

Market Metrics

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Executive summary

This capstone program is based on evaluating how financial metrics relates to each sector and how to explore which components tends to deliver the best overall risk mitigation portfolio decision and how to create a porftolio.

The data used for this project is on companies that are in the SP500 index. First there is an exploratory analysis of the data and how it relates to the metrics from industries and sector segments as well as its price and risk.

Sectors are then evaluated by daily prices in order to determine the best set of clusters that represents the groups of sectors presented in the SP500.

The first portfolio is created per sector to understand which sectors to chose in order to mitigate risks per ROI (Return on investment), then a second porfolio is created in each sector to evaluate the best and worst companies to mitigate risk.

All 57 metrics are then evaluated per sector and the best and worst companies of portfolio in order to understand how they relate with sectors and risk mitigation.

Lastly the price of the chosen companies of porftolio are predicted and the portfolio is rebalanced per period in order to evaluate how prices prediction changes the behavior of risk mitigation.

Introduction

This project aims to understand how financial metrics relates to each sector and how to explore which components tends to deliver the best overall risk mitigation portfolio decision and how to create a portfolio.

This is a personal attempt to merge a brief study on machine learning techniques and financial analysis from courses from michigan coursera and harvardx. From my perspectiva, most of the financial analysis is usually based on the ratio of risk versus return of an investment.

The issue is that studies teach us how to evaluate companies based on a set of benchmarked metrics and to evaluate data manually, my intent is to organize it in a broader perspective and gather as much data as

possible in order to evaluate critically how financial metrics work per companies segments and how to use this information to evaluate risk and return of a portfolio investment.

This is a broad area of study and many metrics and analysis are beyond my understanding. This means that conceptual mistakes can happen, but I'm willing to evaluate this in order to achieve a better understanding of the market.

Getting Data

Libraries

Load the packages needed for this project:

- Handle API: `library(httr)` and `library(jsonlite)`
- Tidy metrics: `library(tidyverse)`
- List manipulation: `library(purrr)`
- Data preparation: `library(recipes)` and `library(janitor)`
- Data exploration visual: `library(patchwork)` and `library(ggstatsplot)`
- Machine learning models: `library(h2o)`
- Time based preparation: `library(anytime)`, `library(timetk)` and `library(tibbletime)`
- Markdown tables: `library(knitr)` and `library(kableExtra)`
- Portfolio Analytics: `library(PortfolioAnalytics)`

```
require(httr) #Working with url
library(jsonlite) #Working with json data for API
library(tidyverse) #Tidy dataframe packages
library(purrr) #list manipulation
library(janitor) # Data cleansing and pivot
library(patchwork) #Easy grid arrange of ggplots
library(tidyquant) #Set of finance packages
library(anytime) #read any type of date format
library(readxl) #read/write excel data
library(stringr) #string manipulation
library(timetk) #tibble format for time based dataframe
library(tibbletime) #tibble format for time based dataframe
library(PortfolioAnalytics) #Portfolio analysis
library(ROI) #Optimization package
library(ROI.plugin.glpk) #Plugins needed
library(ROI.plugin.quadprog) #Plugins needed
library(knitr) #Tables in rmd
library(kableExtra) #Graphics for knitr tables
library(cowplot) #Grid plot for list plots
library(ggstatsplot) #Statistical testing in plot
library(h2o) #Machine learning models
library(lime) #Allow for black box models to be easily evaluated
library(lubridate) #Allow for changes in date format

library(gridExtra)
library(ggdendro)
library(zoo)
library(tsibble)
library(broom)
```

Table 1: API Structure

Category	Information	url
Company Valuation	Symbols List	https://financialmodelingprep.com/api/v3/company/stock/list
Company Valuation	Company Profile	https://financialmodelingprep.com/api/v3/company/profile/
Company Valuation	Income Statement	https://financialmodelingprep.com/api/v3/financials/income-statement/
Company Valuation	Balance Sheet Statement	https://financialmodelingprep.com/api/v3/financials/balance-sheet-statement/
Company Valuation	Cash Flow Statement	https://financialmodelingprep.com/api/v3/financials/cash-flow-statement/
Company Valuation	Company Financial Ratios	https://financialmodelingprep.com/api/v3/financial-ratios/
Company Valuation	Company Enterprise Value	https://financialmodelingprep.com/api/v3/enterprise-value/
Company Valuation	Company Key Metrics	https://financialmodelingprep.com/api/v3/company-key-metrics/
Company Valuation	Company Rating	https://financialmodelingprep.com/api/v3/company/rating/
Stock Price	Stock Real-time Price	https://financialmodelingprep.com/api/v3/stock/real-time-price/
Stock Price	Historical Daily Price	https://financialmodelingprep.com/api/v3/historical-price-full/

```
options(scipen=999)
```

Data

The data obtained is from an API from financialmodelingprep.com which consists of:

```
API_Structure <- tribble(
  ~Category, ~Information, ~url, ~Options, ~TimeUpdate,
  "Company Valuation", "Symbols List", "https://financialmodelingprep.com/api/v3/company/stock/list", NULL,
  "Company Valuation", "Company Profile", "https://financialmodelingprep.com/api/v3/company/profile/", "C",
  "Company Valuation", "Income Statement", "https://financialmodelingprep.com/api/v3/financials/income-statement/",
  "Company Valuation", "Balance Sheet Statement", "https://financialmodelingprep.com/api/v3/financials/balance-sheet-statement/",
  "Company Valuation", "Cash Flow Statement", "https://financialmodelingprep.com/api/v3/financials/cash-flow-statement/",
  "Company Valuation", "Company Financial Ratios", "https://financialmodelingprep.com/api/v3/financial-ratios/",
  "Company Valuation", "Company Enterprise Value", "https://financialmodelingprep.com/api/v3/enterprise-value/",
  "Company Valuation", "Company Key Metrics", "https://financialmodelingprep.com/api/v3/company-key-metrics/",
  "Company Valuation", "Company Rating", "https://financialmodelingprep.com/api/v3/company/rating/", "C",
  "Stock Price", "Stock Real-time Price", "https://financialmodelingprep.com/api/v3/stock/real-time-price/",
  "Stock Price", "Historical Daily Price", "https://financialmodelingprep.com/api/v3/historical-price-full/"
) %>%
  mutate(id = row_number()) %>%
  select(id, everything())

kable(API_Structure[, -1], caption = "API Structure") %>%
  kable_styling(full_width = F)
```

Brief overview of stock lists

In order to use the API structure two functions are created to help getting the data

```
#Company informations
GetCompanyProfile <- function(url, company = NULL){

headers = c(
```

```

  `Upgrade-Insecure-Requests` = '1'
)

params = list(
  `datatype` = 'json'
)

res <- httr::GET(url = paste0(url, "/", company),
  httr::add_headers(.headers=headers), query = params)

data <- content(res, as = "text")

data <- fromJSON(data, flatten = T) %>%
  flatten_dfr()

return(data)
}

#Get data from API structure
GetData <- function(url, company = NULL, Period = NULL){

headers = c(
  `Upgrade-Insecure-Requests` = '1'
)

params = list(
  `datatype` = 'json'
)

if (is.null(company) & is.null(Period)) {
  res <- httr::GET(url = url,
    httr::add_headers(.headers=headers), query = params)
} else if (is.null(Period)) {
  res <- httr::GET(url = paste0(url, "/", company),
    httr::add_headers(.headers=headers), query = params)
} else {
  res <- httr::GET(url = paste0(url, "/", company, "?period=", Period),
    httr::add_headers(.headers=headers), query = params)
}

data <- content(res, as = "text")

data <- fromJSON(data, flatten = T) %>%
  detect(is.data.frame) %>%
  as_tibble()

return(data)

```

```
}
```

Let's get all company symbols from the API

```
Stock_Lists <- GetData(url = "https://financialmodelingprep.com/api/v3/company/stock/list")
```

```
glimpse(Stock_Lists)
```

```
## Observations: 13,854
## Variables: 4
## $ symbol   <chr> "SPY", "CMCSA", "KMI", "INTC", "MU", "GDX", "GE", "BAC", "...
## $ name     <chr> "SPDR S&P 500", "Comcast Corporation Class A Common Stock"...
## $ price    <dbl> 254.19, 38.22, 12.64, 50.08, 37.38, 25.50, 7.08, 21.98, 33...
## $ exchange <chr> "NYSE Arca", "Nasdaq Global Select", "New York Stock Excha..."
```

There is 13584 symbols, in order to explore the data we must choose a sample set from this dataset. In order to understand each sector, SP500 companies are a good choice since it is usually used to define how the US market is and represents a great variety of sectors and industries segments.

```
#SP500 Indexes
```

```
SP500 <- tq_index("SP500")
```

```
## Getting holdings for SP500
```

```
Stock_Lists <- GetData(url = "https://financialmodelingprep.com/api/v3/company/stock/list") %>%
  filter(symbol %in% SP500$symbol) %>% #Symbols of SP500
  filter(!symbol %in% c("J", "AMCR")) #Companies that doesn't have data from API and causes
```

```
glimpse(Stock_Lists)
```

```
## Observations: 502
## Variables: 4
## $ symbol   <chr> "CMCSA", "KMI", "INTC", "MU", "GE", "BAC", "AAPL", "MSFT",...
## $ name     <chr> "Comcast Corporation Class A Common Stock", "Kinder Morgan...
## $ price    <dbl> 38.22, 12.64, 50.08, 37.38, 7.08, 21.98, 252.86, 146.57, 1...
## $ exchange <chr> "Nasdaq Global Select", "New York Stock Exchange", "Nasdaq..."
```

Project Data

From the API structure the data required for this project is: 1. Segments: Data with information of sectors and industries segments of stocks 2. PriceSectors: Price of companies grouped by industries and sectors segments 3. KeyMetrics: Key financial metrics of stock market and companies 4. Historical prices: Stock market prices of companies

After exhaustive analysis, the capacity of memory for this project is at 400 stock market symbols and because of that the 502 stocks will be reduced to 400 on each data

- Segments:

```
segments <- Stock_Lists[1:400, ] %>% #Filter data for memory capacity
  mutate(Company_Profile = map(symbol, ~GetCompanyProfile(API_Structure[2,4], company = ..1)))
  select(Company_Profile) %>% #Select nested list
  unnest() %>% # Unnest it
  mutate(industry = case_when(industry == "" ~ "Funds", TRUE ~ industry), #Set sectors and in
         sector = case_when(sector == "" ~ "Funds", TRUE ~ sector)) %>%
  select(symbol, companyName, industry, sector) #Select the data required for this dataframe
```

```
glimpse(segments)
```

```
## Observations: 400
## Variables: 4
## $ symbol      <chr> "CMCSA", "KMI", "INTC", "MU", "GE", "BAC", "AAPL", "MSF...
## $ companyName <chr> "Comcast Corporation Class A Common Stock", "Kinder Mor...
## $ industry     <chr> "Entertainment", "Oil & Gas - Midstream", "Semiconducto...
## $ sector       <chr> "Consumer Cyclical", "Energy", "Technology", "Technolog..."
```

- PriceSectors:

```
PriceSectors <- Stock_Lists[1:400, ] %>% #Filter data for memory capacity
  mutate(Company_Profile = map(symbol, ~GetCompanyProfile(API_Structure[2,4],
                                                         company = ..1))) %>% #Get Data
  select(Company_Profile) %>% #Select nested list
  unnest() %>% # unnest it
  mutate(industry = case_when(industry == "" ~ "Funds", TRUE ~ industry), #Set sectors as Funds
         sector = case_when(sector == "" ~ "Funds", TRUE ~ sector))
```

```
glimpse(PriceSectors)
```

```
## Observations: 400
## Variables: 17
## $ symbol      <chr> "CMCSA", "KMI", "INTC", "MU", "GE", "BAC", "AAPL"...
## $ price       <dbl> 38.22, 12.64, 50.08, 37.38, 7.08, 21.98, 252.86, ...
## $ beta        <chr> "1.061551", "0.75548", "0.90978", "1.951096", "1....
## $ volAvg      <chr> "25631996", "16375424", "27534578", "27161027", "...
## $ mktCap      <chr> "1.74016823E11", "2.86303601E10", "2.14192161E11"...
## $ lastDiv     <chr> "0.84", "0.8", "1.26", "0", "0.04", "0.6", "2.92"...
## $ range       <chr> "34.44-47.74", "12.32-22.58", "42.86-69.29", "32....
## $ changes     <dbl> 2.18, -0.09, 5.47, 2.91, 0.42, 1.54, 10.65, 11.15...
## $ changesPercentage <chr> "(+6.05%)", "(-0.71%)", "(+12.26%)", "(+8.44%)", ...
## $ companyName <chr> "Comcast Corporation Class A Common Stock", "Kind...
## $ exchange    <chr> "Nasdaq Global Select", "New York Stock Exchange"...
## $ industry    <chr> "Entertainment", "Oil & Gas - Midstream", "Semico...
## $ website     <chr> "https://corporate.comcast.com", "http://www.kind...
## $ description <chr> "Comcast Corp is a media and technology company. ...
## $ ceo         <chr> "Brian L. Roberts", "Steven J. Kean", "Brian M. K...
## $ sector      <chr> "Consumer Cyclical", "Energy", "Technology", "Tec...
## $ image       <chr> "https://financialmodelingprep.com/images-New-jpg..."
```

- KeyMetrics:

Since there are 57 metrics in the API dataset, a description of each metric and measure formula was created

```
#metrics
path <- "Market KeyMetrics.xlsx"

Metrics_Info <- path %>%
  excel_sheets() %>%
  set_names() %>%
  map(read_excel, path = path)

kable(head(Metrics_Info$KeyMetrics), caption = "10 Metrics info") %>%
  kable_styling(full_width = F)
```

Table 2: 10 Metrics info

Segment	Metric	Explanation
Fundamental	Revenue per Share	Ratio that computes the total revenue earned per share over a desig
Income Statement	Net Income per Share	How much of a firm's net income was to each share of common sto
Fundamental	Operating Cash Flow per Share	Company's ability to generate cash
Fundamental	Free Cash Flow per Share	How much cash a business generates after accounting for capital ex
Fundamental	Cash per Share	Available cash to a business divided by the number of equity share
Fundamental	Book Value per Share	Value of allshares divided by the number of shares issued.

```
KeyMetrics <- Stock_Lists[1:400, ] %>% #Filter data for memory capacity
  mutate(Company_Key_Metrics = map(symbol, ~GetData(API_Structure[8,4], company = ..1))) %>%
  select(symbol, name, Company_Key_Metrics) %>% #Select data and nested API data
  unnest(Company_Key_Metrics) %>% # Unnest it
  gather(key = "metric", value = "value", -symbol, -date, -name) %>% # Pivot the metrics per
  inner_join(segments, by = "symbol") %>% #Get segments data to enrich the dataset
  inner_join(Metrics_Info$KeyMetrics, by = c("metric"="Metric")) %>% #Get the description a
  select(-companyName) %>% # Remove duplicate columns
  mutate(value = as.double(value), date = anydate(date)) %>% # Fix data structure
  group_by(metric, Explanation, Formula) %>% # Nest data per metric
  nest()
```

```
glimpse(KeyMetrics)
```

```
## Observations: 57
## Variables: 4
## Groups: metric, Explanation, Formula [57]
## $ metric      <chr> "Revenue per Share", "Net Income per Share", "Operating...
## $ Explanation <chr> "Ratio that computes the total revenue earned per share...
## $ Formula     <chr> "Total revenue / shares", "Net income / average outstan...
## $ data        <list<df[,7]>> CMCSA ...
```

- Historical prices:

```
HistoricalPrices <- Stock_Lists[1:400, ] %>% #Filter data for memory capacity
  #Get Data per symbo
  mutate(Historical_Daily_Price = map(symbol, ~GetData(API_Structure[11,4],
    company = ..1) %>%
    mutate(date = anytime(date)))) %>%

  #Adjust monthly price
  mutate(Monthly_AdjPrice = map(Historical_Daily_Price, ~..1 %>%
    tq_transmute(select = close,
      mutate_fun = to.monthly,
      indexAt = "lastof"))) %>%

  select(-price) %>% # Remove duplicated column
  inner_join(segments, by = "symbol") %>% #Enrich dataframe with segments data
  select(symbol:exchange, industry:sector, everything(), -companyName) #Select and or
```

```
glimpse(HistoricalPrices)
```

```
## Observations: 400
## Variables: 7
```

```
## $ symbol      <chr> "CMCSA", "KMI", "INTC", "MU", "GE", "BAC", "...
## $ name        <chr> "Comcast Corporation Class A Common Stock", ...
## $ exchange    <chr> "Nasdaq Global Select", "New York Stock Exch...
## $ industry    <chr> "Entertainment", "Oil & Gas - Midstream", "S...
## $ sector      <chr> "Consumer Cyclical", "Energy", "Technology",...
## $ Historical_Daily_Price <list> [<tbl_df[1259 x 13]>, <tbl_df[1259 x 13]>, ...
## $ Monthly_AdjPrice <list> [<tbl_df[61 x 2]>, <tbl_df[61 x 2]>, <tbl_d...
```

Overview of data

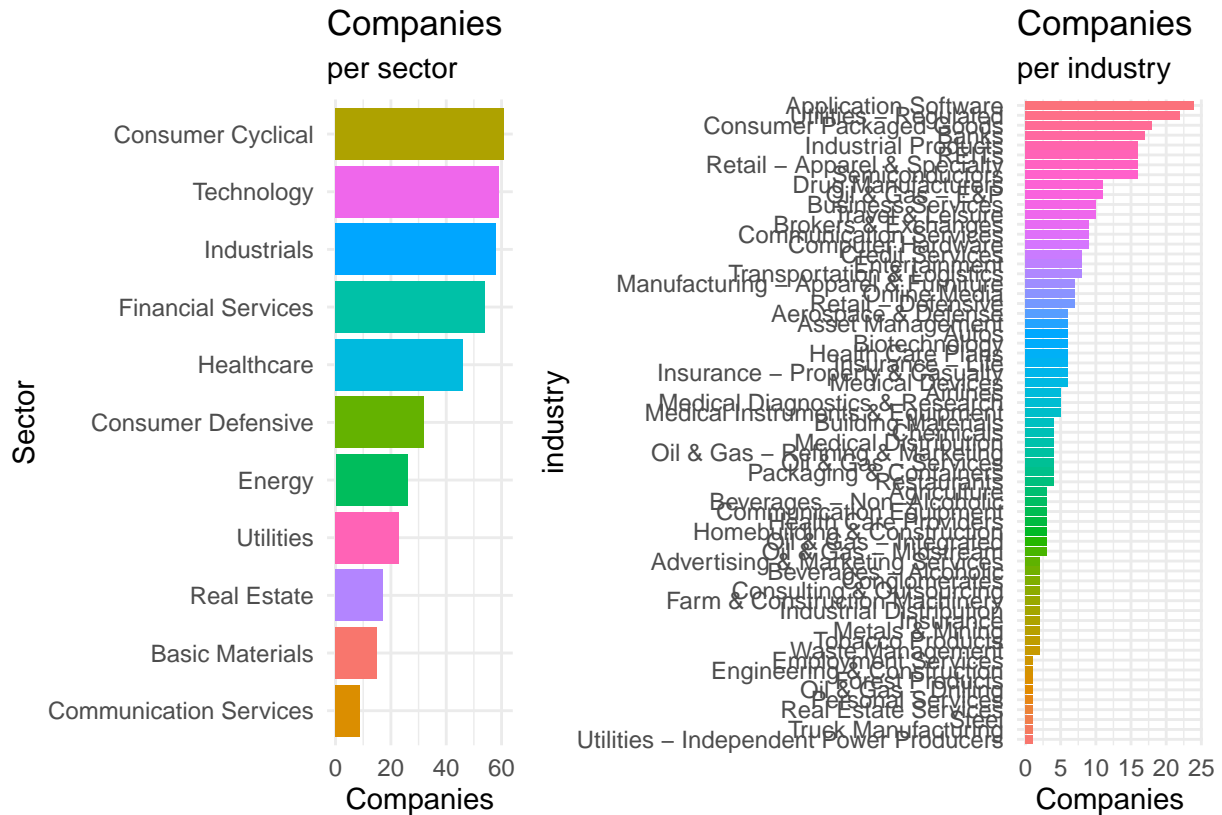
Industry & Sector

Let's check the amount of companies per sector and industry segments

```
p1 <- segments %>%
  mutate(industry = fct_rev(fct_infreq(sector))) %>%
  ggplot() +
  aes(x = industry, fill = sector) +
  geom_bar() +
  coord_flip() +
  scale_fill_hue() +
  guides(fill = "none") +
  theme_minimal()+
  labs(title = "Companies", subtitle = "per sector", y = "Companies", x = "Sector")

p2 <- segments %>%
  mutate(industry = fct_rev(fct_infreq(industry))) %>%
  ggplot() +
  aes(x = industry, fill = industry) +
  geom_bar() +
  coord_flip() +
  scale_fill_hue() +
  guides(fill = "none") +
  theme_minimal() +
  labs(title = "Companies", subtitle = "per industry", y = "Companies")

p1 | p2
```

Some discoveries on SP500 companies segments:

1. The maximum amount of companies per sector is around 60 and it seems to be centered around 6 sectors and skewed to the right which could relate to some sectors having more companies in average or being more advantageous to the portfolio.
2. Industries segments shows that 6 sectors are mixed in the amount of companies, having software, consumer packaged goods and banks as top amount of companies in SP500

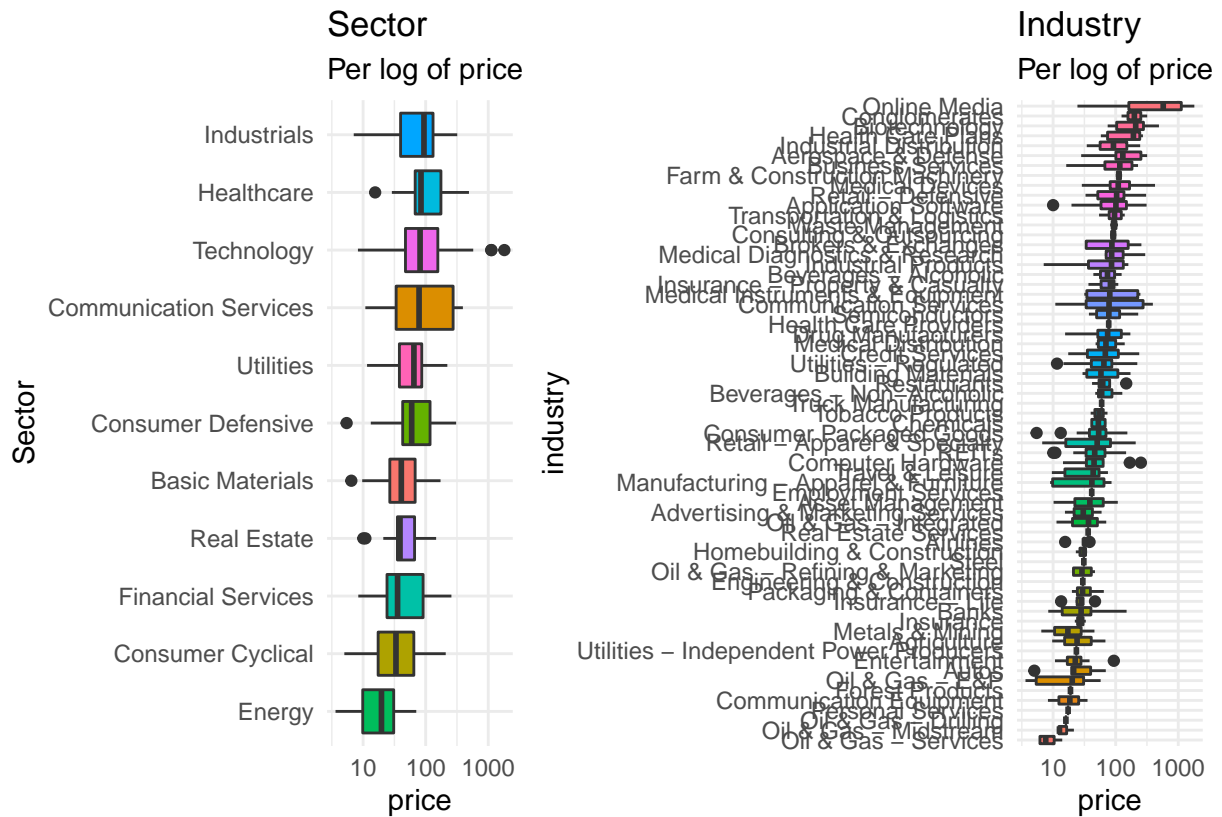
Now let's see how does price is distributed per segments:

```
p1 <- PriceSectors %>%
  mutate(industry = fct_reorder(sector, price)) %>%
  ggplot() +
  aes(x = industry, y = price, fill = sector) +
  geom_boxplot() +
  scale_y_log10() +
  coord_flip() +
  scale_fill_hue() +
  guides(fill = "none") +
  theme_minimal() +
  labs(title = "Sector", subtitle = "Per log of price", x = "Sector")

p2 <- PriceSectors %>%
  mutate(industry = fct_reorder(industry, price)) %>%
  ggplot() +
  aes(x = industry, y = price, fill = industry) +
  geom_boxplot() +
```

```
scale_y_log10() +
coord_flip() +
scale_fill_hue() +
guides(fill = "none") +
theme_minimal() +
labs(title = "Industry", subtitle = "Per log of price")
```

p1 | p2



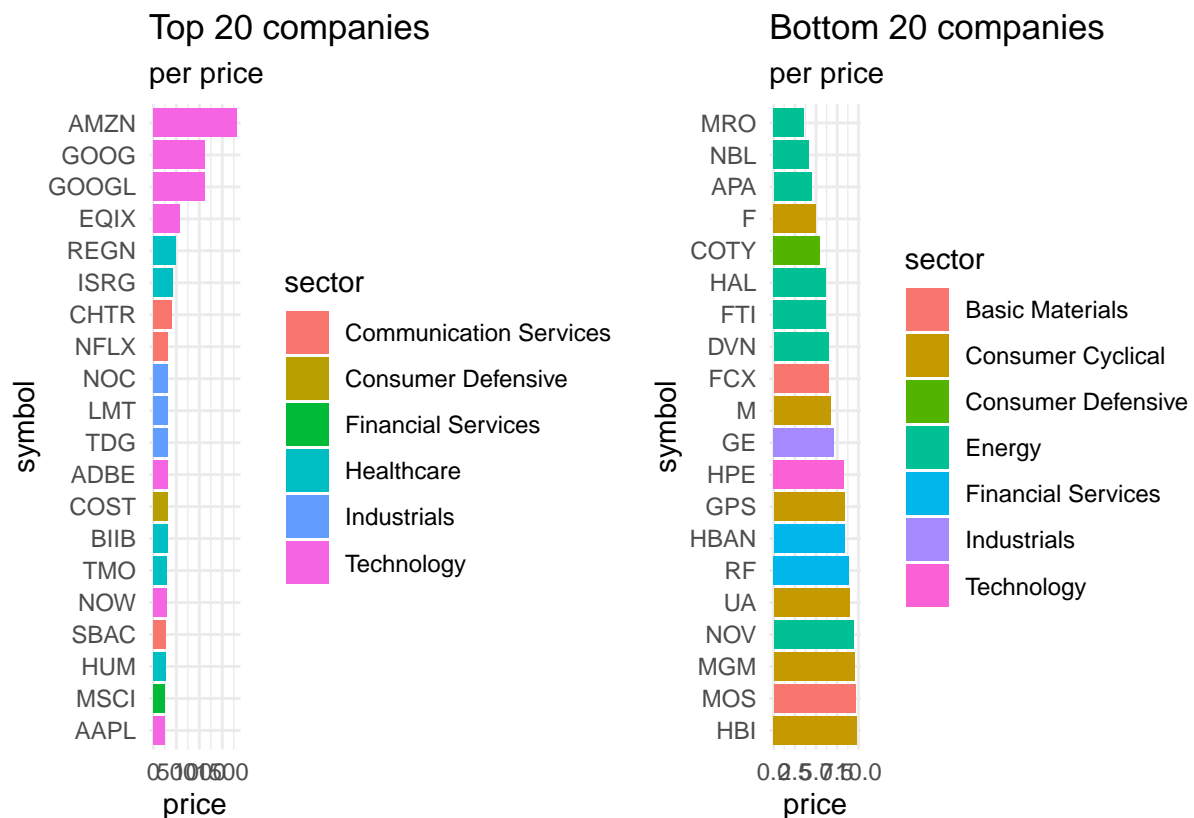
It seems that price per sector is usually around at the same mean with some variability, this variability is explained by the huge amount of difference on industry segment. This means that industry segment is a better metric to evaluate the dispersion of price rather than sectors.

Let's check the top/bottom 20 companies prices

```
p1 <- PriceSectors %>%
mutate(price = as.double(price)) %>%
arrange(-price) %>%
head(20) %>%
mutate(symbol = fct_reorder(symbol, price)) %>%
ggplot() +
aes(x = symbol, y = price, fill = sector) +
geom_col() +
coord_flip() +
scale_fill_hue() +
theme_minimal() +
labs(title = "Top 20 companies", subtitle = "per price")
```

```
p2 <- PriceSectors %>%
  mutate(price = as.double(price)) %>%
  filter(price > 0) %>%
  arrange(price) %>%
  head(20) %>%
  mutate(symbol = fct_rev(fct_reorder(symbol, price))) %>%
  ggplot() +
  aes(x = symbol, y = price, fill = sector) +
  geom_col() +
  coord_flip() +
  scale_fill_hue() +
  theme_minimal() +
  labs(title = "Bottom 20 companies", subtitle = "per price")
```

p1 | p2



It does seem that those 6 sectors variability grants them in general the top 20 and bottom companies price

Now let's see how does risk is distributed per segments:

```
p1 <- PriceSectors %>%
  mutate(beta = as.double(beta)) %>%
  mutate(industry = fct_reorder(sector, beta)) %>%
  ggplot() +
  aes(x = industry, y = beta, fill = sector) +
  geom_boxplot() +
```

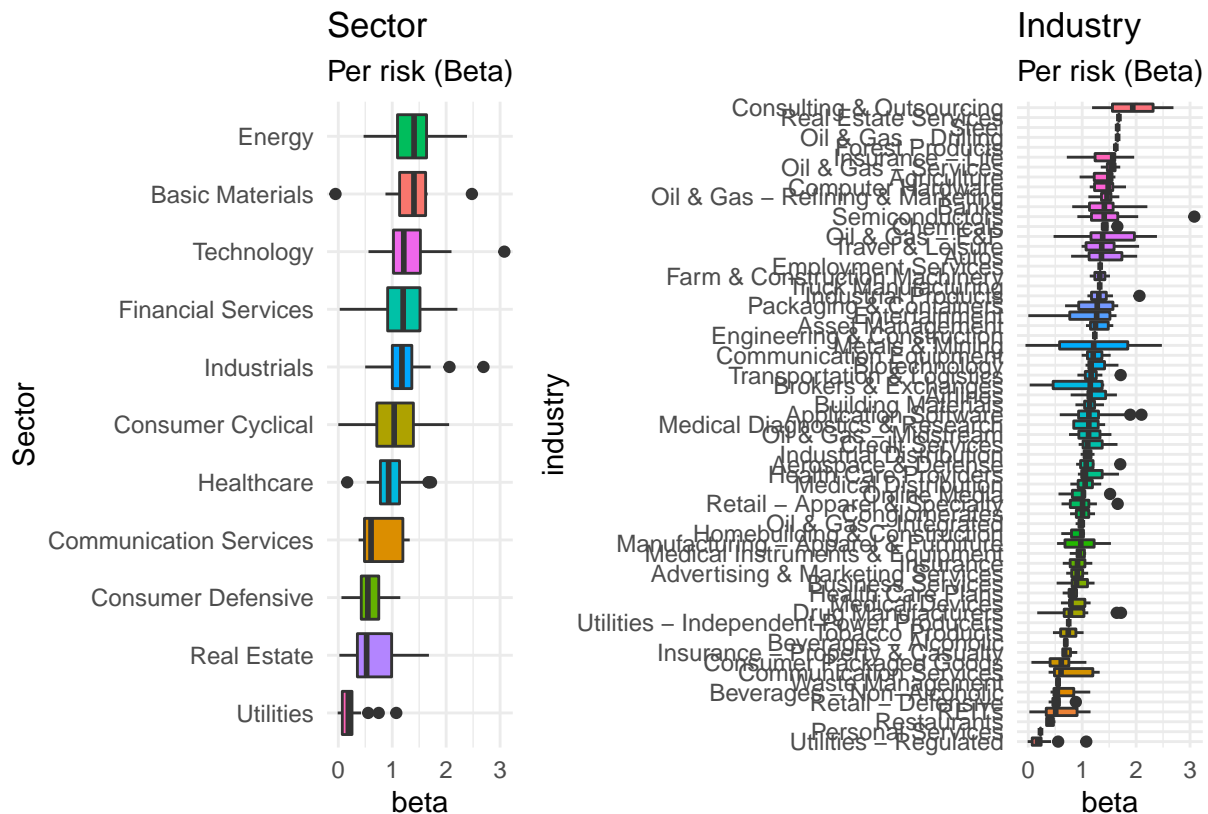
```

coord_flip() +
scale_fill_hue() +
guides(fill = "none") +
theme_minimal() +
labs(title = "Sector", subtitle = "Per risk (Beta)", x = "Sector")

p2 <- PriceSectors %>%
mutate(beta = as.double(beta)) %>%
mutate(industry = fct_reorder(industry, beta)) %>%
ggplot() +
aes(x = industry, y = beta, fill = industry) +
geom_boxplot() +
coord_flip() +
scale_fill_hue() +
guides(fill = "none") +
theme_minimal() +
labs(title = "Industry", subtitle = "Per risk (Beta)")

```

p1 | p2



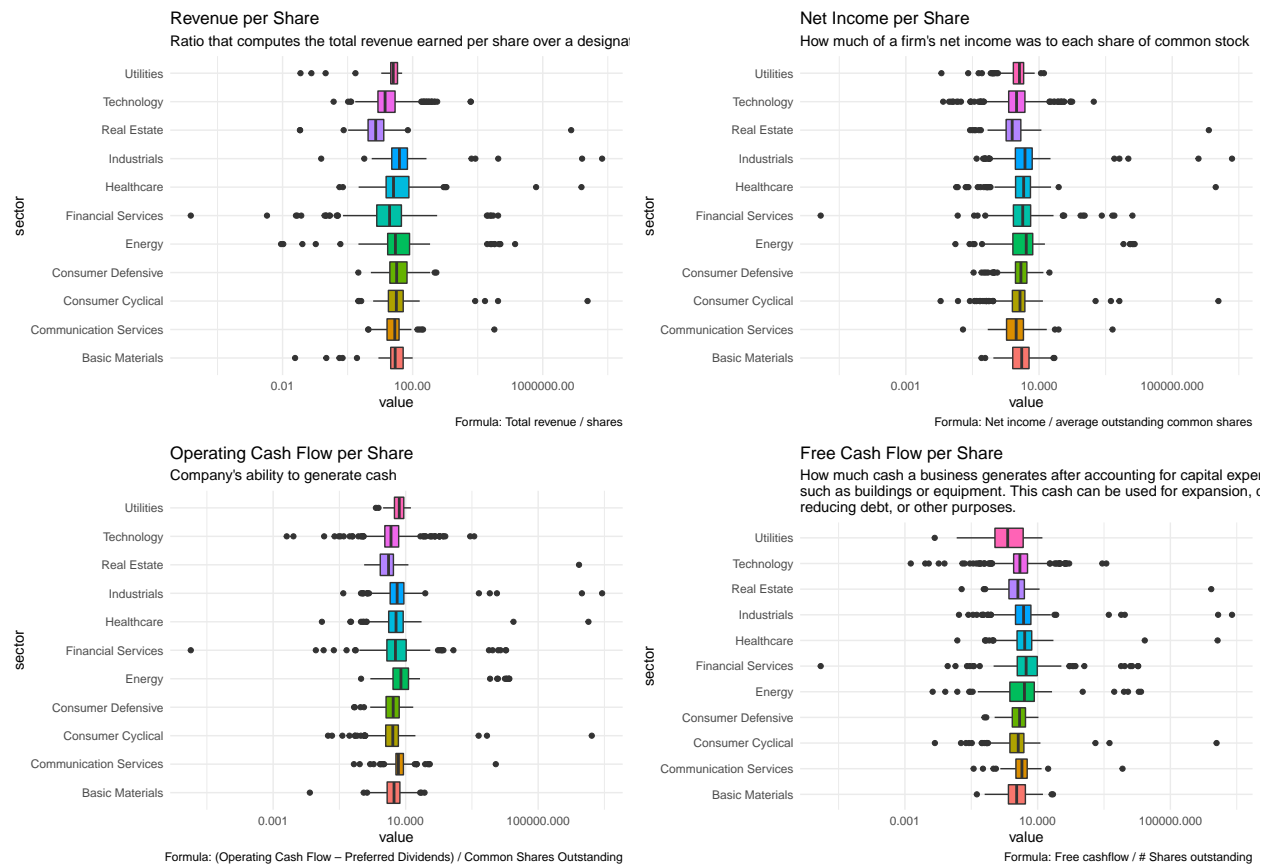
It seems that risk per sector changes slightly and it's quite impressive to see that energy and basic materials are on the top risk sector. On industry side, it seems some industries have a lot of variability on risk and consulting & outsourcing industry is on the top, it seems counterintuitive, I was expected to see financial services and technology being riskier.

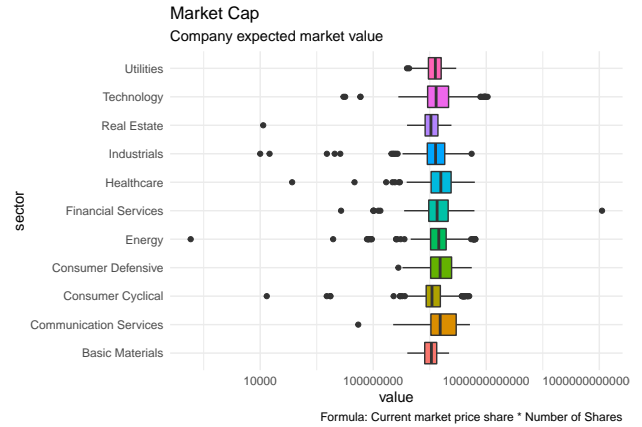
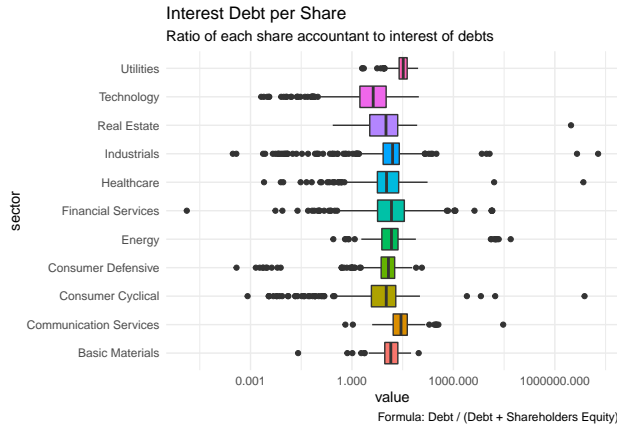
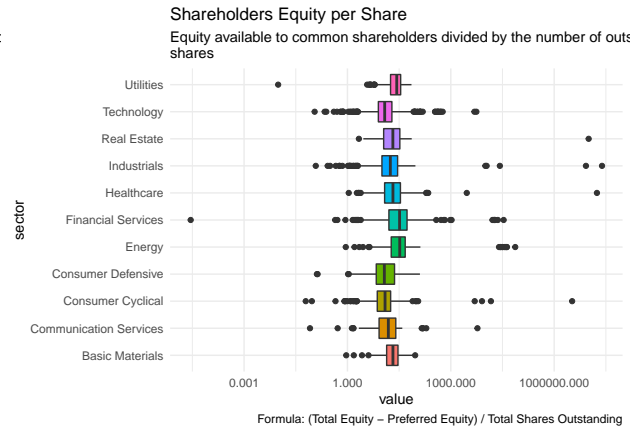
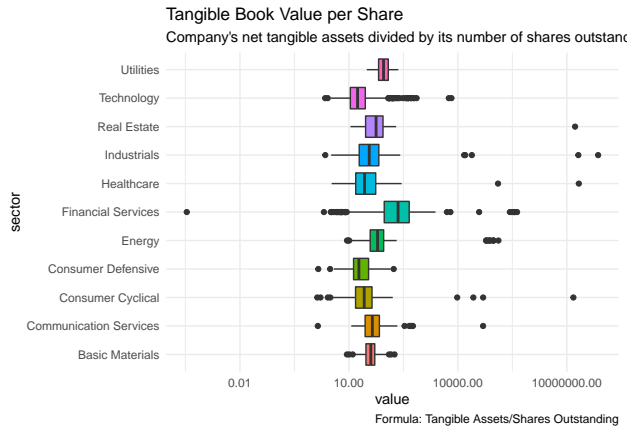
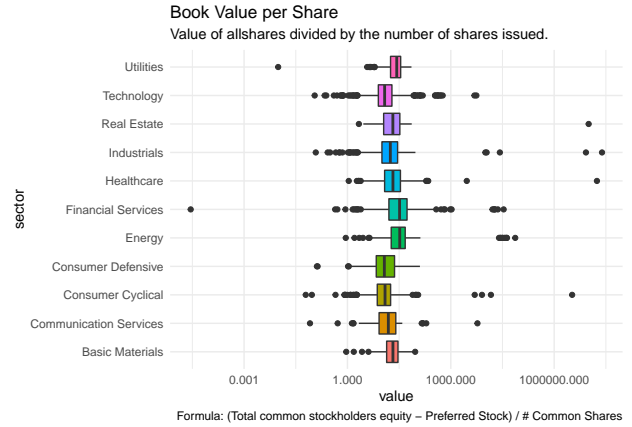
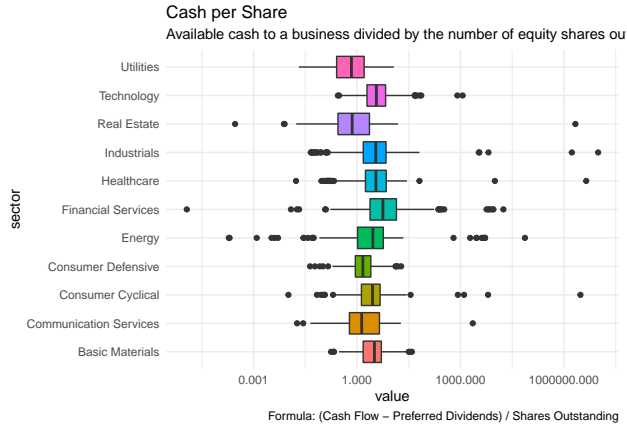
KeyMetrics

Since there are 57 metrics, it's important to create a ggplot function and use it in each sector, this function will include in the labs of plot the brief explanation and the formula in order to help understand each metric

```
plots <- function(data, metric, Explanation, Formula){
  ggplot(data) +
    aes(x = sector, y = value, fill = sector) +
    geom_boxplot() +
    scale_fill_hue() +
    scale_y_continuous(trans = "log10") +
    theme_minimal() +
    coord_flip() +
    guides(fill = "none") +
    labs(title = metric, subtitle = Explanation, caption = paste0("Formula: ", Formula))
}
```

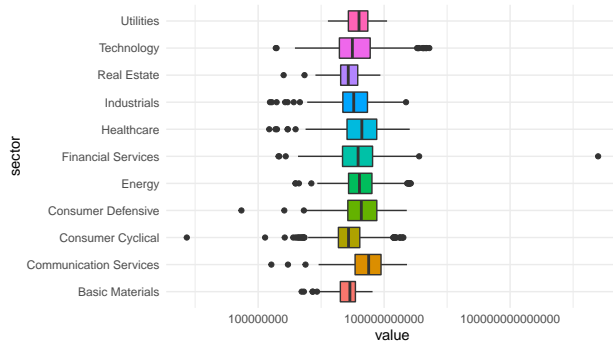
- Plots:





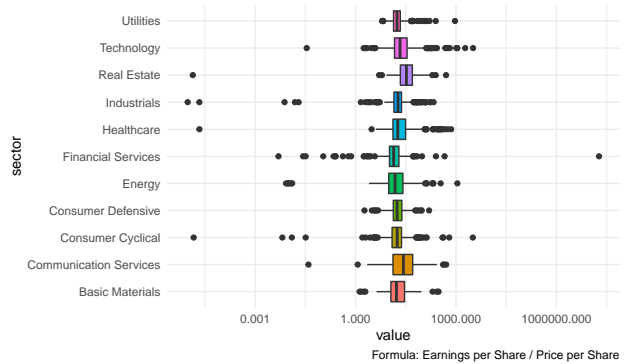
Enterprise Value

Measure of a company's total value, often used as a more comprehensive alternative to equity market capitalization



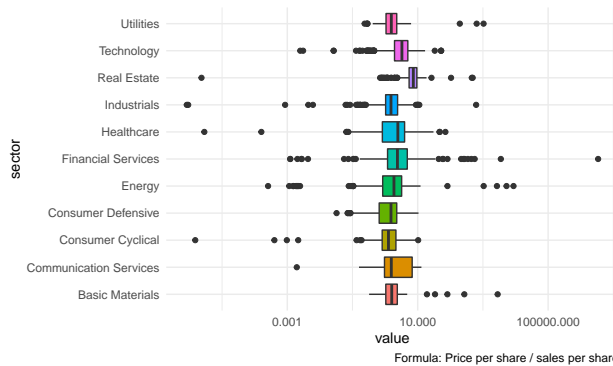
PE ratio

Price to earnings ratio is a measure to determine the relative value of a company's shares in an apples-to-apples comparison



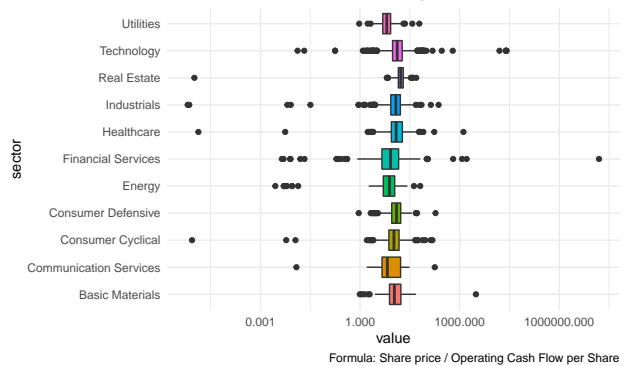
Price to Sales Ratio

Company's market capitalization divided by the revenue of the past 12 months. The lower the PS ratio, the more attractive the investment



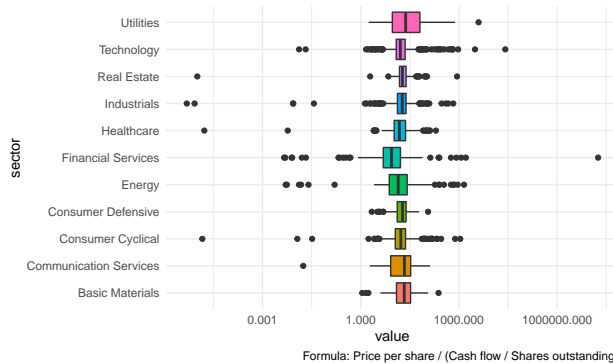
POCF ratio

Price to cash flow stock valuation indicator or multiple that measures the value of a stock's price relative to its operating cash flow



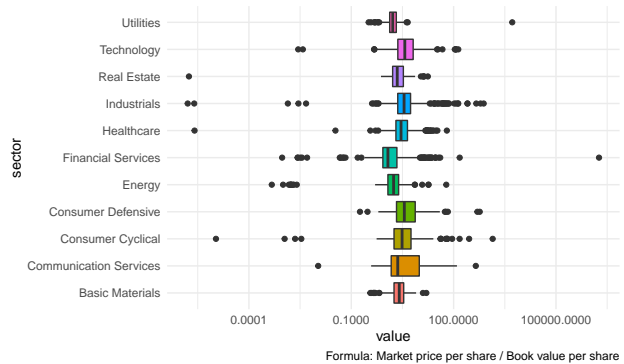
PFCF ratio

Price to free cash flow ratio is a valuation method used to compare a company's current share price to its per-share free cash flow



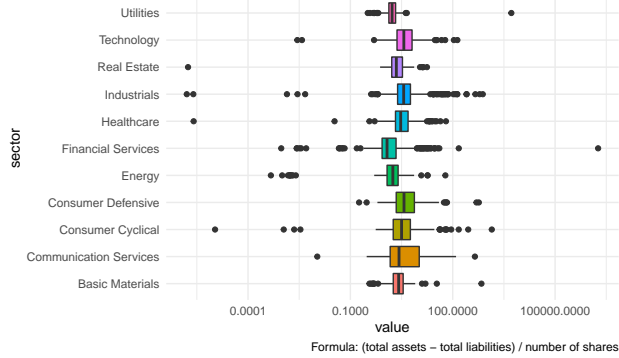
PB ratio

Price to book ratio is to compare a firm's market to book value and is determined by dividing price per share by book value



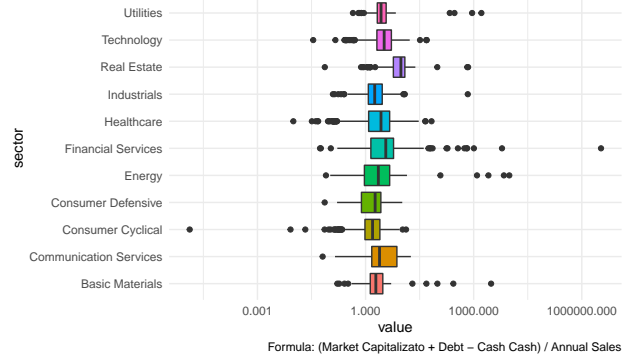
PTB ratio

Price to book ratio is to compare a firm's market to book value and is de by dividing price per share by book



EV to Sales

Enterprise value to sales is a business valuation method that compares value of a company with its sales



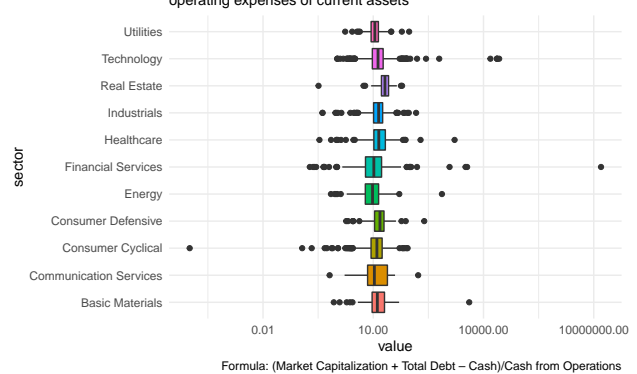
Enterprise Value over EBITDA

Good measure to estimate the cash flow of a company



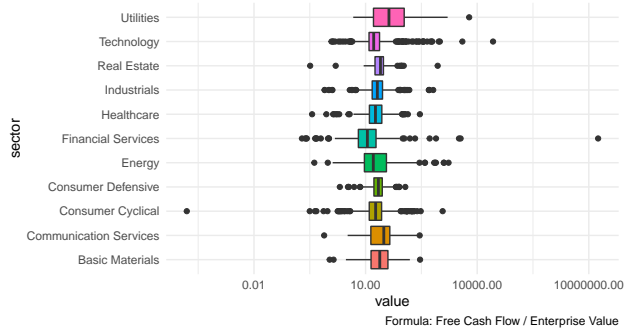
EV to Operating cash flow

Enterprise value to op cash flow is a good to measure the percentage al operating expenses of current assets



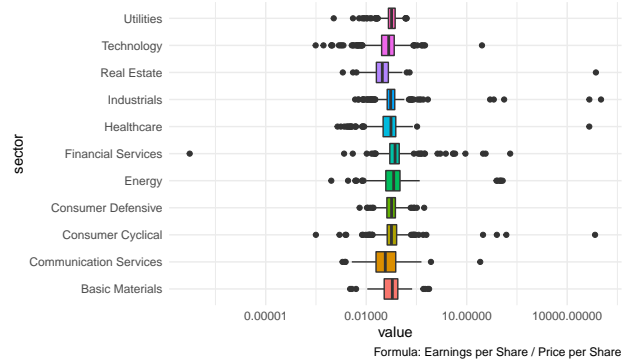
EV to Free cash flow

Compares the total valuation of the company with its ability to generate cashflow. he lower the ratio of enterprise value to the free cash flow figt the faster a company can pay back the cost of its acquisition or generat to reinvest in its business



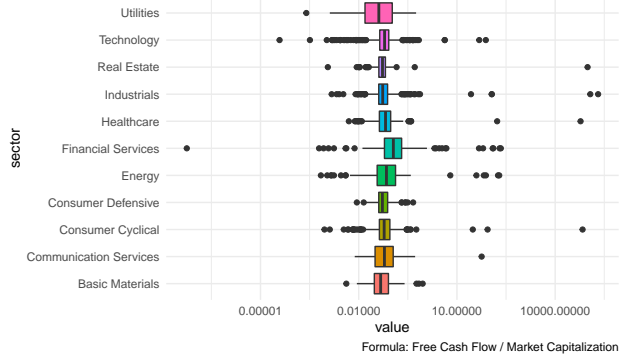
Earnings Yield

Earnings per share for the most recent 12-month period divided by the market price per share.



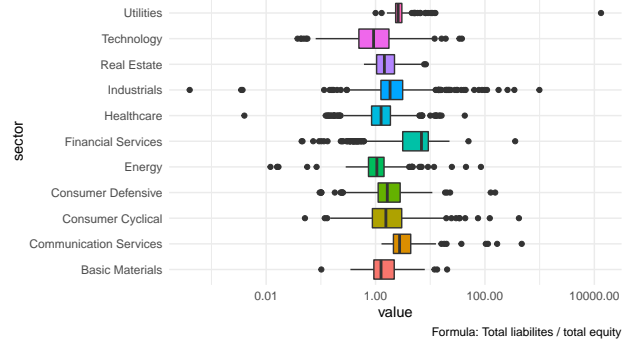
Free Cash Flow Yield

Financial solvency ratio that compares the free cash flow per share against its market value per share



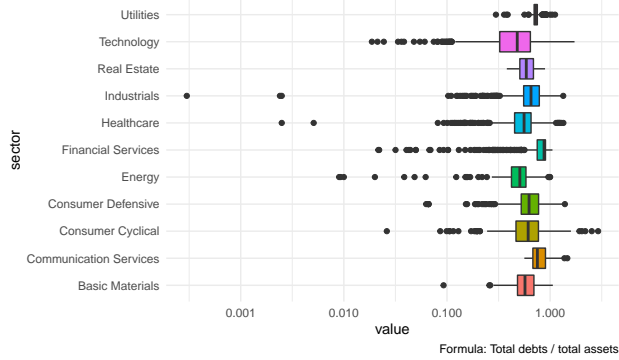
Debt to Equity

Financial ratio indicating the relative proportion of shareholders' equity to debt used to finance a company's assets. Closely related to leveraging, ratio is also known as risk, gearing or leverage



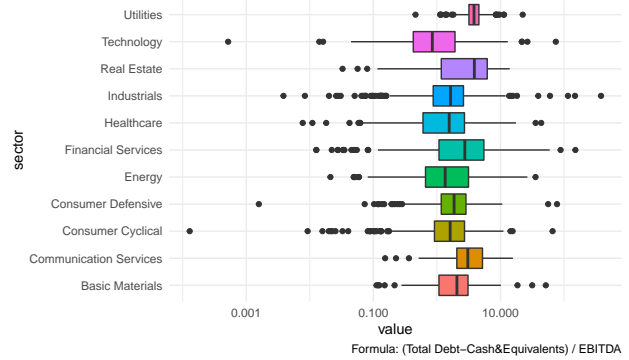
Debt to Assets

Indicator of a company's financial leverage. It tells you the percentage of company's total assets that were financed by creditors



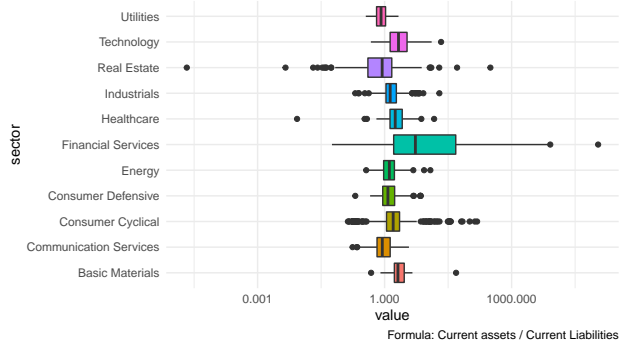
Net Debt to EBITDA

Measurement of leverage, calculated as a company's interest-bearing debt minus cash or cash equivalents, divided by its EBITDA



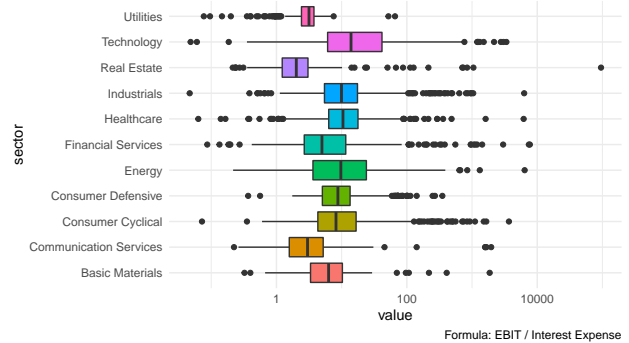
Current ratio

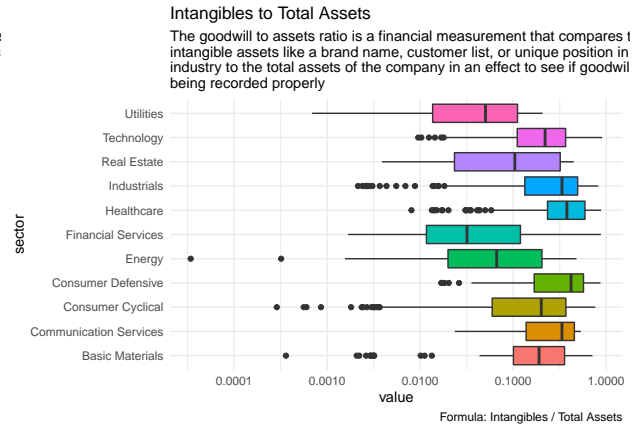
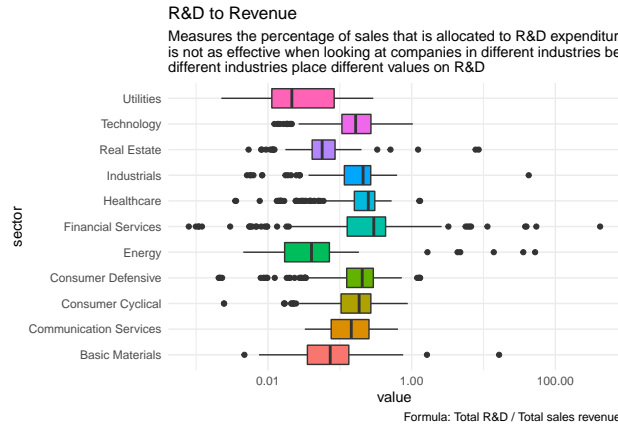
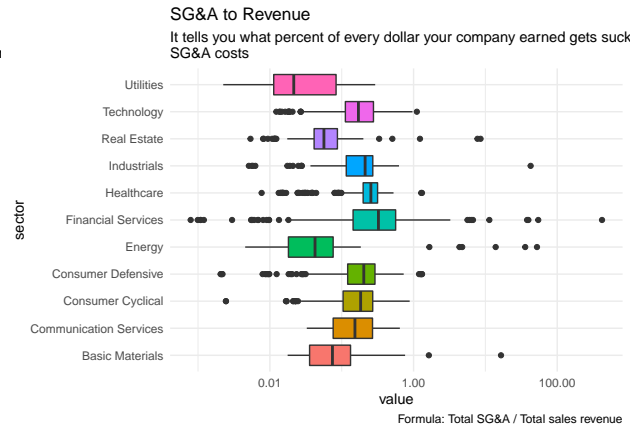
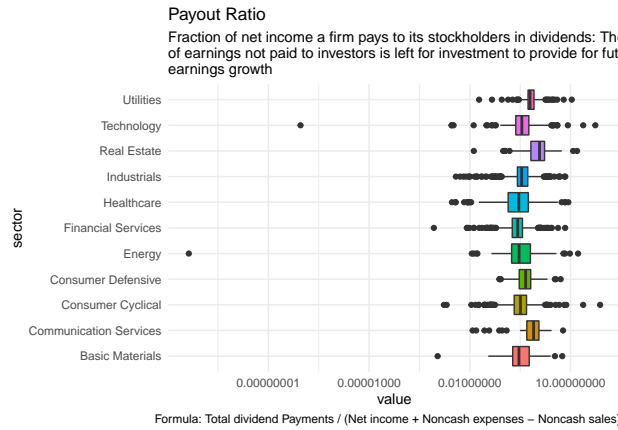
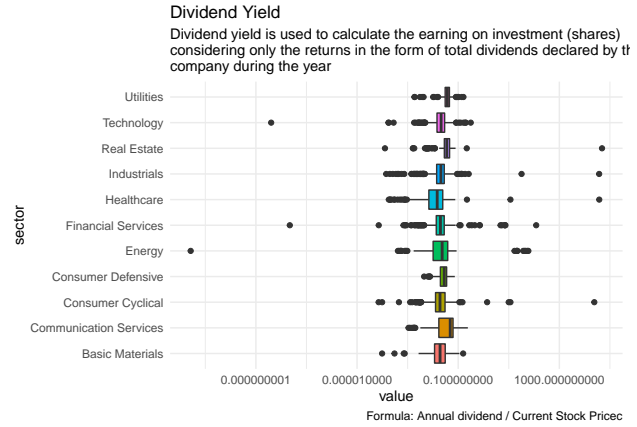
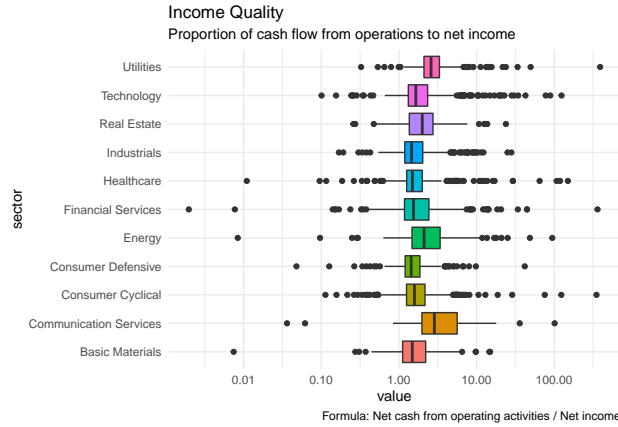
Liquidity ratio that measures whether a firm has enough resources to meet short-term obligations. It compares a firm's current assets to its current liabilities



Interest Coverage

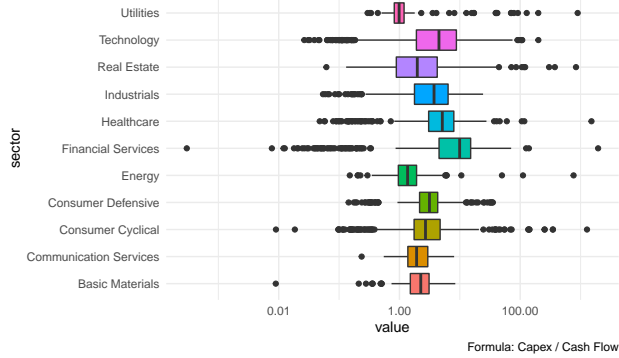
Measure of a company's ability to meet its interest payments. Interest coverage ratio is equal to earnings before interest and taxes (EBIT) for a time period often one year, divided by interest expenses for the same time period





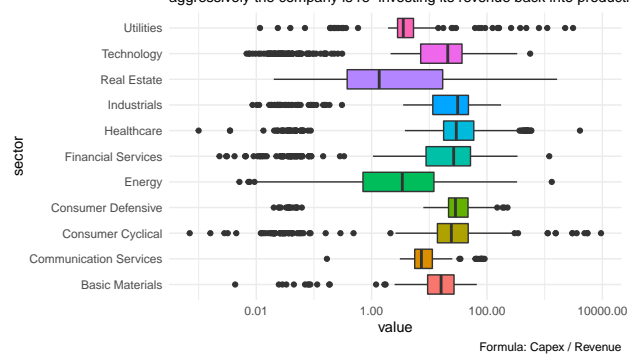
Capex to Operating Cash Flow

Assesses how much of a company's cash flow from operations is being capital expenditure



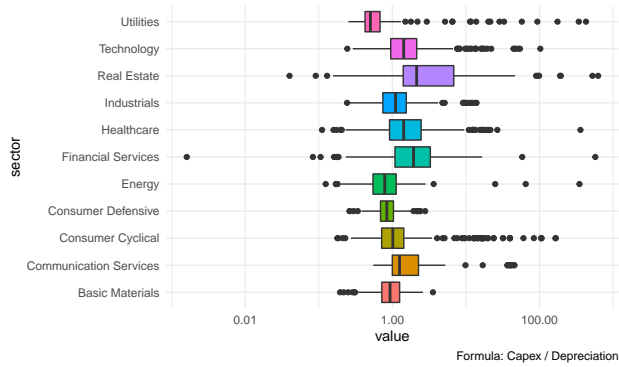
Capex to Revenue

The Capex to Revenue ratio measures a company's investments in property, plant, and equipment and other capital assets to its total sales. The ratio shows how aggressively the company is re-investing its revenue back into production.



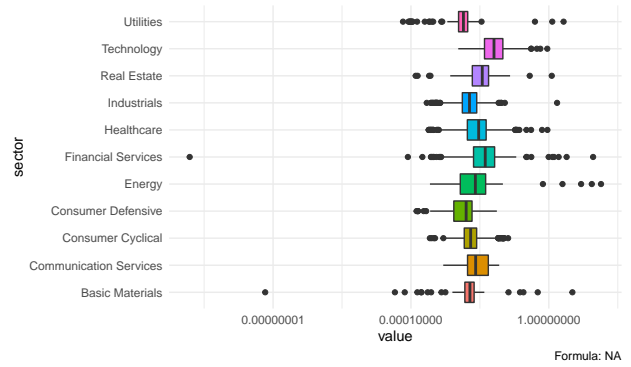
Capex to Depreciation

If a company regularly has more CapEx than depreciation, its asset base is growing.



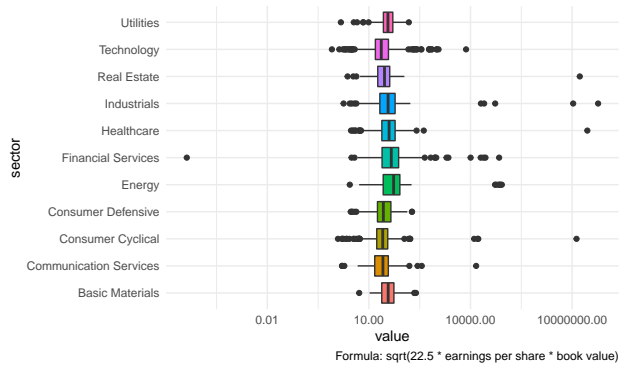
Stock-based compensation to Revenue

Represents a noncash expense that reduces book income, which isn't treated by the IRS as a deductible expense.



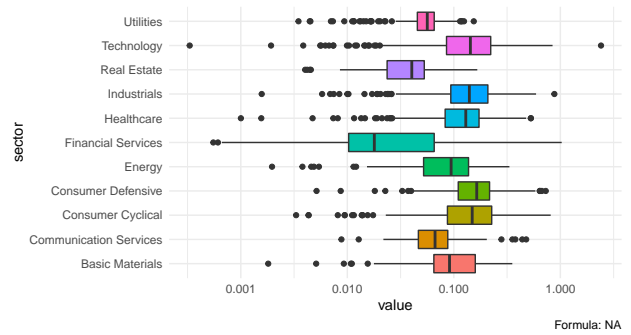
Graham Number

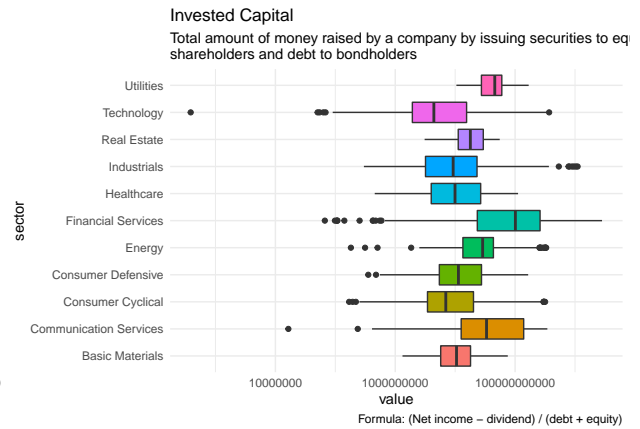
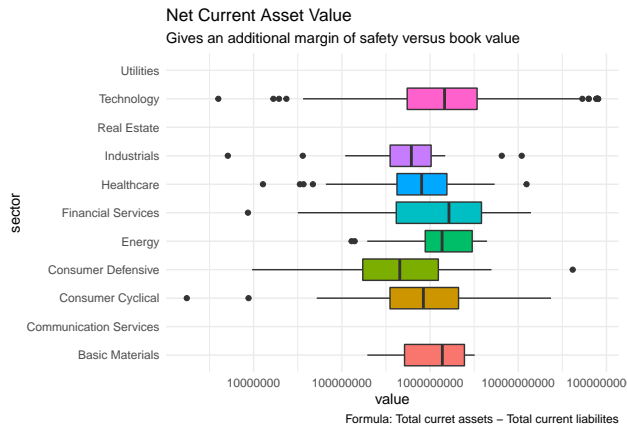
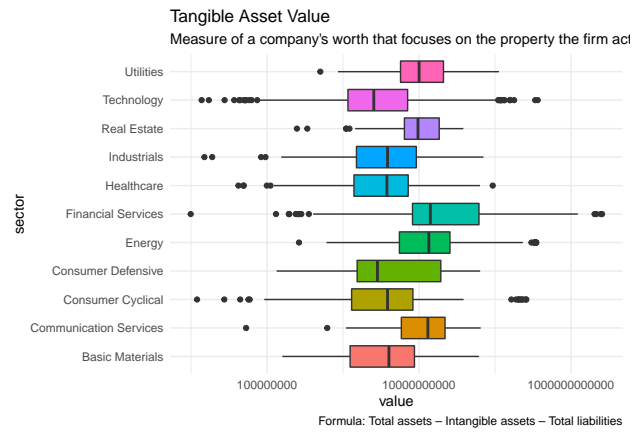
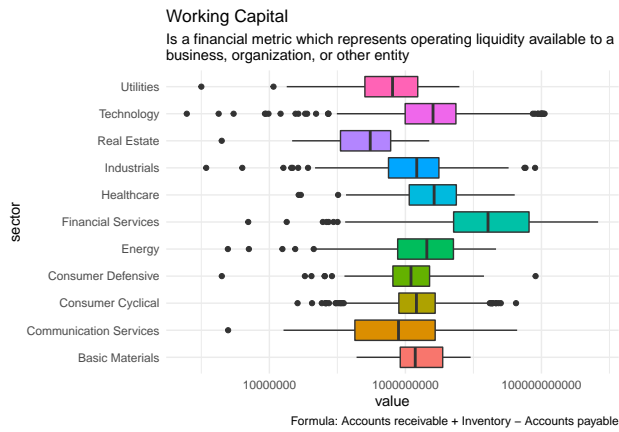
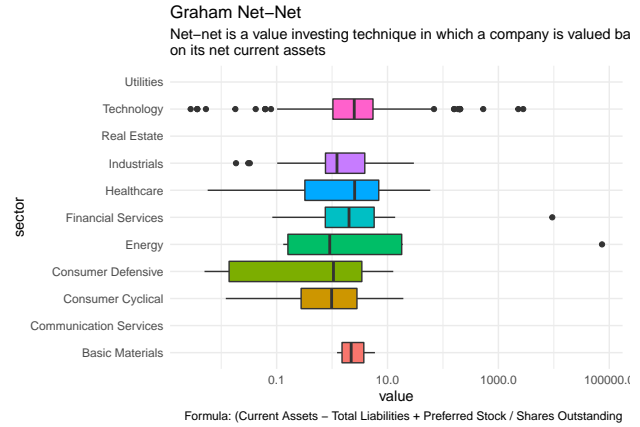
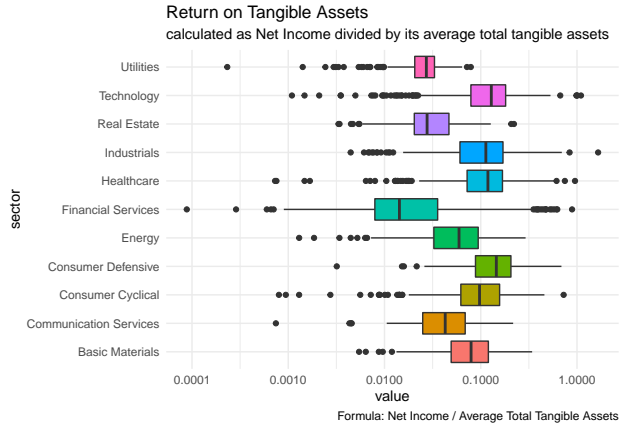
The Graham number is a figure that measures a stock's fundamental value by taking into account the company's earnings per share and book value per share.



ROIC

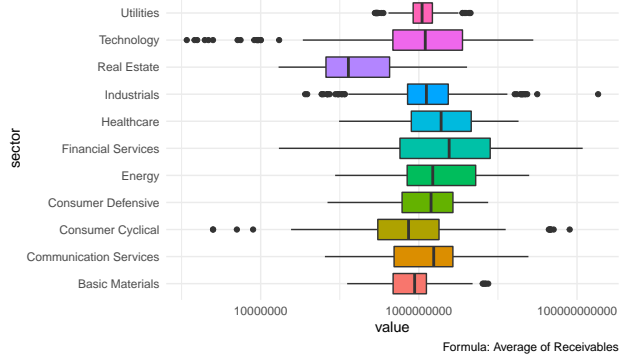
Return on invested capital, is a ratio used in finance, valuation and accounting, as a measure of the profitability and value-creating potential of companies relative to the amount of capital invested by shareholders and debtholders.





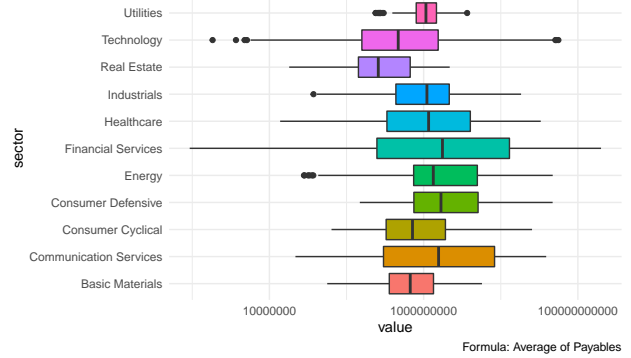
Average Receivables

Total amount of money owed to your business by your customers from : account divided by AR periods



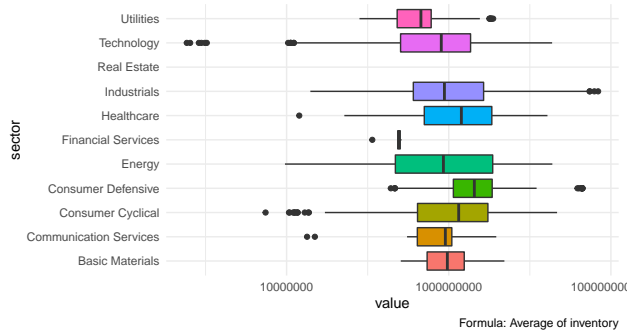
Average Payables

Total amount of money the business owes the customers account divid of periods



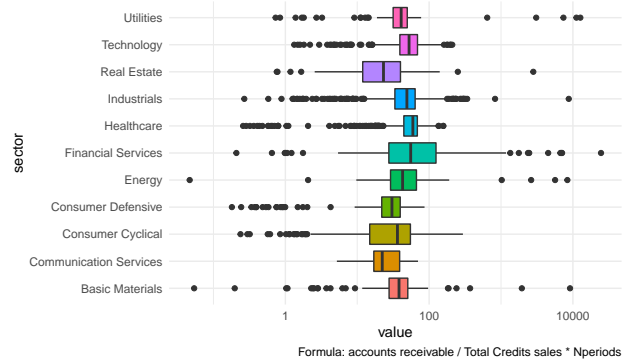
Average Inventory

Average inventory is the mean value of an inventory within a certain tim period, which may vary from the median value of the same data set, an computed by averaging the starting and ending inventory values over a period



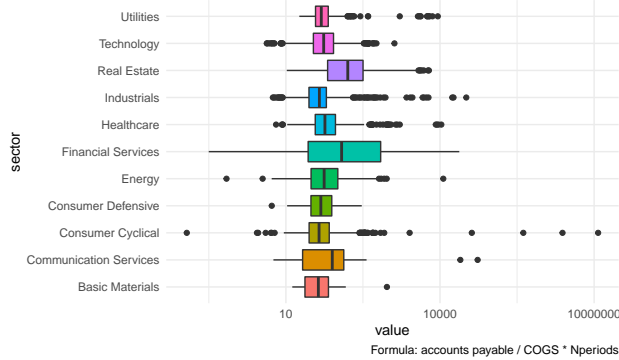
Days Sales Outstanding

Measure of the average number of days that it takes a company to colle after a sale has been made



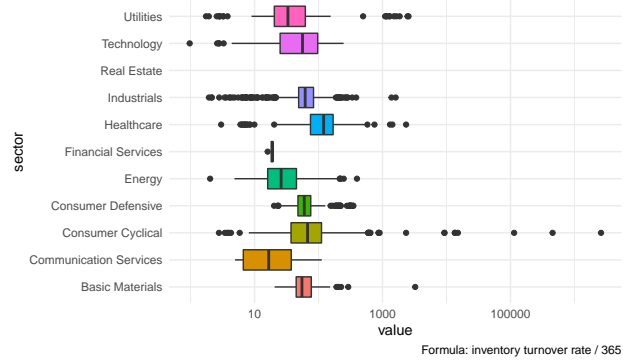
Days Payables Outstanding

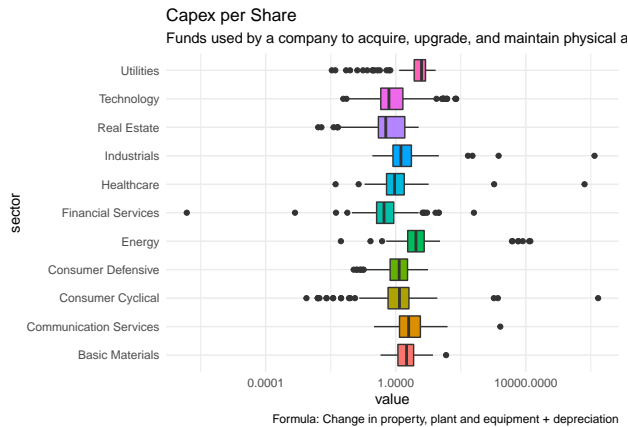
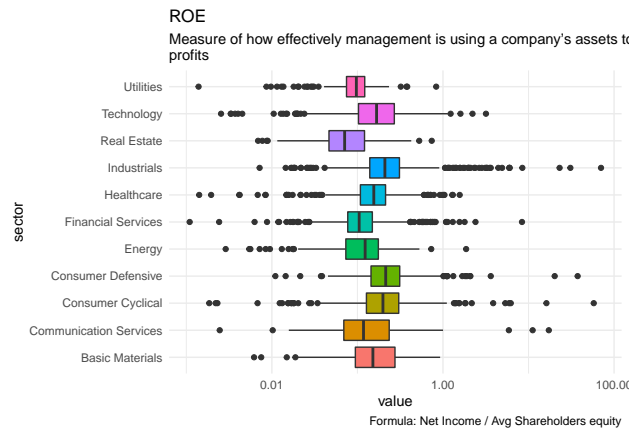
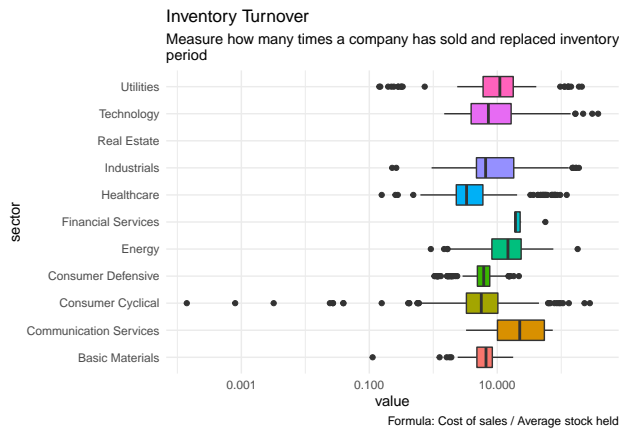
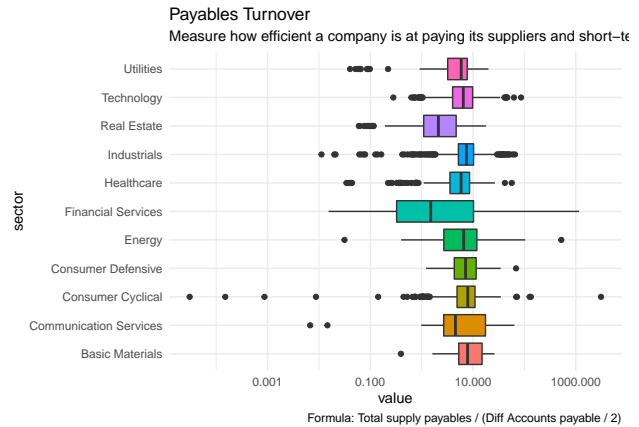
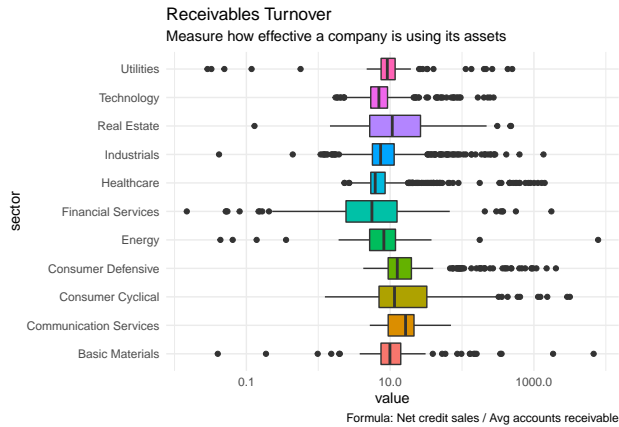
Financial ratio that indicates the average time (in days) that a company to pay its bills and invoices to its trade creditors



Days of Inventory on Hand

Measure of how quickly a business uses up the average inventory it ke stock





It seems that some metrics could be correlated and many of them tends to have the same pattern per sectors. That lead us to the question on how to evaluate them in risk mitigation assets, this will be done in the next chapter.

We can see that metrics that clearly show a difference in results per sectors are:

1. Debt to equity
2. Current ratio
3. Interest coverage
4. SG&A to revenue
5. R&D to revenue
6. Intangibles to assets
7. Capex to operatig cash flow

8. Capex to revenue
9. ROIC
10. Return on tangible assets
11. Working capital
12. Tangible Asset Value
13. Average Inventory
14. Days sales outstanding
15. Days payables outstanding
16. Days of inventory on hand
17. Receivables turnover
18. Inventory turnover
19. ROE

It is important to notice that x-axis is on log scale, that means that other metrics could be included as well

Let's check how these metrics are correlated

```
KeyMetrics %>%
  unnest(data) %>%
  ungroup() %>% #removes grouped data, otherwise select will bring grouped attributes as well
  select(sector, metric, symbol, date, value) %>% # select variables needed to spread
  spread(key = metric, value = value) %>% # spread metrics to column that will be correlated
  select(-sector, -symbol, -date) %>% # remove columns not needed
  drop_na() %>% #Remove any na on metrics data, to fix correlation function return NA
  cor() %>% # Apply correlation function
  as.data.frame() %>% # Convert matrix class to data frame
  rownames_to_column("Metric") %>% # Include row names id from matrix to a column named data frame
  gather("metric", "correlation", -Metric) %>% # gather all correlation into a single column
  filter(Metric != metric) %>% # Remove any metrics equal (That results in correlation 1)
  arrange(-correlation) %>% # Arrange correlation, this will be used in id creation later
  filter(correlation >= 0.8) %>% # Filter only correlations greater than 0.8
  mutate(id = case_when(Metric == lag(metric, 1) ~ 1, TRUE ~ 0)) %>% # Column created to remove dupli
  filter(id == 1) %>% # Removing duplicates
  select(-id) %>% # Removing aux column
  kable(caption = "Correlation of metrics greather than 80%") %>%
  kable_styling(full_width = F)
```

\begin{table}

\caption{Correlation of metrics greather than 80%}

Metric	metric	correlation
Book Value per Share	Shareholders Equity per Share	1.0000000
Enterprise Value	Market Cap	1.0000000
EV to Operating cash flow	POCF ratio	1.0000000
EV to Free cash flow	PFCF ratio	0.9999999
Enterprise Value over EBITDA	Market Cap	0.9999999
PB ratio	PTB ratio	0.9999999
Enterprise Value	Enterprise Value over EBITDA	0.9999999
Enterprise Value over EBITDA	PE ratio	0.9999999
PE ratio	Market Cap	0.9999998
Market Cap	PE ratio	0.9999998
PE ratio	Enterprise Value	0.9999998
Enterprise Value	PE ratio	0.9999998
EV to Sales	Price to Sales Ratio	0.9999993
Enterprise Value over EBITDA	PFCF ratio	0.9999987
PFCF ratio	Market Cap	0.9999986
Market Cap	PFCF ratio	0.9999986
PFCF ratio	Enterprise Value	0.9999986
Enterprise Value	PFCF ratio	0.9999986
PFCF ratio	PE ratio	0.9999986
PE ratio	PFCF ratio	0.9999986
PFCF ratio	EV to Operating cash flow	0.9999986
EV to Operating cash flow	PFCF ratio	0.9999986
PFCF ratio	POCF ratio	0.9999985
Enterprise Value over EBITDA	EV to Free cash flow	0.9999984
EV to Free cash flow	EV to Operating cash flow	0.9999984
EV to Free cash flow	Market Cap	0.9999984
Enterprise Value	EV to Free cash flow	0.9999984
EV to Free cash flow	PE ratio	0.9999983
EV to Free cash flow	POCF ratio	0.9999982
Enterprise Value over EBITDA	EV to Operating cash flow	0.9999974
Enterprise Value over EBITDA	POCF ratio	0.9999973
EV to Operating cash flow	Market Cap	0.9999973
Enterprise Value	EV to Operating cash flow	0.9999973
Market Cap	POCF ratio	0.9999973
POCF ratio	Enterprise Value	0.9999973
Enterprise Value	POCF ratio	0.9999973
EV to Operating cash flow	PE ratio	0.9999972
PE ratio	POCF ratio	0.9999972
Enterprise Value over EBITDA	Price to Sales Ratio	0.9999972
Price to Sales Ratio	Market Cap	0.9999971
Market Cap	Price to Sales Ratio	0.9999971
Price to Sales Ratio	Enterprise Value	0.9999971
Enterprise Value	Price to Sales Ratio	0.9999971
Price to Sales Ratio	PE ratio	0.9999971
PE ratio	Price to Sales Ratio	0.9999971
Price to Sales Ratio	PFCF ratio	0.9999959
PFCF ratio	Price to Sales Ratio	0.9999959
Price to Sales Ratio	EV to Free cash flow	0.9999956
EV to Free cash flow	Price to Sales Ratio	0.9999956
Enterprise Value over EBITDA	PB ratio	0.9999952
PB ratio	Market Cap	0.9999952
Market Cap	PB ratio	0.9999952
PB ratio	Enterprise Value	0.9999952
Enterprise Value	PB ratio	0.9999952
Enterprise Value over EBITDA	PTB ratio	0.9999952
PB ratio	PE ratio	0.9999951
Market Cap	PTB ratio	0.9999951

\end{table}

This is very interesting, it seems that 32 metrics have a correlation with one of these metrics by greather than 80% as we could see in the metrics plots.

That actually makes sense because these metrics formulas are shared or have a common hierarchy formula variable.

That still lead us the question of risk mitigation on portfolio assets to these metrics, even though they're correlated that doesn't mean that these assets will follow the same pattern. In the next chapter this will be analyzed

Price

Let's take a look on market price in SP500 and per sector.

```
#Candlestick for SP500
HistoricalPrices %>%
  select(sector, Historical_Daily_Price) %>%
  unnest() %>%
  group_by(date) %>%
  summarise(close = mean(close), open = mean(open), low = mean(low), high = mean(high)) %>%
  ggplot(aes(x = date, y = close)) +
  geom_candlestick(aes(open = open, high = high, low = low, close = close)) +
  labs(title = "SP500 Candlestick Chart",
        subtitle = "Mean OHLC per sector",
        y = "Closing Price", x = "") +
  theme_tq()
```

SP500 Candlestick Chart

Mean OHLC per sector



This candlestick time series plot shows some very interesting analysis:

1. Huge drop in the market due to coronavirus, it does seem to be one of the worst drops in the market for SP500.
2. Market has a lot of drops and ups, but usually shows some trends upwards stoped by some peaked collapses that we know are related to economy breakdowns.

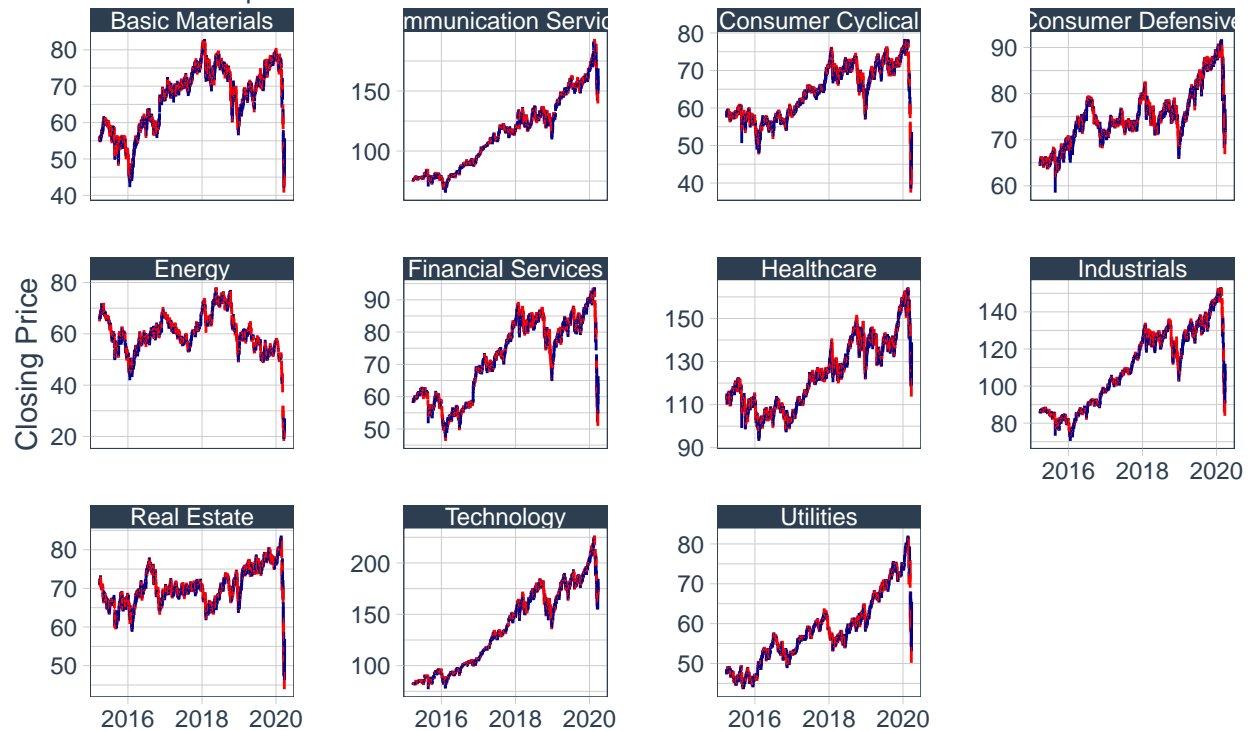
Let's evaluate the same plot per sector

```
#Candlestick per sector
Sector_Daily_OHLC <- HistoricalPrices %>%
  select(sector, Historical_Daily_Price) %>%
  unnest() %>%
  group_by(sector, date) %>%
  summarise(close = mean(close), open = mean(open), low = mean(low), high = mean(high))

Sector_Daily_OHLC %>%
  ggplot(aes(x = date, y = close, group = sector)) +
  geom_candlestick(aes(open = open, high = high, low = low, close = close)) +
  labs(title = "Sectors Candlestick Chart",
       subtitle = "Mean OHLC per sector",
       y = "Closing Price", x = "") +
  facet_wrap(~ sector, ncol = 4, scale = "free_y") +
  theme_tq()
```

Sectors Candlestick Chart

Mean OHLC per sector



It does seem that all sectors were heavily impacted, although technology and communication services were a bit less impacted in percent to its previous downfall price

Another interesting thing is that some sectors seem to have a similar pattern, by looking at them it seems we have 3 groups of sectors.

Let's take a look on these clusters, we'll use a silhouette method to define the optimal amount of clusters in sectors price

```
Clustering <- function(Cluster_DF, Df_aux){
  require(gridExtra)
  require(ggdendro)
  require(zoo)
  require(purrr)
  require(tsibble)
  require(broom)

  # Clustering
  hc <- hclust(dist(t(Df_aux[,-1])), "ave")

  # 8.1 DF clusters
  library(factoextra)
  NbClust <- fviz_nbclust(Df_aux[,-1], FUN = hcut, method = "silhouette")

  k <- which.max(NbClust$data$y)
```

```

cut_avg <- cutree(hc, k = k) %>%
  tidy() %>%
  rename("Data"="names", "cluster"="x")

# Number of clusters plot
NbClustersPlot <- plot(NbClust)

### Plot
hcdata <- dendro_data(hc)
names_order <- hcdata$labels$label

# Use the following to remove labels from dendrogram so not doubling up - but good for checking
hcdata$labels$label <- ''
p1 <- gg dendrogram(hcdata, rotate=TRUE, leaf_labels=FALSE)

# Autoplot only accepts time series data type
Zoo_DF <- read.zoo(Df_aux)

# Scale the time series and plot
maxs <- apply(Zoo_DF, 2, max)
mins <- apply(Zoo_DF, 2, min)
joined_ts_scales <- scale(Zoo_DF, center = mins, scale = maxs - mins)

new_data <- joined_ts_scales[,rev(as.character(names_order))]]

p2 <- autoplot(new_data, facets = Series ~ . ) +
  xlab('') + ylab('') + theme(legend.position="none")

gp1<-ggplotGrob(p1)
gp2<-ggplotGrob(p2)

grid <- grid.arrange(gp2, gp1, ncol=2, widths=c(4,2))

aux <- data.frame(Model_Name = Cluster_DF) %>%
  mutate(Clustered = purrr::map(Model_Name, ~cut_avg),
         hc = purrr::map(Model_Name, ~hc),
         NbClust= purrr::map(Model_Name, ~NbClust),
         NbClustersPlot= purrr::map(Model_Name, ~NbClustersPlot),
         p1= purrr::map(Model_Name, ~p1),
         p2= purrr::map(Model_Name, ~p2),
         grid = purrr::map(Model_Name, ~grid)
  )

return(aux)
}

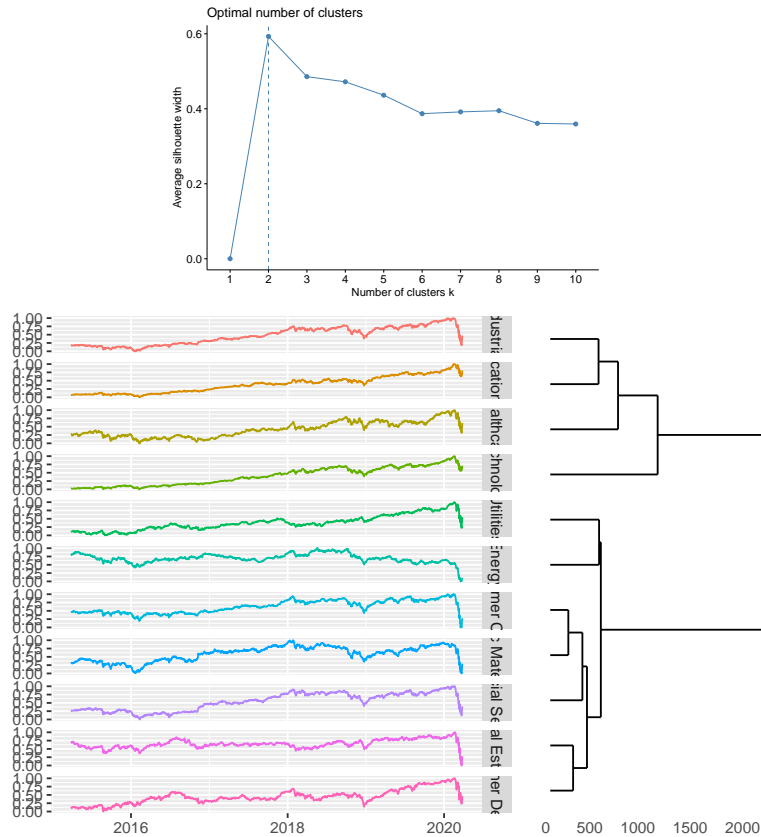
Clust_DF <- Sector_Daily_OHLC %>%
  select(sector, date, close) %>%
  spread(sector, close) %>%

```

```
filter_all(all_vars(!is.na(.)))
```

```
Clusters <- Clustering("Sectors", Clust_DF)
```

Welcome! Want to learn more? See two factoextra-related books at <https://goo.gl/ve3WBa>



That's interesting! We have 2 groups of clusters, let's organize them:

```
Clusters_sectors <- map_dfr(Clusters$Clustered, ~..1) %>%
  rename("sector"=Data) %>%
  arrange(cluster)
```

```
kable(Clusters_sectors, caption = "Sector Clusters") %>%
  kable_styling(full_width = F)
```

Now let's see how returns are occurring annually per sector

```
#Annual returns per sectors
HistoricalPrices %>%
  unnest(Monthly_AdjPrice) %>%
  group_by(sector) %>%
  tq_transmute(select = close, mutate_fun = periodReturn, period = "yearly", type = "arithmetic") %>%
  ggplot(aes(x = date, y = yearly.returns, fill = sector)) +
    geom_col() +
    geom_hline(yintercept = 0, color = palette_light()[[1]]) +
    scale_y_continuous(labels = scales::percent) +
```

Table 3: Sector Clusters

sector	cluster
Basic Materials	1
Consumer Cyclical	1
Consumer Defensive	1
Energy	1
Financial Services	1
Real Estate	1
Utilities	1
Communication Services	2
Healthcare	2
Industrials	2
Technology	2

```

labs(title = "Sectors: Annual Returns",
     y = "Annual Returns", x = "") +
facet_wrap(~ sector, ncol = 4, scales = "free_y") +
theme_tq() +
theme(axis.text.x = element_text(angle = 90, hjust = 1),
      legend.position = "none") +
scale_fill_tq()

```



It seems that in general, the market has some downsides and upsides in annual return for all sectors, but it

seems we have a huge drop on return until this moment of 2020 due to coronavirus.

Another interesting result from this plot is that some sectors have some good percentual margin increase, but that could be done due to low price being affected by any trend just as it seems to occur with basic materials.

The last analysis is to understand how prices moves quarterly, for that we'll get a min/max quarterly price per sector plot

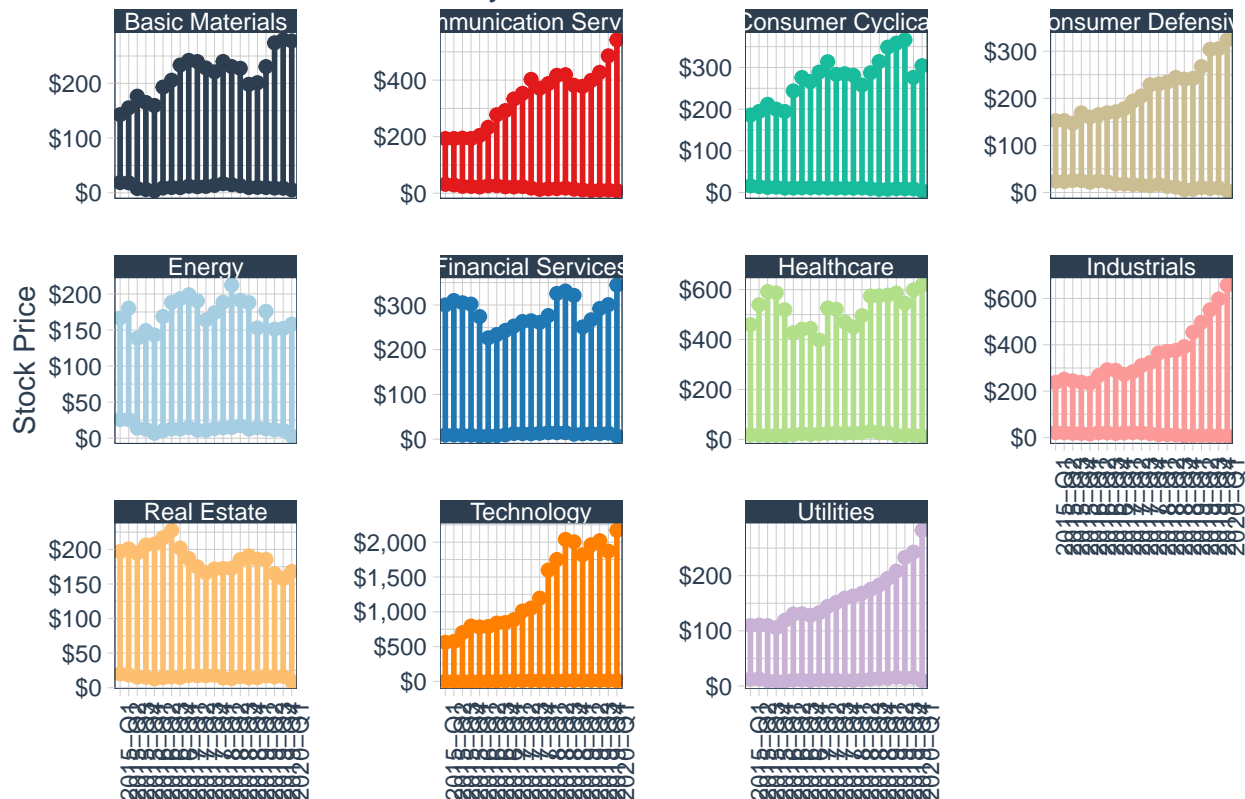
```
#Quarterly max min per sector
Sector_max_by_qtr <- HistoricalPrices %>%
  unnest(Historical_Daily_Price) %>%
  group_by(sector) %>%
  tq_transmute(select = close, mutate_fun = apply.quarterly, FUN= max,
               col_rename = "max.close") %>%
  mutate(year.qtr = paste0(lubridate::year(date), "-Q",
                           lubridate::quarter(date))) %>%
  select(-date)

Sector_min_by_qtr <- HistoricalPrices %>%
  unnest(Historical_Daily_Price) %>%
  group_by(sector) %>%
  tq_transmute(select = close, mutate_fun = apply.quarterly,
               FUN= min, col_rename = "min.close") %>%
  mutate(year.qtr = paste0(lubridate::year(date), "-Q",
                           lubridate::quarter(date))) %>%
  select(-date)

Sector_by_qtr <- left_join(Sector_max_by_qtr, Sector_min_by_qtr,
                          by = c("sector" = "sector", "year.qtr" = "year.qtr"))

Sector_by_qtr %>%
  ggplot(aes(x = year.qtr, color = sector)) +
  geom_segment(aes(xend = year.qtr, y = min.close, yend = max.close),
              size = 1) +
  geom_point(aes(y = max.close), size = 2) +
  geom_point(aes(y = min.close), size = 2) +
  facet_wrap(~ sector, ncol = 4, scale = "free_y") +
  labs(title = "Sector: Min/Max Price By Quarter",
       y = "Stock Price", color = "") +
  theme_tq() +
  scale_color_tq() +
  scale_y_continuous(labels = scales::dollar) +
  theme(axis.text.x = element_text(angle = 90, hjust = 1),
        axis.title.x = element_blank(),
        legend.position = "none")
```

Sector: Min/Max Price By Quarter



This is interesting, all sectors have as low price as zero as well as higher prices. This could mean that companies could be integrated into SP500 quarterly and therefore have low prices due to start in the market, or that the market variability is across all sectors evenly.

The major difference is that some sectors are more variable than others, and there are those that achieve higher prices in the long run such as technology sectors

Portfolio Analysis

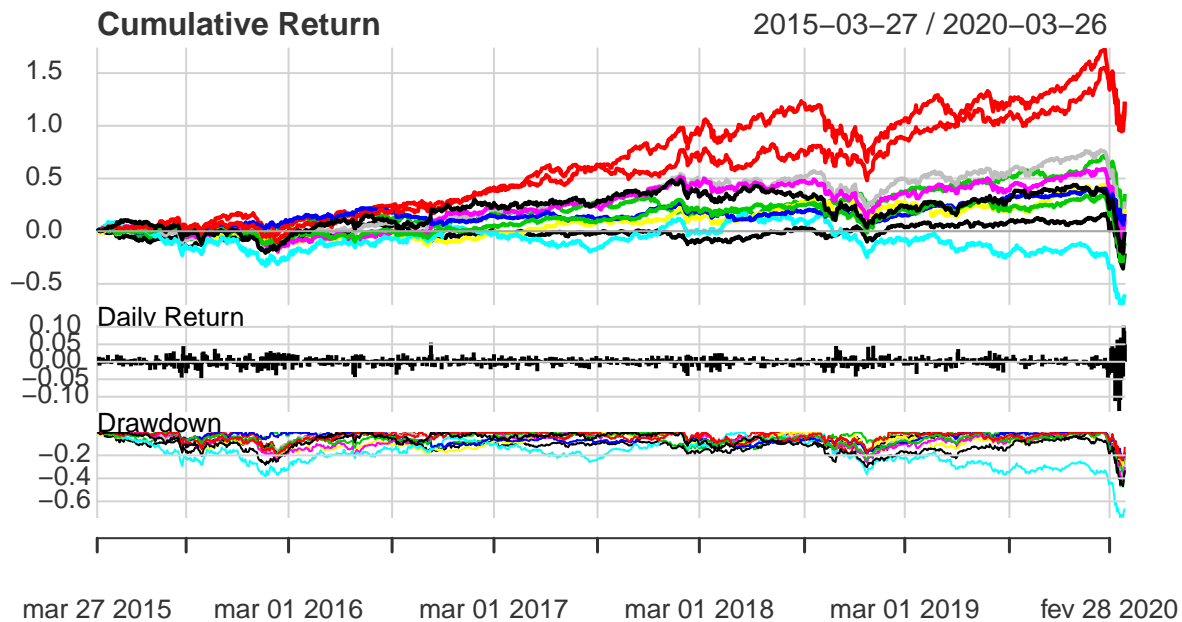
Sectors

Let's make a portfolio with risk mitigation in order to evaluate how the optimization tries to deal with sector returns

```
Sector>Returns <- Sector_Daily_OHLC %>%
  group_by(sector) %>%
  tq_transmute(select      = close,
                mutate_fun = periodReturn,
                period      = "daily",
                col_rename  = "close") %>%
  spread(sector, close) %>%
  filter_all(all_vars(!is.na(.))) %>%
  tk_xts(data = ., date_var = date, silent = TRUE) #Its needed to run porfolio.spec

charts.PerformanceSummary(Sector>Returns,main = "Sectors Performance", legend.loc = NULL)
```


Sectors Performance



Let's run the portfolio in order to minimize risk and evaluate it's sector allocation called weight

```
Optimize <- function>Returns){
  # Create the portfolio specification
  port_spec <- portfolio.spec(colnames>Returns)) %>%

  # Add a full investment constraint such that the weights sum to 1
  add.constraint(portfolio = ., type = "full_investment") %>%

  # Add a long only constraint such that the weight of an asset is between 0 and 1
  add.constraint(portfolio = ., type = "long_only") %>%

  # Add an objective to minimize portfolio standard deviation
  add.objective(portfolio = ., type = "risk", name = "StdDev")

  # Solve the optimization problem
  opt <- optimize.portfolio>Returns, portfolio = port_spec,
    optimize_method = "ROI", trace=TRUE)

  return(opt)
}

SectorReturns <- Optimize(Sector_Returns) %>%
```

```
extractWeights() %>%
data.frame(Name = names(.), weights = round(.,3), row.names = NULL) %>%
select(-.)
```

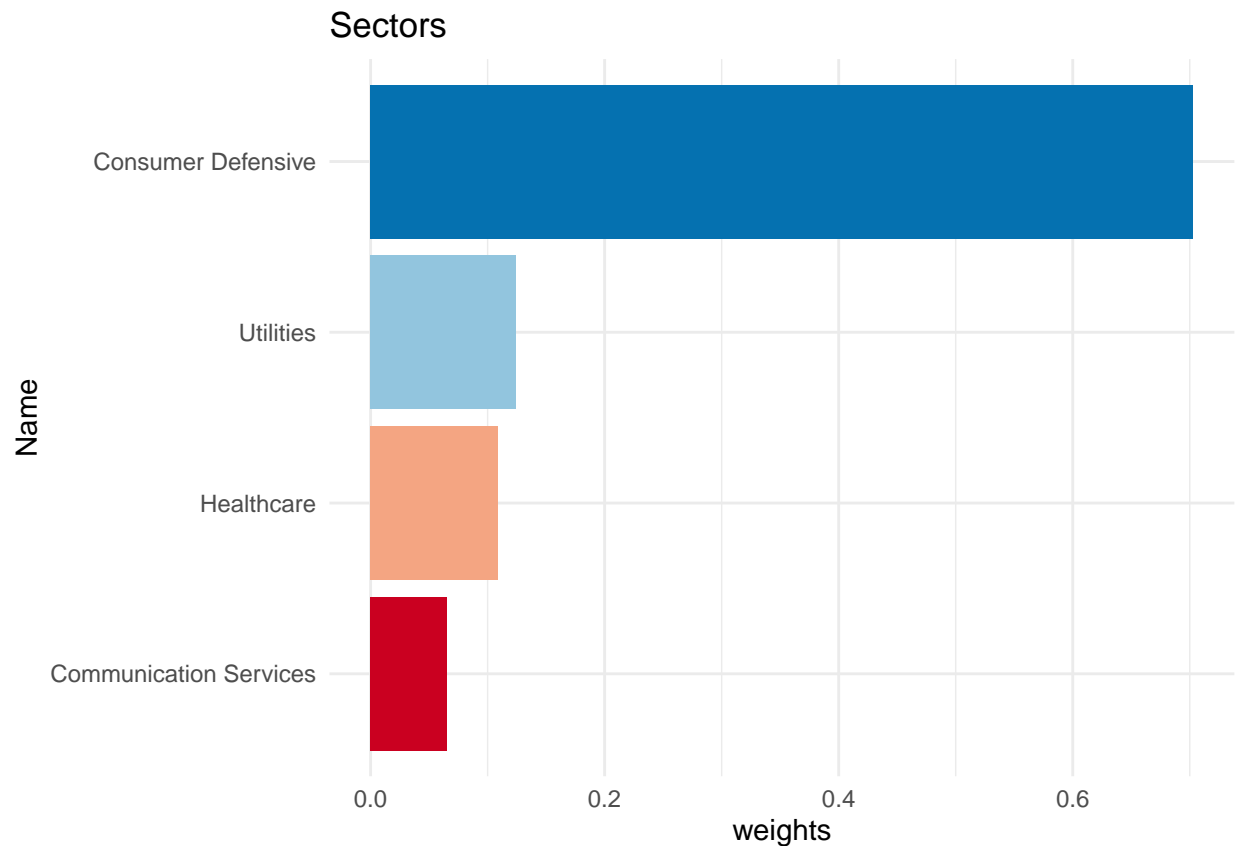
Let's plot these weights

```
plots2 <- function(weights, sector=NULL){

  plot <- weights %>%
    mutate(Name = fct_reorder(Name, weights)) %>%
    filter(weights > 0.01) %>%
    ggplot(aes(x = Name, y=weights, fill = Name)) +
    geom_col() +
    scale_fill_brewer(palette = "RdBu") +
    theme_minimal() +
    coord_flip() +
    guides(fill = "none") +
    labs(title = paste0("Sectors ", sector))

  return(plot)
}

plots2(SectorReturns)
```



Let's check how each company per sector is structured in this portfolio analysis.

Companies per sector

Since there are 400 countries and the main idea here is to understand how metrics relate to risk mitigation, we'll record only the final result of the best and worst weight allocation of portfolio companies per sector

#Since we have to model this grouped per sector, all this piece of script is doing is merging the same

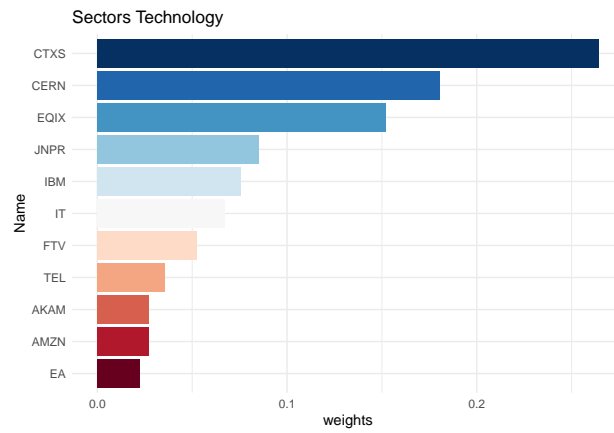
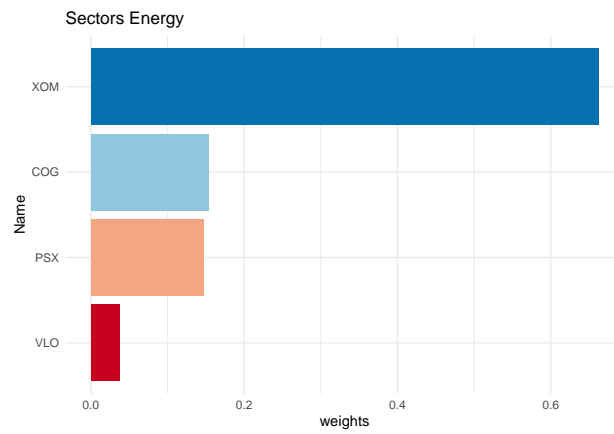
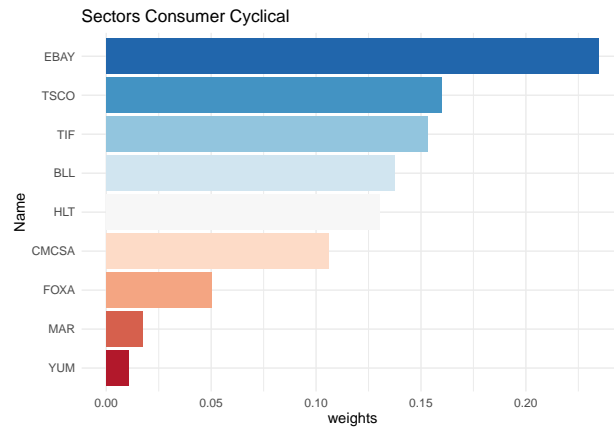
```
Symbol>Returns <- HistoricalPrices %>%
  select(symbol, sector, Historical_Daily_Price) %>%
  unnest() %>%
  group_by(sector) %>%
  nest() %>%
  mutate(data = map(data, ~..1 %>%
    select(symbol, date, close) %>%
    group_by(symbol) %>%
    tq_transmute(select      = close,
                  mutate_fun = periodReturn,
                  period      = "daily",
                  col_rename  = "close") %>%
    spread(symbol, close) %>%
    filter_all(all_vars(!is.na(.))) %>%
    tk_xts(data = ., date_var = date, silent = TRUE)))

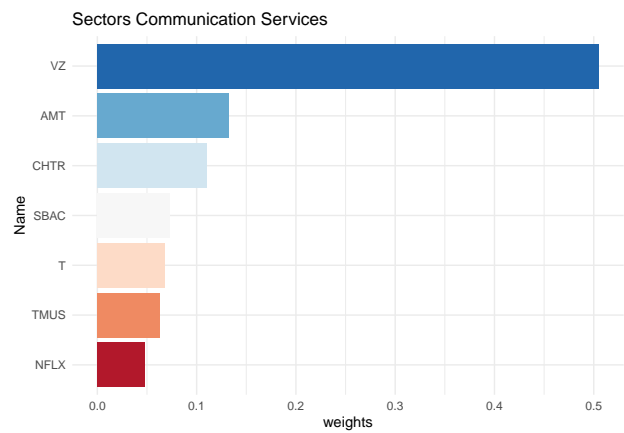
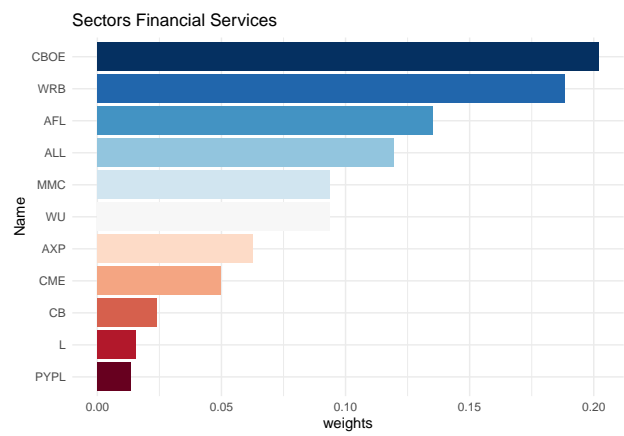
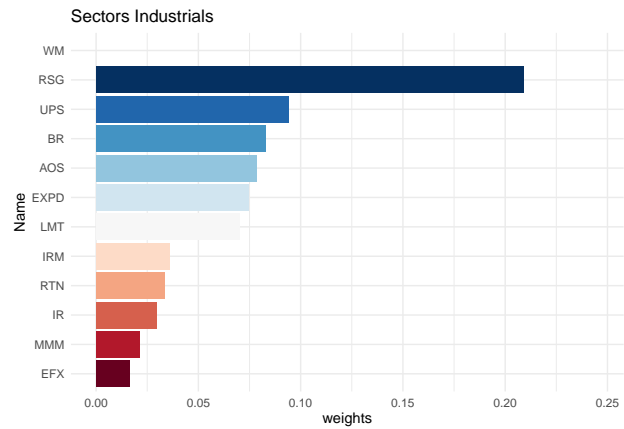
#Optimizing per each purrr list of sectors
Symbol>Returns <- Symbol>Returns %>%
  mutate(optimize = map(data, ~Optimize(..1)))

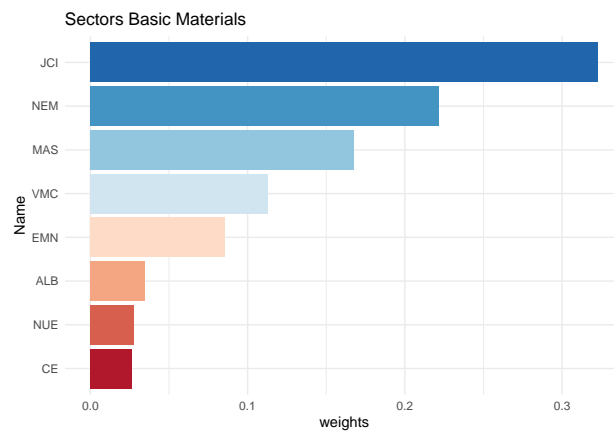
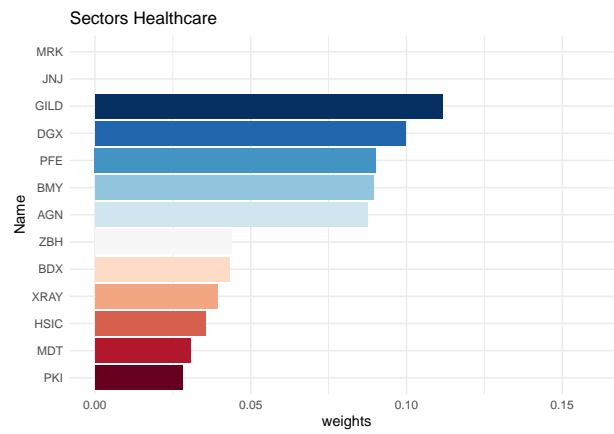
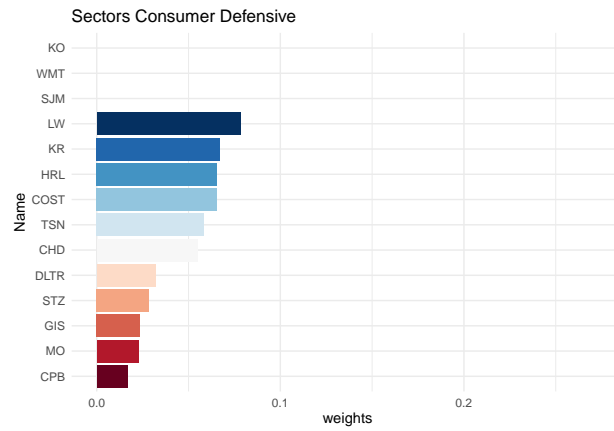
#Simple extract weights and organizing it to be able to plot
Symbol>Returns <- Symbol>Returns %>%
  mutate(weights = map(optimize, extractWeights),
         weights = map(weights, ~data.frame(Name = names(..1),
                                             weights = ..1, row.names = NULL)))

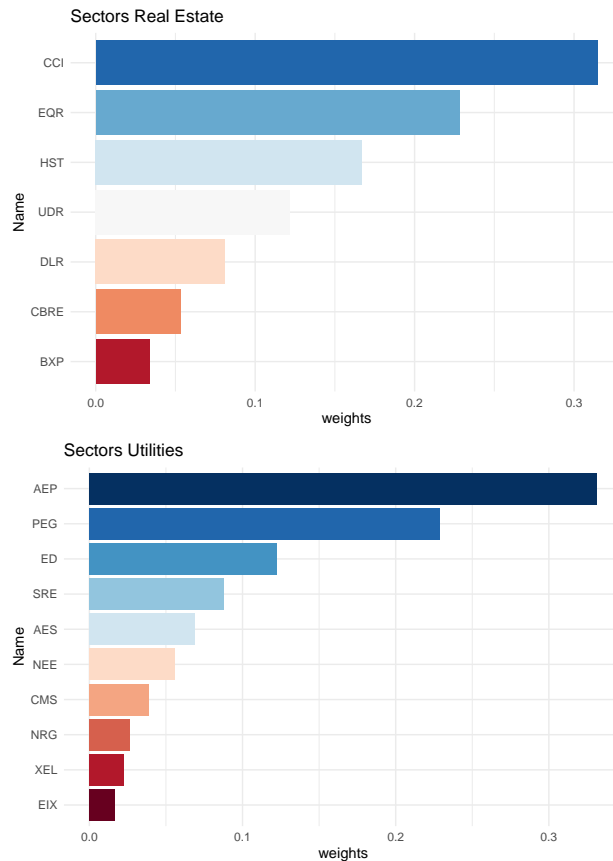
#Extracting worst and best symbols and plotting each sector weights
Symbol>Returns <- Symbol>Returns %>%
  mutate(Best = map(weights, ~ filter(..1, weights == max(weights)) %>%
    select(Name)),
         Worst = map(weights, ~ filter(..1, weights == min(weights)) %>%
    select(Name)),
         plots = map(weights, ~plots2(..1, sector)))

walk(Symbol>Returns$plots, plot)
```









Now we can analyse each metric per best and worst companies allocated portfolio for risk mitigation.

KeyMetrics x Portfolio Mitigation

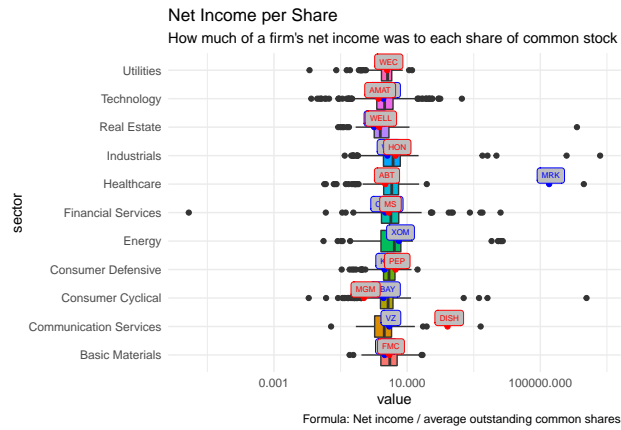
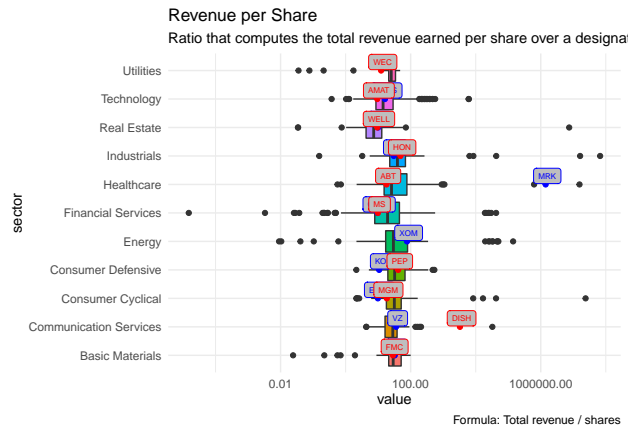
Best x Worst companies per sector

All we have to do know is to include the best and worst companies per sector in the keyMetrics dataset and plot each metric including the position of both best and worst companies in order to understand if these metrics relate to a decision on risk mitigation portfolio

Table 4: Best and Worst company per Portfolio risk mitigation

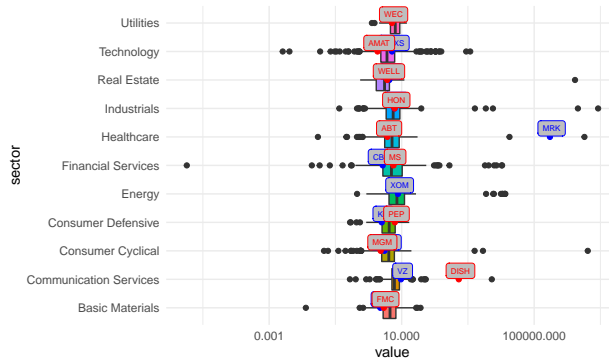
sector	Best	Worst
Consumer Cyclical	EBAY	MGM
Energy	XOM	FTI
Technology	CTXS	AMAT
Industrials	WM	HON
Financial Services	CBOE	MS
Communication Services	VZ	DISH
Consumer Defensive	KO	PEP
Healthcare	MRK	ABT
Basic Materials	JCI	FMC
Real Estate	CCI	WELL
Utilities	AEP	WEC

Plots



Operating Cash Flow per Share

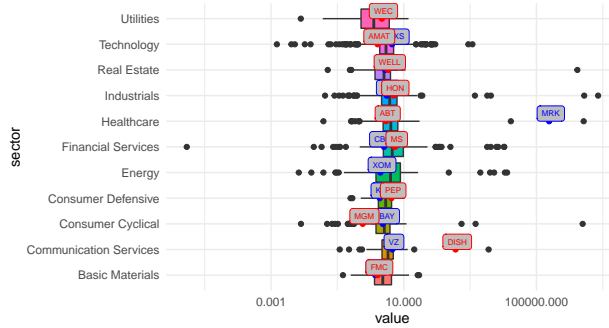
Company's ability to generate cash



Formula: (Operating Cash Flow – Preferred Dividends) / Common Shares Outstanding

Free Cash Flow per Share

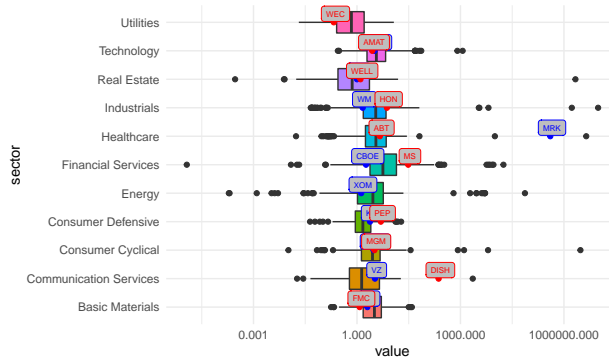
How much cash a business generates after accounting for capital expenditures such as buildings or equipment. This cash can be used for expansion, reducing debt, or other purposes.



Formula: Free cashflow / # Shares outstanding

Cash per Share

Available cash to a business divided by the number of equity shares outstanding



Formula: (Cash Flow – Preferred Dividends) / Shares Outstanding

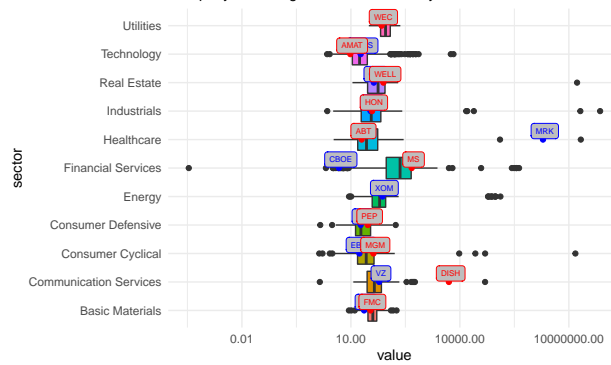
Book Value per Share

Value of allshares divided by the number of shares issued.



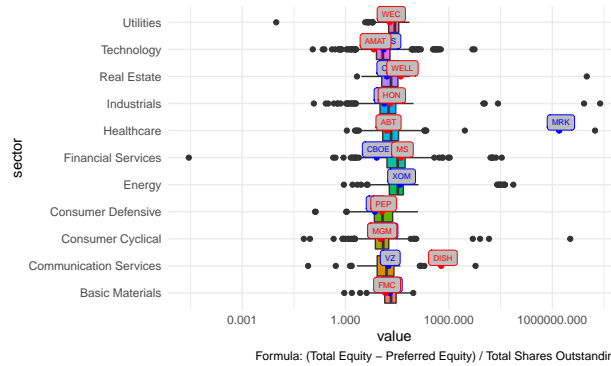
Tangible Book Value per Share

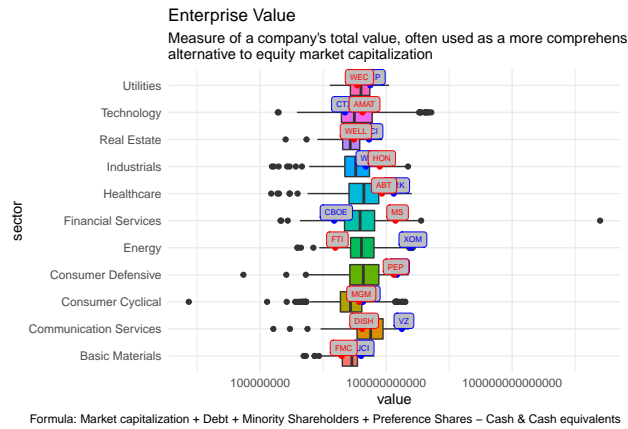
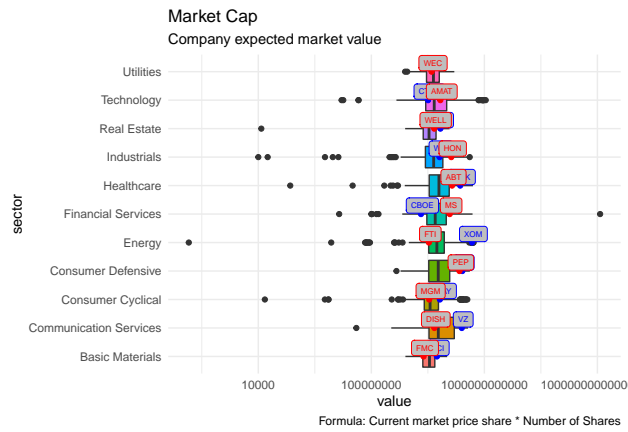
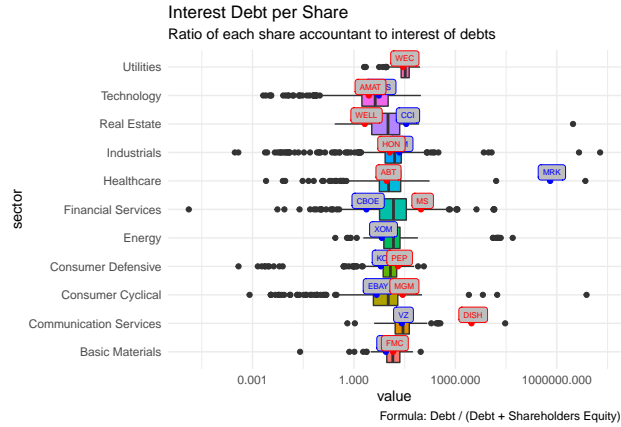
Company's net tangible assets divided by its number of shares outstanding



Shareholders Equity per Share

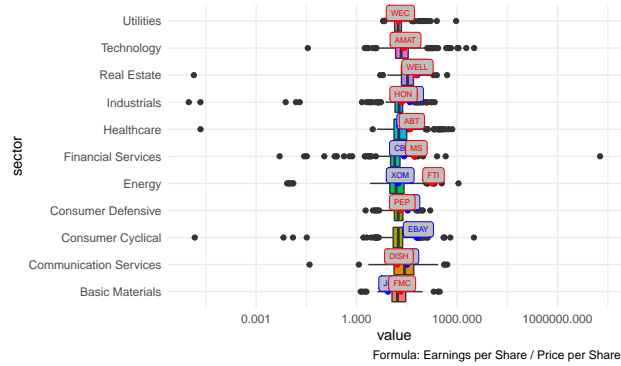
Equity available to common shareholders divided by the number of outstanding shares





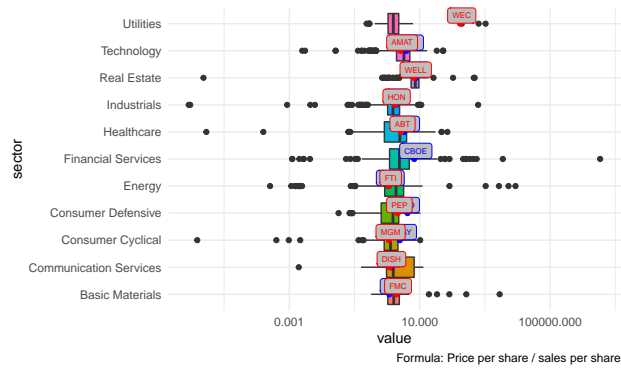
PE ratio

Price to earnings ratio is a measure to determine the relative value of a company's shares in an apples-to-apples comparison



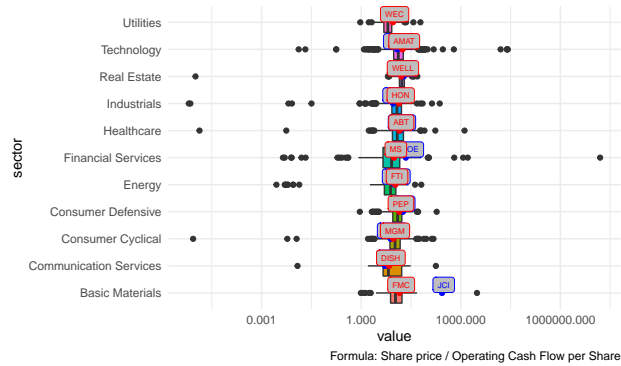
Price to Sales Ratio

Company's market capitalization divided by the revenue of the past 12 months. The lower the PS ratio, the more attractive the investment



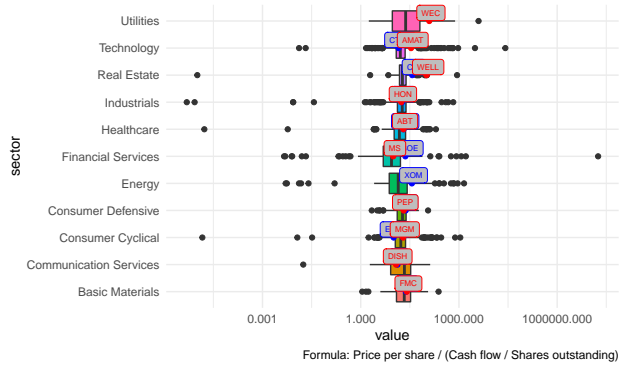
POCF ratio

Price to cash flow stock valuation indicator or multiple that measures the value of a stock's price relative to its operating cash flow



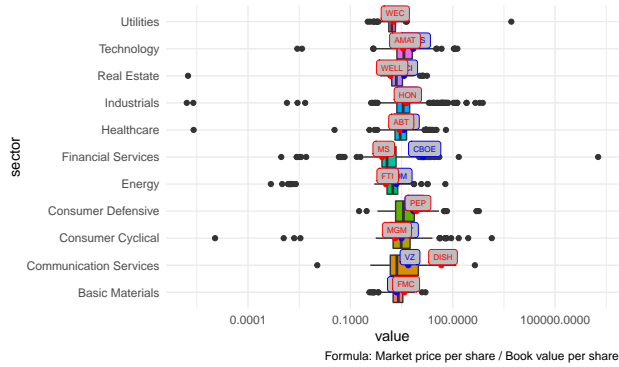
PFCF ratio

Price to free cash flow ratio is a valuation method used to compare a company's current share price to its per-share free cash flow



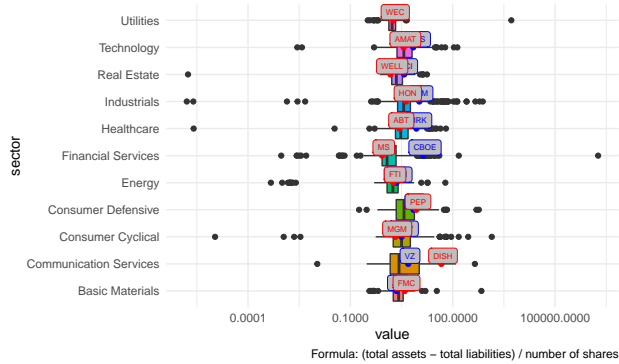
PB ratio

Price to book ratio is to compare a firm's market to book value and is determined by dividing price per share by book



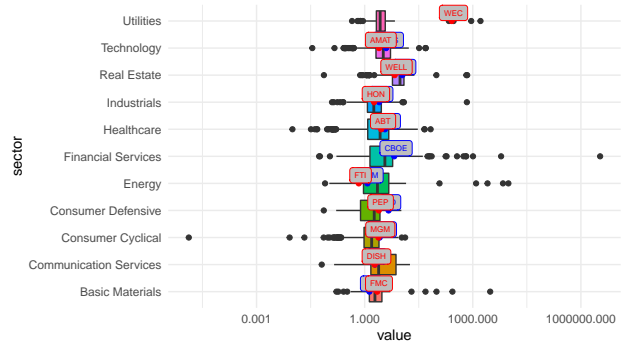
PTB ratio

Price to book ratio is to compare a firm's market to book value and is determined by dividing price per share by book



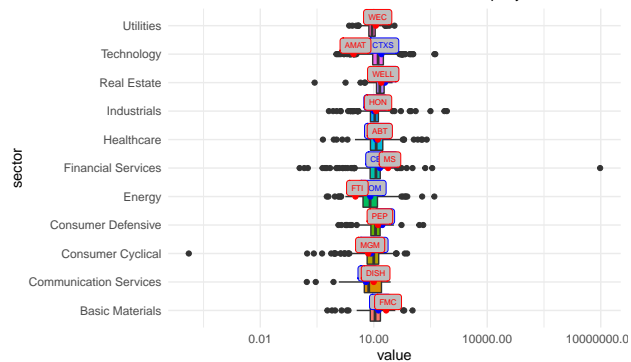
EV to Sales

Enterprise value to sales is a business valuation method that compares value of a company with its sales



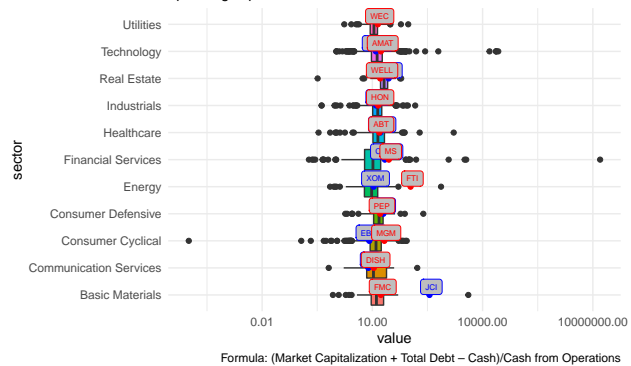
Enterprise Value over EBITDA

Good measure to estimate the cash flow of a company



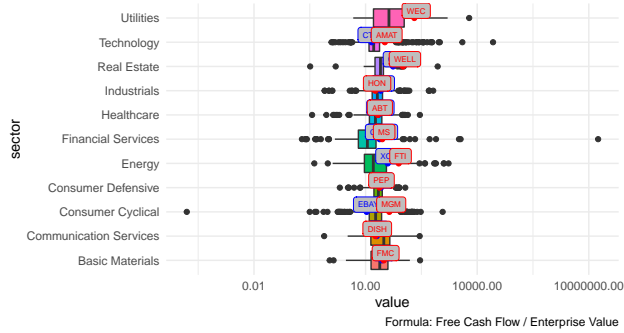
EV to Operating cash flow

Enterprise value to op cash flow is a good to measure the percentage at operating expenses of current assets



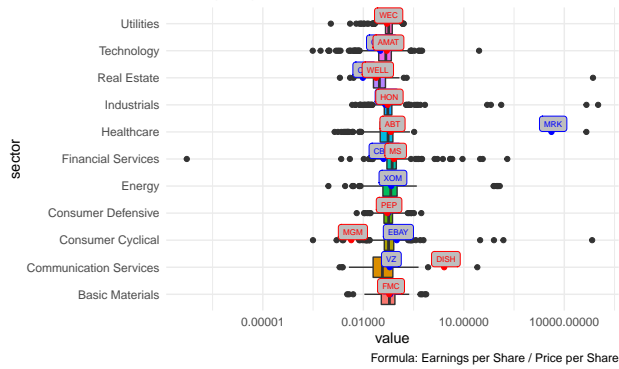
EV to Free cash flow

Compares the total valuation of the company with its ability to generate cashflow. the lower the ratio of enterprise value to the free cash flow figure the faster a company can pay back the cost of its acquisition or generate to reinvest in its business



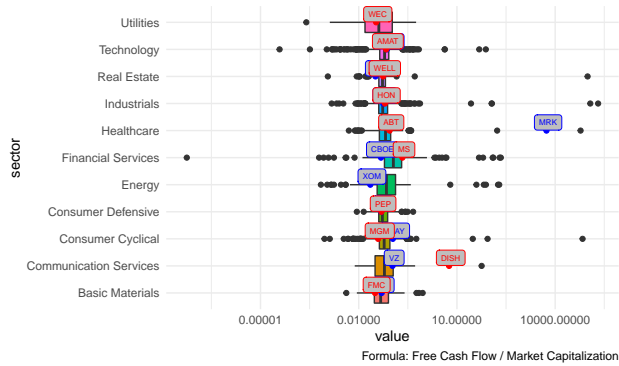
Earnings Yield

Earnings per share for the most recent 12-month period divided by the market price per share.



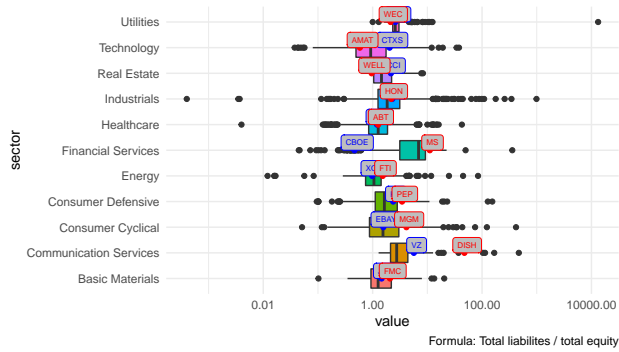
Free Cash Flow Yield

Financial solvency ratio that compares the free cash flow per share against its market value per share



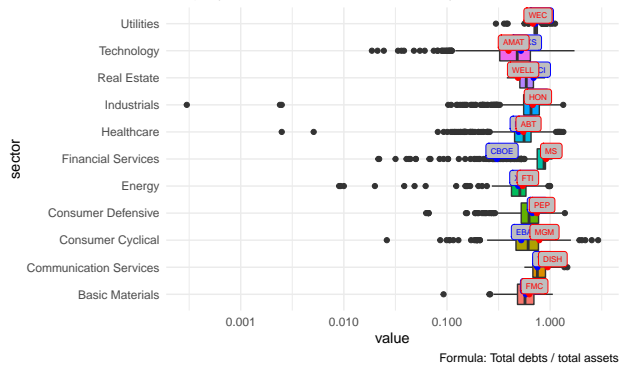
Debt to Equity

Financial ratio indicating the relative proportion of shareholders' equity : debt used to finance a company's assets. Closely related to leveraging, ratio is also known as risk, gearing or leverage



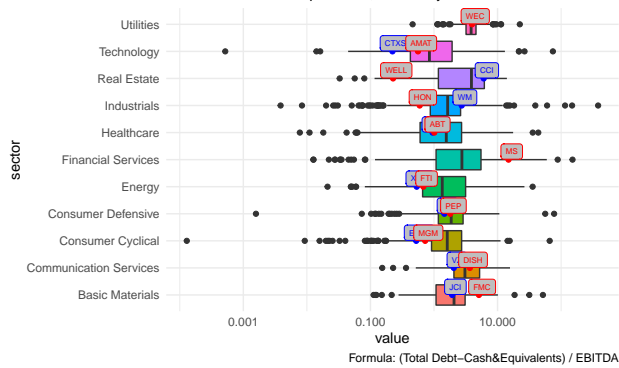
Debt to Assets

Indicator of a company's financial leverage. It tells you the percentage of company's total assets that were financed by creditors



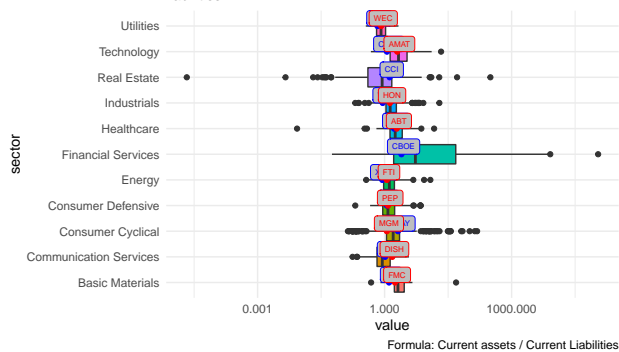
Net Debt to EBITDA

Measurement of leverage, calculated as a company's interest-bearing debt minus cash or cash equivalents, divided by its EBITDA



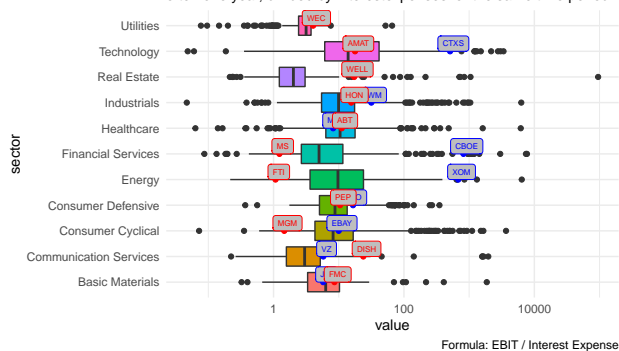
Current ratio

Liquidity ratio that measures whether a firm has enough resources to meet its short-term obligations. It compares a firm's current assets to its current liabilities



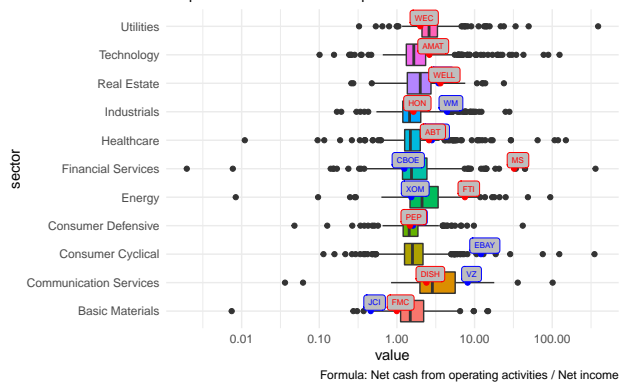
Interest Coverage

Measure of a company's ability to meet its interest payments. Interest coverage ratio is equal to earnings before interest and taxes (EBIT) for a time period often one year, divided by interest expenses for the same time period



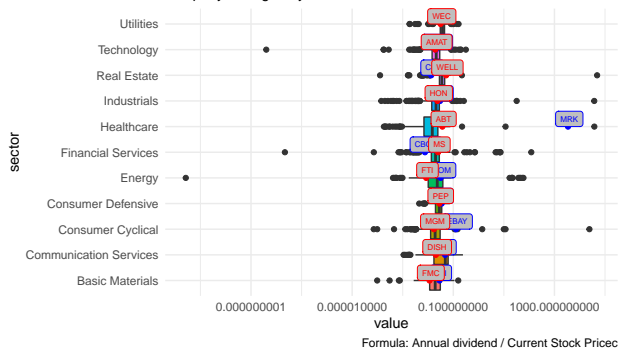
Income Quality

Proportion of cash flow from operations to net income



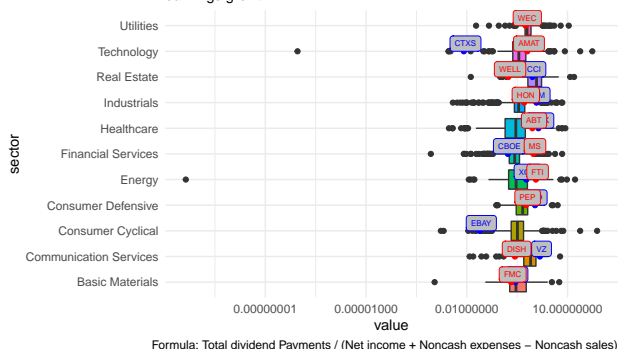
Dividend Yield

Dividend yield is used to calculate the earning on investment (shares) considering only the returns in the form of total dividends declared by the company during the year



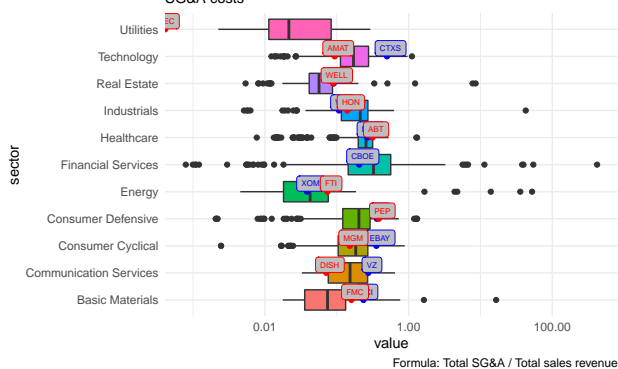
Payout Ratio

Fraction of net income a firm pays to its stockholders in dividends: The of earnings not paid to investors is left for investment to provide for future earnings growth



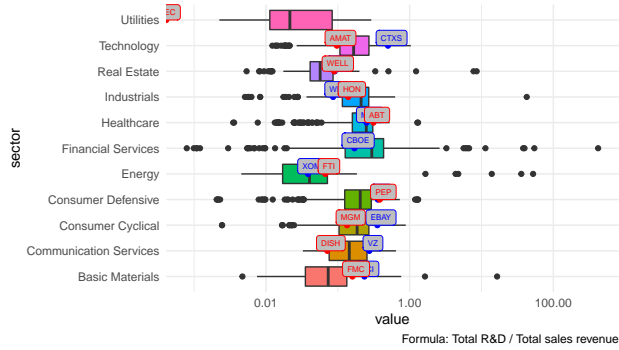
SG&A to Revenue

It tells you what percent of every dollar your company earned gets sucked SG&A costs



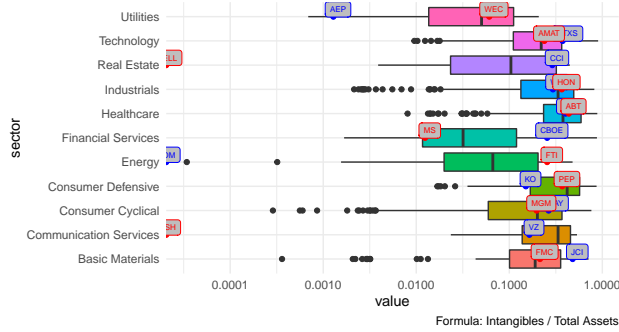
R&D to Revenue

Measures the percentage of sales that is allocated to R&D expenditure: is not as effective when looking at companies in different industries because different industries place different values on R&D



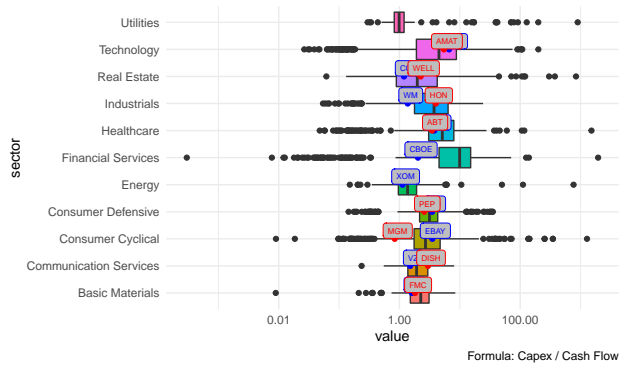
Intangibles to Total Assets

The goodwill to assets ratio is a financial measurement that compares intangible assets like a brand name, customer list, or unique position in industry to the total assets of the company in an effort to see if goodwill is being recorded properly



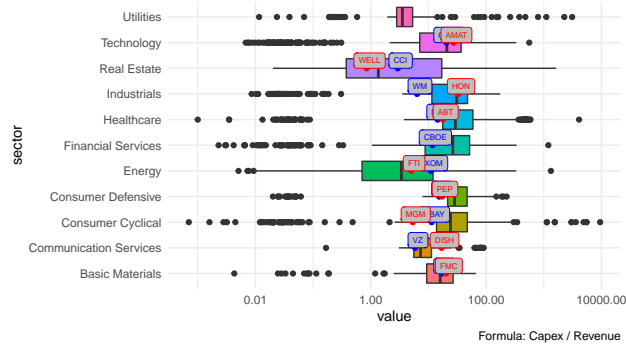
Capex to Operating Cash Flow

Assesses how much of a company's cash flow from operations is being capital expenditure



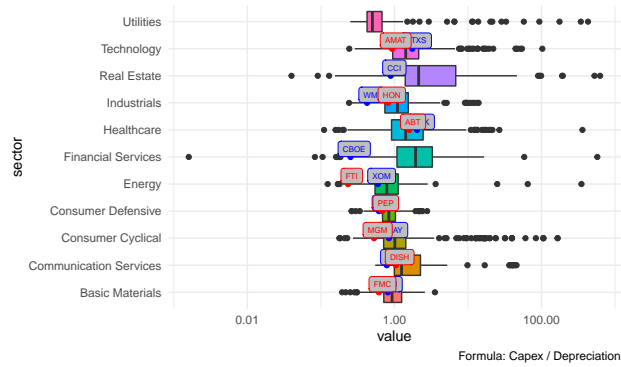
Capex to Revenue

The Capex to Revenue ratio measures a company's investments in property, plant, and equipment and other capital assets to its total sales. The ratio shows how aggressively the company is re-investing its revenue back into product



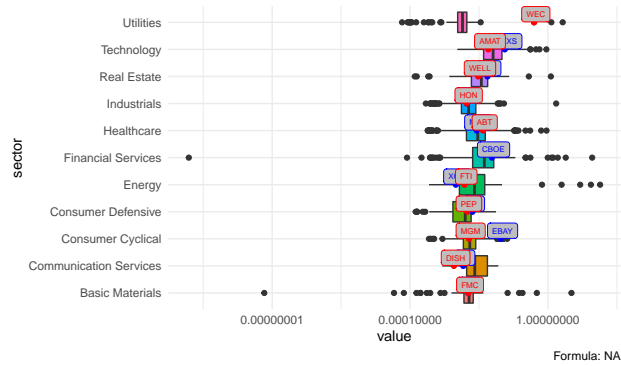
Capex to Depreciation

If a company regularly has more CapEx than depreciation, its asset base is growing



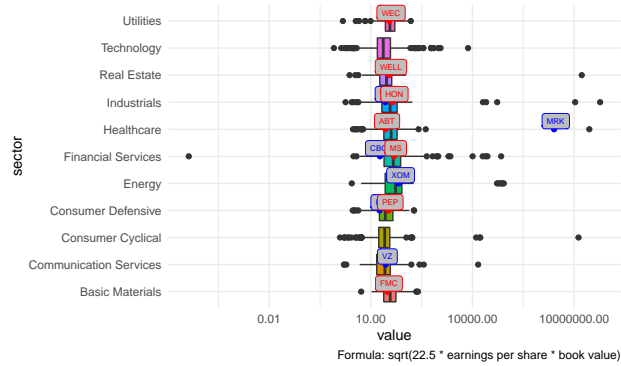
Stock-based compensation to Revenue

Represents a noncash expense that reduces book income, which isn't deductible for the IRS as a deductible expense



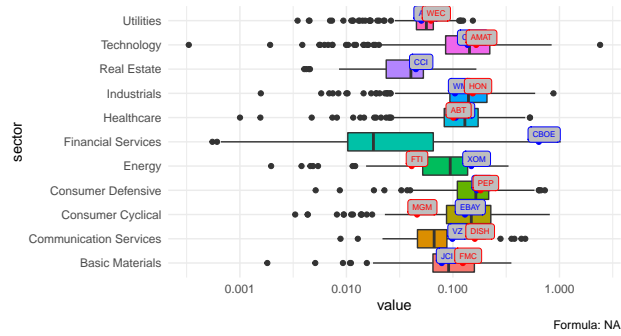
Graham Number

The Graham number is a figure that measures a stock's fundamental value taking into account the company's earnings per share and book value per share.



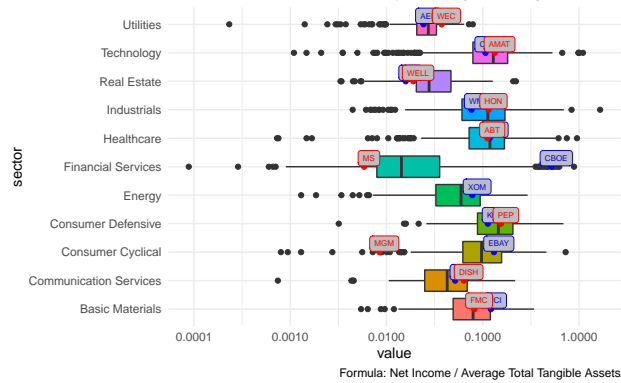
ROIC

Return on invested capital, is a ratio used in finance, valuation and accounting, as a measure of the profitability and value-creating potential of companies relative to the amount of capital invested by shareholders and debtholders.



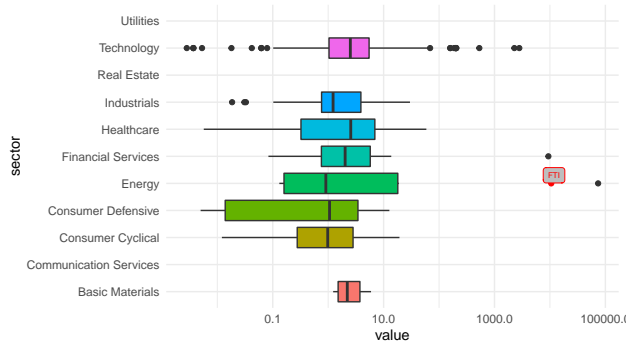
Return on Tangible Assets

calculated as Net Income divided by its average total tangible assets



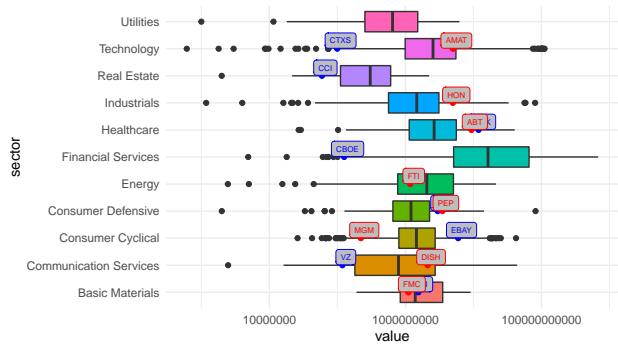
Graham Net-Net

Net-net is a value investing technique in which a company is valued based on its net current assets



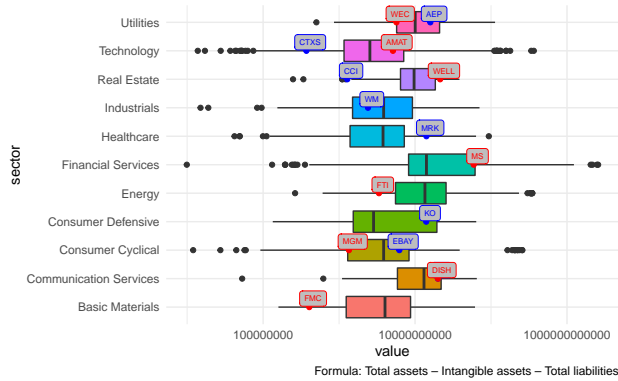
Working Capital

Is a financial metric which represents operating liquidity available to a business, organization, or other entity



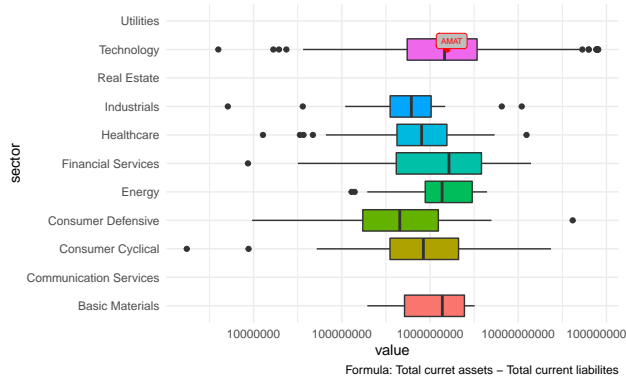
Tangible Asset Value

Measure of a company's worth that focuses on the property the firm acts



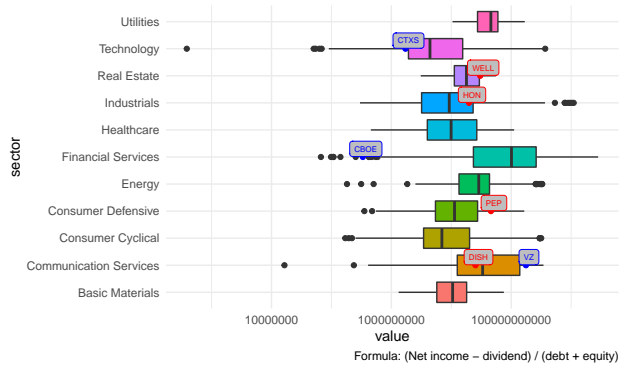
Net Current Asset Value

Gives an additional margin of safety versus book value



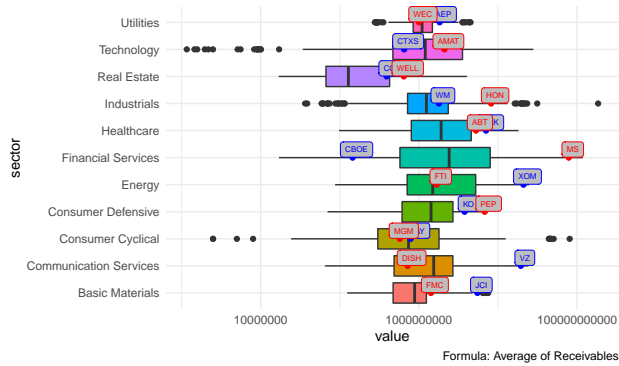
Invested Capital

Total amount of money raised by a company by issuing securities to equity shareholders and debt to bondholders



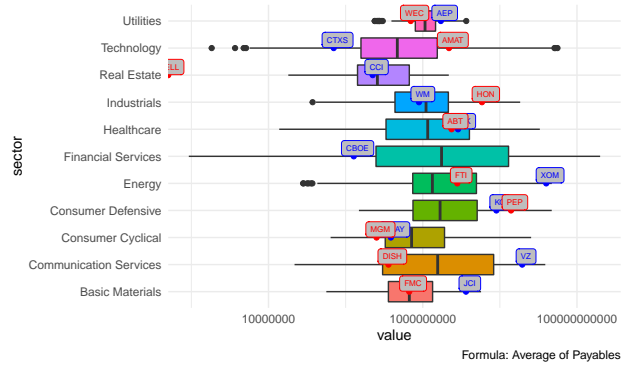
Average Receivables

Total amount of money owed to your business by your customers from : account divided by AR periods



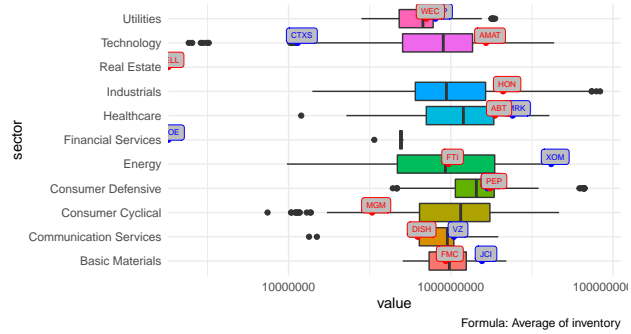
Average Payables

Total amount of money the business owes the customers account divid of periods



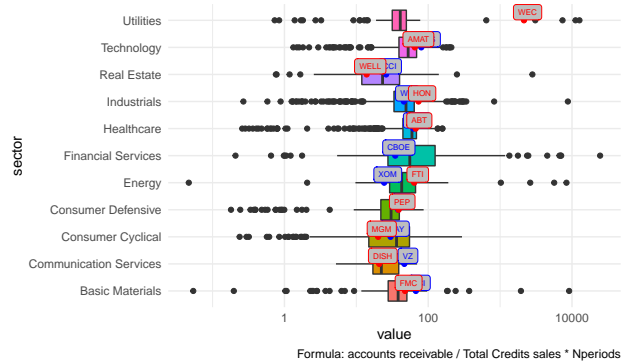
Average Inventory

Average inventory is the mean value of an inventory within a certain tim period, which may vary from the median value of the same data set, an computed by averaging the starting and ending inventory values over a period



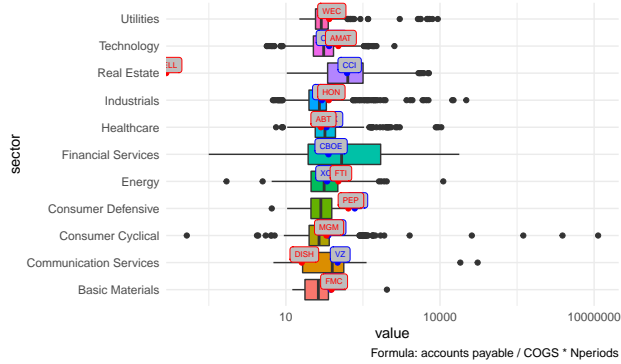
Days Sales Outstanding

Measure of the average number of days that it takes a company to colle after a sale has been made



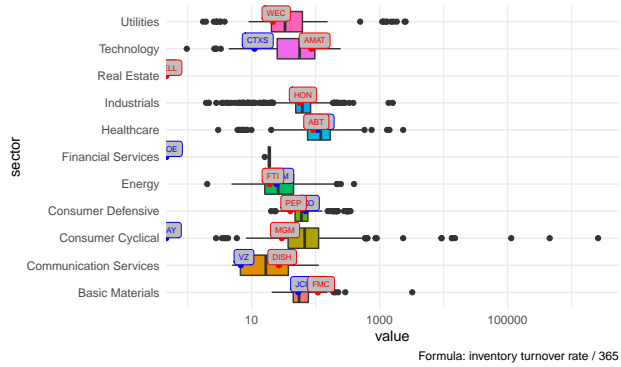
Days Payables Outstanding

Financial ratio that indicates the average time (in days) that a company to pay its bills and invoices to its trade creditors



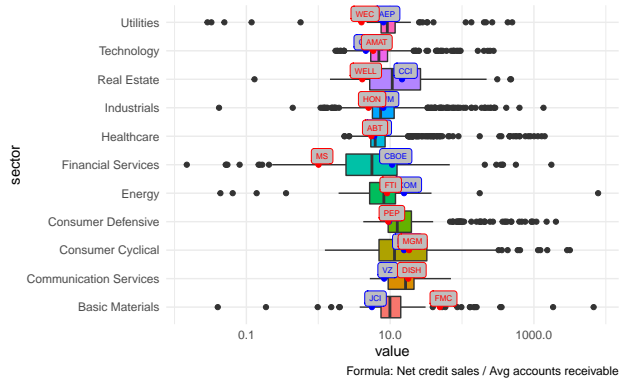
Days of Inventory on Hand

Measure of how quickly a business uses up the average inventory it keeps in stock



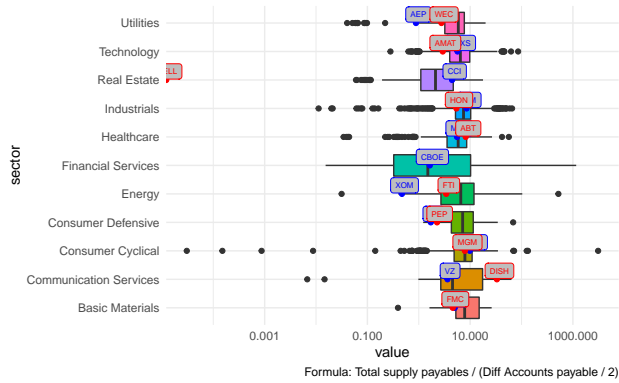
Receivables Turnover

Measure how effective a company is using its assets



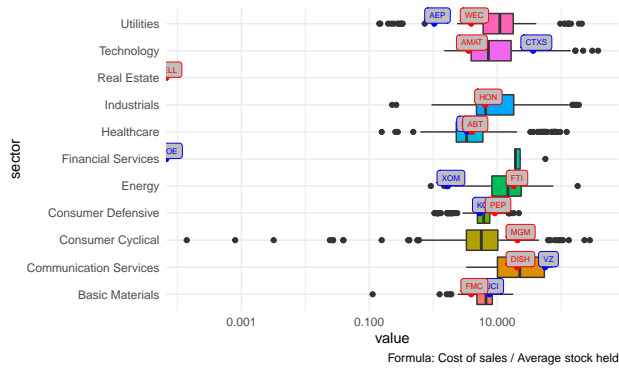
Payables Turnover

Measure how efficient a company is at paying its suppliers and short-term



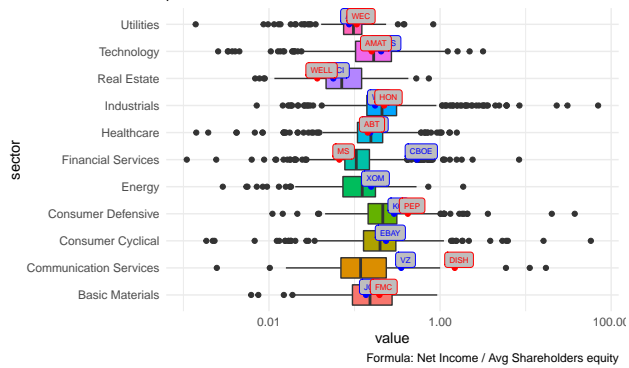
Inventory Turnover

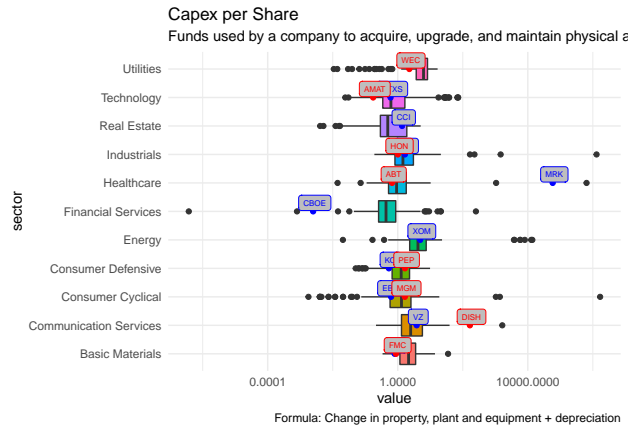
Measure how many times a company has sold and replaced inventory over a period



ROE

Measure of how effectively management is using a company's assets to generate profits





Thats awesome!! It does seem that some metrics and sector differ in relation to portfolio risk mitigation.

Let's just remember first that:

1. Sectors are correlated and we managed to find 2 clusters between them, this will be ignored in order to evaluate them per each sector
2. Metrics are correlated and we found that 32 of them are strongly correlated, but the main goal of this project is to evaluate per metric how they infer as a good result or bad result for risk mitigation. This is important though, if you're willing to analyze any subject including these metrics together, the strongest correlation will bias your model.
3. Prices have erratic movement that might injury any machine learning models and must be annomalized, this will be used for last chapter of this project when we model forecast for prices

Model

In order to model this, we'll follow the strategy:

1. List group sectors and get symbols weight the porftolio risk mitigation
2. Model how each metric value associates to the risk weight

In order to model it we'll use a GLM function from H2O wich consists of the formula:

$$\hat{y} = x^T \beta + \beta_0$$

Let's model it:

```
#Part 1
ListGroups <- Symbol>Returns %>%
  select(sector, weights) %>%
  unnest() %>%
  rename("symbol"="Name") #Rename to make it easier for innner join

# Join weight symbols, remove sector from nested data and nest it again...
KeyMetrics <- KeyMetrics %>%
  mutate(data2 = map(data, ~..1 %>%
    inner_join(ListGroups, by = c("sector","symbol"))))

# Part 2
```

```
#Let's create a function with h2o to help us model per sector
```

```
h2o.init(max_mem_size = "5g")
```

```
##
```

```
## H2O is not running yet, starting it now...
```

```
##
```

```
## Note: In case of errors look at the following log files:
```

```
## C:\Users\EDUARD~1.ALM\AppData\Local\Temp\RtmpABkP1t\h2o_eduardo_almeida_started_from_r.out
```

```
## C:\Users\EDUARD~1.ALM\AppData\Local\Temp\RtmpABkP1t\h2o_eduardo_almeida_started_from_r.err
```

```
##
```

```
##
```

```
## Starting H2O JVM and connecting: Connection successful!
```

```
##
```

```
## R is connected to the H2O cluster:
```

```
## H2O cluster uptime: 3 seconds 491 milliseconds
```

```
## H2O cluster timezone: America/Sao_Paulo
```

```
## H2O data parsing timezone: UTC
```

```
## H2O cluster version: 3.26.0.2
```

```
## H2O cluster version age: 8 months !!!
```

```
## H2O cluster name: H2O_started_from_R_eduardo.almeida_snc915
```

```
## H2O cluster total nodes: 1
```

```
## H2O cluster total memory: 4.44 GB
```

```
## H2O cluster total cores: 8
```

```
## H2O cluster allowed cores: 8
```

```
## H2O cluster healthy: TRUE
```

```
## H2O Connection ip: localhost
```

```
## H2O Connection port: 54321
```

```
## H2O Connection proxy: NA
```

```
## H2O Internal Security: FALSE
```

```
## H2O API Extensions: Amazon S3, Algos, AutoML, Core V3, Core V4
```

```
## R Version: R version 3.6.2 (2019-12-12)
```

```
h2o.no_progress()
```

```
H2o_Model <- function(Data,x, y){
```

```
  require(h2o)
```

```
  require(tidyverse)
```

```
  require(purrr)
```

```
  Data$sector <- as.factor(Data$sector)
```

```
  Data_h2o <- as.h2o(Data)
```

```
  set.seed(123)
```

```
  automl_glm <- h2o.glm(
```

```
    x = x,
```

```
    y = y,
```

```
    training_frame = Data_h2o)
```

```
  Name_Model <- "H2O_GLM"
```

```
  coef <- h2o.coef(automl_glm) %>%
```

```

    as.data.frame()

    #Model summary
    CV_Summary <- h2o.performance(automl_glm)

    #lime
    # explainer <- lime(x = Data[,x],
    #                   # model = automl_glm)

    # explanation <- explain(x = Data[,x], explainer = explainer, bin_continuous = TRUE,
    #                         # feature_select = "auto", n_features = 2)

    # Features_Plot <- plot_features(explanation, cases = 1)

    aux <- data.frame(Model_Name = Name_Model) %>%
      mutate(Model = map(Model_Name, ~automl_glm),
             coefs = map(Model_Name, ~coef),
             CV_Summary = map(Model_Name, ~CV_Summary)#,
             #explanation = map(Model_Name, ~explanation),
             #Features_Plot = map(Model_Name, ~Features_Plot)
      )

    return(aux)
  }

  # Let's model
  KeyMetrics <- KeyMetrics %>%
    mutate(H2o_Model = map(data2, ~H2o_Model(..1, x = c("value", "sector"),
                                                       y = "weights")))

  h2o.shutdown(prompt = F)

  ## [1] TRUE

  #Organize coefficients for kable
  Coeficients <- KeyMetrics %>%
    mutate(coefs = map(H2o_Model, ~..1$coefs %>%
      reduce(as.data.frame) %>%
      rownames_to_column(var = "Parameter")) %>%
    ungroup() %>%
    select(metric, coefs) %>%
    unnest(coefs) %>%
    rename("value" = ".") %>%
    mutate(Parameter = gsub(Parameter, pattern = "sector.", replacement = "")) %>%
    spread(key = Parameter, value = value) %>%
    select(metric, Intercept, value, everything()) %>%
    arrange(-Intercept, -value)

```

Let's check the coefficients

```
kable(Coefiecients, caption = "Metrics coefficients per sectors", digits = 3) %>%
  kable_styling(bootstrap_options = "striped", full_width = F, font_size = 10)
```

This is great! As showed in the charts before, it does seem that metrics and sectors differs between each other in terms of risk mitigation.

In order to understand this table we must first understand how it works:

1. The value is a weight multiplication to the metric value, when it's negative it means that metrics value that are negatives will deliver higher risk mitigation.
2. When we get a difference between values and sector weights we can actually see that some sectors tend to increase or decrease the final risk mitigation by the metric

That means that we can actually measure theses metrics by comparing the highest ratio of difference from value to sector values in regards of negative x positive weights in order to understand:

1. Metrics that deliver the higher information gain for each sector
2. Metrics that deliver higher information gain in overall

This will not be done in this project.

Conclusion

This projects seeked to evaluate how each metric is related to a risk mitigation in a portfolio and how it differs per sectors.

For future projects we can measure:

1. Metrics that deliver the higher information gain for each sector
2. Metrics that deliver higher information gain in overall
3. Impact of other variables such as macroeconomic metrics and sentiment analysis of news
4. Predict the future price of models and re-model it for portfolio mitigation
5. Compare companies that are not in SP500 or have lower prices but have a good result on metrics and assess how it is used for risk mitigation with a lower price bond

```
sessionInfo()
```

```
## R version 3.6.2 (2019-12-12)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 18362)
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=Portuguese_Brazil.1252 LC_CTYPE=Portuguese_Brazil.1252
## [3] LC_MONETARY=Portuguese_Brazil.1252 LC_NUMERIC=C
## [5] LC_TIME=Portuguese_Brazil.1252
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
## other attached packages:
## [1] factoextra_1.0.6      broom_0.5.4
## [3] tsibble_0.8.6         ggdendro_0.1-20
## [5] gridExtra_2.3         lime_0.5.1
## [7] h2o_3.26.0.2          ggstatsplot_0.3.1
## [9] cowplot_1.0.0         kableExtra_1.1.0
```

Table 5: Metrics coefficients per sectors

metric	Intercept	value	Basic Materials	Communication Services	Consumer Cyclical
Debt to Assets	0.041	-0.013	0.035	0.077	-0.033
Working Capital	0.033	0.000	0.035	0.074	-0.033
Payables Turnover	0.033	0.000	0.035	0.075	-0.033
Invested Capital	0.033	0.000	0.035	0.075	-0.033
Net Current Asset Value	0.033	0.000	0.035	0.075	-0.033
Stock-based compensation to Revenue	0.033	-0.001	0.035	0.075	-0.033
Current ratio	0.033	0.000	0.035	0.075	-0.033
Days Payables Outstanding	0.033	0.000	0.035	0.075	-0.033
Days of Inventory on Hand	0.033	0.000	0.035	0.075	-0.033
EV to Sales	0.033	0.000	0.035	0.075	-0.033
Price to Sales Ratio	0.033	0.000	0.035	0.075	-0.033
POCF ratio	0.033	0.000	0.035	0.075	-0.033
EV to Operating cash flow	0.033	0.000	0.035	0.075	-0.033
PB ratio	0.033	0.000	0.035	0.075	-0.033
PTB ratio	0.033	0.000	0.035	0.075	-0.033
Enterprise Value over EBITDA	0.033	0.000	0.035	0.075	-0.033
PE ratio	0.033	0.000	0.035	0.075	-0.033
Market Cap	0.033	0.000	0.035	0.075	-0.033
PFCF ratio	0.033	0.000	0.035	0.075	-0.033
EV to Free cash flow	0.033	0.000	0.035	0.075	-0.033
Enterprise Value	0.033	0.000	0.035	0.075	-0.033
Days Sales Outstanding	0.033	0.000	0.035	0.075	-0.033
Net Debt to EBITDA	0.033	0.000	0.035	0.075	-0.033
SG&A to Revenue	0.033	0.000	0.035	0.075	-0.033
R&D to Revenue	0.033	0.000	0.035	0.075	-0.033
Receivables Turnover	0.033	0.000	0.035	0.075	-0.033
Debt to Equity	0.033	0.000	0.035	0.075	-0.033
Revenue per Share	0.033	0.000	0.035	0.075	-0.033
Capex per Share	0.033	0.000	0.035	0.075	-0.033
Graham Net-Net	0.033	0.000	0.035	0.075	-0.033
ROE	0.033	0.000	0.035	0.075	-0.033
Tangible Book Value per Share	0.033	0.000	0.035	0.075	-0.033
Interest Debt per Share	0.033	0.000	0.035	0.075	-0.033
Net Income per Share	0.033	0.000	0.035	0.075	-0.033
Operating Cash Flow per Share	0.033	0.000	0.035	0.075	-0.033
Free Cash Flow per Share	0.033	0.000	0.035	0.075	-0.033
Free Cash Flow Yield	0.033	0.000	0.035	0.075	-0.033
Cash per Share	0.033	0.000	0.035	0.075	-0.033
Graham Number	0.033	0.000	0.035	0.075	-0.033
Earnings Yield	0.033	0.000	0.035	0.075	-0.033
Shareholders Equity per Share	0.033	0.000	0.035	0.075	-0.033
Book Value per Share	0.033	0.000	0.035	0.075	-0.033
Dividend Yield	0.033	0.000	0.035	0.075	-0.033
Payout Ratio	0.033	0.000	0.035	0.075	-0.033
Income Quality	0.033	0.000	0.035	0.075	-0.033
Capex to Revenue	0.033	0.000	0.035	0.075	-0.033
Interest Coverage	0.033	0.000	0.035	0.075	-0.033
Capex to Operating Cash Flow	0.033	0.000	0.035	0.075	-0.033
Tangible Asset Value	0.032	0.000	0.036	0.075	-0.033
Capex to Depreciation	0.032	0.000	0.035	0.074	-0.033
Average Payables	0.032	0.000	0.036	0.074	-0.033
Inventory Turnover	0.032	0.000	0.035	0.074	-0.033
Return on Tangible Assets	0.032	0.015	0.035	0.076	-0.033
Average Receivables	0.032	0.000	0.036	0.074	-0.033
ROIC	0.031	0.019	0.035	0.076	-0.033

```

## [11] knitr_1.26 ROI.plugin.quadprog_0.2-5
## [13] ROI.plugin.glpk_0.3-0 ROI_0.3-3
## [15] PortfolioAnalytics_1.1.0 foreach_1.4.7
## [17] tibbletime_0.1.3 timetk_0.1.2
## [19] readxl_1.3.1 anytime_0.3.7
## [21] tidyquant_0.5.10 quantmod_0.4-15
## [23] TTR_0.23-6 PerformanceAnalytics_2.0.4
## [25] xts_0.12-0 zoo_1.8-7
## [27] lubridate_1.7.4 patchwork_1.0.0
## [29] janitor_1.2.1 forcats_0.4.0
## [31] stringr_1.4.0 dplyr_0.8.3
## [33] purrr_0.3.3 readr_1.3.1
## [35] tidyr_1.0.2 tibble_2.1.3
## [37] ggplot2_3.3.0 tidyverse_1.3.0
## [39] jsonlite_1.6 httr_1.4.1
##
## loaded via a namespace (and not attached):
## [1] estimability_1.3 coda_0.19-3
## [3] multcomp_1.4-12 data.table_1.12.8
## [5] inline_0.3.15 RCurl_1.95-4.12
## [7] generics_0.0.2 callr_3.4.0
## [9] TH.data_1.0-10 webshot_0.5.2
## [11] xml2_1.2.2 httpuv_1.5.2
## [13] StanHeaders_2.21.0-1 assertthat_0.2.1
## [15] gower_0.2.1 WRS2_1.0-0
## [17] xfun_0.11 hms_0.5.3
## [19] evaluate_0.14 promises_1.1.0
## [21] fansi_0.4.1 dbplyr_1.4.2
## [23] htmlwidgets_1.5.1 DBI_1.1.0
## [25] reshape_0.8.8 Quandl_2.10.0
## [27] stats4_3.6.2 ellipsis_0.3.0
## [29] paletteer_1.1.0 rcompanion_2.3.25
## [31] backports_1.1.5 insight_0.8.2
## [33] ggcorrplot_0.1.3 libcoin_1.0-5
## [35] jmvcore_1.2.5 vctrs_0.2.1
## [37] sjlabelled_1.1.3 abind_1.4-5
## [39] withr_2.1.2 metaBMA_0.6.2
## [41] bdsmatrix_1.3-4 emmeans_1.4.5
## [43] prettyunits_1.0.2 fastGHQuad_1.0
## [45] mnormt_1.5-6 cluster_2.1.0
## [47] lazyeval_0.2.2 Rglpk_0.6-4
## [49] crayon_1.3.4 labeling_0.3
## [51] glmnet_3.0-2 pkgconfig_2.0.3
## [53] slam_0.1-47 nlme_3.1-142
## [55] statsExpressions_0.3.1 palr_0.2.0
## [57] pals_1.6 rlang_0.4.2
## [59] lifecycle_0.1.0 miniUI_0.1.1.1
## [61] groupedstats_0.2.1 skimr_2.1
## [63] LaplacesDemon_16.1.4 MatrixModels_0.4-1
## [65] sandwich_2.5-1 registry_0.5-1
## [67] EMT_1.1 modelr_0.1.5
## [69] dichromat_2.0-0 cellranger_1.1.0
## [71] matrixStats_0.55.0 broomExtra_2.5.0
## [73] lmttest_0.9-37 Matrix_1.2-18

```


## [75]	loo_2.2.0	mc2d_0.1-18
## [77]	carData_3.0-3	boot_1.3-23
## [79]	represx_0.3.0	base64enc_0.1-3
## [81]	processx_3.4.1	viridisLite_0.3.0
## [83]	rjson_0.2.20	oompaBase_3.2.9
## [85]	bitops_1.0-6	parameters_0.6.0
## [87]	ggExtra_0.9	shape_1.4.4
## [89]	multcompView_0.1-8	coin_1.3-1
## [91]	ggsignif_0.6.0	scales_1.1.0
## [93]	magrittr_1.5	plyr_1.8.5
## [95]	compiler_3.6.2	rstantools_2.0.0
## [97]	bbmle_1.0.23.1	RColorBrewer_1.1-2
## [99]	lme4_1.1-21	cli_2.0.1
## [101]	pbapply_1.4-2	ps_1.3.0
## [103]	TMB_1.7.16	Brodingnag_1.2-6
## [105]	MASS_7.3-51.4	mgcv_1.8-31
## [107]	tidyselect_0.2.5	stringi_1.4.3
## [109]	yaml_2.2.0	ggrepel_0.8.1
## [111]	bridgesampling_1.0-0	grid_3.6.2
## [113]	tools_3.6.2	parallel_3.6.2
## [115]	rio_0.5.16	rstudioapi_0.10
## [117]	foreign_0.8-72	ipmisc_1.2.0
## [119]	pairwiseComparisons_0.2.5	farver_2.0.1
## [121]	digest_0.6.23	shiny_1.4.0
## [123]	nortest_1.0-4	quadprog_1.5-8
## [125]	jmv_1.2.5	Rcpp_1.0.3
## [127]	car_3.0-6	metafor_2.1-0
## [129]	ez_4.4-0	BayesFactor_0.9.12-4.2
## [131]	performance_0.4.4	metaplan_0.7-11
## [133]	later_1.0.0	psych_1.9.12.31
## [135]	effectsize_0.2.0	sjstats_0.17.9
## [137]	colorspace_1.4-1	rvest_0.3.5
## [139]	fs_1.3.1	splines_3.6.2
## [141]	rematch2_2.1.0	expm_0.999-4
## [143]	shinythemes_1.1.2	mapproj_1.2.7
## [145]	jcolors_0.0.4	xtable_1.8-4
## [147]	nloptr_1.2.1	rstan_2.19.2
## [149]	zeallot_0.1.0	modeltools_0.2-23
## [151]	scico_1.1.0	R6_2.4.1
## [153]	broom.mixed_0.2.4	pillar_1.4.3
## [155]	htmltools_0.4.0	mime_0.8
## [157]	glue_1.3.1	fastmap_1.0.1
## [159]	minqa_1.2.4	codetools_0.2-16
## [161]	maps_3.3.0	pkgbuild_1.0.6
## [163]	mvtnorm_1.0-12	lattice_0.20-38
## [165]	numDeriv_2016.8-1.1	curl_4.3
## [167]	DescTools_0.99.34	gtools_3.8.1
## [169]	logspline_2.1.15	zip_2.0.4
## [171]	openxlsx_4.1.4	survival_3.1-8
## [173]	rmarkdown_2.0	repr_1.1.0
## [175]	munsell_0.5.0	iterators_1.0.12
## [177]	sjmisc_2.8.3	haven_2.2.0
## [179]	reshape2_1.4.3	gtable_0.3.0
## [181]	bayestestR_0.5.2	