Application of R for Finance - Assignment 2

Stocks Return Analysis and Fama-French 3 Model

Group 30

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Data Preparation

Required libraries

Load the following libraries for data analysis and visualisation.

```r
library(dplyr)
library(lubridate)
library(ggplot2)
```

Data Frame

Load the dataset **sp500__2023__2024.csv** into a data frame.

This dataset contains company identifiers, trading information, and classification codes. List below summarises the main variables.

```r
# load the data
data <- read.csv("sp500_2023_2024.csv")
```

```r
# remove any rows with NA values in the prcod column
data <- data %>%
  filter(!is.na(prcod))
```

```r
# inspect the strucutre
head(data)
```

A data.frame: 6 × 11

	tic <chr>	datadate <chr>	conm <chr>	exchg <int>	sic <int>	cshtrd <dbl>	prccd <dbl>	prchd <dbl>	prcld <dbl>	prcod <dbl>	gvkey <int>
1	PNW	03/01/2023	PINNACLE WEST CAPITAL CORP	11	4911	1442534	74.63	76.4125	73.380	76.25	1075

	tic <chr>	datadate <chr>	conm <chr>	exchg <int>	sic <int>	cshtrd <dbl>	prccd <dbl>	prchd <dbl>	prcld <dbl>	prcod <dbl>	gvkey <int>
2	PNW	04/01/2023	PINNACLE WEST CAPITAL CORP	11	4911	954218	75.39	76.0950	74.630	75.10	1075
3	PNW	05/01/2023	PINNACLE WEST CAPITAL CORP	11	4911	994775	73.65	75.0950	73.305	74.88	1075
4	PNW	06/01/2023	PINNACLE WEST CAPITAL CORP	11	4911	729808	75.46	76.0200	74.480	74.49	1075
5	PNW	09/01/2023	PINNACLE WEST CAPITAL CORP	11	4911	656127	75.55	76.4800	75.240	75.24	1075
6	PNW	10/01/2023	PINNACLE WEST CAPITAL CORP	11	4911	763254	75.65	75.6950	74.880	75.31	1075

Part I - Q&A

In the first section, we interrogate the data following the Assignment Specification.

Q1 - Unique tickers

```
# indentify the amount of unique tickers
length(unique(data$tic))
print(paste("There are", length(unique(data$tic)), "unique tickers"))
```

502

```
[1] "There are 502 unique tickers"
```

Q2 - Unique companies

```
# indentify the amount of unique companies
length(unique(data$conm))
print(paste("There are", length(unique(data$conm)), "unique companies"))
```

499

```
[1] "There are 499 unique companies"
```

Q3 - Top 5 Mean Trading Volume Companies

```
# indentify the top 5 companies by largest mean trading volume
top_5_volume <- data %>%
  group_by(conm) %>%
  summarize(mean_volume = mean(cshtrd, na.rm = TRUE)) %>%
  arrange(desc(mean_volume)) %>%
  slice_head(n = 5)

# display in a table
top_5_volume
```

A tibble: 5 × 2

conm <chr>	mean_volume <dbl>
TESLA INC	115314383
NVIDIA CORP	113131835
PALANTIR TECHNOLOG INC	60056251
APPLE INC	57736403
ADVANCED MICRO DEVICES	57143415

Q4 - Top 3 Total Trading Volume Exchanges

```r
# indentify the top 3 exchanges by total largest total trading volume
top_3_exchanges <- data %>%
  group_by(exchg) %>%
  summarize(total_volume = sum(cshtrd, na.rm = TRUE)) %>%
  arrange(desc(total_volume)) %>%
  slice_head(n = 3)

# display in a table
top_3_exchanges
```

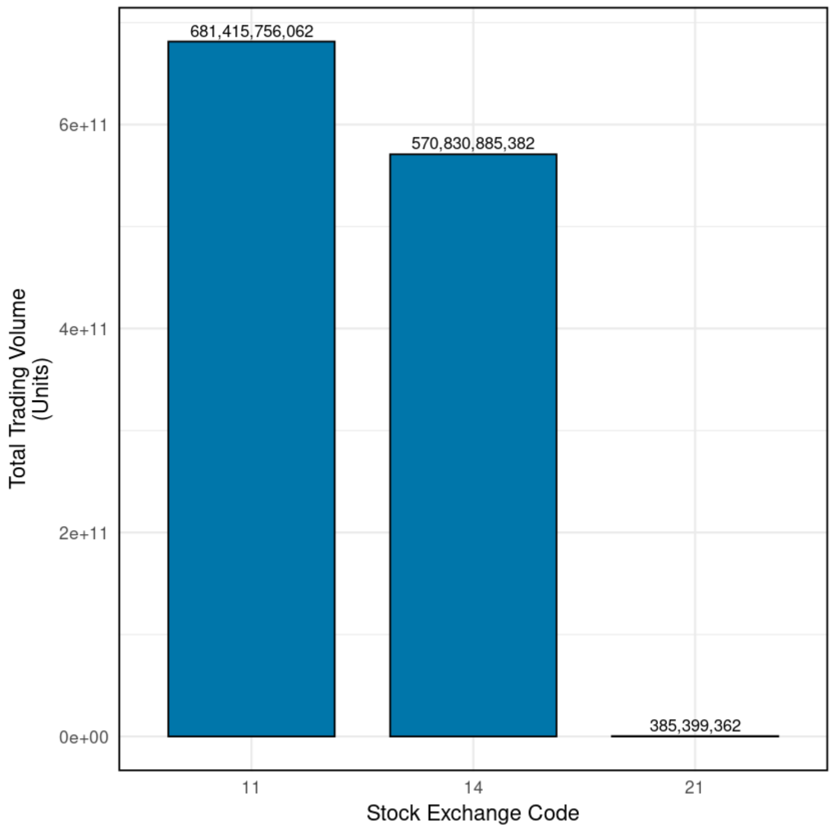
A tibble: 3 × 2

exchg <int>	total_volume <dbl>
11	681415756062
14	570830885382
21	385399362

Q5 - Visualisation of Top 3 Total Trading Volume Exchanges

```r
# display in a bar plot
ggplot(top_3_exchanges, aes(x = as.factor(exchg), y = total_volume)) +
  geom_col(width = 0.75, fill = "#0076AA", color = "black") +
  geom_text(aes(label = scales::comma(total_volume)), vjust = -0.4, size = 3.5) +
  labs(x = "Stock Exchange Code", y = "Total Trading Volume\n(Units)") +
  theme_minimal(base_size = 13) +
  theme(panel.border = element_rect(color = "black", fill = NA, size = 1))
```

Figure 1: Top 3 Exchanges by Total Trading Volume



Q6 - Companies with More Than One Ticker

```
# indentify companies have more than one ticker
ticker_counts <- data %>%
  group_by(conm) %>%
  summarize(ticker_count = n_distinct(tic)) %>%
  filter(ticker_count > 1)

# display the result
ticker_counts
```

A tibble: 3 × 2

conm <chr>	ticker_count <int>
ALPHABET INC	2
FOX CORP	2
NEWS CORP	2

Q7 - Ticker with the Largest Positive Mean Return

```
# indentify the ticker with the largest positive mean return (simple daily return)
mean_returns <- data %>%
  group_by(tic) %>%
  mutate(ret = (prccd - lag(prccd)) / lag(prccd)) %>%
  summarize(mean_return = mean(ret, na.rm = TRUE)) %>%
  arrange(desc(mean_return)) %>%
  slice_head(n = 1)

# display the resuly
mean_returns
```

A tibble: 1 × 2

tic <chr>	mean_return <dbl>
PLTR	0.005785119

Q8 - Company with the Largest Positive Mean Return

```
# indentify the company with the largest positive mean return (simple daily return)
mean_returns_company <- data %>%
  group_by(conm) %>%
  mutate(ret = (prccd - lag(prccd)) / lag(prccd)) %>%
  summarize(mean_return = mean(ret, na.rm = TRUE)) %>%
  arrange(desc(mean_return)) %>%
  slice_head(n = 1)

# display the result
mean_returns_company
```

A tibble: 1 × 2

conm <chr>	mean_return <dbl>
PALANTIR TECHNOLOG INC	0.005785119

Q9 - Industry Represented by the Most Companies

```
# indentify the industry is represented by the most companies
industry_counts <- data %>%
  group_by(sic) %>%
  summarize(company_count = n_distinct(conm)) %>%
  arrange(desc(company_count)) %>%
  slice_head(n = 1)

# display the result
industry_counts
```

A tibble: 1 × 2

sic <int>	company_count <int>
6798	28

Part II - Extended Analysis

In the second section, we first calculate the weekly returns with following formulas to carry out the extended analysis. After categorising the data into decile groups, a specific security is picked for further analysis.

$$R_{\text{weekly}} = \frac{P_t - P_{t-1}}{P_{t-1}}$$

where:

- R_{weekly} = Simple weekly return
- P_t = Closing price at the end of the current week
- P_{t-1} = Closing price at the end of the previous week

Q1 - Weekly Returns

```r
# calculate the simple weekly returns
weekly_returns <- data %>%
  mutate(datadate = as.Date(datadate, format = "%d/%m/%Y")) %>%
  group_by(tic) %>%
  arrange(datadate) %>%
  mutate(Week = floor_date(datadate, unit = "week")) %>%
  group_by(tic, Week) %>%
  summarise(Weekly_Close = last(prccd)) %>%
  arrange(tic, Week) %>%
  mutate(Weekly_Return = (Weekly_Close / lag(Weekly_Close)) - 1) %>%
  ungroup()
```

Q2 - Decile Classification

```r
# categorise data into decile groups, labelled 0%, 10%, 20%, ...
quantile_result <- weekly_returns %>%
  mutate(
    deciles = cut(
      Weekly_Return,
      breaks = quantile(
        Weekly_Return,
        probs = c(0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1),
        type = 5,
        na.rm = TRUE
      ),
      include.lowest = TRUE,
      labels = c("0%", "10%", "20%", "30%", "40%", "50%", "60%", "70%", "80%", "90%")
    )
  )

# display the result
head(quantile_result)
```

A tibble: 6×5

tic <chr>	Week <date>	Weekly_Close <dbl>	Weekly_Return <dbl>	deciles <fct>
A	2023-01-01	147.67	NA	NA
A	2023-01-08	156.92	0.062639670	90%
A	2023-01-15	155.92	-0.006372674	30%
A	2023-01-22	155.69	-0.001475115	40%
A	2023-01-29	154.55	-0.007322243	30%
A	2023-02-05	152.55	-0.012940796	30%

Q3 - Top Ticker in each Decile Group

```r
# identify the top ticker in each decile group
top_tickers <- quantile_result %>%
  group_by(deciles) %>%
  filter(Weekly_Return == max(Weekly_Return)) %>%
  select(deciles, tic, Weekly_Return) %>%
  arrange(deciles)

# display the result in a table
top_tickers
```

A grouped_df: 11 × 3

deciles <fct>	tic <chr>	Weekly_Return <dbl>
0%	DVN	-0.041509434
10%	FDS	-0.024781950
20%	CNC	-0.014084507
20%	TRMB	-0.014084507
30%	NWS	-0.005443235
40%	CDNS	0.002281542
50%	AIG	0.010124311
60%	HLT	0.018477517
70%	RL	0.029158383
80%	SJM	0.046984764
90%	SMCI	0.784176534

Q4 - Ticker Selection from 60% Decile Group

Here, we select the **top ticker** from 60% decile group for the following analysis.

```
# display the top ticker in 60% decile group
top_60_ticker <- top_tickers %>%
  filter(deciles == "60%")
print(top_60_ticker$tic)
```

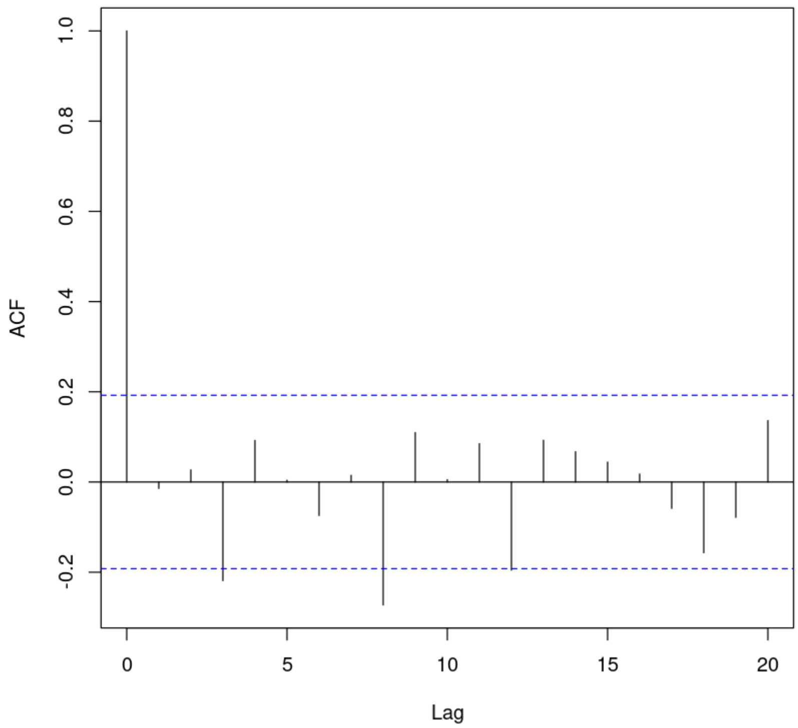
```
[1] "HLT"
```

Q5 - Autocorrelation Anlysis

```
# plot the autocorrelation function for HLT's entire set of weekly returns
wdc_data <- weekly_returns %>%
  filter(tic == "HLT") %>%
  na.omit()

# Autocorrelate
acf(wdc_data$Weekly_Return, main="")
```

Figure 2: Autocorrelation HLT Weekly Returns



Part III - Fama-French 3 Factor Model

In the last section, we first load and clean the the **fama_french_weekly.csv** to provide the weekly Fama-French 3 factors for modelling. Next, the selected ticker **HLT** is fitted the Fama-French 3 factor model.

```
# load and clean the data
fama_french_data <- read.csv("fama_french_weekly.csv", skip=4)
fama_french_data$datadate <- as.Date(as.character(fama_french_data$X), format="%Y%m%d")
fama_french_data <- select(fama_french_data, datadate, Mkt.RF, SMB, HML, RF)
```

```
# for each column except datadate, divided by 100 to convert to decimal format
fama_french_data <- fama_french_data %>%
  mutate(across(-datadate, ~ . / 100))
```

```
fama_french_data %>%
    filter(datadate >= as.Date("2023-01-01")) %>%
    slice(1)

rearrange_wdc_data <- data %>%
  filter(tic == "HLT") %>%
  mutate(datadate = as.Date(datadate, format = "%d/%m/%Y")) %>%
  arrange(datadate)

# calculate the weekly returns for WDC and make sure the datadate is aligned with Fama-Frenc
rearrange_wdc_data <- rearrange_wdc_data %>%
  mutate(Week = floor_date(datadate, unit = "week", week_start = 5)) %>%
  group_by(Week) %>%
  summarise(Weekly_Close = last(prccd)) %>%
  arrange(Week) %>%
  mutate(Weekly_Return = (Weekly_Close / lag(Weekly_Close)) - 1) %>%
  na.omit()

# display the data
head(rearrange_wdc_data)
```

A data.frame: 1 × 5

datadate <date>	Mkt.RF <dbl>	SMB <dbl>	HML <dbl>	RF <dbl>
2023-01-06	0.0137	0.0027	0.0125	9e-04

A tibble: 6 × 3

Week <date>	Weekly_Close <dbl>	Weekly_Return <dbl>
2023-01-06	135.00	0.0643330180
2023-01-13	135.06	0.0004444444
2023-01-20	144.06	0.0666370502
2023-01-27	147.09	0.0210329030
2023-02-03	150.80	0.0252226528
2023-02-10	148.28	-0.0167108753

```
# merge the data
merged_data <- merge(rearrange_wdc_data, fama_french_data, by.x = "Week", by.y = "datadate")
```

```r
# display the merged data
head(merged_data)
```

A data.frame: 6 × 7

	Week <date>	Weekly_Close <dbl>	Weekly_Return <dbl>	Mkt.RF <dbl>	SMB <dbl>	HML <dbl>	RF <dbl>
1	2023-01-06	135.00	0.0643330180	0.0137	0.0027	0.0125	9e-04
2	2023-01-13	135.06	0.0004444444	0.0302	0.0337	-0.0324	9e-04
3	2023-01-20	144.06	0.0666370502	-0.0069	0.0012	-0.0115	9e-04
4	2023-01-27	147.09	0.0210329030	0.0257	-0.0009	-0.0122	9e-04
5	2023-02-03	150.80	0.0252226528	0.0181	0.0354	-0.0199	9e-04
6	2023-02-10	148.28	-0.0167108753	-0.0149	-0.0320	0.0266	9e-04

```r
# calculate excess returns
merged_data <- merged_data %>%
  mutate(Excess_Return = Weekly_Return - Mkt.RF)
```

```r
# model fitting
model <- lm(Excess_Return ~ Mkt.RF + SMB + HML, data = merged_data)
summary(model)
```

```

Call:
lm(formula = Excess_Return ~ Mkt.RF + SMB + HML, data = merged_data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.061769 -0.021092  0.001118  0.017433  0.063231 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)  
(Intercept)  0.006137   0.002632   2.332   0.0217 *
```

```
Mkt.RF      -0.760352   0.152090  -4.999 2.52e-06 ***
SMB         -0.123988   0.172396  -0.719   0.4737
HML          0.080787   0.153443   0.526   0.5997
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02573 on 98 degrees of freedom
Multiple R-squared:  0.2763,    Adjusted R-squared:  0.2541
F-statistic: 12.47 on 3 and 98 DF,  p-value: 5.642e-07
```

Analysis Report

This report applied R-based analysis to stock returns and Fama-French 3 factor model.