

- Significance level : 0.05

Ⅲ. Security Analysis

✓ 1. Induce SML of CAPM.

- to check alpha and beta

- by fitting the data to <u>simple linear regression model</u>.

```r
# find overpriced stocks
index_overpriced <- rep(0, 1930)
alpha_overpriced <- rep(0, 1930)
for (i in 1:1930) {
  each_premium <- as.vector(risk_premium[, i])
  fit <- lm(each_premium ~ market_premium[, 1])
  summary_fit <- summary(fit)
  if ((summary_fit$coefficients[1,1] < 0) &
      (summary_fit$coefficients[1, 4] < 0.05) &
      (summary_fit$fstatistic[1] > qf(0.95, 1, 22))) {
    index_overpriced[i] <- 1 # find which alpha is smaller than zero statistically.
    alpha_overpriced[i] <- summary_fit$coefficients[1,1]
  } else {
    index_overpriced[i] <- 0
    alpha_overpriced[i] <- 0
  }
}
table(index_overpriced)
# 14 stocks are overpriced
```

```r
# find underpriced stock
index_underpriced <- rep(0, 1930)
alpha_underpriced <- rep(0, 1930)
beta_underpriced <- rep(0, 1930)
for (i in 1:1930) {
  each_premium <- as.vector(risk_premium[, i])
  fit <- lm(each_premium ~ market_premium[, 1])
  summary_fit <- summary(fit)
  if ((summary_fit$coefficients[1, 3] > qt(0.975, 22)) &
      (summary_fit$coefficients[1,1] > 0) &
      (summary_fit$fstatistic[1] > qf(0.95, 1, 22))) {
    index_underpriced[i] <- 1
    # find which alpha is larger than zero with respect to hypothesis testing
    alpha_underpriced[i] <- summary_fit$coefficients[1,1]
    beta_underpriced[i] <- summary_fit$coefficients[2,1]
  } else {
    index_underpriced[i] <- 0
    beta_underpriced[i] <- 0
  }
}
table(index_underpriced) # 7 stocks are underpriced
```

∴ 14 overpriced stocks & 7 underpriced stocks were found.

Ⅲ. Security Analysis

✓ 1. Induce SML of CAPM.

	Code	Name	Industry	alpha
1	19180	THN	Electronic	0.053
2	51380	PC Direct	Retail	0.029
3	65770	CS	IT H/W	0.064
4	101490	S&S Tech	IT H/w	0.058
5	104460	DY P&F	Machine & Equipment	0.058
6	133820	FineBeSteel	Steel Metal	0.04
7	215200	Megastudy Edu	Services	0.107

Underpriced stocks

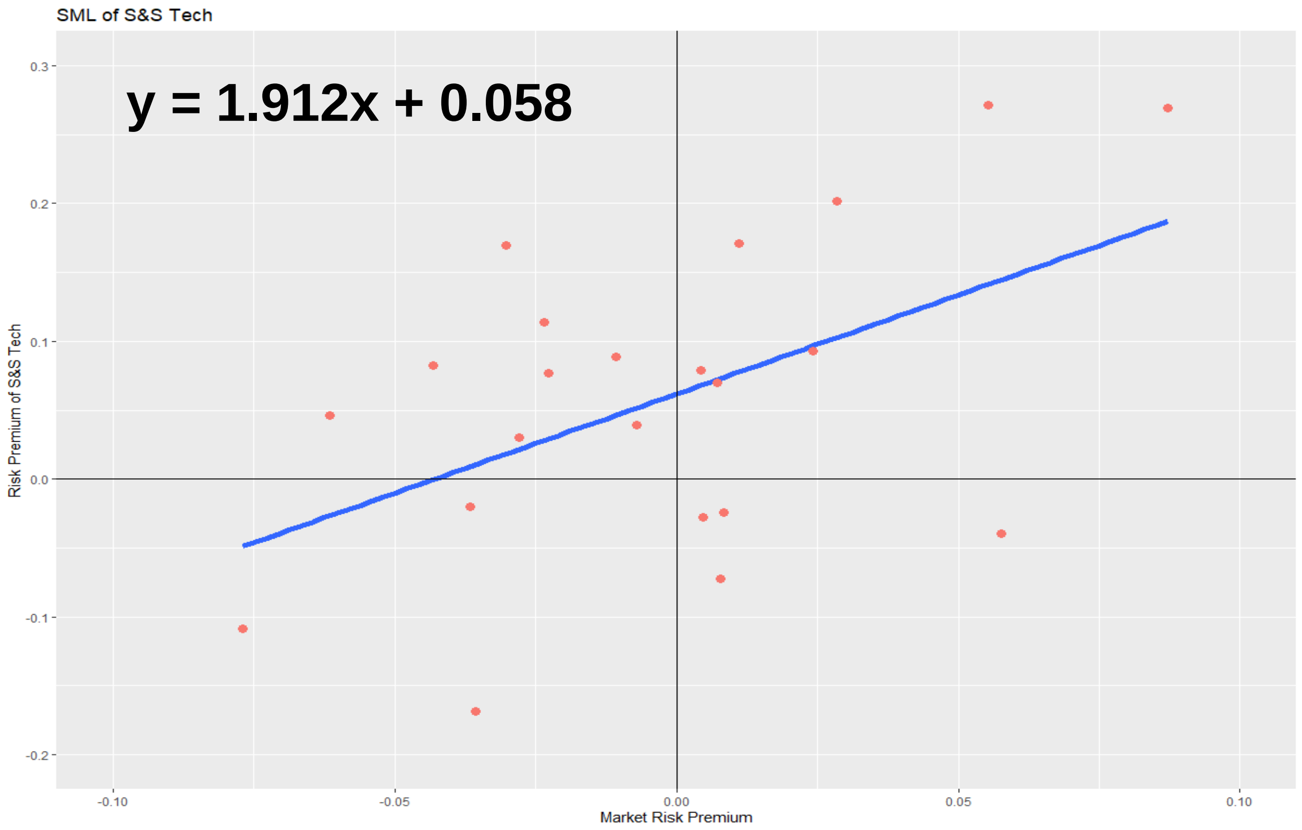
	Code	Name	Industry	alpha
1	32830	Samsung Life Insurance	Finance	-0.02
2	88350	Hanwha Life Insurance	Finance	-0.041
3	82640	Tong Yang Life Insurance Co.	Finance	-0.026
4	19680	DaeKyo	Service	-0.011
5	145990	Samyang Corp	Food & Beverage	-0.018
6	58650	Seah Holdings	Steel Metal	-0.019
7	2020	Kolon	Finance	-0.04
8	6220	Jeju Bank	Finance	-0.019
9	100130	Dongguk S&C	Metal	-0.031
10	71970	STX Heavy Industries Co.	Machine	-0.08
11	69640	Hansae MK	Retail	-0.036
12	9310	Charm Engeneering	Machine	-0.032
13	3280	Heung-A	Transportation Warehouse	-0.051
14	103130	Woongjin Energy	Electronic	-0.062

Overpriced stocks

Ⅲ. Security Analysis

✓ 1. Induce SML of CAPM.

- visualized the SML of one of the underpriced stocks.



$$\underbrace{E(r_i) - r_f}_{y} = \alpha_i + \beta_i \overbrace{\{E(r_m) - r_f\}}^{x}$$

<S&S Tech>
alpha = 0.058
beta = 1.912

Ⅲ. Security Analysis

✓ 2. Find low price-ratio and low beta stocks.

In Stock Investment,

we thought the simple criteria(whether the alpha is positive) is not efficient.

So we compared the 7 stocks based on the price ratio and beta.

Among this 7 stocks, chose relatively low price ratio stocks.

(considering PSR, PBR in priority)

&

chose relatively low beta stocks.

Ⅲ. Security Analysis

2. Find low price-ratio and low beta stocks.

Why should we consider these security conditions?

1. PSR - Considering the condition of new firm

→ It is difficult for start-up firms to make profits at the beginning of their establishment.

→ For the case of start-up firms, PER is meaningless.

2. PBR - For comparison between another industries

→ When using only PSR, it is difficult to compare different industries.

3. Beta - To exclude stocks with high volatility

→ The bigger the beta, the more sensitive it is to the market.

→ The risk of fluctuation increases

Ⅲ. Security Analysis

✓ 2. Find low price-ratio and low beta stocks.

Name	Industry	alpha	beta	PER	PBR	PCR	PSR
THN	Electronic	0.053	1.397	14.508	1.8	4.772	0.195
PC Direct	Retail	0.029	0.577	NA	1.465	14.284	0.214
CS	IT H/W	0.064	2.58	13.92	2.525	40.765	0.972
S&S Tech	IT H/w	0.058	1.912	NA	2.382	15.435	3.112
DY P&F	Machine & Equipment	0.058	1.319	11.126	2.426	13.454	1.032
FineBeSteel	Steel Metal	0.04	1.816	NA	1.011	NA	0.703
Megastudy Edu	Services	0.107	2.575	10.55	1.998	4.7	1.209

Ⅲ. Security Analysis

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Megastudy Edu	Services	0.107	2.575	10.55	1.998	4.7	1.209

Ⅲ. Security Analysis

✓ 2. Find low price-ratio and low beta stocks.

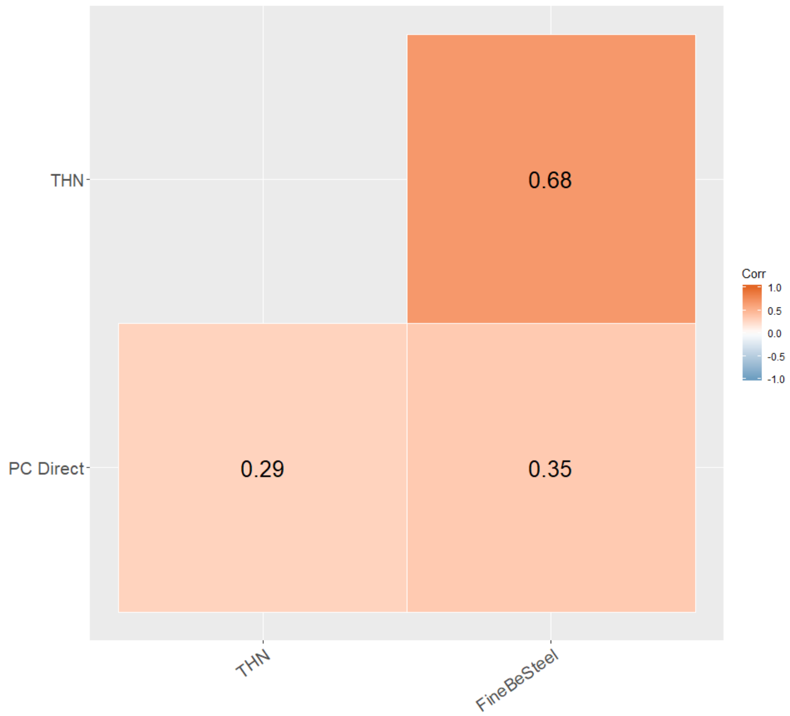
```
Value_matrix <- underpriced_stock_capm[, complete.cases(t(underpriced_stock_capm))]
chosen_stock <-
  Value_matrix %>%
  filter(beta <= 2,
         PBR <= 2,
         PSR <= 2)
chosen_stock[,'Name']
chosen_stock
# 3 stocks (THN, PC Direct and FineBeSteel) are chosen.

# 3 stocks' return
underpriced_capm_return <- return_mat[, underpriced]
colnames(underpriced_capm_return) <-
  colnames(underpriced_capm_return) %>%
  str_remove('X')
colnames(underpriced_capm_return) <-
  c('Megastudy Edu', 'S&S Tech', 'DY P&F', 'FineBeSteel', 'THN', 'CS', 'PC Direct')
three_stock_return <- underpriced_capm_return[, chosen_stock[, 'Name']]
write.csv(three_stock_return, 'data/three_stock_return.csv')
```

∴ **THN, PC Direct and FineBeSteel were selected.**

Ⅲ. Security Analysis

3. Identify the correlation between stocks.

-finally pick stocks of which correlation is low.



We want to make portfolio with two stocks not to include 'short sale'

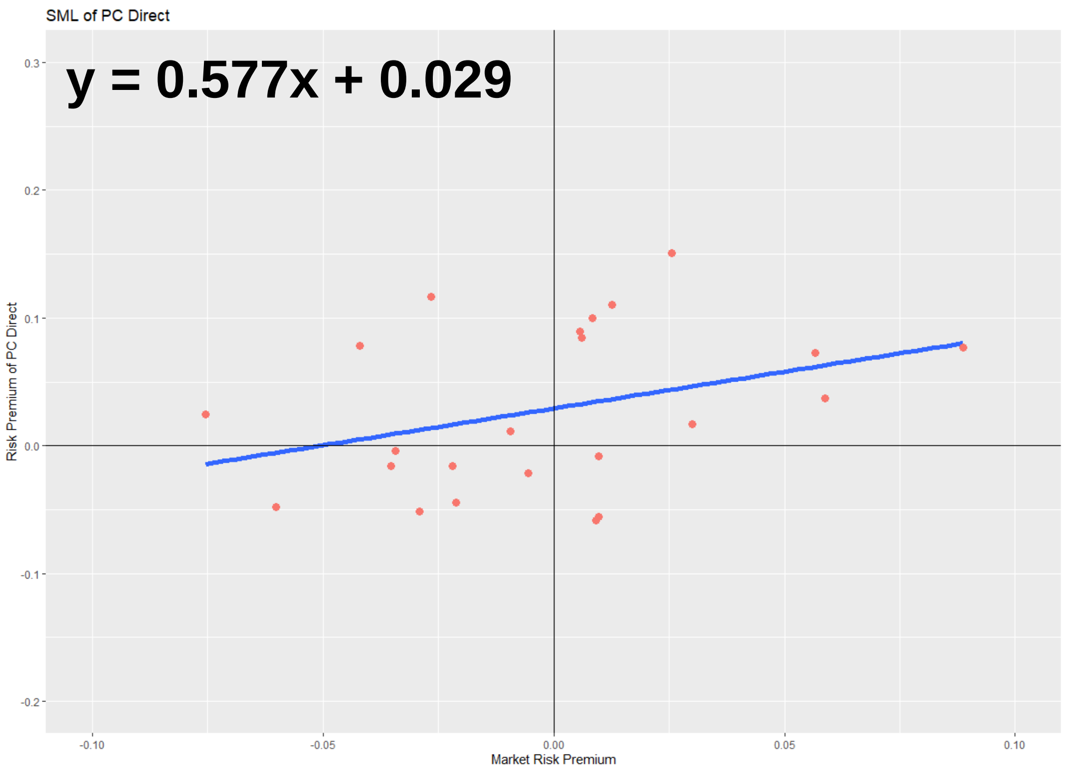
- exclude 'FineBeSteel' that has biggest correlation.

∴ Finally, THN & PC Direct were picked.

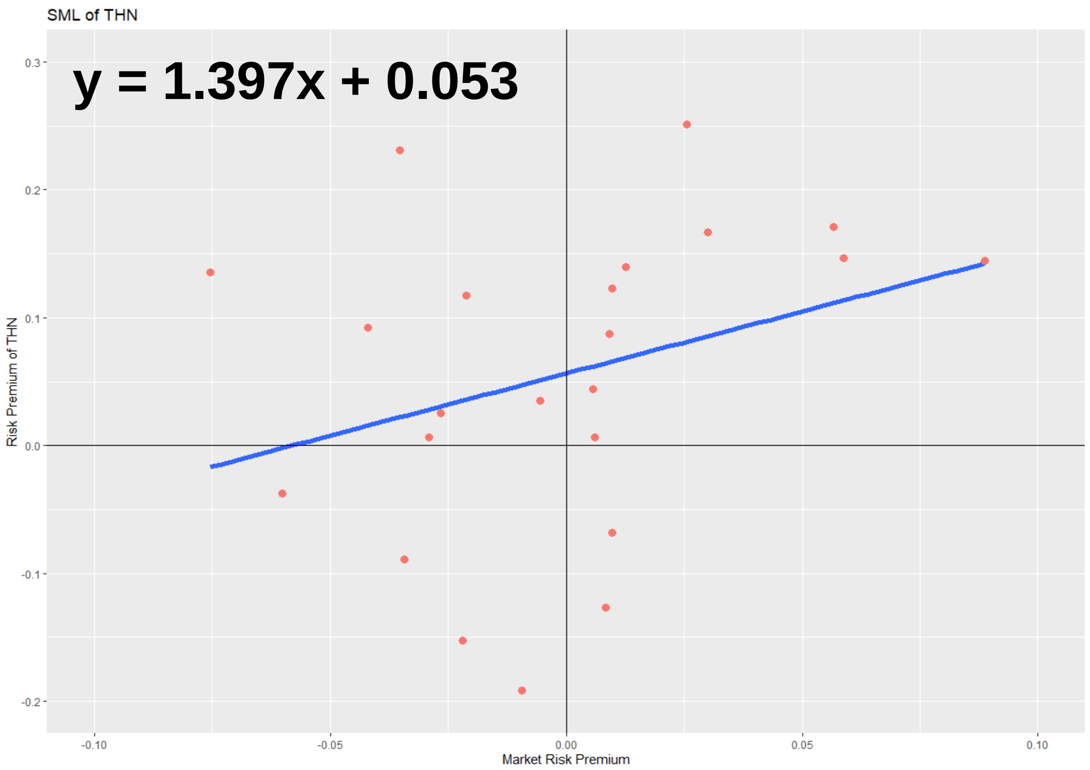
Ⅲ. Security Analysis

✓ 3. Identify the correlation between stocks.

-finally pick stocks of which correlation is low.



SML of PC Direct



SML of THN

Ⅲ. Security Analysis

✓ 4. Form Tangent Portfolio.

	CD	THN	PC Direct	KOSPI 200
2017-11-30	0.0014	0.0251	0.1166	-0.0266
2017-12-28	0.0014	-0.0681	-0.0081	0.0097
2018-01-31	0.0014	0.2515	0.1509	0.0256
2018-02-28	0.0014	-0.0374	-0.0478	-0.0602
2018-03-30	0.0014	0.0874	-0.0587	0.0092
2018-04-30	0.0014	0.1228	-0.0556	0.0097
2018-05-31	0.0014	0.2306	-0.0156	-0.0352
2018-06-29	0.0014	-0.0889	-0.0037	-0.0342
2018-07-31	0.0014	-0.1915	0.011	-0.0093
2018-08-31	0.0014	0.0439	0.0896	0.0057
2018-09-28	0.0014	0.0063	0.0844	0.006
2018-10-31	0.0014	-0.2359	-0.043	-0.1251
2018-11-30	0.0016	0.1667	0.0171	0.03
2018-12-28	0.0016	0.1171	-0.0442	-0.0212
2019-01-31	0.0016	0.1447	0.0771	0.0888
2019-02-28	0.0016	0.0348	-0.0215	-0.0055
2019-03-29	0.0016	-0.1522	-0.0157	-0.0219
2019-04-30	0.0015	0.1399	0.1104	0.0126
2019-05-31	0.0015	0.1355	0.0249	-0.0754
2019-06-28	0.0015	0.171	0.0728	0.0567
2019-07-31	0.0013	0.0923	0.0783	-0.042
2019-08-30	0.0012	0.0063	-0.0516	-0.029
2019-09-30	0.0013	0.1466	0.0374	0.0589
2019-10-31	0.0012	-0.1268	0.1	0.0084

Ⅲ. Security Analysis

✓ 4. Form Tangent Portfolio.

	CD	THN	PC Direct	KOSPI 200
Expected Rate of Return	0.14%	4.26%	2.52%	-0.6%
Risk	0	13.26%	6.41%	4.53%
Beta	0	1.397	0.577	1
		Correlation = 0.287		

Ⅲ. Security Analysis

✓ 4. Form Tangent Portfolio.

Define $V_1 = \mu_1 - \mu_f$ and $V_2 = \mu_2 - \mu_f$ (excess expected returns)

Then the **tangency portfolio** (point T in the plot) uses weight

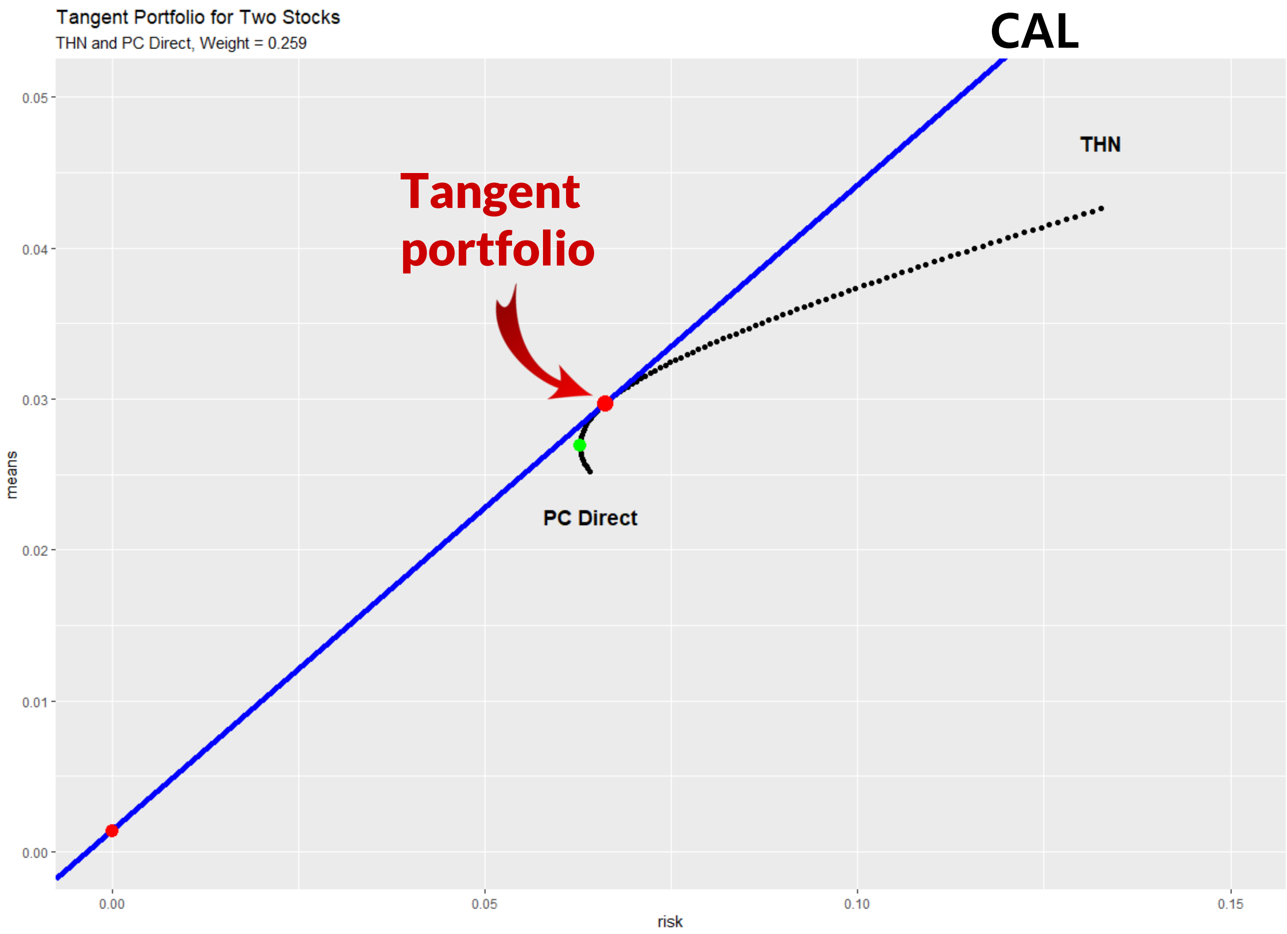
$$w_T = \frac{V_1\sigma_2^2 - V_2\rho_{12}\sigma_1\sigma_2}{V_1\sigma_2^2 + V_2\sigma_1^2 - (V_1 + V_2)\rho_{12}\sigma_1\sigma_2}$$

Weight of Tangent Portfolio : 0.259

Weight of Minimum Variance Portfolio : 0.1

Ⅲ. Security Analysis

✓ 4. Form Tangent Portfolio.



Expected rate of Return of Tangent Portfolio : 2.9%
Risk of Tangent Portfolio : 0.061
Sharpe Ratio : 0.428

$$r_P = 0.741\, r_{PC} + 0.259\, r_{THN}$$

Ⅳ. Conclusion

- To maximize the utility, we attempted to search out underpriced stocks by linear regression analysis.
- After the analysis,
  we considered 4 main criteria for judging whether the stock is underpriced.
  * alpha, price ratio(PSR&PBR), beta, correlation
- Finally, we could select 2 stocks satisfied with the security conditions.
  → THN & PC Direct were picked
- With these 2 stocks, we formed tangent portfolio.
  → Expected return : 0.0297 / Risk : 0.061 / Shape ratio : 0.428

Thanks for listening !