Homework 3

Group Members: Yash Shah, Zheng Wan and Larry Sang

Load Libraries

In [ ]:
```
import numpy as np
import pandas as pd
import yfinance as yf
import datetime
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

Download Stock Adj.Close Data

In [ ]:
```
def fetch_sp500_data(start_date, end_date):
    def get_sp500_tickers():
        table = pd.read_html('https://en.wikipedia.org/wiki/List_of_S%26P_500_companies')
        sp500 = table[0]
        tickers = sp500['Symbol'].tolist()
        tickers = [ticker.replace('.', '-') for ticker in tickers]
        return tickers

    def download_data(tickers, start_date, end_date):
        try:
            data = yf.download(tickers, start=start_date, end=end_date)['Adj Close']
            return data
        except Exception as e:
            print(f"Failed to download data: {e}")
            return None

    tickers = get_sp500_tickers()
    return download_data(tickers, start_date, end_date)

start_date = '2010-01-01'
end_date = datetime.date.today().strftime('%Y-%m-%d')

sp500_data = fetch_sp500_data(start_date, end_date)
if sp500_data is not None:
    sp500_data.head()
```

```
[*********************100%%**********************]  503 of 503 completed
```

In [ ]:
```
sp500_data.head()
```

Out[ ]:

Ticker	A	AAL	AAPL	ABBV	ABNB	ABT	ACGL	ACN	ADBE	ADI	...	
Date												
2010-01-04	20.122227	4.496876	6.461976	NaN	NaN	18.952160	7.994444	32.212471	37.090000	22.530378	...	52.8
2010-01-05	19.903643	5.005957	6.473149	NaN	NaN	18.799036	7.967778	32.411549	37.700001	22.494810	...	52.7
2010-01-06	19.832928	4.798553	6.370184	NaN	NaN	18.903440	7.933333	32.756104	37.619999	22.452120	...	53.6
2010-01-07	19.807215	4.939965	6.358407	NaN	NaN	19.060047	7.886667	32.725479	36.889999	22.274269	...	53.4
2010-01-08	19.800795	4.845691	6.400682	NaN	NaN	19.157484	7.871111	32.595314	36.689999	22.402321	...	53.3

5 rows × 503 columns

Calculate log returns

In [ ]:

```
def calculate_log_returns(data):
    """
    Calculate log returns directly from the adjusted close prices.
    """
    log_prices = np.log(data)  # Calculate the natural logarithm of the adjusted close prices
    log_returns = np.diff(log_prices, axis=0) * 100  # Calculate the difference between successive
    log_returns = np.vstack([np.zeros(data.shape[1]), log_returns])  # Append zeros for the first 

    return pd.DataFrame(log_returns, index=data.index, columns=data.columns)

if sp500_data is not None:
    stock_returns = calculate_log_returns(sp500_data)
```

In [ ]:

```
stock_returns
```

Out[ ]:

Ticker	A	AAL	AAPL	ABBV	ABNB	ABT	ACGL	ACN	ADBE	ADI
Date										
2010-01-04	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2010-01-05	-1.092225	10.724575	0.172758	NaN	NaN	-0.811231	-0.334110	0.616112	1.631272	-0.157993
2010-01-06	-0.355919	-4.231412	-1.603425	NaN	NaN	0.553835	-0.433244	1.057451	-0.212432	-0.189959
2010-01-07	-0.129732	2.904369	-0.185054	NaN	NaN	0.825043	-0.589966	-0.093536	-1.959530	-0.795287
2010-01-08	-0.032418	-1.926840	0.662674	NaN	NaN	0.509908	-0.197437	-0.398542	-0.543629	0.573240
...	...	...	...	...	...	...	...	...	...	...
2024-05-16	0.149159	-1.009088	0.063229	0.341326	0.948845	0.267360	0.965991	-0.168685	-0.510211	-0.758375
2024-05-17	-0.051858	-0.406507	0.015801	1.251637	-1.044912	-0.746564	2.172147	-1.442169	0.113833	-0.018680
2024-05-20	0.265486	-1.435916	0.614319	-1.123947	0.486247	-0.849014	-0.815276	0.692617	0.260300	1.575709
2024-05-21	-0.629240	-3.432917	0.683387	-0.995461	-1.563008	-0.242518	1.466683	-0.676143	-0.587664	-0.386989
2024-05-22	-0.521958	0.497695	-0.756696	-2.058727	-0.969290	1.790404	1.027653	1.136310	0.430738	10.306840

3621 rows × 503 columns

In [ ]:

```
print(stock_returns.shape)
```

```
(3621, 503)
```

Load FF Data

In [ ]:

```
# Load Fama-French factors data
ff_data = pd.read_csv('/content/F-F_Research_Data_5_Factors_2x3_daily.CSV', sep=',', skiprows=2, e
# Convert the first column to a datetime format
ff_data['Date'] = pd.to_datetime(ff_data.iloc[:,0], format='%Y%m%d')

# Now 'Date' is a datetime object which can be used for merging, indexing, etc.
ff_data.set_index('Date', inplace=True)  # Set Date as the index if needed

ff_data.head()
```

Out[ ]:

	Unnamed: 0	Mkt-RF	SMB	HML	RMW	CMA	RF
Date							
1963-07-01	19630701	-0.67	0.02	-0.35	0.03	0.13	0.012
1963-07-02	19630702	0.79	-0.28	0.28	-0.08	-0.21	0.012
1963-07-03	19630703	0.63	-0.18	-0.10	0.13	-0.25	0.012
1963-07-05	19630705	0.40	0.09	-0.28	0.07	-0.30	0.012
1963-07-08	19630708	-0.63	0.07	-0.20	-0.27	0.06	0.012

In [ ]:

```
ff_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 15290 entries, 1963-07-01 to 2024-03-28
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  15290 non-null  int64
 1   Mkt-RF      15290 non-null  float64
 2   SMB         15290 non-null  float64
 3   HML         15290 non-null  float64
 4   RMW         15290 non-null  float64
 5   CMA         15290 non-null  float64
 6   RF          15290 non-null  float64
dtypes: float64(6), int64(1)
memory usage: 955.6 KB
```

Calculate Excess Return

In [ ]:

```
aligned_data = stock_returns.merge(ff_data, left_index=True, right_index=True, how='inner', suff
aligned_data.head()
```

Out[ ]:

Date	A	AAL	AAPL	ABBV	ABNB	ABT	ACGL	ACN	ADBE	ADI	...	
2010-01-04	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.
2010-01-05	-1.092225	10.724575	0.172758	NaN	NaN	-0.811231	-0.334110	0.616112	1.631272	-0.157993	...	3.
2010-01-06	-0.355919	-4.231412	-1.603425	NaN	NaN	0.553835	-0.433244	1.057451	-0.212432	-0.189959	...	-0.
2010-01-07	-0.129732	2.904369	-0.185054	NaN	NaN	0.825043	-0.589966	-0.093536	-1.959530	-0.795287	...	2.
2010-01-08	-0.032418	-1.926840	0.662674	NaN	NaN	0.509908	-0.197437	-0.398542	-0.543629	0.573240	...	-2.

5 rows × 510 columns

In [ ]:

```
aligned_data.tail()
```

Out[ ]:

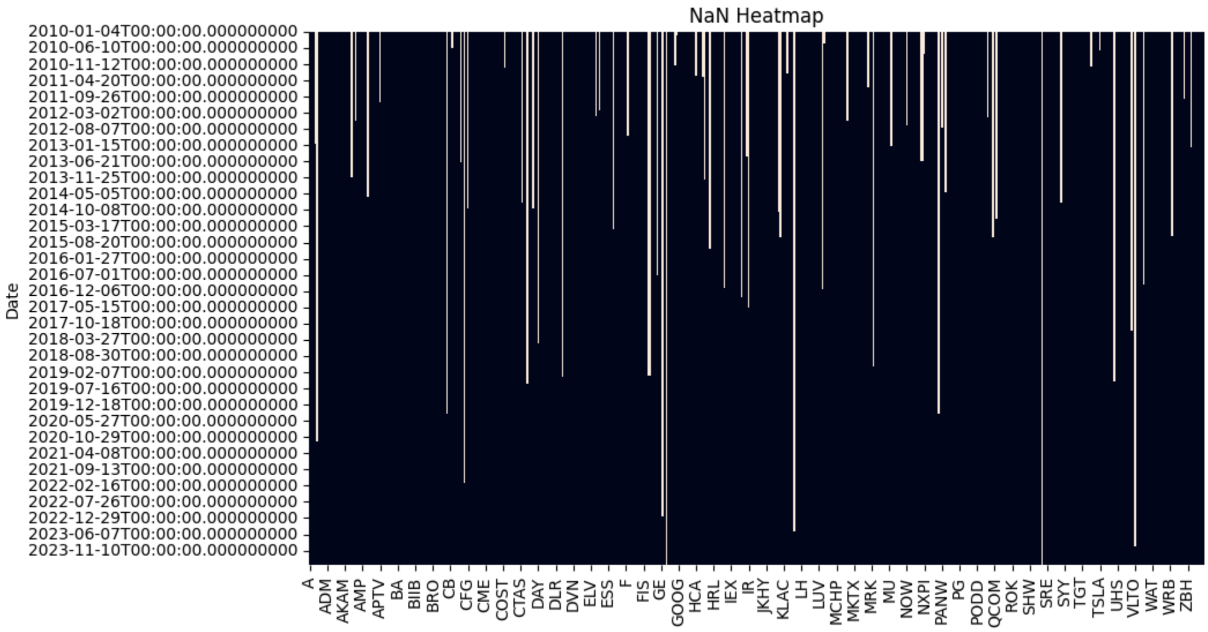
Date	A	AAL	AAPL	ABBV	ABNB	ABT	ACGL	ACN	ADBE	ADI	..
2024-03-22	-0.871075	0.270270	0.529610	0.533783	-0.190449	-0.846549	-0.011030	-2.206583	-2.321109	-0.843930	..
2024-03-25	-1.290075	0.672500	-0.833503	0.044817	0.077418	-0.507746	0.341276	-1.096357	1.531696	-1.499476	..
2024-03-26	-0.793188	0.000000	-0.669489	0.369008	-0.357807	1.345329	-0.440580	0.766928	0.072918	-0.879901	..
2024-03-27	2.028996	2.515024	2.099071	0.645277	-0.587177	1.760203	0.977661	1.343528	-0.632416	2.286319	..
2024-03-28	-1.270170	0.326266	-1.061522	0.965651	-0.875158	0.158496	1.043941	1.649364	0.039646	2.280725	..

5 rows × 510 columns

In [ ]:

```
# Create a heatmap showing where NaN values are located
plt.figure(figsize=(10, 6))
```

```
sns.heatmap(aligned_data.isna(), cbar=False)
plt.title('NaN Heatmap')
plt.show()
```



In [ ]:
```
print(aligned_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3583 entries, 2010-01-04 to 2024-03-28
Columns: 510 entries, A to RF_ff
dtypes: float64(509), int64(1)
memory usage: 14.0 MB
None
```

In [ ]:
```
# Calculate NaN counts
nan_counts_aligned = aligned_data.isna().sum()

# Identify columns with NaN counts over 3600
columns_with_excessive_nans = nan_counts_aligned[nan_counts_aligned > 3581].index.tolist()

# Output these column names
print("Columns with more than 3581 NaN values in aligned data:", columns_with_excessive_nans)
```

```
Columns with more than 3581 NaN values in aligned data: ['GEV', 'SOLV']
```

In [ ]:
```
#drop nan columns
aligned_data = aligned_data.drop(columns=['GEV', 'SOLV'])
print(aligned_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3583 entries, 2010-01-04 to 2024-03-28
Columns: 508 entries, A to RF_ff
dtypes: float64(507), int64(1)
memory usage: 13.9 MB
None
```

In [ ]:
```
#drop unnamed column
aligned_data = aligned_data.drop(columns='Unnamed: 0')
#fillna with 0
aligned_data = aligned_data.fillna(0)
aligned_data.isnull().sum()
```

```
Out[ ]: A          0
        AAL        0
        AAPL       0
        ABBV       0
        ABNB       0
                  ..
        SMB        0
        HML        0
        RMW        0
        CMA_ff     0
        RF_ff      0
        Length: 507, dtype: int64
```

Question 1

We assume that the errors are homoscedastic

```
In [ ]: def perform_regression(data, stock_symbol):
            # Calculate excess returns
            y = data[stock_symbol] - data['RF_ff']
            X = data[['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA_ff']]
            X = sm.add_constant(X)  # Add a constant term for the intercept

            model = sm.OLS(y, X)
            results = model.fit()
            # Concatenate the results: params, t-values, and R-squared
            return pd.concat([results.params, results.tvalues, pd.Series(results.rsquared, index=['R_squa

        # Get a list of stock columns, assuming they are named differently from the Fama-French factor and
        stock_columns = [col for col in aligned_data.columns if col not in ['Mkt-RF', 'SMB', 'HML', 'RMW

        # Prepare DataFrame to store results
        results_df = pd.DataFrame(index=stock_columns, columns=np.arange(13))  # 500x13 matrix

        # Iterate over each stock to perform regression
        for stock in stock_columns:
            regression_result = perform_regression(aligned_data, stock)
            results_df.loc[stock] = regression_result.values

        # Naming columns appropriately
        results_df.columns = ['const', 'Beta_Mkt-RF', 'Beta_SMB', 'Beta_HML', 'Beta_RMW', 'Beta_CMA',
                              't_const', 't_Beta_Mkt-RF', 't_Beta_SMB', 't_Beta_HML', 't_Beta_RMW', 't_Bet

        # Display the final results dataframe
        results_df.head()
```

Out[ ]:

	const	Beta_Mkt-RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA	t_const	t_Beta_Mkt-RF	t_Beta_SMB	t_
A	-0.007775	1.138112	0.08595	-0.188327	-0.233239	0.21963	-0.375027	56.23692	2.321009	
AAL	-0.032421	1.276904	0.782809	0.723129	0.185004	-0.30601	-0.714597	28.831743	9.659683	
AAPL	0.015599	1.174487	-0.145672	-0.509957	0.574021	0.022829	0.771478	59.504205	-4.033373	
ABBV	0.018512	0.606628	-0.150625	-0.154016	0.204799	0.248734	0.822247	27.602609	-3.74559	
ABNB	-0.006691	0.260295	0.176061	-0.217525	-0.581733	-0.410123	-0.278259	11.090145	4.099482	

```
In [ ]: print(results_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 501 entries, A to ZTS
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   const          501 non-null    object
 1   Beta_Mkt-RF    501 non-null    object
 2   Beta_SMB       501 non-null    object
 3   Beta_HML       501 non-null    object
 4   Beta_RMW       501 non-null    object
 5   Beta_CMA       501 non-null    object
 6   t_const        501 non-null    object
 7   t_Beta_Mkt-RF  501 non-null    object
 8   t_Beta_SMB     501 non-null    object
 9   t_Beta_HML     501 non-null    object
 10  t_Beta_RMW     501 non-null    object
 11  t_Beta_CMA     501 non-null    object
 12  R_squared      501 non-null    object
dtypes: object(13)
memory usage: 71.0+ KB
None
```

Question 2

In [ ]:
```
# Compute descriptive statistics for each column
descriptive_stats = results_df.describe()
descriptive_stats
```

Out[ ]:

	const	Beta_Mkt-RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA	t_const	t_Beta_Mkt-RF	t_Beta_SM
count	501.000000	501.000000	501.00000	501.000000	501.000000	501.00000	501.000000	501.00000	501.0000
unique	501.000000	501.000000	501.00000	501.000000	501.000000	501.00000	501.000000	501.00000	501.0000
top	-0.007775	1.138112	0.08595	-0.188327	-0.233239	0.21963	-0.375027	56.23692	2.3210
freq	1.000000	1.000000	1.00000	1.000000	1.000000	1.00000	1.000000	1.00000	1.0000

In [ ]:
```
specific_statistics_df = pd.DataFrame({ 'Mean': results_df.mean(), 'Variance': results_df.var(), '
specific_statistics_df
```

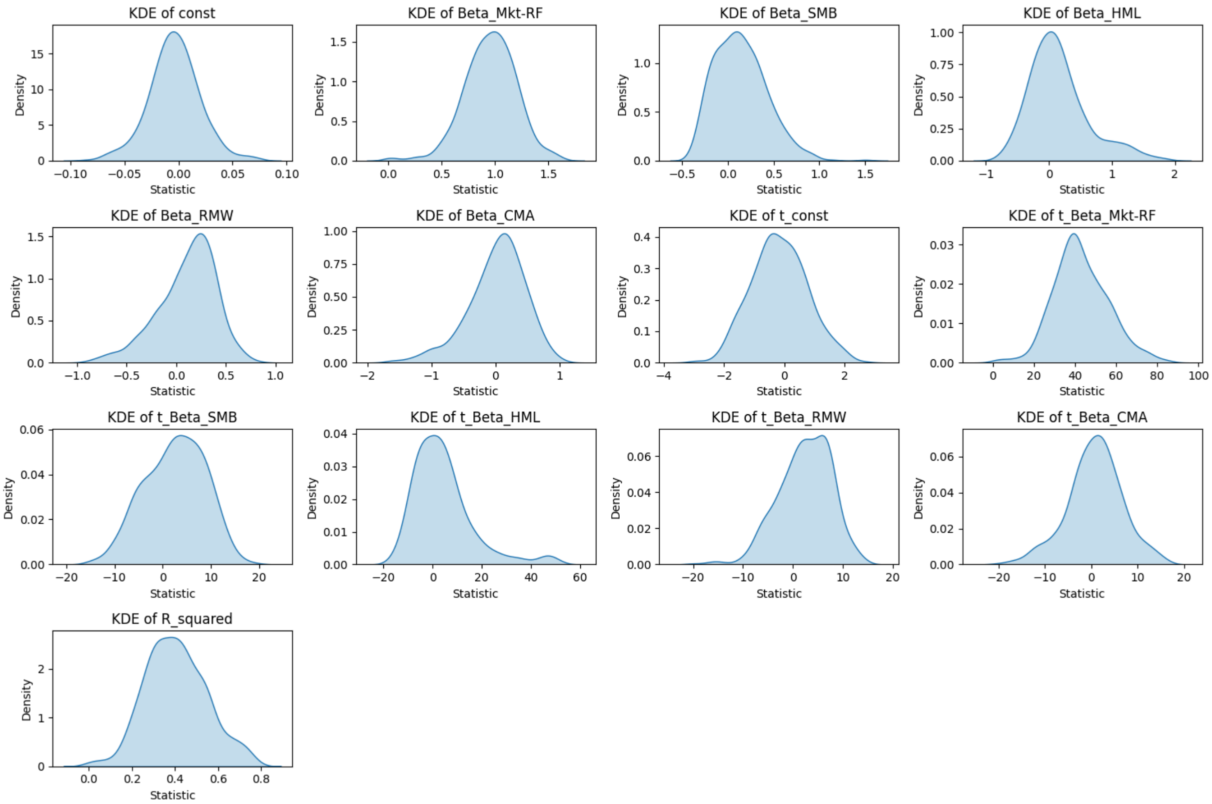
Out[ ]:

	Mean	Variance	Std	Min	Max	25th-Percentile	Median	75th-Percentile	Interquarti Ran
const	-0.003985	0.000568	0.023825	-0.085995	0.074503	-0.017763	-0.004424	0.009619	0.0273
Beta_Mkt-RF	0.95302	0.059303	0.243522	0.011003	1.625679	0.808387	0.964493	1.116613	0.3082
Beta_SMB	0.141555	0.080598	0.283898	-0.382431	1.500669	-0.079197	0.114561	0.310572	0.3897
Beta_HML	0.152294	0.223866	0.473145	-0.791585	1.851552	-0.171166	0.075534	0.354732	0.5258
Beta_RMW	0.104772	0.084814	0.291228	-0.886514	0.806333	-0.057984	0.163143	0.314278	0.3722
Beta_CMA	0.017264	0.198087	0.44507	-1.630325	1.011251	-0.229019	0.072839	0.319178	0.5481
t_const	-0.170591	0.851274	0.922645	-2.993332	2.639704	-0.79633	-0.21911	0.433426	1.2297
t_Beta_Mkt-RF	42.811866	177.921632	13.338727	2.032174	84.996567	33.912175	41.213239	50.890895	16.9787
t_Beta_SMB	2.422807	38.912651	6.238001	-15.175865	19.12439	-2.304776	2.733872	7.191828	9.4966
t_Beta_HML	4.181732	150.296726	12.259557	-16.134004	51.147552	-4.468432	2.118037	8.610153	13.0785
t_Beta_RMW	2.29522	27.925017	5.284413	-20.041011	14.419552	-1.067548	2.693142	6.242952	7.3105
t_Beta_CMA	0.71066	36.035356	6.002946	-20.270872	16.397065	-2.730444	1.123545	4.380678	7.1111
R_squared	0.404089	0.020148	0.141945	0.004186	0.770315	0.304445	0.39616	0.499521	0.1950

Question 3

In [ ]:

```
plt.figure(figsize=(15, 10))

# Plot each t-statistic's density
for i, col in enumerate(results_df):
    plt.subplot(4, 4, i + 1)  # Adjust subplot layout based on how many plots you need
    sns.kdeplot(results_df[col], fill=True)
    plt.title(f'KDE of {col}')
    plt.xlabel('Statistic')
    plt.ylabel('Density')

plt.tight_layout()
plt.show()
```



---

1. Constant (Alpha)

The constant term in a Fama-French model regression is often referred to as alpha. Alpha represents the asset's or portfolio's excess return that is not explained by the risk factors included in the model. It is essentially the intercept of the regression:

- **Positive Alpha:** Indicates that the asset or portfolio has performed better than predicted by the model after accounting for the risks (as defined by the model factors). This suggests superior performance relative to the benchmarks set by the model's factors.
- **Negative Alpha:** Indicates underperformance relative to the expected returns given the risks taken, as per the model's factors.

Interpretation:

Alpha is particularly significant for investment managers and investors as it represents the return gained from active management rather than the market performance. A statistically significant alpha (one whose t-statistic suggests it is significantly different from zero) is highly valued as it implies skill or other advantage.

2. Beta Coefficients

Beta coefficients in the FF model measure the sensitivity of the returns of a stock or portfolio to the movements in the factors of the model. Each factor has its own beta coefficient:

- **Market Beta (Beta_Mkt-RF):** This coefficient measures the sensitivity of the stock/portfolio returns to the excess market returns (market returns minus the risk-free rate). A beta greater than 1 indicates that the asset is more volatile than the market, while a beta less than 1 indicates it is less volatile.
- **Size Beta (Beta_SMB, Small Minus Big):** This measures the sensitivity of the returns to the size premium, which is the tendency for stocks in smaller firms to outperform stocks in larger firms, on average.

- **Value Beta (Beta_HML, High Minus Low):** This is the sensitivity of the returns to the value premium, which captures the excess returns of stocks with high book-to-market ratios over those with low ratios.
- **Profitability Beta (Beta_RMW, Robust Minus Weak):** This coefficient measures how much the returns of the stock/portfolio are affected by profitability factors. It captures the performance differential between companies with robust operating profitability versus those with weak profitability.
- **Investment Beta (Beta_CMA, Conservative Minus Aggressive):** It indicates sensitivity to the investment factor, reflecting the difference in returns between firms that invest conservatively and those that invest aggressively.

Zero Hypothesis Testing:

The t-statistic tests the null hypothesis that the coefficient is equal to zero, which implies that the factor has no effect on the dependent variable (returns of a stock or portfolio in this case).

Significance Levels:

- A large absolute value of the t-statistic (typically greater than 2 or less than -2 in absolute terms for a 95% confidence level) indicates that the null hypothesis can be rejected, suggesting that the coefficient is statistically significant.
- A small t-statistic (close to zero) suggests that the coefficient is not significantly different from zero, indicating that the factor does not have a statistically significant impact on the returns.

Positive vs. Negative T-Statistics:

- **Positive T-Statistic:** Indicates a positive relationship between the factor and the asset returns if the coefficient is positive. This means as the factor value increases, the asset return also tends to increase.
- **Negative T-Statistic:** Indicates a negative relationship if the coefficient is negative. This means as the factor value increases, the asset return tends to decrease.

Question 4

In [ ]:
```
def get_sp500_tickers_and_industry():
    # Fetch the table from Wikipedia
    table = pd.read_html('https://en.wikipedia.org/wiki/List_of_S%26P_500_companies')
    sp500 = table[0]
    # Select only the 'Symbol' and 'GICS Sector' columns
    tickers_and_industry = sp500[['Symbol', 'GICS Sector']]
    # Replace dots with hyphens in the tickers for Yahoo Finance compatibility
    tickers_and_industry['Symbol'] = tickers_and_industry['Symbol'].apply(lambda x: x.replace('.'
    return tickers_and_industry
```

In [ ]:
```
# Example of using the function
sp500_tickers_and_industry = get_sp500_tickers_and_industry()
sp500_tickers_and_industry
```

```
<ipython-input-21-683ee2b45575>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/inde
xing.html#returning-a-view-versus-a-copy
  tickers_and_industry['Symbol'] = tickers_and_industry['Symbol'].apply(lambda x: x.replace('.',
'-'))
```

Out[ ]:

	Symbol	GICS Sector
0	MMM	Industrials
1	AOS	Industrials
2	ABT	Health Care
3	ABBV	Health Care
4	ACN	Information Technology
...	...	...
498	XYL	Industrials
499	YUM	Consumer Discretionary
500	ZBRA	Information Technology
501	ZBH	Health Care
502	ZTS	Health Care

503 rows × 2 columns

In [ ]:

```
# 11 different industries
sp500_tickers_and_industry['GICS Sector'].value_counts()
```

Out[ ]:

```
GICS Sector
Industrials               79
Financials                71
Information Technology    65
Health Care               64
Consumer Discretionary    52
Consumer Staples          38
Utilities                 31
Real Estate               31
Materials                 28
Communication Services    22
Energy                    22
Name: count, dtype: int64
```

In [ ]:

```
merged_df = pd.merge(sp500_tickers_and_industry.iloc[:, :2], results_df, left_on=sp500_tickers_anc
merged_df.dropna(inplace=True)

merged_df
```

Out[ ]:

	Symbol	GICS Sector	const	Beta_Mkt-RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA	t_const	t_Beta_
0	MMM	Industrials	-0.035003	0.906726	0.122174	0.12269	0.419638	0.335622	-2.075251	55.07
1	AOS	Industrials	0.016212	0.977351	0.513165	0.019682	0.40028	0.141365	0.765313	47.26
2	ABT	Health Care	-0.003555	0.857237	-0.303362	-0.310888	0.03303	0.442011	-0.209752	51.81
3	ABBV	Health Care	0.018512	0.606628	-0.150625	-0.154016	0.204799	0.248734	0.822247	27.60
4	ACN	Information Technology	0.004007	1.051777	-0.09799	-0.056495	0.225434	-0.158084	0.240426	64.65
...	...	...	...	...	...	...	...	...	...	
498	XYL	Industrials	-0.001922	0.87252	0.202361	0.111647	0.424743	-0.120883	-0.09552	44.4
499	YUM	Consumer Discretionary	0.002131	0.855736	-0.025149	0.016591	0.312886	0.145933	0.106465	43.79
500	ZBRA	Information Technology	-0.003372	1.202707	0.501743	-0.242654	0.145436	-0.076895	-0.113664	41.53
501	ZBH	Health Care	-0.023844	0.861923	0.180859	0.128883	0.1249	-0.057783	-1.113279	41.22
502	ZTS	Health Care	0.002493	0.732893	-0.120301	-0.316396	0.238063	-0.088294	0.129052	38.86

501 rows × 15 columns

In [ ]:

```python
# Convert columns that should be numeric but are not
numeric_cols = ['const','Beta_Mkt-RF', 'Beta_SMB', 'Beta_HML', 'Beta_RMW', 'Beta_CMA',
                't_const', 't_Beta_Mkt-RF', 't_Beta_SMB', 't_Beta_HML', 't_Beta_RMW', 't_Beta_CMA'

# Explicitly convert these columns to numeric, forcing errors to NaN to catch problematic data
for col in numeric_cols:
    merged_df[col] = pd.to_numeric(merged_df[col], errors='coerce')

# Now group by 'GICS Sector' and calculate the mean, std, and median
grouped = merged_df.groupby('GICS Sector')[numeric_cols].agg(['mean', 'std', 'median'])

# Print the grouped DataFrame
grouped
```

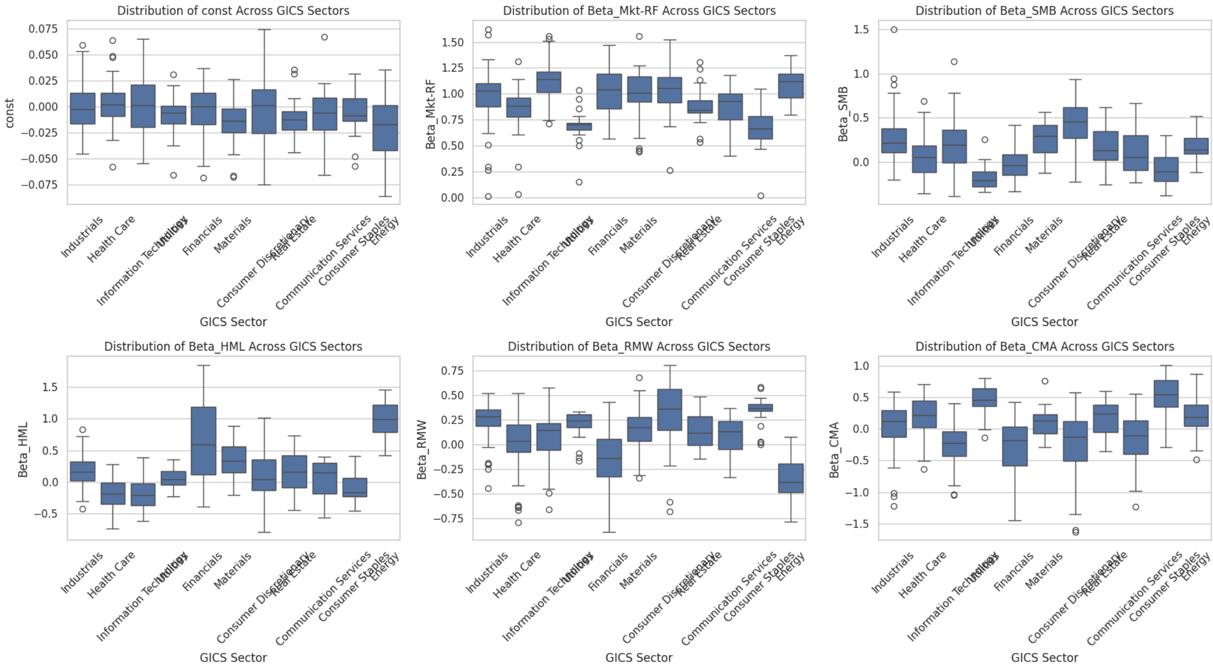
Out[ ]:

	const			Beta_Mkt-RF			Beta_SMB			Beta_
	mean	std	median	mean	std	median	mean	std	median	m
GICS Sector										
Communication Services	-0.006980	0.028110	-0.006198	0.876468	0.213943	0.926999	0.139816	0.293375	0.054778	0.03
Consumer Discretionary	-0.002712	0.031251	0.001231	1.034876	0.210075	1.055063	0.437360	0.280234	0.455245	0.08
Consumer Staples	-0.005260	0.018420	-0.008549	0.667051	0.174427	0.666207	-0.066874	0.187370	-0.105525	-0.08
Energy	-0.020616	0.030164	-0.017213	1.093009	0.166521	1.117744	0.175873	0.160445	0.142496	0.98
Financials	-0.002876	0.020016	0.000115	1.040015	0.186582	1.043003	-0.015483	0.176550	-0.036057	0.69
Health Care	0.003325	0.019610	0.002272	0.858218	0.180773	0.885909	0.062089	0.229202	0.053755	-0.20
Industrials	-0.000816	0.020362	-0.002288	0.978704	0.251597	1.025750	0.268986	0.272040	0.215839	0.16
Information Technology	0.001271	0.028177	0.001631	1.136259	0.198019	1.138960	0.205351	0.278408	0.192826	-0.19
Materials	-0.016374	0.021250	-0.014101	0.994533	0.261768	1.006873	0.251536	0.200096	0.294534	0.33
Real Estate	-0.011472	0.017947	-0.012193	0.889885	0.160771	0.846345	0.161278	0.231871	0.136027	0.14
Utilities	-0.008340	0.018431	-0.005902	0.691450	0.142937	0.706297	-0.174554	0.129052	-0.206780	0.05

11 rows × 39 columns

In [ ]:

```
# List of all factors including the constant
factors = ['const', 'Beta_Mkt-RF', 'Beta_SMB', 'Beta_HML', 'Beta_RMW', 'Beta_CMA']

# Set plot dimensions and style
plt.figure(figsize=(18, 10))
sns.set(style="whitegrid")

# Create a subplot for each factor
for i, factor in enumerate(factors, 1):
    plt.subplot(2, 3, i)  # Adjust the grid size based on the number of factors
    sns.boxplot(x='GICS Sector', y=factor, data=merged_df)
    plt.xticks(rotation=45)
    plt.title(f'Distribution of {factor} Across GICS Sectors')

# Adjust layout for better spacing between plots
plt.tight_layout()
plt.show()
```



Based on the provided output, we can observe variations in the estimated factor coefficients across the 11 sectors of the Global Industry Classification Standard (GICS). Here's a summary of the differences:

1. **Constant (const):** The average constant term differs across sectors, ranging from slightly negative values in sectors like Utilities and Real Estate to slightly positive values in sectors like Information Technology and Health Care.

2. **Beta_Mkt-RF:** The average sensitivity to market changes (Beta_Mkt-RF) varies across sectors, with Financials, Information Technology, and Energy having relatively higher average values compared to sectors like Consumer Staples and Utilities.

3. **Beta_SMB:** Sectors like Consumer Discretionary and Materials exhibit higher average sensitivity to small-cap stocks (Beta_SMB), while sectors like Consumer Staples and Utilities have negative or lower average values.

4. **Beta_HML:** Financials and Energy sectors tend to have higher average sensitivity to the high-minus-low factor (Beta_HML), indicating a stronger performance relative to value stocks.

5. **Beta_RMW:** Consumer Staples and Consumer Discretionary sectors show higher average sensitivity to the robust-minus-weak factor (Beta_RMW), suggesting variations in profitability performance across sectors.

6. **Beta_CMA:** Consumer Staples, Utilities, and Health Care sectors tend to have higher average sensitivity to the conservative-minus-aggressive factor (Beta_CMA), implying differences in investment characteristics.

7. **T-statistics:** The significance of the coefficients varies across sectors. For instance, Financials generally exhibit high t-statistics for most coefficients, indicating greater significance compared to other sectors.

8. **R-squared:** The R-squared values, representing the explanatory power of the model, vary across sectors, with Financials having relatively higher values compared to sectors like Consumer Staples and Health Care.

In summary, there are notable differences in the estimated factor coefficients across sectors, reflecting the diverse characteristics and performance of companies within each sector according to the GICS classification.

Question 5

In [ ]:

```
results_df
```

Out[ ]:

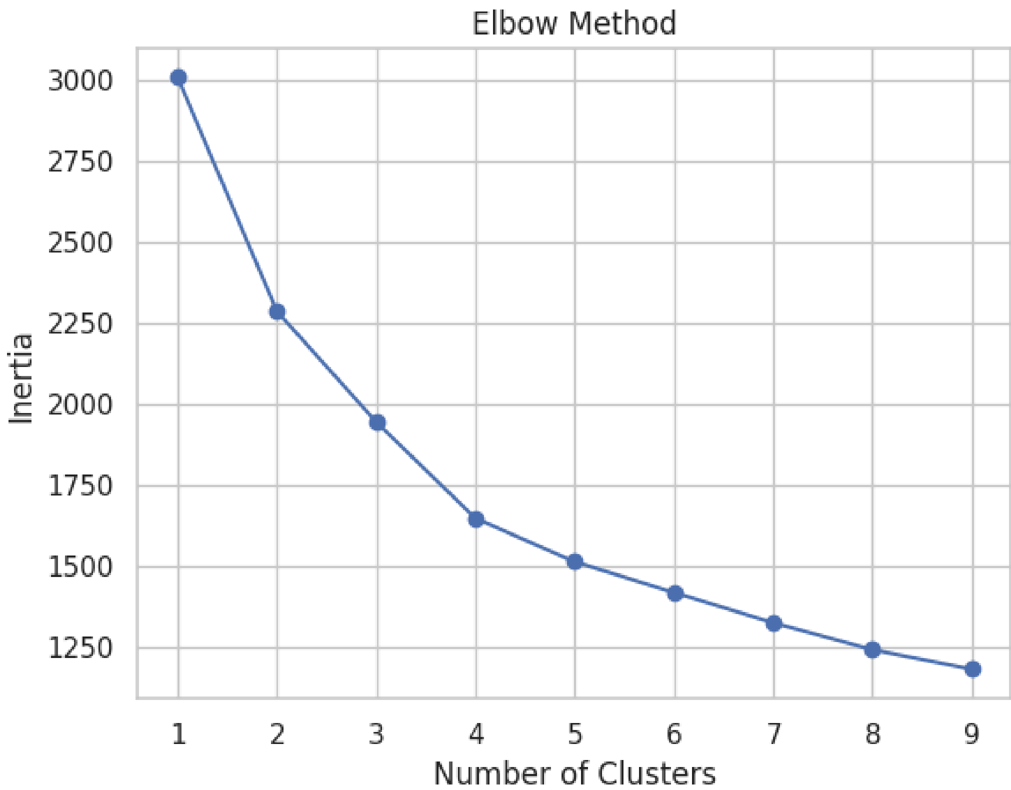
	const	Beta_Mkt-RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA	t_const	t_Beta_Mkt-RF	t_Beta_SMB	t_
A	-0.007775	1.138112	0.08595	-0.188327	-0.233239	0.21963	-0.375027	56.23692	2.321009	
AAL	-0.032421	1.276904	0.782809	0.723129	0.185004	-0.30601	-0.714597	28.831743	9.659683	
AAPL	0.015599	1.174487	-0.145672	-0.509957	0.574021	0.022829	0.771478	59.504205	-4.033373	
ABBV	0.018512	0.606628	-0.150625	-0.154016	0.204799	0.248734	0.822247	27.602609	-3.74559	
ABNB	-0.006691	0.260295	0.176061	-0.217525	-0.581733	-0.410123	-0.278259	11.090145	4.099482	
...	...	...	...	...	...	...	...	...	...	
XYL	-0.001922	0.87252	0.202361	0.111647	0.424743	-0.120883	-0.09552	44.42935	5.63138	
YUM	0.002131	0.855736	-0.025149	0.016591	0.312886	0.145933	0.106465	43.792694	-0.703368	
ZBH	-0.023844	0.861923	0.180859	0.128883	0.1249	-0.057783	-1.113279	41.227399	4.727712	
ZBRA	-0.003372	1.202707	0.501743	-0.242654	0.145436	-0.076895	-0.113664	41.535701	9.469721	
ZTS	0.002493	0.732893	-0.120301	-0.316396	0.238063	-0.088294	0.129052	38.860775	-3.486047	

501 rows × 14 columns

In [ ]:

```
# features
features = merged_df[['const', 'Beta_Mkt-RF', 'Beta_SMB', 'Beta_HML', 'Beta_RMW', 'Beta_CMA']]
features_clean = features.dropna()

scaler = StandardScaler()
scaled_features = scaler.fit_transform(features_clean)

# Elbow method to determine the optimal number of clusters
inertia = []
range_values = range(1, 10)  # Test for 1 to 10 clusters

for i in range_values:
    kmeans = KMeans(n_clusters=i)
    kmeans.fit(scaled_features)
    inertia.append(kmeans.inertia_)

plt.plot(range_values, inertia, 'o-')
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
```



In [ ]:
```
results_df['Cluster'] = kmeans.fit_predict(scaled_features)

# Analyze cluster centroids
results_df.groupby('Cluster').mean()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
```

Out[ ]:

Cluster	const	Beta_Mkt-RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA	t_const	t_Beta_Mkt-RF	t_Beta_SMB
0	-0.01325	0.928356	0.104812	0.242233	0.141867	0.195827	-0.508099	42.762058	1.028536
1	-0.005962	0.946867	0.159773	0.164759	0.126232	-0.004624	-0.2531	43.687153	3.162636
2	-0.005515	1.00571	0.179694	0.223753	0.091615	-0.063901	-0.233524	44.959928	3.12608
3	0.002702	0.903342	0.143397	0.124992	0.114455	0.011163	0.048288	40.931863	2.350291
4	-0.000082	0.947425	0.117657	0.164623	0.116465	0.032346	-0.019978	41.405455	1.806126
5	-0.00264	0.997024	0.135934	0.051421	0.042607	0.07475	-0.131819	43.194752	2.719996
6	-0.001445	0.984322	0.180463	0.02722	0.205567	0.020999	-0.075377	43.355953	3.379193
7	-0.0043	0.950043	0.120901	0.158512	0.081671	0.041696	-0.242779	42.92149	1.564022
8	-0.004878	0.947177	0.131332	0.172061	0.077245	-0.009635	-0.138255	42.183596	2.230231

In [ ]:

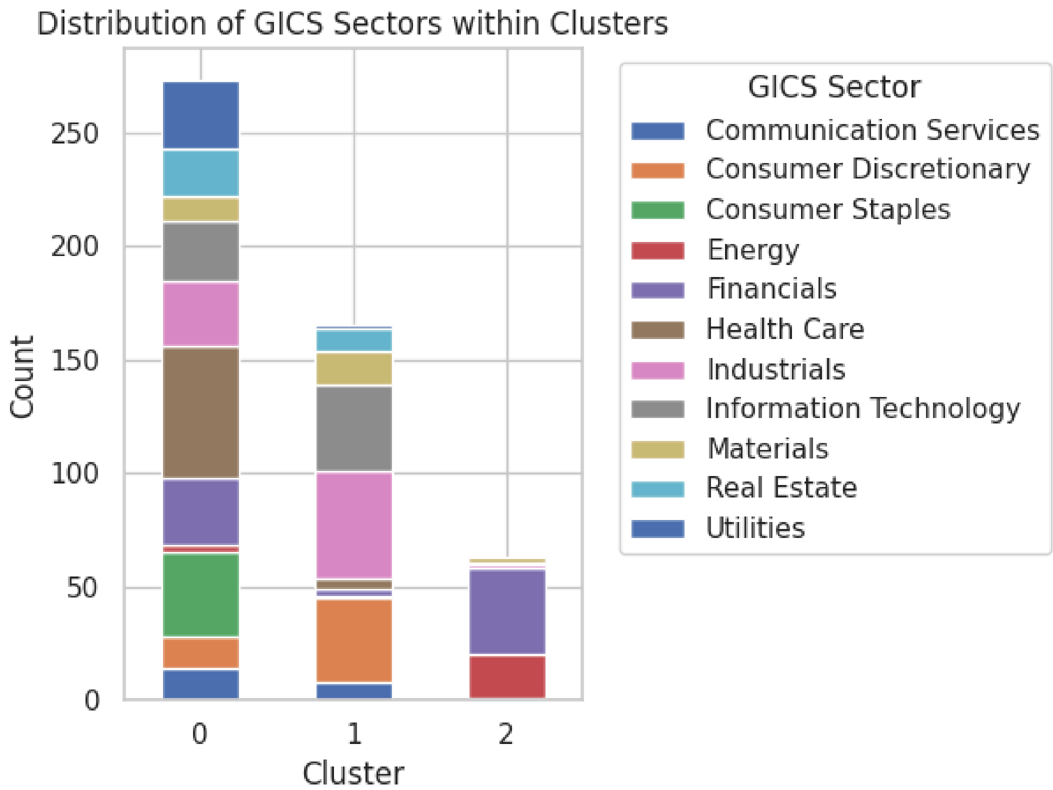
```
# Choose the optimal number of clusters based on the elbow method
optimal_k = 3

# Perform K-Means clustering with the chosen number of clusters
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
kmeans.fit(scaled_features)

# Add the cluster labels to the DataFrame
merged_df['Cluster'] = kmeans.labels_
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to su
ppress the warning
  warnings.warn(
```

In [ ]:

```
# Count the number of companies from each GICS sector within each cluster
cluster_sector_counts = merged_df.groupby(['Cluster', 'GICS Sector']).size().unstack(fill_value=0)

# Plot
plt.figure(figsize=(12, 6))
cluster_sector_counts.plot(kind='bar', stacked=True)
plt.title('Distribution of GICS Sectors within Clusters')
plt.xlabel('Cluster')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.legend(title='GICS Sector', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

```
<Figure size 1200x600 with 0 Axes>
```



In [ ]:

```
# Count the number of companies from each GICS sector within each cluster
cluster_sector_counts = merged_df.groupby(['Cluster', 'GICS Sector']).size().unstack(fill_value=0)

# Loop through each cluster
for cluster in range(cluster_sector_counts.shape[0]):
    # Sum the counts of each GICS sector within the current cluster
    sector_counts = cluster_sector_counts.iloc[cluster].sort_values(ascending=False)

    # Display the sector counts for the current cluster in descending order
    print(f"\nCluster {cluster + 1} - Industry Occurrences (Descending Order):")
    for sector, count in sector_counts.items():
        print(f"{sector}: {count}")
```

```
Cluster 1 - Industry Occurrences (Descending Order):
Health Care: 58
Consumer Staples: 37
Financials: 30
Utilities: 30
Industrials: 29
Information Technology: 26
Real Estate: 21
Communication Services: 14
Consumer Discretionary: 14
Materials: 11
Energy: 3

Cluster 2 - Industry Occurrences (Descending Order):
Industrials: 47
Information Technology: 38
Consumer Discretionary: 37
Materials: 15
Real Estate: 10
Communication Services: 8
Health Care: 5
Financials: 3
Consumer Staples: 1
Utilities: 1
Energy: 0

Cluster 3 - Industry Occurrences (Descending Order):
Financials: 38
Energy: 19
Industrials: 2
Materials: 2
Consumer Discretionary: 1
Information Technology: 1
Communication Services: 0
Consumer Staples: 0
Health Care: 0
Real Estate: 0
Utilities: 0
```

- **Cluster 1**:
  - **Dominant Industries**: Health Care (58 occurrences), Consumer Staples (37 occurrences), and Financials (30 occurrences).
  - **Secondary Industries**: Utilities, Industrials, Information Technology, Real Estate, Communication Services, Consumer Discretionary, Materials, and Energy.
  - **Observation**: Cluster 1 is primarily composed of Health Care and Consumer Staples companies, indicating a focus on stable and defensive sectors. This contrasts with the interpretation in Image 1, where Financials and Energy were more prominent.
- **Cluster 2**:
  - **Dominant Industries**: Industrials (47 occurrences), Information Technology (38 occurrences), and Consumer Discretionary (37 occurrences).
  - **Secondary Industries**: Materials, Real Estate, Communication Services, Health Care, Financials, Consumer Staples, Utilities, and Energy.
  - **Observation**: Cluster 2 is heavily focused on Industrials and Information Technology, indicating a mix of traditional and innovative sectors. This partially aligns with Image 1's interpretation of Cluster 3 but also includes Consumer Discretionary prominently.
- **Cluster 3**:
  - **Dominant Industries**: Financials (38 occurrences), Energy (19 occurrences), and Industrials (2 occurrences).
  - **Secondary Industries**: Materials, Consumer Discretionary, Information Technology, and no occurrences in Communication Services, Consumer Staples, Health Care, Real Estate, and Utilities.

- **Observation**: Cluster 3 is primarily composed of Financials and Energy companies, indicating a strong presence of traditional sectors. This aligns closely with Image 1's Cluster 1 interpretation.

Conclusion:

The cluster logic in Image 2 suggests:

- **Cluster 1**: Focuses on stable and defensive sectors, particularly Health Care and Consumer Staples, differing from the traditional sector focus (Financials and Energy) in Image 1.
- **Cluster 2**: Represents a mix of traditional and innovative sectors, prominently featuring Industrials and Information Technology, which aligns with the innovative sector focus in Image 1's Cluster 3.
- **Cluster 3**: Consists mainly of Financials and Energy, matching the traditional sector focus indicated in Image 1 for Cluster 1.

Question 6

In [ ]:

```
# Print the top five companies with the highest constants
top_five_highest = results_df.sort_values(by='const', ascending=False).head(5)
print("Top Five Companies with the Highest Constants:")
top_five_highest[['const']]

# Print the top five companies with the lowest constants
top_five_lowest = results_df.sort_values(by='const', ascending=True).head(5)
print("Top Five Companies with the Lowest Constants:")
top_five_lowest[['const']]
```

```
Top Five Companies with the Highest Constants:
         const
TSLA  0.074503
DPZ   0.073427
NFLX  0.067213
NVDA  0.065252
DXCM  0.063511
Top Five Companies with the Lowest Constants:
        const
APA -0.085995
CCL -0.074538
IVZ -0.068464
FCX -0.067522
MOS -0.066352
```

Tesla (TSLA), Domino's Pizza (DPZ), Netflix (NFLX), NVIDIA (NVDA), DexCom (DXCM) (Continuous glucose monitoring devices production and sales)

APA:

Primary Business: Exploration and production of oil and natural gas

Carnival Corporation & plc (CCL):

Primary Business: Cruise line operator

Invesco Ltd. (IVZ):

Primary Business: Investment management and financial services

Freeport-McMoRan Inc. (FCX):

Primary Business: Mining company primarily for copper, gold, and molybdenum

The Mosaic Company (MOS):

Primary Business: Producer and marketer of concentrated phosphate and potash crop nutrients

---

Top 5 Companies:

1. **Innovation Leaders:** Tesla, Netflix, NVIDIA, DexCom, and Domino's Pizza are synonymous with disruptive innovation and cutting-edge technologies in their respective industries.
2. **Growth Potential:** Positioned for high growth, these companies dominate their markets with innovative products and services, offering significant growth opportunities for investors.
3. **Environmental Impact:** Many of the top 5 companies prioritize sustainability and contribute positively to environmental goals, especially through initiatives like electric vehicles (Tesla) and sustainable healthcare solutions (DexCom).
4. **Market Leadership:** Enjoying strong brand recognition and market dominance, these companies lead their industries with innovative business models and technologies.

Bottom 5 Companies:

1. **Traditional Industries:** APA, Carnival Corporation & plc, Invesco Ltd., Freeport-McMoRan Inc., and The Mosaic Company operate in more traditional sectors, potentially facing slower growth and environmental challenges.
2. **Less Innovation:** These companies may have less emphasis on innovation compared to the top 5, relying on established business models rather than disruptive technologies.
3. **Environmental Concerns:** Some of the bottom 5 companies, such as those in oil and gas exploration and mining, may have a larger environmental footprint and face challenges in transitioning to sustainable practices.
4. **Market Position:** While still significant players in their industries, these companies may have lower brand recognition and face competition from larger, more innovative firms.

In summary, the top 5 companies shine for their innovation, growth potential, and environmental consciousness, while the bottom 5 may face challenges associated with traditional industries and environmental concerns.

Question 7

In [ ]:

```
# Resampling to monthly frequency by summing up daily returns
monthly_returns = stock_returns.resample('M').sum()
monthly_returns.head()
```

Out[ ]:

Ticker	A	AAL	AAPL	ABBV	ABNB	ABT	ACGL	ACN	ADBE	ADI
Date										
2010-01-31	-11.034242	10.724575	-10.821477	0.0	0.0	-2.103048	-0.571464	-2.600688	-13.828019	-16.101565
2010-02-28	11.544141	32.238363	6.334690	0.0	0.0	2.499668	3.353810	-2.519912	7.023056	8.118328
2010-03-31	8.904873	0.272497	13.843066	0.0	0.0	-2.992008	3.022261	4.834923	2.056620	-0.769260
2010-04-30	5.294921	-3.884003	10.527973	0.0	0.0	-2.088891	-0.882576	4.823456	-5.133795	3.779129
2010-05-31	-11.379213	22.229455	-1.625615	0.0	0.0	-7.296562	-2.763417	-15.110014	-4.629318	-1.801753

5 rows × 503 columns

In [ ]:

```
monthly_returns.tail()
```

Out[ ]:

Ticker	A	AAL	AAPL	ABBV	ABNB	ABT	ACGL	ACN	ADBE	
Date										
2024-01-31	-6.638632	3.504111	-4.314468	6.857986	5.710128	3.241718	10.424240	3.993932	3.488562	-3.1
2024-02-29	5.430187	9.703365	-1.871721	6.846565	8.844993	4.737925	6.071734	2.951500	-9.769574	-0.2
2024-03-31	5.763948	-2.127054	-5.264823	3.378792	4.646809	-4.288207	5.389302	-7.813903	-10.467066	3.5
2024-04-30	-5.834872	-12.768533	-0.672888	-10.372114	-3.950688	-6.510836	1.182935	-13.752439	-8.640626	1.4
2024-05-31	10.931505	4.274466	11.536738	-1.880582	-10.538154	-1.091146	9.342293	2.039471	4.458047	17.9

5 rows × 503 columns

In [ ]:

```
# Load monthly Fama-French data
monthly_ff_data = pd.read_csv('/content/F-F_Research_Data_5_Factors_2x3.csv', sep=',', skiprows=2,
monthly_ff_data['Date'] = pd.to_datetime(monthly_ff_data['Unnamed: 0'], format='%Y%m')
monthly_ff_data['Date'] = monthly_ff_data['Date'] + pd.offsets.MonthEnd(0)
monthly_ff_data.set_index('Date', inplace=True)
monthly_ff_data.head()
```

```
<ipython-input-32-c30ab442c401>:2: ParserWarning: Falling back to the 'python' engine because the 'c' engine does not support skipfooter; you can avoid this warning by specifying engine='python'.
  monthly_ff_data = pd.read_csv('/content/F-F_Research_Data_5_Factors_2x3.csv', sep=',', skiprows=2, skipfooter=62, encoding='ISO-8859-1')
```

Out[ ]:

	Unnamed: 0	Mkt-RF	SMB	HML	RMW	CMA	RF
Date							
1963-07-31	196307	-0.39	-0.41	-0.97	0.68	-1.18	0.27
1963-08-31	196308	5.07	-0.80	1.80	0.36	-0.35	0.25
1963-09-30	196309	-1.57	-0.52	0.13	-0.71	0.29	0.27
1963-10-31	196310	2.53	-1.39	-0.10	2.80	-2.01	0.29
1963-11-30	196311	-0.85	-0.88	1.75	-0.51	2.24	0.27

In [ ]:

```
monthly_ff_data.tail()
```

Out[ ]:

	Unnamed: 0	Mkt-RF	SMB	HML	RMW	CMA	RF
Date							
2023-11-30	202311	8.84	-0.12	1.64	-3.91	-1.00	0.44
2023-12-31	202312	4.87	7.32	4.93	-3.07	1.32	0.43
2024-01-31	202401	0.71	-5.74	-2.38	0.69	-0.96	0.47
2024-02-29	202402	5.06	-0.78	-3.49	-1.99	-2.14	0.42
2024-03-31	202403	2.83	-1.16	4.19	1.48	1.18	0.43

In [ ]:

```
# Assuming the structure is the same
aligned_monthly_data = monthly_returns.merge(monthly_ff_data, left_index=True, right_index=True,
aligned_monthly_data
```

Out[ ]:

	A	AAL	AAPL	ABBV	ABNB	ABT	ACGL	ACN	ADBE	
Date										
2010-01-31	-11.034242	10.724575	-10.821477	0.000000	0.000000	-2.103048	-0.571464	-2.600688	-13.828019	-16.101
2010-02-28	11.544141	32.238363	6.334690	0.000000	0.000000	2.499668	3.353810	-2.519912	7.023056	8.118
2010-03-31	8.904873	0.272497	13.843066	0.000000	0.000000	-2.992008	3.022261	4.834923	2.056620	-0.769
2010-04-30	5.294921	-3.884003	10.527973	0.000000	0.000000	-2.088891	-0.882576	4.823456	-5.133795	3.779
2010-05-31	-11.379213	22.229455	-1.625615	0.000000	0.000000	-7.296562	-2.763417	-15.110014	-4.629318	-1.801
...	...	...	...	...	...	...	...	...	...	
2023-11-30	21.215178	10.867347	10.775981	0.853418	6.583741	9.804655	-3.510365	11.452782	13.835708	15.321
2023-12-31	8.591304	10.019834	1.349113	8.466174	7.470711	5.394111	-11.941247	5.196695	-2.386651	8.423
2024-01-31	-6.638632	3.504111	-4.314468	6.857986	5.710128	3.241718	10.424240	3.993932	3.488562	-3.172
2024-02-29	5.430187	9.703365	-1.871721	6.846565	8.844993	4.737925	6.071734	2.951500	-9.769574	-0.281
2024-03-31	5.763948	-2.127054	-5.264823	3.378792	4.646809	-4.288207	5.389302	-7.813903	-10.467066	3.534

171 rows × 509 columns

In [ ]:

```
#assume homoscedasticity

# Get a list of stock columns, assuming they are named differently from the Fama-French factor and
stock_columns_monthly = [col for col in aligned_data.columns if col not in ['Mkt-RF', 'SMB', 'HM

# Prepare DataFrame to store results
results_df_monthly = pd.DataFrame(index=stock_columns_monthly, columns=np.arange(13))  # 500x13 ma

# Iterate over each stock to perform regression
for stock in stock_columns_monthly:
    regression_result_monthly = perform_regression(aligned_monthly_data, stock)
    results_df_monthly.loc[stock] = regression_result_monthly.values
```

```python
# Naming columns appropriately
results_df_monthly.columns = ['const', 'Beta_Mkt-RF', 'Beta_SMB', 'Beta_HML', 'Beta_RMW', 'Beta_CM
                              't_const', 't_Beta_Mkt-RF', 't_Beta_SMB', 't_Beta_HML', 't_Beta_RMW', 't_Bet

# Display the final results dataframe
results_df_monthly.head()
```

Out[ ]:

	const	Beta_Mkt-RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA	t_const	t_Beta_Mkt-RF	t_Beta_SMB	t_
A	-0.222612	1.243967	-0.006633	-0.124369	-0.263861	0.213143	-0.538652	12.744165	-0.035854	
AAL	-0.563243	1.107936	1.074715	0.406795	0.37375	0.146339	-0.601113	5.006304	2.562243	
AAPL	0.338842	1.145427	-0.071539	-0.501703	0.769265	-0.166059	0.731912	10.475399	-0.345198	
ABBV	0.398521	0.603032	0.057738	0.000578	0.306183	0.341071	0.839374	5.377579	0.271665	
ABNB	-0.177141	0.33837	0.153905	-0.20792	-0.731501	-0.05623	-0.392465	3.174072	0.76173	

In [ ]:

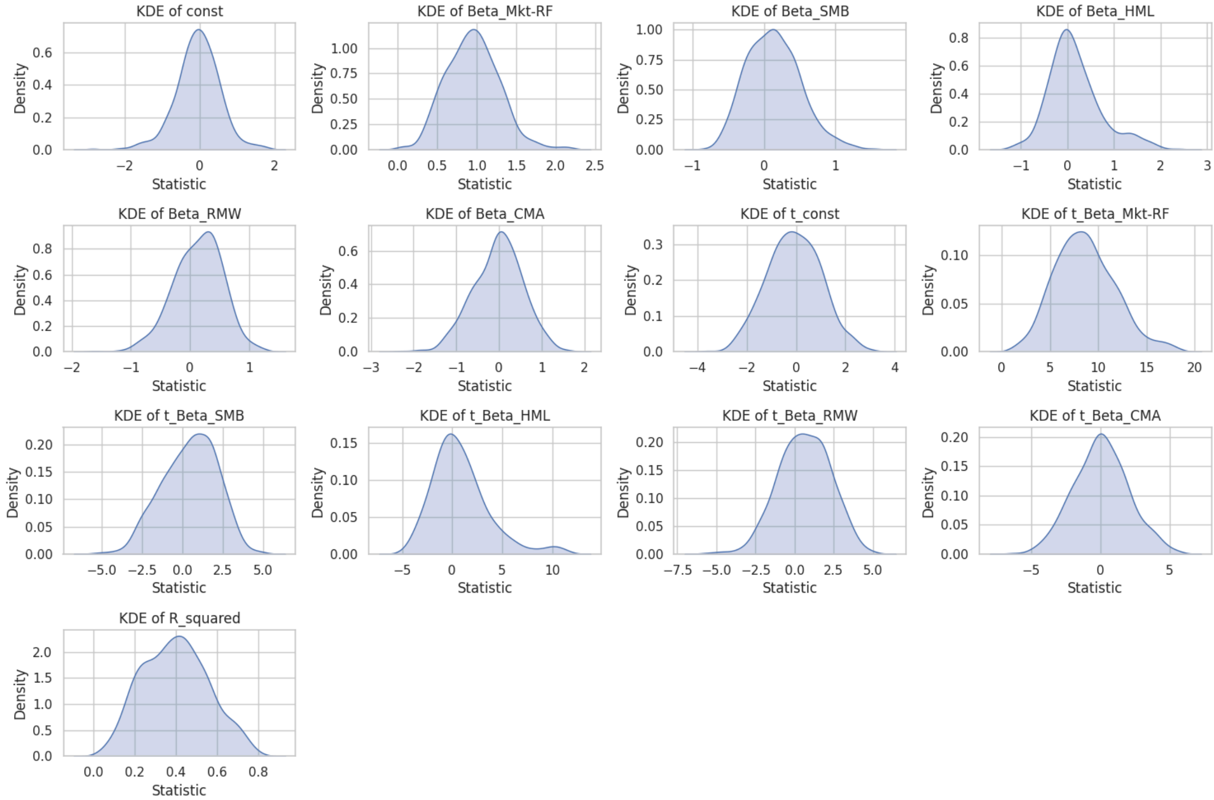
```python
specific_statistics_df_monthly = pd.DataFrame({'Mean': results_df_monthly.mean(), 'Variance': res
specific_statistics_df_monthly
```

Out[ ]:

	Mean	Variance	Std	Min	Max	25th-Percentile	Median	75th-Percentile	Interquartile-Range
const	-0.056718	0.340513	0.583535	-2.844448	1.776241	-0.379976	-0.051095	0.293179	0.673155
Beta_Mkt-RF	0.948045	0.109662	0.331152	0.054713	2.155143	0.708814	0.945214	1.160216	0.451403
Beta_SMB	0.132499	0.139029	0.372866	-0.790023	1.527303	-0.1427	0.124065	0.378398	0.521098
Beta_HML	0.156787	0.320979	0.56655	-1.175438	2.384608	-0.207779	0.04848	0.433864	0.641643
Beta_RMW	0.130506	0.173169	0.416136	-1.60255	1.25151	-0.144484	0.169237	0.407504	0.551988
Beta_CMA	-0.028839	0.338386	0.581709	-2.300042	1.644976	-0.41734	0.002986	0.360311	0.777652
t_const	-0.088921	1.178452	1.085565	-3.580679	3.111024	-0.833826	-0.087523	0.697318	1.531145
t_Beta_Mkt-RF	8.617532	9.660142	3.108077	1.484811	17.989481	6.475262	8.476509	10.642812	4.16755
t_Beta_SMB	0.419269	2.804487	1.67466	-5.248681	4.889476	-0.729148	0.577441	1.670469	2.399617
t_Beta_HML	0.809865	8.280254	2.877543	-4.808503	11.360337	-1.122966	0.24312	2.06015	3.183116
t_Beta_RMW	0.599707	2.770204	1.664393	-5.590671	5.023724	-0.542952	0.62481	1.790221	2.333173
t_Beta_CMA	0.025782	3.919241	1.979707	-6.268723	5.550638	-1.299651	0.009997	1.323902	2.623553
R_squared	0.396374	0.024556	0.156703	0.042713	0.792814	0.269615	0.396852	0.504905	0.23529

In [ ]:

```python
plt.figure(figsize=(15, 10))

# Plot each t-statistic's density
for i, col in enumerate(results_df_monthly):
    plt.subplot(4, 4, i + 1)
    sns.kdeplot(results_df_monthly[col], fill=True)
    plt.title(f'KDE of {col}')
    plt.xlabel('Statistic')
    plt.ylabel('Density')

plt.tight_layout()
plt.show()
```



Summary and Comparison

- **Constant Term (const)**: Both monthly and daily models show a similar distribution centered around 0.
- **Market Risk Premium (Beta_Mkt-RF)**: The monthly model shows a stronger relationship with the market risk premium (mean around 1) compared to the daily model (mean around 0.5).
- **Size Factor (Beta_SMB), Value Factor (Beta_HML), Profitability Factor (Beta_RMW), Investment Factor (Beta_CMA)**: These factors have similar distributions in both monthly and daily models, with means around 0 and narrow spreads.
- **R-squared (R_squared)**: The monthly model has a higher R-squared value (centered around 0.4) indicating worse explanatory power compared to the daily model (centered around 0.4).

Conclusion

- **Monthly Data**: Provides a stronger relationship with the market risk premium and better overall explanatory power.
- **Daily Data**: Shows a weaker relationship with the market risk premium and lower explanatory power, indicating that daily returns are more volatile and harder to explain using the Fama-French factors.

This comparison suggests that temporal aggregation to a monthly frequency enhances the model's explanatory power and provides a clearer relationship between stock returns and the Fama-French factors.

Question 8

In [ ]:
```
def perform_regression_one_day_ahead(data, stock_symbol):
    # Calculate one-day-ahead excess returns
    y = data[stock_symbol].shift(-1) - data['RF_ff'].shift(-1)
    X = data[['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA_ff']]
    X = sm.add_constant(X)  # Add a constant term for the intercept

    model = sm.OLS(y, X, missing='drop')  # 'missing='drop'' to ignore rows with NaN
    results = model.fit()
    # Concatenate the results: params, t-values, and R-squared
    return pd.concat([results.params, results.tvalues, pd.Series(results.rsquared, index=['R_squa
```

```python
# Ensure 'aligned_data' is the DataFrame with your stock returns and factors
stock_columns = [col for col in aligned_data.columns if col not in ['Mkt-RF', 'SMB', 'HML', 'RMW

# Prepare DataFrame to store results
results_df_one_day_ahead = pd.DataFrame(index=stock_columns, columns=np.arange(13))  # 500x13 matr

# Iterate over each stock to perform regression
for stock in stock_columns:
    regression_result_one_day_ahead = perform_regression_one_day_ahead(aligned_data, stock)
    results_df_one_day_ahead.loc[stock] = regression_result_one_day_ahead.values

# Naming columns appropriately for coefficients, t-stats, and R-squared
results_df_one_day_ahead.columns = ['const', 'Beta_Mkt-RF', 'Beta_SMB', 'Beta_HML', 'Beta_RMW', 'B
                      't_const', 't_Beta_Mkt-RF', 't_Beta_SMB', 't_Beta_HML', 't_Beta_RMW', 't_Bet

# Display the first few rows of the results to verify
results_df_one_day_ahead.head()
```

Out[ ]:

	const	Beta_Mkt-RF	Beta_SMB	Beta_HML	Beta_RMW	Beta_CMA	t_const	t_Beta_Mkt-RF	t_Beta_SMB	t_B
A	0.056034	-0.082469	0.101949	-0.068831	0.005544	-0.098692	1.852791	-2.793897	1.887479	
AAL	0.02474	0.004954	0.374399	-0.103077	0.569802	-0.157091	0.458412	0.094043	3.884388	-
AAPL	0.095384	-0.136136	0.111536	-0.088358	-0.022185	-0.086473	3.227288	-4.719326	2.113014	-
ABBV	0.058295	-0.052975	0.086519	0.027609	0.021247	-0.081843	2.345137	-2.183518	1.948843	
ABNB	0.000408	0.007446	0.046989	-0.039055	-0.059593	-0.070864	0.015563	0.29068	1.002397	

In [ ]:

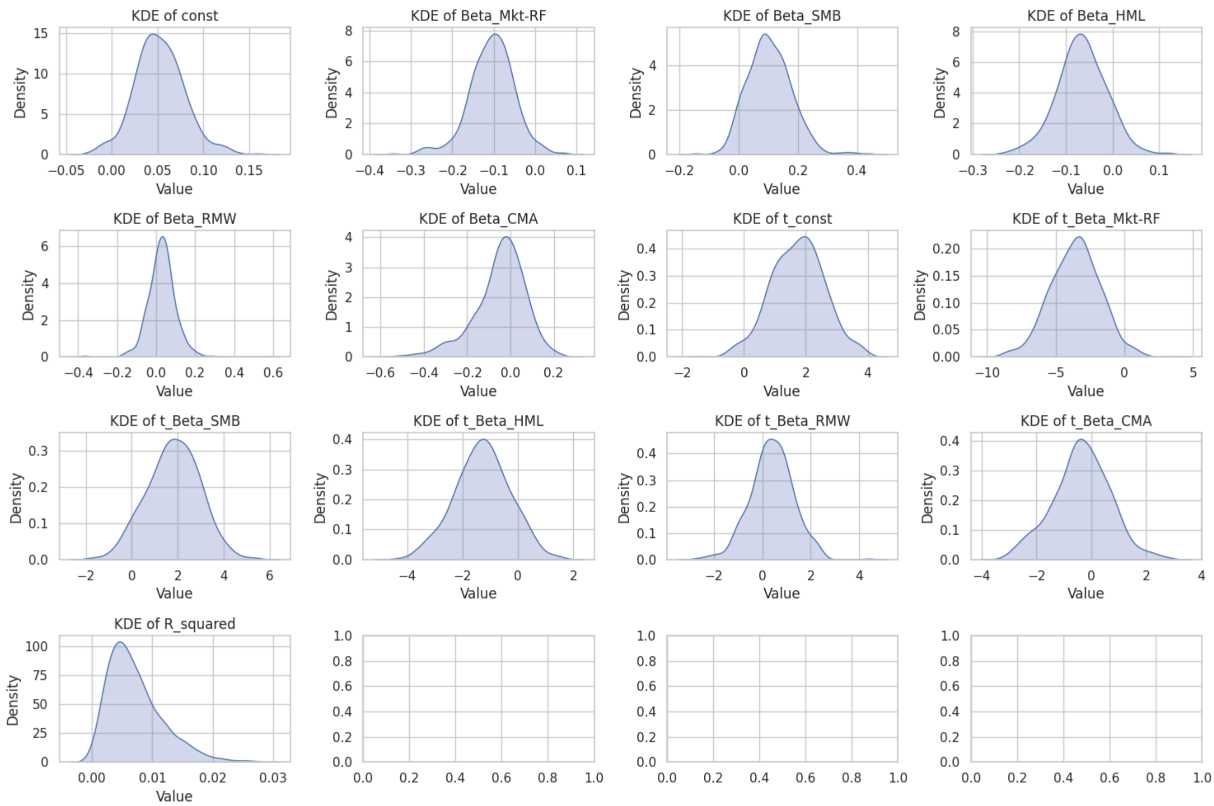
```python
specific_statistics_df_one_day_ahead = pd.DataFrame({
    'Mean': results_df_one_day_ahead.mean(),
    'Variance': results_df_one_day_ahead.var(),
    'Std': results_df_one_day_ahead.std(),
    'Min': results_df_one_day_ahead.min(),
    'Max': results_df_one_day_ahead.max(),
    '25th-Percentile': results_df_one_day_ahead.quantile(0.25),
    'Median': results_df_one_day_ahead.median(),
    '75th-Percentile': results_df_one_day_ahead.quantile(0.75),
    'Interquartile-Range': results_df_one_day_ahead.quantile(0.75) - results_df_one_day_ahead.quan
    'Skewness': results_df_one_day_ahead.skew(),
    'Kurtosis': results_df_one_day_ahead.kurtosis()
})
specific_statistics_df_one_day_ahead
```

Out[ ]:

	Mean	Variance	Std	Min	Max	25th-Percentile	Median	75th-Percentile	Interquartile-Range	S
const	0.052034	0.000721	0.026847	-0.022452	0.160066	0.034362	0.050783	0.068288	0.033926	(
Beta_Mkt-RF	-0.105338	0.002944	0.054263	-0.342536	0.07008	-0.137842	-0.103905	-0.071098	0.066744	-(
Beta_SMB	0.103744	0.005445	0.073788	-0.142763	0.439142	0.054896	0.099439	0.148466	0.09357	(
Beta_HML	-0.066715	0.002807	0.052981	-0.235118	0.12258	-0.098877	-0.066917	-0.032598	0.066279	(
Beta_RMW	0.02823	0.005509	0.074226	-0.378395	0.569802	-0.010197	0.028023	0.065457	0.075654	(
Beta_CMA	-0.049147	0.013888	0.117846	-0.529009	0.235885	-0.100669	-0.033568	0.025028	0.125697	-(
t_const	1.727818	0.738631	0.859436	-1.403594	3.895088	1.130482	1.761702	2.308441	1.177959	-(
t_Beta_Mkt-RF	-3.579276	3.294118	1.814971	-8.847601	3.303182	-4.81995	-3.526113	-2.386374	2.433576	(
t_Beta_SMB	1.801975	1.316842	1.147537	-1.696609	5.447358	1.01567	1.821609	2.603341	1.58767	-(
t_Beta_HML	-1.293079	0.996171	0.998083	-4.352759	1.509027	-1.958456	-1.283461	-0.620487	1.337969	-(
t_Beta_RMW	0.387508	0.787279	0.887287	-2.73006	4.40222	-0.159462	0.388625	0.9477	1.107162	-(
t_Beta_CMA	-0.365682	1.062964	1.031002	-3.10967	2.750536	-1.005139	-0.379771	0.289495	1.294634	-(
R_squared	0.007149	0.00002	0.004526	0.000241	0.027216	0.003813	0.006032	0.009476	0.005663	'

In [ ]:

```
# Plot each t-statistic's density
fig, axes = plt.subplots(4, 4, figsize=(15, 10))  # Adjust subplot grid and figure size as necessa
axes = axes.flatten()  # Flatten the axis array for easy iteration

for i, col in enumerate(results_df_one_day_ahead.columns):
    sns.kdeplot(results_df_one_day_ahead[col], fill=True, ax=axes[i])
    axes[i].set_title(f'KDE of {col}')
    axes[i].set_xlabel('Value')
    axes[i].set_ylabel('Density')

plt.tight_layout()
plt.show()
```



Conclusion

By comparing the two sets of plots, we can conclude the following:

1. **Constant Term Differences**: The first model (immediate regression model) has a higher mean for the constant term, while the second model (one-day-ahead regression model) has a mean closer to zero. This suggests that when using one-day-ahead excess returns, the model estimates a significantly lower constant term.

2. **Factor Coefficient Differences**: The factor coefficients (Betas) in both models are generally close to zero, but the coefficients in the second model (one-day-ahead regression model) are more concentrated. This indicates that the one-day-ahead regression model produces more conservative and consistent estimates for the factors.

3. **R-squared Differences**: The R-squared values for the first model are mostly concentrated in the lower range, indicating limited explanatory power. In contrast, the second model shows a broader distribution with higher mean R-squared values, suggesting that the one-day-ahead regression model better explains the variation in excess returns.

Overall, the one-day-ahead regression model is more conservative in estimating factor coefficients and improves the model's explanatory power compared to the immediate regression model.

Question 9

In [ ]:
```
from sklearn.ensemble import RandomForestRegressor

def perform_random_forest_regression(data, stock_symbol):
    y = data[stock_symbol] - data['RF_ff']
    X = data[['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA_ff']]

    model = RandomForestRegressor(n_estimators=100, random_state=42)
    model.fit(X, y)
    predictions = model.predict(X)
    score = model.score(X, y)  # Coefficient of determination R^2

    return predictions, score

# Example usage
predictions, score = perform_random_forest_regression(aligned_data, 'AAPL')
print("R^2 Score:", score)
```

```
R^2 Score: 0.9285907468411307
```

Analysis and Comparison

- **Higher R^2 Score**: The R^2 score of 0.9286 from the Random Forest Regression model indicates a very high proportion of variance in AAPL's excess returns is explained by the Fama-French factors. This is significantly higher than typical R^2 values seen in linear regression models for stock returns, which usually range between 0.2 to 0.7.

- **Non-linear Relationships**: The Random Forest model captures non-linear relationships and interactions between the factors, which a linear model may not. This is likely why we see a much higher R^2 score.

- **Robustness**: Random Forest models are less prone to overfitting compared to traditional linear regression models when appropriately tuned, providing a more robust fit.

In conclusion, using Random Forest Regression to link Fama-French factors to excess returns results in a substantially improved fit compared to the linear regression model. This demonstrates the effectiveness of machine learning algorithms in capturing complex relationships in financial data.

Question 10

Incorporating additional factors into the Fama-French model can enhance its explanatory power by capturing different dimensions of risk and return in the stock market. Here are some potential factors that could be considered:

1. Momentum Factor (MOM) The momentum factor captures the tendency of stocks that have performed well in the past to continue performing well in the near future, and vice versa. It is calculated as the difference in returns between the top decile and bottom decile of stocks sorted by past performance over a specific period.

2. Low Volatility Factor This factor is based on the observation that stocks with lower volatility tend to generate higher risk-adjusted returns than more volatile stocks. It can be constructed by contrasting the returns of stocks with the lowest volatility with those of the highest volatility.

3. Quality Factor The quality factor refers to stocks that are characterized by low debt, stable earnings growth, and high profitability. Such stocks tend to outperform in the long run, providing a possible factor for consideration.

4. Market Sentiment (VIX or Similar Metrics) Using an index such as the VIX, which measures market volatility expectations, could help model how market sentiment affects returns. The VIX is often referred to as the "fear index" and tends to be inversely related to the market performance.

In [ ]:

```
```