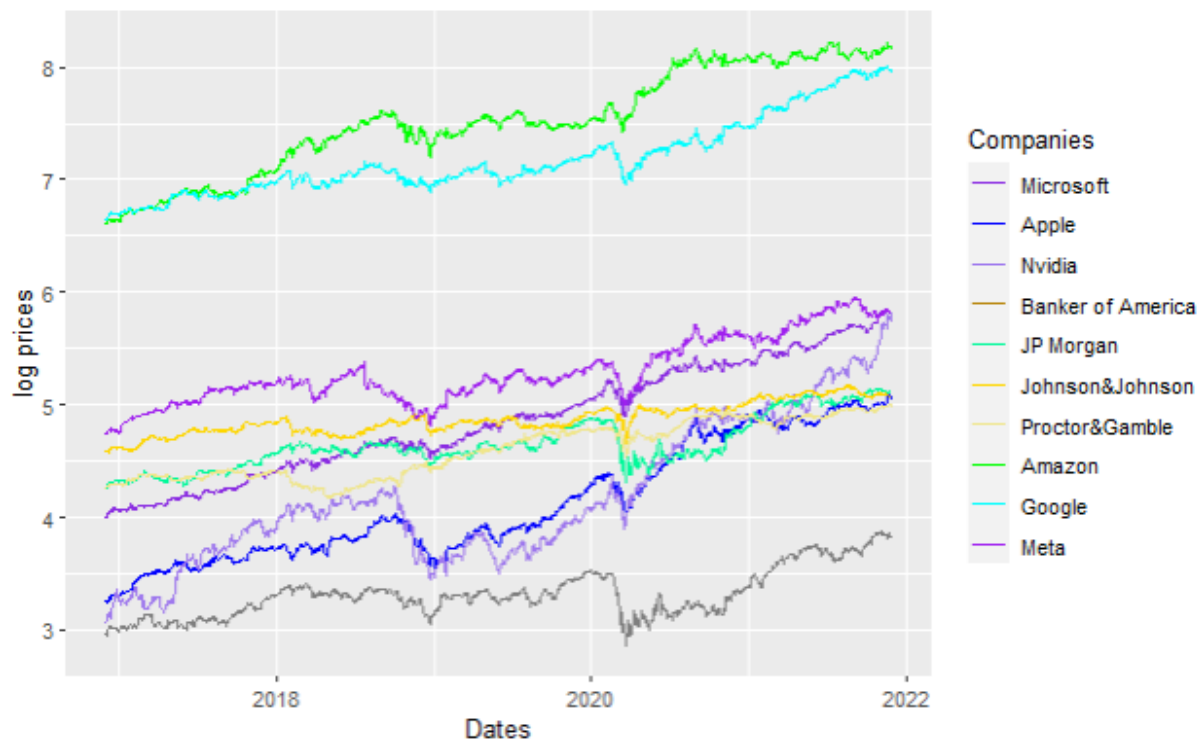


**ST326 Assessed Coursework**

**Candidate No: 26617**

## Question 1



Results:

- Condition Number for 5 Years = 51.39345
- Condition Number for 3 Years = 76.12069
- Condition Number for 1 Year = 78.73177

The condition number represents how much small changes can affect the change in covariance. Here, we can see that the condition number decreases for longer periods showing that the covariance is less sensitive to changes in returns. If the covariance is too high, the covariance matrix would be considered as 'ill conditioned'.

## Question 2

- Portfolio Weights Matrix:

The columns represent the weights for each stock respectively whereas the rows represent the n-th window.

	[.1]	[.2]	[.3]	[.4]	[.5]	[.6]	[.7]	[.8]	[.9]	[.10]
[1.]	0.0131046793	0.0166617761	-0.0022283697	0.01452710538	0.00778338505	-0.0038102723	0.0046111021	-0.0221237575	0.0091154315	0.0002565772
[2.]	-0.0003914665	-0.0120834804	0.0108734632	0.01264233919	-0.00968710731	0.0047779920	-0.0064526277	0.0146691413	0.0090304152	-0.0193024611
[3.]	0.0164694143	0.0046582166	-0.0137498960	-0.01874179703	0.01573704059	0.0020497205	0.0000972153	0.0019352272	-0.0063791942	0.0033924681
[4.]	-0.0024621490	-0.0028932106	0.0062800610	0.01375756435	-0.01603820903	0.0056150051	0.0007560620	0.0131721083	-0.0096960040	-0.0037720114
[5.]	0.0023556845	-0.0075969254	0.0084832171	0.00005161924	-0.00069809797	-0.0006347625	0.0107042915	0.0042363307	-0.0080650240	-0.0102443549
[6.]	0.013869495	0.0111275631	0.0022102621	0.01588962173	0.00047564622	-0.0027383091	-0.0203473666	0.0157611565	0.0089742439	-0.0271899957
[7.]	0.0109972630	0.0050586555	0.0182213534	-0.00064134989	0.00817206790	-0.0103959654	-0.0058502149	-0.0072197465	-0.0160650373	0.0120019633
[8.]	0.0121758685	0.0056930919	0.0045678253	-0.01528211501	-0.00303707222	0.0005045209	-0.0132870199	0.0181750139	0.0146789892	0.0071935016
[9.]	0.0107163654	-0.0126169137	-0.0008441502	0.00942521746	-0.00968388433	-0.0019846793	-0.0213180898	0.0228190232	0.0001535751	0.0055528753
[10.]	0.0043459018	-0.0077661285	-0.0013003946	0.00425547185	0.00866276540	-0.0042445228	0.0161123246	-0.0230425790	-0.0043484078	0.0089579017
[11.]	0.0122536247	0.0062512733	-0.0078014118	0.00084624329	0.00311771214	-0.0012545619	0.0114912506	0.0110702288	0.0076339934	0.0103049921
[12.]	0.0126670509	0.0048013310	0.0017038344	-0.01049800119	0.00265917790	-0.0081314342	-0.0111889473	0.0184841953	-0.0005045967	-0.0015460960
[13.]	0.0015766437	0.0060129381	-0.0165424710	0.00068856041	-0.00433923128	0.0036580561	-0.0087711344	0.0141322899	-0.0087125383	0.0081469215
[14.]	0.0098265563	0.0073719039	-0.0105940007	-0.01002515066	-0.00246695900	0.0025066402	0.0026977270	0.0057037928	0.0024891054	-0.0006804460
[15.]	0.0067616480	0.0029582324	0.0037117454	0.00002037467	-0.00183999733	0.0003510216	-0.0068787597	-0.0014852913	0.0141302283	0.0006676113
[16.]	0.0031956014	-0.0015902677	0.0025317787	-0.00424900412	-0.00176590092	0.0015509830	-0.0003593856	-0.0001032624	0.0025777747	-0.0019400927
[17.]	-0.0025813810	0.0045851048	0.0014282673	-0.00122831371	0.00058217915	0.0007481487	-0.0006451363	0.0007844097	-0.0011284362	-0.0011235594
[18.]	-0.0008239972	0.0003216216	0.0011283723	-0.00244759824	0.00005168046	0.0009906659	-0.0018550920	0.0018634173	-0.0029647138	0.0075187337
[19.]	-0.0086146259	-0.0004632579	0.0023953993	0.00477028684	-0.00247500713	0.0028562852	-0.0030871974	0.0053329764	-0.0039537416	0.0044717823
[20.]	-0.0003035721	0.0021496105	0.0027602380	0.00253966520	-0.00420746487	-0.0006530688	-0.0032824237	0.0039729836	0.0039610530	-0.0042105453
[21.]	0.0147300043	-0.0047113098	-0.0078152116	-0.00091306780	0.00502197974	-0.0007900742	0.0049684742	0.0017326769	-0.0045942088	-0.0006702737
[22.]	-0.0030067506	-0.0011071030	-0.0042959405	0.00560792359	-0.00003920303	0.0096308055	0.0099472349	-0.0127661569	0.0074826119	-0.0082174948
[23.]	0.0063296783	0.0041969099	-0.0026542746	0.00842716654	-0.00397183019	0.0019338251	-0.0010128548	0.0014063002	-0.0126359354	0.0077464892

- Actual Portfolio Returns Vector:

[1] 0.004302202 0.001676419 0.002790726 0.007936236 0.007451894 0.005214206 0.004590902 0.007079834 0.002402769 0.003051465 0.007030528 0.002319708  
 [13] 0.005911825 0.004853638 0.005210535 0.001088308 0.002376646 0.001618484 0.001475593 0.002376786 0.004216996 0.003102510 0.006084842

- Sharpe Ratio = 4.34264

## Question 3

	A	B	C	D	E	F
1	d_new	i_new	m_new	new_shar	AvsAchg	
2	30	60	2	4.836034	0.028142	
3	30	60	3	3.325047	0.056284	
4	30	60	4	2.578385	0.084425	
5	30	65	2	4.922616	0.026858	
6	30	65	3	3.948974	0.047389	
7	30	65	4	3.356544	0.06792	
8	30	70	2	4.642708	0.024928	
9	30	70	3	2.929735	0.041907	
10	30	70	4	2.119179	0.058885	
11	30	75	2	4.212516	0.024613	
12	30	75	3	2.784207	0.03967	
13	30	75	4	2.049487	0.054727	
14	30	80	2	3.217781	0.023292	
15	30	80	3	1.94976	0.035664	
16	30	80	4	1.382062	0.048036	
17	30	85	2	3.605403	0.025275	
18	30	85	3	1.524654	0.038888	
19	30	85	4	0.762779	0.0525	
20	30	90	2	3.771601	0.023662	
21	30	90	3	2.07799	0.034674	
22	30	90	4	1.27221	0.045686	
23	35	60	2	4.003627	0.029397	
24	35	60	3	2.36094	0.058793	
25	35	60	4	1.679112	0.08819	
26	35	65	2	4.725334	0.026631	
27	35	65	3	3.696043	0.047816	

d_new	i_new	m_new	new_sharpe_ratio	AvsAchg
30	60	2	4.836034191	0.028141756
30	60	3	3.325047102	0.056283512
30	60	4	2.57838546	0.084425268
30	65	2	4.922615779	0.026858037
30	65	3	3.948974285	0.047389018
30	65	4	3.356543986	0.06792
30	70	2	4.642708145	0.024928128
30	70	3	2.92973531	0.041906635
30	70	4	2.119179074	0.058885142
30	75	2	4.212515782	0.024613462
30	75	3	2.784206688	0.039670015
30	75	4	2.049486612	0.054726568
30	80	2	3.217780835	0.023292446
30	80	3	1.949759936	0.035664019
30	80	4	1.382062184	0.048035592
30	85	2	3.6054027	0.025275144
30	85	3	1.524653824	0.038887587
30	85	4	0.762779002	0.052500031
30	90	2	3.771601481	0.023662407
30	90	3	2.07799035	0.03467434
30	90	4	1.272210113	0.045686273

I have shown the first few combinations. I have 147 different combinations of parameters with the corresponding Sharpe ratio and average absolute change in portfolio weights which would be inconvenient to add to this document. However, I can provide the whole csv file and script upon request.

In my calculations for Sharpe ratio, I have used the actual returns as stated in the question sheet however I have seen Sharpe ratio calculated using excess return instead.

In practice, we want a smaller AvsAchg as this would mean we need to rebalance the portfolio less often as well as rebalance on a smaller scale. One of the reasons may be because rebalancing leads to costs through commissions and spreads involved when making trades.

Looking at the different combination of parameters and the corresponding values, I have noticed that lower m tends to lead to low AvsAchg whilst a greater value for both d and I leads to higher Sharpe ratio.

Since we want lower AvsAchg and higher Sharpe ratio, I believe the following achieves the best balance between Sharpe ratio and AvsAchg.

d = 55

i = 85

m = 2

Below, I have included a short section of the table when Sharpe ratio is in order from largest to smallest.

d_new	i_new	m_new	new_sharpe_ratio	AvsAchg
55	85	2	5.808097	0.027898
60	85	2	5.640041	0.03033
50	85	2	5.397259	0.026789
30	65	2	4.922616	0.026858
30	60	2	4.836034	0.028142
35	65	2	4.725334	0.026631
30	70	2	4.642708	0.024928
35	75	2	4.557116	0.025915
40	75	2	4.546796	0.029327
55	70	2	4.513191	0.032819
60	75	2	4.493631	0.033459
40	70	2	4.437361	0.029559
30	75	2	4.212516	0.024613
45	85	2	4.148544	0.027984
55	75	2	4.109265	0.031198
35	70	2	4.103069	0.026472

# Appendix

```
1
2
3 ----- Question 1 -----
4
5
6
7 ```{r}
8 library(quantmod)
9 library(ggplot2)
10 options(scipen = 1000000)
11
12 tickers = c("MSFT", "AAPL", "NVDA", "BAC", "JPM", "JNJ", "PG", "AMZN", "GOOGL", "FB")
13
14 for (ticker in tickers) {
15   getSymbols(ticker, from = "2016-12-1", to = "2021-11-30") # Extract date from last 5 years beginning first trading day of December 2016
16 }
17 date = index(MSFT)
18
19 # The following extracts just the adjusted closing price
20 MSFT <- (MSFT$MSFT.Adjusted)
21 AAPL <- (AAPL$AAPL.Adjusted)
22 NVDA <- (NVDA$NVDA.Adjusted)
23 BAC <- (BAC$BAC.Adjusted)
24 JPM <- (JPM$JPM.Adjusted)
25 JNJ <- (JNJ$JNJ.Adjusted)
26 PG <- (PG$PG.Adjusted)
27 AMZN <- (AMZN$AMZN.Adjusted)
28 GOOGL <- (GOOGL$GOOGL.Adjusted)
29 FB <- (FB$FB.Adjusted)
30
31 # Creating a data frame of the log of the prices for each stock for each day
32 log_prices <- data.frame(date, log(MSFT), log(AAPL), log(AMZN), log(GOOGL), log(FB), log(NVDA), log(BAC), log(JPM), log(JNJ), log(PG))
33
34 ggplot()+
35   geom_line(log_prices, mapping = aes(x=date, y=MSFT.Adjusted, color="Microsoft"))+
36   geom_line(log_prices, mapping = aes(x=date, y=AAPL.Adjusted, color="Apple"))+
37   geom_line(log_prices, mapping = aes(x=date, y=NVDA.Adjusted, color="Nvidia"))+
38   geom_line(log_prices, mapping = aes(x=date, y=BAC.Adjusted, color="Bank of America"))+
39   geom_line(log_prices, mapping = aes(x=date, y=JPM.Adjusted, color="JP Morgan"))+
40   geom_line(log_prices, mapping = aes(x=date, y=JNJ.Adjusted, color="Johnson&Johnson"))+
41   geom_line(log_prices, mapping = aes(x=date, y=PG.Adjusted, color="Proctor&Gamble"))+
42   geom_line(log_prices, mapping = aes(x=date, y=AMZN.Adjusted, color="Amazon"))+
43   geom_line(log_prices, mapping = aes(x=date, y=GOOGL.Adjusted, color="Google"))+
44   geom_line(log_prices, mapping = aes(x=date, y=FB.Adjusted, color="Meta"))+
45   scale_color_manual(name = "Companies", values = c("Microsoft" = "blueviolet", "Apple" = "blue", "Nvidia" = "mediumpurple2", "Banker of America" = "darkgoldenrod", "JP Morgan" = "mediumspringgreen", "Johnson&Johnson" = "Gold", "Proctor&Gamble" = "Khaki", "Amazon" = "Green", "Google" = "cyan", "Meta" = "purple")) +
46   labs(x='Dates', y='log prices')
47
48 # Calculating the log returns for each day
49 MSFT_r <- diff(log(MSFT),1)
50 AAPL_r <- diff(log(AAPL),1)
51 AMZN_r <- diff(log(AMZN),1)
52 GOOGL_r <- diff(log(GOOGL),1)
53 FB_r <- diff(log(FB),1)
54 NVDA_r <- diff(log(NVDA),1)
55 BAC_r <- diff(log(BAC),1)
56 JPM_r <- diff(log(JPM),1)
57 JNJ_r <- diff(log(JNJ),1)
58 PG_r <- diff(log(PG),1)
59
60 # Creating a data frame for the log returns
61 returns <- data.frame(MSFT_r, AAPL_r, AMZN_r, GOOGL_r, FB_r, NVDA_r, BAC_r, JPM_r, JNJ_r, PG_r)
62 returns <- returns[-c(1),] # Removes first row since we do not have log returns for the first day of the dataset
63
64 # Calculating covariance matrix of the returns
65 cov_returns <- cov(returns)
66
67 # Calculating eigenvalues of the covariance
68 ev_returns <- eigen(cov_returns)
69
70 # Calculating condition number
71 condition_No <- abs(max(ev_returns$values)/min(ev_returns$values))
72
73 # Saving the the dates as a csv so that I can use this to identify the index number of certain dates
74 write.csv(date, "C:\\Users\\antho\\OneDrive\\Documents\\LSE\\YEAR 3\\ST326\\Coursework\\dates.csv", row.names = FALSE)
75
76 # Using the csv above, I found the index number for 2018-12-03, which is the first trading in December 2018
77 # The following calculates the condition number using only the past 3 years of data
78 startdate3 = date[505]
79 returns_3 <- returns[505:1256,]
80 cov_returns3 <- cov(returns_3)
81 ev_returns3 <- eigen(cov_returns3)
82 condition_No3 <- abs(max(ev_returns3$values)/min(ev_returns3$values))
83
84 startdate1 = date[1007]
85 returns_1 <- returns[1007:1256,]
86 cov_returns1 <- cov(returns_1)
87 ev_returns1 <- eigen(cov_returns1)
88 condition_No1 <- abs(max(ev_returns1$values)/min(ev_returns1$values))
89
90 ```
```

```

91
92
93 ----- Question 2 -----
94
95
96 I am first gonna define a function which carries out the one-fund theorem.
97
98 ```{r}
99
100 function1 <- function(x,y,z){
101
102   returns_window <- returns[z:x,]
103   meanReturns_window <- colMeans(returns_window)
104   covariance_window <- cov(returns_window)
105   bondyields_window <- bondyields[z:x]
106   meanYield <- mean(bondyields_window)
107   target_return <- m*meanYield
108
109   # Now applying the formula to calculate the market portfolio weighting, page 70 of lecture notes
110   excess_returns = meanReturns_window - (meanYield*one_col)
111   excess_returns = as.vector(excess_returns)
112
113   inv_covariance_window = solve(covariance_window)
114
115   numerator_mkt = inv_covariance_window %% excess_returns
116   denominator_mkt = (one_row%%inv_covariance_window)%%excess_returns
117
118   denominator_mkt <- as.numeric(denominator_mkt)
119   mkt_weights = numerator_mkt/denominator_mkt
120
121   # Applying formula to calculate optimal portfolio weights, page 70 of lecture notes
122   numerator_opt = (target_return - meanYield)*(denominator_mkt)
123   denominator_opt = t(excess_returns) %% numerator_mkt
124
125   opt_weights = mkt_weights %% (numerator_opt/denominator_opt)
126   bond_weight = 1 - sum(opt_weights)
127
128   # Calculating the actual return of the portfolio after the 50 days
129   returns_mat <- as.matrix(returns)
130   portfolio_returns = sum(returns_mat[x:y,] %% opt_weights) + sum(bond_weight*bondyields[x:y])
131
132   results_matrix[1] <- target_return
133   results_matrix[2] <- portfolio_returns
134   new <- append(results_matrix, t(opt_weights), after = 2)
135   return(new)
136 }
137
138 ```
139
140 Now computing carrying out the one-fund theorem for specific parameters.
141
142 ```{r}
143 bondyields <- read.csv("bondyield.csv")
144 bondyields <- bondyields[bondyields$Adj.Close != "null",]
145 bondyields <- (bondyields$Adj.Close)
146 bondyields <- as.numeric(bondyields)
147 bondyields <- bondyields/25200
148
149 results_matrix <- c()
150
151 one_row <- c(1,1,1,1,1,1,1,1,1,1)
152 one_col <- t(one_row)
153
154 t = 100
155 d = 60
156 m = 2
157 i = 50
158
159 No_sets = floor((NROW(bondyields)-t)/i)
160
161 result1 <- matrix(data = NA, nrow= No_sets, ncol=12)
162
163 # Calculating for the first window
164 result1[1,] <- function1(t,t+i,t-d+1)
165
166 # Calculating for the second window
167 result1[2,] <- function1(t+i,t+2*i,t+i-d+1)
168
169 # Calculating for the remaining windows
170 for (k in (3:No_sets)) {
171   start_date = t + (k-1)*i
172   end_date = start_date + i
173   w = start_date - d + 1
174   result1[k,] <- function1(start_date, end_date, w)
175 }
176
177 # Extracting appropriate data from the result matrix
178 target_returns <- result1[,1]
179 actual_returns <- result1[,2]
180 portfolio_weights <- result1[,3:12]
181
182 mean_returns = mean(actual_returns)
183 vol_returns = sd(actual_returns)
184 sharpe_ratio = (mean_returns/vol_returns) * sqrt(250/i)
185
186
187 ```

```

```

188
189
190
191 ----- Question 3 -----
192
193
194
195 ```{r}
196
197 # Pre-defining vectors to store Sharpe Ratios and AvsAchg
198 new_sharpe_ratio <- c()
199 AvsAchg <- c()
200
201 # Created an intermediate to store the values of the sum of absolute change in portfolio weight for each time period. Then I can sum each time period to find
202 AvsAchg
203 intermediate <- c()
204
205 a=1
206
207 # Defining combinations of parameters
208 d_new = c(30,35,40,45,50,55,60)
209 i_new = c(60,65,70,75,80,85,90)
210 m_new = c(2,3,4)
211
212 # Created embedded for loops to compute Sharpe Ratios and AvsAchg for each combination of parameters
213 for (u in d_new) {
214   for (p in i_new) {
215     for (o in m_new) {
216
217       t_new = u
218       m=o
219       No_sets = floor((NROW(bondyields) - t_new)/p)
220
221       # Pre-defining vectors and matrices to store values from the function
222       new_actual_returns <- c()
223       new_portfolio_weights <- matrix(0,nrow = No_sets, 10)
224       result1 <- matrix(data = NA, nrow= No_sets, ncol=12) # This will store target return, actual return, and portfolio weights
225
226       for (k in (1:No_sets)) {
227         start_date = t_new + (k-1)*p
228         end_date = start_date + p
229         w = start_date - u + 1
230
231         # Calling function with the new parameters
232         result1[k,] <- function1(start_date, end_date, w)
233
234         new_actual_returns[k] <- result1[k,2]
235         new_portfolio_weights[k,] <- result1[k,3:12]
236       }
237
238       # Following for loop adds the sum of absolute change for each time period to a vector
239       for (k in (2:No_sets)) {
240         intermediate[k-1] = sum(abs(new_portfolio_weights[k,]-new_portfolio_weights[k-1,]))
241       }
242
243       new_sharpe_ratio[a] = (mean(new_actual_returns)/sd(new_actual_returns)) * sqrt(250/i)
244       AvsAchg[a] = (1/p) * sum(intermediate)
245
246       a = a+1
247     }
248   }
249 }
250
251 # The following creates a table of the different combinations of parameters and the corresponding sharpe ratio
252 library(data.table)
253 sharpe_ratio_table = cbind(CJ(d_new, i_new, m_new), new_sharpe_ratio, AvsAchg)
254 write.csv(sharpe_ratio_table,"C:\\Users\\antho\\OneDrive\\Documents\\LSE\\YEAR 3\\ST326\\Coursework\\FinalResults.csv", row.names = FALSE)
255
256 ```

```