Financial Analysis of the Impact of COVID-19 on Pharmaceutical Companies

STAT 5261 Final Project

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1. Introduction

We choose 4 stocks from 4 top pharmaceutical companies: Pfizer (PFE), Johnson & Johnson (JNJ), Merk (MRK), and Novartis (NVS) to analyze the impact of Covid - 19 from January 2nd, 2018 to November 1st, 2022 via statistical modeling and analysis.

2. Data Description

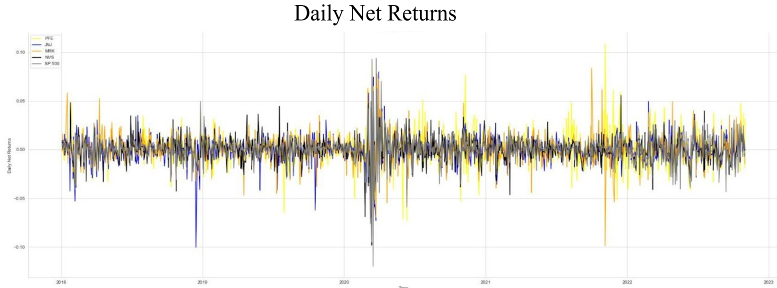
2.1 Daily Prices

Daily Prices

The chart shows four stocks' trends of daily prices from Jan 2nd, 2018 to Nov 1st, 2022. During the period of Covid - 19, all stocks have a sudden decrease, but after that, there are increasing trends. However, in 2022, the trend seems to decrease. Johnson & Johnson has the largest daily prices.

2.2 Daily Net Returns

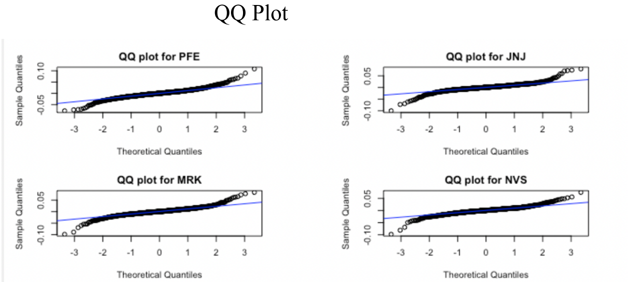
Daily Net Returns



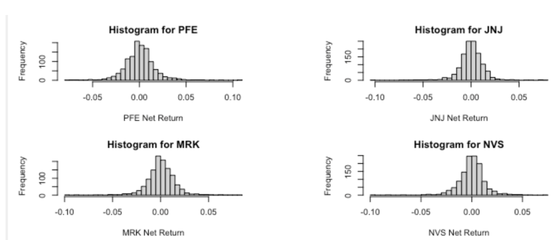
The chart shows the daily net returns of 4 stocks and the S&P 500. Compared with S&P 500, all stocks have a similar trend while Merk is more volatile. Even though Johnson & Johnson has the largest prices, its net return is similar to other companies. Those stocks are stationary overall.

2.3 Normality

QQ Plot



Histogram



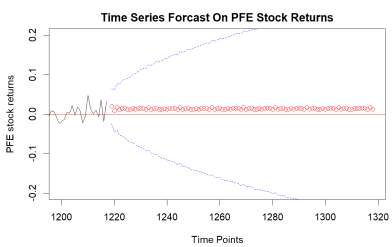
The graph of the QQ Plot and the graph of the Histogram are to check the normality for four stocks. In the QQ Plot, points are not fitted on the line very well, and they are symmetric with heavy tails as in the Histogram. Thus, we can conclude that all net returns for four stocks are not normally distributed.

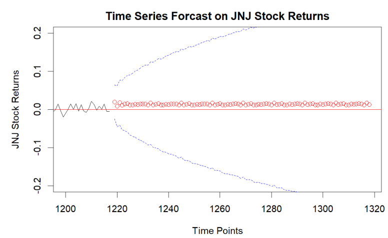
3. Time-Series Analysis

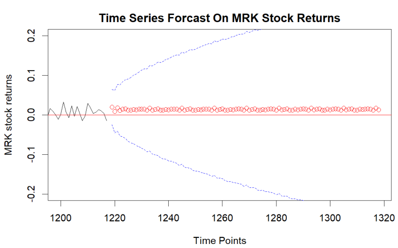
The stock market can have a significant impact on individuals and the economy as a whole. As a result, effectively predicting stock trends can reduce the risk of loss while increasing profit. Therefore, our group decided to utilize time-series analysis to have a general picture of the future development of these four stocks by predicting their future returns, so that we can check if the investment in these four stocks in the future is profitable.

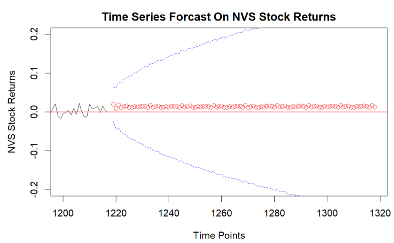
Considering economic time series often exhibit strong seasonal variation, we involve the seasonal ARIMA model. Through checking the consistency of variances, differencing the data, observing ACF and PACF graphs, and minimizing the AICC values, we finally choose the model:

SARIMA (1,1,0)×(1,1,1). Due to the similar features and conditions shared by these four stocks, we figure out this model works for all four stocks' future returns.









The red horizontal lines show the mean value of the return. Obviously, we can observe that predicted returns are very stable in the future and slightly greater than the mean value. Hence, we can conclude that positive returns for these four stocks in the future are expected. The slight scale above the mean value can be explained by the fact that governments try to control the overall prices of vaccines in the market, under the situation of COVID-19, and the spread of medical technologies also spreads the potential profits brought by vaccines. However, we still can expect stable positive returns of investment on these four stocks in the future.

4. Portfolio Theory

In this part, we will consider two kinds of portfolio, which are the Minimum Variance Portfolio and Tangency Portfolio for two scenarios, which are short is allowed and short is not allowed.

A minimum Variance Portfolio is an investing method that maximizes returns and minimizes volatility. By diversifying holdings, we can reduce the volatility, so the investments that may be risky on their own balance each other out when held together.

Also, a line with a larger slope gives a higher expected return for a given level of risk, so the larger the Sharpe ratio is, the better regardless of what level of risk anyone is willing to accept. The optimal portfolio of having a risk-free asset within is the one with a point on the efficient frontier that has the highest Sharpe ratio.

4.1 Minimum Variance Portfolio that Short is not Allowed

Weights of stocks on MVP (short not allowed)

NVS_Close	JNJ_Close	MRK_Close	PFE_Close
0.424091	0.344434	0.165458	0.066017

Standard Deviation

NVS_Close	JNJ_Close	MRK_Close	PFE_Close
0.0129415	0.0133069	0.0147615	0.0166571

From the chart, we can tell the Minimum Variance Portfolio gives more weight to stocks that have lower volatility. So we can see the standard deviation of these five stocks from low to high corresponds to the weight in MVP from high to low. Among these five stocks, Novartis has the largest weight in the minimum variance portfolio.

4.2 Tangency Portfolio that Short is not Allowed

Weights of stocks on Tangency Portfolio

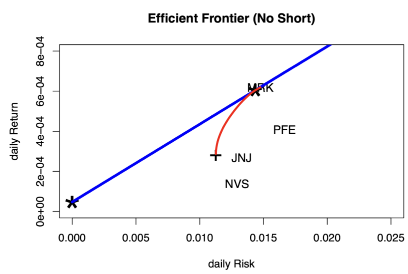
MRK_Close	PFE_Close	JNJ_Close	NVS_Close
0.938782	0.061218	0	0

Sharpe Ratio

MRK_Close	PFE_Close	JNJ_Close	NVS_Close
0.03871308	0.02165547	0.01655303	0.00702399

A tangency portfolio gives more weights on stocks that have a larger Sharpe ratio. We can see the stocks that have higher Sharpe ratios have more weights on the tangency portfolio. Among these 5 stocks, Merk has the largest weight in the portfolio.

4.3 Efficient Frontier that Short is not Allowed



The star mark at the lower end of the blue line is the risk-free rate. The star mark at the upper part of the blue line is the tangency portfolio. The plus mark at the lower end of the red line is MVP.

4.4 Minimum Variance Portfolio that Short is Allowed

Weights of stocks on MVP

NVS_Close	JNJ_Close	MRK_Close	PFE_Close
0.424091	0.344434	0.165458	0.066017

The weight of each stock in the minimum variance portfolio is similar to the weight in MVP that short is not allowed.

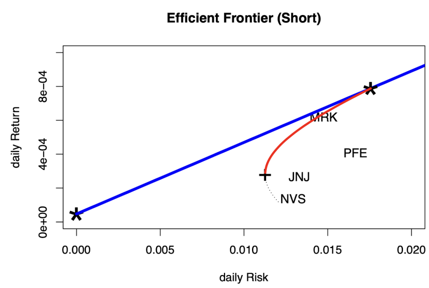
4.5 Tangency Portfolio that Short is Allowed

Weights of stocks on Tangency Portfolio

MRK_Close	PFE_Close	JNJ_Close	NVS_Close
1.7647639	0.3705868	-0.243378	-0.891973

The weight of each stock in the tangency portfolio has changed significantly compared to the weight in the tangency portfolio that short is not allowed. In this portfolio, we have negative weights for Johnson & Johnson and Novartis. Since in this portfolio short is allowed, it means we need to short corresponding weights for these two stocks.

4.6 Efficient Frontier that Short is Allowed



The star mark at the lower end of the blue line is the risk-free rate. The star mark at the upper part of the blue line is the tangency portfolio. The plus mark at the lower end of the red line is MVP.

4.7 Conclusion for Portfolio Theory

In this part, we talked about two kinds of portfolios in two scenarios. But for both scenarios, we can see the weight on Pfizer is counter-intuitive since it is well-known that Pfizer is one of the biggest companies that produce COVID-19 vaccines. This phenomenon is due to the government's control of the price of vaccines.

5. Copula

Copula

Copula	Normal	T	Gumbel	Frank	Clayton
AIC	-1323.602	-1321.46	-794.5565	-939.3584	-1182.146
BIC	-1318.497	-1311.251	-789.4516	-934.2534	-1177.041
Likelihood	662.8008	662.7302	398.2783	470.6792	592.0729

For the five copula models we fit, we choose the model that has the lowest AIC and BIC values and the highest likelihood value. According to the table, we choose a Normal copula for the four stocks in the project.

6. Risk Management

After considering the performance of four individual stocks from pharmaceutical companies and their complex portfolios, measuring the market risk is also an important process during the investment. Assuming the investor has $100,000, how much risk does he need to take when making the investment?

6.1 Risk Management with One Asset

The first case is the investor chooses to invest all the money into one stock. Two widely used statistical measures, *Value at Risk* (VaR) and *Expected Shortfall* (ES), are calculated for each asset. Specifically, the 5% Value at Risk indicates there is 95% confidence that over the next day, the loss will not be greater than the 5% VaR estimate. Meanwhile, the related expected shortfall shows the expected loss when the worst 5% cases happen.

For the parametric estimation of VaR and ES, the stock returns are assumed to follow the normal distribution and the t-distribution separately. Also, the nonparametric estimation is applied to make a comparison, which is solely based on the historical quantile of the stock returns. However, according to the normality check shown in the data description part, the four chosen stocks barely follow the normal distribution. Therefore, the t-distribution assumption and the non-parametric method may reduce the misspecification of the tail and have more accurate estimations of the risk.

Table 1: Single Asset VaR and ES based on three assumptions

	PFE	JNJ	MRK	NVS
Normal distr VaR	2697.911	2161.117	2365.172	2113.985
Normal distr ES	3393.656	2716.927	2981.743	2654.536
T-distr VaR	2495.908	1838.699	2103.726	1903.058
T-distr ES	3924.809	3035.851	3292.902	3076.322
Non-parametric VaR	2408.359	1885.457	2104.973	2006.720
Non-parametric ES	3718.698	3257.832	3370.176	3024.341

According to the summary table, the PFE, Pfizer stock has the highest loss both in VaR and ES, no matter which assumptions are considered. So, it is for sure that purchasing PFE will have a higher risk among the top four pharmaceutical companies. Moreover, the estimates from the nonparametric approach are extremely similar to the numbers based on the t-distribution assumption, which verifies the violation of stock returns' normality.

6.2 Risk Management for Portfolios of Assets

When the investor chooses to diversify investment, the 5% VaR is further estimated for various portfolios mentioned in the above section, Portfolio Theory. The four portfolios include the minimum variance portfolio (MVP) and tangency portfolio with and without short selling. And the corresponding risk measures are shown as follows:

Table 2: Portfolios of Assets VaR and ES based on two assumptions

Without Short	**MVP**	**Tangency portfolio**
Normal distr VaR	1824.761	2308.217
Non-parametric VaR	1729.105	2096.355
With Short		
Normal distr VaR	1824.761	3748.99
Non-parametric VaR	1729.105	3397.768

First, comparing the VaR between Table 1 and Table 2, the risk of different portfolios is smaller than the risk of one asset, since diversifying assets will significantly reduce the risk. Another interesting thing is, in our case, allowing short selling in portfolios will not profit more, but have a higher risk. So, selling short is not a good move when investing in these four pharmaceutical stocks.

7. Conclusion

7.1 Data Description: The net return of 4 stocks is stationary. They are not normally distributed.

7.2 Time-Series Analysis: Through the model: SARIMA (1,1,0)×(1,1,1), stable and positive returns for these four stocks can be expected in the future. Hence, the investment in these four stocks will be profitable.

7.3 Portfolio Theory: Whenever considering short or not, we should put the most weights on NVS and JNJ for MVP, MRK, and PFE for the tangency portfolio.

7.4 Copula: Based on the criteria of choosing a model, we choose Normal Copula for chosen stocks.

7.5 Risk Management: When measuring single asset risk, the t-distribution assumption and nonparametric method have more accurate estimations of VaR and ES for the four chosen stocks. Besides, constructing portfolios will effectively diversify risk, but in our case, selling short is not recommended.

Appendix (code)

```r
# Data loading
data <- read.csv("/Users/macbook/Downloads/full_close.csv")
n <- dim(data)[1]
data_5 <- data[,c(2,3,5,6)]
return <- data_5[2:n,]/data_5[1:(n-1),]-1
log_return <- log(data_5[2:n,]/data_5[1:(n-1),])

# Data Description
## QQ Plot for Net_Return
layout(matrix(c(1,1,1,1,1,0,2,2,2,2,2,
                3,3,3,3,3,0,4,4,4,4,4,
                0,0,0,5,5,5,5,5,0,0,0), 3, 11, byrow = TRUE))


qqnorm(return[,1], main = 'QQ plot for PFE')
qqline(return[,1], col ='blue')

qqnorm(return[,2], main = 'QQ plot for JNJ')
qqline(return[,2], col ='blue')

qqnorm(return[,3], main = 'QQ plot for MRK')
qqline(return[,3], col ='blue')

qqnorm(return[,4], main = 'QQ plot for NVS')
qqline(return[,4], col ='blue')

layout.show(4)

## Histogram for Net_Return
layout(matrix(c(1,1,1,1,1,0,2,2,2,2,2,
                3,3,3,3,3,0,4,4,4,4,4,
                0,0,0,5,5,5,5,5,0,0,0), 3, 11, byrow = TRUE))


hist(return[,1], breaks = 30, main = 'Histogram for PFE', xlab = "PFE Net Return" )


hist(return[,2], breaks = 30, main = 'Histogram for JNJ', xlab = "JNJ Net Return" )


hist(return[,3], breaks = 30, main = 'Histogram for MRK',xlab = "MRK Net Return" )


hist(return[,4], breaks = 30, main = 'Histogram for NVS', xlab = "NVS Net Return" )

layout.show(4)


# Time-Series Analysis

library(forecast)
```

```
library(fGarch)
library(rugarch)
library(MASS)
returns<-read.csv('C:/users/hongy/Desktop/return.csv',header=T)
PFEr<-ts(returns[,2],frequency=365)[c(1:1218)]
ts.plot(PFEr)

arima_110_111 <- arima(PFEr, order=c(1,1,0), seasonal = list(order = c(1,1,1), period = 12), method="ML

pred<- predict(arima_110_111, n.ahead = 100)
U.tr= pred$pred + 1.96*pred$se
L.tr= pred$pred - 1.96*pred$se

ts.plot(PFEr,xlim=c(1100,length(PFEr))+100,ylim=c(-0.2,0.2), main='Time Series Forcast On PFE Stock Ret
lines(U.tr, col="blue", lty="dashed")
lines(L.tr, col="blue", lty="dashed")
## Predicted values of transformed data
points((length(PFEr)+1):(length(PFEr)+100), pred$pred, col="red")
abline(h=0,col='red')

JNJr<-ts(returns[,3],frequency=365)[c(1:1218)]

ts.plot(JNJr)

ts.plot(JNJr,xlim=c(1100,length(JNJr))+100,ylim=c(-0.2,0.2), main='Time Series Forcast on JNJ Stock Ret
lines(U.tr, col="blue", lty="dashed")
lines(L.tr, col="blue", lty="dashed")
## Predicted values of transformed data
points((length(JNJr)+1):(length(JNJr)+100), pred$pred, col="red")
abline(h=0,col='red')

MRKr<-ts(returns[,5],frequency=365)[c(1:1218)]

ts.plot(MRKr)

ts.plot(MRKr,xlim=c(1100,length(MRKr))+100,ylim=c(-0.2,0.2), main='Time Series Forcast On MRK Stock Ret
lines(U.tr, col="blue", lty="dashed")
lines(L.tr, col="blue", lty="dashed")
## Predicted values of transformed data
points((length(MRKr)+1):(length(MRKr)+100), pred$pred, col="red")
abline(h=0,col='red')

NVSr<-ts(returns[,6],frequency=365)[c(1:1218)]

ts.plot(NVSr)

ts.plot(NVSr,xlim=c(1100,length(NVSr))+100,ylim=c(-0.2,0.2), main='Time Series Forcast On NVS Stock Ret
lines(U.tr, col="blue", lty="dashed")
lines(L.tr, col="blue", lty="dashed")
## Predicted values of transformed data
points((length(NVSr)+1):(length(NVSr)+100), pred$pred, col="red")
abline(h=0,col='red')
```

```r
# Portfolio Theory
## Load data
library(readr)
data=read_csv("full_close.csv")
prices=data
n=dim(prices)[1]
returns =(prices[2:n,]/prices[1:(n-1),]-1) # returns by day
library(tidyr)
library(dplyr)
## mean, covariance, standard deviation of PRICES
mean.p = colMeans(prices)
cov.p = cov(prices)
sd.p = sqrt(diag(cov.p))
## mean, covariance, standard deviation of RETURN
mean.r = colMeans(returns)
cov.r = cov(returns)
sd.r = sqrt(diag(cov.r))
## Skewness Coefficients, Kurtosis Coefficients and beta of PRICES
list=as.list(prices)
sk.p=unlist(lapply(list,function(data){
  (sum((data-mean(data))^3/(sd(data))^3))/length(data)
}))
kt.p=unlist(lapply(list,function(data){
  (sum((data-mean(data))^4/(sd(data))^4))/length(data)
}))
## Info Table
info=cbind(mean.r,sd.r,sk.p,kt.p)
colnames(info)=c("mean","sd","skewness","kurtosis")
sd.r[order(sd.r,decreasing = F)]

##Sharpe's Ratio (using sample mean &sd in month)
rf.m=1.73/100/365 #daily risk free
sharpes.ratio=(mean.r-rf.m)/sd.r
sort(sharpes.ratio,decreasing = T)
cat("\n The biggest sharpe ratio is MRK:",max(sharpes.ratio))

library(quadprog)
library(Ecdat)
efficient.portfolio <-
function(er, cov.mat, target.return, shorts=TRUE)
{
  # compute minimum variance portfolio subject to target return
  #
  # inputs:
  # er                      N x 1 vector of expected returns
  # cov.mat               N x N covariance matrix of returns
  # target.return     scalar, target expected return
  # shorts          logical, allow shorts is TRUE
  #
  # output is portfolio object with the following elements
  # call                    original function call
  # er                      portfolio expected return
  # sd                      portfolio standard deviation
```

```
  # weights             N x 1 vector of portfolio weights
  #
  call <- match.call()
  #
  # check for valid inputs
  #
  asset.names <- names(er)
  er <- as.vector(er)                     # assign names if none exist
  N <- length(er)
  cov.mat <- as.matrix(cov.mat)
  if(N != nrow(cov.mat))
    stop("invalid inputs")
  if(any(diag(chol(cov.mat)) <= 0))
    stop("Covariance matrix not positive definite")
  # remark: could use generalized inverse if cov.mat is positive semidefinite
  #
  # compute efficient portfolio
  #
  if(shorts==TRUE){
    ones <- rep(1, N)
    top <- cbind(2*cov.mat, er, ones)
    bot <- cbind(rbind(er, ones), matrix(0,2,2))
    A <- rbind(top, bot)
    b.target <- as.matrix(c(rep(0, N), target.return, 1))
    x <- solve(A, b.target)
    w <- x[1:N]
  } else if(shorts==FALSE){
    Dmat <- 2*cov.mat
    dvec <- rep.int(0, N)
    Amat <- cbind(rep(1,N), er, diag(1,N))
    bvec <- c(1, target.return, rep(0,N))
    result <- solve.QP(Dmat=Dmat,dvec=dvec,Amat=Amat,bvec=bvec,meq=2)
    w <- round(result$solution, 6)
  } else {
    stop("shorts needs to be logical. For no-shorts, shorts=FALSE.")
  }
  #
  # compute portfolio expected returns and variance
  #
  names(w) <- asset.names
  er.port <- crossprod(er,w)
  sd.port <- sqrt(w %*% cov.mat %*% w)
  ans <- list("call" = call,
          "er" = as.vector(er.port),
          "sd" = as.vector(sd.port),
          "weights" = w)
  class(ans) <- "portfolio"
  ans
}

globalMin.portfolio <-function(er, cov.mat, shorts=TRUE){
  # Compute global minimum variance portfolio
  #
```

```r
  # inputs:
  # er              N x 1 vector of expected returns
  # cov.mat     N x N return covariance matrix
  # shorts          logical, allow shorts is TRUE
  #
  # output is portfolio object with the following elements
  # call            original function call
  # er              portfolio expected return
  # sd              portfolio standard deviation
  # weights     N x 1 vector of portfolio weights
  call <- match.call()
  #
  # check for valid inputs
  #
  asset.names <- names(er)
  er <- as.vector(er)                   # assign names if none exist
  cov.mat <- as.matrix(cov.mat)
  N <- length(er)
  if(N != nrow(cov.mat))
    stop("invalid inputs")
  if(any(diag(chol(cov.mat)) <= 0))
    stop("Covariance matrix not positive definite")
  # remark: could use generalized inverse if cov.mat is positive semi-definite
  #
  # compute global minimum portfolio
  #
  if(shorts==TRUE){
    cov.mat.inv <- solve(cov.mat)
    one.vec <- rep(1,N)
    w.gmin <- rowSums(cov.mat.inv) / sum(cov.mat.inv)
    w.gmin <- as.vector(w.gmin)
  } else if(shorts==FALSE){
    Dmat <- 2*cov.mat
    dvec <- rep.int(0, N)
    Amat <- cbind(rep(1,N), diag(1,N))
    bvec <- c(1, rep(0,N))
    result <- solve.QP(Dmat=Dmat,dvec=dvec,Amat=Amat,bvec=bvec,meq=1)
    w.gmin <- round(result$solution, 6)
  } else {
    stop("shorts needs to be logical. For no-shorts, shorts=FALSE.")
  }

  names(w.gmin) <- asset.names
  er.gmin <- crossprod(w.gmin,er)
  sd.gmin <- sqrt(t(w.gmin) %*% cov.mat %*% w.gmin)
  gmin.port <- list("call" = call,
           "er" = as.vector(er.gmin),
           "sd" = as.vector(sd.gmin),
           "weights" = w.gmin)
  class(gmin.port) <- "portfolio"
  gmin.port
}
```

```
efficient.frontier <- function(er, cov.mat, nport=20, alpha.min=-0.5, alpha.max=1.5, shorts=TRUE)
{
  call <- match.call()
  #
  # check for valid inputs
  #
  asset.names <- names(er)
  er <- as.vector(er)
  N <- length(er)
  cov.mat <- as.matrix(cov.mat)
  if(N != nrow(cov.mat))
    stop("invalid inputs")
  if(any(diag(chol(cov.mat)) <= 0))
    stop("Covariance matrix not positive definite")
  #
  # create portfolio names
  #
  port.names <- rep("port",nport)
  ns <- seq(1,nport)
  port.names <- paste(port.names,ns)
  #
  # compute global minimum variance portfolio
  #
  cov.mat.inv <- solve(cov.mat)
  one.vec <- rep(1, N)
  port.gmin <- globalMin.portfolio(er, cov.mat, shorts)
  w.gmin <- port.gmin$weights
  if(shorts==TRUE){
    # compute efficient frontier as convex combinations of two efficient portfolios
    # 1st efficient port: global min var portfolio
    # 2nd efficient port: min var port with ER = max of ER for all assets
    er.max <- max(er)
    port.max <- efficient.portfolio(er,cov.mat,er.max)
    w.max <- port.max$weights
    a <- seq(from=alpha.min,to=alpha.max,length=nport) # convex combinations
    we.mat <- a %o% w.gmin + (1-a) %o% w.max             # rows are efficient portfolios
    er.e <- we.mat %*% er                                   # expected returns of efficient po
    er.e <- as.vector(er.e)
  } else if(shorts==FALSE){
    we.mat <- matrix(0, nrow=nport, ncol=N)
    we.mat[1,] <- w.gmin
    we.mat[nport, which.max(er)] <- 1
    er.e <- as.vector(seq(from=port.gmin$er, to=max(er), length=nport))
    for(i in 2:(nport-1))
      we.mat[i,] <- efficient.portfolio(er, cov.mat, er.e[i], shorts)$weights
  } else {
    stop("shorts needs to be logical. For no-shorts, shorts=FALSE.")
  }

  names(er.e) <- port.names
  cov.e <- we.mat %*% cov.mat %*% t(we.mat) # cov mat of efficient portfolios
  sd.e <- sqrt(diag(cov.e))                   # std of efficient portfolios
  sd.e <- as.vector(sd.e)
```

```r
  names(sd.e) <- port.names
  dimnames(we.mat) <- list(port.names,asset.names)
  #
  # summarize results
  #
  ans <- list("call" = call,
          "er" = er.e,
          "sd" = sd.e,
          "weights" = we.mat)
  class(ans) <- "Markowitz"
  ans
}

tangency.portfolio <- function(er,cov.mat,risk.free, shorts=TRUE)
{
  call <- match.call()
  #
  # check for valid inputs
  #
  asset.names <- names(er)
  if(risk.free < 0)
    stop("Risk-free rate must be positive")
  er <- as.vector(er)
  cov.mat <- as.matrix(cov.mat)
  N <- length(er)
  if(N != nrow(cov.mat))
    stop("invalid inputs")
  if(any(diag(chol(cov.mat)) <= 0))
    stop("Covariance matrix not positive definite")
  # remark: could use generalized inverse if cov.mat is positive semi-definite
  #
  # compute global minimum variance portfolio
  #
  gmin.port <- globalMin.portfolio(er, cov.mat, shorts=shorts)
  if(gmin.port$er < risk.free)
    stop("Risk-free rate greater than avg return on global minimum variance portfolio")
  #
  # compute tangency portfolio
  #
  if(shorts==TRUE){
    cov.mat.inv <- solve(cov.mat)
    w.t <- cov.mat.inv %*% (er - risk.free) # tangency portfolio
    w.t <- as.vector(w.t/sum(w.t))          # normalize weights
  } else if(shorts==FALSE){
    Dmat <- 2*cov.mat
    dvec <- rep.int(0, N)
    er.excess <- er - risk.free
    Amat <- cbind(er.excess, diag(1,N))
    bvec <- c(1, rep(0,N))
    result <- quadprog::solve.QP(Dmat=Dmat,dvec=dvec,Amat=Amat,bvec=bvec,meq=1)
    w.t <- round(result$solution/sum(result$solution), 6)
  } else {
    stop("Shorts needs to be logical. For no-shorts, shorts=FALSE.")
```

```
  }

  names(w.t) <- asset.names
  er.t <- crossprod(w.t,er)
  sd.t <- sqrt(t(w.t) %*% cov.mat %*% w.t)
  tan.port <- list("call" = call,
           "er" = as.vector(er.t),
           "sd" = as.vector(sd.t),
           "weights" = w.t)
  class(tan.port) <- "portfolio"
  return(tan.port)
}
plot.portfolio <- function(object, ...)
{
  asset.names <- names(object$weights)
  barplot(object$weights, names=asset.names,
      xlab="Assets", ylab="Weight", main="Portfolio Weights", ...)
  invisible()
}

##SHORT SELL IS NOT ALLOWED
##mvp with no short sell
mvp.noshort=globalMin.portfolio(mean.r,cov.r,shorts=FALSE)
mvp.ns.sd=mvp.noshort$sd
mvp.ns.er=mvp.noshort$er
mvp.ns.w=mvp.noshort$weights
##Tangency Portfolio
tangency.noshort=tangency.portfolio(mean.r,cov.r,risk.free = rf.m,shorts = FALSE)
tg.ns.er=tangency.noshort$er #tangency return
tg.ns.sd=tangency.noshort$sd
tg.ns.w=tangency.noshort$weights
##Efficient Portfolio Frontier
eff.front.noshort=efficient.frontier(mean.r,cov.r,nport=50, shorts = FALSE)
ef.ns.er=eff.front.noshort$er
ef.ns.sd=eff.front.noshort$sd
ef.ns.w=eff.front.noshort$weights
##Data Table
library(formattable)
noshort.table=data.frame("risk.free.day"=rbind(round(rf.m,5),0) ,
                       "mvp day"=rbind(mvp.ns.er,mvp.ns.sd),
                       "tangency.day"=rbind(tg.ns.er,tg.ns.sd),
                       "mvp year"=rbind(mvp.ns.er*365,mvp.ns.sd*sqrt(365)),
                       "Tangency year"=rbind(tg.ns.er*365,tg.ns.sd*sqrt(365)),
                       "risk.free.year"=rbind(rf.m*365,0),
                       row.names = c("return","risk"))
formattable(noshort.table)
##Value at Risk
s=100000
## t= one month
##Loss~N(-mean.mvp,sd.mvp), assuming mvp is normal
VaR.ns.mvp=(-mvp.ns.er+mvp.ns.sd*qnorm(0.95))*s
VaR.r=(-mean.r+sd.r*qnorm(0.95))*s
##Sharpe Ratio
```

```
sharpe.ns = ( ef.ns.er- rf.m) / ef.ns.sd
## compute Sharpe's ratios
(tg.ns.sharpe=max(sharpe.ns))
assets.ns.sharpe=(mean.r -rf.m)/sd.r

sort(mvp.ns.w,decreasing = T)

sort(tg.ns.w,decreasing = T)

sort(sd.r,decreasing = F)

##SHORT SELL IS NOT ALLOWED
##Portfolio Plot

plot(ef.ns.sd,ef.ns.er,type="l",main="Efficient Frontier (No Short)",
     xlab="daily Risk", ylab="daily Return",
     ylim = c(0,0.0008),xlim=c(0,0.025),lty=3)

text(sqrt(cov.r[1,1]),mean.r[1],'PFE',cex=1.1)
text(sqrt(cov.r[2,2]),mean.r[2],'JNJ',cex=1.1)
text(sqrt(cov.r[3,3]),mean.r[3],'MRK',cex=1.1)
text(sqrt(cov.r[4,4]),mean.r[4],'NVS',cex=1.1)

points(0, rf.m, cex = 4, pch = "*") # show risk-free asset
sharpe = ( ef.ns.er- rf.m) / ef.ns.sd # compute Sharpe's ratios
ind = (sharpe == max(sharpe)) # Find maximum Sharpe's ratio
lines(c(0, 2), rf.m + c(0, 2) * (ef.ns.er[ind] - rf.m) / ef.ns.sd[ind], lwd = 4, lty = 1, col = "blue")
points(ef.ns.sd[ind], ef.ns.er[ind], cex = 4, pch = "*") # tangency portfolio
ind2 = (ef.ns.sd == min(ef.ns.sd)) # find minimum variance portfolio
points(ef.ns.sd[ind2], ef.ns.er[ind2], cex = 2, pch = "+") # min var portfolio
ind3 = (ef.ns.er > ef.ns.er[ind2])
lines(ef.ns.sd[ind3], ef.ns.er[ind3], type = "l", lwd = 3, col = "red") # plot efficient frontier

##SHORT SELL IS ALLOWED
##ALL VARIABLES are in MONTH
##mvp
mvp.short=globalMin.portfolio(mean.r ,cov.r,shorts=TRUE)
mvp.s.sd=mvp.short$sd
mvp.s.er=mvp.short$er
mvp.s.w=mvp.short$weights
##Tangency Portfolio
tangency.short=tangency.portfolio(mean.r ,cov.r,risk.free = rf.m,shorts = TRUE)
tg.s.er=tangency.short$er #tangency return
tg.s.sd=tangency.short$sd
tg.s.w=tangency.short$weights
##SHORT SELL IS ALLOWED
##Efficient Portfolio Frontier
eff.front.short=efficient.frontier(mean.r ,cov.r,nport=50,
                                   shorts = TRUE)
ef.s.er=eff.front.short$er
ef.s.sd=eff.front.short$sd
ef.s.w=eff.front.short$weights
##Data Table
```

```r
library(formattable)
short.table=data.frame("risk.free.day"=rbind(rf.m,0) ,
                       "mvp day"=rbind(mvp.s.sd,mvp.s.sd),
                       "tangency.day"=rbind(tg.s.er,tg.s.sd),
                       "mvp year"=rbind(mvp.s.er*365,mvp.s.sd*sqrt(365)),
                       "Tangency year"=rbind(tg.s.er*365,tg.s.sd*sqrt(365)),
                       "risk.free.year"=rbind(rf.m*365,0),
                       row.names = c("return","risk")
                       )
formattable(short.table)
##Value at Risk
s=100000
## t= one month
##Loss~N(-mean.mvp,sd.mvp), assuming mvp is normal
VaR.s.mvp=(-mvp.s.er+mvp.s.sd*qnorm(0.95))*s
VaR.s.mvp
VaR.s.tg=(-tg.s.er+tg.s.sd*qnorm(0.95))*s
VaR.s.tg
##Sharpe Ratio
sharpe.s = ( ef.s.er- rf.m) / ef.s.sd # compute Sharpe's ratios
(tg.s.sharpe=max(sharpe.s))
assets.s.sharpe=(mean.r -rf.m)/sd.r

sort(mvp.s.w,decreasing = T)

sort(tg.s.w,decreasing = T)

efficient.portfolio(scale(mean.r),cov.r,0.005,shorts=FALSE)

##Portfolio Plot
plot(ef.s.sd,ef.s.er,type="l",main="Efficient Frontier (Short)",
     xlab="daily Risk", ylab="daily Return",
     ylim = c(0,0.001),xlim=c(0,0.02),lty=3)

text(sqrt(cov.r[1,1]),mean.r[1],'PFE',cex=1.1)
text(sqrt(cov.r[2,2]),mean.r[2],'JNJ',cex=1.1)
text(sqrt(cov.r[3,3]),mean.r[3],'MRK',cex=1.1)
text(sqrt(cov.r[4,4]),mean.r[4],'NVS',cex=1.1)

points(0, rf.m, cex = 4, pch = "*") # show risk-free asset
sharpe = ( ef.s.er- rf.m) / ef.s.sd # compute Sharpe's ratios
ind = (sharpe == max(sharpe)) # Find maximum Sharpe's ratio
lines(c(0, 2), rf.m + c(0, 2) * (ef.s.er[ind] - rf.m) / ef.s.sd[ind], lwd = 4, lty = 1, col = "blue") #
points(ef.s.sd[ind], ef.s.er[ind], cex = 4, pch = "*") # tangency portfolio
ind2 = (ef.s.sd == min(ef.s.sd)) # find minimum variance portfolio
points(ef.s.sd[ind2], ef.s.er[ind2], cex = 2, pch = "+") # min var portfolio
ind3 = (ef.s.er > ef.s.er[ind2])
lines(ef.s.sd[ind3], ef.s.er[ind3], type = "l", xlim = c(0, 1),
      ylim = c(0, 0.3), lwd = 3, col = "red") # plot efficient frontier

# Copula
library(copula)
library(VineCopula)
```

```r
library(tidyverse)
## Gaussian, t, archimedean, clayton, gumbel
data = read.csv("full_close.csv")
cop.norm = normalCopula(dim=4)
fit.copnorm = fitCopula(cop.norm,pobs(data),method="ml")
fit.copnorm
AIC(fit.copnorm)
BIC(fit.copnorm)
logLik(fit.copnorm)
cop.t = tCopula(dim=4)
fit.copt = fitCopula(cop.t,pobs(data),method = "ml")
fit.copt
AIC(fit.copt)
BIC(fit.copt)
logLik(fit.copt)
cop.gumbel = gumbelCopula(dim=4)
fit.copgumbel = fitCopula(cop.gumbel,pobs(data),method = "ml")
fit.copgumbel
AIC(fit.copgumbel)
BIC(fit.copgumbel)
logLik(fit.copgumbel)
cop.archm = archmCopula(family = "frank",dim=4)
fit.archm = fitCopula(cop.archm, pobs(data),method = "ml")
fit.archm
AIC(fit.archm)
BIC(fit.archm)
logLik(fit.archm)
cop.clayton = claytonCopula(dim=4)
fit.copclayton = fitCopula(cop.clayton,pobs(data),method = "ml")
fit.copclayton
AIC(fit.copclayton)
BIC(fit.copclayton)
logLik(fit.copclayton)
```

```r
# Risk Management
## Normal distribution method
library(PerformanceAnalytics)
s = 100000
VaR.gaussian=sapply(return,function(data_5){-s*VaR(data_5, method="gaussian")})
VaR.gaussian
ES.gaussian=sapply(return,function(data_5){-s*ES(data_5, method="gaussian")})
ES.gaussian

## t distribution method
library(MASS)
info <- data.frame(matrix(ncol = 5, nrow = 2))

colnames(info) <- c('PFE_Close', 'JNJ_Close', 'ABBV_Close',
                    'MRK_Close', 'NVS_Close')

for (i in 1:5){
  alpha = 0.05
  fitt = fitdistr(return[,i], "t")
  param = as.numeric(fitt$estimate)
  mean = param[1]
  df = param[3]
  sd = param[2] * sqrt((df) / (df - 2))
  lambda = param[2]
  qalpha = qt(alpha, df = df)
  VaR_par = -100000 * (mean + lambda * qalpha)
  es1 = dt(qalpha, df = df) / (alpha)
  es2=(df+qalpha^2)/(df-1)
  es3=-mean+lambda*es1*es2
  ES_par = 100000*es3
  info[1,i] = VaR_par
  info[2,i] = ES_par
}

info

## Nonparametrix Method
VaR.nonparam=sapply(return,function(data_5){-s*VaR(data_5, method="historical")})
VaR.nonparam
ES.nonparam=sapply(return,function(data_5){-s*ES(data_5, method="historical")})
ES.nonparam
```