RISK AND RETURN ANALYSIS ON INVESTMENT PORTFOLIO FOR CLIENT

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Introduction

This study provides an in-depth risk and return analysis customised for a high net worth customer with a sizeable portfolio of 94 million USD who lives in Palo Alto, California. With 17.5% invested in IXN (equity), 22.1% in QQQ (equity), 28.5% in IEF (fixed income), 8.9% in VNQ (real assets), and 23% in GLD (commodities). The client's investment profile looks to be somewhat balanced based on the information given. The distribution of assets among various asset classes suggests a diversification strategy, which is frequently linked to a balanced strategy. An aggressive profile would have a larger share of stocks and riskier assets, whereas a conservative profile would generally have a bigger allocation to fixed-income assets.
The client appears to have a mix of equities for growth potential, fixed income for stability and income, exposure to real assets and commodities for diversification.
In *figure 1* below, a visualization of the client's balanced portfolio can be seen below.

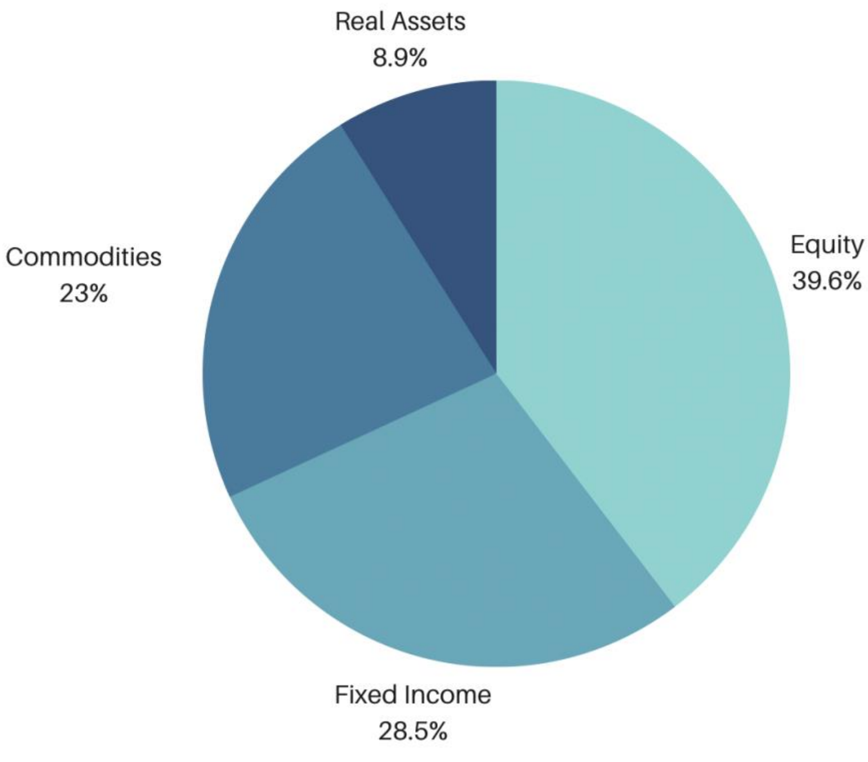


Figure 1 Portfolio Asset Class Allocations

In terms of the value of investment that has gone into each of the investments, *table 1* below shows the money evaluation for each asset.

Table 1 Value of each Asset

Asset	Allocation	Value
GLD	23.0%	$ 21,850,000.00
IEF	28.5%	$ 27,075,000.00
IXN	17.5%	$ 16,625,000.00
QQQ	22.1%	$ 20,995,000.00
VNQ	8.9%	$ 8,455,000.00
	TOTAL	**$ 95,000,000.00**

Current Portfolio Returns, its Risk, Spread and CAPM

A thorough portfolio return analysis for the high net worth client's investment assets will be conducted in the following section. The annualized returns for 12 months, 18 months, and 24 months will be specifically looked at in order to give a clear picture of the performance of the portfolio across various time periods. To evaluate the overall profitability and efficiency of the client's investment plan throughout the course of the stated periods, it may be helpful to first look at the overall return the entire portfolio throughout the time span of 24 months, which can be seen in *figure 2* below. One can see that the portfolio is relatively steady, though is currently on a downwards trend.

Figure 2 Total Portfolio Return over 24 Months

In the following *figures 3 through 5*, the individual returns on each of these assets can be seen as well as their individual values in terms of $USD in *tables 2 throgh 4*, throughout 24 months, 18 months and also 12 months.

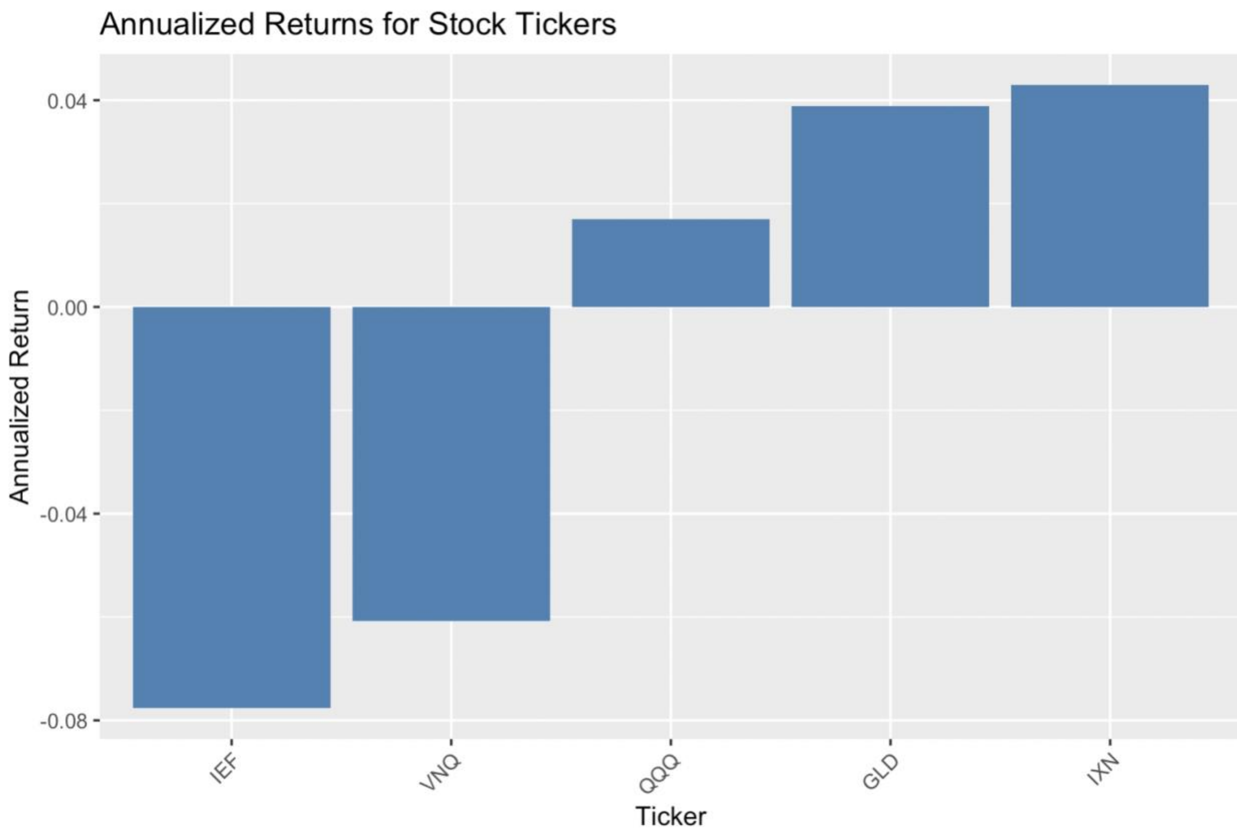


Figure 3 Annualized Returns for Stock Tickers over 24 Months

Table 2 Return Value for Investment placed 24M ago

Asset	Return 24M	Value
GLD	0.044512	$ 972,587.86
IEF	-0.0705037	$ (1,908,888.76)
IXN	0.0660073	$ 1,097,370.70
QQQ	0.0450078	$ 944,938.76
VNQ	-0.0539473	$ (456,124.68)
	TOTAL	**$ 649,883.88**

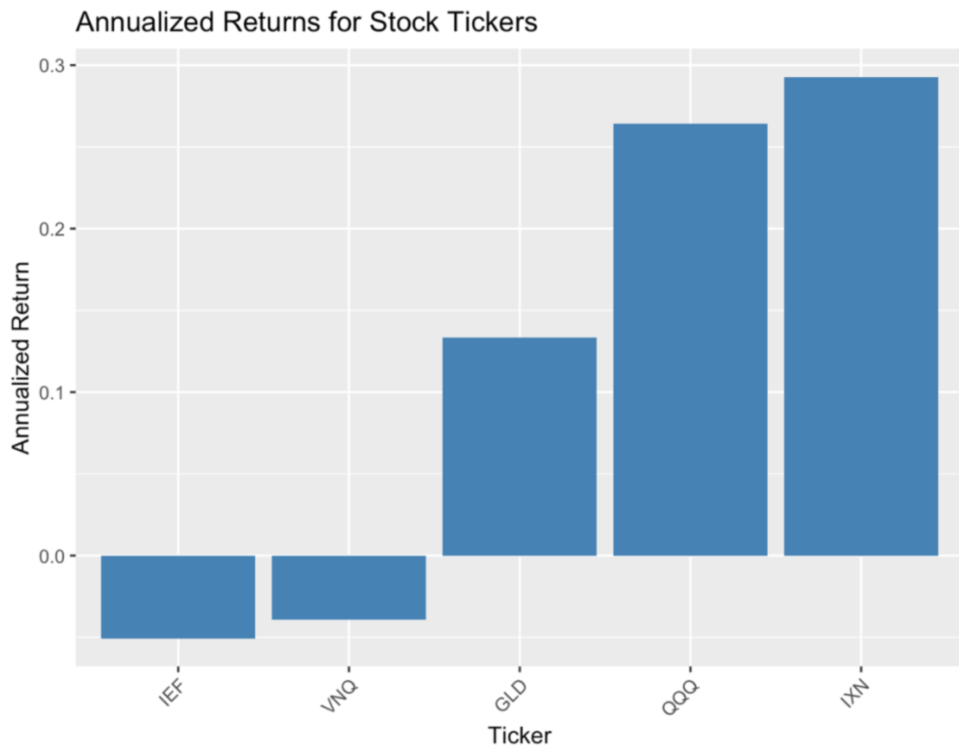


Figure 4 Annualized Returns for Stock Tickers over 18 Months

Table 3 Table 2 Return Value for Investment placed 18M ago

Asset	Return 18M	Value
GLD	5.08%	$ 1,110,363.25
IEF	-8.78%	$ (2,377,860.52)
IXN	-1.07%	$ (178,369.63)
QQQ	-2.29%	$ (480,538.81)
VNQ	-14.75%	$ (1,246,910.68)
	TOTAL	$ (3,173,316.39)

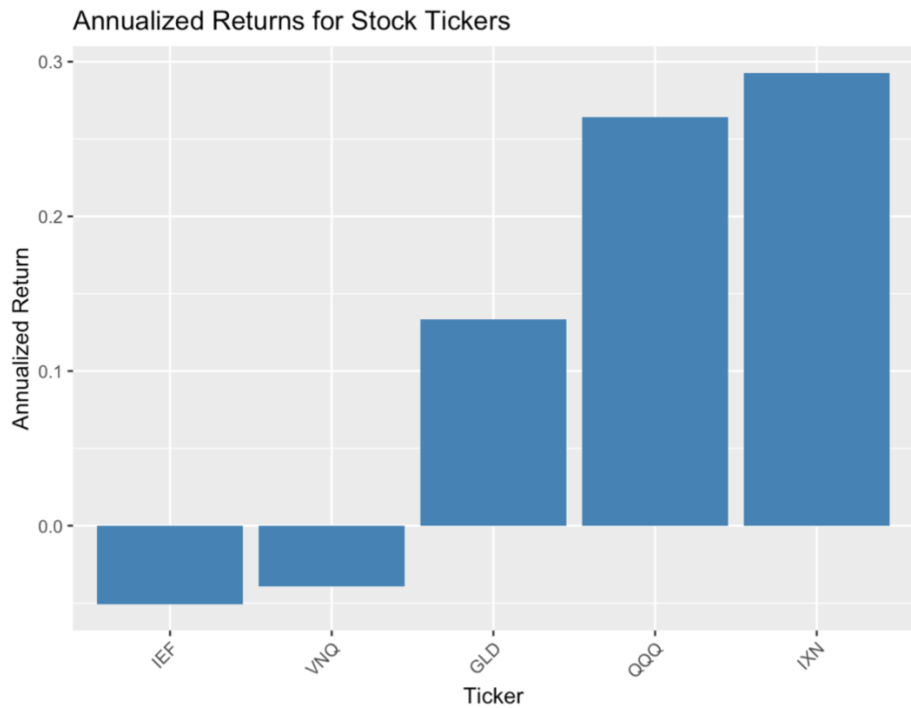


Figure 5 Annualized Returns for Stock Tickers over 12 Months

Table 4 Table 2 Return Value for Investment placed 12M ago

Asset	Return 12M	Value
GLD	7.52%	$ 1,642,262.82
IEF	-4.73%	$ (1,281,934.37)
IXN	36.98%	$ 6,147,639.88
QQQ	34.18%	$ 7,175,948.65
VNQ	-4.10%	$ (346,492.33)
	TOTAL	**$ 13,337,424.66**

Correlation

Now, after the analysis on the return, if investments had been placed during certin time frames, it is also important to note how each of this assets are correlated with one another. Knowing this, can help one mitigate the risk, a diversified portfolio usually has lesser correlated assets. In *figure 6* below, the correlation of these assets over the previous two years can be seen.

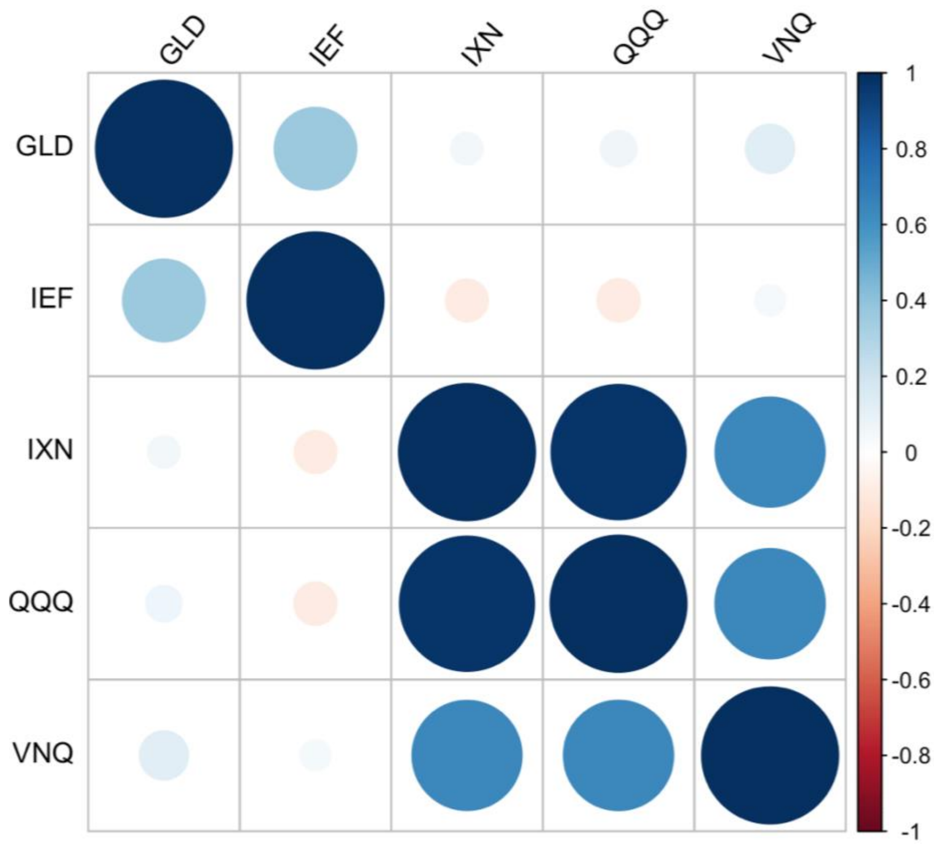


Figure 6 Correlation of Assets

Through the graphic above, it shows clearer that we have a strong correlation between QQQ & IXN, VNQ & IXN, and also VNQ & QQQ. The strong correlation between QQQ and IXN is explainable as both of them are equity assets, which is why these two assets are moving in the market in the same way.

Spread

Based on the portfolio presented, it is also a good idea to dive deeper into the spread of each asset that compose the portfolio with the current allocations. The spread of an acid and therefore the allocated risk are really important because it can help us determine whether we should sell or buy more of a certain asset in the portfolio. The higher the spread the more it fluctuates and the higher the risk of holding this asset. In *table 5* below one can find the spread and risk allocation for the assets within the portfolio.

Table 5 Spread and all time sigma

Asset	GLD	IEF	IXN	QQQ	VNQ	Total Portfolio
Spread	28.926%	12.265%	31.111%	30.607%	62.410%	**21.457%**
All Time Risk (Sigma)	4.934%	1.911%	5.640%	5.482%	6.623%	**3.018%**

To visualize these spreads In the following *figures 7 through 12* these can be found.

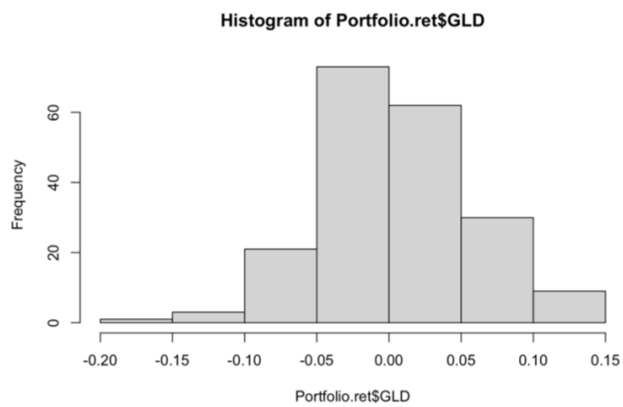


Figure 7 Spread: GLD

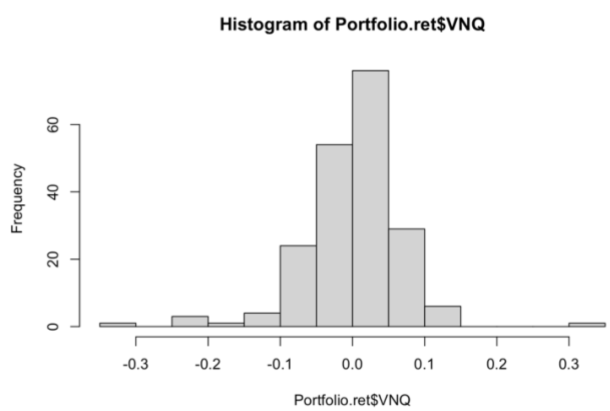


Figure 8 Spread VNQ

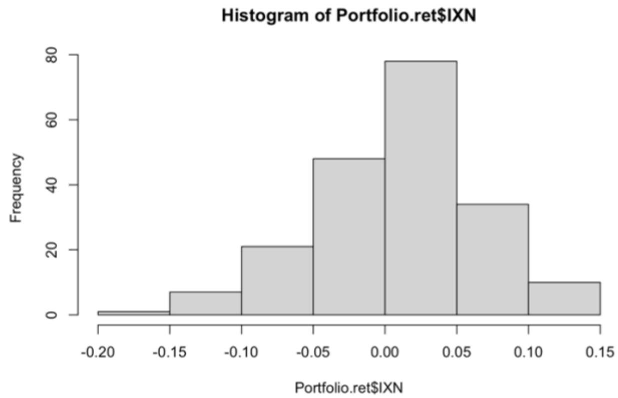


Figure 9 Spread: IXN

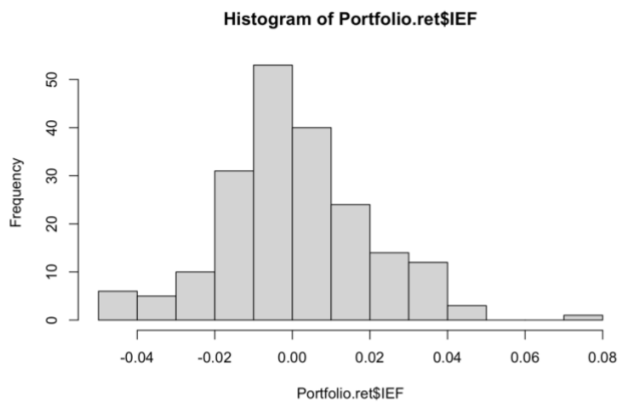


Figure 10 Spread: IEF

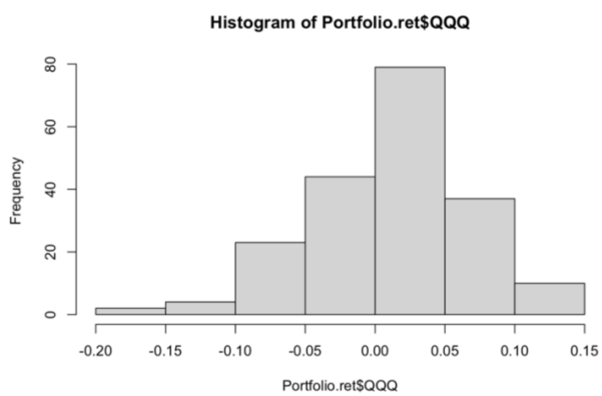


Figure 11 Spread: QQQ

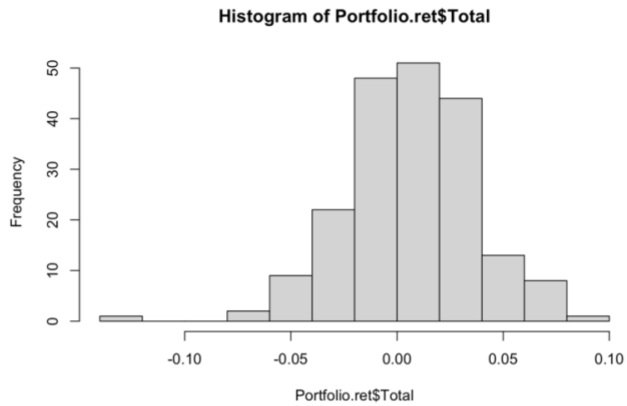


Figure 12 Spread: Total Portfolio

Risk

To get a deeper look into the portfolio within the last 12 months below shows each asset's risk also known as Sigma as well as for the entire portfolio. Combining what one has learned in the previous section about the spread and all time risk, as well as returns, of each asset in the portfolio, VNQ is one asset that stands out to us already at this point. Over the past 24, 18 and 12 months VNQ has always had negative returns similarly to IEF but the spread and risk are slightly concerning. At this point in the analysis, it may be interesting to consider selling the VNQ stock and buying more in a already holding asset or a new one. The risks over the past 12 months can be seen in *table 6* below.

Table 6 Risk for 12M

Asset	GLD	IEF	IXN	QQQ	VNQ	Total Portfolio
12M Risk (Sigma)	4.565%	2.958%	7.907%	7.061%	6.765%	**4.793%**

CAPM Model

Another analysis tool that was used in order to determine the efficiency and performance of an asset was the CAPM model. This model is used to portray the market value and expected future return and residuals and their securities are placed. It is ideal to remain as close to the line as possible, which has a linear upward trend showing growth potential. These CAPM models for each of these assets can be seen in *figures 13 through 17* below. The asset of V&Q stands out here again. The CAPM model shows that not only does VNQs trendline have a significantly smaller slope than the other assets, but considering VNQ has had only negative outcomes for the client so far, the point stands again that VNQ may have to be an asset to be sold.

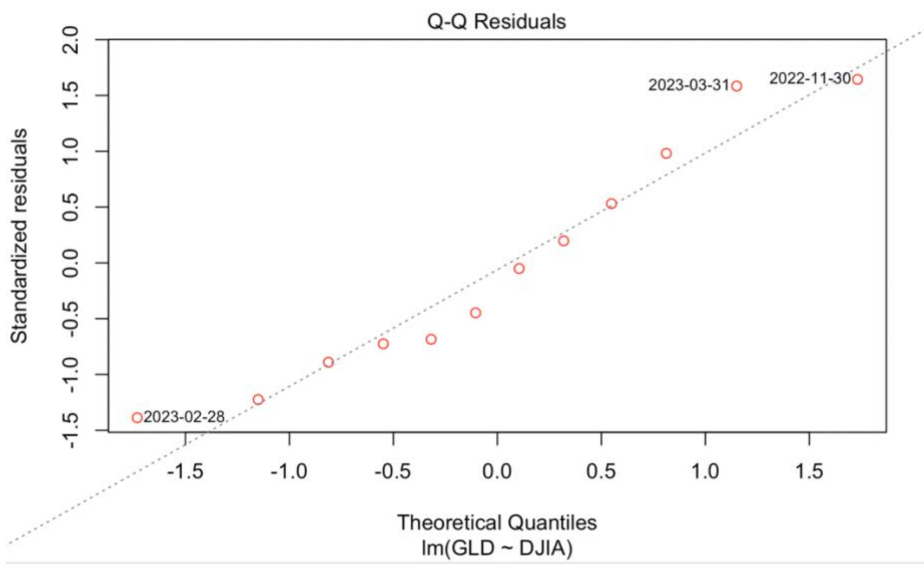


Figure 13 CAPM: GLD

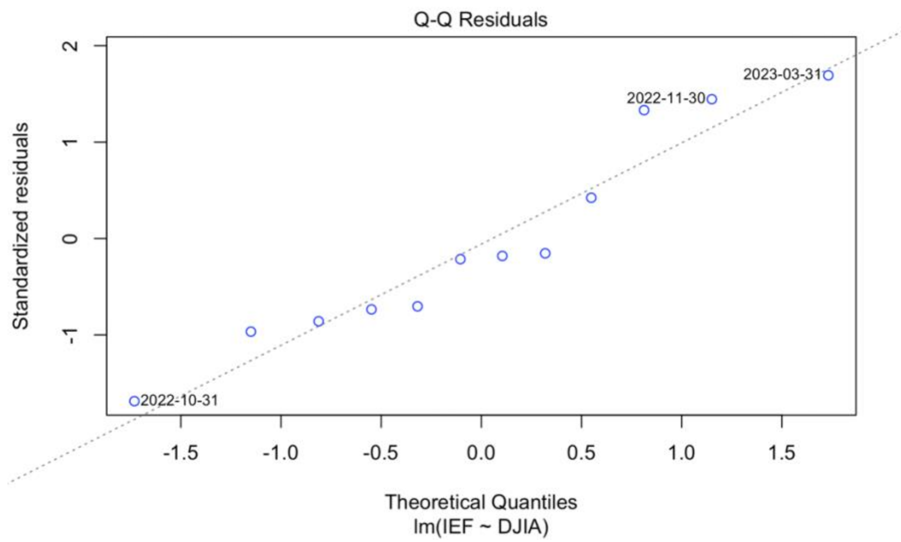


Figure 14 CAPM: IEF

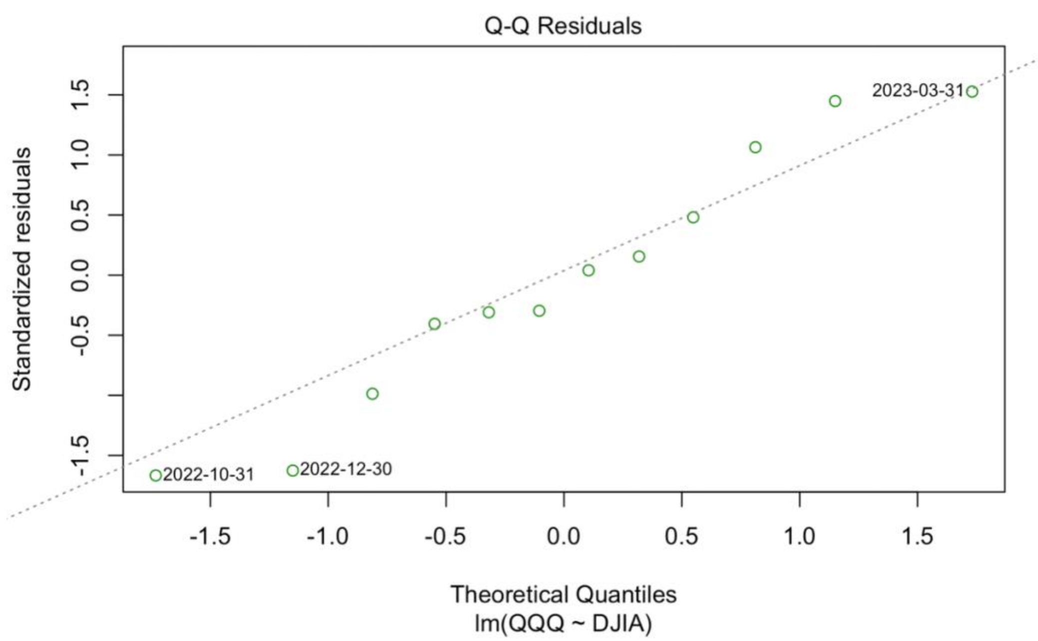


Figure 15 CAPM: QQQ

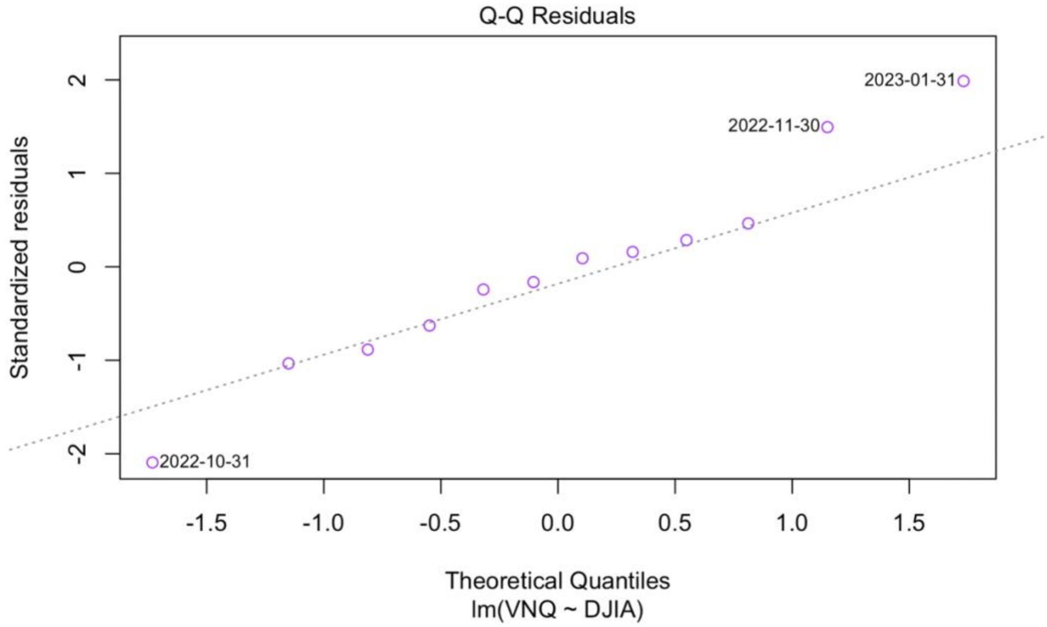


Figure 16 CAPM: VNQ

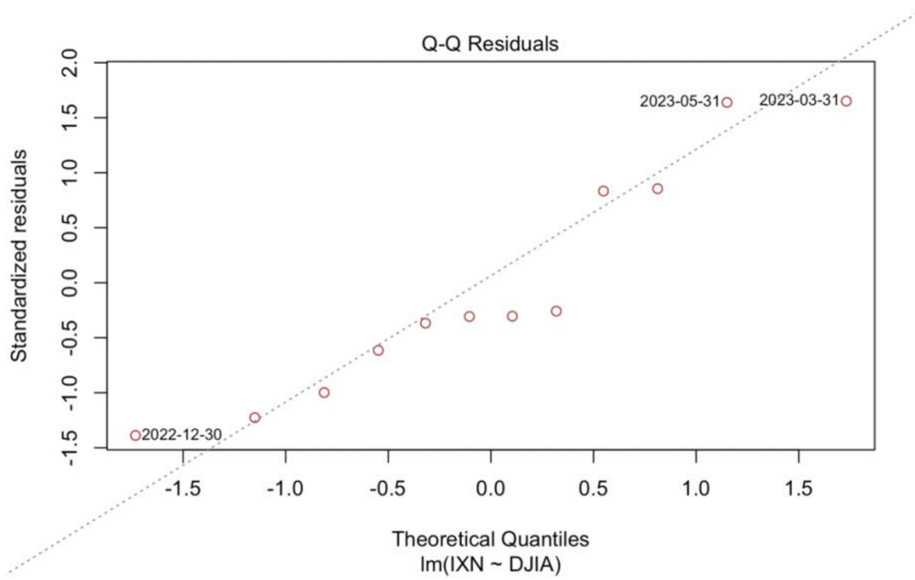


Figure 17 CAPM IXN

Efficient Frontier

The usage of an efficient frontier model gives the user also a view into the risk to return trade And *figure 17* below one can see that the risk and return trade off for the top assets in the portfolio are at a steady point with a low volatility and an expected rate of return. As we've seen through all the other infographics shown above and through all the previously conducted analysis the top three acids referred to our IXN, QQQ and GLD.

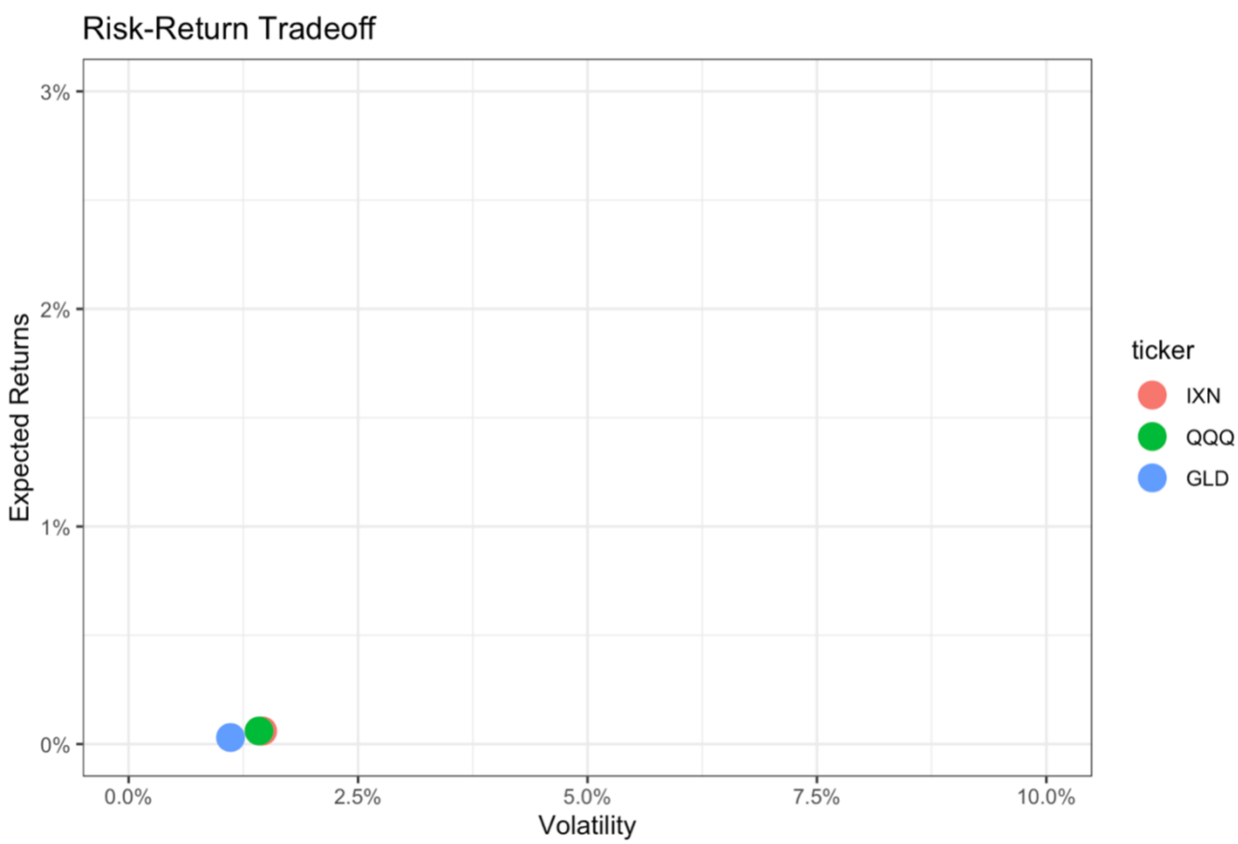


Figure 18 Risk Return Tradeoff

Proposal of New Portfolio

Sharpe Ratio

In order to determine a new portfolio, the current assets can also be analyzed on their Sharpe ratio. What this ratio tells us is the ideal holding a mound of each asset where the amount of benefits (return) for the amount of risk being taken has been maximized. The outcomes of conducting a Sharpe ratio analysis for each of these assets can be seen in *table X* below.

Table 7 Sharpe Ratio

Asset	**GLD**	**IEF**	**IXN**	**VNQ**	**QQQ**
Sharpe Ratio	17.69%	-30.67%	23.82%	-18.34%	24.43%

What is interesting to see is that our ideas previously about possibly selling the holding of VN Q is correct. But not only is it VNQ but also IEF, both of these assets have a negative sharp ratio which tells us that there is no positive benefit by holding these assets for the risk that we are taking.

In order to keep the portfolio based on the different asset classes in a similar and balanced way, two different new assets were chosen. In order to still have a fixed income asset FNAX was chosen which is the fidelity US bond index fund, and to replace the real asset SRET was deemed a great choice for this portfolio. SRET is the Global X SuperDividend Reit ETF, who has holdings globally which also adds another aspect to the portfolio of having an international aspect in order to diversify not only the asset classes but also the asset markets.

The new allocation for each asset based on their individual sharp ratios can be found in *figure 18* below.

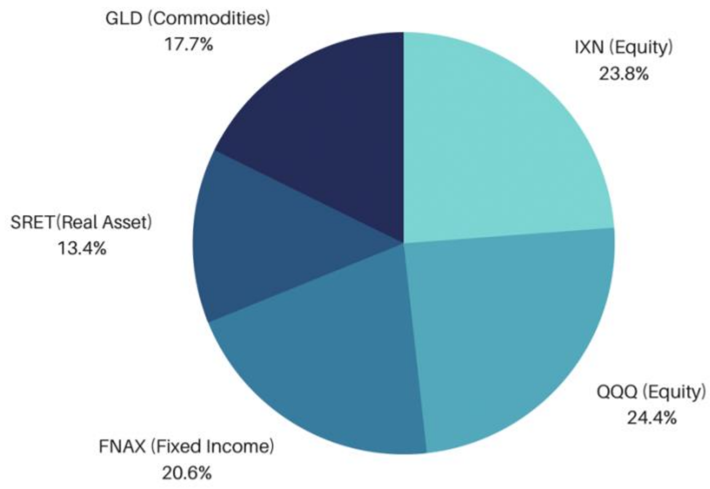


Figure 19 New Portfolio Asset Allocation

Expected Risk

In order to also talk about the aspect of risk when conducting and building a new portfolio risk is also another aspect of this. Compared to the old portfolio the risks remain at the same level with the total portfolio risk increase by less than a percent. The portfolio is also more diversified within the asset classes and globally well only holding less than 1% more risk which can be deemed as very beneficial to the client.

Table 8 Expected Risk New Portfolio

Asset	**GLD**	**FXNAX**	**IXN**	**QQQ**	**SRET**	**Total Portfolio**
12M Risk (Sigma)	4.565%	4.441%	7.907%	7.061%	7.375%	**5.215%**

Expected Return

In order to visualize what this new portfolio can provide for the client, we predicted what future return the client can expect for six months, 12 months and 18 months for each of the portfolios, the old and the new. The model that was used for this was ARMA and also the ARIMA models. This model was used as all of these assets have a stationary trend.

In *table 9* below the prediction of returns for the old portfolio can be seen.

Table 9 Predicted Returns Old Portfolio

Asset	6M	Value	12M	Value	18M	Value
GLD	2.0275%	$ 443,016.65	2.5846%	$ 699,777.17	0.8350%	$ 182,446.72
IEF	0.4152%	$ 112,422.43	0.3986%	$ 66,270.57	0.3191%	$ 86,393.22
IXN	4.6446%	$ 772,159.00	1.6243%	$ 341,026.55	1.9287%	$ 320,645.84
QQQ	5.2324%	$ 1,098,538.39	5.2894%	$ 447,219.95	5.3365%	$ 1,120,406.78
VNQ	-0.0577%	$ (4,880.17)	0.0235%	$ 22,283.12	0.8490%	$ 71,780.63
	Total	$ 2,421,256.30	Total	$ 1,576,577.37	Total	$ 1,781,673.20

In *table 10* below one can find the new returned expected returns generated by the new portfolio allocations. While only having 1% more risk with this new portfolio the benefit is clearly significantly higher which will make this portfolio a success to our client in Palo Alto.

Table 10 Predicted Returns New Portfolio

Asset	6M	Value	12M	Value	18M	Value
GLD	1.0192%	$ 171,278.65	2.5846%	$ 434,352.92	0.8350%	$ 140,325.32
FNAX	1.1560%	$ 226,114.85	1.1707%	$ 228,987.56	1.1799%	$ 230,779.61
IXN	5.2938%	$ 1,197,942.83	5.3120%	$ 1,202,050.44	5.3335%	$ 1,206,922.24
QQQ	5.2324%	$ 1,214,357.14	5.2894%	$ 1,227,593.65	5.3365%	$ 1,238,531.12
SRET	6.4361%	$ 821,825.20	6.9279%	$ 884,616.38	7.0044%	$ 894,385.91
	Total	$ 3,631,518.68	Total	$ 3,977,600.96	Total	$ 3,710,944.20

Conclusion

Through the analysis by using different frameworks of finding the Sigmas, the Betas, Correlations, usage of the CAPM, ARMA&ARIMA, Sharpe ratio, Efficient Frontier, Sprea, return and Tracking error some mentioned in this report but not limited to, a new portfolio for a client was created. This new portfolio seems to be a success as per the expected returns for the upcoming future while also remaining within the investors profile of the client. While only adding a little bit of risk we are getting a significant reward, in the eyes of an investor, we have achieved our goal.

Appendix

Code

```
###################################
# Created by Alyssa Brunen
##################################
### Hult Inter. Business School
##################################
# Modeling and Analytics MFIN
##################################
# Wealth and Investment Management
##################################
# Individual Assignment A1
##################################


### Loading Libraries
library(rpart)
library(ggplot2)
library(lattice)
library(rpart.plot)
library(caret)
library(tidyverse)
library(tseries)
library(rugarch)
library(dplyr)
library(corrplot)
library(dplyr)
library(quantmod)
library(readxl)

### Downloading Tickers

VNQ_ticker <- getSymbols("VNQ", auto.assign=FALSE)
QQQ_ticker <- getSymbols("QQQ", auto.assign=FALSE)
IXN_ticker <- getSymbols("IXN", auto.assign=FALSE)
IEF_ticker <- getSymbols("IEF", auto.assign=FALSE)
GLD_ticker <- getSymbols("GLD", auto.assign=FALSE)

### Combine all tickers

joined_prices <- merge.xts(GLD_ticker, IEF_ticker, IXN_ticker, QQQ_ticker, VNQ_ticker)

### Dataframe with only Adjusted Prices
```

```
Portfolio_Adj.Prices <- joined_prices[, c(6, 12, 18, 24, 30)]

### Data Frame for Returns only
Portfolio_Returns_no.alloc <- as.data.frame(Portfolio_Adj.Prices) %>%
  mutate(GLD_ROR=(GLD.Adjusted-lag(GLD.Adjusted))/lag(GLD.Adjusted)) %>%
  mutate(IEF_ROR=(IEF.Adjusted-lag(IEF.Adjusted))/lag(IEF.Adjusted)) %>%
  mutate(IXN_ROR=(IXN.Adjusted-lag(IXN.Adjusted))/lag(IXN.Adjusted)) %>%
  mutate(QQQ_ROR=(QQQ.Adjusted-lag(QQQ.Adjusted))/lag(QQQ.Adjusted)) %>%
  mutate(VNQ_ROR=(VNQ.Adjusted-lag(VNQ.Adjusted))/lag(VNQ.Adjusted))

### Create Returns

GLD_returns <- monthlyReturn(getSymbols("GLD", auto.assign=FALSE))
IEF_returns <- monthlyReturn(getSymbols("IEF", auto.assign=FALSE))
IXN_returns <- monthlyReturn(getSymbols("IXN", auto.assign=FALSE))
QQQ_returns <- monthlyReturn(getSymbols("QQQ", auto.assign=FALSE))
VNQ_returns <- monthlyReturn(getSymbols("VNQ", auto.assign=FALSE))

Portfolio_MonthlyROR_no.alloc <- merge.xts(GLD_returns, IEF_returns,
IXN_returns,QQQ_returns,VNQ_returns)


# Return Visualization from 2007
chart_Series(GLD_returns)
chart_Series(IEF_returns)
chart_Series(IXN_returns)
chart_Series(QQQ_returns)
chart_Series(VNQ_returns)


###Renaming the Column Names

colnames(Portfolio_MonthlyROR_no.alloc)[1] <- "GLD"
colnames(Portfolio_MonthlyROR_no.alloc)[2] <- "IEF"
colnames(Portfolio_MonthlyROR_no.alloc)[3] <- "IXN"
colnames(Portfolio_MonthlyROR_no.alloc)[4] <- "QQQ"
colnames(Portfolio_MonthlyROR_no.alloc)[5] <- "VNQ"


### Creating Portfolio Data frame with correct allocation for each Asset

IXN_alloc <- 0.175
QQQ_alloc <- 0.221
IEF_alloc <- 0.285
VNQ_alloc <- 0.089
GLD_alloc <- 0.23
```

```
Portfolio.ret <- as.data.frame(Portfolio_MonthlyROR_no.alloc)%>%
  mutate(GLD_alloc*GLD+ IXN_alloc*IXN+ QQQ_alloc* QQQ + IEF_alloc*IEF +
VNQ_alloc*VNQ )

colnames(Portfolio.ret)[6] <- "Total"

##########################################################################
## Question 1: What is the most recent 12M*, 18M, 24M (months) return for each of the
securities? (And Total)
##########################################################################


time_index <- nrow(Portfolio.ret)

### GLD 12M
Portfolio.ret$GLD[time_index:(time_index-11)]

## GLD 18M
Portfolio.ret$GLD[time_index:(time_index-17)]

## GLD 24M
Portfolio.ret$GLD[time_index:(time_index-23)]

### IXN 12M
Portfolio.ret$IXN[time_index:(time_index-11)]

### IXN 18M
Portfolio.ret$IXN[time_index:(time_index-17)]

### IXN 24M
Portfolio.ret$IXN[time_index:(time_index-23)]

###IEF 12M
Portfolio.ret$IEF[time_index:(time_index-11)]


### IEF 18M
Portfolio.ret$IEF[time_index:(time_index-17)]

### IEF 24M
Portfolio.ret$IEF[time_index:(time_index-23)]
```

```
### QQQ 12M
Portfolio.ret$QQQ[time_index:(time_index-11)]


#### Total Portfolio
Portfolio.ret$Total[time_index:(time_index-11)]


Portfolio.ret$Total[time_index:(time_index-23)]


########
## Return Visualization Code
#Returns.all <- as.data.frame(Portfolio_Adj.Prices) %>%     #this means we take the p1-p0 so one up
#  mutate(GLD_returns=(GLD.Adjusted-lag(GLD.Adjusted))/lag(GLD.Adjusted)) %>%  #lag is the p0 and the first variable is the p1
#  mutate(IEF_returns=(IEF.Adjusted-lag(IEF.Adjusted))/lag(IEF.Adjusted)) %>%
#  mutate(IXN_returns=(IXN.Adjusted-lag(IXN.Adjusted))/lag(IXN.Adjusted)) %>%
#  mutate(QQQ_returns=(QQQ.Adjusted-lag(QQQ.Adjusted))/lag(QQQ.Adjusted)) %>%
#  mutate(VNQ_returns=(VNQ.Adjusted-lag(VNQ.Adjusted))/lag(IEF.Adjusted)) %>%

  ### Visualization of Anual return for each Asset
tickers <- c("GLD", "QQQ", "VNQ", "IXN", "IEF")

get_stock_data <- function(ticker) {
  stock_data <- getSymbols(ticker, src = "yahoo", from = "2022-07-25", to = "2023-07-25", auto.assign = FALSE)
  return(stock_data)
}

all_data <- lapply(tickers, get_stock_data)
names(all_data) <- tickers

# Step 3: Analyze the data and calculate performance metrics
get_returns <- function(stock_data) {
  daily_returns <- na.omit(ROC(Ad(stock_data)))
  annualized_returns <- ((1 + mean(daily_returns))^252) - 1
  return(annualized_returns)
}

returns <- sapply(all_data, get_returns)

# Step 4: Create visual representation (bar plot) of the annualized returns
returns_df <- data.frame(Ticker = names(returns), Annualized_Return = returns)
plot <- returns_df %>%
```

```
  ggplot(aes(x = reorder(Ticker, Annualized_Return), y = Annualized_Return)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  labs(title = "Annualized Returns for Stock Tickers",
       x = "Ticker", y = "Annualized Return") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

# Display the plot
print(plot)

# Step 5: Suggest the ticker with the highest annualized return
best_ticker <- returns_df[which.max(returns_df$Annualized_Return), "Ticker"]
cat("Based on historical data up to July 25th, the suggested ticker for an investor is:", best_ticker,
"\n")

############################################################################

############################################################################
## Question 2: What are the correlations between your assets? Are there any interesting
correlations?
############################################################################

# For all time


cor(Portfolio.ret,)

# Output:
#            GLD         IEF         IXN         QQQ        VNQ
#GLD   1.00000000  0.36358849  0.05601218  0.07115042 0.12841838
#IEF   0.36358849  1.00000000 -0.09669245 -0.09775812 0.05071319
#IXN   0.05601218 -0.09669245  1.00000000  0.97345862 0.64457320
#QQQ   0.07115042 -0.09775812  0.97345862  1.00000000 0.64747924
#VNQ   0.12841838  0.05071319  0.64457320  0.64747924 1.00000000

# For last 12M

cor(Portfolio.ret[time_index:(time_index-11),], )
# Output:
#           GLD         IEF         IXN         QQQ        VNQ
#GLD   1.0000000   0.9071300   0.4802408   0.4554878  0.4945006
#IEF   0.9071300   1.0000000   0.7363601   0.7370020  0.7284763
#IXN   0.4802408   0.7363601   1.0000000   0.9810553  0.7579519
#QQQ   0.4554878   0.7370020   0.9810553   1.0000000  0.7615618
#VNQ   0.4945006   0.7284763   0.7579519   0.7615618  1.0000000
```

```
## Correlation Visualtization

cor_matrix<- cor(Portfolio.ret[,c( "GLD", "IEF", "IXN", "QQQ", "VNQ", "Total")])

corrplot(cor_matrix, method = "circle", tl.col = "black", tl.srt = 50)

cor_matrix2<- cor(Portfolio.ret[,c( "GLD", "IEF", "IXN", "QQQ", "VNQ")])

corrplot(cor_matrix2, method = "circle", tl.col = "black", tl.srt = 50)

cor_matrix4<- cor(Portfolio_MonthlyROR_no.alloc[,c( "GLD", "IEF", "IXN", "QQQ",
"VNQ")])

corrplot(cor_matrix4, method = "circle", tl.col = "black", tl.srt = 50)


############################################################################
## Question 3: What is the most recent 12M sigma (risk) for each of the securities (and for the
entire portfolio)?
############################################################################

spread <- function(x){
  my_min <- min(x, na.rm = TRUE)
  my_max<- max(x, na.rm = TRUE)
  my_spread <- my_max - my_min
  my_sd <- sd(x, na.rm = TRUE)
  return (c(my_spread, my_sd))
}

# Spread for each asset:
spread(x=Portfolio.ret$GLD)
# [1] 0.28926156 0.04936472
spread(x=Portfolio.ret$IEF)
# [1] 0.12265384 0.01911386
spread(x=Portfolio.ret$IXN)
# [1] 0.31110491 0.05641641
spread(x=Portfolio.ret$QQQ)
# [1] 0.30606874 0.05483589
spread(x=Portfolio.ret$VNQ)
# [1] 0.62410660 0.06625582

# Spread for Total Portfolio
spread(x=Portfolio.ret$Total)
# [1] 0.21457414 0.03020739
```

```
hist(Portfolio.ret$Total)
hist(Portfolio.ret$GLD)
hist(Portfolio.ret$VNQ)
hist(Portfolio.ret$IXN)
hist(Portfolio.ret$IEF)
hist(Portfolio.ret$QQQ)


##### RISK Calculation (AKA Sigma)

GLD_sigma <- sd(Portfolio.ret$GLD [time_index:(time_index-11)])
# [1] 0.04565563
IEF_sigma <- sd(Portfolio.ret$IEF [time_index:(time_index-11)])
# [1] 0.02958028
IXN_sigma <- sd(Portfolio.ret$IXN [time_index:(time_index-11)])
# [1] 0.07907487
QQQ_sigma <- sd(Portfolio.ret$QQQ [time_index:(time_index-11)])
# [1] 0.07061041
VNQ_sigma <- sd(Portfolio.ret$VNQ [time_index:(time_index-11)])
# [1] 0.06765254

# Total Portfolio
Total_sigma <- sd(Portfolio.ret$Total [time_index:(time_index-11)])
# [1] 0.04793094

# Use Total with a benchmark portfolio

Bench <- monthlyReturn(getSymbols("DJIA", auto.assign = FALSE))
Bench_Portfolio <- merge.xts(Portfolio_MonthlyROR_no.alloc, Bench)
colnames(Bench_Portfolio)[6] <- "DJIA"
time_index <- nrow(Bench_Portfolio)

DJIASigma <- sd(Bench_Portfolio$DJIA[time_index:(time_index-11)])

cor(Portfolio.ret[,c( "GLD", "IEF", "IXN", "QQQ", "VNQ")])


cor(Bench_Portfolio[,c( "GLD", "IEF", "IXN", "QQQ", "VNQ", "DJIA")])
cor_matrix3<- cor(Bench_Portfolio[time_index:(time_index-11),], )
corrplot(cor_matrix3, method = "circle", tl.col = "black",tl.srt=50)


##########
#########
```

```
#Tracking Error#



GLD_TE <- sd(Portfolio.ret$GLD[time_index:(time_index-11)]-
        Bench_Portfolio$DJIA[time_index:(time_index-11)])

IEF_TE <- sd(Portfolio.ret$IEF[time_index:(time_index-11)]-
        Bench_Portfolio$DJIA[time_index:(time_index-11)])

IXN_TE <- sd(Portfolio.ret$IXN[time_index:(time_index-11)]-
        Bench_Portfolio$DJIA[time_index:(time_index-11)])

QQQ_TE <- sd(Portfolio.ret$QQQ[time_index:(time_index-11)]-
        Bench_Portfolio$DJIA[time_index:(time_index-11)])

VNQ_TE <- sd(Portfolio.ret$VNQ[time_index:(time_index-11)]-
        Bench_Portfolio$DJIA[time_index:(time_index-11)])



# For all time

###########################################################################
## Question 4: Based on the previous 3 questions, which holdings would you sell, which
holdings would you buy?
###########################################################################

# sharpe rate: its negative it moves slower thank market, sell

riskfree <- 0.0015

# we will calculate the expected return (of the last 12 months) with the mean() function

GLD_SHARPE <- (mean(Portfolio.ret$GLD[time_index:(time_index-11)])-
riskfree)/GLD_sigma
# 0.1769205
IEF_SHARPE <- (mean(Portfolio.ret$IEF[time_index:(time_index-11)])-riskfree)/IEF_sigma
# -0.3067268
IXN_SHARPE <- (mean(Portfolio.ret$IXN[time_index:(time_index-11)])-riskfree)/IXN_sigma
# 0.2381766
VNQ_SHARPE <- (mean(Portfolio.ret$VNQ[time_index:(time_index-11)])-
riskfree)/VNQ_sigma
# -0.1833891
```

```
QQQ_SHARPE <- (mean(Portfolio.ret$QQQ[time_index:(time_index-11)])-
riskfree)/QQQ_sigma
# 0.2442542

############ efficient Frontier for 10 stocks
library(quantmod)
library(tseries)
library(stats)
library(quadprog)

enddate <- "2022-2-28"
t<-1389 #The first time you run this, you'll see the error so adjust the t with the requested number

myvector <- c()
nstocks <- 5
pricinglist <- as.data.frame(matrix(ncol=nstocks, nrow=t))
colnames(pricinglist) <- c("VNQ","QQQ", "GLD", "IEF", "IXN")
#the pricinglist data starts form 2016-8-22 - this is the first row

for (i in 1:(ncol(pricinglist))){
  current_ticker <- colnames(pricinglist)[i]
  newtable <- getSymbols(current_ticker, src = "yahoo", from="2016-8-22", to=enddate,
auto.assign=FALSE)
  pricinglist[,i] <- newtable[,6]
}

#forecasting the next price using a backpropagation training algorithm in a neural network.
# a Autoregressive Model of fourth order AR4 was used.


newpricingdataset <- pricinglist

#creating a dataset with monthly ROR for each day using continuous compounding
dailyROR <- as.data.frame(matrix(ncol=ncol(newpricingdataset),
nrow=nrow(newpricingdataset)-25))
colnames(dailyROR) <- colnames(pricinglist)
for (c in 1:(ncol(newpricingdataset))){
  for (r in 1:(nrow(newpricingdataset)-25)){
    dailyROR[r,c] <-
log(as.numeric(newpricingdataset[(r+25),c])/as.numeric(newpricingdataset[r,c]))
  }
}
#The most current expected return for n+25 (n is today) is in the last row of the above dataset

#calculating Expected(R) for all securities
averet <- as.matrix(dailyROR[nrow(dailyROR),], nrow=1)
```

```
#calculating covariance matrix
rcov <- cov(dailyROR[(nrow(dailyROR)-125):(nrow(dailyROR)),]) #125 stands for 6 trading
months
target.r <- 1/1000
#using solver to get to optimal weights


effFrontier = function(averet, rcov, nports, shorts, wmax, wmin)
{
  mxret <- max(averet)
  mnret <- -mxret
  n.assets <- ncol(averet)
  reshigh <- rep(wmax, n.assets)
  reslow <- rep(wmin, n.assets)
  min.rets <- seq(mnret, mxret, length.out=nports)
  vol <- rep(NA, nports)
  ret <- rep(NA, nports)
  pw <- data.frame(matrix(ncol=nports, nrow=n.assets))
  for (i in 1:nports)
  {
    port.sol <- NULL
    try(port.sol <- portfolio.optim(x=averet, pm=min.rets[i], covmat=rcov,   reshigh = reshigh,
reslow= reslow, shorts=F)
        , silent=T)
    if(!is.null(port.sol))
    {
      vol[i] <- sqrt(as.vector(port.sol$pw %*% rcov %*% port.sol$pw))
      ret[i] <- averet %*% port.sol$pw
      pw[,i] <- port.sol$pw
    }
  }
  return(list(vol=vol, ret = ret, weights = pw))

}

maxSharpe <- function(averet, rcov, shorts=F, wmax=0.2, min.weight=0.01)
{
  optim.callback=function(param, averet, rcov, reshigh, reslow, shorts)
  {
    port.sol = NULL
    try(port.sol <- portfolio.optim(x=averet, pm=param, covmat=rcov,
                                reshigh=reshigh, reslow=reslow, shorts=shorts),silent=T)
    if(is.null(port.sol)) { ratio= 10^9} else
    {
      m.return <- averet %*% port.sol$pw
      m.risk <- sqrt(as.vector(port.sol$pw %*% rcov %*% port.sol$pw))
```

```
    ratio <- m.return/m.risk
    assign("w", port.sol$pw, inherits=T)
   }
  return(ratio)
 }

 ef <- effFrontier(averet=averet, rcov=rcov, shorts=shorts, wmax=wmax, nports = 100,
wmin=min.weight)
 n <- ncol(averet)
 reshigh <- rep(wmax, n)
 reslow <- rep(min.weight, n)

 max.sh <- which.max(ef$ret/ef$vol)


 if(is.na(ef$ret[max.sh-1])){lowerinterval<-ef$ret[max.sh]}else{lowerinterval <- ef$ret[max.sh-
1]}
 if(is.na(ef$ret[max.sh+1])){upperinterval<-ef$ret[max.sh]}else{upperinterval <-
ef$ret[max.sh+1]}

 w <- rep(0, ncol(averet))
 xmin <- optimize(f=optim.callback, interval = c(lowerinterval, upper=upperinterval),
            averet=averet, rcov=rcov, reshigh=reshigh, reslow=reslow, shorts=shorts)
 return(w)
 return(xmin)
}

z <- maxSharpe(averet, rcov, shorts=F, wmax=0.4)
print(z)

## Output: > print(z)
# "VNQ",      "QQQ",      "GLD",     "IEF",     "IXN"
# 0.15103069 0.03896931 0.40000000 0.40000000 0.01000000
##########################################################################
## Question 5: How will your portfolio risk and expected returns change after rebalancing
(selling and buying)?
##########################################################################

### Reallocation
IXN_alloc2 <- 0.01000000
QQQ_alloc2 <- 0.03896931
IEF_alloc2 <- 0.40000000
VNQ_alloc2 <- 0.15103069
GLD_alloc2 <- 0.40000000
```

```
Portfolio.ret.newalloc <- as.data.frame(Portfolio_MonthlyROR_no.alloc)%>%
  mutate(GLD_alloc2*GLD+ IXN_alloc2*IXN+ QQQ_alloc2* QQQ + IEF_alloc2*IEF +
VNQ_alloc2*VNQ )

colnames(Portfolio.ret.newalloc)[0] <- "Date"
colnames(Portfolio.ret.newalloc)[6] <- "Total"


########################################################################
## Question 6: Can you build an efficient frontier for this portfolio (select 3 assets with similar
high sharpe)? What can you say based on the efficient frontier?
########################################################################

### Balance/ efficient frontier  for all 10

############ efficient Frontier for 10 stocks
library(quantmod)
library(tseries)
library(stats)
library(quadprog)

enddate <- "2023-7-25"
t<-504 #The first time you run this, you'll see the error so adjust the t with the requested number

myvector <- c()
nstocks <- 5
pricinglist <- as.data.frame(matrix(ncol=nstocks, nrow=t))
colnames(pricinglist) <- c("QQQ", "GLD","IXN","SRET", "FXNAX")
#the pricinglist data starts form 2016-8-22 - this is the first row

for (i in 1:(ncol(pricinglist))){
  current_ticker <- colnames(pricinglist)[i]
  newtable <- getSymbols(current_ticker, src = "yahoo", from="2021-7-22", to=enddate,
auto.assign=FALSE)
  pricinglist[,i] <- newtable[,6]
}

#forecasting the next price using a backpropagation training algorithm in a neural network.
# a Autoregressive Model of fourth order AR4 was used.


newpricingdataset <- pricinglist

#creating a dataset with monthly ROR for each day using continuous compounding
dailyROR <- as.data.frame(matrix(ncol=ncol(newpricingdataset),
nrow=nrow(newpricingdataset)-25))
```

```
colnames(dailyROR) <- colnames(pricinglist)
for (c in 1:(ncol(newpricingdataset))){
  for (r in 1:(nrow(newpricingdataset)-25)){
    dailyROR[r,c] <-
log(as.numeric(newpricingdataset[(r+25),c])/as.numeric(newpricingdataset[r,c]))
  }
}
#The most current expected return for n+25 (n is today) is in the last row of the above dataset

#calculating Expected(R) for all securities
averet <- as.matrix(dailyROR[nrow(dailyROR),], nrow=1)
#calculating covariance matrix
rcov <- cov(dailyROR[(nrow(dailyROR)-125):(nrow(dailyROR)),]) #125 stands for 6 trading
months
target.r <- 1/1000
#using solver to get to optimal weights


effFrontier = function(averet, rcov, nports, shorts, wmax, wmin)
{
  mxret <- max(averet)
  mnret <- -mxret
  n.assets <- ncol(averet)
  reshigh <- rep(wmax, n.assets)
  reslow <- rep(wmin, n.assets)
  min.rets <- seq(mnret, mxret, length.out=nports)
  vol <- rep(NA, nports)
  ret <- rep(NA, nports)
  pw <- data.frame(matrix(ncol=nports, nrow=n.assets))
  for (i in 1:nports)
  {
    port.sol <- NULL
    try(port.sol <- portfolio.optim(x=averet, pm=min.rets[i], covmat=rcov,   reshigh = reshigh,
reslow= reslow, shorts=F)
        , silent=T)
    if(!is.null(port.sol))
    {
      vol[i] <- sqrt(as.vector(port.sol$pw %*% rcov %*% port.sol$pw))
      ret[i] <- averet %*% port.sol$pw
      pw[,i] <- port.sol$pw
    }
  }
  return(list(vol=vol, ret = ret, weights = pw))

}
```

```
maxSharpe <- function(averet, rcov, shorts=F, wmax=0.2, min.weight=0.01)
{
  optim.callback=function(param, averet, rcov, reshigh, reslow, shorts)
  {
    port.sol = NULL
    try(port.sol <- portfolio.optim(x=averet, pm=param, covmat=rcov,
                              reshigh=reshigh, reslow=reslow, shorts=shorts),silent=T)
    if(is.null(port.sol)) { ratio= 10^9} else
    {
      m.return <- averet %*% port.sol$pw
      m.risk <- sqrt(as.vector(port.sol$pw %*% rcov %*% port.sol$pw))
      ratio <- m.return/m.risk
      assign("w", port.sol$pw, inherits=T)
    }
    return(ratio)
  }

  ef <- effFrontier(averet=averet, rcov=rcov, shorts=shorts, wmax=wmax, nports = 100,
wmin=min.weight)
  n <- ncol(averet)
  reshigh <- rep(wmax, n)
  reslow <- rep(min.weight, n)

  max.sh <- which.max(ef$ret/ef$vol)


  if(is.na(ef$ret[max.sh-1])){lowerinterval<-ef$ret[max.sh]}else{lowerinterval <- ef$ret[max.sh-
1]}
  if(is.na(ef$ret[max.sh+1])){upperinterval<-ef$ret[max.sh]}else{upperinterval <-
ef$ret[max.sh+1]}

  w <- rep(0, ncol(averet))
  xmin <- optimize(f=optim.callback, interval = c(lowerinterval, upper=upperinterval),
                 averet=averet, rcov=rcov, reshigh=reshigh, reslow=reslow, shorts=shorts)
  return(w)
  return(xmin)
}

z <- maxSharpe(averet, rcov, shorts=F, wmax=0.3)
print(z)


### check 6 and 7 on the code

##################################
### Extra: CAPM
```

```
time_index2 <- nrow(Bench_Portfolio) #this is how many monthly observations we have in our data frame
last_12_months <- Bench_Portfolio[(time_index2-11) : time_index2, ]
##we will use the RUS1000 as the benchmark to regress against
GLD_reg <- lm(GLD ~ DJIA ,data=last_12_months)  #we run a linear regression with the bencharmk returns (RUS1000) as X and asset returns as Y
summary(GLD_reg)

IXN_reg <- lm(IXN ~ DJIA ,data=last_12_months)  #we run a linear regression with the bencharmk returns as X and asset returns as Y
summary(IXN_reg)

QQQ_reg <- lm(QQQ ~ DJIA ,data=last_12_months)  #we run a linear regression with the bencharmk returns as X and asset returns as Y
summary(QQQ_reg)

VNQ_reg <- lm(VNQ ~ DJIA ,data=last_12_months)  #we run a linear regression with the bencharmk returns as X and asset returns as Y
summary(VNQ_reg)

IEF_reg <- lm(IEF ~ DJIA ,data=last_12_months)  #we run a linear regression with the bencharmk returns as X and asset returns as Y
summary(IXN_reg)



#How do our residuals look like in this model? are these models good?
#we want to see residuals(standardized) that are linear
plot(GLD_reg, which=2, col=c("red"))
plot(IEF_reg, which=2, col=c("blue"))
plot(QQQ_reg, which=2, col=c("green4"))
plot(IXN_reg, which=2, col=c("brown"))
plot(VNQ_reg, which=2, col=c("purple"))

##########################################################################
## ARMA/ARIMA
library(tidyverse)
library(tseries)
library(rugarch)

adf.test(Portfolio.ret$GLD)
#p value below 0.05 = Data stationary
adf.test(Portfolio.ret$IEF)
#p value below 0.05 = Data stationary
adf.test(Portfolio.ret$IXN)
#p value below 0.05 = Data stationary
```

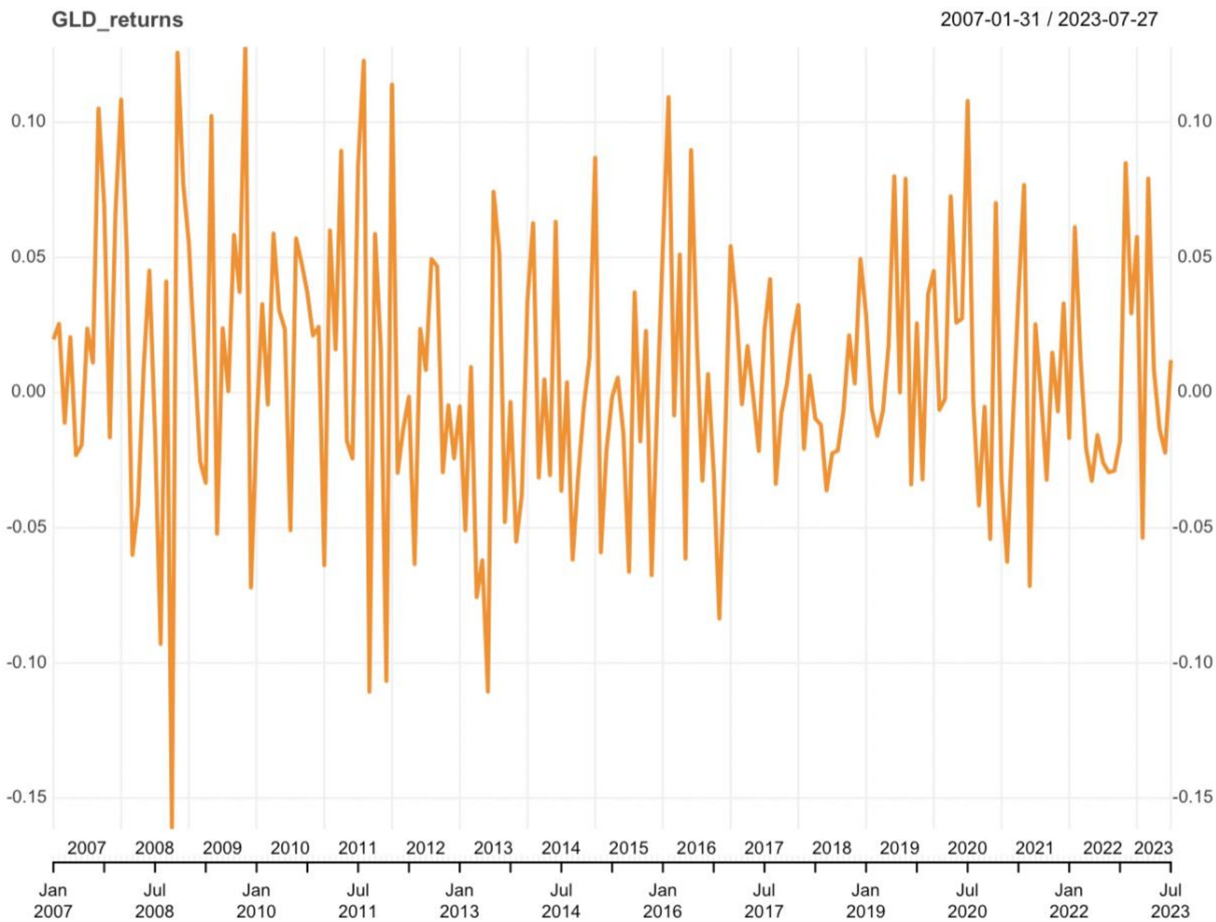
```
adf.test(Portfolio.ret$VNQ)
#p value below 0.05 = Data stationary
adf.test(Portfolio.ret$QQQ)
#p value below 0.05 = Data stationary

# ACF and PACF for GLD
acf(Portfolio.ret$GLD)
pacf(Portfolio.ret$GLD)
GLD_TS <- ts(Portfolio.ret$GLD, frequency = 5)
GLD_Dec <- decompose(GLD_TS)
plot(GLD_Dec)
GLD_arima <- arima(Portfolio.ret$GLD,
                   order=c(11,0,11))
predict(GLD_arima, n.ahead =18)

# for IXN
acf(Portfolio.ret$IXN)
pacf(Portfolio.ret$IXN)
IXN_TS <- ts(Portfolio.ret$IXN, frequency = 5)
IXN_dec <- decompose(IXN_TS)
plot(IXN_dec)
IXN_arima <- arima(Portfolio.ret$IXN,
                order=c(5,0,6))
predict(IXN_arima, n.ahead =18)

# For IEF
acf(Portfolio.ret$IEF)
pacf(Portfolio.ret$IEF)
IEF_TS <- ts(Portfolio.ret$IEF, frequency = 5)
IEF_dec <- decompose(IXN_TS)
plot(IEF_dec)
IEF_arima <- arima(Portfolio.ret$IEF,
                order=c(5,0,6))
predict(IEF_arima, n.ahead =18)

# for QQQ
acf(Portfolio.ret$QQQ)
pacf(Portfolio.ret$QQQ)
QQQ_TS <- ts(Portfolio.ret$QQQ, frequency = 5)
QQQ_dec <- decompose(QQQ_TS)
plot(QQQ_dec)
QQQ_arima <- arima(Portfolio.ret$QQQ,
                order=c(6,0,6))
predict(QQQ_arima, n.ahead =18)

# For VNQ
```

```
acf(Portfolio.ret$VNQ)
pacf(Portfolio.ret$VNQ)
VNQ_TS <- ts(Portfolio.ret$VNQ, frequency = 5)
VNQ_dec <- decompose(VNQ_TS)
plot(VNQ_dec)
VNQ_arima <- arima(Portfolio.ret$VNQ,
               order=c(2,0,2))
predict(VNQ_arima, n.ahead =18)


######

# NEW PORTFOLIO

GLD_alloc2 <- 0.1769
QQQ_alloc2 <- 0.2443
IXN_alloc2 <- 0.2382
SRET_alloc2 <- 0.13441
FXNAX_alloc2 <- 0.20589


GLD_returns2 <- monthlyReturn(getSymbols("GLD", auto.assign=FALSE))
SRET_returns2 <- monthlyReturn(getSymbols("SRET", auto.assign=FALSE))
IXN_returns2 <- monthlyReturn(getSymbols("IXN", auto.assign=FALSE))
QQQ_returns2<- monthlyReturn(getSymbols("QQQ", auto.assign=FALSE))
FXNAX_returns2 <- monthlyReturn(getSymbols("FXNAX", auto.assign=FALSE))

Portfolio2 <- merge.xts(GLD_returns2, SRET_returns2,
IXN_returns2,QQQ_returns2,FXNAX_returns2)


colnames(Portfolio2)[1] <- "GLD"
colnames(Portfolio2)[2] <- "SRET"
colnames(Portfolio2)[3] <- "IXN"
colnames(Portfolio2)[4] <- "QQQ"
colnames(Portfolio2)[5] <- "FXNAX"


Portfolio2allo <- as.data.frame(Portfolio2)%>%
  mutate(GLD_alloc2*GLD+ IXN_alloc2*IXN+ QQQ_alloc2* QQQ + SRET_alloc2*SRET +
FXNAX_alloc2*FXNAX )

colnames(Portfolio2allo)[6] <- "Total"


SRET_sigma2 <- sd(Portfolio2allo$SRET[time_index:(time_index-11)])
```

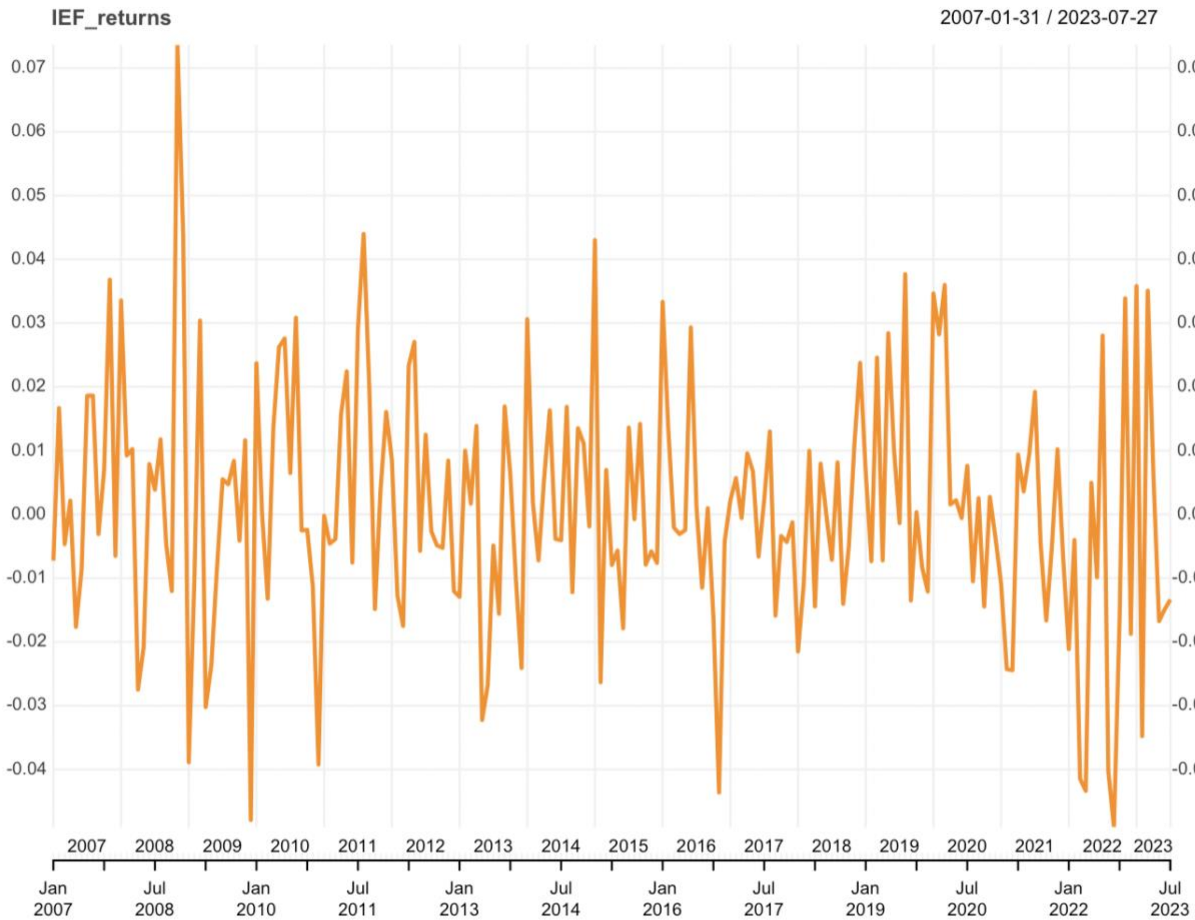
```
# [1]
FXNAX_sigma2 <- sd(Portfolio2allo$FXNAX[time_index:(time_index-11)])


# Total Portfolio
Total_sigma2 <- sd(Portfolio2allo$Total [time_index:(time_index-11)])
# [1] 0.04793094

GLD_SHARPE2 <- (mean(Portfolio2allo$GLD[time_index:(time_index-11)])-
riskfree)/GLD_sigma
# 0.1769205
SRET_SHARPE2 <- (mean(Portfolio2$SRET[time_index:(time_index-11)])-
riskfree)/SRET_sigma2

FXNAX_SHARPE2 <- (mean(Portfolio2allo$FXNAX[time_index:(time_index-11)])-
riskfree)/FXNAX_sigma2



### expected return
## SRET
acf(Portfolio2allo2$SRET)
pacf(Portfolio2allo2$SRET)
SRET_TS <- ts(Portfolio2allo2$SRET, frequency = 5)
SRET_dec <- decompose(SRET_TS)
plot(SRET_dec)
SRET_arima <- arima(Portfolio2allo2$SRET,
             order=c(9,0,8))
predict(SRET_arima, n.ahead =18)

acf(Portfolio2allo$GLD)
pacf(Portfolio2allo$GLD)
GLD_TS2 <- ts(Portfolio2allo$GLD, frequency = 5)
GLD_Dec2 <- decompose(GLD_TS2)
plot(GLD_Dec2)
GLD_arima2 <- arima(Portfolio2allo$GLD,
             order=c(11,0,11))
predict(GLD_arima2, n.ahead =18)

acf(Portfolio2allo2$FXNAX)
pacf(Portfolio2allo2$FXNAX)
FXNAX_TS2 <- ts(Portfolio2allo$FXNAX, frequency = 5)
FXNAX_Dec2 <- decompose(FXNAX_TS2)
plot(FXNAX_Dec2)
FXNAX_arima2 <- arima(Portfolio2allo$FXNAX,
              order=c(5,0,5))
```

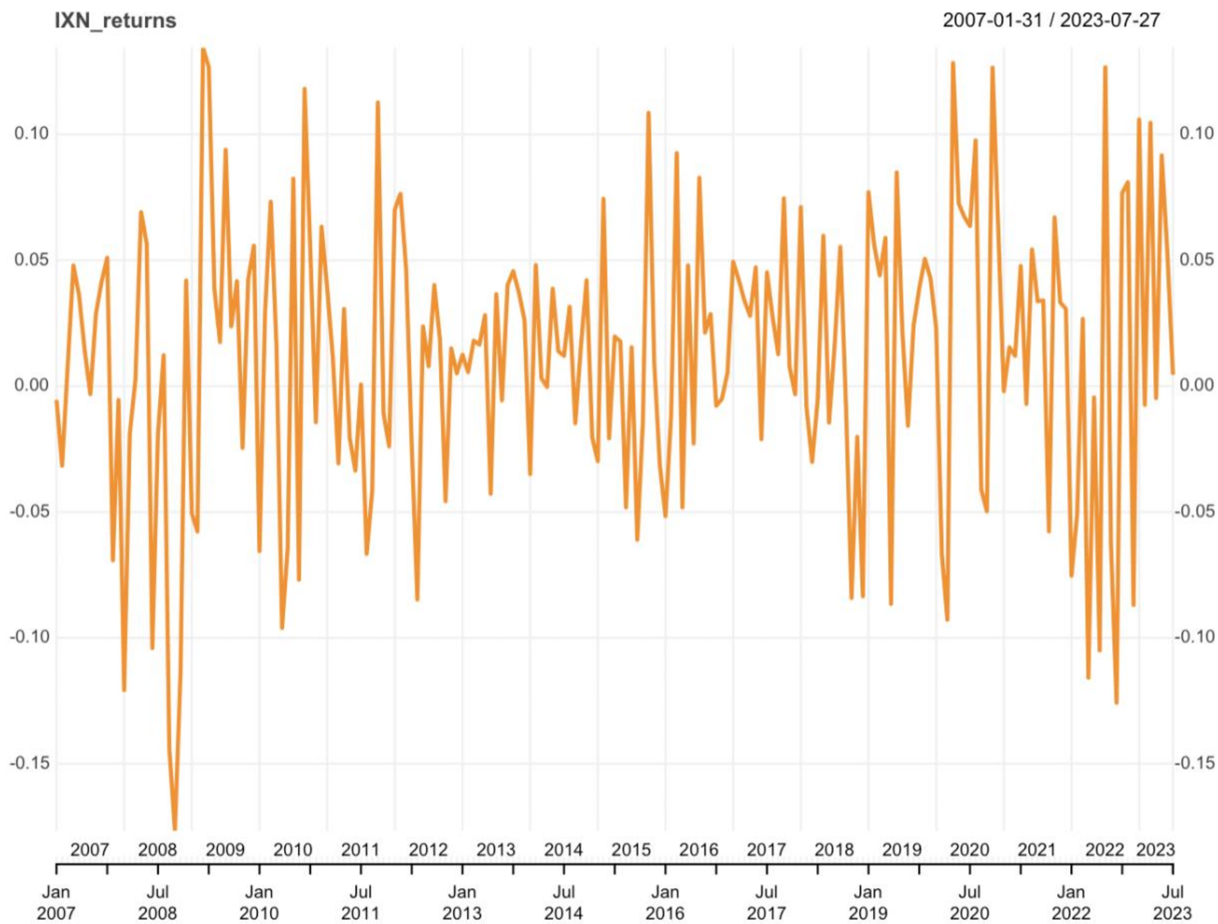
```
predict(FXNAX_arima2, n.ahead =18)


acf(Portfolio2allo$IXN)
pacf(Portfolio2allo$IXN)
IXN_TS2 <- ts(Portfolio2allo$IXN, frequency = 5)
IXN_dec2 <- decompose(IXN_TS2)
plot(IXN_dec2)
IXN_arima2 <- arima(Portfolio2allo$IXN,
                    order=c(6,0,6))
predict(IXN_arima2, n.ahead =18)

acf(Portfolio2allo$QQQ)
pacf(Portfolio2allo$QQQ)
QQQ_TS2 <- ts(Portfolio2allo$QQQ, frequency = 5)
QQQ_dec2 <- decompose(QQQ_TS2)
plot(QQQ_dec2)
QQQ_arima <- arima(Portfolio.ret$QQQ,
                   order=c(6,0,6))
predict(QQQ_arima, n.ahead =18)



### effficient frontier

library(data.table)
library(scales)
library(ggplot2)
library(quantmod)
library(reshape2)
ticker1 <- "IXN"
ticker2<- "QQQ"
ticker3<- "GLD"
mydf1 <- as.data.frame(getSymbols(ticker1, auto.assign=FALSE))
mydf2 <- as.data.frame(getSymbols(ticker2, auto.assign=FALSE))
mydf3 <- as.data.frame(getSymbols(ticker3, auto.assign=FALSE))

combined_df <- cbind(mydf1[,4], mydf2[,4], mydf3[,4])

dt <- as.data.frame(combined_df)
colnames(dt) <- c(ticker1, ticker2, ticker3)
dt$date = as.Date(rownames(mydf1))
dt <- melt(dt, id="date")
colnames(dt) <- c("date", "ticker","price")
dt <- data.table(dt)
# create indexed values
```

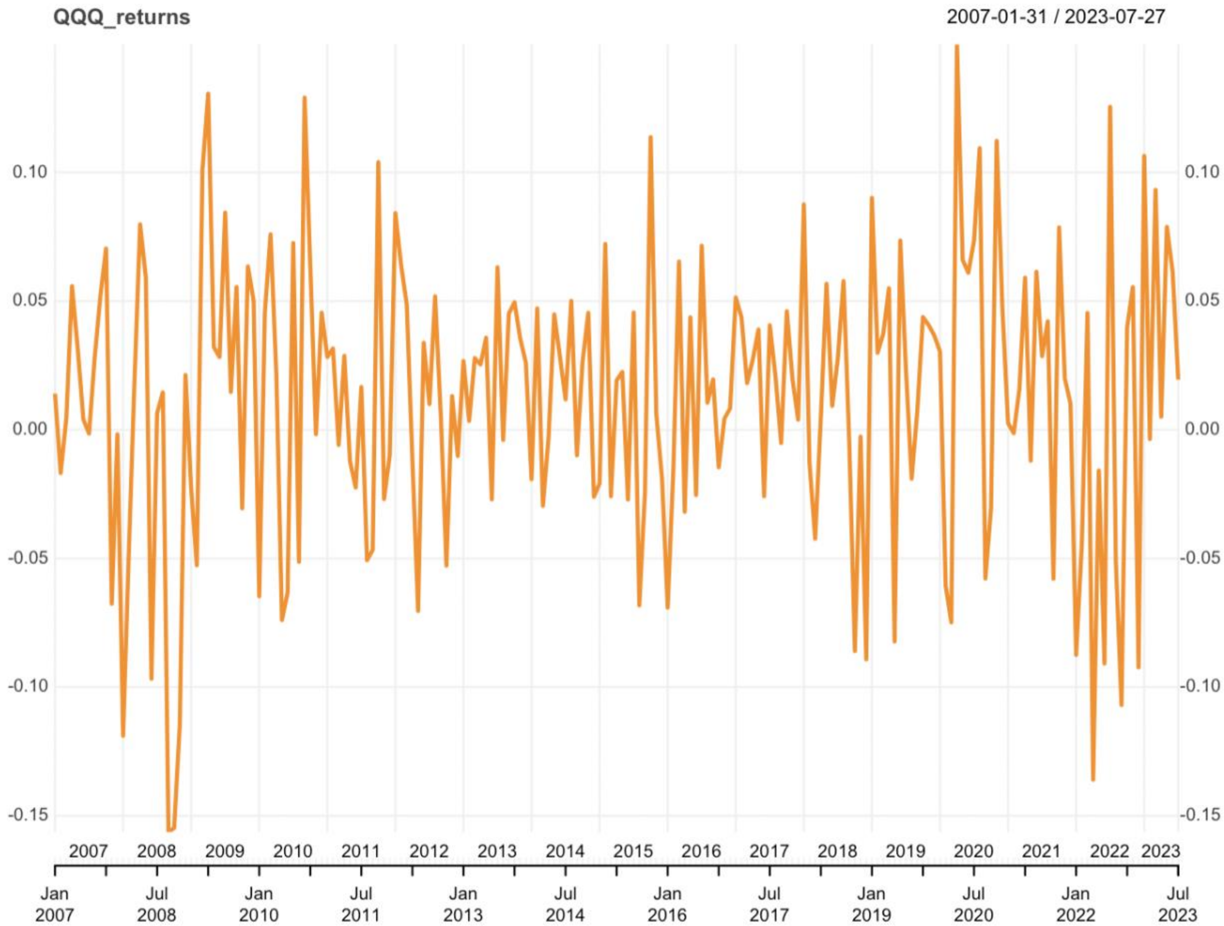
```
dt[, idx_price := price/price[1], by = ticker]
# plot the indexed values
ggplot(dt, aes(x = date, y = idx_price, color = ticker)) +
  geom_line() +
  # Miscellaneous Formatting
  theme_bw() + ggtitle("Price Developments") +
  xlab("Date") + ylab("Pricen(Indexed 2000 = 1)") +
  scale_color_discrete(name = "Company")

# calculate the arithmetic returns
dt[, ret := price / shift(price, 1) - 1, by = ticker]

# summary table
# take only non-na values
tab <- dt[!is.na(ret), .(ticker, ret)]

# calculate the expected returns (historical mean of returns) and volatility (standard deviation of
returns)
tab <- tab[, .(er = round(mean(ret), 4),
               sd = round(sd(ret), 4)),
           by = "ticker"]

ggplot(tab, aes(x = sd, y = er, color = ticker)) +
  geom_point(size = 5) +
  # Miscellaneous Formatting
  theme_bw() + ggtitle("Risk-Return Tradeoff") +
  xlab("Volatility") + ylab("Expected Returns") +
  scale_y_continuous(label = percent, limits = c(0, 0.03)) +
  scale_x_continuous(label = percent, limits = c(0, 0.1))
```

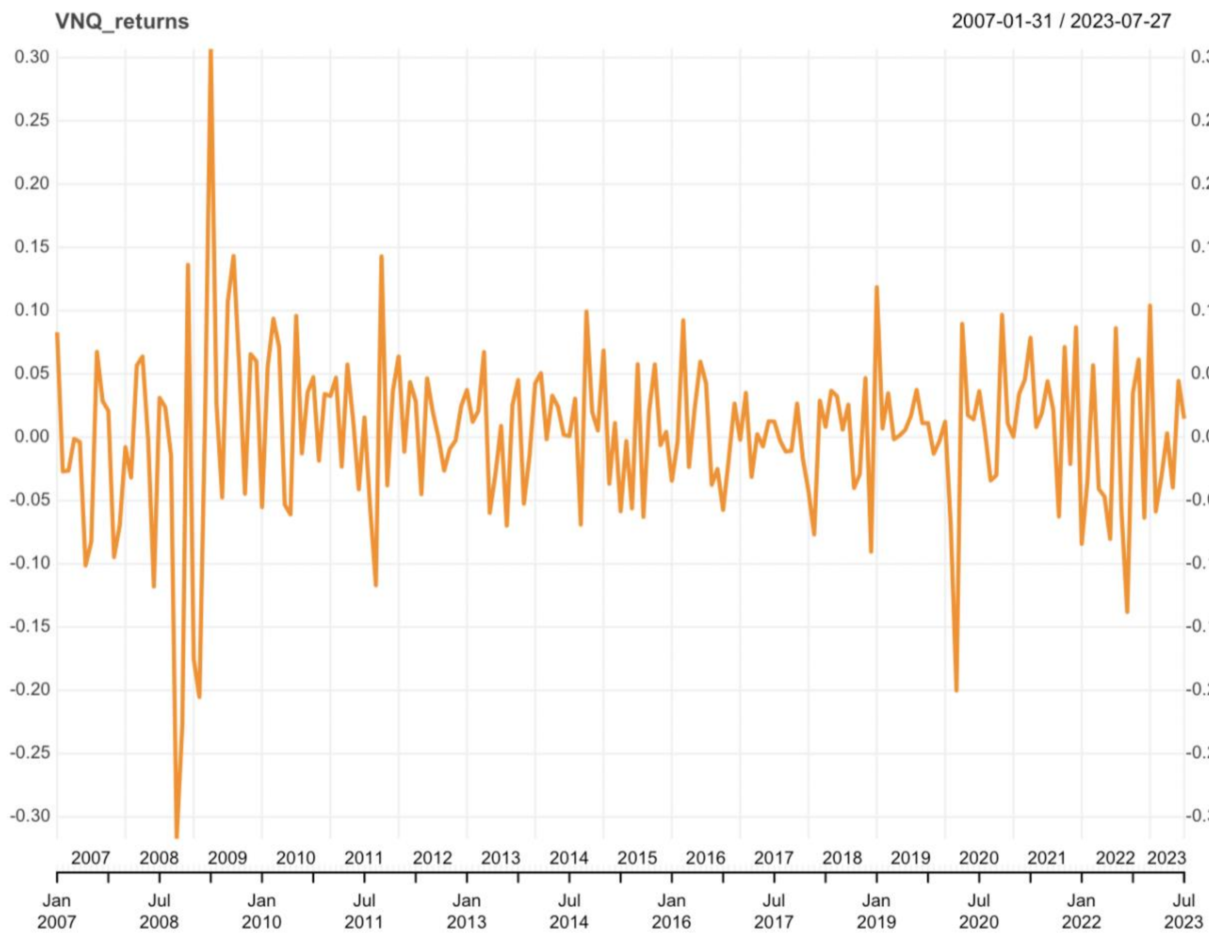


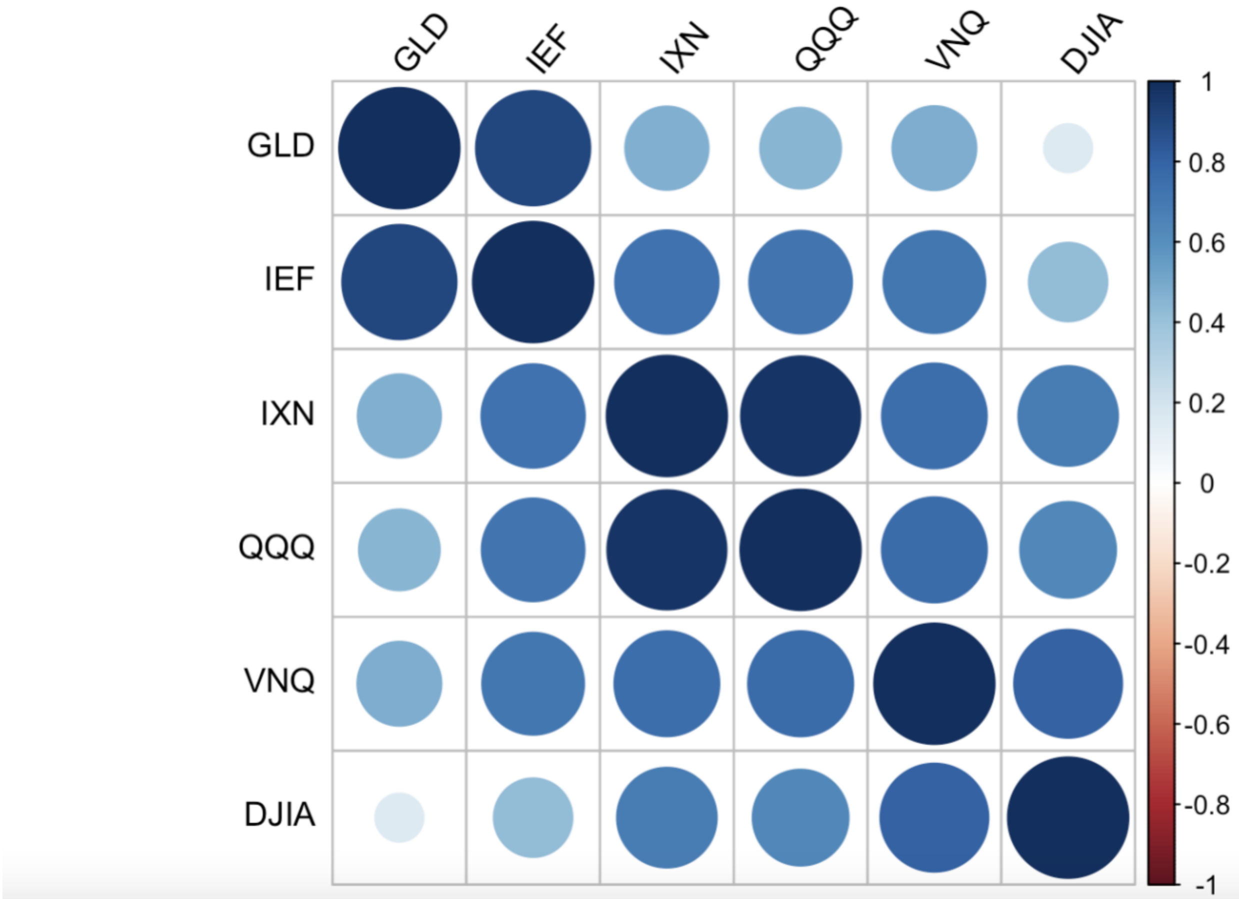
GLD_returns
2007-01-31 / 2023-07-27
0.10
0.05
0.00
-0.05
-0.10
-0.15
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023
Jan 2007
Jul 2008
Jan 2010
Jul 2011
Jan 2013
Jul 2014
Jan 2016
Jul 2017
Jan 2019
Jul 2020
Jan 2022
Jul 2023


IEF_returns
2007-01-31 / 2023-07-27
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
-0.03
-0.04
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023
Jan 2007
Jul 2008
Jan 2010
Jul 2011
Jan 2013
Jul 2014
Jan 2016
Jul 2017
Jan 2019
Jul 2020
Jan 2022
Jul 2023


IXN_returns
2007-01-31 / 2023-07-27
0.10
0.05
0.00
-0.05
-0.10
-0.15
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Jan 2007
Jul 2008
Jan 2010
Jul 2011
Jan 2013
Jul 2014
Jan 2016
Jul 2017
Jan 2019
Jul 2020
Jan 2022
Jul 2023


QQQ_returns
2007-01-31 / 2023-07-27
0.10
0.05
0.00
-0.05
-0.10
-0.15
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023
Jan 2007
Jul 2008
Jan 2010
Jul 2011
Jan 2013
Jul 2014
Jan 2016
Jul 2017
Jan 2019
Jul 2020
Jan 2022
Jul 2023


VNQ_returns
2007-01-31 / 2023-07-27
0.30
0.25
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023
Jan 2007
Jul 2008
Jan 2010
Jul 2011
Jan 2013
Jul 2014
Jan 2016
Jul 2017
Jan 2019
Jul 2020
Jan 2022
Jul 2023


GLD
IEF
IXN
QQQ
VNQ
DJIA
GLD
IEF
IXN
QQQ
VNQ
DJIA
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1