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.

```
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.

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

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

```
# 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

```r
# identify 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

```r
# identify 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

```r
# identify 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

```
# identify 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
```

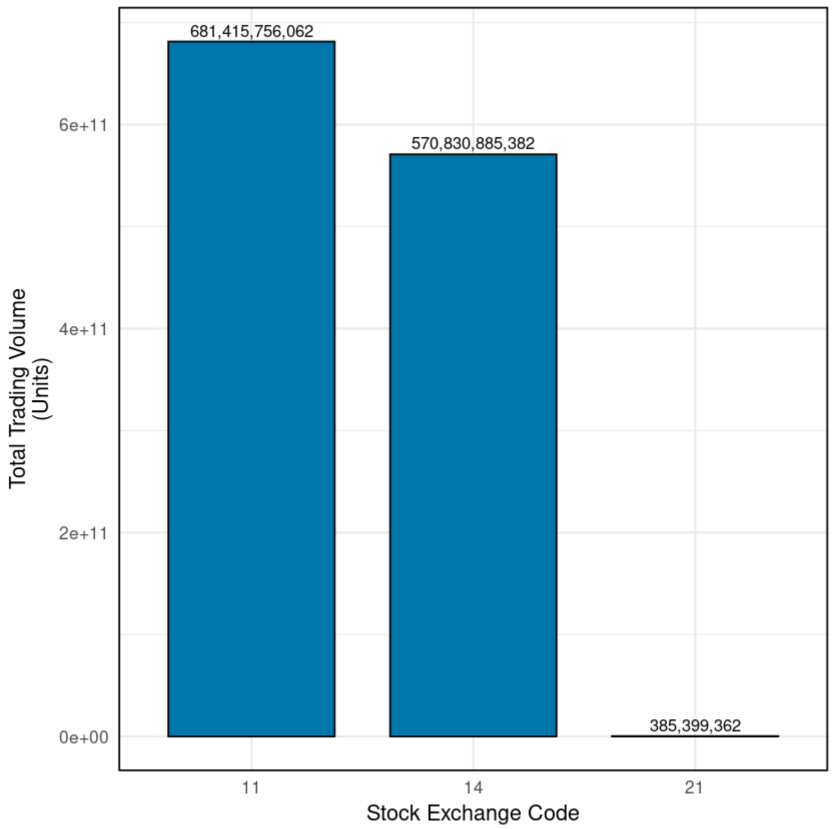
A tibble: 3 × 2

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

Q5 - Visualisation of Top 3 Total Trading Volume Exchanges

```
# 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

```
# identify 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

```
# identify 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

```
# identify 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

```
# identify 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

```
# 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

```
# 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

```
# 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.

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

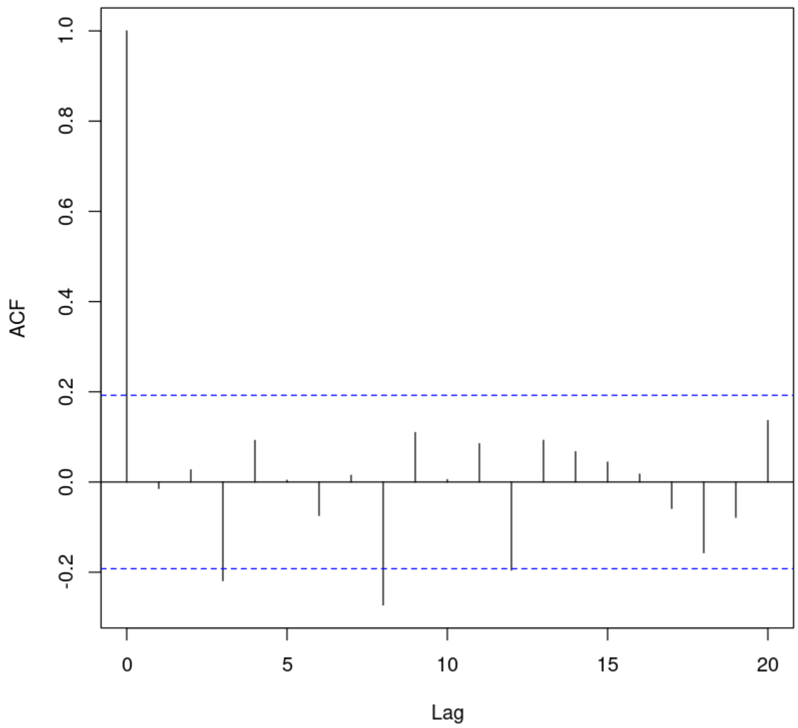
```
[1] "HLT"
```

Q5 - Autocorrelation Anlysis

```r
# 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))
```

```r
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

```r
# 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	0.0210329033	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 (ChatGPT-AI written)

The extended analysis evaluates the performance characteristics of **Hilton Worldwide Holdings (HLT)** within the broader S&P 500 context, highlighting its relative positioning, risk exposures, and return dynamics.

The **decile results** first show a markedly skewed return distribution, where only a few firms deliver exceptionally high weekly gains. HLT, situated in the 60 per cent decile, exemplifies a moderately performing stock with consistent but not extreme returns. The autocorrelation function confirms that its weekly returns exhibit no meaningful serial dependence, indicating that price movements are largely random and efficiently reflect available information.

In the **Fama–French 3 factor model**, HLT displays a significantly negative market beta (–0.76, $p < 0.001$), underscoring its defensive nature and resilience during market downturns. The size (SMB) and value (HML) loadings are insignificant, suggesting that HLT's performance is not systematically influenced by these risk factors. The adjusted R^2 of 0.25 implies that most of its variation arises from idiosyncratic firm characteristics rather than macro factors. Importantly, the positive alpha of 0.61 per cent per week indicates sustained abnormal returns, pointing to potential market undervaluation or superior operational efficiency.

Taken together, these findings portray HLT as a stable, defensive equity delivering moderate but reliable performance, whose excess returns may stem from firm-specific strengths beyond the scope of traditional risk-factor models.