GR5261 Group 5 Final Project Report

Chen Chen (cc4291), Yufan Zhang (yz3385), Qiwen Gao (qg2165)

Due 12/17/2019

Part I: Summary

The goal of this project to do a series of analysis for 15 assets' 7-year monthly returns based on our learning in this class, and the results show that our assets are relatively stationable compared to the market, and more results could be found in the following sections. With the development of the times, the financial industry and the technology industry become more and more important fields. Finance and technology are the rising industries. In order to find out some financial statistical characters of financial and technology industries, we select top 15 market cap companies in those two industries as research objects. After obtaining returns of 15 assets and risk-free rate, we calculate their statistics, construct portfolios, implement asset allocation, analyze principal components, manage risks, and finally find an appropriate joint distribution for returns.

Part II: Data Description

We select 15 stocks from different companies among Financial Industry and Technology Industry (**Appendix: Table 1**). There are 6 from Financial Industry, which are JPM, V, BAC, MA, WFC, and HSBC. The other 9 companies are from Technology, which are MSFT, GOOGL, FB, AAPL, AMZN, IBM, ORCL, ADBE, and VZ. We collect their monthly close price from Nov. 2012 to Nov. 2019 in Yahoo Finance, and then compute their monthly return. We also find the close price for S&P 500 as a market index indicator. For the risk-free rate, we decide to use 3-month treasury bill monthly rate from FRED website. In the further calculation, we take average of T-bill rate from Nov. 2012 to Nov. 2019, and use as the risk-free rate.

Part III: Descriptive Statistics

In this part, we discuss the sample statistics of our assets using different descriptive methods. We use 15 assets and we look at 7 years of monthly closing prices and returns.

Sample Statistics

The summarized table of sample statistics is in **Appendix: Table 2**. The mean of 15 assets returns are generally around 1.538%, and the standard deviation of 15 assets are generally around 0.06117. Skewness and Kurtosis indicates the shape of our data here. Among 15 assets, V, BAC, HSBC, MSFT, GOOGL, FB, AMZN, ORCL and ADBE has positive skewness, which means that the data are positively skewed or skewed right. JPM, MA, WFC, AAPL, IBM and VZ are negatively skewed or skewed left. The β_i of V, HSBC, GOOGL, and VZ are larger than 1, so they are aggressive assets, and the β_i of the left assets are smaller than 1, so they are non-aggressive assets. AAPL has the highest sharpe ratio/slope, which is 0.2967. Annual numbers indicates the return per year, and they will provide us with an overall idea of the performance of each asset based on a year standard.

Monthly Prices and Returns

The monthly closing prices plots could be seen in **Appendix: Figure 1**, and we can see from the graph that all 15 assets are below the monthly closing price for S&P500. Most of 15 assets are relatively flat compared to the others, while there are two unusually large assets: AMZN and GOOGL. They are generally increasing within the time period and have good monthly closing price compared to the other assets. IBM is slightly larger at the beginning months of our research time period, while it drops a little bit after the times. Most of the monthly closing prices for our assets are within the range from 0 to \$350.

The monthly return plots can be found in **Appendix: Figure 2**. It can be seen that each asset is pretty similar to the pattern change of S&P500. The fluctuation of these assets are relatively stationary over the time, and the average fluctuation of them are around the means. There are also some extremely fluctuations as well, such as FB. There is one time that FB has a large level of monthly returns over the time. We will discuss these unusual situations in the following parts.

Outlier Check

We did outlier check procedure to technically find the usually large or small returns. The table in **Appendix: Table 3** shows the extreme values of each asset. The positive values indicates the unusually large returns, and negative values indicates the unusually small returns. We take FB as an example, there is an extreme large return at the 2013/7/1, and we did the research about the possible reasons behind this change. The launch of Facebook Pay helped spark a rise in FB stock above a cup-with-handle buy point. Among the big-cap winners of the decade, FB stock soared almost 600% from July 2013 to July 2018.

Equity Curve

We calculated the equity curve for all 15 assets as well as SP500 and plot it in **Appendix: Figure 3**. It is the growth of a \$1 in each of the asset over the time period from 2012 to 2019. From this graph, we can see the change of the assets over time. There are about 10 assets which are above the curve of SP500. These 10 assets (ordered from the smallest price to the largest price) include: AAPL, JPM, BAC, GOOGL, V, MSFT, MA, FB, AMZN, ADBE. Among those which are above SP500, there are three extremely large assets: FB, ADBE, AMZN.

Histograms, Boxplots and QQ-plots

Based on histograms in **Appendix: Figure 4**, Most assets look normal distributed, and we need to fit the distributions later to see whether there is some other situations.

The boxplots (**Appendix: Figure 5**) shows the most of our 15 assets have positive means. FB has some large outliers that we explained the reasons before.

The Q-Q plots of all the assets are shown in **Appendix: Figure 6**. Those lines are pretty close to linear if we ignore the outliers. As such, it is reasonable to see that all 15 assets are normally distributed. VZ, GOOGL, FB are most likely to be non-linear assets compared to the other assets.

Test for Stationarity

We use Augmented Dickey-Fuller (ADF) t-test to test for stationarity. Our null hypothesis is that the returns of asset i is not stationary. Then we computed the 15 tests for each asset and recorded their p-values, which could be seen below. Small p-values indicate that the return is stationary.

Based on the results of our tests (**Appendix Table 4**), all the 15 assets are stationary as they have small p-values at the significant level at 0.05.

Fit Distributions

Based on the table (**Appendix: Table 5**), most of our assets are normally distributed and t-distributed. There is only one asset is Skewed t distribution, which is FB.

Pairwise Scatter Plots

As the scatter plots (**Appendix: Table 6 and Figure 7**) are hard to tell the relationships among 15 assets, we create the correlation table to compute the relationships. From the table, we can see that almost all the 15 assets are positive associated except for two negative associations, which are VZ v.s. BAC and VZ v.s. FB. The reason behind this is probability that VZ is a communication company which has less relationship with banks and technology companies. Furthermore, compared to all the other assets, VZ has a relatively small relationships to them, which are around the range from 0.009 to 0.285. As such, VZ is likely to be a special company among the 15 companies we selected.

Sample Covariance Matrix

We build the covariance matrix in **Appendix: Table 7**. All the covariance among 15 assets are positive, and there are generally small covariance. There is one company we need to pay more attention on that VZ is special here as its covariance is almost close to 0.

Part IV: Data Analysis

In this section, we summarized the results of your statistical analysis by topics in the following:

Portfolio Theory

In this Portfolio Theory part, we construct minimum variance portfolio portfolio (MVP) and tangency portfolio for our assets data in two scenarios: with and without allowed short sales.

Under each circumstance, we first estimate the portfolio mean, standard deviation, expected shortfalls for the MVP. Then we compare the estimated return and risk of our generated portfolio with each singular data asset to see the performance of the MVP portfolio. Then we assume a \$100,000 investment for the MVP portfolio over one month investment horizon. We calculate the 5% value-at-risk and make comparisons with the VaR of the individual assets. By using the computed estimations of the portfolio mean, variance and covariances, we compute the efficient portfolio frontier with the Markowitz method. For the constructed tangency portfolio, we calculate its expected return, variance and standard deviation as well. In addition to that, we compute the Sharpe ratio, and compare the Sharpe ratio with the individual assets.

Allow Short Sales

We start with the case when short sales are allowed, which means the investor sales the asset that he/she does not owned, then repurchases the asset and returns it to the lender. In this case, weights for some assets in the portfolio can be negative. Appendix graph: Efficient portfolio Frontier when short sales allowed graph

• Minimum Variance Portfolio (MVP)

JPM	V	BAC	MA	WFC	HSBC	MSFT	GOOGL	FB	AAPL	AMZN	IBM	ORCL	ADBE	VZ
0.145	0.2833	-0.11	-0.0292	0.0459	0.211	-0.1054	0.1193	0.0263	0.0613	-0.1604	0.1011	0.023	0.0953	0.2935

From the MVP weights, we can see that 4 assets (BAC, MA,MSFT,AMZN) should be shorted. The assets with relatively low standard deviation take higher weights, while ones with the higher standard deviation either take smaller weights or are shorted. The mean of the MVP is 0.0774, standard deviation is 0.0977, 5% VaR is 3994, expected shortfall is 5172 and Sharpe ratio is 0.716. Comparing with the 15 assets, although the mean value of MVP is not the highest, the Sharpe ratio of MVP is the highest. Here the

MVP mean	0.0774
MVP sd	0.0977
VaR	3994
Expected shortfall	5172
Sharpe ratio	0.716

MVP has the lowest standard deviation, lowest VaR and lowest expected shortfall. We can see that the portfolio diversifies the overall risk.

• Tangency Portfolio

JPM	V	BAC	MA	WFC	HSBC	MSFT	GOOGL	FB	AAPL	AMZN	IBM	ORCL	ADBE	VZ
0.3916	0.1798	0.0044	0.2025	-0.1083	-0.2036	0.1342	0.0317	0.1417	-0.0189	-0.0331	-0.1893	-0.0577	0.2197	0.3053

The mean of the Tangency portfolio is 0.336, standard deviation is 0.144, 5% VaR is 4043, expected shortfall is 5781 and Sharpe ratio is 2.28. Among the 15 assets, AAPL has the highest Sharpe ratio, which equals 0.2967. Comparing with the 15 assets, the Sharpe ratio of the tangency portfolio is much higher. The tangency portfolio also has the lowest VaR and lowest expected shortfall, comparing with the 15 individual assets.

Tangency mean	0.336
Tangency sd	0.144
VaR	4043
Expected shortfall	5781
Sharpe ratio	2.28

Short sale not allowed

The weights of the assets in the portfolio can't be negative when short sales are not allowed, Appendix graph: Efficient portfolio Frontier when short sales not allowed graph

• Minimum Variance Portfolio (MVP)

JPM	V	BAC	MA	WFC	HSBC	MSFT	GOOGL	FB	AAPL	AMZN	IBM	ORCL	ADBE	VZ
0.0346	0.2153	0	0	0.046	0.1413	0	0.0093	0.0351	0.0291	0	0.0659	0.0581	0.0251	0.3401

After adding the restriction of not allowing short sale, now our MVP portfolio only includes 11 assets, and the rest 4 assets (BAC, MA, MSFT, AMZN) have weights equal 0. When short sales are not allowed, the mean of the MVP is 0.11, standard deviation is 0.104, 5% VaR is 4008, expected shortfall is 5260 and Sharpe ratio is 0.99. Comparing with the 15 assets, although the mean value of MVP is not the highest, the Sharpe ratio of MVP is the highest. Here the MVP has the lowest standard deviation, lowest VaR and lowest expected shortfall. We can see that the portfolio also diversifies the

MVP mean	0.11
MVP sd	0.104
VaR	4008
Expected shortfall	5260
Sharpe ratio	0.99

overall risk. However, comparing with the condition that short sales are allowed, the standard deviation of MVP with forbidden short sales is higher, which means the risk is less diversified.

• Tangency Portfolio

JPM	V	BAC	MA	WFC	HSBC	MSFT	GOOGL	FB	AAPL	AMZN	IBM	ORCL	ADBE	VZ
0.0649	0.1681	0	0.1369	0	0	0.1832	0	0.1113	0	0	0	0	0.2751	0.0606

After adding the restriction of not allowing short sale, now our tangency portfolio only includes 7 assets (JPM, V, MA, MSFT, FB, ADBE, VZ), and the rest 8 assets have weights equal 0. The mean of the Tangency portfolio is 0.273, standard deviation is 0.141, 5% VaR is 4407, expected shortfall is 6104 and Sharpe ratio is 1.89. Among the 15 assets, AAPL has the highest Sharpe ratio, which equals 0.2967. Comparing with the 15 assets, the Sharpe ratio of the tangency portfolio is much higher. The tangency portfolio also has the lowest VaR and lowest expected shortfall, comparing with the 15 individual

Tangency mean	0.273
Tangency sd	0.141
VaR	4407
Expected shortfall	6104
Sharpe ratio	1.89

assets. Comparing with the condition that short sales are allowed, the standard deviation of Tangency portfolio with forbidden short sales is higher, and the Sarpe ratio is lower, which means the current portfolio is less efficient.

Asset Allocation

In this asset allocation part, suppose there are no short sales allowed and we have an initial investment of \$100,000. First, we use only the risky assets to construct an efficient portfolio, aiming to achieve a target expected return of 6% per year. We calculate the monthly risk, monthly 5% value-at-risk and expected shortfall on this efficient portfolio.

Then we repeat the same procedures of calculation on the combination of T-Bills and the tangency portfolio. We want to see the allocation of investment to the assets and the risk-free asset.

• Only include risky assets (no T-bills)

In the case when there are no T-Bills included, we only use the risky assets to construct our portfolio. We want to achieve an expected return of 6% per year, (or 0.5% per month).

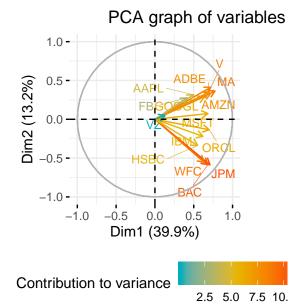
There are only 8 assets(V, WFC, HSBC, FB, AAPL, IBM, ORCL, VZ) included in the efficient portfolio when there are no T-Bills. With respect to the investment, 13.19% should be allocated to V, 4.42% to WFC, 22.67% to HSBC, 0.03% to FB, 2.9% to AAPL, 13.03% to IBM, 7.42% to ORCL and 36.25% to VZ. The monthly risk of this portfolio is 0.0309, 5% VaR is 4579 and expected shortfall is 5869.

• Include risky assets and risk-free assets (T-Bills)

Here we have both risk assets and the risk-free assets in the portfolio to achieve the target expected 6% annually return. By calculation, we should invest 80.2% of our investment to the risk-free asset, which is the T-Bill in our portfolio. The rest of 19.8% investment should be put in the risky assets. There are 7 risky assets included, which are JPM, V, MA, MSFT, FB, ADBE and VZ. 1.28% of the money should be invested to JPM, 3.33% to V, 2.71% to MA, 3.63% to MSFT, 2.2% to FB, 5.45% to ADBE and 1.2% to VZ. The monthly risk of this portfolio is 0.0084, 5% VaR is 823 and expected shortfall is 1159. We can see that the monthly risk of this portfolio is much lower than the one without risk-free asset, which means this portfolio diversifies the risk better than the previous one. The 5% VaR and expected shortfall of this portfolio are also lower than the one without including the risk-free asset.

Principal Component Analysis

By computing the sample correlation matrix of the returns on our assets (Appendix: Table 6), we could find all the correlation relationships between each company. The more close to 1, means higher correlation. And the more close to 0, means lower correlation. The most highly correlated assets are JPM and BAC. The correlation between JPM and BAC is 0.84582. They are both best banks in America, and their business activities will interact with each other, so it is easy to understand that they are highly correlated. VZ and ADBE are two companies that are least correlated due to the fact that their correlation is only 0.0086. VZ and ADBE are two different companies that one is a mobile company and another is a computer software company, so they are not related with each other. By looking at the whole correlation matrix, we could see that most of the correlations are not high, they are around or lower than 0.5. So, we think diversification will help us reduce risk with these assets and if we can reduce some of highly correlated assets will reduce more risk.



After analyzing the correlation of assets, we consider using principal component analysis to reduce dimensions and to get the main combinations of our assets. Based on our analysis result,

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15
Proportion of Variance	0.324	0.262	0.121	0.094	0.048	0.044	0.033	0.025	0.022	0.013	0.005	0.005	0.002	0.001	0
Cumulative Proportion	0.324	0.586	0.707	0.801	0.849	0.893	0.926	0.951	0.973	0.987	0.992	0.997	0.999	1.000	1

we find the first principal component explains the most, and it explains 32.4% of the total variance. Till the 5th principal component, the cumulative variance can be explained is 84.96% and it is relatively high proportion, so we decide to keep first five principal components. We also obtain the factor loading for each of the five principal components (**Appendix: Table 8**), and based on the factor loadings, we could get the linear combination of our assets for each principal component.

Next, we run the factor analysis, which can help us explain returns with small number of factors. Based on the hypothesis test, we find when we use five factors, the p-value exceeds 0.05, which results in accepting H0 (five factors are sufficient). We also compute loadings of each factor attached in the **Appendix: Table 9**. Based on the loadings, although we do not know what does each factor represent, we could find a direction of each factor. Take factor 1 and factor 2

Number of Factors	4	5
Cumulative Var	0.567	0.625
P-value	0.0412	0.132
Sufficient	NO	YES

as examples, JPM and BAC have the highest loadings, so we could understand that factor 1 is an indicator that relative with bank area. For factor 2, AMZN and GOOGL have the highest loadings, which means factor 2 is an indicator that connect with rising technology industry.

Risk Management

Risk management is an important part of a daily financial activity. Value-at-Risk (VaR) and expected shortfall (ES) are two indicators used in risk management. VaR measures the potential loss in value of a risky asset or portfolio over a defined period for a given confidence interval. ES is a conditional expectation of loss given loss is larger than VaR.

We estimate 5% VaR and ES on \$100,000 investment over one month investment horizon for each asset and portfolio based on normal distribution first. Then, we conclude that for assets, FB has the highest VaR (12444) and ES (16307), and V has the lowest VaR (5467) and ES (7368). For portfolios, tangency portfolio without short sale has the highest VaR (4407) and has the highest ES (6104). MVP with short sale has both lowest VaR (3994) and ES (5172).

We repeat the above step based on nonparametric method. We find BAC has the highest VaR (11899) and AAPL has highest ES (14278). Same as before, V has the lowest VaR (5941) and ES (6704). For portfolios, tangency portfolio without short sale has the highest VaR (4706) and tangency portfolio with short sale has highest ES (6423). While, tangency portfolio with short sale has lowest VaR (3457). Moreover, MVP without short sale has lowest ES (5622).

The results for above are attached in **Appendix: Table 10**, **Table 11**.

Next, we use bootstrap method to simulate the standard errors and 95% confidence intervals of VaR and ES for 15 assets and different portfolios based on normal method and nonparametric method. All bootstrap results are in **Appendix: Table 12**, **Table 13**, **Table 14**.

Copulas

We use different copulas to fit the joint distribution of our returns. By computing AICs and BICs for Gaussian copula, t copula, Clayton copula and Gumbel copula, we find t copula has the lowest AIC and BIC, which means t copula fits best among those copulas. The t copula is a dependence structure of the multivariate t distribution, and it is better to capture extreme values situation. Also, by doing research, we find that the t copula is often observed in financial return data. In the t copula, it has the same upper and lower tail dependence, which means our joint distribution has this property. Furthermore, this fit result shows that the t copula is an

	DF	AIC	BIC
Gaussian	1	-338	-336
t	2	-375	-370
clayton	1	-312	-309
gumbel	1	-261	-259

appropriate distribution for returns' joint distribution and matches with the finding of the t copula.

Part V: Conclusion

The Data Description part analyze 15 assets from different perspectives, and we mainly focus on EDA for our data. Methods include sample statistics, the plots of monthly prices and returns compared to SP500, outlier check, Equity curve for 15 assets compared to SP500, histogram, qq-plots, tests for stationarity, fitting distributions, correlation and covariance matrix. Each method indicates one characteristic of the assets. The overall result shows that our assets are stationable, and only GOOGL, AMZN, FB, those big companies may have some extreme values based on some news.

When constructing the portfolios, we find that the minimum variance portfolio with allowed short sales has the lowest standard deviation, which implies that it has the lowest risk. The tangency portfolio with allowed short sales has the highest Sharpe ratio. When short sales are not allowed, the portfolios become less effective. If we want to achieve the expected target return of 6% per year, the best way of asset allocation for diversifying the risk is to invest 80.2% of money to the risk-free asset, and the rest to the risky assets, since the monthly risk is the lowest under this circumstance.

After construct portfolio with all assets, we want to use principal component analysis to reduce the dimension of factors. We run the PCA test and find when we keep 5 principal components, 85% of variance can be explained. Also, in factor analysis we find 5 factors are sufficient.

In order to manage risks for 15 assets and portfolios, we compute VaR and ES for them. By studying their VaRs and ESs, we could have a brief understanding of risk. Since confidence interval could provide a reference area for investors, we use bootstrap method to find the 95% confidence intervals of VaR and ES for assets and portfolios.

In the last part, we use different copulas to fit the joint distribution of returns and find T Copula fits best.

After doing all the analysis above, we have a better understanding of our assets, also, we have utilized what we have learnt in financial statistical methods to this project.

Part VI: Appendix

The following shows the tables and figues we mentioned before:

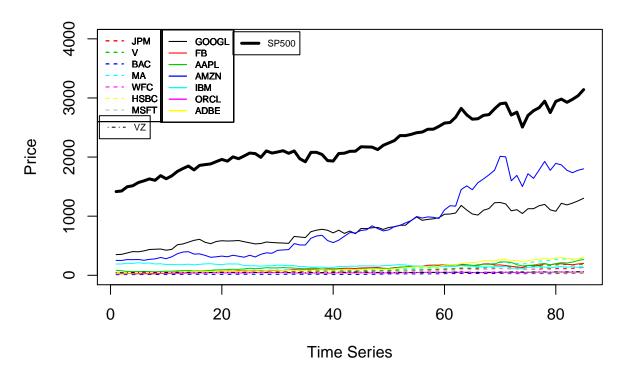
Table 1: Data Description

Assets	Company.Names
JPM	JPMorgan Chase & Co.
V	Visa Inc.
BAC	Bank of America Corporation
MA	Mastercard Incorporated
WFC	Wells Fargo & Company
HSBC	HSBC Holdings plc
MSFT	Microsoft Corporation
GOOGL	Alphabet Inc.
FB	Facebook Inc.
AAPL	Apple Inc.
AMZN	Amazon.com, Inc.
$_{\mathrm{IBM}}$	International Business Machines Corporation
ORCL	Oracle Corporation
ADBE	Adobe Inc.
VZ	Verizon Communications Inc.

Table 2: Sample Statistics

	avg	sd	S	K	beta	Sharpe.Ratio	Annual.Average	Annual.SD
JPM	0.016	0.058	-0.119	0.009	1.168	-0.051	0.187	0.200
V	0.020	0.046	0.037	-0.328	0.901	0.030	0.242	0.158
BAC	0.018	0.077	0.125	0.679	1.431	-0.200	0.210	0.267
MA	0.023	0.049	-0.293	0.064	1.071	0.108	0.272	0.171
WFC	0.007	0.053	-0.656	0.700	1.070	0.048	0.089	0.183
HSBC	-0.002	0.054	0.316	0.292	0.774	-0.126	-0.029	0.186
MSFT	0.022	0.058	0.253	1.082	1.015	0.108	0.270	0.199
GOOGL	0.017	0.057	0.770	1.278	0.971	0.051	0.208	0.198
FB	0.028	0.092	1.527	5.389	1.062	0.147	0.331	0.320
AAPL	0.017	0.075	-0.358	-0.243	1.167	0.297	0.202	0.261
AMZN	0.027	0.080	0.190	0.482	1.532	0.029	0.322	0.277
$_{\mathrm{IBM}}$	-0.002	0.061	-0.309	2.132	1.230	-0.021	-0.026	0.211
ORCL	0.008	0.052	0.029	-0.582	1.130	-0.032	0.096	0.179
ADBE	0.028	0.059	0.182	-0.452	1.096	0.051	0.337	0.204
VZ	0.005	0.048	-0.080	-0.550	0.446	0.040	0.058	0.165

Figure 1: Monthly Closing Price for 15 Assets



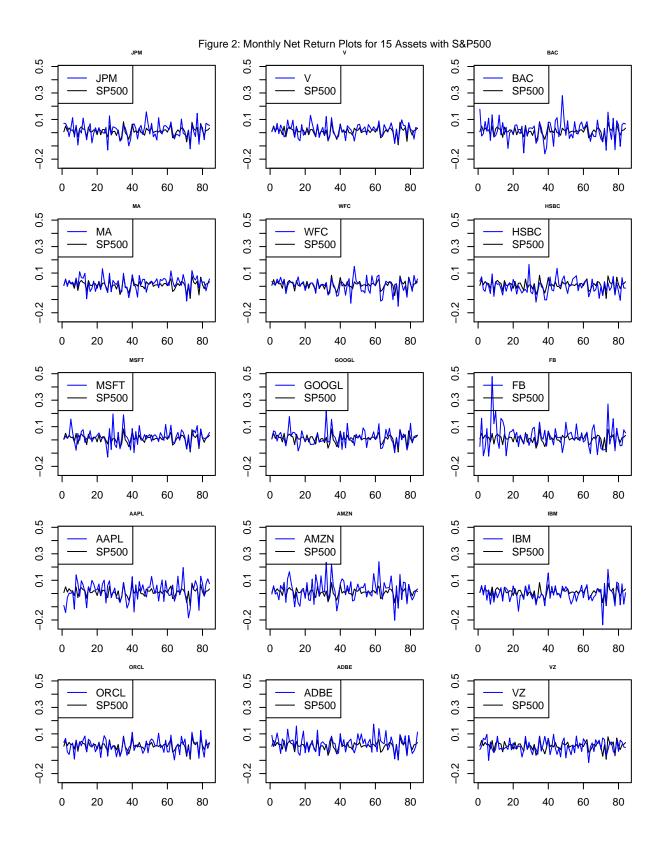
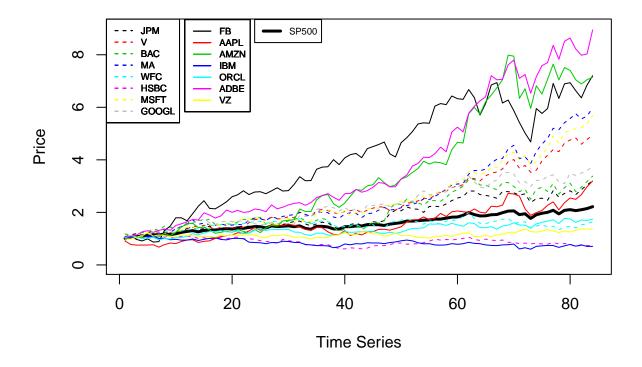
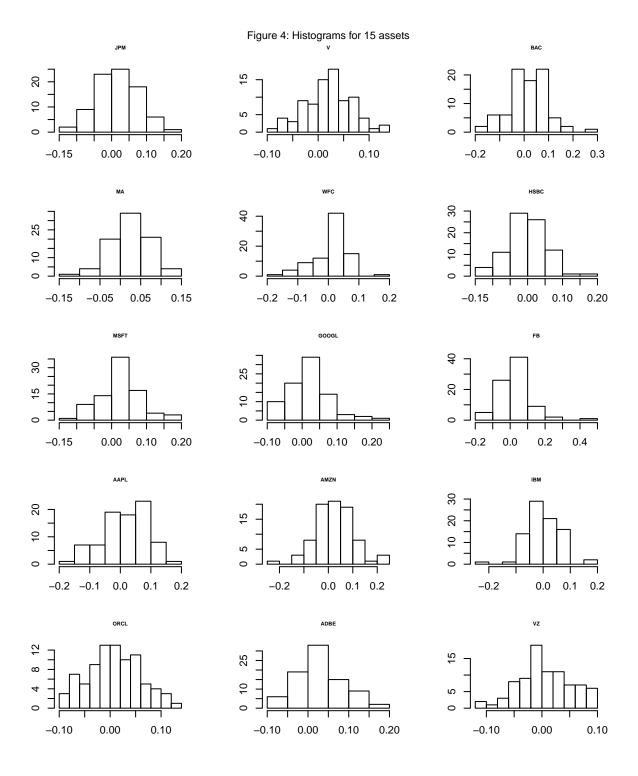


Table 3: Outlier Check Summary

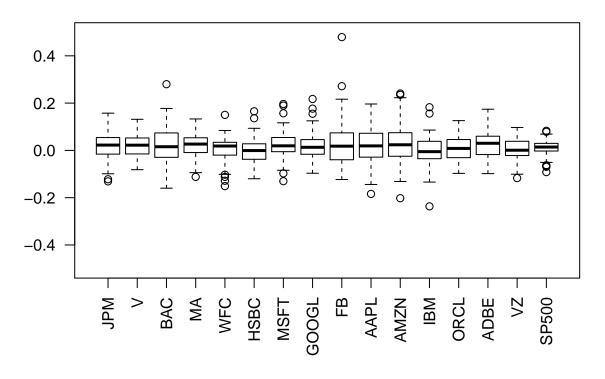
names	Outliers
JPM	-0.1310323,-0.1220433
V	N/A
BAC	0.2800001
MA	-0.1120345
WFC	$ -0.1283465 \; , \; 0.1501848, \; -0.1120401, \; -0.1027221, \; -0.1510685 $
HSBC	0.1652970 ,0.1358779
MSFT	0.15693802, -0.13024755, 0.19626166, 0.18933577, -0.0970
GOOGL	0.1765820 ,0.2175025 ,0.1551138
FB	0.4790997, 0.2715692
AAPL	-0.1840446
AMZN	0.2351126, 0.2406390, -0.2021917
$_{\mathrm{IBM}}$	0.1558422, -0.2366246 , 0.1825460
ORCL	N/A
ADBE	N/A
VZ	-0.1170704
SP500	$\hbox{-0.06258082}\ ,\ 0.08298312\ , \hbox{-0.06940336},\ \hbox{-0.09177689}\ ,\ 0.07868440,\ \hbox{-0.06577773}$

Figure 3: Equity curve for each asset









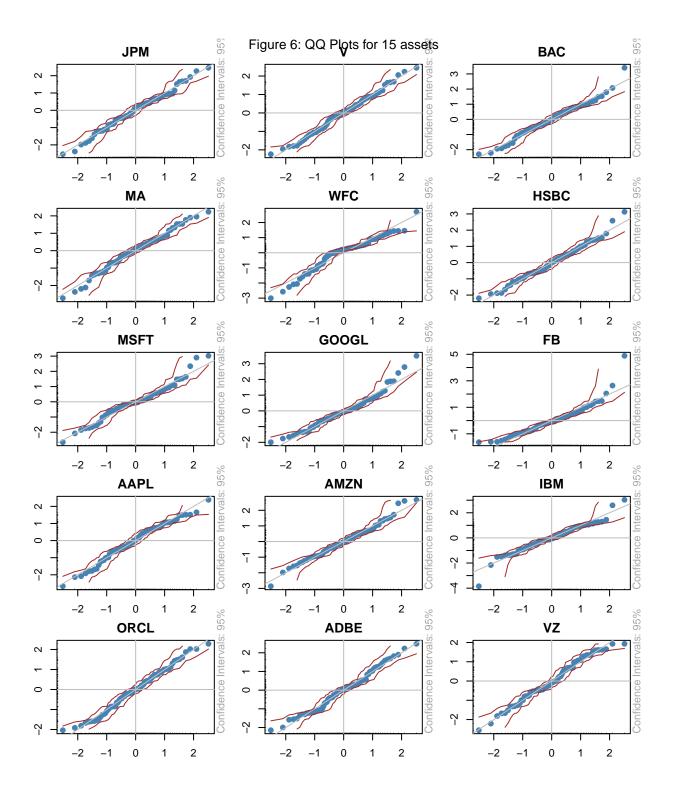


Table 4: Stationary Test Result

P.value	Result
0.010	JPM is Stationary
0.010	V is Stationary
0.019	BAC is Stationary
0.022	MA is Stationary
0.010	WFC is Stationary
0.043	HSBC is Stationary
0.010	MSFT is Stationary
0.010	GOOGL is Stationary
0.010	FB is Stationary
0.010	AAPL is Stationary
0.010	AMZN is Stationary
0.010	IBM is Stationary
0.021	ORCL is Stationary
0.015	ADBE is Stationary
0.010	VZ is Stationary

Table 5: Fit Distribution Result

names	AIC_t	AIC_standard.t	AIC_sstd	AIC_n	Choice
JPM	-236	-234	-225	-238	Normal
V	-276	-272	-265	-278	Normal
BAC	-188	-187	-179	-189	Normal
MA	-262	-261	-250	-264	Normal
WFC	-254	-254	-232	-253	T
HSBC	-249	-247	-245	-250	Normal
MSFT	-242	-242	-232	-238	T
GOOGL	-242	-242	-241	-239	T
FB	-170	-170	-172	-159	Skewed T
AAPL	-191	-188	-176	-193	Normal
AMZN	-182	-181	-178	-183	Normal
$_{\mathrm{IBM}}$	-232	-232	-225	-229	T
ORCL	-255	-249	-243	-257	Normal
ADBE	-232	-228	-225	-234	Normal
VZ	-268	-262	-259	-270	Normal

Figure 7: Pairwise Scatter plots

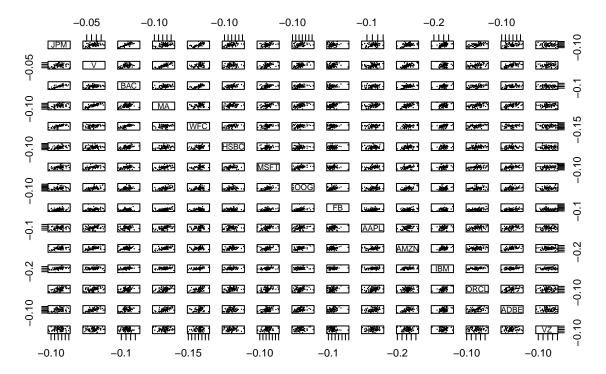


Table 6: Correction Matrix

	JPM	V	BAC	MA	WFC	HSBC	MSFT	GOOGL	FB	AAPL	AMZN	IBM	ORCL	ADBE	VZ
JPM	1.000	0.303	0.846	0.382	0.731	0.509	0.425	0.263	0.089	0.167	0.315	0.473	0.537	0.324	0.009
V	0.303	1.000	0.269	0.807	0.281	0.226	0.498	0.536	0.250	0.351	0.595	0.243	0.419	0.595	0.120
BAC	0.846	0.269	1.000	0.327	0.740	0.479	0.383	0.295	0.161	0.194	0.293	0.461	0.439	0.301	-0.055
MA	0.382	0.807	0.327	1.000	0.276	0.328	0.481	0.474	0.375	0.452	0.612	0.372	0.444	0.616	0.042
WFC	0.731	0.281	0.740	0.276	1.000	0.405	0.339	0.309	0.151	0.174	0.240	0.397	0.443	0.234	0.185
HSBC	0.509	0.226	0.479	0.328	0.405	1.000	0.351	0.233	0.232	0.047	0.387	0.322	0.354	0.200	0.081
MSFT	0.425	0.498	0.383	0.481	0.339	0.351	1.000	0.498	0.089	0.362	0.422	0.341	0.420	0.459	0.285
GOOGL	0.263	0.536	0.295	0.474	0.309	0.233	0.498	1.000	0.319	0.265	0.619	0.298	0.248	0.403	0.168
FB	0.089	0.250	0.161	0.375	0.151	0.232	0.089	0.319	1.000	0.262	0.326	0.164	0.310	0.369	-0.072
AAPL	0.167	0.351	0.194	0.452	0.174	0.047	0.362	0.265	0.262	1.000	0.335	0.240	0.418	0.399	0.085
AMZN	0.315	0.595	0.293	0.612	0.240	0.387	0.422	0.619	0.326	0.335	1.000	0.391	0.350	0.587	0.053
$_{\mathrm{IBM}}$	0.473	0.243	0.461	0.372	0.397	0.322	0.341	0.298	0.164	0.240	0.391	1.000	0.555	0.372	0.033
ORCL	0.537	0.419	0.439	0.444	0.443	0.354	0.420	0.248	0.310	0.418	0.350	0.555	1.000	0.429	0.033
ADBE	0.324	0.595	0.301	0.616	0.234	0.200	0.459	0.403	0.369	0.399	0.587	0.372	0.429	1.000	0.009
VZ	0.009	0.120	-0.055	0.042	0.185	0.081	0.285	0.168	-0.072	0.085	0.053	0.033	0.033	0.009	1.000

Table 7: Sample Covariance Matrix

	JPM	V	BAC	MA	WFC	HSBC	MSFT	GOOGL	FB	AAPL	AMZN	IBM	ORCL	ADBE	VZ
JPM	0.003	0.001	0.004	0.001	0.002	0.002	0.001	0.001	0.000	0.001	0.001	0.002	0.002	0.001	0.000
V	0.001	0.002	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.002	0.000
BAC	0.004	0.001	0.006	0.001	0.003	0.002	0.002	0.001	0.001	0.001	0.002	0.002	0.002	0.001	0.000
MA	0.001	0.002	0.001	0.002	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.001	0.001	0.002	0.000
WFC	0.002	0.001	0.003	0.001	0.003	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000
HSBC	0.002	0.001	0.002	0.001	0.001	0.003	0.001	0.001	0.001	0.000	0.002	0.001	0.001	0.001	0.000
MSFT	0.001	0.001	0.002	0.001	0.001	0.001	0.003	0.002	0.000	0.002	0.002	0.001	0.001	0.002	0.001
GOOGL	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.003	0.002	0.001	0.003	0.001	0.001	0.001	0.000
FB	0.000	0.001	0.001	0.002	0.001	0.001	0.000	0.002	0.009	0.002	0.002	0.001	0.001	0.002	0.000
AAPL	0.001	0.001	0.001	0.002	0.001	0.000	0.002	0.001	0.002	0.006	0.002	0.001	0.002	0.002	0.000
AMZN	0.001	0.002	0.002	0.002	0.001	0.002	0.002	0.003	0.002	0.002	0.006	0.002	0.001	0.003	0.000
$_{\mathrm{IBM}}$	0.002	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.004	0.002	0.001	0.000
ORCL	0.002	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.002	0.003	0.001	0.000
ADBE	0.001	0.002	0.001	0.002	0.001	0.001	0.002	0.001	0.002	0.002	0.003	0.001	0.001	0.003	0.000
VZ	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002

Figure 8: Portfolios (Short Sales Allowed)

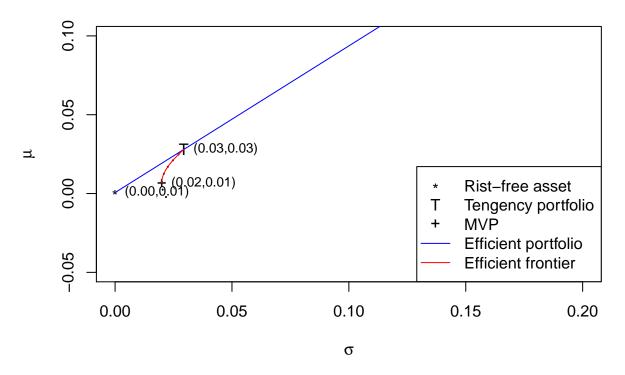


Figure 9: Portfolios (Short Sales Not Allowed)

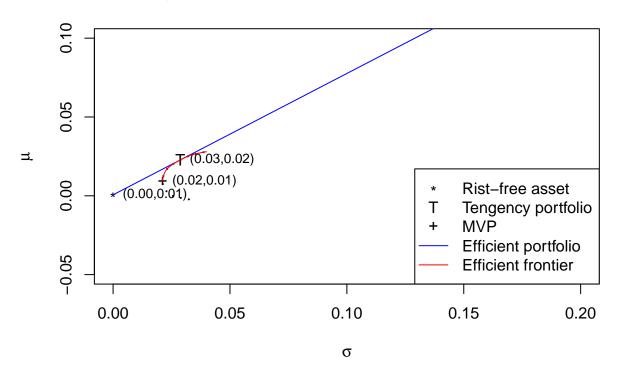


Table 8: Principal Components Loadings

	PC1	PC2	PC3	PC4	PC5
JPM	-0.293	-0.360	0.096	-0.006	0.206
V	0.354	-0.199	0.212	0.007	0.207
BAC	-0.288	-0.353	0.050	0.058	0.265
MA	0.341	-0.263	0.045	0.009	0.160
WFC	-0.337	-0.241	0.117	0.018	0.337
HSBC	-0.222	-0.214	0.066	0.420	-0.142
MSFT	0.112	-0.161	0.532	-0.257	-0.028
GOOGL	0.276	-0.093	0.310	0.286	-0.063
FB	0.197	-0.012	-0.534	0.348	0.134
AAPL	0.248	-0.030	-0.211	-0.523	0.262
AMZN	0.325	-0.224	0.111	0.275	-0.244
$_{\mathrm{IBM}}$	-0.122	-0.321	-0.099	-0.190	-0.710
ORCL	-0.054	-0.348	-0.235	-0.374	-0.152
ADBE	0.332	-0.244	-0.055	-0.069	-0.005
VZ	-0.066	0.404	0.366	-0.140	-0.088

Table 9: Factor Loadings

	Factor1	Factor2	Factor3	Factor4	Factor5
JPM	0.879	0.136	0.123	0.187	-0.023
V	0.126	0.494	0.842	0.128	0.094
BAC	0.912	0.151	0.094	0.065	-0.093
MA	0.203	0.607	0.548	0.154	0.001
WFC	0.783	0.074	0.133	0.133	0.174
HSBC	0.485	0.290	-0.001	0.124	0.064
MSFT	0.338	0.418	0.235	0.176	0.302
GOOGL	0.210	0.616	0.223	-0.016	0.191
FB	0.051	0.436	0.014	0.212	-0.105
AAPL	0.085	0.388	0.123	0.311	0.070
AMZN	0.182	0.782	0.204	0.073	0.039
$_{\mathrm{IBM}}$	0.419	0.362	-0.044	0.367	0.015
ORCL	0.363	0.236	0.168	0.883	0.012
ADBE	0.178	0.611	0.294	0.194	-0.026
VZ	0.025	0.015	0.033	0.005	0.861

Table 10: VaR and ES for Assets

Assets	VaR under Normal	ES under Normal	VaR under Nonparametric	ES under Nonparametric
JPM	7944	10359	8559	10644
V	5467	7368	5941	6704
BAC	10936	14159	11899	13906
MA	5849	7912	5969	8705
WFC	7934	10137	9856	11908
HSBC	9044	11282	8933	10453
MSFT	7212	9616	7587	9319
GOOGL	7665	10052	6537	7904
FB	12444	16307	10272	11588
AAPL	10706	13851	11805	14278
AMZN	10490	13834	9400	12829
$_{\mathrm{IBM}}$	10250	12797	8685	12911
ORCL	7693	9849	7512	8541
ADBE	6882	9344	6005	7563
VZ	7369	9364	7360	8992

Table 11: VaR and ES for Portfolios

Portfolios	VaR under Normal	ES under Normal	VaR under Nonparametric	ES under Nonparametric
MVP+Short Sale	3994	5172	4569	5843
Tangency+Short Sale	4043	5781	3457	6423
MVP+No Short Sale	4008	5260	3557	5622
Tangency+No Short Sale	4407	6104	4706	6194

Table 12: Assets SE and CIs under Normal Bootstraping

Assets	SE of VaR	SE of ES	CI of VaR	CI of ES
JPM	341	416	[6394,7725]	[8444,10056]
V	340	415	[1439,2763]	[2464,4065]
BAC	336	410	[12382, 13689]	[16044, 17637]
MA	336	410	[2213, 3510]	[3549, 5142]
WFC	336	410	[6375,7683]	[7999,9598]
HSBC	337	410	[8602,9895]	[10293,11880]
MSFT	336	409	[4934,6239]	[6964,8549]
GOOGL	335	408	[5848,7146]	[7839,9423]
FB	337	410	[15392, 16716]	[20336,21939]
AAPL	337	410	[11919, 13234]	[15430, 17029]
AMZN	337	409	[11483, 12796]	[15388, 16984]
$_{\mathrm{IBM}}$	333	406	[11006, 12314]	[13316,14914]
ORCL	334	406	[5900,7201]	[7433,9020]
ADBE	334	407	[4275, 5578]	[6419,8004]
VZ	334	406	[5249,6557]	[6454, 8044]

Table 13: Assets SE and CIs under Nonparametric Bootstraping

Assets	SE of VaR	SE of ES	CI of VaR	CI of ES
JPM	1730	1473	[5261,11828]	[8365,14072]
V	884	704	[5077,8429]	[5505,8400]
BAC	1897	1347	[8793, 17224]	[11829, 17197]
MA	1801	1440	$[2653,\!8053]$	[6207, 12063]
WFC	1766	1607	[7123, 13314]	[9164, 15427]
HSBC	1409	937	[7302,11520]	[9198,12884]
MSFT	1088	1380	[5664,10152]	[6277,11612]
GOOGL	815	809	[4846,7518]	[6156,9511]
FB	1613	905	[8509, 13870]	[10916, 14238]
AAPL	1663	1660	[9264, 16422]	[10152, 17390]
AMZN	1737	2670	[5951,13017]	[6853,17293]
$_{\mathrm{IBM}}$	1351	3543	[4563,9684]	[4212,17237]
ORCL	660	595	[6017,8865]	[7496,9707]
ADBE	1012	1148	[3414,7649]	[5473,9800]
VZ	1095	1244	[4930, 9286]	[6605,11404]

Table 14: Portfolios SE and CIs under Normal and Nonparametric Bootstraping

Portfolios	SE of VaR	SE of ES	CI of VaR	CI of ES
MVP+Normal+Short sale	558	639	[2986,5086]	[4017,6436]
MVP+Nonparametric+Short sale	975	786	[2901,6705]	[4626,7674]
Tangency+Normal+Short sale	810	964	[2534, 5652]	[4034,7673]
Tangency+Nonparametric+Short sale	1808	1642	[-1284,5300]	[4076,9781]
MVP+Normal+No Short sale	558	638	[2986, 5166]	[4085,6597]
MVP+Nonparametric+No Short sale	1061	882	[1000,4211]	[4207,7486]
Tangency+Normal+No Short sale	711	815	[3067, 5871]	[4572,7786]
Tangency+Nonparametric+No Short sale	923	985	[2394,6820]	[4378, 8123]