# Daily Return Analysis: Similarities and Differences

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# Introduction

- Asset Selection
- Educated Guesses and Expectations

# Asset Selection

- AMD (AMD) - Growth Stock, we anticipate that many group will select NVIDIA for their analysis, so we chose another firm in this industry for comparison.

- Tesla (TSLA) - Growth Stock, we are curious about how Tesla’s stock behave as electric car becoming more popular around the globe.

- Delta Airline (DAL) - Cyclical Stock, rise and fall as the business cycle.

- Ford Motor (F) - Cyclical Stock, we are curious about how intensified competition in EV car manufacturing will affect Ford’s stock behaviour.

- Coca-Cola Company (KO) - Non-Cyclical (Defensive) Stock, meaning coca-cola can provide a stable return regardless of the business cycle . Important to note that Coca-Cola has two affiliations. The Coca-Cola Company is the parent company of the Coca-Cola consolidated. We selected the parent company out of curiosity.

# Educated Guesses and Expectations

- Daily data are less volatile compared to monthly data, because in short run, investors cannot react swiftly. Monthly data is the aggregation of daily data.

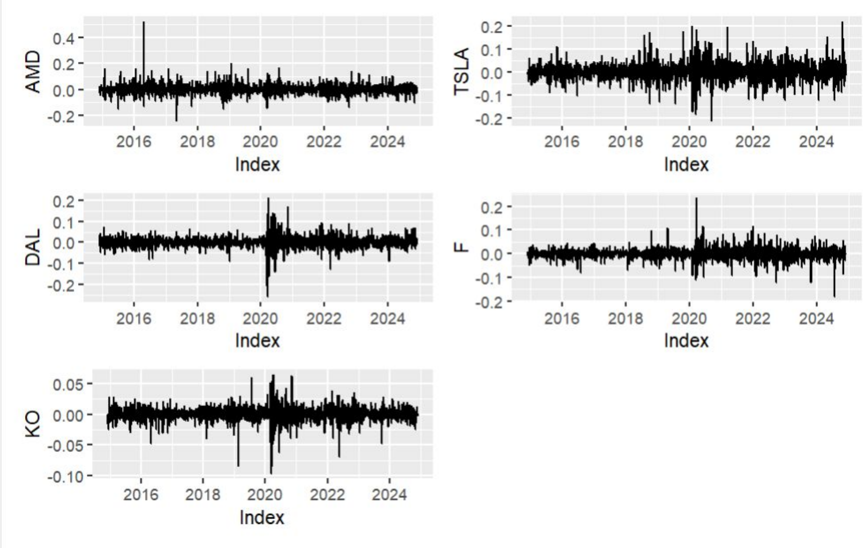
- Assets can still be highly correlated with each other. E.g., Ford and Tesla will have strong correlation, yet their direction cannot be determined.

- Normal Distribution: We have large amount of data observation.

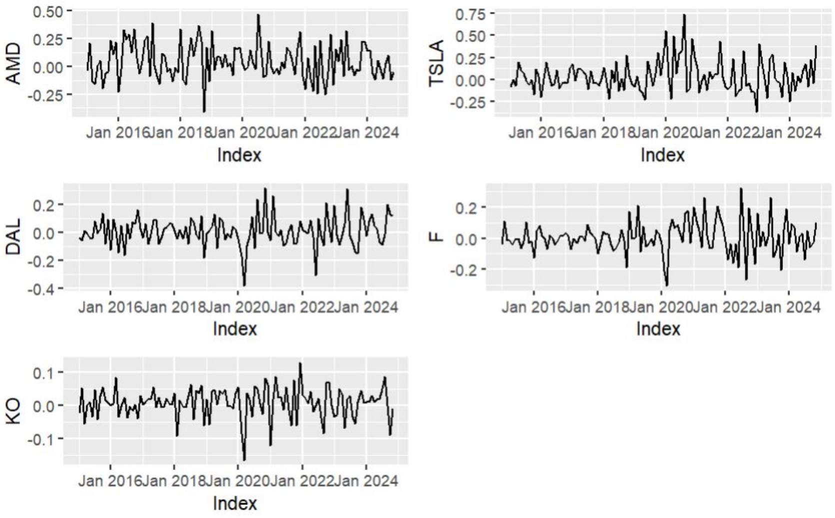
# Daily Prices and Return

- **Time Plot**
- Equity Curve
- **Sample Statistics**
- Risk-Return Analysis
- **Sharpe’s Ratio and SE**
- **Scatter Plot**

# Time Plot

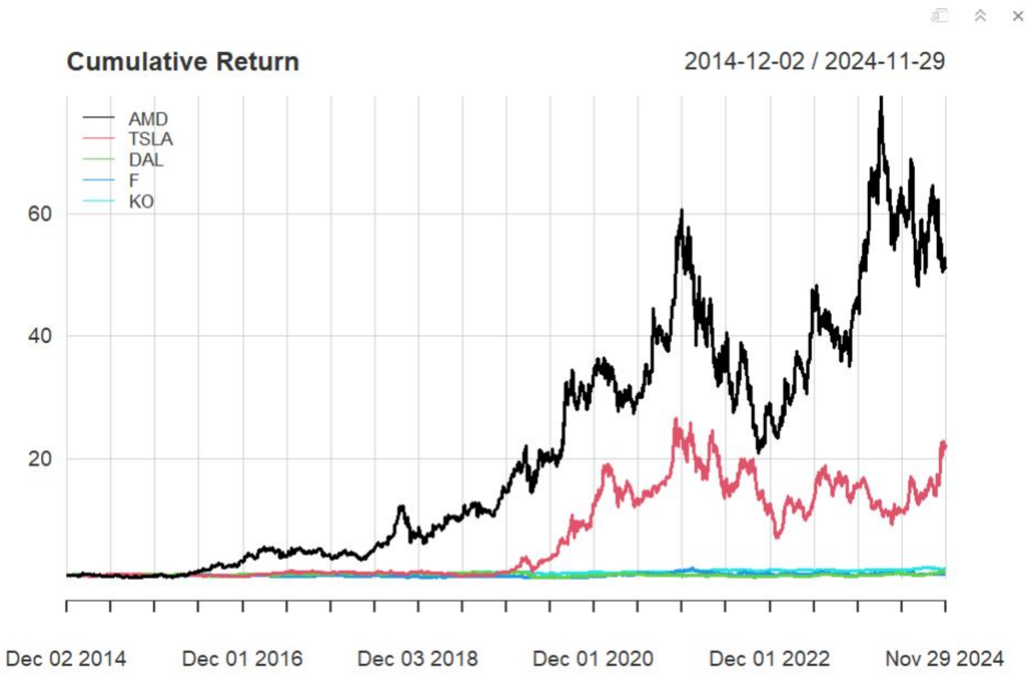


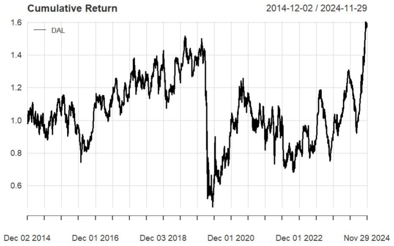
AMD
TSLA
DAL
F
KO
2016 2018 2020 2022 2024
Index

AMD
TSLA
DAL
F
KO
Jan 2016 Jan 2018 Jan 2020 Jan 2022 Jan 2024
Index

# Equity Curve – Same curve as Daily Price



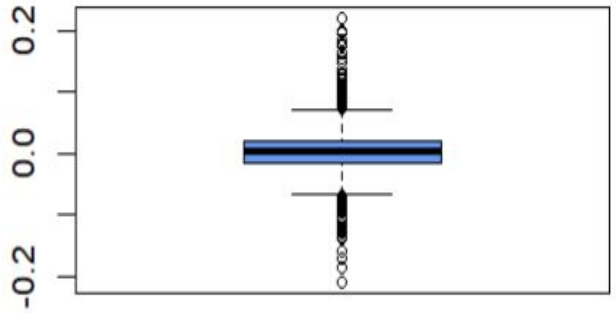





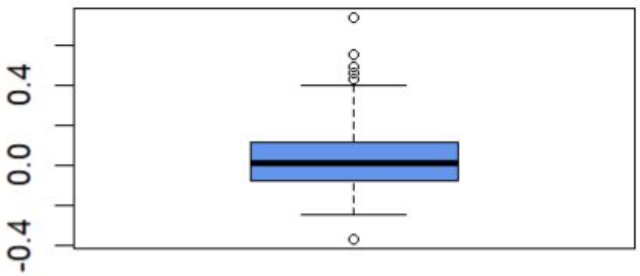
# Sample Statistics – Typical Box Plot Comparison

Daily - Tesla

Notice: In general, daily data is more volatile than monthly data because stock price can be easily influenced by random news.



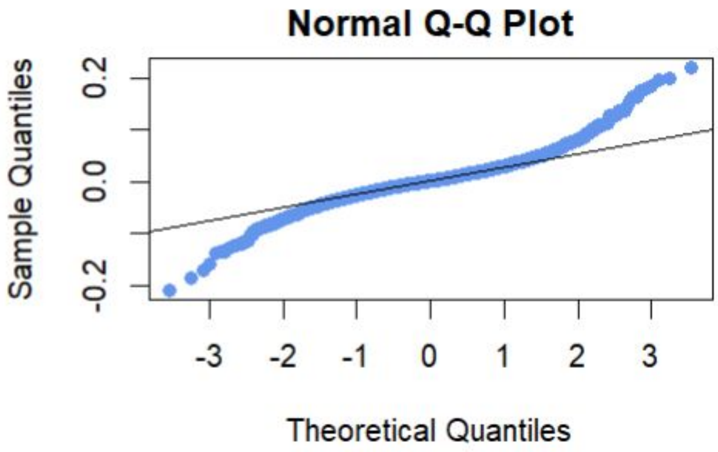

Monthly - Tesla



# Sample Statistics Cont. Typical QQ-plot comparison

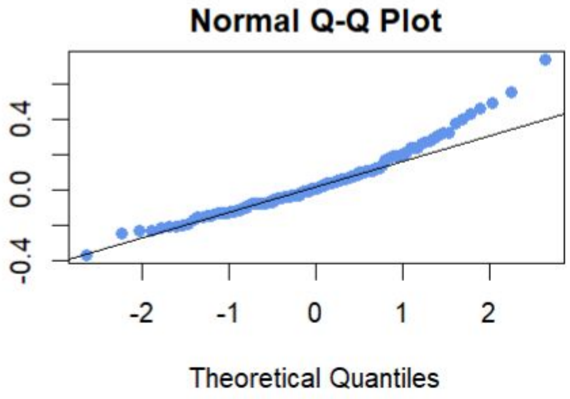
Daily - Tesla

Notice: All Daily data exhibit this type of graph, indicating data too peaked in the middle, as what box plot suggest

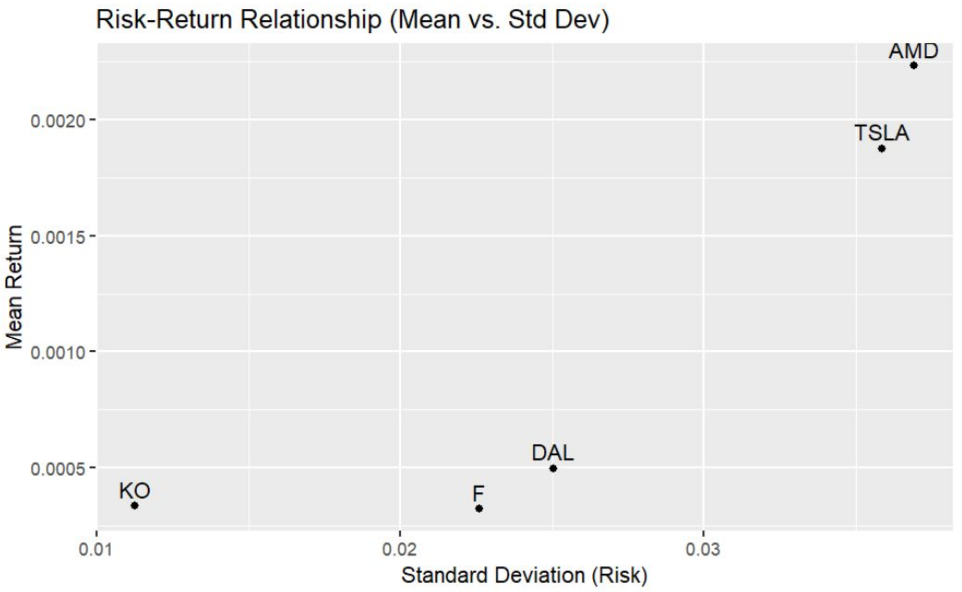



Monthly - Tesla

Most Monthly data fit the normal distribution



# Risk-Return Analysis



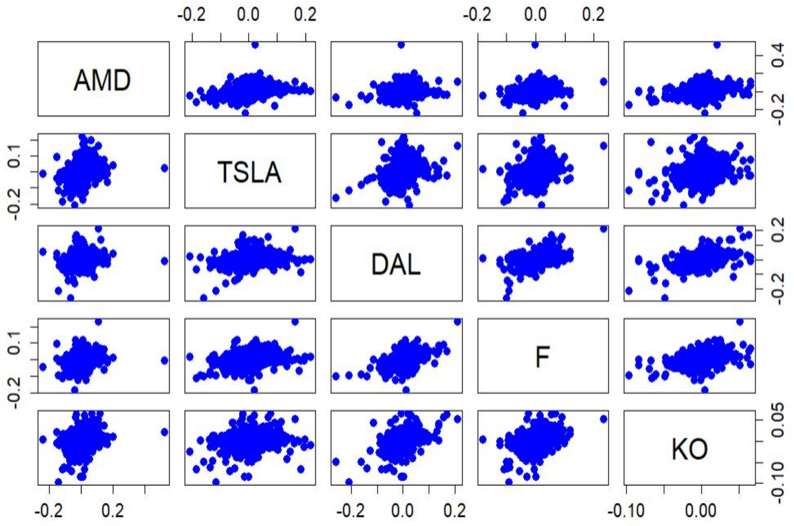
# Sharpe's Ratio and SE

95% Confidence Intervals for Mean and Standard Deviation

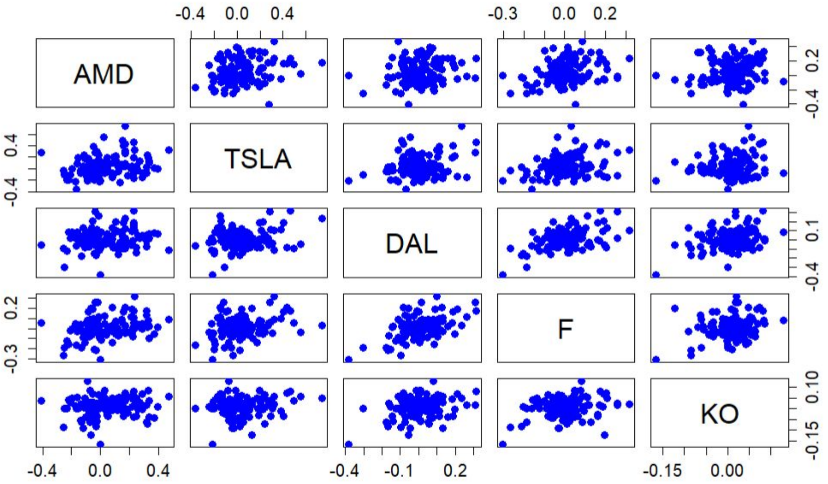
| | Mean | Mean_SE | Mean_Lower_CI | Mean_Upper_CI | SD | SD_SE | SD_Lower_CI | SD_Upper_CI |
|---|---|---|---|---|---|---|---|---|
| AMD | 0.002232 | 0.000736 | 0.000761 | 0.003704 | 0.0369 | 0.000520 | 0.0359 | 0.0379 |
| TSLA | 0.001876 | 0.000715 | 0.000446 | 0.003306 | 0.0359 | 0.000506 | 0.0349 | 0.0369 |
| DAL | 0.000497 | 0.000499 | -0.000501 | 0.001495 | 0.0250 | 0.000353 | 0.0243 | 0.0257 |
| F | 0.000323 | 0.000451 | -0.000579 | 0.001224 | 0.0226 | 0.000319 | 0.0220 | 0.0232 |
| KO | 0.000334 | 0.000224 | -0.000113 | 0.000782 | 0.0112 | 0.000158 | 0.0109 | 0.0115 |

# Scatter Plot

Daily Return




Monthly Return



# Value at Risk Analysis

# And

# Rolling Sample Statistics

# Calculate 1% and 5% normal value-at-risk of $100,000

```
# Define the z-scores for 1% and 5% confidence
levels

z_1_percent <- qnorm(0.01)

z_5_percent <- qnorm(0.05)


# Calculate 1% and 5% VaR for each asset

VaR_1_percent <- (expected_returns + z_1_percent *
standard_deviations) * investment

VaR_5_percent <- (expected_returns + z_5_percent *
standard_deviations) * investment
```

1% and 5% Value-at-Risk (VaR) for Each Asset ($100,000 Investment)

| | Asset | Expected_Return | Standard_Deviation | VaR_1_Percent | VaR_5_Percent |
|---|---|---|---|---|---|
| AMD | AMD | 0.002232 | 0.0369 | -8363 | -5848 |
| TSLA | TSLA | 0.001876 | 0.0359 | -8157 | -5712 |
| DAL | DAL | 0.000497 | 0.0250 | -5774 | -4068 |
| F | F | 0.000323 | 0.0226 | -5227 | -3686 |
| KO | KO | 0.000334 | 0.0112 | -2579 | -1814 |

Result

# Meaning of VaR for Daily Return

At both the 1% and 5% confidence levels, **AMD** is expected to incur the largest losses among the assets over the one-month investment horizon. This indicates that **AMD** is the riskiest asset in this portfolio.

**Coca-cola** is expected to have the smallest losses among the assets. This suggests that **Coca-cola** is the least risky asset in terms of potential loss, reflecting greater stability and less sensitivity to adverse market conditions.

```
Asset with the highest 1% VaR: AMD

Asset with the lowest 1% VaR: KO

Asset with the highest 5% VaR: AMD

Asset with the lowest 5% VaR: KO
```

# Bootstrap for estimated SE and CI

We use the bootstrap to compute estimated standard errors and 95% confidence intervals for your 1% and 5% VaR estimates.

| | VaR.01 | SE | LCL (0.95) | UCL (0.95) |
|---|---|---|---|---|
| AMD | -8023 | 338.4 | -8698 | -7371 |
| TSLA | -7833 | 196.6 | -8227 | -7457 |
| DAL | -5610 | 221.6 | -6053 | -5185 |
| F | -5093 | 176.3 | -5451 | -4760 |
| KO | -2546 | 93.7 | -2732 | -2364 |

| | VaR.05 | SE | LCL (0.95) | UCL (0.95) |
|---|---|---|---|---|
| AMD | -5680 | 243.6 | -6166 | -5211 |
| TSLA | -5552 | 146.7 | -5847 | -5272 |
| DAL | -3986 | 163.3 | -4313 | -3673 |
| F | -3619 | 130.7 | -3885 | -3373 |
| KO | -1797 | 69.8 | -1935 | -1662 |

# Bootstrap for estimated SE and CI

At a 5% confidence level, the maximum expected loss for AMD over the next month is -$5680. This is accompanied by a standard error of **243.6** and a 95% confidence interval between **-6166 and -5211**.

**KO** is the least risky at the 5% level. Its standard error is **69.8**, with a 95% confidence interval ranging from **-1935 to -1662**.

| | VaR.05 | SE | LCL (0.95) | UCL (0.95) |
|---|---|---|---|---|
| AMD | -5680 | 243.6 | -6166 | -5211 |
| TSLA | -5552 | 146.7 | -5847 | -5272 |
| DAL | -3986 | 163.3 | -4313 | -3673 |
| F | -3619 | 130.7 | -3885 | -3373 |
| KO | -1797 | 69.8 | -1935 | -1662 |

# Difference and meaning  of lower and upper

AMD has the highest 5% normal VaR values at -$5680 and Coca-cola has the lowest at -$1797. The bootstrap SE values are fairly small (about 20-25 times smaller than the VaR values) and the confidence intervals are not too wide.

The rankings are same for the 1% VaR values: AMD has the highest VaR at -\$8023, and Coca-cola has the lowest at -\$2546. The bootstrap standard errors are about 20 times smaller than the VaR estimate2.

The **standard errors** and **confidence intervals** reflect the precision of these VaR estimates. Higher standard errors and wider confidence intervals, such as those seen for **AMD** and **TSLA**, indicate greater uncertainty in the estimates, while lower values for **KO** indicate more reliable and consistent risk estimates.

# Normal vs. Empirical VaR: Computational Differences

The **normal distribution VaR** is based on the assumption that returns follow a normal (Gaussian) distribution. To calculate the VaR, we use the estimated mean and standard deviation of the returns. Essentially, this approach assumes a symmetric distribution of returns, meaning it expects both positive and negative returns to behave predictably around the mean.

The **empirical VaR** does **not make any assumptions** about the distribution of returns. Instead, it uses the historical data directly to determine the quantile of interest. For example, the **5% empirical VaR** is simply the 5th percentile of the sorted historical returns. Therefore, empirical VaR is sometimes more reflective of the true risk, especially in cases where the return distribution is not normally distributed.

# Normal vs. Empirical VaR: Computational Differences

Repeat the VaR analysis use the empirical 1% and 5% quantiles of the return distributions (which do not assume a normal distribution - this method is often called historical simulation). How different are the results from those based on the normal distribution?

| | Normal VaR.05 | Empirical VaR.05 | Normal VaR.01 | Empirical VaR.01 |
|---|---|---|---|---|
| AMD | -5680 | -5137 | -8023 | -8589 |
| TSLA | -5552 | -4996 | -7833 | -8623 |
| DAL | -3986 | -3472 | -5610 | -6241 |
| F | -3619 | -3207 | -5093 | -6025 |
| KO | -1797 | -1561 | -2546 | -3128 |

# Normal vs. Empirical VaR: Computational Differences

**Normal VaR vs. Empirical VaR at 5% :**

For AMD, the normal VaR at 5% is -5680, whereas the empirical VaR is -5137. Similarly, for other assets like TSLA, the normal VaR is -5552 while the empirical VaR is -4996. **In all cases, the empirical VaR is less negative than the normal VaR.** This suggests that the normal VaR overestimates the potential loss compared to the historical data for the 5% quantile. The normal distribution assumes a wider dispersion of returns, which may not always reflect the actual risk as observed in historical data.

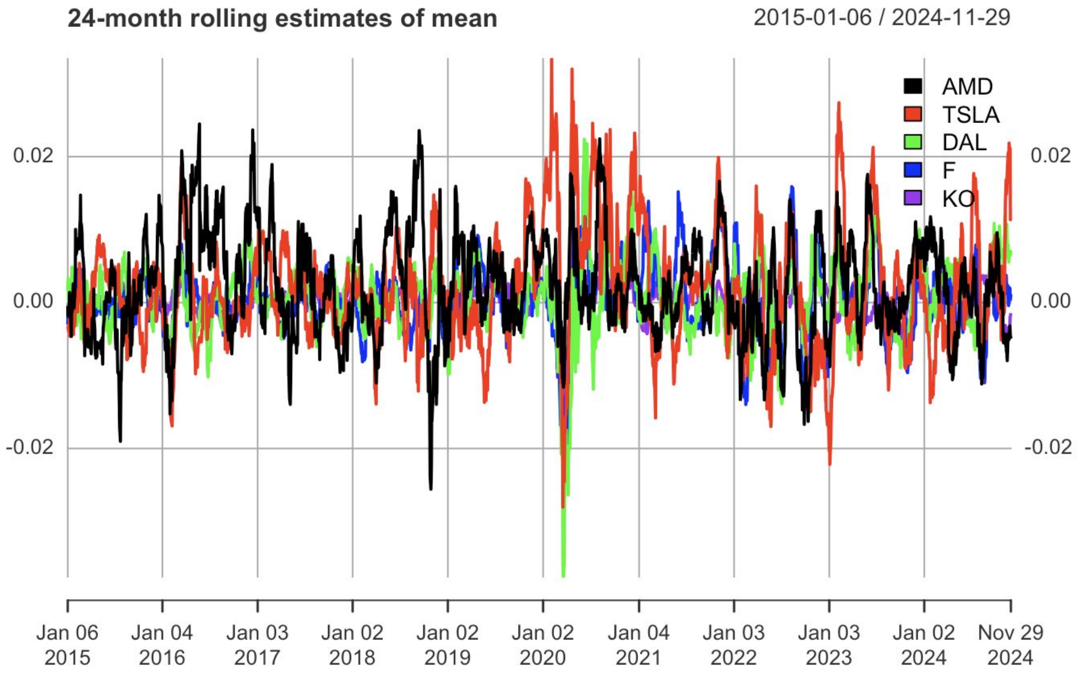
At the **1% level**, the **empirical VaR is more negative** than the normal VaR. This suggests that the historical data shows a higher likelihood of extreme losses compared to what the normal distribution predicts. This is likely due to fat tails or extreme events that are observed in real-world financial data but are not well captured by a normal distribution — What is it?

The **differences between normal and empirical VaR** highlight the shortcomings of assuming normality for financial returns:

The **normal VaR** tends to **underestimate** the risk of extreme events (tail risk), as it assumes a symmetric distribution and does not account for the possibility of fat tails.

The **empirical VaR** takes into account the **actual observed behavior** of returns, including periods of market stress or unusual volatility, which makes it a better representation of risk in non-normal distributions.

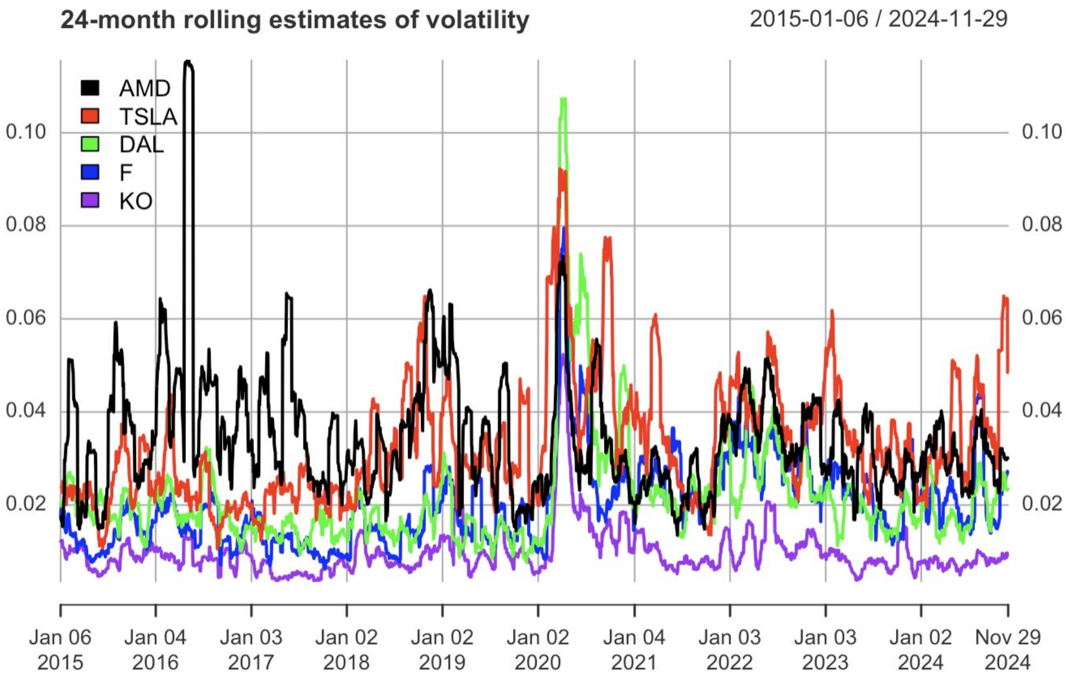
# Trend of rolling estimates of means and volatility




Covariance stationarity implies that the mean and variance  of the time series do not change significantly over time.

Based on the plots, rolling mean estimates are fluctuating around zero for all assets, but with noticeable variations, particularly during certain periods. Most of the assets show some level of mean reversion, where the mean tends to revert back to zero over time. However, there are also periods where the mean shifts significantly (e.g., around 2020).

# Trend of rolling estimates of means and volatility




The volatility shows more pronounced changes over time compared to the mean. Volatility spikes, particularly around early 2020, can be observed for all the assets. This indicates that the assumption of constant volatility over the whole period is questionable.

The plots clearly show a large volatility spike around early 2020, corresponding to the onset of the pandemic. This event led to a substantial increase in volatility across all assets, for example Tesla (TSLA) and AMD, the volatility was particularly high, indicating significant uncertainty and price fluctuations during that period.

# Portfolio Theory

- Equally Weighted Portfolio
- Global Min & VaR at 1% and 5%
- Efficient Portfolio Frontier
- Target Mean / Risk

```
```{r}
# Daily
Sigma.d = cov(project.Returns)
equallyWeights.d = matrix(1/5,5,1)
expectR.d = apply(project.Returns,2, mean)
daily.e = getPortfolio(expectR.d,Sigma.d,equallyWeights.d)
daily.e
```
```

```
Call:
getPortfolio(er = expectR.d, cov.mat = Sigma.d, weights =
equallyWeights.d)

Portfolio expected return:     0.00105
Portfolio standard deviation:  0.0178
Portfolio weights:
 AMD TSLA  DAL    F   KO
 0.2  0.2  0.2  0.2  0.2
```

# Global Minimum Variance Portfolio

```
Call:
globalMin.portfolio(er = expectR.d, cov.mat = Sigma.d, shorts = TRUE)

Portfolio expected return:     0.000425
Portfolio standard deviation:  0.011
```

```
Call:
globalMin.portfolio(er = expectR.d, cov.mat = Sigma.d, shorts = FALSE)

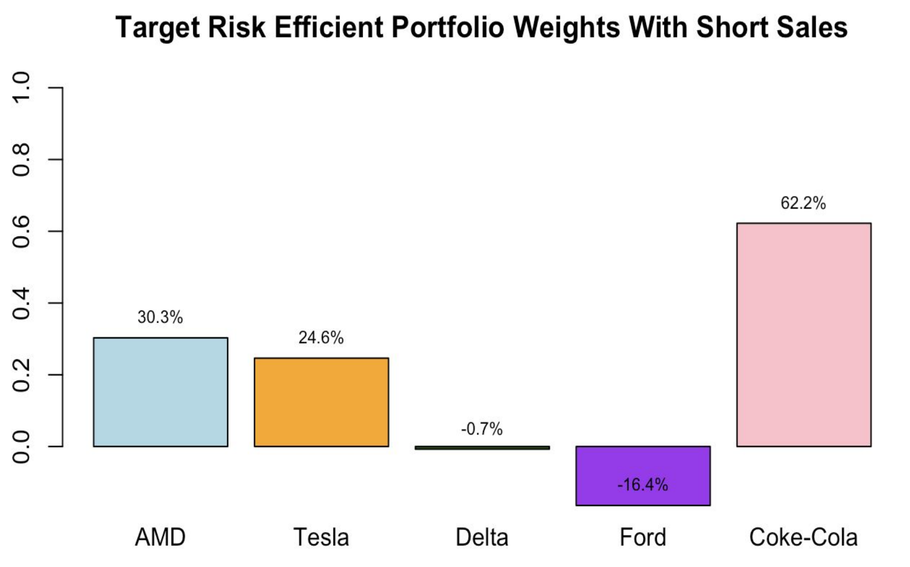
Portfolio expected return:     0.000425
Portfolio standard deviation:  0.011
```

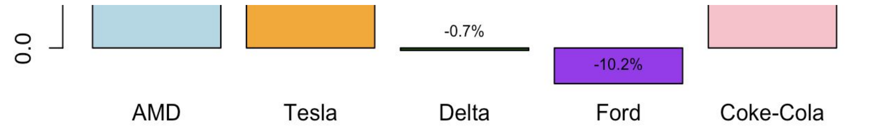
1% and 5% Value-at-Risk (VaR) for Global Minimum Variance Portfolios ($100,000 Investment)

| Portfolio | VaR_1_Percent | VaR_5_Percent |
|---|---|---|
| GMVP No Short Sales | -2515 | -1766 |
| GMVP With Short Sales | -2515 | -1766 |

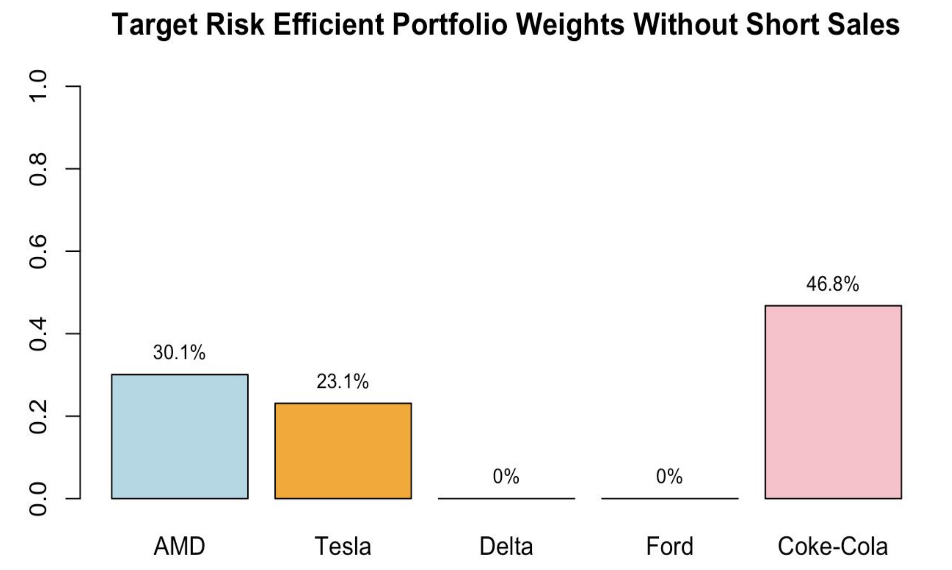
# Target Return and Risk

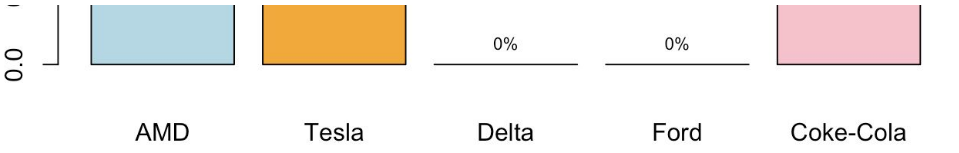
```
efficient.portfolio(er = expectR.d, cov.mat = Sigma.d, target.return = 0.00105,
    shorts = TRUE)
```

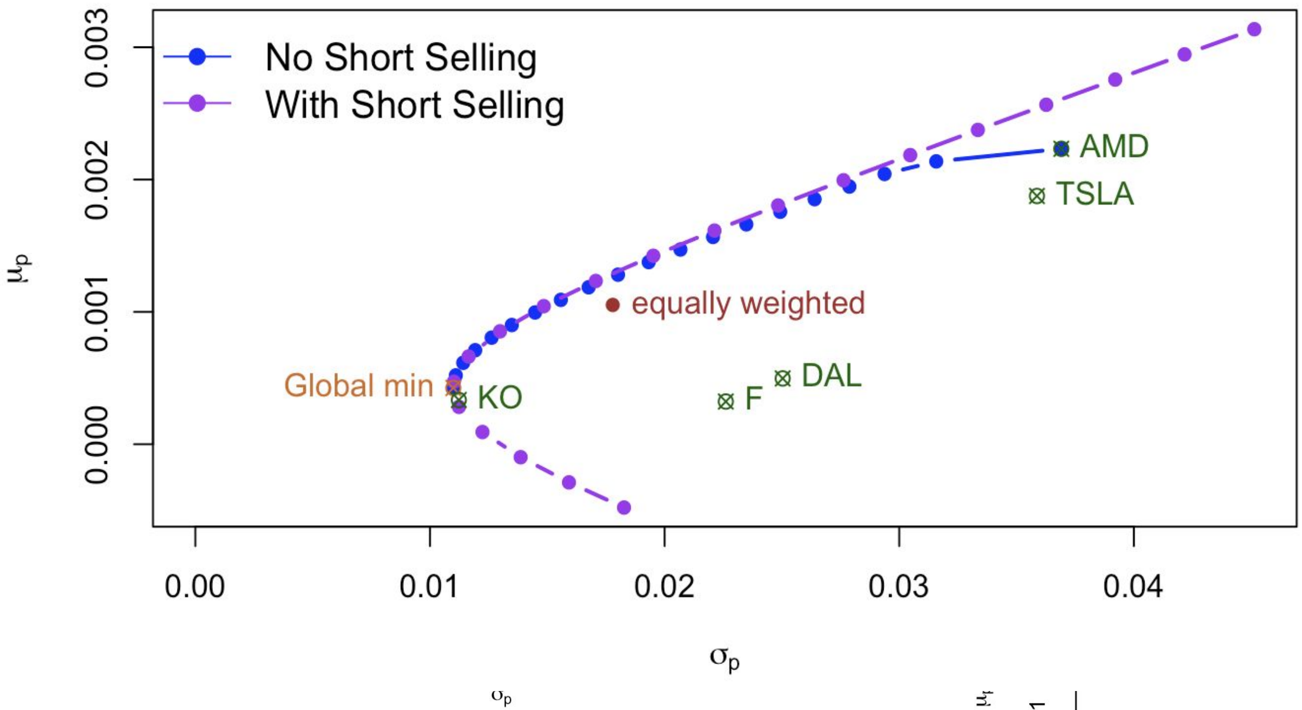


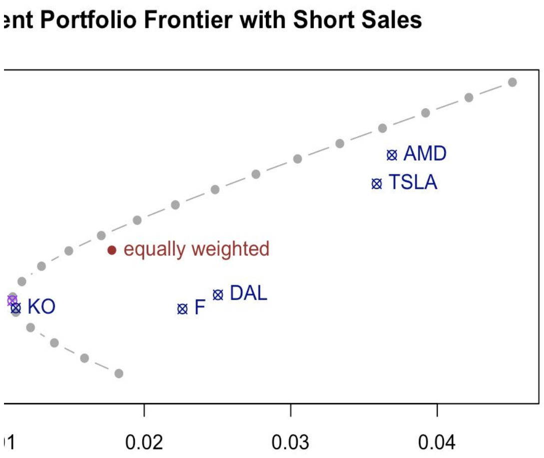



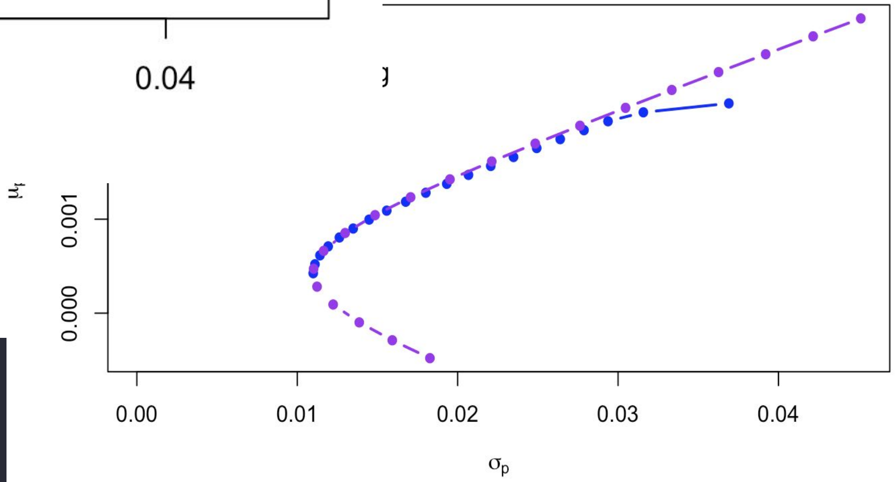

```
efficient.portfolio(er = expectR.d, cov.mat = Sigma.d, target.return = 0.00105,
    shorts = FALSE)
```






```
Expected return for no short-sale portfolio: 0.000425
Expected return for short-sale portfolio: 0.000473
Cost in expected return: 4.76e-05
```

# Tangency Portfolio with a monthly risk free rate, 0.00167

```
rf.d = (1+0.00167)^(1/30) - 1
tan.p = tangency.portfolio(expectR.d, Sigma.d, rf.d, shorts = TRUE)
sigma.vec = sqrt(diag(Sigma.d))
summary(tan.p , rf.d)
sr = (expectR.d-rf.d)/sigma.vec
sr
```

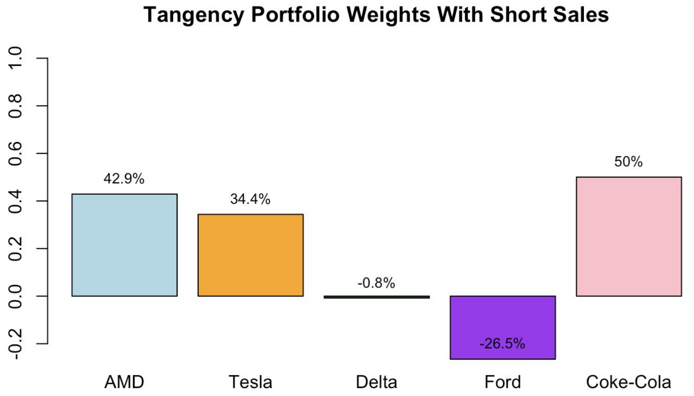
```
Call:
tangency.portfolio(er = expectR.d, cov.mat = Sigma.d, risk.free = rf.d,
    shorts = TRUE)

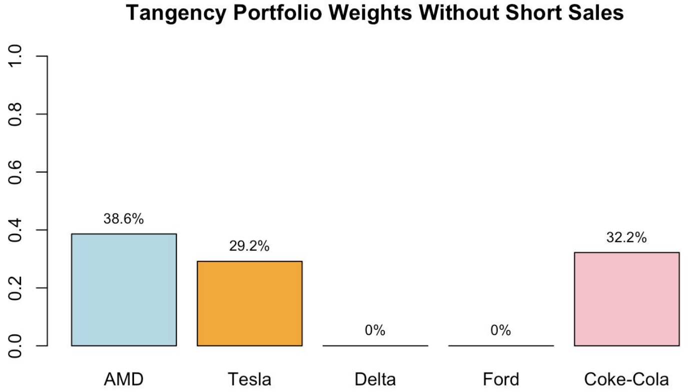
Portfolio expected return:     0.00168
Portfolio standard deviation:  0.0231
Portfolio Sharpe Ratio:        0.0705
```

| AMD | TSLA | DAL | F | KO |
|---|---|---|---|---|
| 0.0590 | 0.0507 | 0.0176 | 0.0118 | 0.0248 |

```
tangency.portfolio(er = expectR.d, cov.mat = Sigma.d, risk.free = rf.d,
    shorts = FALSE)

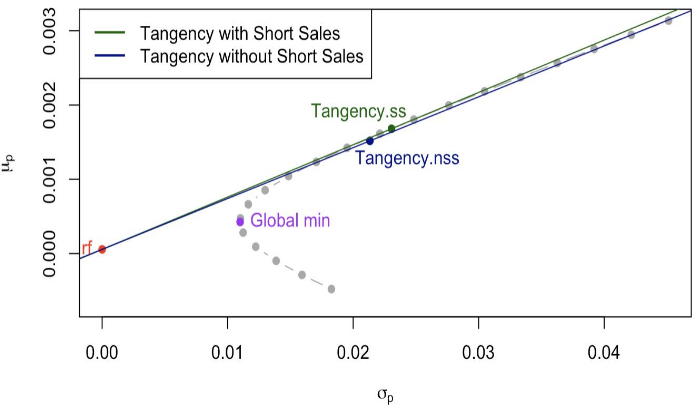
Portfolio expected return:     0.00152
Portfolio standard deviation:  0.0213
Portfolio Sharpe Ratio:        0.0685
```

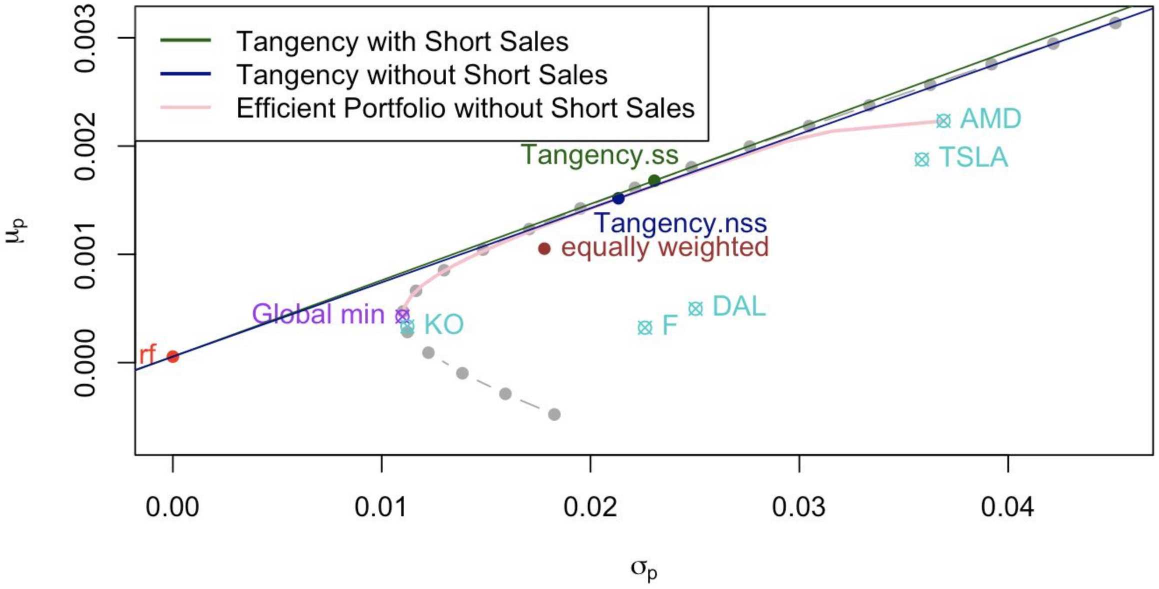


# Efficient Frontier

```
ss.mu.tan.tbills = rf.d + x.tan*(tan.p$er - rf.d)
ss.sig.tan.tbills = x.tan * tan.p$sd
```



# Risk Budgeting

```
W6 = 100000
sigma.vec = sqrt(diag(Sigma.d))
x.weights = daily.e$weights
d = x.weights * W6
mu = as.numeric(crossprod(x.weights, expectR.d))
sig = as.numeric(sqrt(t(x.weights) %*% Sigma.d %*% x.weights))
MCR = (Sigma.d %*% x.weights)/sig
CR = x.weights * MCR
PCR = CR / sig
rho = MCR/sigma.vec
beta = PCR / x.weights
```

| | Dollar | Weight | Vol | MCR | CR | PCR | Rho | Beta |
|---|---|---|---|---|---|---|---|---|
| AMD | 2e+04 | 0.2 | 0.0369 | 0.02598 | 0.00520 | 0.2921 | 0.704 | 1.460 |
| TSLA | 2e+04 | 0.2 | 0.0359 | 0.02571 | 0.00514 | 0.2891 | 0.717 | 1.445 |
| DAL | 2e+04 | 0.2 | 0.0250 | 0.01673 | 0.00335 | 0.1880 | 0.668 | 0.940 |
| F | 2e+04 | 0.2 | 0.0226 | 0.01540 | 0.00308 | 0.1731 | 0.681 | 0.866 |
| KO | 2e+04 | 0.2 | 0.0112 | 0.00513 | 0.00103 | 0.0577 | 0.457 | 0.289 |
| PORT | 1e+05 | 1.0 | NA | NA | 0.01779 | 1.0000 | 1.000 | 1.000 |

# Asset Allocation

- **Target Expected Return with no Short Sale**
- **Daily SD and Daily 1% and 5% value-at-risk**
- **Target Expected Return with RF**

**Efficient Portfolio** that achieves our target return.

Suppose we wanted to achieve a target expected return of 20% per year using our chosen 5 stocks and no short sales

```
# given target return is lower than our global min return
target_return <- (1+0.2)^(1/365)-1

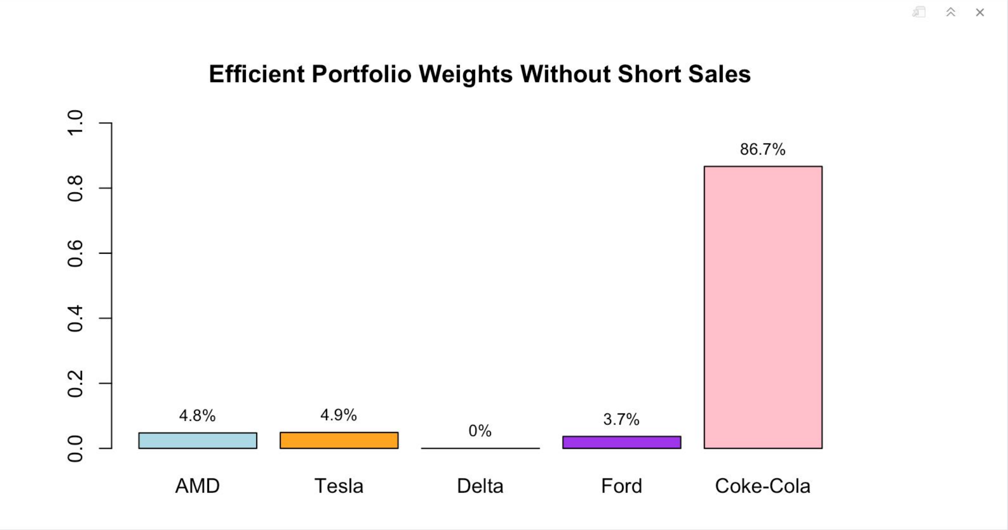
efficient_portfolio = efficient.portfolio(expectR.d, Sigma.d, target_return, shorts = FALSE)
efficient_portfolio
```

```
Call:
efficient.portfolio(er = expectR.d, cov.mat = Sigma.d, target.return = target_return,
    shorts = FALSE)
```

```
Portfolio expected return:     5e-04
Portfolio standard deviation:  0.0111
Portfolio weights:
   AMD   TSLA    DAL      F     KO
0.0476 0.0489 0.0000 0.0368 0.8667
```

# Efficient portfolio Weights w/ no Short Sales

```{r}
efficientp.bar = barplot(efficient_portfolio$weights, col = c("lightblue", "orange",
"darkgreen","purple","pink"), main = "Efficient Portfolio Weights Without Short Sales", names.arg = c( "AMD",
"Tesla", "Delta", "Ford", "Coke-Cola"), ylim = c(0,1))
text(x=efficientp.bar, y=efficient_portfolio$weights, labels = paste0(round(efficient_portfolio$weights, 3) *
100, "%"), pos = 3, cex = 0.8, col = "black")
```




**Portfolio Weights:**

- AMD: 4.8%
- Tesla: 4.9%
- Delta Airlines: 0% (not included in the portfolio due to no short sales and likely low contribution to the target return with minimal risk).
- Ford: 3.7%
- Coca-Cola: 86.7% (dominates the portfolio, likely due to its stability or significant contribution to achieving the target return).

# Daily SD and VaR

Based on an initial $100,000 investment, compute the monthly SD on our efficient portfolio and the monthly 1% and 5% value-at-risk.

```
Portfolio expected return:     5e-04
Portfolio standard deviation:  0.0111
Portfolio weights:
   AMD   TSLA    DAL      F     KO
0.0476 0.0489 0.0000 0.0368 0.8667
```

```
W7 = 100000
q.R.05 = (qnorm(0.05, efficient_portfolio$er, efficient_portfolio$sd))
W7*q.R.05
q.R.01 = (qnorm(0.01, efficient_portfolio$er, efficient_portfolio$sd) )
W7*q.R.01
```

```
       [,1]
[1,] 0.0452
[1] 0.000397
       [,1]
[1,] 0.0444
[1] -1769
[1] -2523
```

**Value-at-Risk (VaR) for $100,000:**

- **5% VaR:** Loss of $2523 or more with 5% probability.
- **1% VaR:** Loss of $1769 or more with 1% probability.

**Efficient Portfolio Risk (Daily SD):**

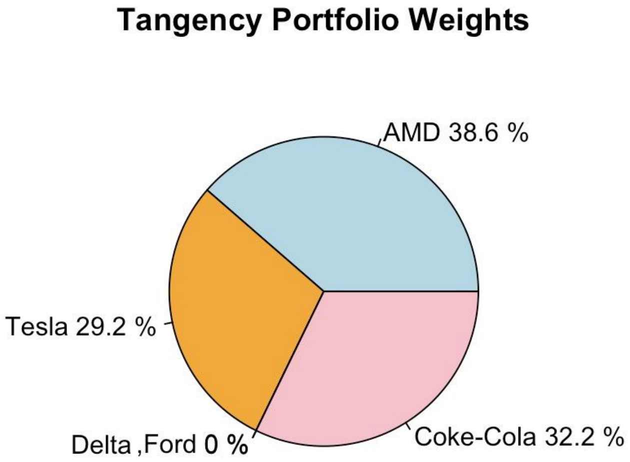
- Daily standard deviation: 0.0111, indicating the volatility or risk associated with the portfolio's returns

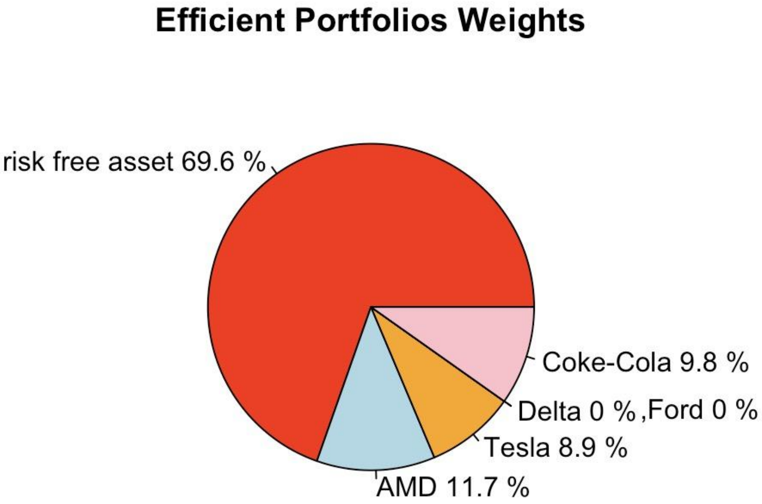
# Target Expected Return with RF

Suppose we wanted to achieve a target expected return of 20% per year using the 5 stocks and a risk free asset (with monthly return **0.00167**), with **no short sales** of the risky assets.

```
```{r}
rf_rate <- (1+0.00167)^(1/30)-1
tp = tangency.portfolio(expectR.d, Sigma.d, rf_rate, shorts = FALSE)
x.t = (target_return - rf_rate)/(tp$er - rf_rate)
x.t
x.rf= 1 - x.t
x.rf
W7*x.rf
W7*x.t*tp$weights
```
```

```
[1] 0.304
[1] 0.696
[1] 69619
  AMD  TSLA   DAL     F    KO
11734  8862     0     0  9785
```



# Executive Summary

**Daily vs. Monthly Data:**

- Daily data shows higher volatility, capturing immediate market impacts (e.g., financial reports).
- Monthly data smooths short-term fluctuations but reflects broader trends like the pandemic's effect.

**Recommendation:**

- Daily data: Best for frequent traders seeking real-time insights.
- Monthly data: Ideal for long-term, trend-focused investors.

**Portfolio Construction:**

- Core investment logic: Maximize returns while minimizing risk.
- Coca-Cola reduces portfolio risk, acting as a stabilizer, as well as the risk-free asset
- Tesla and AMD drive returns due to high growth potential.

# Reflections and Concerns

- Accuracy of methods we used
- High volatility in daily data
- Function suitability

# Q & A

Thank you for the amazing quarter! Good luck on final!