Analyze Stock (Price) Performance with Linear Regression and Hypothesis Testing Using Python

Task 1: Load and inspect the Stock Price Dataset

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
pd.options.display.float_format = "{:,.2f}".format
```

In [ ]:
```
prices = pd.read_csv("stock_prices.csv", index_col = "Date", parse_dates =
prices
```

Out[ ]:

Date	AAPL	AJG	AVB	DLR	ICE	INCY	KHC	LLY	MCHP	MDT	MOH
2019-12-31	73.41	95.23	209.70	119.74	92.55	87.32	32.13	131.43	52.36	113.45	135.69
2020-01-02	75.09	95.51	207.24	118.00	92.67	85.97	31.61	132.21	53.80	114.56	133.37
2020-01-03	74.36	95.31	209.23	119.94	94.67	77.90	31.24	131.77	52.62	113.88	132.54
2020-01-06	74.95	95.75	209.58	118.86	94.70	77.34	31.31	132.26	51.87	114.89	137.35
2020-01-07	74.60	94.72	205.02	117.69	94.43	77.14	30.76	132.51	55.35	114.49	139.26
...	...	...	...	...	...	...	...	...	...	...	...
2022-12-23	131.86	188.41	163.03	100.87	102.81	81.36	40.52	367.90	69.93	77.50	335.08
2022-12-27	130.03	189.28	162.80	100.35	102.11	79.59	40.96	364.88	69.03	77.64	334.37
2022-12-28	126.04	187.95	161.08	99.40	102.27	79.44	40.44	365.22	67.87	76.30	332.42
2022-12-29	129.61	190.17	162.65	101.30	104.10	79.48	40.68	367.02	70.45	77.81	333.27
2022-12-30	129.93	188.54	161.52	100.27	102.59	80.32	40.71	365.84	70.25	77.72	330.22

757 rows × 15 columns

Column Information (stock_prices.csv)

- AAPL: Daily Stock Prices for Apple Inc.
- AJG: Daily Stock Prices for Arthur J. Gallagher & Co.
- AVB: Daily Stock Prices for AvalonBay Communities Inc.

- DLR: Daily Stock Prices for Digital Realty Trust Inc.
- ICE: Daily Stock Prices for Intercontinental Exchange Inc.
- INCY: Daily Stock Prices for Incyte Corporation
- KHC: Daily Stock Prices for The Kraft Heinz Company
- LLY: Daily Stock Prices for Eli Lilly And Co.
- MCHP: Daily Stock Prices for Microchip Technology Inc.
- MDT: Daily Stock Prices for Medtronic PLC
- MOH: Daily Stock Prices for Molina Healthcare Inc.
- NDAQ: Daily Stock Prices for Nasdaq Inc.
- PRU: Daily Stock Prices for Prudential Financial Inc.
- STLD: Daily Stock Prices for Steel Dynamics
- TER: Daily Stock Prices for Teradyne Inc.

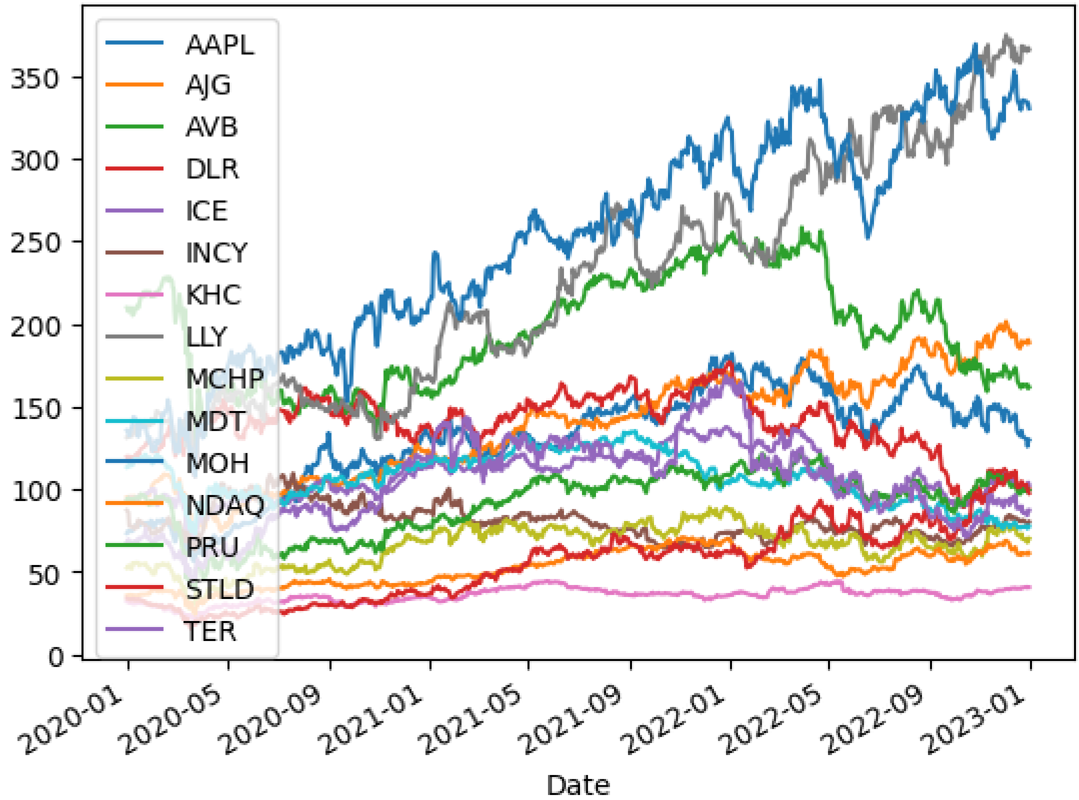
In [ ]:
```
prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 757 entries, 2019-12-31 to 2022-12-30
Data columns (total 15 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   AAPL    757 non-null    float64
 1   AJG     757 non-null    float64
 2   AVB     757 non-null    float64
 3   DLR     757 non-null    float64
 4   ICE     757 non-null    float64
 5   INCY    757 non-null    float64
 6   KHC     757 non-null    float64
 7   LLY     757 non-null    float64
 8   MCHP    757 non-null    float64
 9   MDT     757 non-null    float64
 10  MOH     757 non-null    float64
 11  NDAQ    757 non-null    float64
 12  PRU     757 non-null    float64
 13  STLD    757 non-null    float64
 14  TER     757 non-null    float64
dtypes: float64(15)
memory usage: 94.6 KB
```

In [ ]:
```
symbols = prices.columns.to_list()
```

In [ ]:
```
prices.plot()
```

Out[ ]:
```
<AxesSubplot:xlabel='Date'>
```



In [ ]:
```
returns = prices.pct_change().dropna()*100
```

In [ ]:
```
returns
```

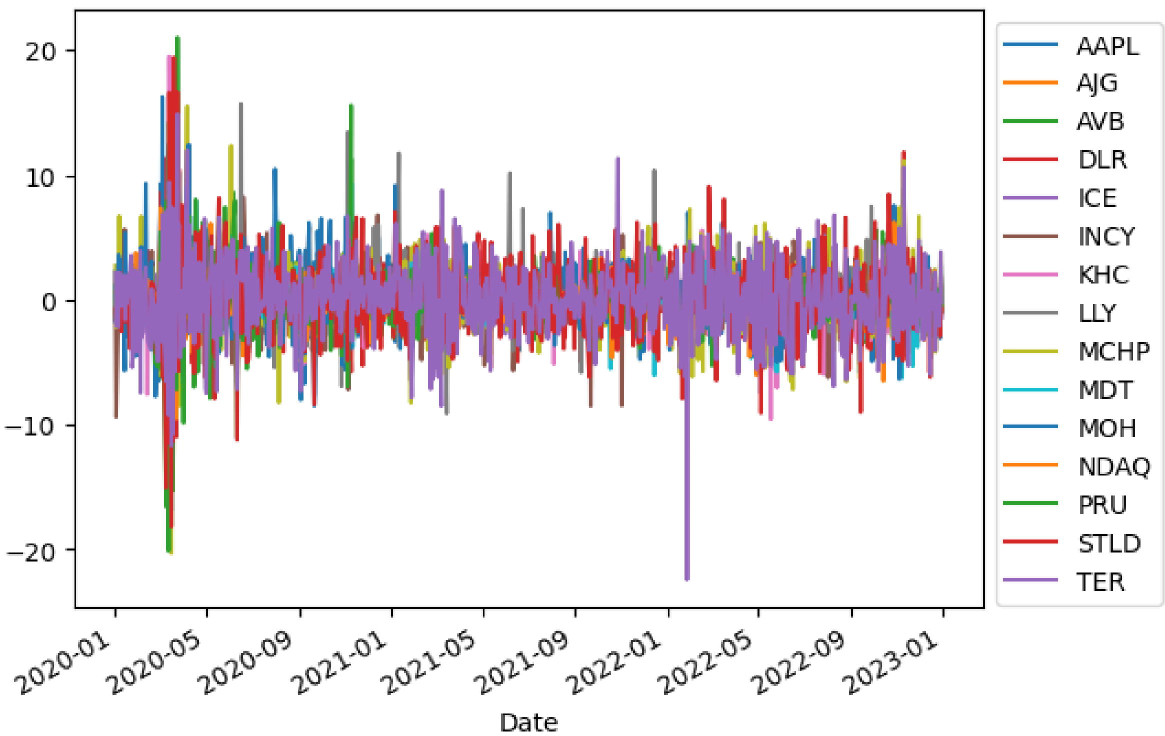
Out[ ]:

Date	AAPL	AJG	AVB	DLR	ICE	INCY	KHC	LLY	MCHP	MDT	MOH	NDAQ	P
2020-01-02	2.28	0.29	-1.17	-1.45	0.13	-1.55	-1.62	0.59	2.75	0.98	-1.71	0.67	'
2020-01-03	-0.97	-0.21	0.96	1.64	2.16	-9.39	-1.17	-0.33	-2.19	-0.59	-0.62	0.43	-1
2020-01-06	0.80	0.46	0.17	-0.90	0.03	-0.72	0.22	0.37	-1.43	0.89	3.63	-0.06	0
2020-01-07	-0.47	-1.08	-2.18	-0.98	-0.29	-0.26	-1.76	0.19	6.71	-0.35	1.39	-1.65	-(
2020-01-08	1.61	0.14	0.41	0.87	-0.88	-0.79	-0.55	0.91	-1.26	1.76	3.25	-0.55	0
...	...	...	...	...	...	...	...	...	...	...	...	...	
2022-12-23	-0.28	0.20	0.73	1.01	0.34	0.30	0.40	0.71	0.03	0.47	-0.07	0.36	(
2022-12-27	-1.39	0.46	-0.14	-0.52	-0.68	-2.18	1.09	-0.82	-1.29	0.18	-0.21	-0.49	-(
2022-12-28	-3.07	-0.70	-1.06	-0.95	0.16	-0.19	-1.27	0.09	-1.68	-1.73	-0.58	-0.46	-0
2022-12-29	2.83	1.18	0.97	1.91	1.79	0.05	0.59	0.49	3.80	1.98	0.26	1.93	1
2022-12-30	0.25	-0.86	-0.69	-1.02	-1.45	1.06	0.07	-0.32	-0.28	-0.12	-0.92	-0.84	-0

756 rows × 15 columns

In [ ]:

```
returns.plot()
plt.legend(bbox_to_anchor=(1,1))
plt.show()
```



In [ ]:

Column Information (factors.csv)

The Return of the risk-free Asset:
RF: the one-month Treasury bill rate (from Ibbotson Associates).

Fama/French 5 Factors:

- The "MARKET RISK" factor:
  MktPrem: Market Risk Premium (Rm-Rf). The excess return of the market portfolio (Rm) over the risk-free asset (Rf). Market Portfolio Return: Value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ.

- The "SIZE" factor:
  SMB: SMB (Small Minus Big Company Size) is the average return on nine small stock portfolios minus the average return on nine big stock portfolios.

- The "VALUE" factor:
  HML: HML (High Minus Low [Book Value/Market Value]) is the average return on two value portfolios (high book value/market value) minus the average return on two growth portfolios (low book value/market value).

- The "OPERATING PROFITABILITY" factor:
  RMW: RMW (Robust Minus Weak) is the average return on two robust operating profitability portfolios minus the average return on two weak operating profitability portfolios.

- The "INVESTMENT" factor:
  CMA: CMA (Conservative Minus Aggressive) is the average return on two conservative investment portfolios minus the average return on two aggressive investment portfolios.

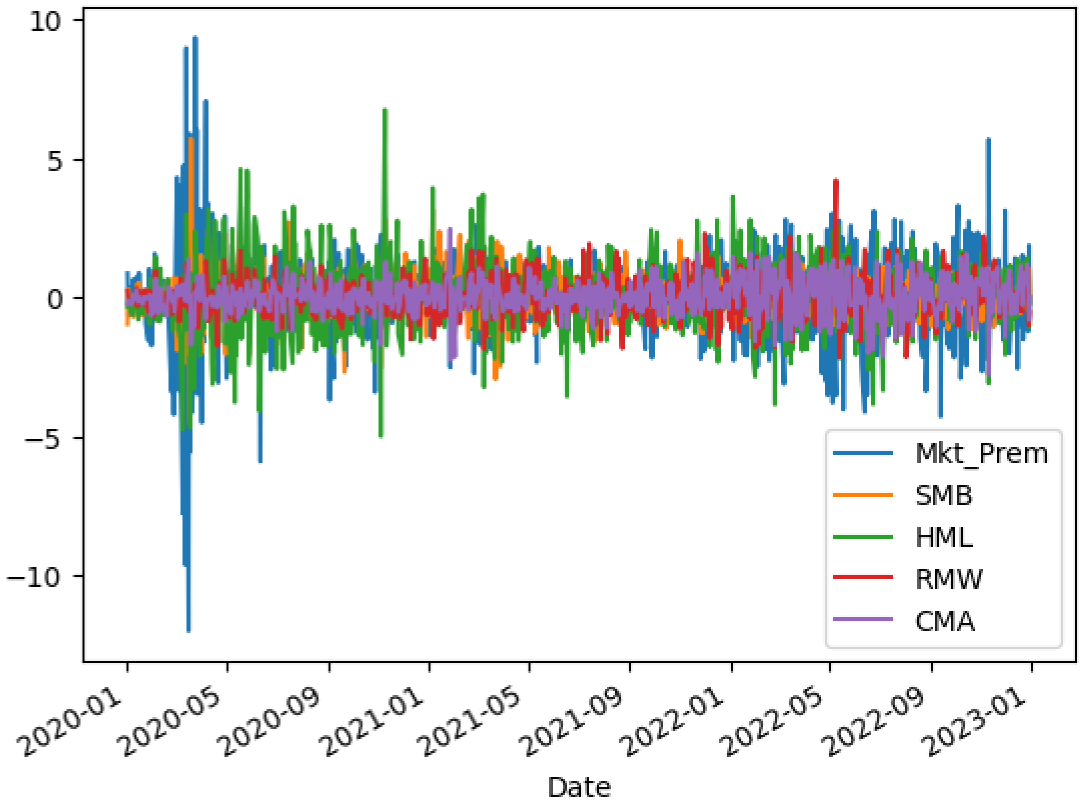
In [ ]:
```
factors = pd.read_csv('factors.csv',index_col='Date',parse_dates=(['Date'])
```

In [ ]:
```
factors.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 756 entries, 2020-01-02 to 2022-12-30
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Mkt_Prem  756 non-null    float64
 1   SMB       756 non-null    float64
 2   HML       756 non-null    float64
 3   RMW       756 non-null    float64
 4   CMA       756 non-null    float64
 5   RF        756 non-null    float64
dtypes: float64(6)
memory usage: 41.3 KB
```

In [ ]:
```
factors.drop(['RF'],axis=1).plot()
```

Out[ ]:
```
<AxesSubplot:xlabel='Date'>
```



In [ ]:
```
five_factors = factors.drop(['RF'],axis=1).columns.to_list()
```

In [ ]:
```
five_factors
```

Out[ ]:
```
['Mkt_Prem', 'SMB', 'HML', 'RMW', 'CMA']
```

In [ ]:
```
data = pd.concat([returns,factors],axis=1,join='inner')
```

In [ ]:
```
data
```

Out[ ]:

Date	AAPL	AJG	AVB	DLR	ICE	INCY	KHC	LLY	MCHP	MDT	...	NDAQ	PRU
2020-01-02	2.28	0.29	-1.17	-1.45	0.13	-1.55	-1.62	0.59	2.75	0.98	...	0.67	1.17
2020-01-03	-0.97	-0.21	0.96	1.64	2.16	-9.39	-1.17	-0.33	-2.19	-0.59	...	0.43	-1.67
2020-01-06	0.80	0.46	0.17	-0.90	0.03	-0.72	0.22	0.37	-1.43	0.89	...	-0.06	0.25
2020-01-07	-0.47	-1.08	-2.18	-0.98	-0.29	-0.26	-1.76	0.19	6.71	-0.35	...	-1.65	-0.11
2020-01-08	1.61	0.14	0.41	0.87	-0.88	-0.79	-0.55	0.91	-1.26	1.76	...	-0.55	0.64
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2022-12-23	-0.28	0.20	0.73	1.01	0.34	0.30	0.40	0.71	0.03	0.47	...	0.36	0.91
2022-12-27	-1.39	0.46	-0.14	-0.52	-0.68	-2.18	1.09	-0.82	-1.29	0.18	...	-0.49	-0.21
2022-12-28	-3.07	-0.70	-1.06	-0.95	0.16	-0.19	-1.27	0.09	-1.68	-1.73	...	-0.46	-0.99
2022-12-29	2.83	1.18	0.97	1.91	1.79	0.05	0.59	0.49	3.80	1.98	...	1.93	1.54
2022-12-30	0.25	-0.86	-0.69	-1.02	-1.45	1.06	0.07	-0.32	-0.28	-0.12	...	-0.84	-0.42

756 rows × 21 columns

In [ ]:
```
data[symbols] = data[symbols].sub(data['RF'],axis=0)
```

In [ ]:
```
data = data.drop(['RF'],axis=1)
```

In [ ]:
```
data
```

Out[ ]:

	AAPL	AJG	AVB	DLR	ICE	INCY	KHC	LLY	MCHP	MDT	MOH	NDAQ	P
Date													
2020-01-02	2.28	0.29	-1.18	-1.46	0.12	-1.55	-1.62	0.59	2.74	0.97	-1.72	0.67	1
2020-01-03	-0.98	-0.22	0.95	1.64	2.15	-9.39	-1.18	-0.34	-2.20	-0.60	-0.63	0.42	-1
2020-01-06	0.79	0.46	0.16	-0.91	0.03	-0.72	0.22	0.37	-1.44	0.88	3.62	-0.07	0
2020-01-07	-0.48	-1.08	-2.18	-0.99	-0.29	-0.26	-1.76	0.18	6.70	-0.35	1.38	-1.66	-(
2020-01-08	1.60	0.13	0.41	0.86	-0.88	-0.80	-0.56	0.90	-1.27	1.75	3.24	-0.56	0
...	...	...	...	...	...	...	...	...	...	...	...	...	
2022-12-23	-0.30	0.19	0.71	1.00	0.33	0.28	0.38	0.69	0.01	0.45	-0.09	0.34	0
2022-12-27	-1.40	0.45	-0.16	-0.53	-0.70	-2.19	1.07	-0.84	-1.30	0.16	-0.23	-0.51	-0
2022-12-28	-3.08	-0.72	-1.07	-0.96	0.14	-0.20	-1.29	0.08	-1.70	-1.74	-0.60	-0.48	-1
2022-12-29	2.82	1.17	0.96	1.90	1.77	0.03	0.58	0.48	3.79	1.96	0.24	1.91	1
2022-12-30	0.23	-0.87	-0.71	-1.03	-1.47	1.04	0.06	-0.34	-0.30	-0.13	-0.93	-0.86	-0.

756 rows × 20 columns

In [ ]:
```
filter_list = five_factors + ['AAPL']
```

In [ ]:
```
apple_stock = data[filter_list]
```

In [ ]:
```
apple_stock
```

Out[ ]:

	Mkt_Prem	SMB	HML	RMW	CMA	AAPL
Date						
2020-01-02	0.86	-0.97	-0.34	0.24	-0.22	2.28
2020-01-03	-0.67	0.30	0.01	-0.14	-0.10	-0.98
2020-01-06	0.36	-0.21	-0.55	-0.17	-0.26	0.79
2020-01-07	-0.19	-0.03	-0.25	-0.13	-0.25	-0.48
2020-01-08	0.47	-0.17	-0.64	-0.20	-0.17	1.60
...	...	...	...	...	...	...
2022-12-23	0.51	-0.34	1.15	0.86	0.46	-0.30
2022-12-27	-0.51	-0.42	1.43	1.13	1.19	-1.40
2022-12-28	-1.23	-0.30	-0.29	-0.96	-0.03	-3.08
2022-12-29	1.87	1.03	-1.07	-1.01	-0.82	2.82
2022-12-30	-0.22	0.12	-0.03	-0.53	0.01	0.23

756 rows × 6 columns

In [ ]:

```
apple_stock.corr()
```

Out[ ]:

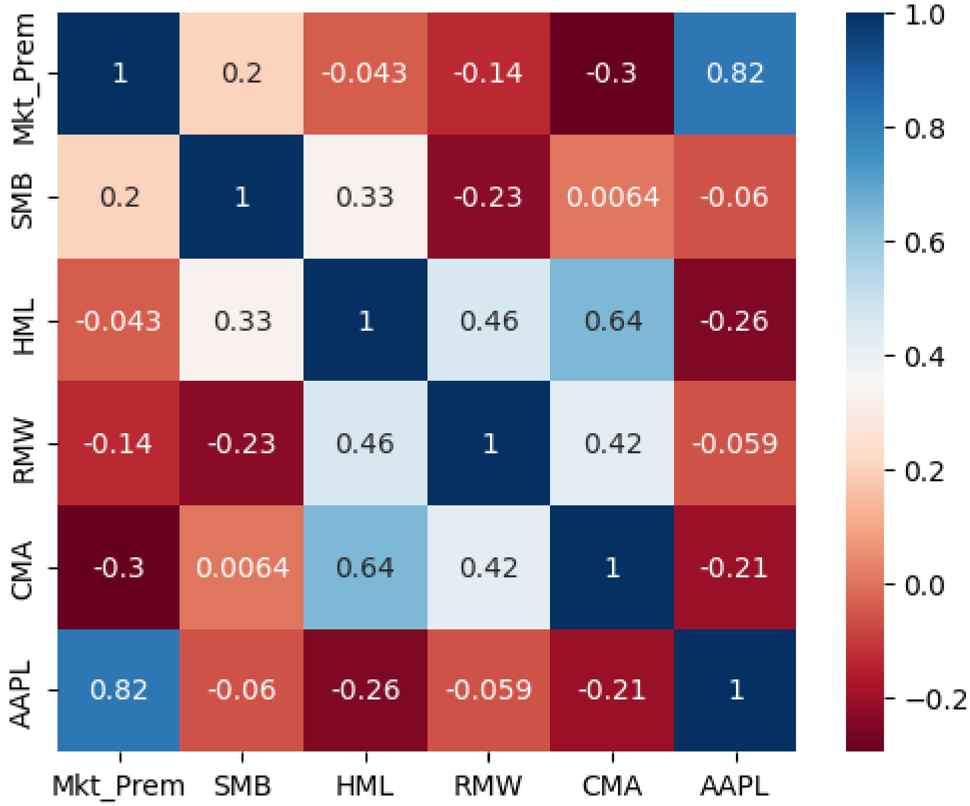
	Mkt_Prem	SMB	HML	RMW	CMA	AAPL
Mkt_Prem	1.00	0.20	-0.04	-0.14	-0.30	0.82
SMB	0.20	1.00	0.33	-0.23	0.01	-0.06
HML	-0.04	0.33	1.00	0.46	0.64	-0.26
RMW	-0.14	-0.23	0.46	1.00	0.42	-0.06
CMA	-0.30	0.01	0.64	0.42	1.00	-0.21
AAPL	0.82	-0.06	-0.26	-0.06	-0.21	1.00

In [ ]:

```
sns.heatmap(apple_stock.corr(),cmap='RdBu',square=True,annot=True)
```

Out[ ]:

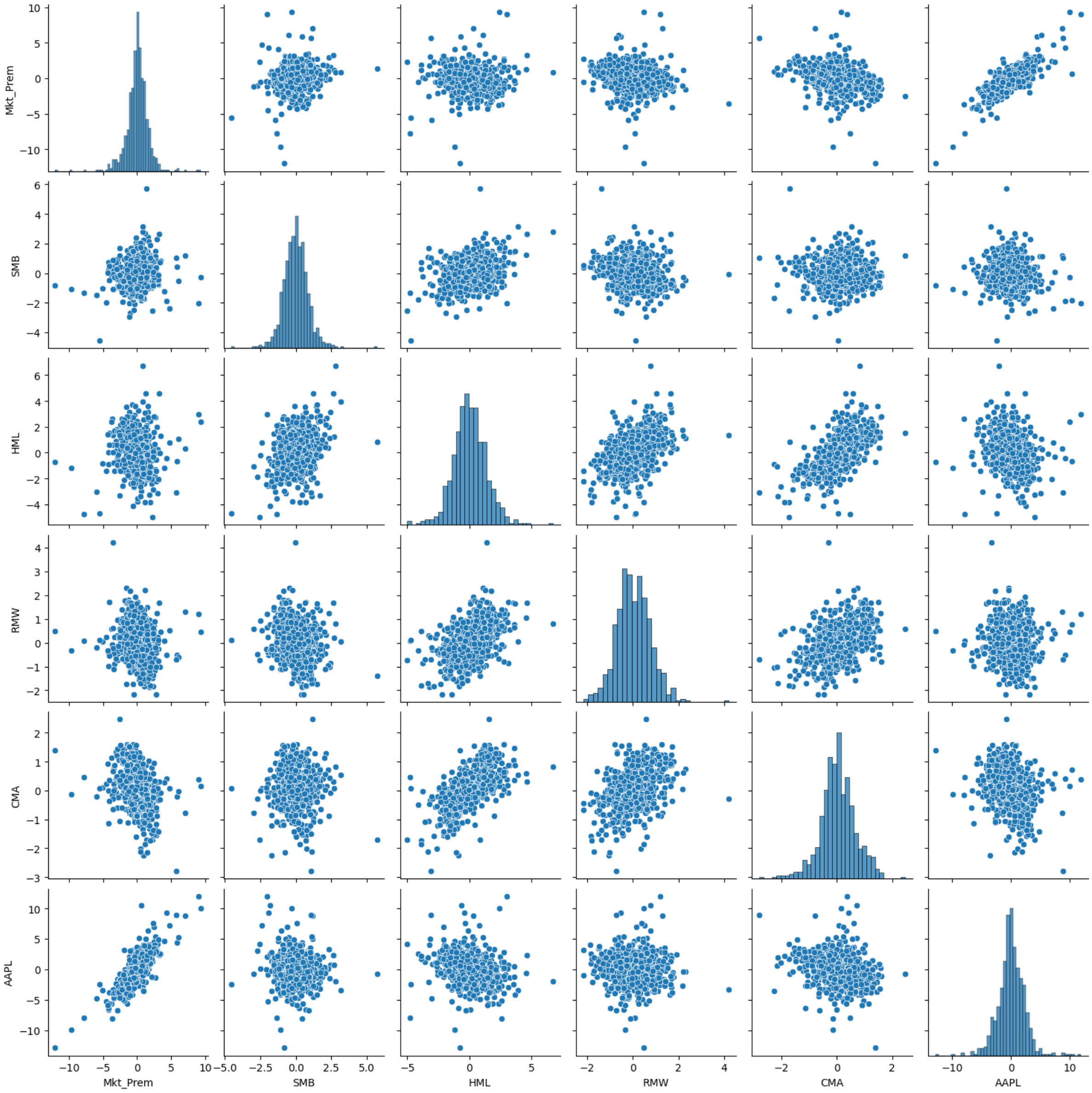
```
<AxesSubplot:>
```



Mkt_Prem has the most correlation with the dependent variable AAPL

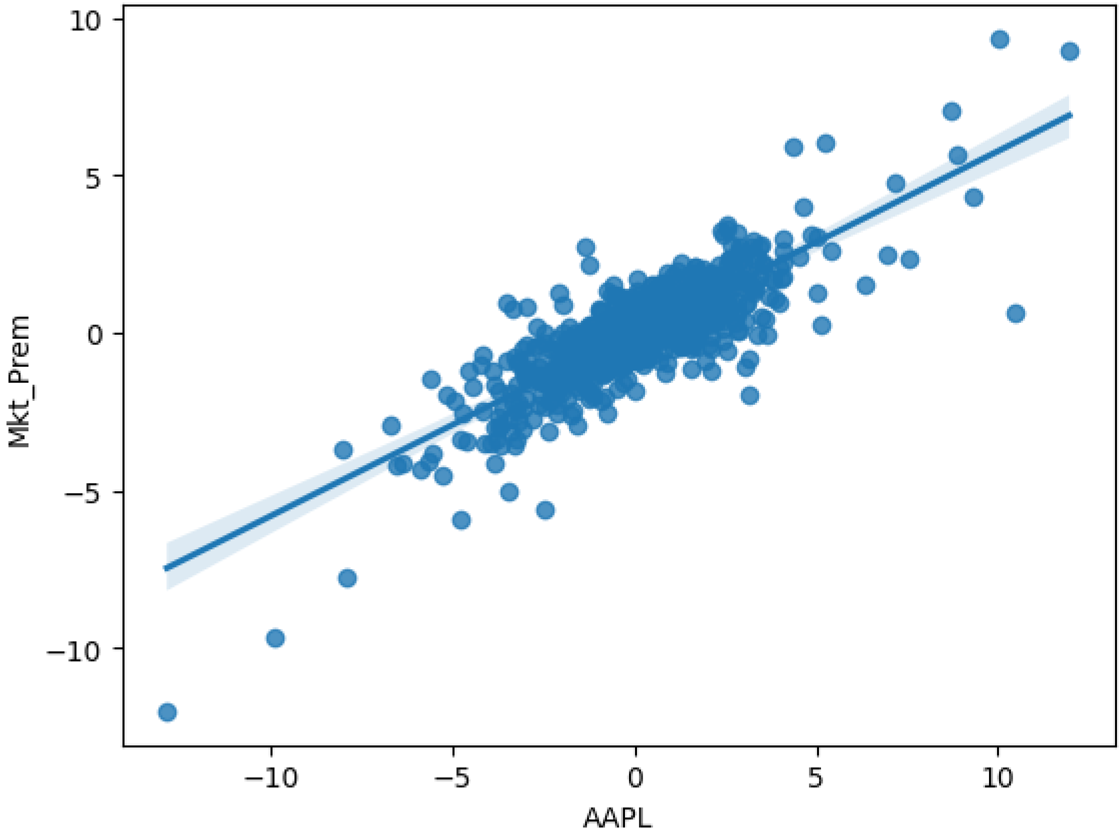
In [ ]:
```
sns.pairplot(apple_stock)
```

Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x7f2fdc09ca60>
```



In [ ]:
```
sns.regplot(x='AAPL',y='Mkt_Prem',data=apple_stock)
```

Out[ ]:
```
<AxesSubplot:xlabel='AAPL', ylabel='Mkt_Prem'>
```



In [ ]:
```
model = smf.ols('AAPL ~ Mkt_Prem + SMB + HML + RMW + CMA',data = apple_stocl
```

In [ ]:
```
result = model.fit()
```

In [ ]:
```
result.summary()
```

Out[ ]: OLS Regression Results

Dep. Variable:	AAPL	**R-squared:**	0.804
Model:	OLS	**Adj. R-squared:**	0.803
Method:	Least Squares	**F-statistic:**	615.7
Date:	Mon, 15 Jan 2024	**Prob (F-statistic):**	1.29e-262
Time:	21:51:14	**Log-Likelihood:**	-1094.5
No. Observations:	756	**AIC:**	2201.
Df Residuals:	750	**BIC:**	2229.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0165	0.038	0.438	0.661	-0.058	0.091
Mkt_Prem	1.3084	0.025	52.765	0.000	1.260	1.357
SMB	-0.1903	0.053	-3.564	0.000	-0.295	-0.085
HML	-0.7681	0.045	-17.063	0.000	-0.857	-0.680
RMW	0.4220	0.065	6.502	0.000	0.295	0.549
CMA	1.0952	0.086	12.768	0.000	0.927	1.264

Omnibus:	137.137	**Durbin-Watson:**	1.880
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	839.010
Skew:	0.656	**Prob(JB):**	6.47e-183
Kurtosis:	7.991	**Cond. No.**	4.13

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [ ]:
```
coef = pd.DataFrame(columns=['Intercept','Mkt_Prem','SMB','HML','RMW','CMA']
signif = pd.DataFrame(columns = ['Intercept','Mkt_Prem','SMB','HML','RMW','(

for i in symbols:
    stock = data[five_factors + [i]]
    model = smf.ols(i +'~ Mkt_Prem + SMB + HML + RMW + CMA',data=stock)
    results = model.fit()
    coef.loc[i] = results.params
    signif.loc[i] = results.pvalues < 0.05
    signif.loc[i,'rsquared'] = results.rsquared
```

In [ ]:
```
coef
```

Out[ ]:

	Intercept	Mkt_Prem	SMB	HML	RMW	CMA
AAPL	0.02	1.31	-0.19	-0.77	0.42	1.10
AJG	0.07	0.88	-0.25	0.24	0.07	-0.15
AVB	-0.06	0.88	-0.02	0.43	0.15	-0.11
DLR	-0.04	0.86	-0.48	-0.17	0.03	0.28
ICE	0.01	0.83	-0.32	0.12	-0.19	-0.10
INCY	-0.01	0.66	-0.12	-0.29	-0.34	0.41
KHC	-0.02	0.79	-0.34	0.19	0.20	0.77
LLY	0.10	0.74	-0.34	-0.28	0.13	0.82
MCHP	0.03	1.47	0.52	-0.28	0.30	-0.11
MDT	-0.07	0.82	-0.05	0.37	-0.00	-0.17
MOH	0.09	0.89	-0.05	-0.17	0.14	0.61
NDAQ	0.06	0.97	-0.36	0.02	-0.12	0.06
PRU	-0.01	1.29	-0.12	1.30	-0.23	-0.43
STLD	0.12	1.16	0.66	0.69	0.24	-0.09
TER	0.03	1.38	0.50	-0.48	0.12	0.05

In [ ]:

```
signif
```

Out[ ]:

	Intercept	Mkt_Prem	SMB	HML	RMW	CMA	rsquared
AAPL	False	True	True	True	True	True	0.80
AJG	False	True	True	True	False	False	0.58
AVB	False	True	False	True	False	False	0.49
DLR	False	True	True	True	False	True	0.40
ICE	False	True	True	True	True	False	0.55
INCY	False	True	False	True	True	True	0.28
KHC	False	True	True	True	True	True	0.42
LLY	False	True	True	True	False	True	0.28
MCHP	False	True	True	True	True	False	0.67
MDT	False	True	False	True	False	False	0.54
MOH	False	True	False	False	False	True	0.30
NDAQ	False	True	True	False	False	False	0.62
PRU	False	True	False	True	True	True	0.84
STLD	False	True	True	True	False	False	0.56
TER	False	True	True	True	False	False	0.60

In [ ]:

```
signif[five_factors].mean().sort_values(ascending=False).mul(100)
```

Out[ ]:
```
Mkt_Prem   100.00
HML         86.67
SMB         66.67
CMA         46.67
RMW         40.00
dtype: float64
```

The Market Premium is always significant and the marginal benefits of adding more factors is declining.

In [ ]:
```
signif['rsquared'].mean()
```

Out[ ]:
```
0.5282455279880509
```

On average the Fama/French 5 factor model explains about 53% of the Stock performance.

In [ ]:
```
```