Financial Data Analysis of Airlines

Data 690 Financial Data Science
Professor: Abdullah Karasan

TEAM 4

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INTRODUCTION

- **Objective and Scope**

  The project aimed to analyze the financial performance of five selected airlines, using the S&P 500 Index as a market benchmark, over a five-year period from 2019 to 2024.the analysis spans from 2019 to 2024, covering pre-pandemic, pandemic, and post-pandemic market conditions.

- **Data Collection and Preparation**

  Stock price data for the airlines and the S&P 500 Index were collected, followed by data cleaning to ensure accuracy and completeness for analysis.

- **Summary Statistics**

  Detailed statistics provided initial insights into each airline's performance, highlighting differences in volatility and average stock prices.

- **Exploratory Data Analysis (EDA)**

  EDA techniques, including time series plots of stock prices, were used to visualize performance trends over the specified period.

- **Statistical Analysis for In-depth Insights**

  Statistical measures like mean, standard deviation, Z score, and confidence interval have been determined.

- **Main Financial Concepts**

  Financial Concepts such as return, risk, covariance, correlation, risk return ratio have been determined.

- **Capital Asset Pricing Model (CAPM) Analysis**

  CAPM was utilized to evaluate expected returns based on systematic risk, offering insights into each airline's market performance relative to overall market movements and performance measurements such as Sharpe and Treynor Ratios are determined.

- **Application of Modern Portfolio Theory (MPT)**

  MPT principles guided the exploration of optimal investment strategies and portfolio construction, enhancing investment decision-making.

- **Time Series Analysis**

  The time series analysis focused on evaluating and forecasting airline stock prices with methods like decomposition, stationarity testing, ARIMA and SARIMA models to understand patterns and predict future trends.

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MOTIVATION

- The project seeks to dissect the impact of the COVID-19 pandemic on airline stocks, comparing their performance with the broader S&P 500 index, to gauge the industry's resilience and strategic responses.
- It aims to offer a detailed examination of airline stock behavior from 2019 to 2024, encapsulating pre-pandemic, pandemic, and post-pandemic market conditions, providing insights into the financial dynamics during crisis periods.
- Through the application of financial models and theories, the project bridges the gap between academic understanding and real-world market fluctuations, enhancing our knowledge of economic resilience.
- The endeavor contributes to a comprehensive understanding of how airlines navigated the challenges posed by the pandemic, offering lessons on adaptability and strategic planning in the face of global economic disruptions.

MAIN FINANCIAL CONCEPTS

Return

```
# Annualizing the returns
annual_returns = daily_returns.mean() * 252
print(annual_returns)
```

```
Ticker
AAL      0.010167
JBLU    -0.062182
LUV     -0.019150
RYAAY    0.206151
UAL      0.033867
^GSPC    0.151584
dtype: float64
```

Risk

```
#Annualizing the risk
annual_risk = daily_returns.std() * np.sqrt(252)
print(annual_risk)
```

```
Ticker
AAL      0.612494
JBLU     0.558842
LUV      0.397472
RYAAY    0.406074
UAL      0.592375
^GSPC    0.213234
dtype: float64
```

Correlation

```
# Calculating correlation matrix of daily returns
correlation_matrix = daily_returns.corr()
print(correlation_matrix)
```

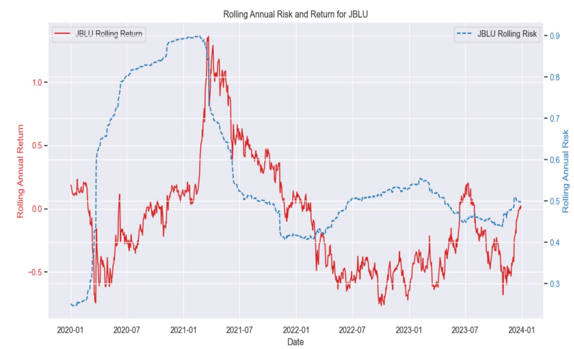
Ticker	AAL	JBLU	LUV	RYAAY	UAL	^GSPC
Ticker						
AAL	1.000000	0.789332	0.732772	0.518209	0.854692	0.482458
JBLU	0.789332	1.000000	0.736299	0.587489	0.787428	0.493511
LUV	0.732772	0.736299	1.000000	0.551456	0.780400	0.566794
RYAAY	0.518209	0.587489	0.551456	1.000000	0.610320	0.497248
UAL	0.854692	0.787428	0.780400	0.610320	1.000000	0.527668
^GSPC	0.482458	0.493511	0.566794	0.497248	0.527668	1.000000

Covariance

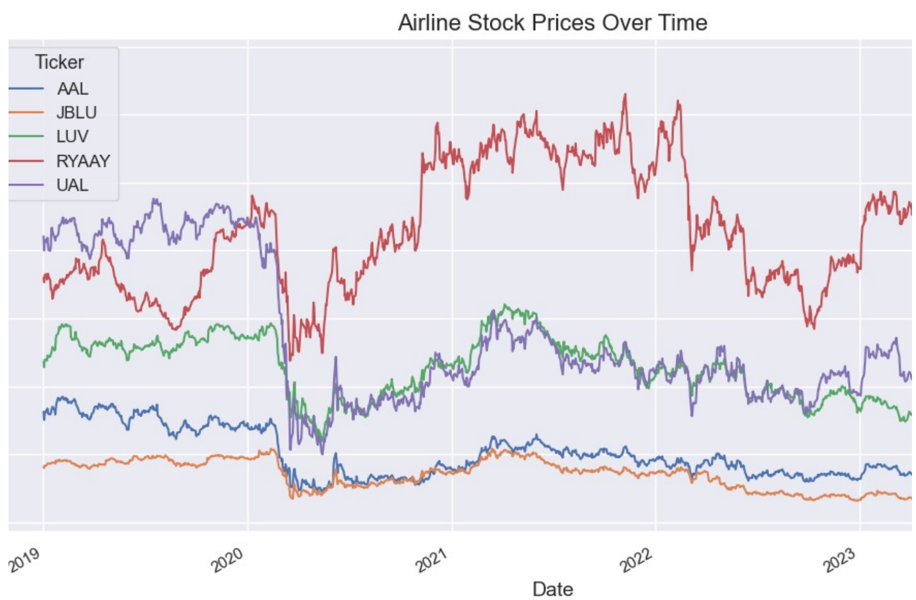
]:
```
# Calculating covariance matrix of daily returns
covariance_matrix = daily_returns.cov() * 252
# Display the results
print(covariance_matrix)
```

Ticker	AAL	JBLU	LUV	RYAAY	UAL	^GSPC
Ticker						
AAL	0.375149	0.270178	0.178393	0.128888	0.310104	0.063011
JBLU	0.270178	0.312305	0.163550	0.133320	0.260673	0.058809
LUV	0.178393	0.163550	0.157984	0.089007	0.183747	0.048038
RYAAY	0.128888	0.133320	0.089007	0.164896	0.146811	0.043056
UAL	0.310104	0.260673	0.183747	0.146811	0.350908	0.066652
^GSPC	0.063011	0.058809	0.048038	0.043056	0.066652	0.045469

RISK RETURN RATIO



ANALYSIS

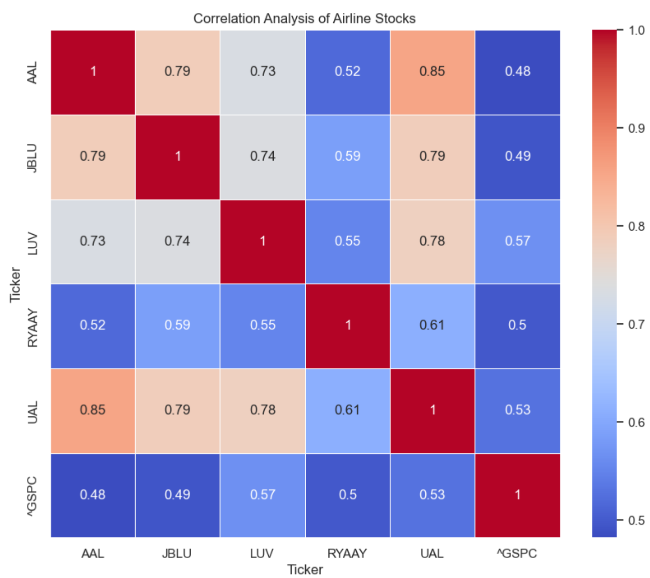


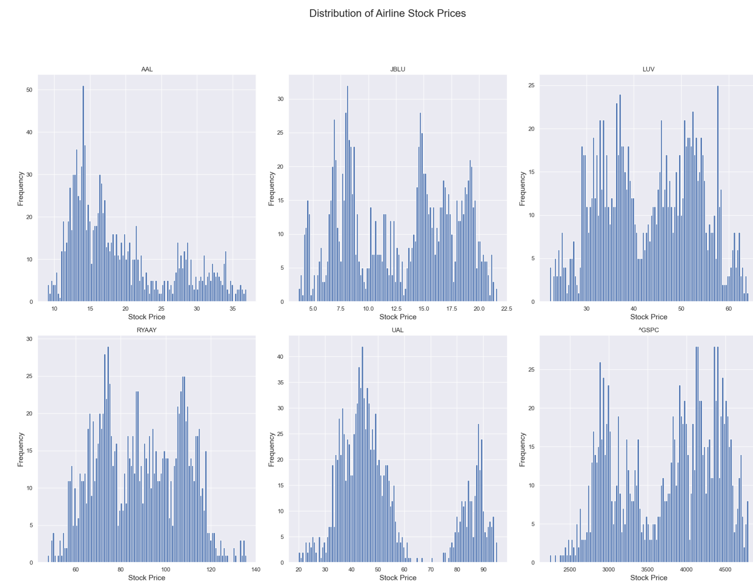
Summary Statistics

```
airline_stock_prices.describe()
```

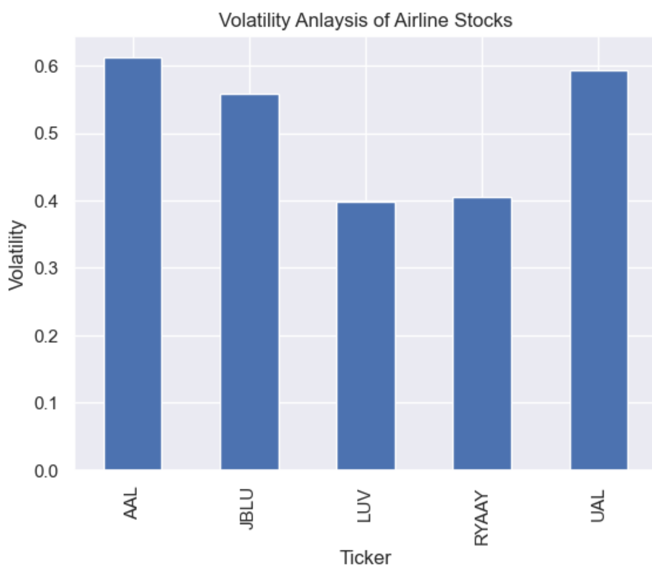
Ticker	AAL	JBLU	LUV	RYAAY	UAL	GSPC
count	1258.000000	1258.000000	1258.000000	1258.000000	1258.000000	1258.000000
mean	19.277631	12.844269	43.375246	88.637043	53.287504	3755.831541
std	7.000581	4.842476	10.095553	18.808973	19.375327	634.050177
min	9.040000	3.690000	22.230000	47.509998	19.920000	2237.399902
25%	13.835000	8.202500	34.757500	72.910002	40.027500	3128.659973
50%	16.835000	13.880000	43.965000	87.759998	46.465000	3907.449951
75%	23.437500	16.980000	51.932499	105.857500	57.700000	4305.090088
max	36.930000	21.639999	64.099998	135.740005	95.279999	4796.560059

ANALYSIS

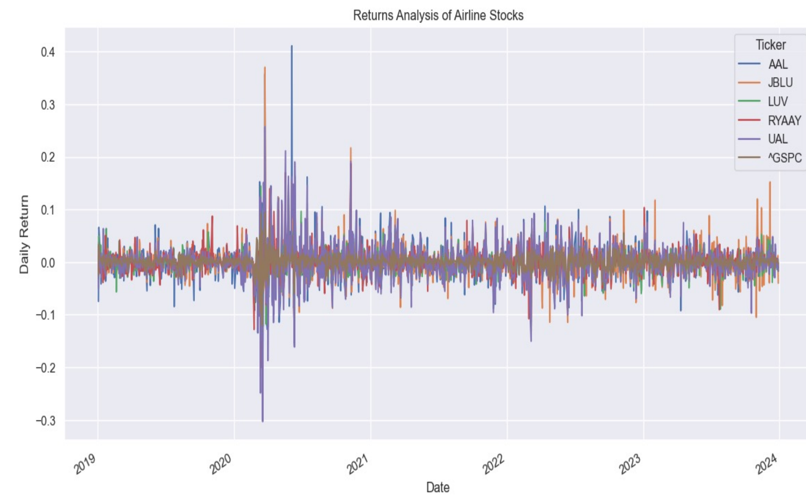

Correlation Analysis of Airline Stocks
AAL
JBLU
LUV
RYAAY
UAL
^GSPC
Ticker
Ticker
1.0
0.9
0.8
0.7
0.6
0.5


Distribution of Airline Stock Prices
AAL
JBLU
LUV
RYAAY
UAL
^GSPC
Stock Price
Frequency

ANALYSIS

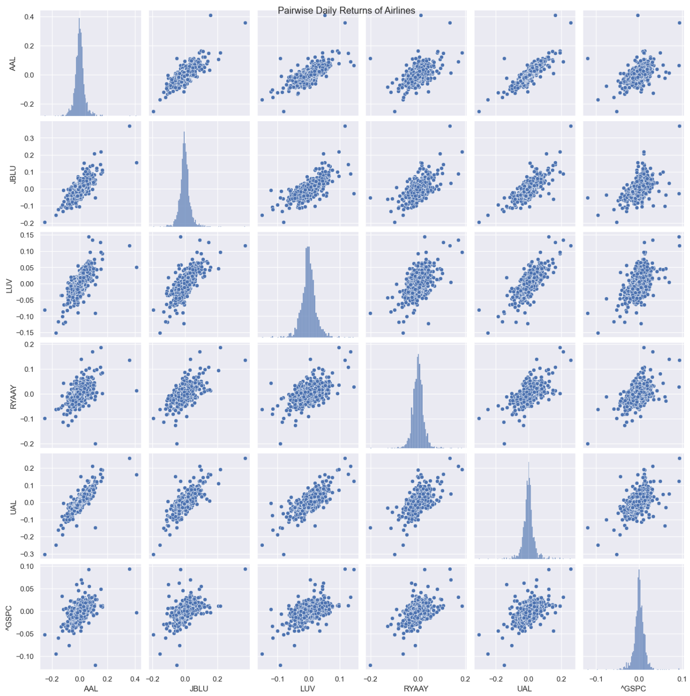


Volatility Anlaysis of Airline Stocks
Volatility
0.0
0.1
0.2
0.3
0.4
0.5
0.6
AAL
JBLU
LUV
RYAAY
UAL
Ticker



Returns Analysis of Airline Stocks
Daily Return
Ticker
AAL
JBLU
LUV
RYAAY
UAL
^GSPC
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
2019
2020
2021
2022
2023
2024
Date

ANALYSIS



Pairwise Daily Returns of Airlines
AAL
JBLU
LUV
RYAAY
UAL
^GSPC

ANALYSIS

CAPM Analysis for American Airlines (AAL):

OLS Regression Results

click to scroll output; double click to hide		R-squared:	0.233
Model:	OLS	Adj. R-squared:	0.232
Method:	Least Squares	F-statistic:	380.7
Date:	Wed, 10 Apr 2024	Prob (F-statistic):	2.88e-74
Time:	12:38:11	Log-Likelihood:	2474.9
No. Observations:	1257	AIC:	-4946.
Df Residuals:	1255	BIC:	-4935.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
excess_return_GSPC	1.3858	0.071	19.513	0.000	1.246	1.525
const	-0.0008	0.001	-0.831	0.406	-0.003	0.001

Omnibus:	786.697	Durbin-Watson:	1.860
Prob(Omnibus):	0.000	Jarque-Bera (JB):	34852.998
Skew:	2.257	Prob(JB):	0.00
Kurtosis:	28.398	Cond. No.	74.5

CAPM Analysis for Southwest Airlines (LUV):

OLS Regression Results

Dep. Variable:	excess_return_LUV	R-squared:	0.321
Model:	OLS	Adj. R-squared:	0.321
Method:	Least Squares	F-statistic:	594.0
Date:	Wed, 10 Apr 2024	Prob (F-statistic):	9.86e-108
Time:	12:38:12	Log-Likelihood:	3095.4
No. Observations:	1257	AIC:	-6187.
Df Residuals:	1255	BIC:	-6177.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
excess_return_GSPC	1.0565	0.043	24.372	0.000	0.971	1.142
const	-0.0007	0.001	-1.221	0.222	-0.002	0.000

Omnibus:	128.654	Durbin-Watson:	2.015
Prob(Omnibus):	0.000	Jarque-Bera (JB):	865.144
Skew:	0.168	Prob(JB):	1.37e-188
Kurtosis:	7.050	Cond. No.	74.5

CAPM Analysis for United Airlines (UAL):

OLS Regression Results

Dep. Variable:	excess_return_UAL	R-squared:	0.278
Model:	OLS	Adj. R-squared:	0.278
Method:	Least Squares	F-statistic:	484.3
Date:	Wed, 10 Apr 2024	Prob (F-statistic):	4.99e-91
Time:	12:38:13	Log-Likelihood:	2555.4
No. Observations:	1257	AIC:	-5107.
Df Residuals:	1255	BIC:	-5097.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
excess_return_GSPC	1.4659	0.067	22.006	0.000	1.335	1.597
const	-0.0007	0.001	-0.835	0.404	-0.003	0.001

Omnibus:	255.393	Durbin-Watson:	1.849
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5390.216
Skew:	0.338	Prob(JB):	0.00
Kurtosis:	13.122	Cond. No.	74.5

CAPM Analysis for Ryanair (RYAAY):

OLS Regression Results

Dep. Variable:	excess_return_RYAAY	R-squared:	0.247
Model:	OLS	Adj. R-squared:	0.247
Method:	Least Squares	F-statistic:	412.2
Date:	Wed, 10 Apr 2024	Prob (F-statistic):	1.78e-79
Time:	12:38:14	Log-Likelihood:	3003.5
No. Observations:	1257	AIC:	-6003.
Df Residuals:	1255	BIC:	-5993.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
excess_return_GSPC	0.9469	0.047	20.304	0.000	0.855	1.038
const	0.0002	0.001	0.396	0.692	-0.001	0.001

Omnibus:	255.189	Durbin-Watson:	1.906
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2250.181
Skew:	0.675	Prob(JB):	0.00
Kurtosis:	9.414	Cond. No.	74.5

CAPM Analysis for JetBlue Airways (JBLU):

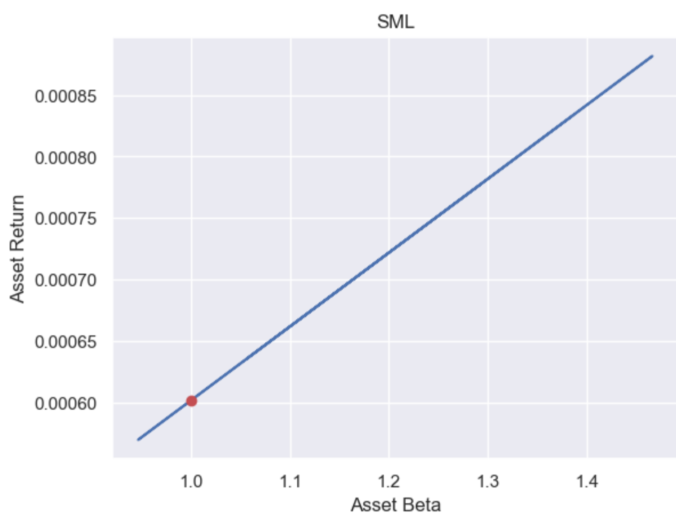
OLS Regression Results

Dep. Variable:	excess_return_JBLU	R-squared:	0.244
Model:	OLS	Adj. R-squared:	0.243
Method:	Least Squares	F-statistic:	404.1
Date:	Wed, 10 Apr 2024	Prob (F-statistic):	3.91e-78
Time:	12:38:15	Log-Likelihood:	2599.0
No. Observations:	1257	AIC:	-5194.
Df Residuals:	1255	BIC:	-5184.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
excess_return_GSPC	1.2934	0.064	20.102	0.000	1.167	1.420
const	-0.0010	0.001	-1.185	0.236	-0.003	0.001

Omnibus:	368.770	Durbin-Watson:	1.981
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5426.633
Skew:	0.942	Prob(JB):	0.00
Kurtosis:	13.003	Cond. No.	74.5

ANALYSIS



Sharpe and Treynor Ratios

```
stock_returns.columns[:5].tolist()
```

```
['AAL', 'JBLU', 'LUV', 'RYAAY', 'UAL']
```

```
stocks = stock_returns.columns[:5].tolist()
def sharpe(stocks, rf, n_assets):
    sharpe_ratios = {}
    for i,j in zip(stocks, range(n_assets)):
        sharpe_ratios[i] = np.round((stock_returns.iloc[:,j].mean()-rf)/np.std(stock_returns.iloc[:,j]),4)

    return sharpe_ratios
```

```
n_assets = 5
sharpe(stocks[:5], rf, n_assets)
```

```
{'AAL': 0.001, 'JBLU': -0.007, 'LUV': -0.003, 'RYAAY': 0.032, 'UAL': 0.0036}
```

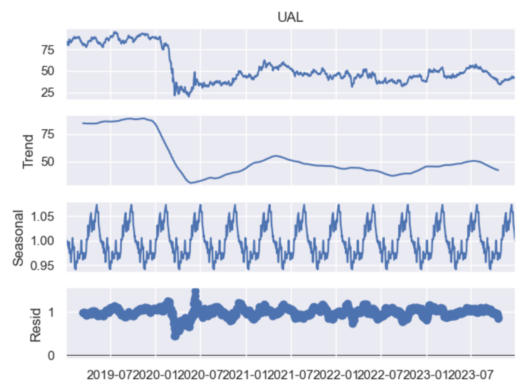
```
def treynor(stocks, rf, n_assets):
    treynor_ratios = {}
    for i,j in zip(stocks, range(n_assets)):
        treynor_ratios[i] = np.round((stock_returns.iloc[:,j].mean()-rf)/(df_all['betas'].iloc[j]),4)

    return treynor_ratios
```

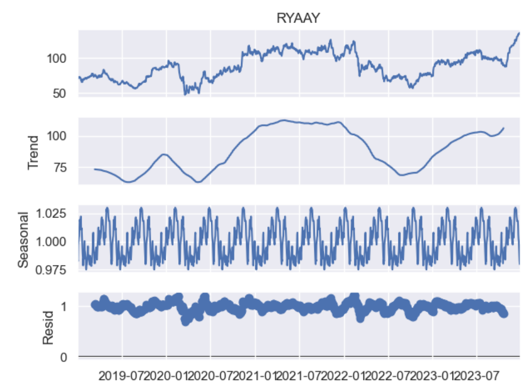
```
treynor(stocks, rf, n_assets)
```

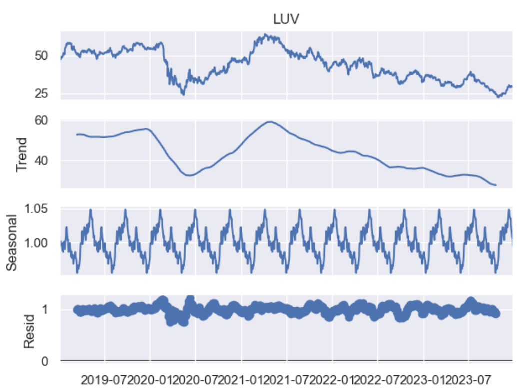
```
{'AAL': 0.0, 'JBLU': -0.0002, 'LUV': -0.0001, 'RYAAY': 0.0009, 'UAL': 0.0001}
```

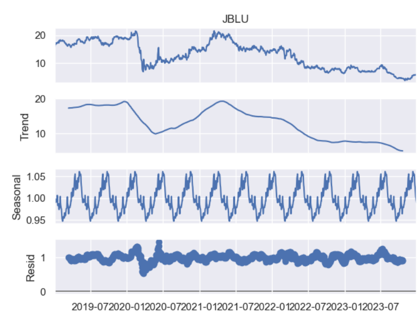
FINDINGS AND INSIGHTS

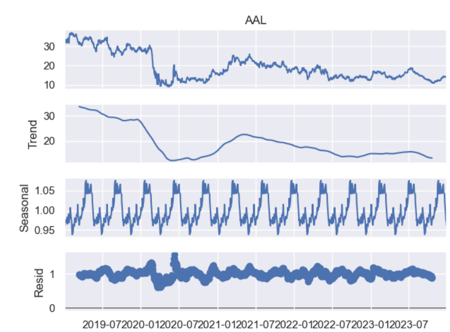
Decomposing





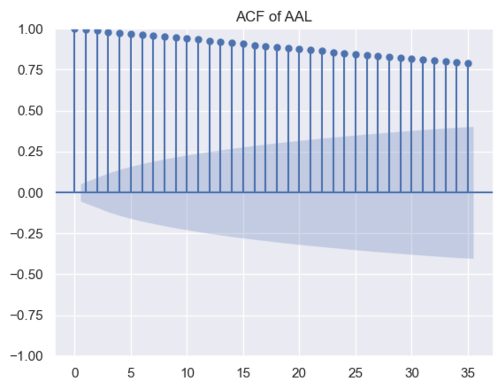


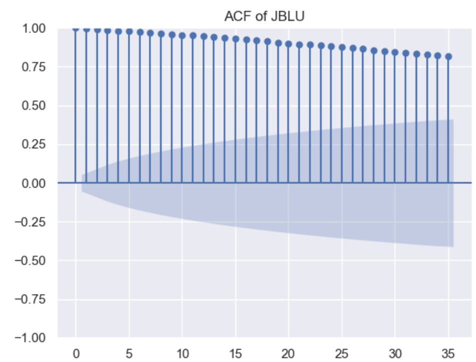


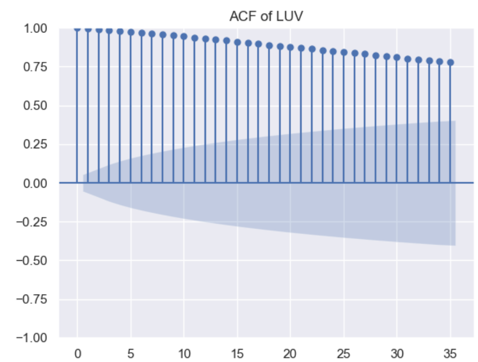


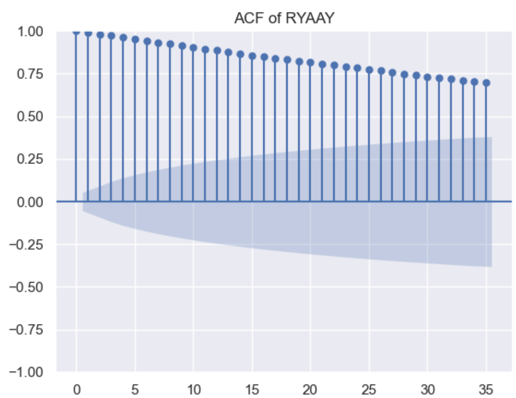
FINDINGS AND INSIGHTS

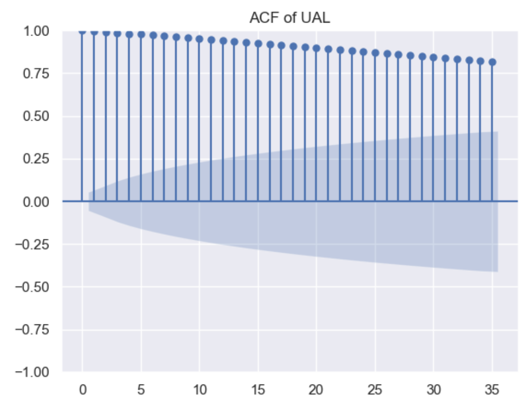
Non-Stationary Data(ACF)





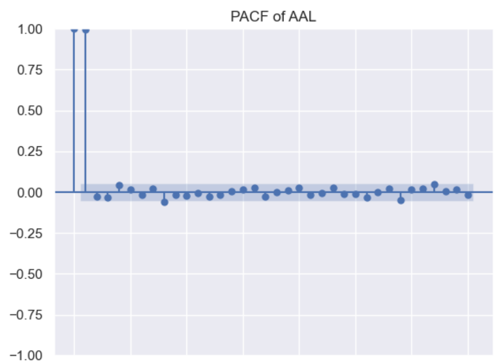


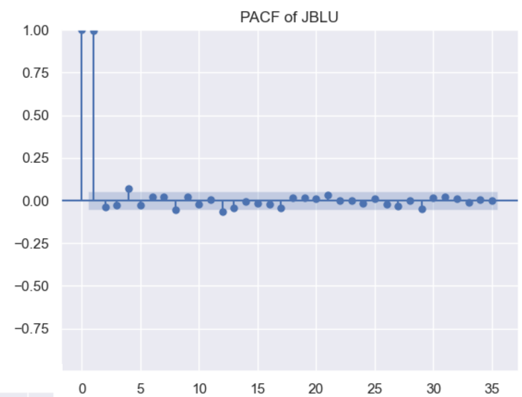


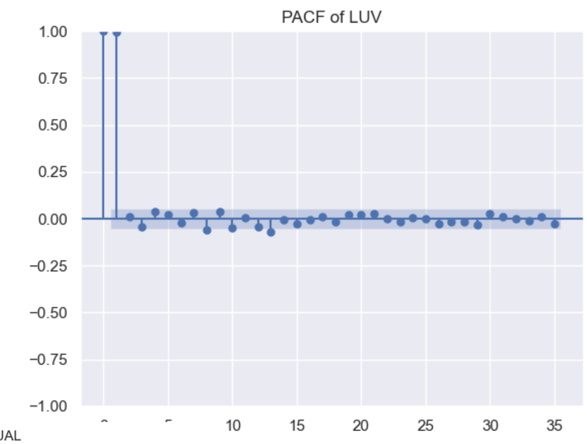


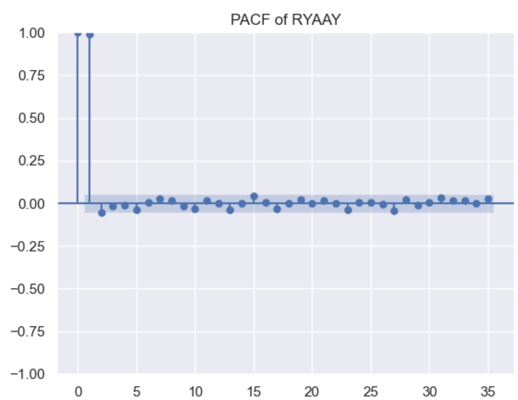
FINDINGS AND INSIGHTS

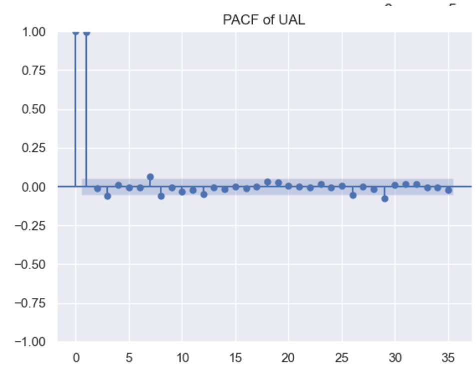
Non-Stationary Data(PACF)



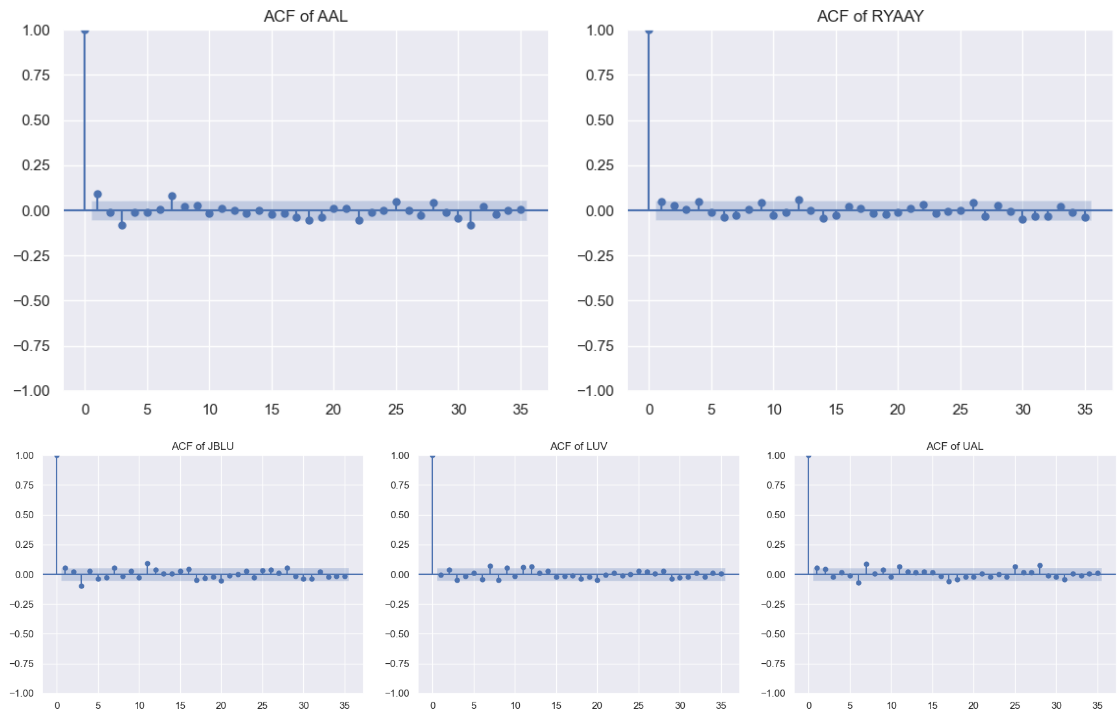




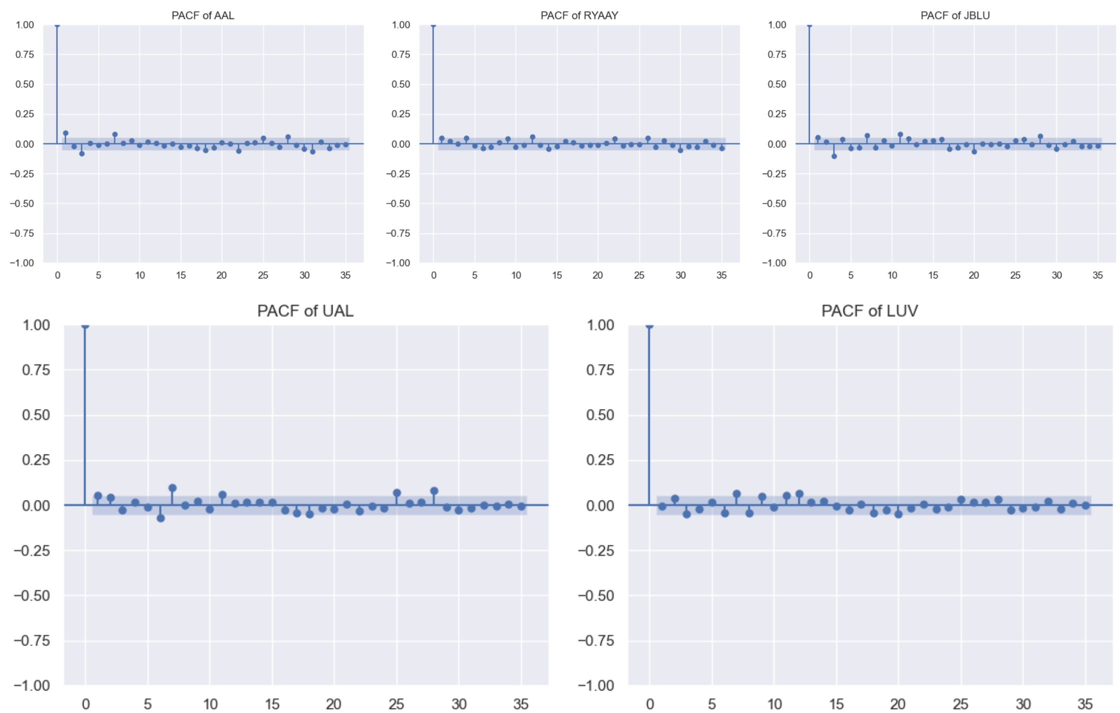




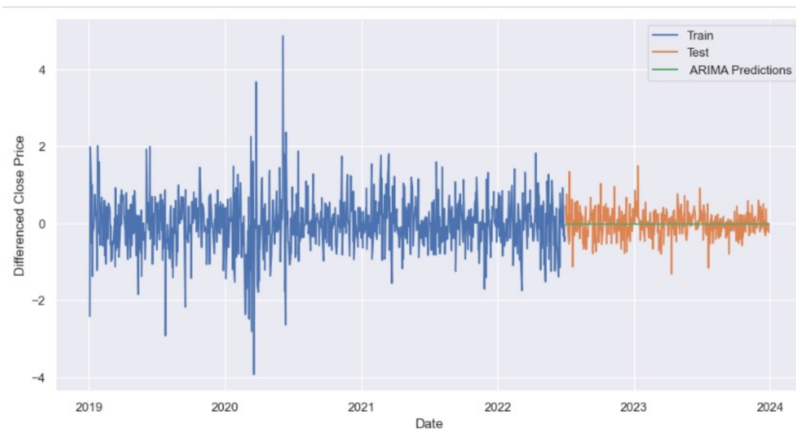
FINDINGS AND INSIGHTS Data(ACF)



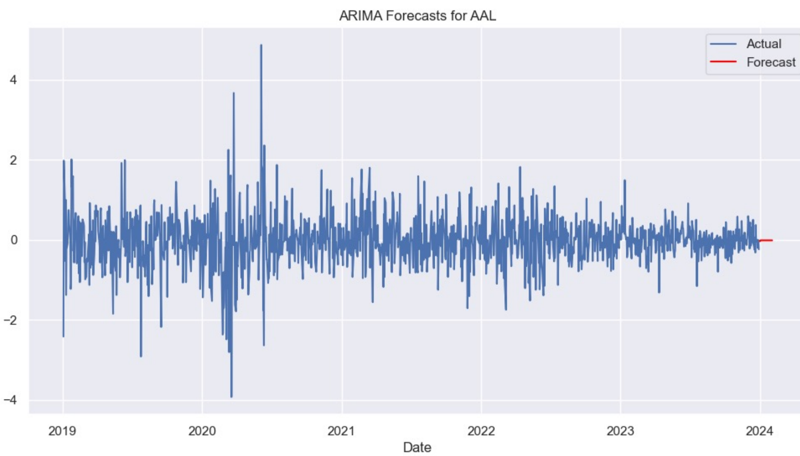
FINDINGS AND INSIGHTS Stationary Data(PACF)



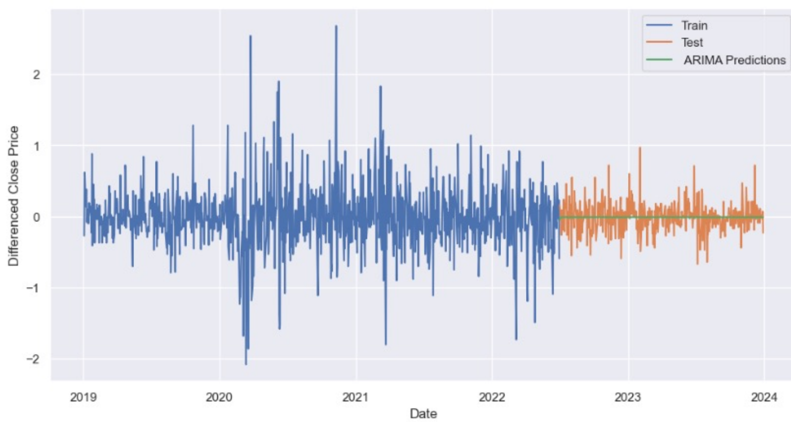
ARIMA



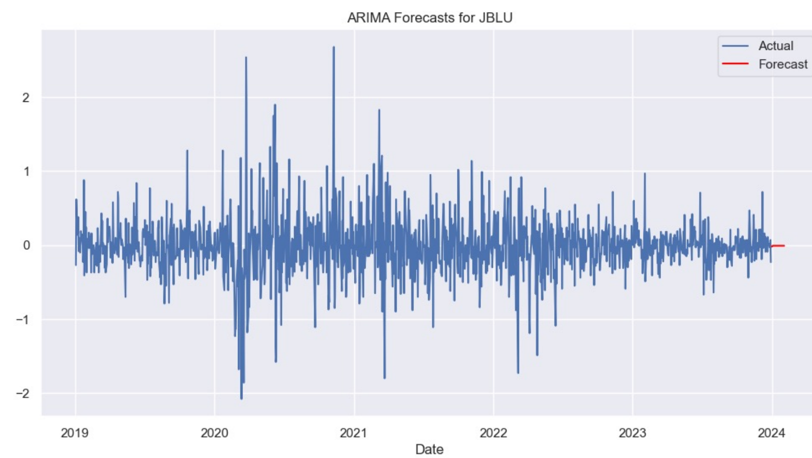

```
Performance metrics for AAL:
        MAE       MSE      RMSE
0  0.259153  0.120357  0.346925
```



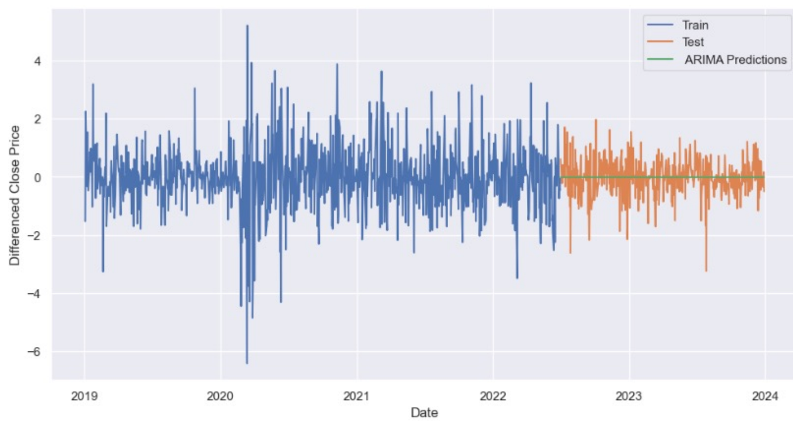
ARIMA




```
Performance metrics for JBLU:
        MAE       MSE      RMSE
0  0.150673  0.042782  0.206837
```

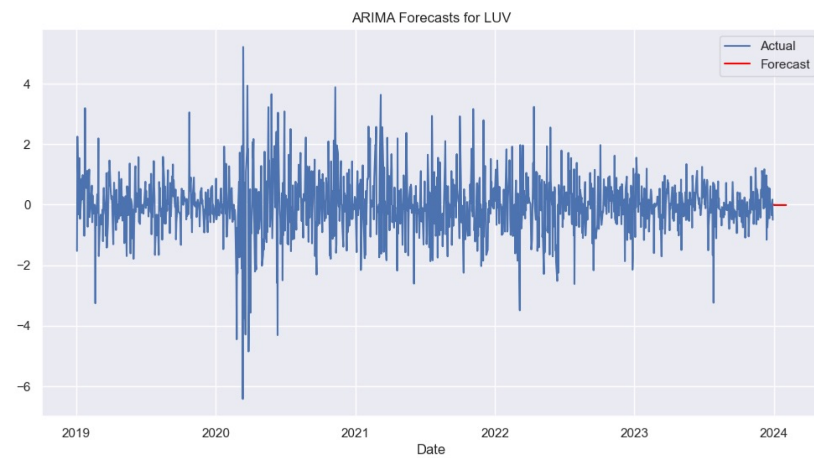


ARIMA

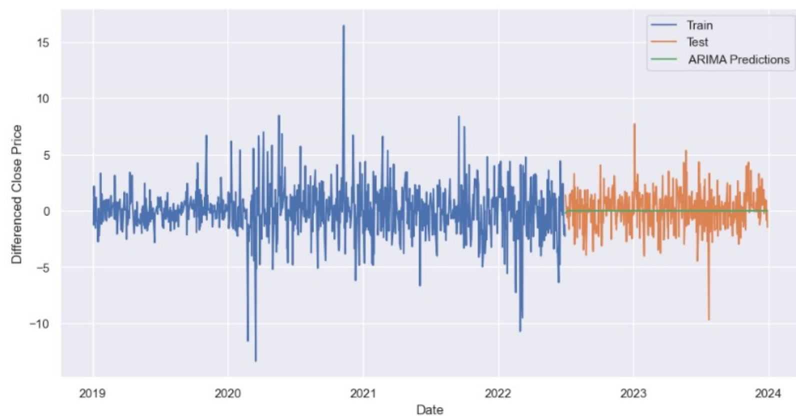


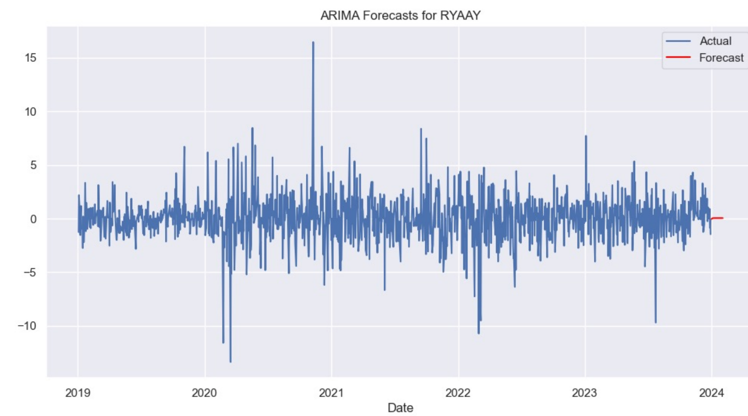
Performance metrics for LUV:

	MAE	MSE	RMSE
0	0.490267	0.439252	0.662761



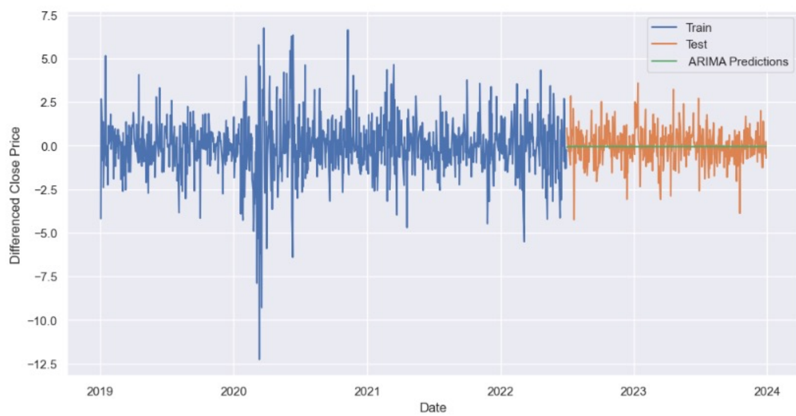
ARIMA



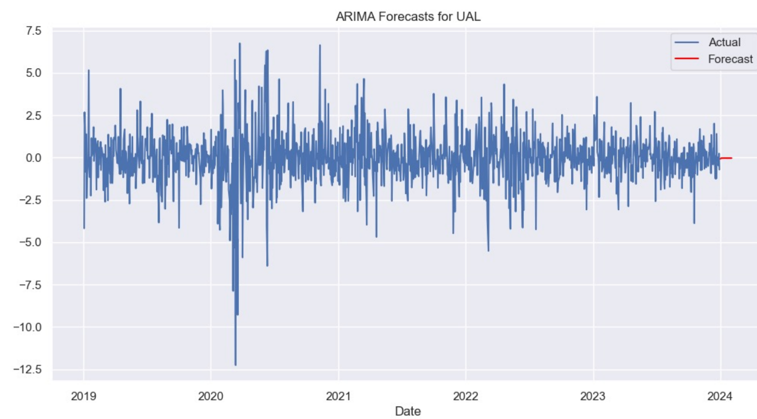



```
Performance metrics for RYAAY:
        MAE       MSE      RMSE
0  1.291677  2.993635  1.730212
```

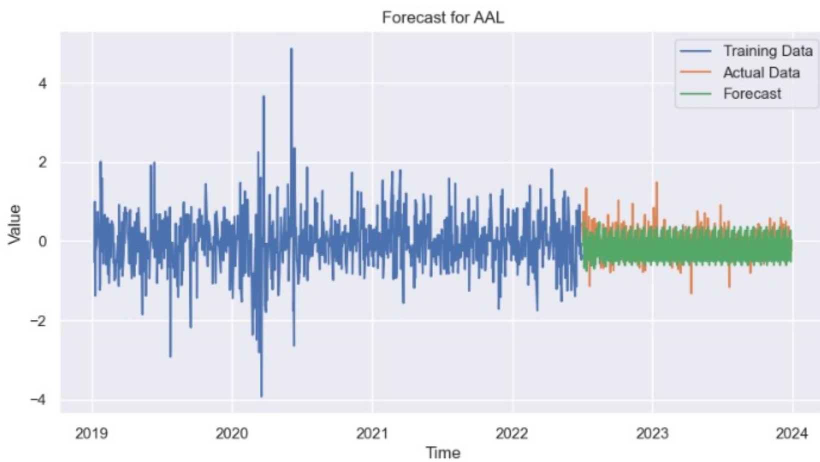
ARIMA



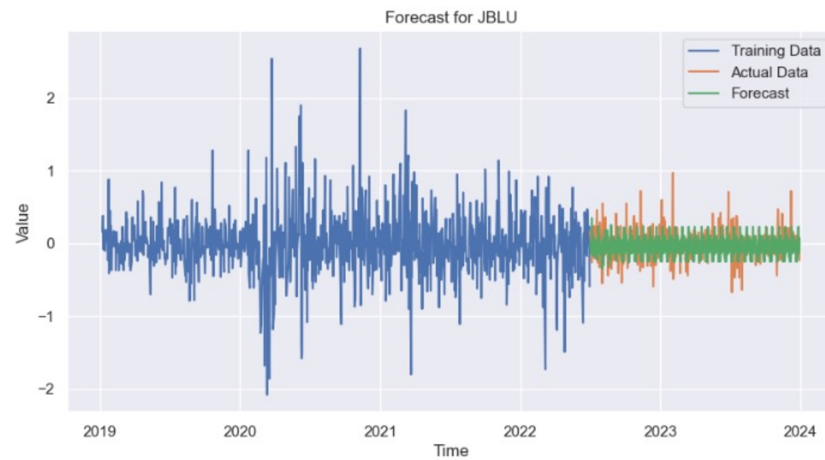

```
Performance metrics for UAL:
        MAE       MSE      RMSE
0  0.768934  1.063417  1.031221
```



SARIMA

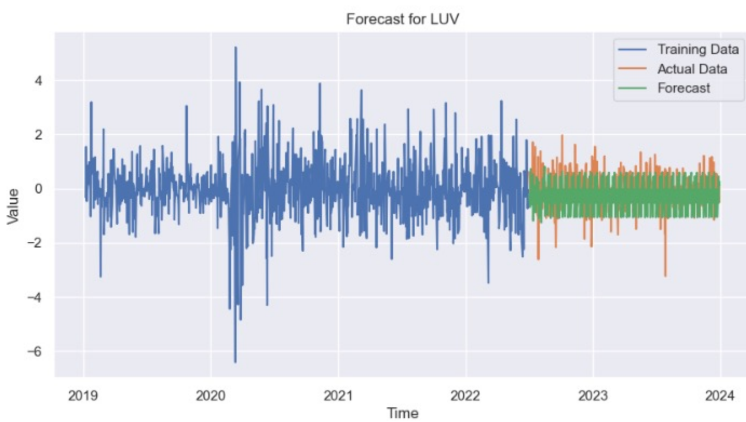



```
Performance Metrics for AAL:
Mean Squared Error (MSE): 0.2268041272586227
Mean Absolute Error (MAE): 0.383451503908823
Root Mean Squared Error (RMSE): 0.4762395691861636
```

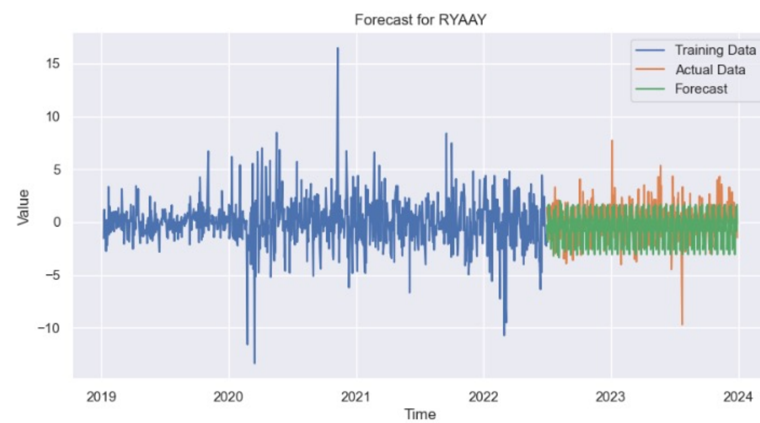



```
Performance Metrics for JBLU:
Mean Squared Error (MSE): 0.06384621214687021
Mean Absolute Error (MAE): 0.1987167664074846
Root Mean Squared Error (RMSE): 0.25267808006803877
```

SARIMA

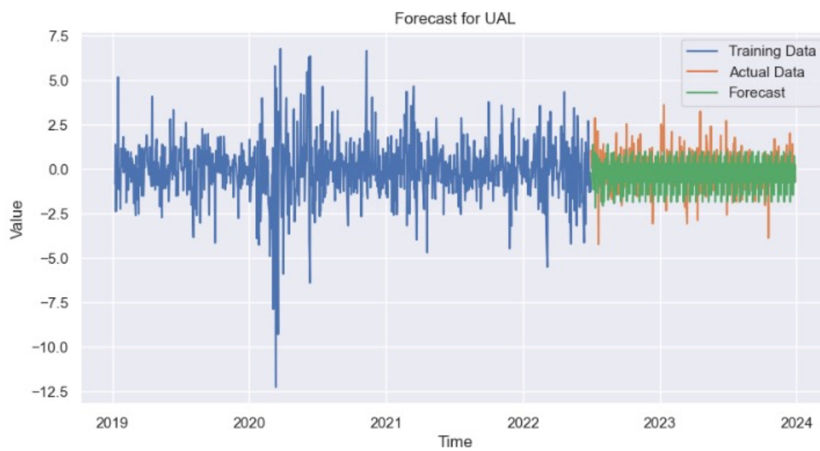



```
Performance Metrics for LUV:
Mean Squared Error (MSE): 0.7743829757708941
Mean Absolute Error (MAE): 0.6941135695711492
Root Mean Squared Error (RMSE): 0.8799903270893914
```




```
Performance Metrics for RYAAY:
Mean Squared Error (MSE): 5.853387275701544
Mean Absolute Error (MAE): 1.890592738080868
Root Mean Squared Error (RMSE): 2.419377456227437
```

SARIMA




```
Performance Metrics for UAL:
Mean Squared Error (MSE): 1.9613802469426187
Mean Absolute Error (MAE): 1.1130828898729628
Root Mean Squared Error (RMSE): 1.400492858583227
```

CONCLUSION

- **Volatility and Risk Analysis**
  Ryanair (RYAAY) exhibited the lowest average and median stock prices, indicating a potentially lower market valuation compared to other airlines.
  American Airlines (AAL) and United Airlines (UAL) had higher volatility, with significant price fluctuations throughout the period analyzed.
- **Impact of COVID-19**
  All airline stocks experienced a sharp decline in 2020 due to the pandemic, with partial recovery seen since then. However, stock prices remain below pre-pandemic levels.
- **CAPM Analysis**
  The analysis showed that airline stocks have varying beta values, indicating differing levels of market risk and potential return. Higher beta values suggest a stock is more volatile than the market.
- **Risk-Adjusted Returns**
  Ryanair and United Airlines displayed positive Sharpe and Treynor ratios, suggesting they are performing well relative to their risks.
  American Airlines, JetBlue, and Southwest Airlines showed lower or negative ratios, indicating less favorable risk-adjusted returns.
- **Portfolio Analysis using Modern Portfolio Theory (MPT)**
  The application of MPT principles aimed to identify efficient portfolios, highlighting the trade-off between risk and return.
  The analysis suggests potential strategies for optimizing portfolios, taking into consideration the balance between reward and risk in the airline sector.

Thank
you