Abstract

In the financial world, the main goal of any organisation or individual is to make profit. These individuals and organisations invest their money in various forms including bonds and shares. Since the turn of the century, there have been various tactics and plans put in place by various entities to maximize profit. This is the case in the stock market. For example, various news outlets like the Wall Street Journal, Yahoo Finance have platforms either paid or free that give historical records of stocks and also financial advice.

The trading of stocks is on a stock exchange and there are numerous examples with the most notable one being the New York Stock Exchange (NYSE) which is the largest stock exchange in the World by market capitalisation. Other notable stock exchanges are NASDAQ, Shanghai Stock Exchange, Tokyo Stock Exchange, Hong Kong Stock Exchange, and London Stock Exchange.

1.0 Introduction

This project shall like into five companies listed on the New York Stock Exchange (NYSE) and Standard and Poor 500 index companies (S&P 500).

The study report will deal fully with finding the expected return and the standard deviation of the stocks and the portfolio. There will also be derivations and calculations of correlation and the variance-covariance matrix. From the calculations, there will be calculations and derivations for the Sharpe Ratio and standard deviation and expected return for plotting the Efficient Frontier Curve. Achieving this will involve adjusting different constraints and setting various objectives using the Solver function in Microsoft Excel. There will be a graph of the Efficient Frontier Curve showing the Capital Market Line (CML) and calculations for the Beta of each asset in the portfolio and the Value at Risk (VaR).

R programming language will be the go-to in the next phase and there will be a calculation of the volatility of one of the five assets using the ARCH/GARCH method and a comparison of the method while picking the best.

At the end of the study, there will be a clear explanation of all calculations and derivations in a non-technical language that can provide potential investors and people the help in choosing the most efficient portfolio and the implications.

2.0 Literature Review

This project deals with the stocks of five companies that, include AAPL (Apple), NVDA (Nvidia), BABA (Alibaba), ATVI (Activision), and CRM (Salesforce), starting from 1st January 2017 to 31st December 2020. These listed companies all trade in the New York Stock Exchange. There will be a brief discussion of each company's history.

2.1 APPLE (APPL)

Apple Inc. is a multinational technology company headquartered in Cupertino, California, USA. Founded in 1976, its CEO is Tim Cook. It designs, manufactures, and sells smartphones, personal computers, tablets, wearables, and accessories. It deals in Semiconductors, Electronics, Technology Hardware & Equipment, and Electrical Engineering. As of 2nd December 2022, it has a revenue of $378.7b, assets worth $381.2b, and profits of $100.6b for the 2022 fiscal year [1]. Apple is the world's largest technology company by market capitalization, with $2.351 trillion and a share price of $147.81 as of 2nd December 2022 [2].

2.2 NVIDIA (NVDA)

Nvidia Corporation is a computer graphics processors, chipsets, and related multimedia software developing company headquartered in Santa Clara, California, USA. It does not have manufacturing facilities. Founded in January 1993, its CEO is Jensen Huang. It has a market capitalization of $420.54b and a share price of $168.76 as of 2nd December 2022 [3]. As of 2nd December 200, it has a revenue of $26.9b, assets worth $44.2b, and profits of $9.8b [4].

2.3 Alibaba Group (BABA)

Alibaba Group Holding Ltd. Is a Hangzhou, China-based company that engages in E-Commerce, Tech, Internet, and Retail. It has a market capitalization of $240.69b in 2022, a loss of 27.21% from its 2021 market cap of $330.67 [5]. It operates Core Commerce, Cloud Computing, Digital Media and Entertainment, Innovation

Initiatives, and Others. It has a revenue of $129.8b, assets of $276.2b, and profits of $10.2b as of 2nd December 2022 [6].

2.4 Activision Blizzard (ATVI)

Activision Blizzard Inc is a Consumer Durables company that develops and publishes interactive software products and entertainment content, particularly for the console, P.C., and mobile platforms. The company was founded in 2008 with headquarters in Santa Monica, California, United States, and has Robert A Kotick as CEO. As of 2nd December 200, it has revenue of $8.8b, assets of $25.1b, and profits of $2.7b [7]. The company has a market cap of $59.29b and a share price of $75.76 as of 2nd December 2022 [8].

2.5 Salesforce.com (CRM)

Salesforce.com is an I.T., Internet, Software & Services industry company that designs and develops cloud-based enterprise software for customer relationship management. The company, founded in 1999, has its headquarters in San Francisco, California, United States. It had a revenue of $21.3b, assets worth $66.3b, and profits of $4.1b for the 2021 fiscal year. It had a share price of $144.56 and a market capitalization of $59.29b as of 2nd December 2022 [9].

3.0 Expected Return, Volatility, and Correlation between the Asset Return

3.0.1 Expected Return and volatility

Before going into the calculations, defining, and understanding the above terms is essential.

The expected return determines if a portfolio of a specified number of assets has a positive or negative average net outcome [10]. It is also known as drift.

Expected return $\boldsymbol{\mu_p = \sum_{i=1}^{N} W_i \mu_i}$

Where W_i Is the weight of the asset from 1 to N,

μ_i is the expected return of the individual asset from 1 to N
Remember that the sum of individual weights of all assets in a portfolio is always 1.

On the other hand, portfolio volatility is a measure of portfolio risk. A portfolio tends to deviate from its mean return [11]. The volatility is also known as the **standard deviation** of the expected return.

Standard deviation $\boldsymbol{\sigma_p = \sqrt{\sum_{i=1}^{N} W_i W_j \rho_{ij} \sigma_i \sigma_j}}$

Where W_i is the weight of the asset for asset i,

W_j is the weight of the asset for asset j,

ρ_{ij} is the correlation coefficient of the assets I and j,

σ_i is the standard deviation of asset I,

σ_j is the standard deviation of asset j.

Below are the expected returns of the five stocks in the portfolio.

		APPLE	ACTIVISION	ALIBABA	NVIDIA	SALESFORCE
2		APPLE	ACTIVISION	ALIBABA	NVIDIA	SALESFORCE
3	DAILY EXP RETURN	0.001710761	0.001178304	0.001190063	0.002076829	0.001380834
4	ANN EXP RETURN	0.431111807	0.296932707	0.299895906	0.523360981	0.347970223
5	VARIANCE	0.000398284	0.000507539	0.000458996	0.000896994	0.000482861
6	ANN VARIANCE	0.100367524	0.127899816	0.115667094	0.226042424	0.121681038
7	S.D	0.316808339	0.357630837	0.340098653	0.475439191	0.348828092

Figure 1: The Expected Return and Volatility of the five stocks in the portfolio is given by "ANN EXP RETURN" and "S.D" respectively.

From the above image, the standard deviation and expected return of each asset is shown below.

Asset	Expected Return	Volatility
Apple	0.431111807	0.316808339
Activision	0.296932707	0.357630837
Alibaba	0.299895906	0.340098653
Nvidia	0.523360981	0.475439191
Salesforce	0.347970223	0.348828092

Table 1: The Expected Return and Volatility of each asset in the portfolio

Key Point: Calculating the **expected return** of each stock in the portfolio involves finding the average of the difference in daily returns and multiplying by 252 days (this is the number of days the stock market is open in a year).

*=AVERAGE(H4:H1009)*252*

Key Point: Calculating the volatility of each stock in the portfolio involves using the standard deviation of all the daily recordings across the 4 years and multiplying it by the square root of 252 days.

*=STDEV(H4:H1009)*SQRT(252)*

P26 =SQRT(MMULT(MMULT(TRANSPOSE($O$18:$O$22),$O$10:$S$14),$O$18:$O$22))

		M	N	O	P	Q
22	398		SALESFORCE	0.2		
23	957		TOTAL	1		
24	121					
25	378		EXPECTED RETURN		0.379854325	
26	946		STANDARD DEVIATION		0.288137653	
27	025		Sharpe Ratio	1.318308527		
28	964					
29	219		Risk (Not Given)	0.00		
30	032					

Sheet1 | AAPL(APPLE) | LINEAR REGRESSION | ACTIVISION(ATVI) | SOLUTION | BABA(ALIBABA) | NVDA(NVIDIA)

Figure 2: The **Volatility** (Standard deviation) and **Expected Return** of the portfolio

The expected return of the portfolio is **0.379854325** or **37.98%** and the volatility as **0.288137653** or **28.81%**

3.0.2 Correlation

Correlation between the asset return or coefficient correlation measures the relationship between two assets. Its value ranges from -1 to +1. A correlation of +1 shows a positive and perfect relationship. A correlation of -1 shows a negative and inverse relationship, and a correlation of 0 shows no relationship [12].

Below is the correlation of the stocks

		CORRELATION			
	APPLE	ACTIVISION	ALIBABA	NVIDIA	SALESFORCE
APPLE	1				
ACTIVISION	0.489608456	1			
ALIBABA	0.505665116	0.390852607	1		
NVIDIA	0.615752841	0.494530009	0.541028532	1	
SALESFORCE	0.585134554	0.469847635	0.461044991	0.562024207	1

Figure 3: The correlation between the stocks in the portfolio.

Key Point: Calculating the correlation of the portfolio involves using the correlation analysis tool in the Data Analysis tool pack to calculate the correlation of the daily differences in stock prices.

3.1.1 Solver, Portfolio Risk and Percentage of Investment

The solver function is a Microsoft Excel add-in used for What-if analysis. Using the Solver function to determine the portfolio risk and the percentage of investment, there was first an assumption that each asset in the portfolio is of equal weight. Since there are five assets in the portfolio, each comes to 0.2 or 20%.

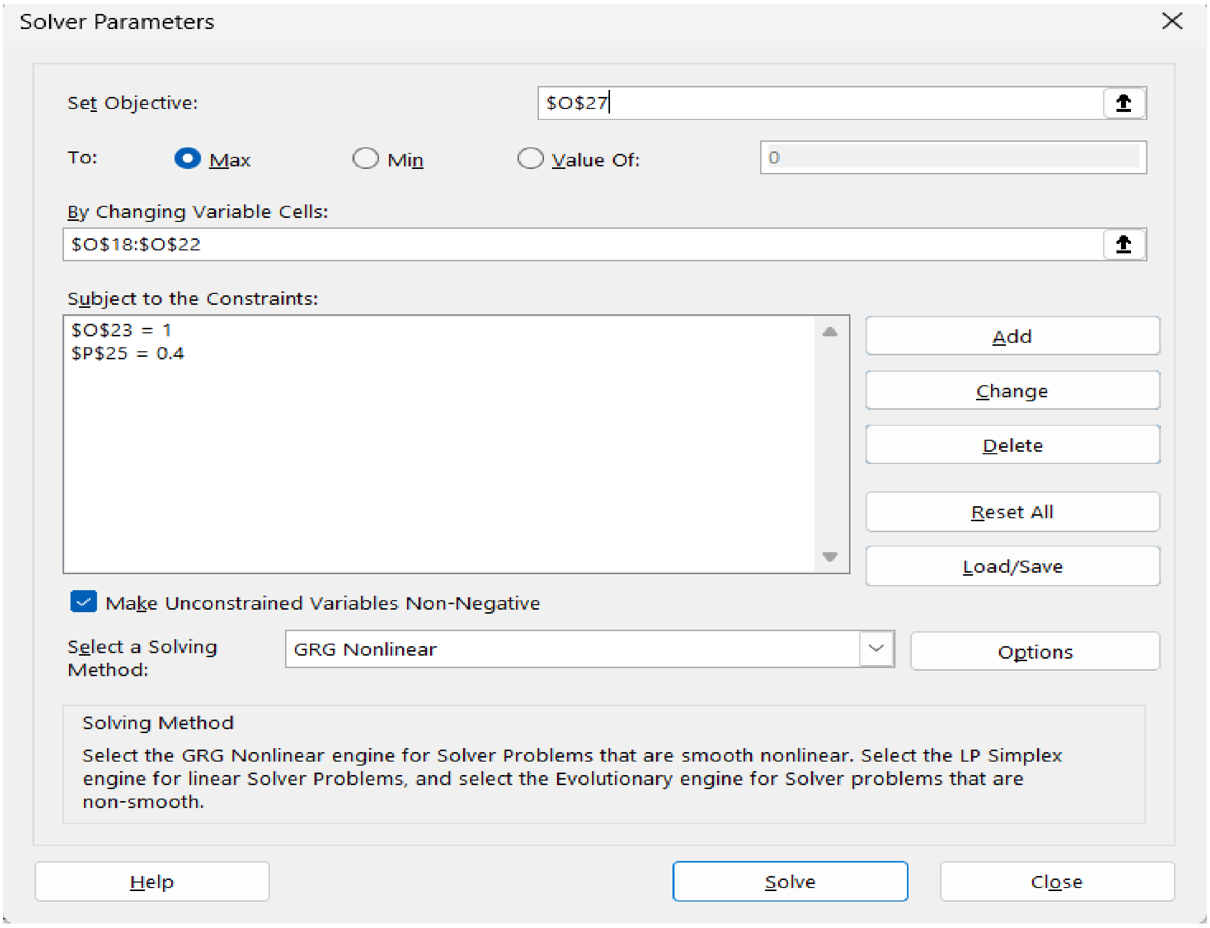

Figure 4: The Solver function

Key Point: From the figure above, the Sharpe Ratio is set as the objective while varying the weights of the individual assets. The sum of the weights is set to 1 and the expected return set to **0.4** or **40%** in this case.

N	O	P
EQUALLY WEIGHTED ASSETS		
APPLE	0.2	
ACTIVISION	0.2	
ALIBABA	0.2	
NVIDIA	0.2	
SALESFORCE	0.2	
TOTAL	**1**	
EXPECTED RETURN		0.379854325
STANDARD DEVIATION		0.288137653
Sharpe Ratio	1.318308527	

Figure 5: The **Equally weighted** assets of the portfolio.

The was a constant adjustment of the portfolio's expected return using the Solver function, and there were adjustments for the expected return of 29%, 32%, 34%, 37%, 40%, 42%, 45%, 48%, 50% and 51%. All these while setting the **Sharpe Ratio** as the objective.

APPLE(W1)	ACTIVISION(W2)	ALIBABA(W3)	NVIDIA(W4)	SALESFORCE(W5	Volatility	Exp Return
0	0.454292936	0.515540176	0	0.030166888	0.287749233	0.299999998
0.085866541	0.322327172	0.388118367	0	0.203687921	0.271415366	0.32
0.243875318	0.256476569	0.315271776	0	0.184376337	0.265892513	0.340000001
0.480888504	0.157700702	0.206001916	0	0.155408878	0.269329024	0.370000001
0.593289052	0.087975496	0.122921139	0.074702838	0.121111475	0.283951988	0.400000001
0.651500276	0.045390604	0.071048391	0.13452955	0.097531179	0.29696272	0.420000001
0.731292506	0	0	0.235069569	0.033637925	0.320639888	0.45000007
0.470037827	0	0	0.529962173	0	0.363072796	0.48000038
0.253233719	0	0	0.746766281	0	0.409309387	0.50000038
0.144831665	0	0	0.855168335	0	0.43630789	0.51000038

Figure 6: The weights, volatilities and expected returns used to plot the Efficient Frontier Curve

Key Point: The calculation of the Volatility will be

$$\sigma_P = \sqrt{w_A^2\sigma_A^2} + w_B^2\sigma_B^2 + w_C^2\sigma_C^2 + w_D^2\sigma_D^2 + w_D^2\sigma_D^2 + w_E^2\sigma_E^2 + 2W_AW_B\sigma_{AB} + 2W_AW_C\sigma_{AC} + 2W_AW_D\sigma_{AD} + 2W_AW_E\sigma_{AE} + 2W_BW_C\sigma_{BC} + 2W_BW_D\sigma_{BD} + 2W_BW_E\sigma_{BE} + 2W_CW_D\sigma_{CD} + 2W_CW_E\sigma_{CE} + 2W_DW_E\sigma_{DE}$$

Key Point: The calculation of the Expected return will be

$$E(r_p) = W_AR_A + W_BR_B + W_CR_C + W_DR_D + W_ER_E$$

3.1.2 The Efficient Frontier Curve and the Capital Market Line

The Efficient Frontier Curve offers the maximum expected return for a given level of risk or the lowest risk for a defined level of expected return. Portfolio that are below the efficient frontier curve are not optimal as they do not give return for the level of volatility [13].

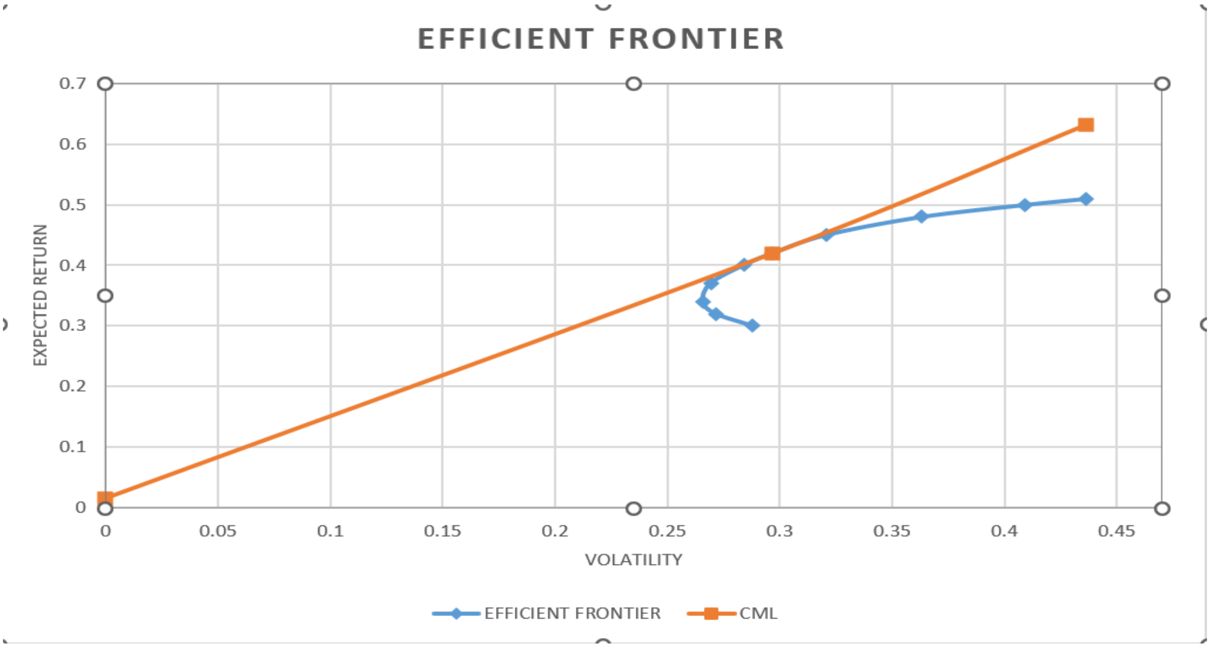

Figure 7: Efficient Frontier Curve showing the Capital Market Line

The Capital Market Line (CML) talks about portfolios that optimally combine risk and return [14].

From the question given, the risk-free rate is 1.5%.

Key Point: In calculating the Capital Market Line, there was consideration for the risk-free rate of 1.5%, Extrapolation and then the ORM which is the Optimum Risk Portfolio.

Key Point: The ORM considers the optimal weighted assets (the derivation of the ORM is by only setting the sum of the weights as the only constraint without varying the expected return). It uses the volatility and expected return of the optimum risk portfolio.

Key Point: The Extrapolation uses the maximum volatility of the various portfolios gotten by Solver and the addition of the risk-free rate and the Sharpe Ratio which is multiplied by its volatility as expected return.

Extrapolation = (risk-free rate + Sharpe Ratio) * Volatility

Risk free rate	0.015

Capital Market Line		
	Volatility	Return
Risk free	0	0.015
ORP	0.296803571	0.419890217
Extrapolation	0.43630789	0.632248014

ORP stands for Optimum Risk Portfolio

OPTIMALLY WEIGHTED ASSETS		
APPLE	0.651180826	
ACTIVISION	0.045624334	
ALIBABA	0.0713331	
NVIDIA	0.134201095	
SALESFORCE	0.097660645	
TOTAL	1	
EXPECTED RETURN		0.419890217
STANDARD DEVIATION		0.296803571
Sharpe Ratio	1.414707431	

Figure 8: The Capital market Line calculation

Economic Significance of the Capital Market Line

The capital market line allows investors to balance risky and risk-free assets to maximize return. There cannot be an understatement with the significance of the CML. Investors use the CML to get the best portfolios that maximize performance. Portfolios on the CML are the best as they give the best volatility/return relationship, thereby maximizing profit.

3.1.3 Sharpe Ratio

The Sharpe ratio is a risk-adjusted measure that evaluates the performance of an investment compared to its risk-free benchmark.

```
=SQRT(N32^2*$O$7^2+O32^2*$P$7^2+P32^2*$Q$7^2+Q32^2*$R$7^2+R32^2*$S$7^2+2*N32*O32*$P$10+2*N32*P32*$Q$10+2*N32*Q32*$R$10+2*N32*R32*$S$10+2*O32*P32*$Q$11+2*O32*Q32*$R$11+2*O32
```

	N	O	P	Q	R	S	T	U
26	STANDARD DEVIATION		0.288137653		STANDARD DEVIATION			
27	Sharpe Ratio	1.318308527			Sharpe Ratio	1.318308527		
28								
29	Risk (Not Given)	0.00						
30								
31	APPLE(W1)	ACTIVISION(W2)	ALIBABA(W3)	NVIDIA(W4)	SALESFORCE(W5)	Volatility	Exp Return	Sharpe Ratio
32	0	0.454292936	0.515540176	0	0.030166888	$S$7^2+2*N32*O32	0.299999998	1.042574451
33	0.085866541	0.322327172	0.388118367	0	0.203687921	0.271415366	0.32	1.179004729
34	0.243875318	0.256476569	0.315271776	0	0.184376337	0.265892513	0.340000001	1.278712205
35	0.480888504	0.157700702	0.206001916	0	0.155408878	0.269329024	0.370000001	1.373784364
36	0.593289052	0.087975496	0.122921139	0.074702838	0.121111475	0.283951988	0.400000001	1.408688854
37	0.651500276	0.045390604	0.071048391	0.13452955	0.097531179	0.29696272	0.420000001	1.414318947
38	0.731292506	0	0	0.235069569	0.033637925	0.320639888	0.45000007	1.403443822
39	0.470037827	0	0	0.529962173	0	0.363072796	0.48000038	1.322049971
40	0.253233719	0	0	0.746766281	0	0.409309387	0.50000038	1.221570761
41	0.144831665	0	0	0.855168335	0	0.43630789	0.51000038	1.168900201
42								
43								

Figure 9: The Sharpe ratios of the adjusted of the range of expected portfolio returns

The Sharpe Ratio is gotten

$$Sharpe\ Ratio\ = \frac{Expected\ Return\ -\ Risk\ Free\ Rate}{Standard\ Deviation}$$

A Sharpe Ratio of more than 1 indicates that the returns on investment is good.

3.1.4 Beta for each asset in the portfolio using Linear Regression

Beta is the measure of the volatility of an asset in comparison to the market.

The derivation of beta for each asset using linear regression involves the S&P 500 stocks and the S&P market itself.

	BETA
Beta for Apple	1.19484557
Beta for Activision	0.834020628
Beta for Alibaba	0.858652939
Beta for Nvidia	1.541669131
Beta for Salesforce	1.150369994

Figure 10: The Beta of each asset in the portfolio using Linear regression analysis

Key Point: Calculating the beta of each asset involves finding the slope of the S&P500 stock and each asset in Microsoft Excel. The inserted values will be the daily change in the asset and the S&P 500.

Beta = Slope(assetN, S&P 500)

Where N is Apple, Activision, Alibaba, Nvidia and Salesforce

The Beta of an asset is a particularly important measure as it tells its relationship with the market. A beta of more than 1 means that the asset is more volatile than the market while a beta of less than 1 is less volatile than the market. From above, one can deduce that **Apple, Nvidia** and **Salesforce** are more volatile than the market while **Activision** and **Alibaba** are less volatile than the market.

3.1.5 Value at Risk

The value at Risk measures the extent in which a firm can make financial losses over a specific period.

Below is the Value at Risk (5%) of the portfolio

OPTIMAL WEIGHTED ASSETS		
APPLE	0.651180826	
ACTIVISION	0.045624334	
ALIBABA	0.0713331	
NVIDIA	0.134201095	
SALESFORCE	0.097660645	
TOTAL	1	
EXPECTED RETURN		0.41989022
STANDARD DEVIATION		0.29680357
Sharpe Ratio	1.414707431	

CALCULATING VAR		
EXPECED RETURN	0.419890217	
EXP VOLATILITY	0.296803571	
TIME(YEAR)	1	
CONFIDENCE LEVEL	0.95	
STRESS EVENT	-1.64485363	
ASSET VALUE	£1,000,000.00	
VAR	0.068308213	£68,308.21

VAR of individual asset	
	VAR of asset
APPLE	0.339332507
ACTIVISION	0.026838532
ALIBABA	0.039904628
NVIDIA	0.104948997
SALESFORCE	0.056034861
TOTAL	0.567059525

	APPLE	**ACTIVISION**	**ALIBABA**	**NVIDIA**	**SALESFORCE**
S.D	0.316808339	0.357630837	0.34009865	0.47543919	0.348828092

Figure 11: Calculation of the Value at Risk (VaR) and each asset contribution to the VAR.

The VAR of the portfolio is **0.069308213** or **6.8308%.**

Calculation of the VaR is below

Key Point: The formula used to calculate the VaR of the asset is

$$VAR_{asset} = Z - score * StdDev\ of\ the\ asset * weight\ of\ the\ asset$$

Key Point: The formula for calculating the VaR of the portfolio is

$$VAR_{portfolio} = Expected\ Return + StdDev\ of\ the\ asset * z - score$$

3.1.6 Estimating the Volatility of a single asset (AAPL) using ARCH/GARCH

The Autoregressive Conditional Heteroskedasticity (ARCH) model is a statistical model that analyses volatility in a time series data in order to forecast volatility. In the financial world, helps calculate risk by providing a model of volatility that more closely resembles real markets [15].

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are most suitable for finding the volatility of returns of stocks, currencies, and cryptocurrencies. Some types of GARCH include the standard GARCH (sGARCH), Nonlinear GARCH (nGARCH) and Exponential GARCH (eGARCH). The main difference between the ARCH model and GARCH model is that while the GARCH method considers the volatility of the previous period while the ARCH model does not [16].

In estimating the volatility of the single asset (AAPL) using ARCH/GARCH, there will be an evaluation of the Akaike Information Criterion (AIC) or Bayesian Information Criterion.

```
Console   Terminal ×   Background Jobs ×
R 4.2.2 · C:/Users/Ajayi/Desktop/coursework/Financial Maths Coursework/
> Exp<-ts(data[,2],start=c(2017,1),frequency = 252)
> #Get the log of each data
> e=diff(log(Exp))
> garch10_spec<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,0)),mean.model=list(a
rmaOrder=c(1,0)),distribution.model="std")
> garch10_fit<-ugarchfit(garch10_spec,data = e)
> infocriteria(garch10_fit)

Akaike       -5.341640
Bayes        -5.317217
Shibata      -5.341689
Hannan-Quinn -5.332360
> garch11_spec<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,1)),mean.model=list(a
rmaOrder=c(1,0)),distribution.model="std")
> garch11_fit<-ugarchfit(garch11_spec,data = e)
> infocriteria(garch11_fit)

Akaike       -5.439633
Bayes        -5.410327
Shibata      -5.439704
Hannan-Quinn -5.428498
> 
```

Figure 12: The Akaike Information Criterion (AIC) for garchorder(1,0) and garchorder(1,1)

```
Console   Terminal ×   Background Jobs ×
R 4.2.2 · C:/Users/Ajayi/Desktop/coursework/Financial Maths Coursework/
Bayes        -5.410327
Shibata      -5.439704
Hannan-Quinn -5.428498
> garch20_spec<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(2,0)),mean.model=list(a
rmaOrder=c(1,0)),distribution.model="std")
> garch20_fit<-ugarchfit(garch20_spec,data = e)
> infocriteria(garch20_fit)

Akaike       -5.377531
Bayes        -5.348224
Shibata      -5.377601
Hannan-Quinn -5.366395
> garch21_spec<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(2,1)),mean.model=list(a
rmaOrder=c(1,0)),distribution.model="std")
> garch21_fit<-ugarchfit(garch21_spec,data = e)
> infocriteria(garch21_fit)

Akaike       -5.436829
Bayes        -5.402638
Shibata      -5.436925
Hannan-Quinn -5.423838
> 
```

Figure 13: The Akaike Information Criterion (AIC) for garchorder(2,0) and garchorder(2,1)

```
Console   Terminal ×   Background Jobs ×
R 4.2.2 · C:/Users/Ajayi/Desktop/coursework/Financial Maths Coursework/
Bayes        -5.402638
Shibata      -5.436925
Hannan-Quinn -5.423838
> garch22_spec<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(2,2)),mean.model=list(a
rmaOrder=c(1,0)),distribution.model="std")
> garch22_fit<-ugarchfit(garch22_spec,data = e)
> infocriteria(garch22_fit)

Akaike       -5.435209
Bayes        -5.396133
Shibata      -5.435334
Hannan-Quinn -5.420361
> garch02_spec<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(0,2)),mean.model=list(a
rmaOrder=c(1,0)),distribution.model="std")
> garch02_fit<-ugarchfit(garch02_spec,data = e)
> infocriteria(garch02_fit)

Akaike       -5.371599
Bayes        -5.342293
Shibata      -5.371670
Hannan-Quinn -5.360464
> 
```

Figure 14: The Akaike Information Criterion (AIC) for garchorder(2,2) and garchorder(0,2)

```
R 4.2.2 · C:/Users/Ajayi/Desktop/coursework/Financial Maths Coursework/
Shibata      -5.371670
Hannan-Quinn -5.360464
> garch12_spec<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,2)),mean.model=list(a
rmaOrder=c(1,0)),distribution.model="std")
> garch12_fit<-ugarchfit(garch12_spec,data = e)
> infocriteria(garch12_fit)

Akaike       -5.436798
Bayes        -5.402607
Shibata      -5.436894
Hannan-Quinn -5.423807
> volatility <- ts(garch11@fit$sigma^2,start=c(2017,1),frequency = 252)
> egarch12_spec<-ugarchspec(variance.model=list(model="eGARCH",garchOrder=c(1,2)),mean.model=list
(armaOrder=c(1,0)),distribution.model="std")
> egarch12_fit<-ugarchfit(egarch12_spec,data = e)
> infocriteria(egarch12_fit)

Akaike       -5.456730
Bayes        -5.417655
Shibata      -5.456855
Hannan-Quinn -5.441883
> |
```

Figure 15: The Akaike Information Criterion (AIC) for garchorder(0,2) and egarchorder(1,2)

There is a provision for the summary of the AICs below:

Garchorder	**AIC**	**BIC**
garch12	-5.341640	-5.317217
garch11	-5.439633	-5.410327
garch20	-5.377531	-5.348224
garch21	-5.436829	-5.402638
garch22	-5.435209	-5.396133
garch02	-5.371599	-5.342293
garch12	-5.436798	-5.4026027
egarch12	-5.456730	-5.417655

Table 2: AIC and BIC of the various garchorders

The lowest AIC and BIC from the table and images above is **egarch1,2** and will therefore be the chosen model.

The exponential general autoregressive conditional heteroskedastic (EGARCH) is another form of the GARCH model. EGARCH model is useful to overcome the weakness in GARCH concerning the issue management of financial time series. In particular, to allow for asymmetric effects between positive and negative asset returns [17].

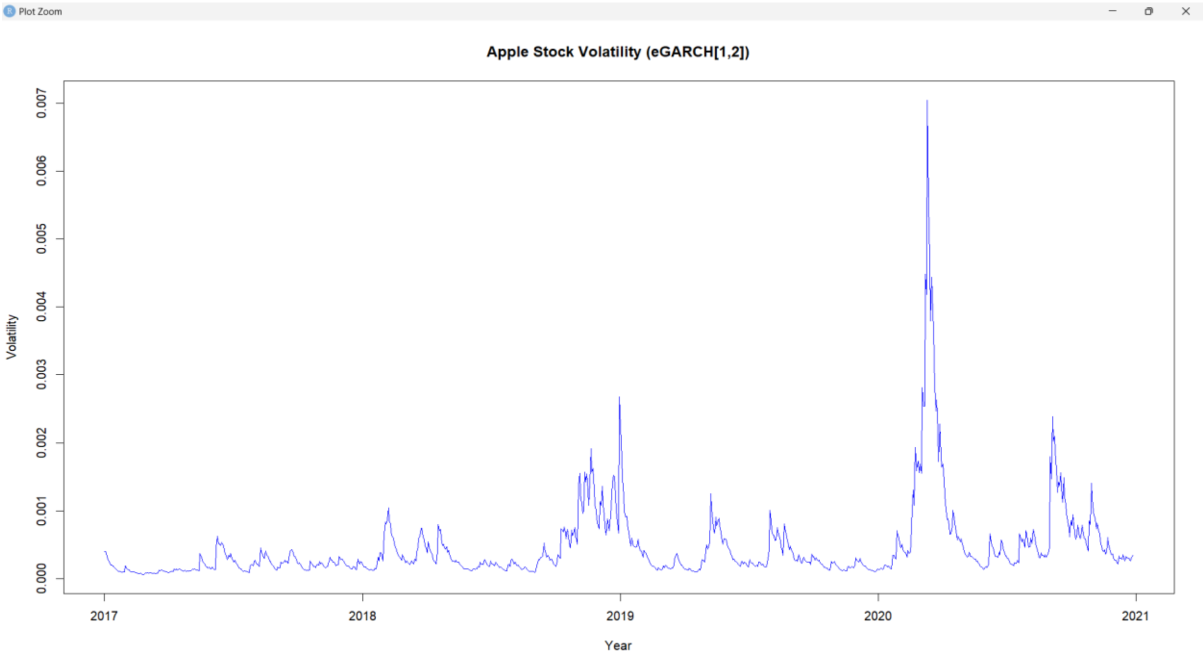

Figure 16: Apple Stock Volatility using egarch(1,2)

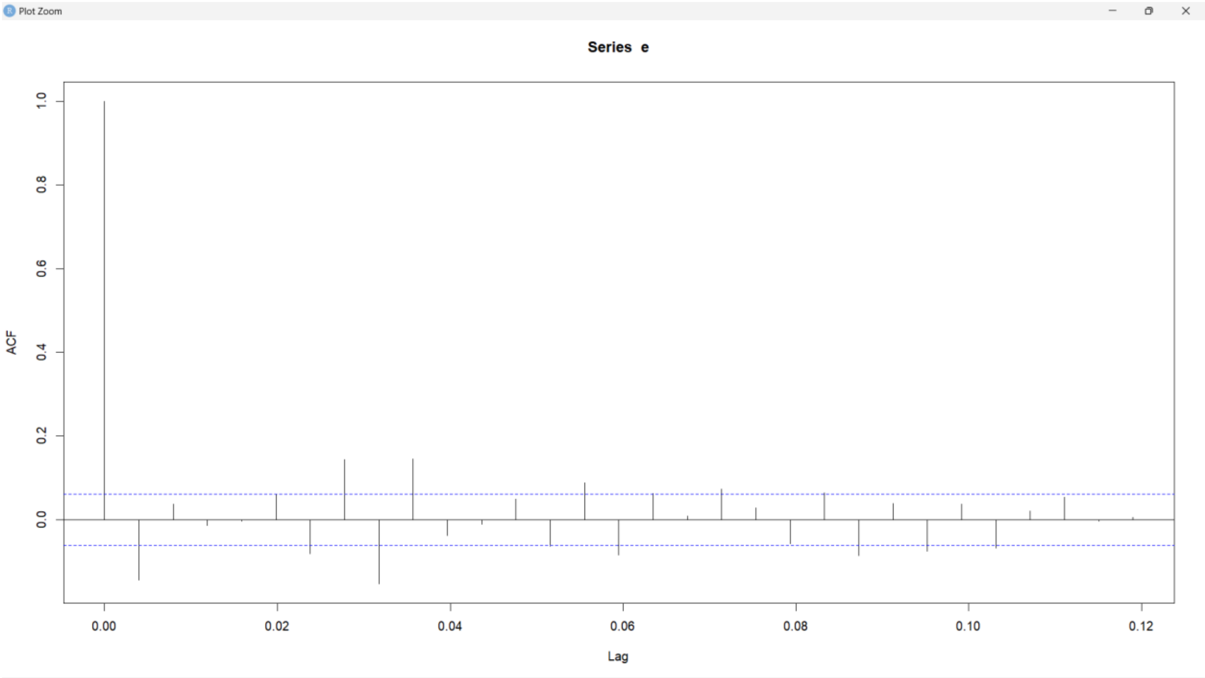

Figure 17: Graph showing Autocorrelation Function (ACF)

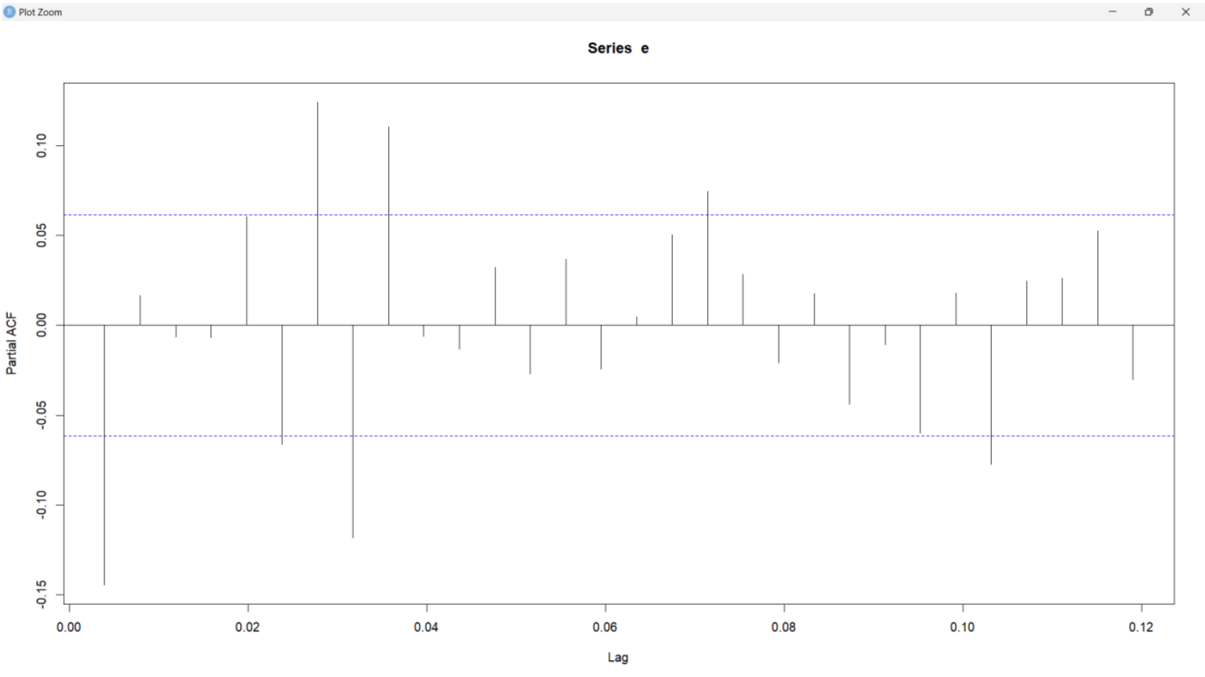

Figure 18: Graph showing Partial Autocorrelation Function (PACF)

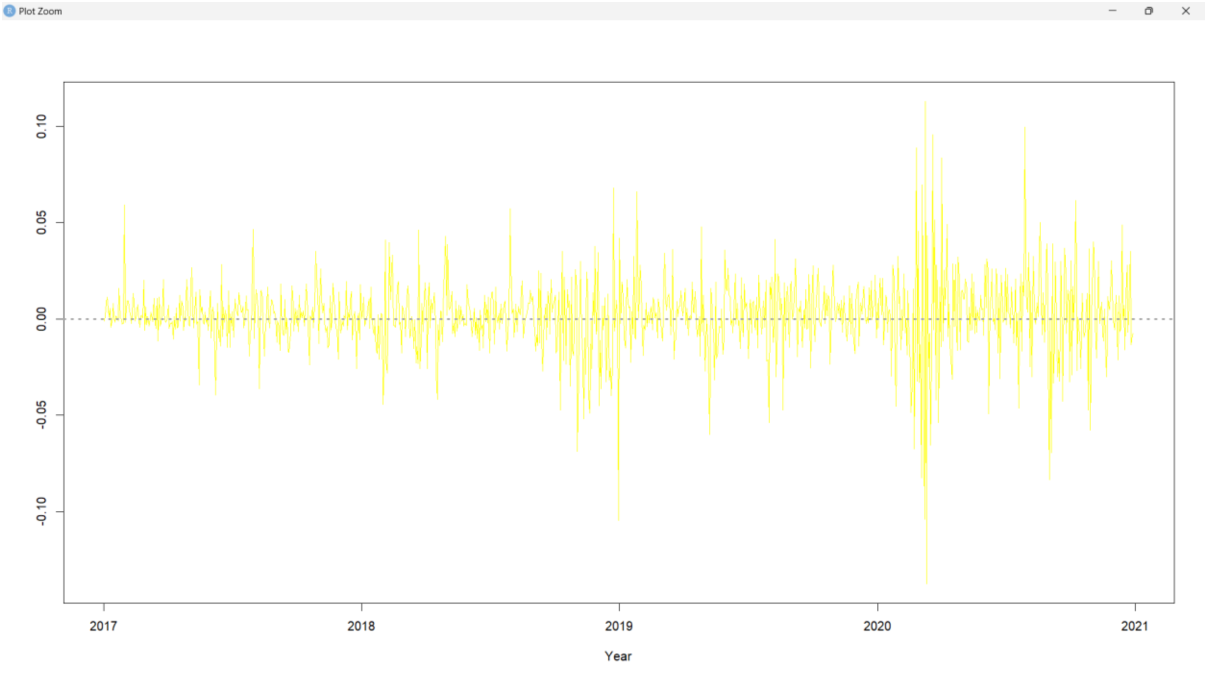

Figure 19: Graph showing the volatility of Apple Stock over time

3.2 Summary of findings

From the various findings above, one can deduce that the portfolio is a little risky and there is a high annual expected return. The level of risk is worth the expected return. There is a certain level of correlation between the assets that shows that the combination of the assets are somehow a good fit. Also, the individual assets are riskier than the market. Considering the return of the portfolio with its risk, the portfolio is a particularly good and has remarkably high returns. This type of portfolio will be highly recommended to investors.

The optimum weighted assets of the portfolio favours more investment into Apple (AAPL) than any other asset. It is not surprising that the Capital Market Line (CML) intercepts the Efficient Frontier Curve at the same point that was gotten through solver. The model has favours less of Activison stock. More than 78% investments should be on Apple and Nvidia stocks.

The extent of possible financial losses within the portfolio is very low at the 95^{th} percentile with less than 0.1%. It is beyond reasonably doubt that this portfolio is worth the risk for the expected return.

3.3 Conclusion

The portfolio offers an incredibly worthwhile investment return for the risk involved. Investments should be more on Apple and Nvidia stocks.

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APPENDICES

APPENDIX A

```
library(rugarch)

data <- read.csv("C:/Users/Ajayi/Desktop/coursework/Financial Maths Coursework/AAPL_asset.csv")

Exp<-ts(data[,2],start=c(2017,1),frequency = 252)

#Get the log of each data

e=diff(log(Exp))

garch10_spec<-
ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,0)),mean.model=list(armaOrder=c(1,0)),
distribution.model="std")

garch10_fit<-ugarchfit(garch10_spec,data = e)

infocriteria(garch10_fit)


garch11_spec<-
ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,1)),mean.model=list(armaOrder=c(1,0)),
distribution.model="std")

garch11_fit<-ugarchfit(garch11_spec,data = e)

infocriteria(garch11_fit)


garch20_spec<-
ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(2,0)),mean.model=list(armaOrder=c(1,0)),
distribution.model="std")

garch20_fit<-ugarchfit(garch20_spec,data = e)

infocriteria(garch20_fit)


garch21_spec<-
ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(2,1)),mean.model=list(armaOrder=c(1,0)),
distribution.model="std")

garch21_fit<-ugarchfit(garch21_spec,data = e)

infocriteria(garch21_fit)


garch22_spec<-
ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(2,2)),mean.model=list(armaOrder=c(1,0)),
distribution.model="std")

garch22_fit<-ugarchfit(garch22_spec,data = e)

infocriteria(garch22_fit)


garch02_spec<-
ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(0,2)),mean.model=list(armaOrder=c(1,0)),
distribution.model="std")
```

```
garch02_fit<-ugarchfit(garch02_spec,data = e)

infocriteria(garch02_fit)


garch12_spec<-
ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,2)),mean.model=list(armaOrder=c(1,0)),
distribution.model="std")

garch12_fit<-ugarchfit(garch12_spec,data = e)

infocriteria(garch12_fit)


egarch12_spec<-
ugarchspec(variance.model=list(model="eGARCH",garchOrder=c(1,2)),mean.model=list(armaOrder=c(1,0)),
distribution.model="std")

egarch12_fit<-ugarchfit(egarch12_spec,data = e)

infocriteria(egarch12_fit)

volatility <- ts(egarch12_fit@fit$sigma^2,start=c(2017,1),frequency = 252)

plot(volatility, col="blue",xlab="Year",ylab="Volatility",main="Apple Stock Volatility (eGARCH[1,2])")
```

APPENDIX B

=STDEV(H4:H1009)*SQRT(252)

	A	B	C	D	E	F	G	H	I	J	K	L
22	31/01/2017	30.34	40.21	101.31	27.30	79.10		-0.002302064	0.015147690	0.002870719	-0.007634975	0.004954898
23	01/02/2017	32.19	40.47	101.57	28.49	78.58		0.060980635	0.006466053	0.002566380	0.043689320	-0.006573957
24	02/02/2017	32.13	40.47	100.84	28.85	80.13		-0.001708738	0.000000000	-0.007187162	0.012637122	0.019725121
25	03/02/2017	32.27	40.01	100.39	28.60	80.21		0.004279157	-0.011366444	-0.004462515	-0.008752925	0.000998378
26	06/02/2017	32.57	40.19	100.90	29.33	79.75		0.009374032	0.004498875	0.005080187	0.025616366	-0.005734946
27	07/02/2017	32.88	40.05	100.83	29.78	80.21		0.009517231	-0.003483454	-0.000693756	0.015514449	0.005768025
28	08/02/2017	33.01	39.19	103.57	29.65	80.70		0.003877442	-0.021473159	0.027174452	-0.004364979	0.006108964
29	09/02/2017	33.11	39.73	103.34	29.10	81.03		0.002877916	0.013779025	-0.002220720	-0.018801113	0.004089219
30	10/02/2017	33.03	47.23	102.36	28.41	80.64		-0.002265519	0.188774226	-0.009483259	-0.023715415	-0.004813032
31	13/02/2017	33.32	45.70	103.10	27.10	80.91		0.008855586	-0.032394664	0.007229386	-0.046118641	0.003348214
32	14/02/2017	33.76	44.98	101.59	27.20	80.92		0.012979218	-0.015754923	-0.014645975	0.003690718	0.000123594
33	15/02/2017	33.88	45.48	101.55	27.25	81.67		0.003629092	0.011116052	-0.000393740	0.002022431	0.009268413
34	16/02/2017	33.84	45.39	100.82	26.81	80.82		-0.001216146	-0.001978892	-0.007188577	-0.016055046	-0.010407738
35	17/02/2017	33.93	45.33	100.52	26.81	81.47		0.002769215	-0.001321877	-0.002975600	-0.000186480	0.008042564
36	21/02/2017	34.18	45.34	102.12	27.77	82.18		0.007220749	0.000220604	0.015917230	0.035810874	0.008714864
37	22/02/2017	34.28	45.23	104.20	27.69	82.08		0.002999268	-0.002426114	0.020368194	-0.002791033	-0.001216841
38	23/02/2017	34.13	45.08	102.46	25.12	82.07		-0.004230180	-0.003316383	-0.016698656	-0.092723005	-0.000121832
39	24/02/2017	34.17	45.55	102.95	25.37	81.78		0.000952172	0.010425909	0.004782354	0.009652702	-0.003533569
40	27/02/2017	34.23	45.69	103.60	26.10	81.54		0.001975706	0.003073546	0.006313745	0.029075498	-0.002934703
41	28/02/2017	34.25	45.13	102.90	25.37	81.35		0.000438180	-0.012256511	-0.006756757	-0.028062446	-0.002330145
42	01/03/2017	34.95	47.14	104.04	25.70	83.81		0.020439448	0.044538001	0.011078717	0.012908948	0.030239705
43	02/03/2017	34.74	46.68	103.19	24.75	82.67		-0.005937478	-0.009758167	-0.008169935	-0.036871291	-0.013602195
44	03/03/2017	34.95	47.07	103.31	24.61	82.22		0.005900979	0.008354756	0.001162903	-0.005757576	-0.005443329
45	06/03/2017	34.84	47.81	102.31	24.42	82.50		-0.003147804	0.015721266	-0.009679605	-0.007721223	0.003405497
46	07/03/2017	34.88	48.06	102.63	24.69	82.97		0.001291804	0.005229032	0.003127749	0.010955257	0.005696970

	N	O	P
22	SALESFORCE	0.2	
23	TOTAL	1	
24			
25	EXPECTED RETURN		0.379854325
26	STANDARD DEVIATION		0.28813765
27	Sharpe Ratio	1.318308527	
28			
29	Risk (Not Given)	0.00	
30			
31	APPLE(W1)	ACTIVISION(W2)	ALIBABA(W3)
32	0	0.454292936	0.51554017
33	0.085866541	0.322327172	0.38811836
34	0.243875318	0.256476569	0.31527177
35	0.480888504	0.157700702	0.20600191
36	0.593289052	0.087975496	0.12292113
37	0.651500276	0.045390604	0.07104839
38	0.731292506	0	0
39	0.470037827	0	0
40	0.253233719	0	0
41	0.144831665	0	0

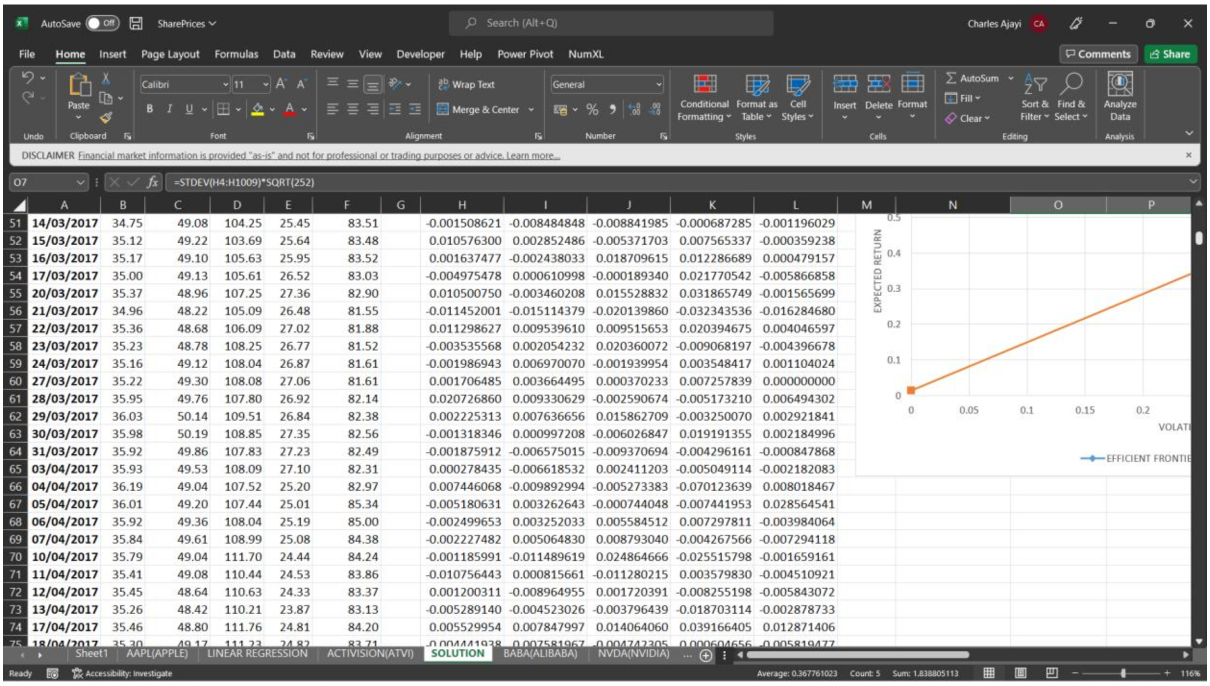
EFFICIENT FR

SOLUTION

=STDEV(H4:H1009)*SQRT(252)

	A	B	C	D	E	F	G	H	I	J	K	L
1			STOCKS							RETURN		
2	Date	APPLE	ACTIVISION	ALIBABA	NVIDIA	SALESFORCE		APPLE	ACTIVISION	ALIBABA	NVIDIA	SALESFORCE
3	03/01/2017	29.04	36.64	88.60	25.50	70.54						
4	04/01/2017	29.01	37.36	90.51	26.10	72.80		-0.001119242	0.019650655	0.021557562	0.023331046	0.032038560
5	05/01/2017	29.15	37.94	94.37	25.44	72.79		0.005085330	0.015524625	0.042647221	-0.025385573	-0.000137363
6	06/01/2017	29.48	37.91	93.89	25.78	73.80		0.011148272	-0.000790722	-0.005086362	0.013367407	0.013875532
7	09/01/2017	29.75	37.70	94.72	26.82	73.96		0.009159528	-0.005539436	0.008840132	0.040543162	0.002168022
8	10/01/2017	29.78	38.38	96.75	26.62	73.98		0.001008488	0.018037135	0.021431588	-0.007550336	0.000270416
9	11/01/2017	29.94	39.20	96.94	26.29	75.77		0.005373184	0.021365294	0.001963824	-0.012303935	0.024195729
10	12/01/2017	29.81	39.13	95.90	25.86	75.21		-0.004175365	-0.001785714	-0.010728286	-0.016356029	-0.007390788
11	13/01/2017	29.76	38.95	96.27	25.86	75.64		-0.001761006	-0.004600051	0.003858186	-0.000096674	0.005717325
12	17/01/2017	30.00	38.95	96.12	25.28	75.02		0.008064516	0.000000000	-0.001558118	-0.022430629	-0.008196721
13	18/01/2017	30.00	39.08	96.00	25.74	75.78		-0.000083333	0.003337612	-0.001248439	0.018198002	0.010130632
14	19/01/2017	29.95	38.86	96.17	26.29	75.57		-0.001750146	-0.005629478	0.001770833	0.021466731	-0.002771180
15	20/01/2017	30.00	38.97	96.06	26.00	76.03		0.001836701	0.002830674	-0.001143808	-0.010935717	0.006087072
16	23/01/2017	30.02	38.53	98.41	26.27	76.16		0.000666667	-0.011290736	0.024463877	0.010383617	0.001709851
17	24/01/2017	29.99	39.10	101.43	26.83	77.11		-0.000916056	0.014793667	0.030687938	0.021315063	0.012473739
18	25/01/2017	30.47	39.56	104.06	26.95	78.47		0.015920647	0.011764706	0.025929212	0.004285847	0.017637142
19	26/01/2017	30.49	39.47	102.75	27.41	77.95		0.000492287	-0.002275025	-0.012588891	0.017255775	-0.006626736
20	27/01/2017	30.49	39.61	102.07	27.94	78.21		0.000082008	0.003546998	-0.006618005	0.019334245	0.003335471
21	30/01/2017	30.41	39.61	101.02	27.51	78.71		-0.002624026	0.000000000	-0.010287058	-0.015657153	0.006393044
22	31/01/2017	30.34	40.21	101.31	27.30	79.10		-0.002302064	0.015147690	0.002870719	-0.007634975	0.004954898

	N	O	P
2		APPLE	ACTIVISION
3	DAILY EXP RETURN	0.001710761	0.00117830
4	ANN EXP RETURN	0.431111807	0.29693270
5	VARIANCE	0.000398284	0.00050753
6	ANN VARIANCE	0.100367524	0.12789981
7	S.D	0.316808339	0.35763083
8			VARIANCE-
9		*APPLE*	*ACTIVISION*
10	APPLE	0.1002677550	0.0554177074
11	ACTIVISION	0.0554177074	0.127772678
12	ALIBABA	0.0544292804	0.047492055
13	NVIDIA	0.0926544086	0.084002201
14	SALESFORCE	0.0645999057	0.058556018
15			
16			
17	EQUALLY WEIGHTED ASSETS		
18	APPLE	0.2	
19	ACTIVISION	0.2	
20	ALIBABA	0.2	
21	NVIDIA	0.2	
22	SALESFORCE	0.2	



	A	B	C	D	E	F	G	H	I	J	K	L
51	14/03/2017	34.75	49.08	104.25	25.45	83.51		-0.001508621	-0.008484848	-0.008841985	-0.000687285	-0.001196029
52	15/03/2017	35.12	49.22	103.69	25.64	83.48		0.010576300	0.002852486	-0.005371703	0.007565337	-0.000359238
53	16/03/2017	35.17	49.10	105.63	25.95	83.52		0.001637477	-0.002438033	0.018709615	0.012286689	0.000479157
54	17/03/2017	35.00	49.13	105.61	26.52	83.03		-0.004975478	0.000610998	-0.000189340	0.021770542	-0.005866858
55	20/03/2017	35.37	48.96	107.25	27.36	82.90		0.010500750	-0.003460208	0.015528832	0.031865749	-0.001565699
56	21/03/2017	34.96	48.22	105.09	26.48	81.55		-0.011452001	-0.015114379	-0.020139860	-0.032343536	-0.016284680
57	22/03/2017	35.36	48.68	106.09	27.02	81.88		0.011298627	0.009539610	0.009515653	0.020394675	0.004046597
58	23/03/2017	35.23	48.78	108.25	26.77	81.52		-0.003535568	0.002054232	0.020360072	-0.009068197	-0.004396678
59	24/03/2017	35.16	49.12	108.04	26.87	81.61		-0.001986943	0.006970070	-0.001939954	0.003548417	0.001104024
60	27/03/2017	35.22	49.30	108.08	27.06	81.61		0.001706485	0.003664495	0.000370233	0.007257839	0.000000000
61	28/03/2017	35.95	49.76	107.80	26.92	82.14		0.020726860	0.009330629	-0.002590674	-0.005173210	0.006494302
62	29/03/2017	36.03	50.14	109.51	26.84	82.38		0.002225313	0.007636656	0.015862709	-0.003250070	0.002921841
63	30/03/2017	35.98	50.19	108.85	27.35	82.56		-0.001318346	0.000997208	-0.006026847	0.019191355	0.002184996
64	31/03/2017	35.92	49.86	107.83	27.23	82.49		-0.001875912	-0.006575015	-0.009370694	-0.004296161	-0.000847868
65	03/04/2017	35.93	49.53	108.09	27.10	82.31		0.000278435	-0.006618532	0.002411203	-0.005049114	-0.002182083
66	04/04/2017	36.19	49.04	107.52	25.20	82.97		0.007446068	-0.009892994	-0.005273383	-0.070123639	0.008018467
67	05/04/2017	36.01	49.20	107.44	25.01	85.34		-0.005180631	0.003262643	-0.000744048	-0.007441953	0.028564541
68	06/04/2017	35.92	49.36	108.04	25.19	85.00		-0.002499653	0.003252033	0.005584512	0.007297811	-0.003984064
69	07/04/2017	35.84	49.61	108.99	25.08	84.38		-0.002227482	0.005064830	0.008793040	-0.004267566	-0.007294118
70	10/04/2017	35.79	49.04	111.70	24.44	84.24		-0.001185991	-0.011489619	0.024864666	-0.025515798	-0.001659161
71	11/04/2017	35.41	49.08	110.44	24.53	83.86		-0.010756443	0.000815661	-0.011280215	0.003579830	-0.004510921
72	12/04/2017	35.45	48.64	110.63	24.33	83.37		0.001200311	-0.008964955	0.001720391	-0.008255198	-0.005843072
73	13/04/2017	35.26	48.42	110.21	23.87	83.13		-0.005289140	-0.004523026	-0.003796439	-0.018703114	-0.002878733
74	17/04/2017	35.46	48.80	111.76	24.81	84.20		0.005529954	0.007847997	0.014064060	0.039166405	0.012871406
75	18/04/2017	35.30	49.17	111.23	24.82	83.71		-0.004441938	0.007581967	-0.004742305	0.000604656	-0.005819477