Stock Price Prediction: Comparison between ARIMA Model and LSTM

Xizhu Lin

In [1]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import adfuller
import statsmodels.api as sm
from sklearn.preprocessing import MinMaxScaler
```

In [3]:
```
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
import pmdarima as pm
```

In [4]:
```
from keras.models import Sequential
from keras.layers import Dense, LSTM
from keras.optimizers import Adam
```

The Boeing Company (BA) & Zoom Video Communications, Inc. (ZM)

Import Data

In [5]:
```
start_date = '2020-01-01'
end_date = '2023-05-12'

ba = yf.download("BA", start_date , end_date)['Close']
zm = yf.download("ZM", start_date , end_date)['Close']
```

```
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
```

In [6]:
```
ba = pd.DataFrame(ba)
# check if there is null values in BA Close price
ba[ba.isna().any(axis=1)]
```

Out[6]:

	Close
Date	

In [7]:
```
# First-order differencing
ba_diff = ba.diff().dropna()
# Log price of BA
ba_lgp = np.log(ba)
# Log Returns of BA
ba_rtn = np.log(ba).diff().dropna()
```

In [8]:
```
zm = pd.DataFrame(zm)
# check if there is null values in ZM Close price
zm[zm.isna().any(axis=1)]
```

Out[8]:

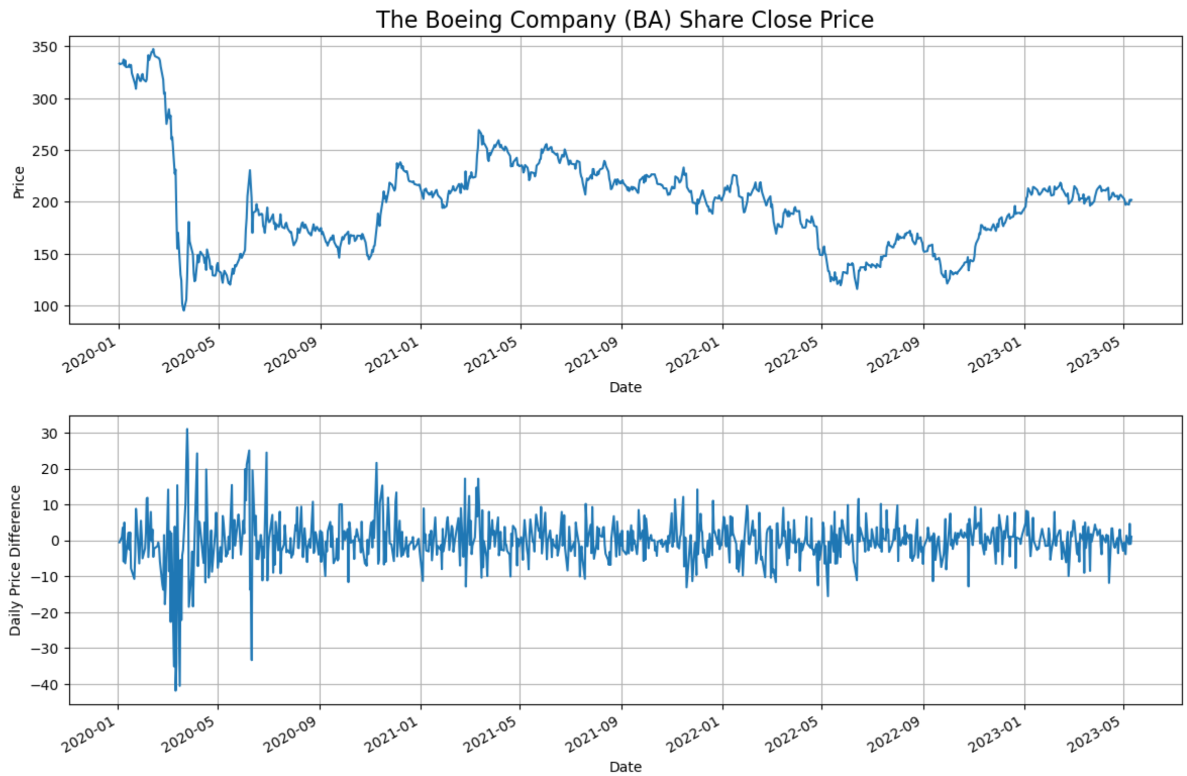
	Close
Date	

In [9]:
```
# First-order differencing
zm_diff = zm.diff().dropna()
# Log price of ZM
zm_lgp = np.log(zm)
# Log Returns of ZM
zm_rtn = np.log(zm).diff().dropna()
```

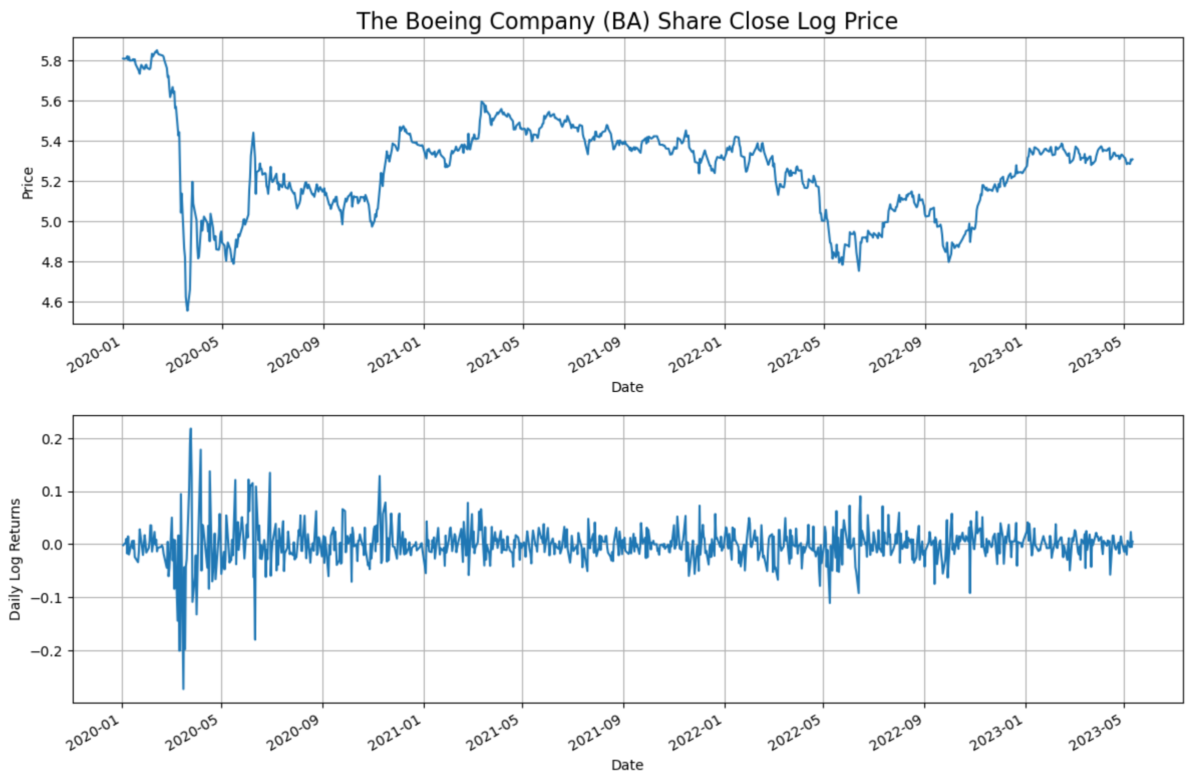
EDA

In [10]:

```
plt.figure(figsize=(12,8))

plt.subplot(2, 1, 1)
ba['Close'].plot()
plt.grid()
plt.ylabel("Price")
plt.title("The Boeing Company (BA) Share Close Price", fontsize = 16)
plt.subplot(2, 1, 2)
ba_diff['Close'].plot()
plt.grid()
plt.tight_layout(pad=1.5)
plt.ylabel("Daily Price Difference")

plt.savefig("images/Boeing_Company_(BA)_stationary_1")
```

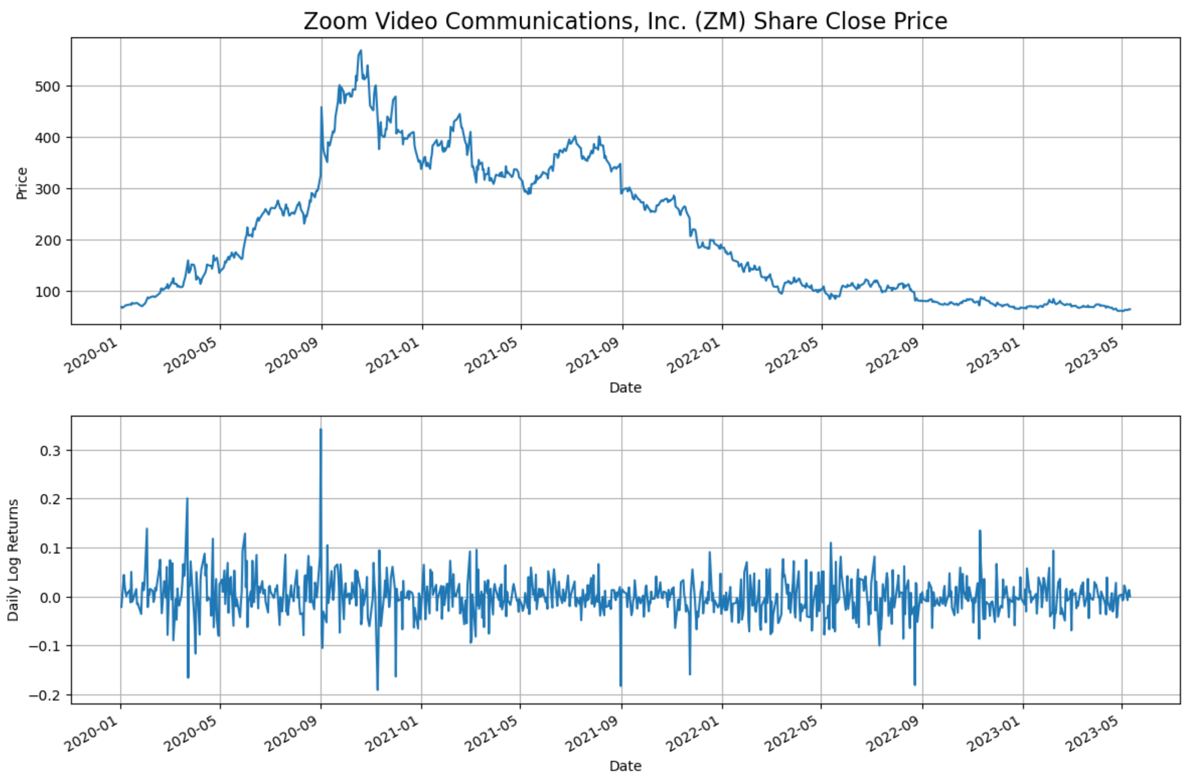


In [11]:
```
plt.figure(figsize=(12,8))

plt.subplot(2, 1, 1)
ba_lgp['Close'].plot()
plt.grid()
plt.ylabel("Price")
plt.title("The Boeing Company (BA) Share Close Log Price", fontsize = 16)
plt.subplot(2, 1, 2)
ba_rtn['Close'].plot()
plt.grid()
plt.tight_layout(pad=1.5)
plt.ylabel("Daily Log Returns")

plt.savefig("images/Boeing_Company_(BA)_stationary_2")
```



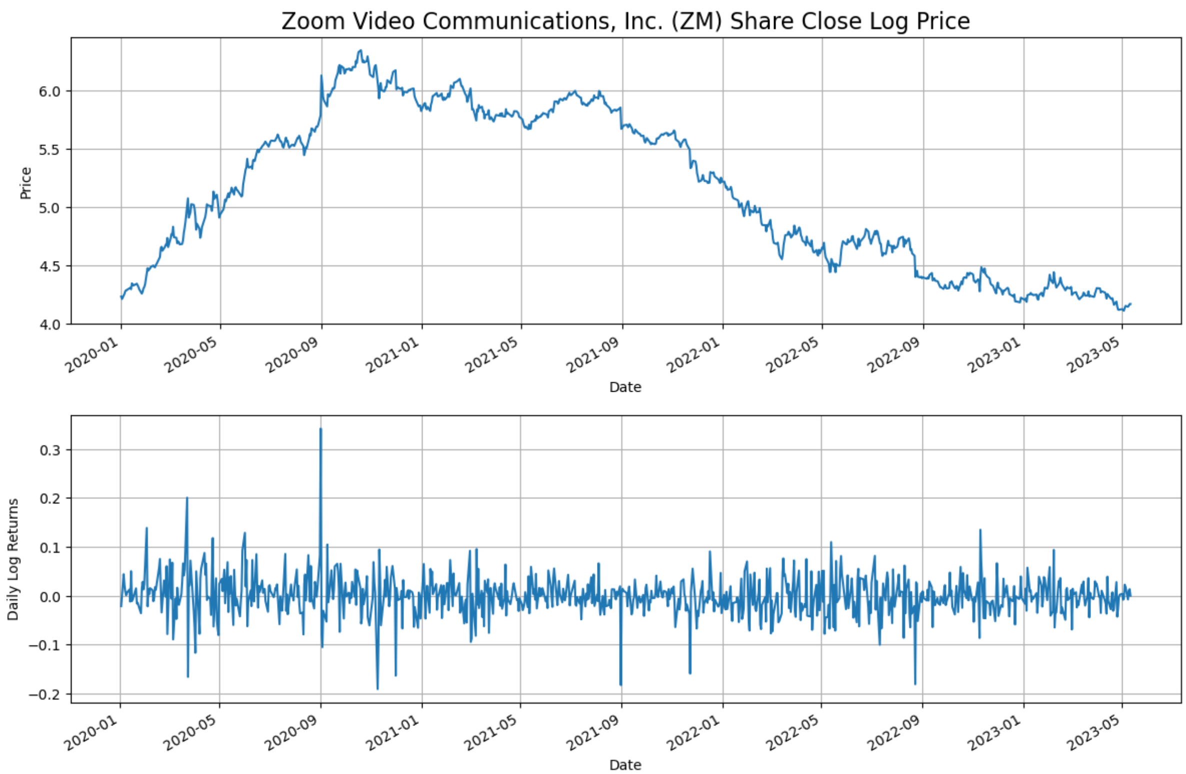
In [12]:

```
plt.figure(figsize=(12,8))

plt.subplot(2, 1, 1)
zm['Close'].plot()
plt.grid()
plt.ylabel("Price")
plt.title("Zoom Video Communications, Inc. (ZM) Share Close Price", fontsize = 16)
plt.subplot(2, 1, 2)
zm_rtn['Close'].plot()
plt.grid()
plt.tight_layout(pad=1.5)
plt.ylabel("Daily Log Returns")

plt.savefig("images/Zoom_(ZM)_stationary_1")
```



In [13]:

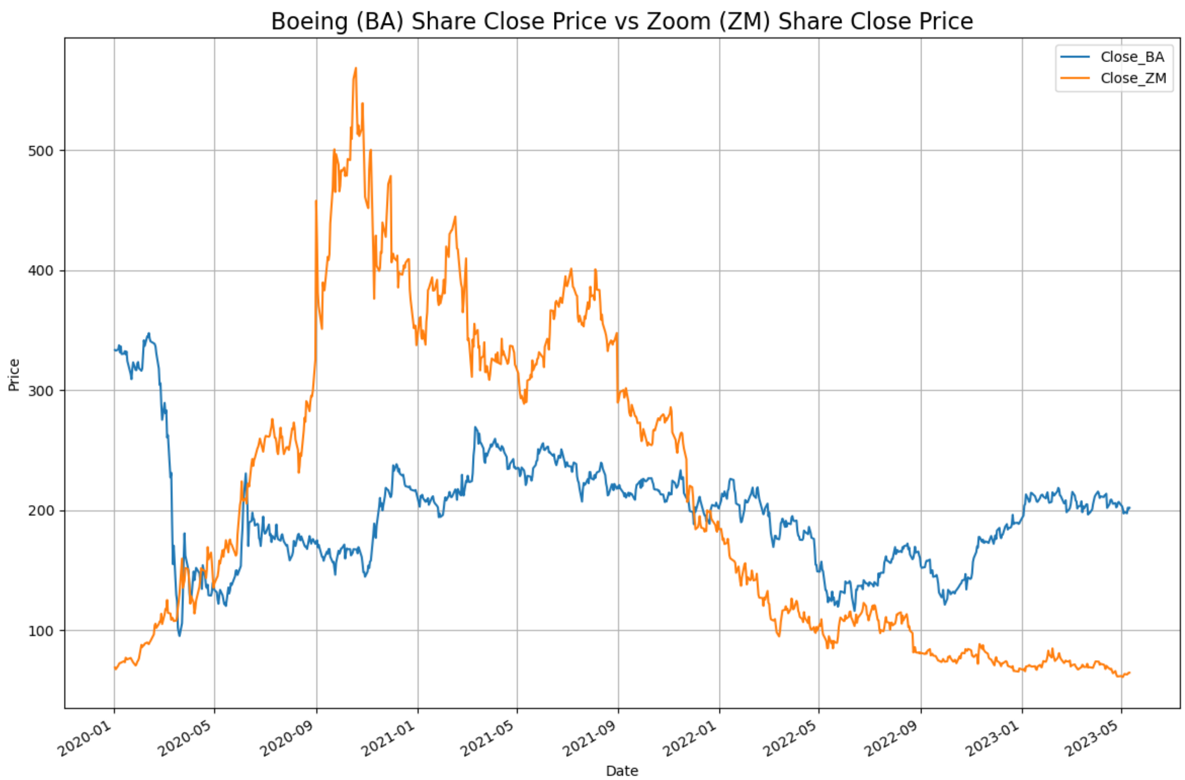
```
plt.figure(figsize=(12,8))

plt.subplot(2, 1, 1)
zm_lgp['Close'].plot()
plt.grid()
plt.ylabel("Price")
plt.title("Zoom Video Communications, Inc. (ZM) Share Close Log Price", fontsize = 16)
plt.subplot(2, 1, 2)
zm_rtn['Close'].plot()
plt.grid()
plt.tight_layout(pad=1.5)
plt.ylabel("Daily Log Returns")

plt.savefig("images/Zoom_(ZM)_stationary_2")
```



In [14]:

```
df = pd.merge(ba, zm, left_index=True, right_index=True)
df = df.rename(columns={'Close_x': 'Close_BA', 'Close_y': 'Close_ZM'})
```

In [15]:
```
plt.figure(figsize=(12,8))

df['Close_BA'].plot()
df['Close_ZM'].plot()
plt.grid()
plt.ylabel("Price")
plt.title("Boeing (BA) Share Close Price vs Zoom (ZM) Share Close Price", fontsize = 16)
plt.legend(bbox_to_anchor = (1,1))
plt.tight_layout(pad=1.5)

plt.savefig("images/Boeing_and_Zoom")
```



Price Prediction Model: ARIMA Model and LSTM

ARIMA Model

Boeing (BA)

In [16]:
```
# Get the number of rows to train the model on
training_ba_len = int(np.ceil(len(ba) * .8 ))
# Create the scaled training data set
train_ba = ba[0:int(training_ba_len)]
# First-order differencing
train_ba_diff = train_ba.diff().dropna()
# Log price
train_ba_lgp = np.log(train_ba)
# Log Returns
train_ba_rtn = np.log(train_ba).diff().dropna()
```

1. Find d in (p, d, q) for ARIMA model and (ADF) test

In [17]:
```python
# BA Pirce d=0
result = adfuller(train_ba)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -3.100203
p-value: 0.026538
	1%: -3.440
	5%: -2.866
	10%: -2.569
```

In [18]:
```python
# BA Pirce d=1
result = adfuller(train_ba_diff)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -15.435893
p-value: 0.000000
	1%: -3.440
	5%: -2.866
	10%: -2.569
```

In [19]:
```python
# BA Log Pirce d=0
result = adfuller(train_ba_lgp)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -3.045616
p-value: 0.030848
	1%: -3.440
	5%: -2.866
	10%: -2.569
```

In [20]:
```python
# BA Log Pirce d=1
result = adfuller(train_ba_rtn)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -8.264118
p-value: 0.000000
	1%: -3.440
	5%: -2.866
	10%: -2.569
```

Choose BA Log Pirce d=1, use train_ba_lgp (log price of BA) d=1 in ARIMA Model

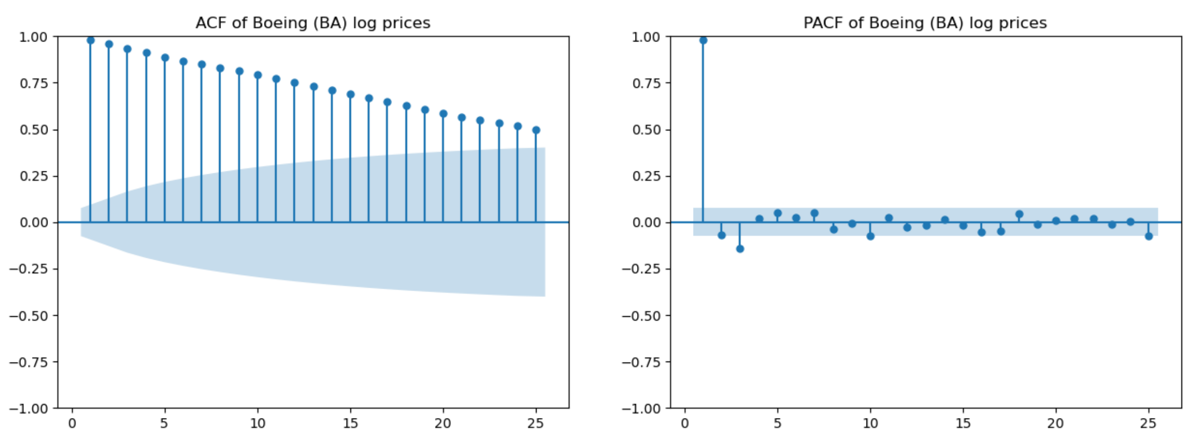
2. Find p and q in (p, d, q) for ARIMA model

Method 1, Step 1: ACF plot and PACF plot

In [21]:
```
def plot_diagnosticsTight2(data, rtn, title1 = 'APPLE'):

    fig, axes = plt.subplots(1,2,figsize=(15,5))
    axes[0].set_ylabel('ACF', fontsize=15)
    axes[0].set_xlabel('Lag', fontsize=15)
    fig = plot_acf(data,lags=25,zero=True, ax = axes[0], title= 'ACF '+ title1, use_vlines = True)
    axes[1].set_ylabel('ACF', fontsize=15)
    axes[1].set_xlabel('Lag', fontsize=15)
    fig = plot_acf(rtn,lags=25,zero=True, ax = axes[1], title= 'ACF Log Returns '+ title1, use_vli
    plt.tight_layout()
    plt.savefig("ACF2.png", dpi = 300)
```

In [22]:
```
def plot_ACF_PACF(data, lag_num, company_name):
    fig, axes = plt.subplots(1,2,figsize=(15,5))

    fig = plot_acf(data.values, lags = lag_num, zero=False, ax = axes[0],
                   title= 'ACF of ' + company_name + ' log prices')

    fig = plot_pacf(data.values, lags = lag_num, zero=False, ax = axes[1],
                   title= 'PACF of ' + company_name + ' log prices')

    # plt.show()
    plt.savefig("images/ACF PACF" + company_name, dpi = 300)
```

In [23]:
```
plot_ACF_PACF(train_ba_lgp, 25, 'Boeing (BA)')

#plt.savefig("images/Boeing_Company_(BA)_ACF_PACF")
```



p=2, q=0

In [24]:
```
p, d, q = 2, 1, 0
ar_model_ba = ARIMA(train_ba_lgp['Close'], order=(p, d, q))
ar_model_ba = ar_model_ba.fit()
ar_model_ba.summary()
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Out[24]:

SARIMAX Results

Dep. Variable:	Close	**No. Observations:**	677
Model:	ARIMA(2, 1, 0)	**Log Likelihood**	1236.277
Date:	Fri, 15 Dec 2023	**AIC**	-2466.554
Time:	20:01:30	**BIC**	-2453.005
Sample:	0	**HQIC**	-2461.308
	- 677		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.0636	0.018	3.577	0.000	0.029	0.098
ar.L2	0.1626	0.017	9.523	0.000	0.129	0.196
sigma2	0.0015	4.04e-05	37.406	0.000	0.001	0.002

Ljung-Box (L1) (Q):	0.05	**Jarque-Bera (JB):**	1515.64
Prob(Q):	0.82	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.26	**Skew:**	-0.08
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.33

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

2. Find p and q in (p, d, q) for ARIMA model

Method 1, Step 2: p-value test

In [25]:
```
# Set the significance level (alpha)
alpha = 0.05

p_values = ar_model_ba.pvalues

significant_predictors = p_values[p_values <= alpha]

print("Significant Predictors:")
print(significant_predictors)
```

```
Significant Predictors:
ar.L1      3.471556e-04
ar.L2      1.684478e-21
sigma2    3.083713e-306
dtype: float64
```

2. Find p and q in (p, d, q) for ARIMA model

Method 2: grid search for min AIC and min BIC

In [26]:
```
def searchARIMA(data, d, max_p, max_q):
    results = []

    aic = np.zeros((max_p, max_q))
    bic = np.zeros((max_p, max_q))

    for i in range(max_p):
        for j in range(max_q):
            model = ARIMA(data, order=(i, d, j))
            model = ARIMA(data, order=(i, d, j))
            res = model.fit()
            aic[i, j] = res.aic
            bic[i, j] = res.bic

            result_dict = {
                'p': i,
                'q': j,
                'aic': aic[i, j],
                'bic': bic[i, j]
            }
            results.append(result_dict)
            # print('p:', i, ' q:', j, ' aic:', aic[i, j], ' bic:', bic[i, j])

    result_df = pd.DataFrame(results)
    return result_df
```

In [27]:
```
result_df = searchARIMA(train_ba_lgp.values, d = 1, max_p = 10, max_q = 10)
result_df
```

	p	q	aic	bic
0	0	0	-2448.614890	-2444.098697
1	0	1	-2449.534203	-2440.501817
2	0	2	-2469.495778	-2455.947199
3	0	3	-2467.608602	-2449.543830
4	0	4	-2465.744453	-2443.163488
...	...	...	...	...
95	9	5	-2460.106052	-2392.363156
96	9	6	-2459.101628	-2386.842539
97	9	7	-2459.114381	-2382.339099
98	9	8	-2457.036662	-2375.745187
99	9	9	-2456.636837	-2370.829169

100 rows × 4 columns

In [28]:
```
min_aic_bic_row = result_df[(result_df['aic'] == result_df['aic'].min()) |
                            (result_df['bic'] == result_df['bic'].min())]
min_aic_bic_row
```

Out[28]:

	p	q	aic	bic
2	0	2	-2469.495778	-2455.947199
46	4	6	-2470.604216	-2420.926092

In [29]:
```
pm.arima.auto_arima(train_ba_lgp)
```

Out[29]:

```
ARIMA
ARIMA(0,1,2)(0,0,0)[0]
```

In general, choose p=2, q=0

In [30]:
```
p, d, q = 2, 1, 0
ar_model_ba = ARIMA(train_ba_lgp['Close'], order=(p, d, q))
ar_model_ba = ar_model_ba.fit()
ar_model_ba.summary()
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Out[30]:

SARIMAX Results

Dep. Variable:	Close	**No. Observations:**	677
Model:	ARIMA(2, 1, 0)	**Log Likelihood**	1236.277
Date:	Fri, 15 Dec 2023	**AIC**	-2466.554
Time:	20:04:53	**BIC**	-2453.005
Sample:	0	**HQIC**	-2461.308
	- 677		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.0636	0.018	3.577	0.000	0.029	0.098
ar.L2	0.1626	0.017	9.523	0.000	0.129	0.196
sigma2	0.0015	4.04e-05	37.406	0.000	0.001	0.002

Ljung-Box (L1) (Q):	0.05	**Jarque-Bera (JB):**	1515.64
Prob(Q):	0.82	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.26	**Skew:**	-0.08
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.33

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [31]:
```
# Set the significance level (alpha)
alpha = 0.05

p_values = ar_model_ba.pvalues

significant_predictors = p_values[p_values <= alpha]

print("Significant Predictors:")
print(significant_predictors)
```

```
Significant Predictors:
ar.L1      3.471556e-04
ar.L2      1.684478e-21
sigma2    3.083713e-306
dtype: float64
```

In [32]:
```
predicted_original_train_ba = ar_model_ba.predict(start=train_ba_lgp.index[0],
                                                  end=train_ba_lgp.index[-1],
                                                  dynamic=False)
predicted_original_train_ba = np.exp(predicted_original_train_ba)
#predicted_original_ba = np.array(predicted_original_ba)
```

In [33]:
```
predicted_original_train_ba = pd.DataFrame(predicted_original_train_ba)

train_val_ba = ba[:int(training_ba_len)]
train_val_ba = pd.merge(train_val_ba, predicted_original_train_ba,
                        left_index=True, right_index=True)
train_val_ba = train_val_ba.rename(columns={'predicted_mean': 'Prediction'})
train_val_ba
```

Out[33]:

	Close	Prediction
Date		
2020-01-02	333.320007	1.000000
2020-01-03	332.760010	333.320008
2020-01-06	333.739990	332.717537
2020-01-07	337.279999	333.711147
2020-01-08	331.369995	337.667707
...	...	...
2022-09-01	153.660004	159.616873
2022-09-02	151.820007	152.947757
2022-09-06	152.389999	150.671611
2022-09-07	155.949997	152.128066
2022-09-08	157.789993	156.274284

677 rows × 2 columns

In [34]:
```
train_mse = mean_squared_error(train_val_ba['Close'], train_val_ba['Prediction'])
train_rmse = np.sqrt(train_mse)
print("The MSE of the Trainning set is", train_mse)
print("The RMSE of the Trainning set is", train_rmse)
```

```
The MSE of the Trainning set is 210.71958656497665
The RMSE of the Trainning set is 14.516183608820077
```

In [35]:
```
# Create the scaled training data set
test_ba = ba[int(training_ba_len):]
# Log price
test_ba_lgp = np.log(test_ba)

forecast_ba = ar_model_ba.get_forecast(steps=len(test_ba_lgp))

predicted_values_ba = forecast_ba.predicted_mean
predicted_original_ba = np.exp(predicted_values_ba)
predicted_original_ba = np.array(predicted_original_ba)
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarnin
g: No supported index is available. Prediction results will be given with an integer index begin
ning at `start`.
  return get_prediction_index(
```

In [36]:

```
predicted_original_ba = pd.DataFrame(index=test_ba_lgp.index, columns=['Prediction'],
                                     data=predicted_original_ba)

test_ba = pd.merge(test_ba, predicted_original_ba,
                   left_index=True, right_index=True)
test_ba
```

Out[36]:

Date	Close	Prediction
2022-09-09	157.520004	158.501649
2022-09-12	158.720001	158.849633
2022-09-13	147.309998	158.988054
2022-09-14	149.259995	159.053558
2022-09-15	149.779999	159.080248
...	...	...
2023-05-05	198.339996	159.101817
2023-05-08	197.259995	159.101817
2023-05-09	201.880005	159.101817
2023-05-10	200.839996	159.101817
2023-05-11	201.839996	159.101817

169 rows × 2 columns

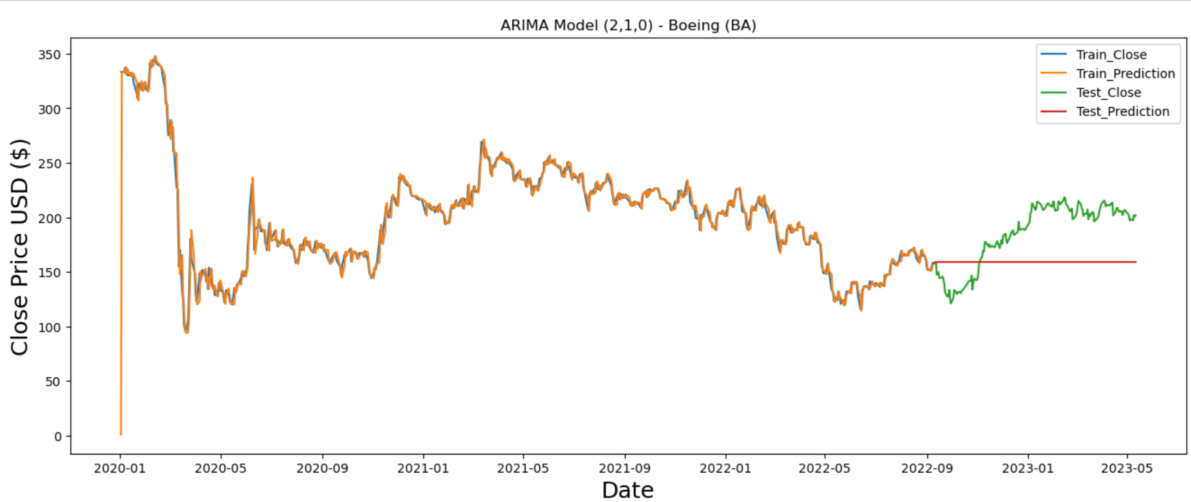
In [37]:

```
test_mse = mean_squared_error(test_ba['Close'], test_ba['Prediction'])
test_rmse = np.sqrt(test_mse)
print("The MSE of the Test set is", test_mse)
print("The RMSE of the Test set is", test_rmse)
```

```
The MSE of the Test set is 1475.7237845602306
The RMSE of the Test set is 38.41515045604053
```

In [38]:

```
# Visualize the data
plt.figure(figsize=(16,6))
plt.title('ARIMA Model (2,1,0) - Boeing (BA)')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train_val_ba[['Close', 'Prediction']])
plt.plot(test_ba[['Close', 'Prediction']])
plt.legend(['Train_Close', 'Train_Prediction','Test_Close', 'Test_Prediction'], loc='upper right')
#plt.show()
plt.savefig("images/Boeing_Company_(BA)_ARIMA_1")
```



In [39]:
```
p, d, q = 2, 0, 0
ar_model_ba = ARIMA(train_ba_lgp['Close'], order=(p, d, q))
ar_model_ba = ar_model_ba.fit()
ar_model_ba.summary()
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Out[39]:

SARIMAX Results

Dep. Variable:	Close	**No. Observations:**	677
Model:	ARIMA(2, 0, 0)	**Log Likelihood**	1229.167
Date:	Fri, 15 Dec 2023	**AIC**	-2450.334
Time:	20:04:54	**BIC**	-2432.263
Sample:	0	**HQIC**	-2443.338
	- 677		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	5.3002	0.089	59.265	0.000	5.125	5.476
ar.L1	1.0705	0.019	55.603	0.000	1.033	1.108
ar.L2	-0.0832	0.018	-4.549	0.000	-0.119	-0.047
sigma2	0.0015	3.61e-05	42.695	0.000	0.001	0.002

Ljung-Box (L1) (Q):	0.25	**Jarque-Bera (JB):**	2340.08
Prob(Q):	0.62	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.26	**Skew:**	-0.54
Prob(H) (two-sided):	0.00	**Kurtosis:**	12.04

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [40]:
```
# Set the significance level (alpha)
alpha = 0.05

p_values = ar_model_ba.pvalues

significant_predictors = p_values[p_values <= alpha]

print("Significant Predictors:")
print(significant_predictors)
```

```
Significant Predictors:
const     0.000000
ar.L1     0.000000
ar.L2     0.000005
sigma2    0.000000
dtype: float64
```

In [41]:

```
predicted_original_train_ba = ar_model_ba.predict(start=train_ba_lgp.index[0],
                                                   end=train_ba_lgp.index[-1],
                                                   dynamic=False)
predicted_original_train_ba = np.exp(predicted_original_train_ba)
#predicted_original_ba = np.array(predicted_original_ba)
predicted_original_train_ba = pd.DataFrame(predicted_original_train_ba)

train_val_ba = ba[:int(training_ba_len)]
train_val_ba = pd.merge(train_val_ba, predicted_original_train_ba,
                        left_index=True, right_index=True)
train_val_ba = train_val_ba.rename(columns={'predicted_mean': 'Prediction'})
train_val_ba
```

Out[41]:

	Close	Prediction
Date		
2020-01-02	333.320007	200.386139
2020-01-03	332.760010	331.342606
2020-01-06	333.739990	330.583051
2020-01-07	337.279999	331.671768
2020-01-08	331.369995	335.357282
...	...	...
2022-09-01	153.660004	160.541874
2022-09-02	151.820007	153.639991
2022-09-06	152.389999	152.202058
2022-09-07	155.949997	152.967068
2022-09-08	157.789993	156.746797

677 rows × 2 columns

In [42]:

```
train_mse = mean_squared_error(train_val_ba['Close'], train_val_ba['Prediction'])
train_rmse = np.sqrt(train_mse)
print("The MSE of the Trainning set is", train_mse)
print("The RMSE of the Trainning set is", train_rmse)
```

```
The MSE of the Trainning set is 74.27961633410533
The RMSE of the Trainning set is 8.618562312480273
```

In [43]:
```
# Create the scaled training data set
test_ba = ba[int(training_ba_len):]
# Log price
test_ba_lgp = np.log(test_ba)

forecast_ba = ar_model_ba.get_forecast(steps=len(test_ba_lgp))

predicted_values_ba = forecast_ba.predicted_mean
predicted_original_ba = np.exp(predicted_values_ba)
predicted_original_ba = np.array(predicted_original_ba)
predicted_original_ba = pd.DataFrame(index=test_ba_lgp.index, columns=['Prediction'],
                                     data=predicted_original_ba)

test_ba = pd.merge(test_ba, predicted_original_ba,
                   left_index=True, right_index=True)
test_ba
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarnin
g: No supported index is available. Prediction results will be given with an integer index begin
ning at `start`.
  return get_prediction_index(
```

Out[43]:

Date	Close	Prediction
2022-09-09	157.520004	158.422824
2022-09-12	158.720001	158.947933
2022-09-13	147.309998	159.458901
2022-09-14	149.259995	159.963682
2022-09-15	149.779999	160.462985
...	...	...
2023-05-05	198.339996	195.649142
2023-05-08	197.259995	195.713897
2023-05-09	201.880005	195.777777
2023-05-10	200.839996	195.840793
2023-05-11	201.839996	195.902958

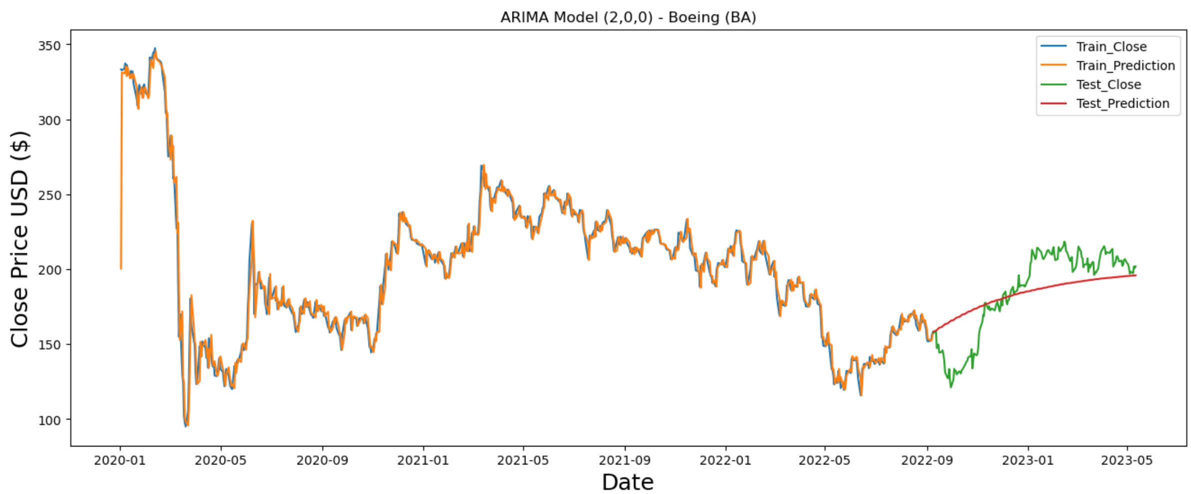
169 rows × 2 columns

In [44]:
```
test_mse = mean_squared_error(test_ba['Close'], test_ba['Prediction'])
test_rmse = np.sqrt(test_mse)
print("The MSE of the Test set is", test_mse)
print("The RMSE of the Test set is", test_rmse)
```

```
The MSE of the Test set is 382.83536670614063
The RMSE of the Test set is 19.56617915450384
```

In [45]:

```
# Visualize the data
plt.figure(figsize=(16,6))
plt.title('ARIMA Model (2,0,0) - Boeing (BA)')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train_val_ba[['Close', 'Prediction']])
plt.plot(test_ba[['Close', 'Prediction']])
plt.legend(['Train_Close', 'Train_Prediction','Test_Close', 'Test_Prediction'], loc='upper right')
#plt.show()
plt.savefig("images/Boeing_Company_(BA)_ARIMA_2")
```



In [46]:

```
pm.arima.auto_arima(train_ba_lgp)
```

Out[46]:

```
ARIMA
ARIMA(0,1,2)(0,0,0)[0]
```

In [47]:

```
p, d, q = 0, 1, 2
ar_model_ba = ARIMA(train_ba_lgp['Close'], order=(p, d, q))
ar_model_ba = ar_model_ba.fit()
ar_model_ba.summary()
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Out[47]:

SARIMAX Results

Dep. Variable:	Close	**No. Observations:**	677
Model:	ARIMA(0, 1, 2)	**Log Likelihood**	1237.748
Date:	Fri, 15 Dec 2023	**AIC**	-2469.496
Time:	20:05:01	**BIC**	-2455.947
Sample:	0	**HQIC**	-2464.250
	- 677		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ma.L1	0.0720	0.017	4.190	0.000	0.038	0.106
ma.L2	0.1834	0.020	9.382	0.000	0.145	0.222
sigma2	0.0015	4.19e-05	35.863	0.000	0.001	0.002

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	1446.36
Prob(Q):	0.95	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.26	**Skew:**	-0.11
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.16

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [48]:

```
# Set the significance level (alpha)
alpha = 0.05

p_values = ar_model_ba.pvalues

significant_predictors = p_values[p_values <= alpha]

print("Significant Predictors:")
print(significant_predictors)
```

```
Significant Predictors:
ma.L1      2.794185e-05
ma.L2      6.489390e-21
sigma2    1.167885e-281
dtype: float64
```

In [49]:
```
predicted_original_train_ba = ar_model_ba.predict(start=train_ba_lgp.index[0],
                                                  end=train_ba_lgp.index[-1],
                                                  dynamic=False)
predicted_original_train_ba = np.exp(predicted_original_train_ba)
#predicted_original_ba = np.array(predicted_original_ba)
predicted_original_train_ba = pd.DataFrame(predicted_original_train_ba)

train_val_ba = ba[:int(training_ba_len)]
train_val_ba = pd.merge(train_val_ba, predicted_original_train_ba,
                        left_index=True, right_index=True)
train_val_ba = train_val_ba.rename(columns={'predicted_mean': 'Prediction'})
train_val_ba
```

Out[49]:

	Close	Prediction
Date		
2020-01-02	333.320007	1.000000
2020-01-03	332.760010	333.320008
2020-01-06	333.739990	332.714107
2020-01-07	337.279999	333.710779
2020-01-08	331.369995	337.725523
...	...	...
2022-09-01	153.660004	159.728619
2022-09-02	151.820007	152.904828
2022-09-06	152.389999	150.667790
2022-09-07	155.949997	152.315716
2022-09-08	157.789993	156.541106

677 rows × 2 columns

In [50]:
```
train_mse = mean_squared_error(train_val_ba['Close'], train_val_ba['Prediction'])
train_rmse = np.sqrt(train_mse)
print("The MSE of the Trainning set is", train_mse)
print("The RMSE of the Trainning set is", train_rmse)
```

```
The MSE of the Trainning set is 210.62604708648428
The RMSE of the Trainning set is 14.512961347929108
```

In [51]:
```
# Create the scaled training data set
test_ba = ba[int(training_ba_len):]
# Log price
test_ba_lgp = np.log(test_ba)

forecast_ba = ar_model_ba.get_forecast(steps=len(test_ba_lgp))

predicted_values_ba = forecast_ba.predicted_mean
predicted_original_ba = np.exp(predicted_values_ba)
predicted_original_ba = np.array(predicted_original_ba)
predicted_original_ba = pd.DataFrame(index=test_ba_lgp.index, columns=['Prediction'],
                                     data=predicted_original_ba)

test_ba = pd.merge(test_ba, predicted_original_ba,
                   left_index=True, right_index=True)
test_ba
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarnin
g: No supported index is available. Prediction results will be given with an integer index begin
ning at `start`.
  return get_prediction_index(
```

Out[51]:

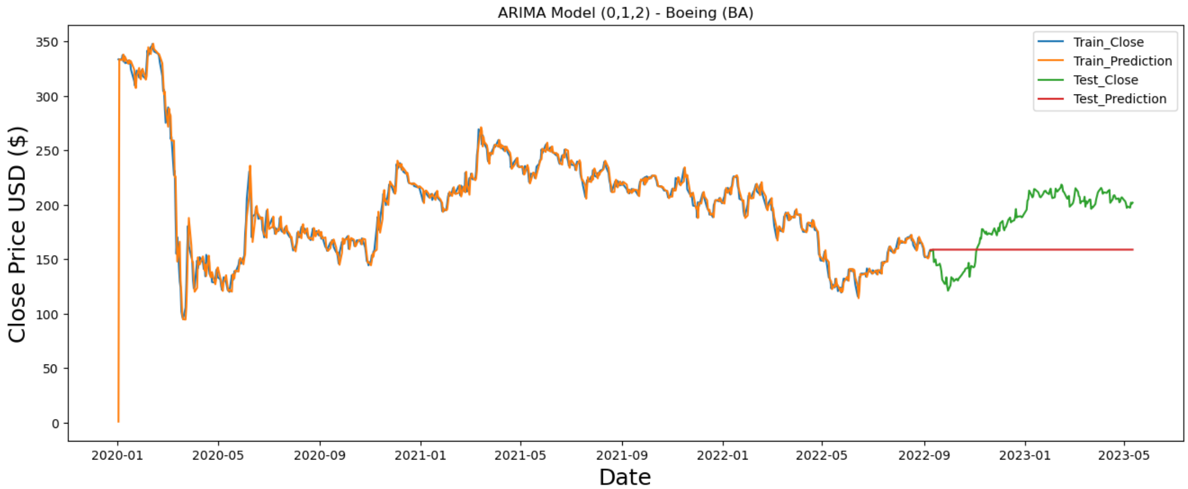
Date	Close	Prediction
2022-09-09	157.520004	158.564732
2022-09-12	158.720001	158.796043
2022-09-13	147.309998	158.796043
2022-09-14	149.259995	158.796043
2022-09-15	149.779999	158.796043
...	...	...
2023-05-05	198.339996	158.796043
2023-05-08	197.259995	158.796043
2023-05-09	201.880005	158.796043
2023-05-10	200.839996	158.796043
2023-05-11	201.839996	158.796043

169 rows × 2 columns

In [52]:
```
test_mse = mean_squared_error(test_ba['Close'], test_ba['Prediction'])
test_rmse = np.sqrt(test_mse)
print("The MSE of the Test set is", test_mse)
print("The RMSE of the Test set is", test_rmse)
```

```
The MSE of the Test set is 1491.442976445892
The RMSE of the Test set is 38.61920476195609
```

In [53]:
```
# Visualize the data
plt.figure(figsize=(16,6))
plt.title('ARIMA Model (0,1,2) - Boeing (BA)')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train_val_ba[['Close', 'Prediction']])
plt.plot(test_ba[['Close', 'Prediction']])
plt.legend(['Train_Close', 'Train_Prediction','Test_Close', 'Test_Prediction'], loc='upper right')
#plt.show()
plt.savefig("images/Boeing_Company_(BA)_ARIMA_3")
```



In [54]:
```
p, d, q = 4, 1, 6
ar_model_ba = ARIMA(train_ba_lgp['Close'], order=(p, d, q))
ar_model_ba = ar_model_ba.fit()
ar_model_ba.summary()
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\base\model.py:607: ConvergenceWarning:
Maximum Likelihood optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

Out[54]:

SARIMAX Results

Dep. Variable:	Close	**No. Observations:**	677
Model:	ARIMA(4, 1, 6)	**Log Likelihood**	1246.302
Date:	Fri, 15 Dec 2023	**AIC**	-2470.604
Time:	20:05:03	**BIC**	-2420.926
Sample:	0	**HQIC**	-2451.370
	- 677		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	-0.5023	0.071	-7.026	0.000	-0.642	-0.362
ar.L2	0.6586	0.077	8.539	0.000	0.507	0.810
ar.L3	-0.4637	0.066	-7.073	0.000	-0.592	-0.335
ar.L4	-0.8479	0.062	-13.669	0.000	-0.969	-0.726
ma.L1	0.5777	0.074	7.776	0.000	0.432	0.723
ma.L2	-0.4433	0.082	-5.402	0.000	-0.604	-0.282
ma.L3	0.5144	0.069	7.415	0.000	0.378	0.650
ma.L4	0.7332	0.073	10.104	0.000	0.591	0.875
ma.L5	0.1076	0.035	3.058	0.002	0.039	0.177
ma.L6	0.1051	0.037	2.819	0.005	0.032	0.178
sigma2	0.0015	4.67e-05	31.334	0.000	0.001	0.002

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	1253.46
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.27	**Skew:**	-0.15
Prob(H) (two-sided):	0.00	**Kurtosis:**	9.66

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [55]:
```
# Set the significance level (alpha)
alpha = 0.05

p_values = ar_model_ba.pvalues

significant_predictors = p_values[p_values <= alpha]

print("Significant Predictors:")
print(significant_predictors)
```

```
Significant Predictors:
ar.L1      2.127745e-12
ar.L2      1.358088e-17
ar.L3      1.515523e-12
ar.L4      1.563808e-42
ma.L1      7.455934e-15
ma.L2      6.600023e-08
ma.L3      1.212720e-13
ma.L4      5.302499e-24
ma.L5      2.226047e-03
ma.L6      4.812607e-03
sigma2    1.630318e-215
dtype: float64
```

In [56]:
```
predicted_original_train_ba = ar_model_ba.predict(start=train_ba_lgp.index[0],
                                                  end=train_ba_lgp.index[-1],
                                                  dynamic=False)
predicted_original_train_ba = np.exp(predicted_original_train_ba)
#predicted_original_ba = np.array(predicted_original_ba)
predicted_original_train_ba = pd.DataFrame(predicted_original_train_ba)

train_val_ba = ba[:int(training_ba_len)]
train_val_ba = pd.merge(train_val_ba, predicted_original_train_ba,
                        left_index=True, right_index=True)
train_val_ba = train_val_ba.rename(columns={'predicted_mean': 'Prediction'})
train_val_ba
```

Out[56]:

Date	Close	Prediction
2020-01-02	333.320007	1.000000
2020-01-03	332.760010	333.320008
2020-01-06	333.739990	332.718327
2020-01-07	337.279999	333.703758
2020-01-08	331.369995	337.720118
...	...	...
2022-09-01	153.660004	159.292708
2022-09-02	151.820007	153.214733
2022-09-06	152.389999	151.324491
2022-09-07	155.949997	152.463883
2022-09-08	157.789993	157.347112

677 rows × 2 columns

In [57]:
```
train_mse = mean_squared_error(train_val_ba['Close'], train_val_ba['Prediction'])
train_rmse = np.sqrt(train_mse)
print("The MSE of the Trainning set is", train_mse)
print("The RMSE of the Trainning set is", train_rmse)
```

```
The MSE of the Trainning set is 209.78057389758536
The RMSE of the Trainning set is 14.483803847663271
```

In [58]:

```
# Create the scaled training data set
test_ba = ba[int(training_ba_len):]
# Log price
test_ba_lgp = np.log(test_ba)

forecast_ba = ar_model_ba.get_forecast(steps=len(test_ba_lgp))

predicted_values_ba = forecast_ba.predicted_mean
predicted_original_ba = np.exp(predicted_values_ba)
predicted_original_ba = np.array(predicted_original_ba)
predicted_original_ba = pd.DataFrame(index=test_ba_lgp.index, columns=['Prediction'],
                                     data=predicted_original_ba)

test_ba = pd.merge(test_ba, predicted_original_ba,
                   left_index=True, right_index=True)
test_ba
```

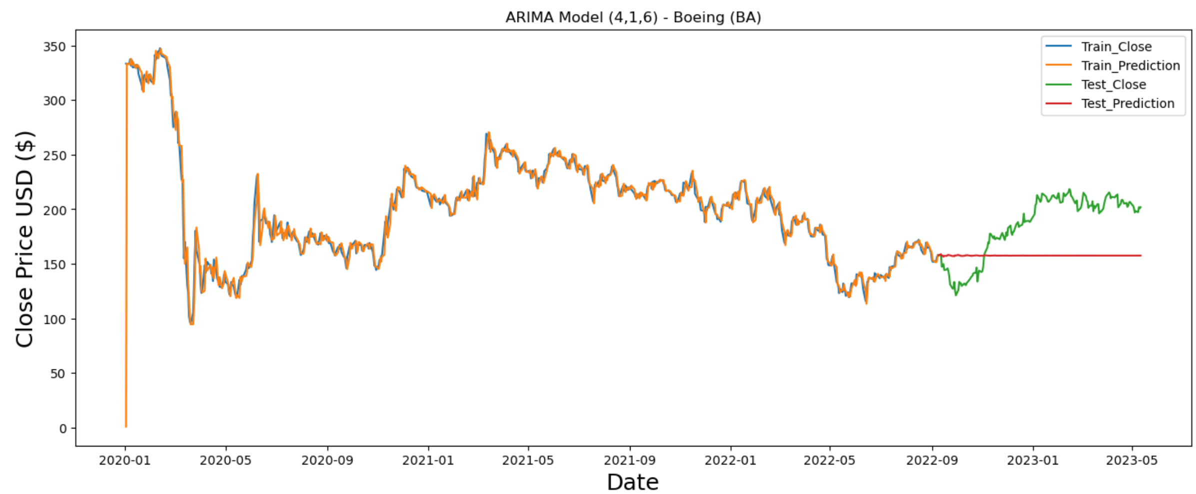
```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarnin
g: No supported index is available. Prediction results will be given with an integer index begin
ning at `start`.
  return get_prediction_index(
```

Out[58]:

	Close	Prediction
Date		
2022-09-09	157.520004	157.986055
2022-09-12	158.720001	158.615432
2022-09-13	147.309998	157.291470
2022-09-14	149.259995	157.533607
2022-09-15	149.779999	156.511250
...	...	...
2023-05-05	198.339996	157.562173
2023-05-08	197.259995	157.563195
2023-05-09	201.880005	157.563325
2023-05-10	200.839996	157.564286
2023-05-11	201.839996	157.563254

169 rows × 2 columns

In [59]:
```
# Visualize the data
plt.figure(figsize=(16,6))
plt.title('ARIMA Model (4,1,6) - Boeing (BA)')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train_val_ba[['Close', 'Prediction']])
plt.plot(test_ba[['Close', 'Prediction']])
plt.legend(['Train_Close', 'Train_Prediction','Test_Close', 'Test_Prediction'], loc='upper right')
#plt.show()
plt.savefig("images/Boeing_Company_(BA)_ARIMA_4")
```



Zoom (ZM)

In [60]:
```
# Get the number of rows to train the model on
training_zm_len = int(np.ceil(len(zm) * .8 ))
# Create the scaled training data set
train_zm = zm[0:int(training_zm_len)]
# First-order differencing
train_zm_diff = train_zm.diff().dropna()
# Log price
train_zm_lgp = np.log(train_zm)
# Log Returns
train_zm_rtn = np.log(train_zm).diff().dropna()
```

1. Find d in (p, d, q) for ARIMA model and (ADF) test

In [61]:
```
# ZM Pirce d=0
result = adfuller(train_zm)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -1.091567
p-value: 0.718423
	1%: -3.440
	5%: -2.866
	10%: -2.569
```

In [62]:

```
# ZM Pirce d=1
result = adfuller(train_zm_diff)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -17.269873
p-value: 0.000000
        1%: -3.440
        5%: -2.866
        10%: -2.569
```

In [63]:

```
# ZM Log Pirce d=0
result = adfuller(train_zm_lgp)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -1.248085
p-value: 0.652576
        1%: -3.440
        5%: -2.866
        10%: -2.569
```

In [64]:

```
# ZM Log Pirce d=1
result = adfuller(train_zm_rtn)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

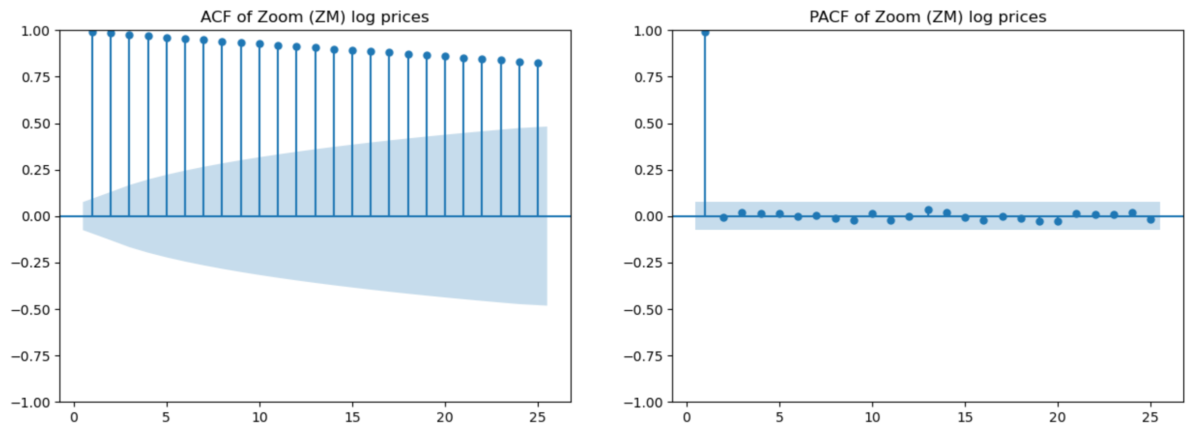
```
ADF Statistic: -26.131050
p-value: 0.000000
        1%: -3.440
        5%: -2.866
        10%: -2.569
```

Choose ZM Log Pirce d=1, use train_zm_lgp (log price of ZM) d=1 in ARIMA Model

2. Find p and q in (p, d, q) for ARIMA model

Method 1, Step 1: ACF plot and PACF plot

In [65]:
```
plot_ACF_PACF(train_zm_lgp, 25, 'Zoom (ZM)')
#plt.savefig("images/Zoom_(ZM)_ACF_PACF")
```



p=0, q=0

In [66]:
```
p, d, q = 0, 1, 0
ar_model_zm = ARIMA(train_zm_lgp['Close'], order=(p, d, q))
ar_model_zm = ar_model_zm.fit()
ar_model_zm.summary()
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Out[66]:

SARIMAX Results

Dep. Variable:	Close	**No. Observations:**	677
Model:	ARIMA(0, 1, 0)	**Log Likelihood**	1160.345
Date:	Fri, 15 Dec 2023	**AIC**	-2318.689
Time:	20:05:06	**BIC**	-2314.173
Sample:	0	**HQIC**	-2316.941
	- 677		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	0.0019	4.69e-05	40.301	0.000	0.002	0.002

Ljung-Box (L1) (Q):	0.03	**Jarque-Bera (JB):**	1646.47
Prob(Q):	0.85	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.59	**Skew:**	0.43
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.60

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Method 1, Step 2: p-value test

In [67]:
```
# Set the significance level (alpha)
alpha = 0.05

p_values = ar_model_zm.pvalues

significant_predictors = p_values[p_values <= alpha]

print("Significant Predictors:")
print(significant_predictors)
```

```
Significant Predictors:
sigma2    0.0
dtype: float64
```

2. Find p and q in (p, d, q) for ARIMA model

Method 2: grid search for min AIC and min BIC

In [68]:
```
result_df = searchARIMA(train_zm_lgp.values, d = 1, max_p = 10, max_q = 10)
result_df
```

	p	q	aic	bic
0	0	0	-2318.689199	-2314.173006
1	0	1	-2316.725490	-2307.693104
2	0	2	-2315.648769	-2302.100190
3	0	3	-2313.926836	-2295.862063
4	0	4	-2312.859576	-2290.278611
...	...	...	...	...
95	9	5	-2296.018761	-2228.275865
96	9	6	-2298.606085	-2226.346996
97	9	7	-2293.419767	-2216.644485
98	9	8	-2291.103879	-2209.812404
99	9	9	-2294.160153	-2208.352485

100 rows × 4 columns

In [69]:
```
min_aic_bic_row = result_df[(result_df['aic'] == result_df['aic'].min()) |
                            (result_df['bic'] == result_df['bic'].min())]
min_aic_bic_row
```

Out[69]:

	p	q	aic	bic
0	0	0	-2318.689199	-2314.173006

In [70]:
```
pm.arima.auto_arima(train_zm_lgp)
```

Out[70]:

```
ARIMA
ARIMA(4,2,1)(0,0,0)[0]
```

In general, choose p=0, q=0

In [71]:

```
p, d, q = 0, 1, 0
ar_model_zm = ARIMA(train_zm_lgp['Close'], order=(p, d, q))
ar_model_zm = ar_model_zm.fit()
ar_model_zm.summary()
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Out[71]:

SARIMAX Results

Dep. Variable:	Close	**No. Observations:**	677
Model:	ARIMA(0, 1, 0)	**Log Likelihood**	1160.345
Date:	Fri, 15 Dec 2023	**AIC**	-2318.689
Time:	20:07:11	**BIC**	-2314.173
Sample:	0	**HQIC**	-2316.941
	- 677		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	0.0019	4.69e-05	40.301	0.000	0.002	0.002

Ljung-Box (L1) (Q):	0.03	**Jarque-Bera (JB):**	1646.47
Prob(Q):	0.85	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.59	**Skew:**	0.43
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.60

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [72]:

```
# Set the significance level (alpha)
alpha = 0.05

p_values = ar_model_zm.pvalues

significant_predictors = p_values[p_values <= alpha]

print("Significant Predictors:")
print(significant_predictors)
```

```
Significant Predictors:
sigma2    0.0
dtype: float64
```

In [73]:
```
predicted_original_train_zm = ar_model_zm.predict(start=train_zm_lgp.index[0],
                                                  end=train_zm_lgp.index[-1],
                                                  dynamic=False)
predicted_original_train_zm = np.exp(predicted_original_train_zm)
#predicted_original_ba = np.array(predicted_original_ba)
```

In [74]:
```
predicted_original_train_zm = pd.DataFrame(predicted_original_train_zm)

train_val_zm = zm[:int(training_zm_len)]
train_val_zm = pd.merge(train_val_zm, predicted_original_train_zm,
                        left_index=True, right_index=True)
train_val_zm = train_val_zm.rename(columns={'predicted_mean': 'Prediction'})
train_val_zm
```

Out[74]:

	Close	Prediction
Date		
2020-01-02	68.720001	1.000000
2020-01-03	67.279999	68.720001
2020-01-06	70.320000	67.279999
2020-01-07	71.900002	70.320000
2020-01-08	72.550003	71.900002
...	...	...
2022-09-01	81.139999	80.400002
2022-09-02	80.790001	81.139999
2022-09-06	80.019997	80.790001
2022-09-07	81.019997	80.019997
2022-09-08	80.230003	81.019997

677 rows × 2 columns

In [75]:
```
train_mse = mean_squared_error(train_val_zm['Close'], train_val_zm['Prediction'])
train_rmse = np.sqrt(train_mse)
print("The MSE of the Trainning set is", train_mse)
print("The RMSE of the Trainning set is", train_rmse)
```

```
The MSE of the Trainning set is 153.99022624434983
The RMSE of the Trainning set is 12.409279843905118
```

In [76]:
```
# Create the scaled training data set
test_zm = zm[int(training_zm_len):]
# Log price
test_zm_lgp = np.log(test_zm)

forecast_zm = ar_model_zm.get_forecast(steps=len(test_zm_lgp))

predicted_values_zm = forecast_zm.predicted_mean
predicted_original_zm = np.exp(predicted_values_zm)
predicted_original_zm = np.array(predicted_original_zm)
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarnin
g: No supported index is available. Prediction results will be given with an integer index begin
ning at `start`.
  return get_prediction_index(
```

In [77]:
```
predicted_original_zm = pd.DataFrame(index=test_zm_lgp.index, columns=['Prediction'],
                                     data=predicted_original_zm)

test_zm = pd.merge(test_zm, predicted_original_zm,
                   left_index=True, right_index=True)
test_zm
```

Out[77]:

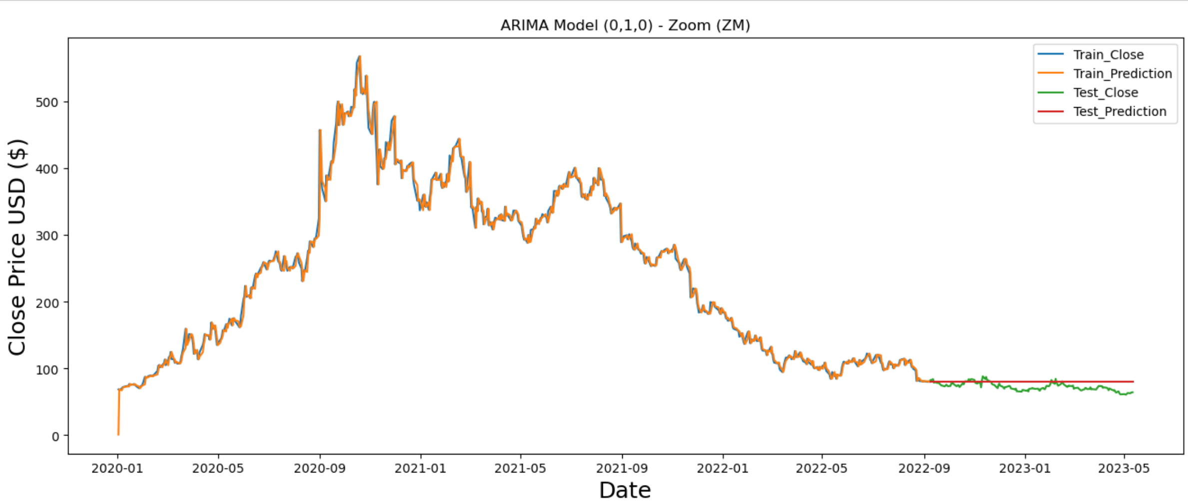
	Close	Prediction
Date		
2022-09-09	82.620003	80.230003
2022-09-12	84.080002	80.230003
2022-09-13	78.860001	80.230003
2022-09-14	79.589996	80.230003
2022-09-15	80.209999	80.230003
...	...	...
2023-05-05	63.400002	80.230003
2023-05-08	62.930000	80.230003
2023-05-09	63.560001	80.230003
2023-05-10	64.430000	80.230003
2023-05-11	64.449997	80.230003

169 rows × 2 columns

In [78]:
```
test_mse = mean_squared_error(test_zm['Close'], test_zm['Prediction'])
test_rmse = np.sqrt(test_mse)
print("The MSE of the Test set is", test_mse)
print("The RMSE of the Test set is", test_rmse)
```

```
The MSE of the Test set is 87.11304903815056
The RMSE of the Test set is 9.333437150275913
```

In [79]:
```
# Visualize the data
plt.figure(figsize=(16,6))
plt.title('ARIMA Model (0,1,0) - Zoom (ZM)')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train_val_zm[['Close', 'Prediction']])
plt.plot(test_zm[['Close', 'Prediction']])
plt.legend(['Train_Close', 'Train_Prediction','Test_Close', 'Test_Prediction'], loc='upper right')
#plt.show()
plt.savefig("images/Zoom_(ZM)_ARIMA_1")
```



In [80]:
```
pm.arima.auto_arima(train_zm_lgp)
```

Out[80]:
```
ARIMA
ARIMA(4,2,1)(0,0,0)[0]
```

In [81]:
```
p, d, q = 4, 2, 1
ar_model_zm = ARIMA(train_zm_lgp['Close'], order=(p, d, q))
ar_model_zm = ar_model_zm.fit()
ar_model_zm.summary()
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
g: A date index has been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Out[81]:

SARIMAX Results

Dep. Variable:	Close	**No. Observations:**	677
Model:	ARIMA(4, 2, 1)	**Log Likelihood**	1160.709
Date:	Fri, 15 Dec 2023	**AIC**	-2309.418
Time:	20:07:20	**BIC**	-2282.329
Sample:	0	**HQIC**	-2298.929
	- 677		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0289	0.029	-1.000	0.317	-0.085	0.028
ar.L2	-0.0563	0.034	-1.658	0.097	-0.123	0.010
ar.L3	-0.0388	0.038	-1.010	0.312	-0.114	0.037
ar.L4	-0.0607	0.037	-1.654	0.098	-0.133	0.011
ma.L1	-0.9878	0.008	-127.046	0.000	-1.003	-0.973
sigma2	0.0019	4.93e-05	37.914	0.000	0.002	0.002

Ljung-Box (L1) (Q):	0.02	**Jarque-Bera (JB):**	1609.25
Prob(Q):	0.89	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.61	**Skew:**	0.35
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.53

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [82]:
```
# Set the significance level (alpha)
alpha = 0.05

p_values = ar_model_zm.pvalues

significant_predictors = p_values[p_values <= alpha]

print("Significant Predictors:")
print(significant_predictors)
```

```
Significant Predictors:
ma.L1     0.0
sigma2    0.0
dtype: float64
```

In [83]:
```
# p, d, q = 0, 2, 1
# ar_model_zm = ARIMA(train_zm_lgp['Close'], order=(p, d, q))
# ar_model_zm = ar_model_zm.fit()
# ar_model_zm.summary()
```

In [84]:
```
# # Set the significance level (alpha)
# alpha = 0.05

# p_values = ar_model_zm.pvalues

# significant_predictors = p_values[p_values <= alpha]

# print("Significant Predictors:")
# print(significant_predictors)
```

In [85]:
```
predicted_original_train_zm = ar_model_zm.predict(start=train_zm_lgp.index[0],
                                                  end=train_zm_lgp.index[-1],
                                                  dynamic=False)
predicted_original_train_zm = np.exp(predicted_original_train_zm)
#predicted_original_ba = np.array(predicted_original_ba)
predicted_original_train_zm = pd.DataFrame(predicted_original_train_zm)

train_val_zm = zm[:int(training_zm_len)]
train_val_zm = pd.merge(train_val_zm, predicted_original_train_zm,
                        left_index=True, right_index=True)
train_val_zm = train_val_zm.rename(columns={'predicted_mean': 'Prediction'})
train_val_zm
```

Out[85]:

Date	Close	Prediction
2020-01-02	68.720001	1.000000
2020-01-03	67.279999	569.671822
2020-01-06	70.320000	65.870172
2020-01-07	71.900002	71.198084
2020-01-08	72.550003	72.942304
...	...	...
2022-09-01	81.139999	80.197569
2022-09-02	80.790001	80.716940
2022-09-06	80.019997	80.308033
2022-09-07	81.019997	79.630285
2022-09-08	80.230003	80.550819

677 rows × 2 columns

In [86]:
```
train_mse = mean_squared_error(train_val_zm['Close'], train_val_zm['Prediction'])
train_rmse = np.sqrt(train_mse)
print("The MSE of the Trainning set is", train_mse)
print("The RMSE of the Trainning set is", train_rmse)
```

```
The MSE of the Trainning set is 526.7243910126432
The RMSE of the Trainning set is 22.95047692342456
```

In [87]:
```
# Create the scaled training data set
test_zm = zm[int(training_zm_len):]
# Log price
test_zm_lgp = np.log(test_zm)

forecast_zm = ar_model_zm.get_forecast(steps=len(test_zm_lgp))

predicted_values_zm = forecast_zm.predicted_mean
predicted_original_zm = np.exp(predicted_values_zm)
predicted_original_zm = np.array(predicted_original_zm)
predicted_original_zm = pd.DataFrame(index=test_zm_lgp.index, columns=['Prediction'],
                                     data=predicted_original_zm)

test_zm = pd.merge(test_zm, predicted_original_zm,
                   left_index=True, right_index=True)
test_zm
```

```
C:\Users\surface\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarnin
g: No supported index is available. Prediction results will be given with an integer index begin
ning at `start`.
  return get_prediction_index(
```

Out[87]:

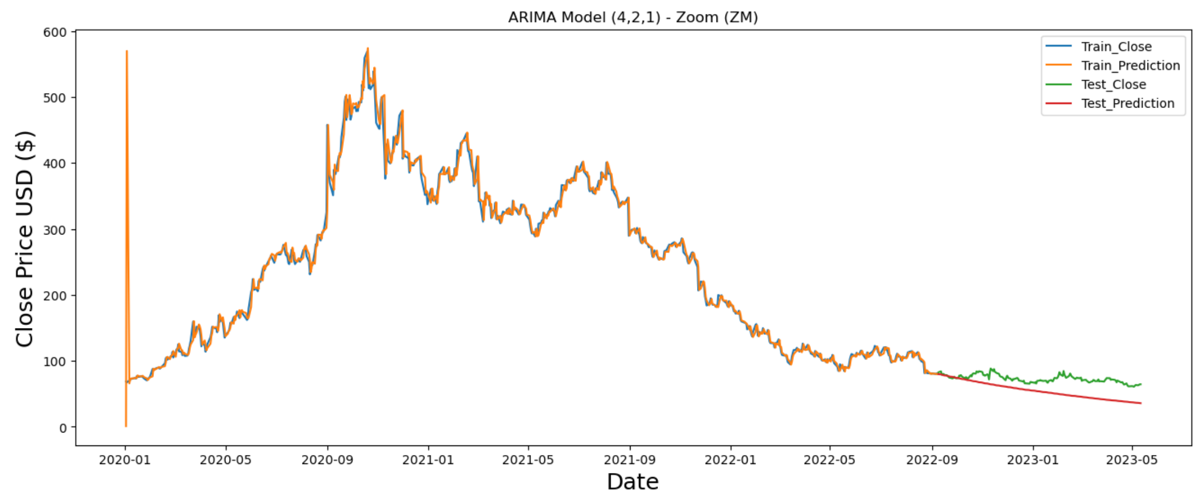
Date	Close	Prediction
2022-09-09	82.620003	79.795424
2022-09-12	84.080002	79.410065
2022-09-13	78.860001	78.968458
2022-09-14	79.589996	78.621022
2022-09-15	80.209999	78.253175
...	...	...
2023-05-05	63.400002	36.491449
2023-05-08	62.930000	36.317871
2023-05-09	63.560001	36.145119
2023-05-10	64.430000	35.973188
2023-05-11	64.449997	35.802076

169 rows × 2 columns

In [88]:
```
test_mse = mean_squared_error(test_zm['Close'], test_zm['Prediction'])
test_rmse = np.sqrt(test_mse)
print("The MSE of the Test set is", test_mse)
print("The RMSE of the Test set is", test_rmse)
```

```
The MSE of the Test set is 426.70324320475163
The RMSE of the Test set is 20.656796537816593
```

In [89]:
```
# Visualize the data
plt.figure(figsize=(16,6))
plt.title('ARIMA Model (4,2,1) - Zoom (ZM)')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train_val_zm[['Close', 'Prediction']])
plt.plot(test_zm[['Close', 'Prediction']])
plt.legend(['Train_Close', 'Train_Prediction','Test_Close', 'Test_Prediction'], loc='upper right')
#plt.show()
plt.savefig("images/Zoom_(ZM)_ARIMA_2")
```



LSTM

Step 1: Normalize your data into interval [0,1] (recommend using MinMaxScaler from sklearn.preprocessing)

In [90]:
```
scaler_ba = MinMaxScaler(feature_range=(0,1))
scaled_ba = scaler_ba.fit_transform(ba)
```

In [91]:
```
scaler_zm = MinMaxScaler(feature_range=(0,1))
scaled_zm = scaler_zm.fit_transform(zm)
```

Step 2: Set 80% of the data as training data and 20% of the data as the testing set

In [92]:
```
# Get the number of rows to train the model on
training_ba_len = int(np.ceil( len(scaled_ba) * .8 ))

training_ba_len
```

Out[92]: 677

In [93]:
```
# Create the scaled training data set
train_ba = scaled_ba[0:int(training_ba_len), :]
```

In [94]:
```
# Get the number of rows to train the model on
training_zm_len = int(np.ceil( len(scaled_zm) * .8 ))

training_zm_len
```

Out[94]: 677

In [95]:
```
# Create the scaled training data set
train_zm = scaled_zm[0:int(training_zm_len), :]
```

Step 3: Pick a lookback window with 10 timestamps

In [96]:
```
def Split_train_data_with_lookback_window(train_data, timestamps):
    x_train = []
    y_train = []

    for i in range(timestamps, len(train_data)):
        x_train.append(train_data[i-10:i, 0])
        y_train.append(train_data[i, 0])
        if i<= timestamps+1:
            print(x_train)
            print(y_train)
            print()

    # Convert the x_train and y_train to numpy arrays
    x_train, y_train = np.array(x_train), np.array(y_train)

    # Reshape the data
    x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))

    return x_train, y_train
```

In [97]:
```
x_train_ba, y_train_ba = Split_train_data_with_lookback_window(train_ba, 10)
```

```
[array([0.94402629, 0.94180795, 0.94568998, 0.95971315, 0.93630163,
       0.95598948, 0.93055776, 0.93174612, 0.94018378, 0.9300823 ])]
[0.9387972920667447]

[array([0.94402629, 0.94180795, 0.94568998, 0.95971315, 0.93630163,
       0.95598948, 0.93055776, 0.93174612, 0.94018378, 0.9300823 ]), array([0.94180795, 0.945689
98, 0.95971315, 0.93630163, 0.95598948,
       0.93055776, 0.93174612, 0.94018378, 0.9300823 , 0.93879729])]
[0.9387972920667447, 0.9077007709514351]
```

In [98]:
```
x_train_zm, y_train_zm = Split_train_data_with_lookback_window(train_zm, 10)
```

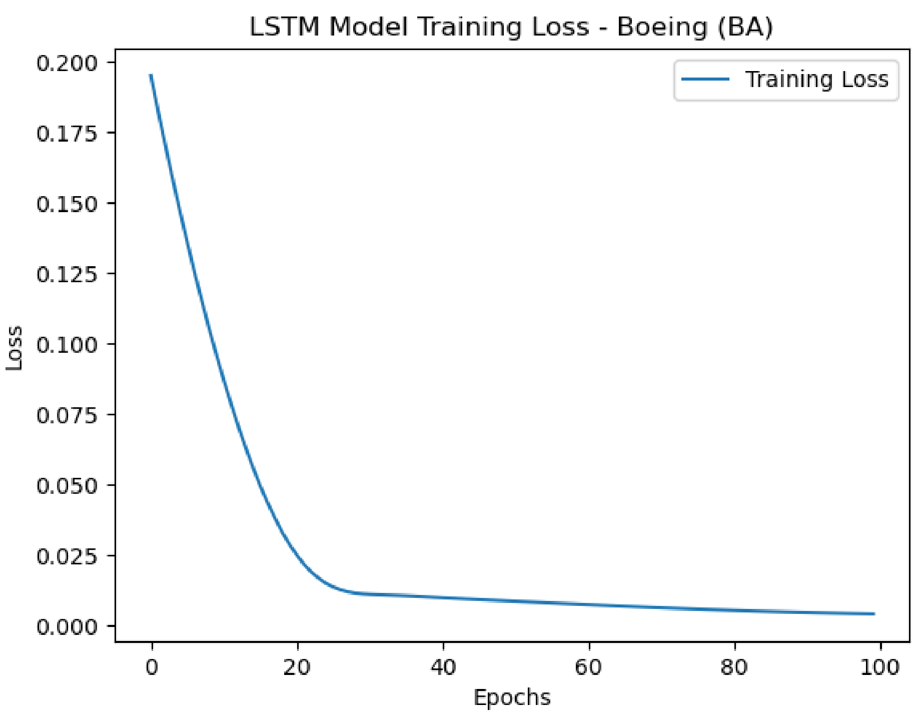
```
[array([0.01556589, 0.01272856, 0.01871847, 0.02183165, 0.0231124 ,
       0.02325032, 0.02417638, 0.02602853, 0.02431432, 0.0317623 ])]
[0.030126891742712686]

[array([0.01556589, 0.01272856, 0.01871847, 0.02183165, 0.0231124 ,
       0.02325032, 0.02417638, 0.02602853, 0.02431432, 0.0317623 ]), array([0.01272856, 0.018718
47, 0.02183165, 0.0231124 , 0.02325032,
       0.02417638, 0.02602853, 0.02431432, 0.0317623 , 0.03012689])]
[0.030126891742712686, 0.029043184652699228]
```

Specify the LSTM model with the following parameters:

In [99]:
```
# Build the LSTM model
lstm_model_ba = Sequential()
lstm_model_ba.add(LSTM(4, input_shape= (x_train_ba.shape[1], 1)))
lstm_model_ba.add(Dense(1))
# Compile the model
lstm_model_ba.compile(optimizer='adam', loss='mean_squared_error')
# Train the model
history = lstm_model_ba.fit(x_train_ba, y_train_ba, batch_size=256, epochs=100, verbose=2)
```

```
Epoch 1/100
3/3 - 5s - loss: 0.1949 - 5s/epoch - 2s/step
Epoch 2/100
3/3 - 0s - loss: 0.1821 - 16ms/epoch - 5ms/step
Epoch 3/100
3/3 - 0s - loss: 0.1700 - 31ms/epoch - 10ms/step
Epoch 4/100
3/3 - 0s - loss: 0.1581 - 16ms/epoch - 5ms/step
Epoch 5/100
3/3 - 0s - loss: 0.1467 - 16ms/epoch - 5ms/step
Epoch 6/100
3/3 - 0s - loss: 0.1357 - 16ms/epoch - 5ms/step
Epoch 7/100
3/3 - 0s - loss: 0.1250 - 16ms/epoch - 5ms/step
Epoch 8/100
3/3 - 0s - loss: 0.1150 - 16ms/epoch - 5ms/step
Epoch 9/100
3/3 - 0s - loss: 0.1050 - 31ms/epoch - 10ms/step
Epoch 10/100
```

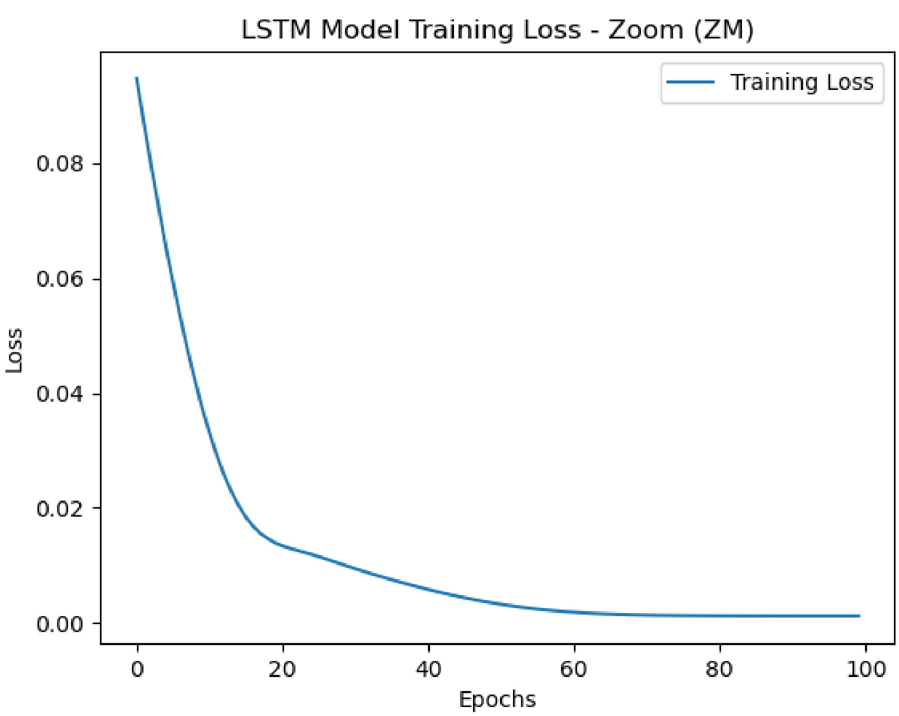
In [100]:
```
# Plot the training loss - Convergence
plt.plot(history.history['loss'], label='Training Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('LSTM Model Training Loss - Boeing (BA)')
plt.legend()
#plt.show()
plt.savefig("images/LSTM Model Trainning Loss - Boeing (BA)")
```



In [101]:
```
# Build the LSTM model
lstm_model_zm = Sequential()
lstm_model_zm.add(LSTM(4, input_shape= (x_train_zm.shape[1], 1)))
lstm_model_zm.add(Dense(1))
# Compile the model
lstm_model_zm.compile(optimizer='adam', loss='mean_squared_error')
# Train the model
history = lstm_model_zm.fit(x_train_zm, y_train_zm, batch_size=256, epochs=100, verbose=2)
```

```
Epoch 1/100
3/3 - 3s - loss: 0.0947 - 3s/epoch - 1s/step
Epoch 2/100
3/3 - 0s - loss: 0.0869 - 16ms/epoch - 5ms/step
Epoch 3/100
3/3 - 0s - loss: 0.0795 - 16ms/epoch - 5ms/step
Epoch 4/100
3/3 - 0s - loss: 0.0725 - 31ms/epoch - 10ms/step
Epoch 5/100
3/3 - 0s - loss: 0.0655 - 16ms/epoch - 5ms/step
Epoch 6/100
3/3 - 0s - loss: 0.0592 - 16ms/epoch - 5ms/step
Epoch 7/100
3/3 - 0s - loss: 0.0532 - 31ms/epoch - 10ms/step
Epoch 8/100
3/3 - 0s - loss: 0.0474 - 24ms/epoch - 8ms/step
Epoch 9/100
3/3 - 0s - loss: 0.0423 - 16ms/epoch - 5ms/step
Epoch 10/100
```

In [102]:
```
# Plot the training loss
plt.plot(history.history['loss'], label='Training Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('LSTM Model Training Loss - Zoom (ZM)')
plt.legend()
#plt.show()
plt.savefig("images/LSTM Model Trainning Loss - Zoom (ZM)")
```



Train set predictions and RMSE

In [103]:
```
y_train_ba = ba[10:training_ba_len].values
```

In [104]:
```
# Get the models predicted price values
train_pred_ba = lstm_model_ba.predict(x_train_ba)
train_pred_ba = scaler_ba.inverse_transform(train_pred_ba)

# Get the root mean squared error (RMSE)
train_rmse_ba = np.sqrt(np.mean(((train_pred_ba - y_train_ba) ** 2)))
train_rmse_ba
```

```
21/21 [==============================] - 1s 2ms/step
```

Out[104]: 16.034497635163348

In [105]:
```
train_val_ba = ba[10:training_ba_len]
train_val_ba['Prediction'] = train_pred_ba
train_val_ba
```

Out[105]:

Date	Close	Prediction
2020-01-16	332.000000	303.658203
2020-01-17	324.149994	303.537445
2020-01-21	313.369995	303.064972
2020-01-22	309.000000	301.855530
2020-01-23	317.790009	300.105621
...	...	...
2022-09-01	153.660004	169.883011
2022-09-02	151.820007	168.658813
2022-09-06	152.389999	167.570267
2022-09-07	155.949997	166.774872
2022-09-08	157.789993	166.342865

667 rows × 2 columns

In [106]:
```
train_mse = mean_squared_error(train_val_ba['Close'], train_val_ba['Prediction'])
train_rmse = np.sqrt(train_mse)
print("The MSE of the Training set is", train_mse)
print("The RMSE of the Training set is", train_rmse)
```

```
The MSE of the Training set is 257.10511441205904
The RMSE of the Training set is 16.034497635163348
```

In [107]:
```
y_train_zm = zm[10:training_zm_len].values
```

In [108]:
```
# Get the models predicted price values
train_pred_zm = lstm_model_zm.predict(x_train_zm)
train_pred_zm = scaler_zm.inverse_transform(train_pred_zm)

# Get the root mean squared error (RMSE)
train_rmse_zm = np.sqrt(np.mean(((train_pred_zm - y_train_zm) ** 2)))
train_rmse_zm
```

```
21/21 [==============================] - 1s 2ms/step
```

Out[108]: 17.990990910365824

In [109]:
```
train_val_zm = zm[10:training_zm_len]
train_val_zm['Prediction'] = train_pred_zm
train_val_zm
```

Out[109]:

Date	Close	Prediction
2020-01-16	76.110001	80.820297
2020-01-17	75.559998	81.387871
2020-01-21	76.730003	81.700119
2020-01-22	75.540001	82.171432
2020-01-23	74.470001	82.221657
...	...	...
2022-09-01	81.139999	88.512329
2022-09-02	80.790001	87.850410
2022-09-06	80.019997	87.322151
2022-09-07	81.019997	86.778160
2022-09-08	80.230003	86.797424

667 rows × 2 columns

In [110]:
```
train_mse = mean_squared_error(train_val_zm['Close'], train_val_zm['Prediction'])
train_rmse = np.sqrt(train_mse)
print("The MSE of the Training set is", train_mse)
print("The RMSE of the Training set is", train_rmse)
```

```
The MSE of the Training set is 323.67575393686565
The RMSE of the Training set is 17.990990910365824
```

Get Test set and Split to X and y

In [111]:
```
# get test data set and split into X and y
def Split_test_data_with_lookback_window(scaled_data, original_data, training_data_len, timestamps
    # Create the testing data set
    test_data = scaled_data[training_data_len - 10: , :]
    # Create the data sets x_test and y_test
    x_test = []
    y_test = original_data[training_data_len:].values

    for i in range(timestamps, len(test_data)):
        x_test.append(test_data[i-timestamps:i, 0])

    # Convert the data to a numpy array
    x_test = np.array(x_test)

    # Reshape the data
    x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1 ))

    return x_test, y_test
```

In [112]:
```
x_test_ba, y_test_ba = Split_test_data_with_lookback_window(scaled_ba, ba, training_ba_len, 10)
```

In [113]:
```
x_test_zm, y_test_zm, = Split_test_data_with_lookback_window(scaled_zm, zm, training_zm_len, 10)
```

Prediction

In [114]:
```
# Get the models predicted price values
pred_ba = lstm_model_ba.predict(x_test_ba)
pred_ba = scaler_ba.inverse_transform(pred_ba)

# Get MSE and RMSE
test_mse_ba = np.mean(((pred_ba - y_test_ba) ** 2))
test_rmse_ba = np.sqrt(test_mse_ba)
print("The MSE of the Test set is", test_mse_ba)
print("The RMSE of the Test set is", test_rmse_ba)
```

```
6/6 [==============================] - 0s 3ms/step
The MSE of the Test set is 85.99911155398644
The RMSE of the Test set is 9.273570593573245
```

In [115]:
```
test_ba = ba[training_ba_len:]
test_ba['Prediction'] = pred_ba
test_ba
```

Out[115]:

Date	Close	Prediction
2022-09-09	157.520004	165.988541
2022-09-12	158.720001	165.416107
2022-09-13	147.309998	165.229538
2022-09-14	149.259995	163.906128
2022-09-15	149.779999	163.000687
...	...	...
2023-05-05	198.339996	201.929199
2023-05-08	197.259995	201.254028
2023-05-09	201.880005	200.478256
2023-05-10	200.839996	200.403427
2023-05-11	201.839996	200.212357

169 rows × 2 columns

In [116]:
```
# Get the models predicted price values
pred_zm = lstm_model_zm.predict(x_test_zm)
pred_zm = scaler_zm.inverse_transform(pred_zm)

# Get MSE and RMSE
test_mse_zm = np.mean(((pred_zm - y_test_zm) ** 2))
test_rmse_zm = np.sqrt(test_mse_zm)
print("The MSE of the Test set is", test_mse_zm)
print("The RMSE of the Test set is", test_rmse_zm)
```

```
6/6 [==============================] - 0s 0s/step
The MSE of the Test set is 62.43103856710199
The RMSE of the Test set is 7.901331442681164
```

In [117]:
```
test_zm = zm[training_zm_len:]
test_zm['Prediction'] = pred_zm
test_zm
```

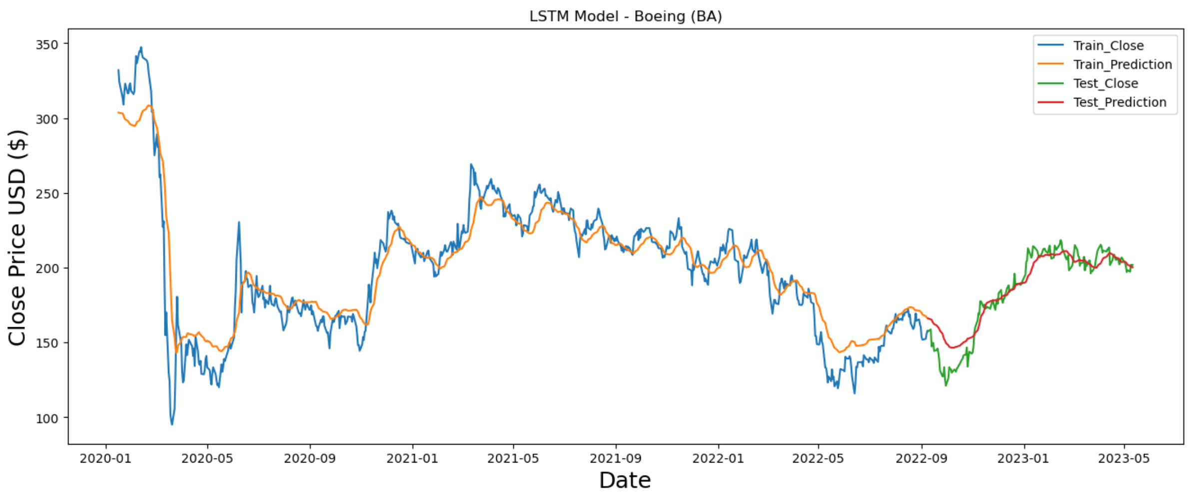
Out[117]:

Date	Close	Prediction
2022-09-09	82.620003	86.598473
2022-09-12	84.080002	86.986015
2022-09-13	78.860001	87.658127
2022-09-14	79.589996	86.942780
2022-09-15	80.209999	86.589653
...	...	...
2023-05-05	63.400002	70.692055
2023-05-08	62.930000	71.057541
2023-05-09	63.560001	71.193703
2023-05-10	64.430000	71.472054
2023-05-11	64.449997	71.893318

169 rows × 2 columns

Plot the true and the predicted price sequences during the training period plus the testing period

In [118]:
```
# Visualize the data
plt.figure(figsize=(16,6))
plt.title('LSTM Model - Boeing (BA)')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train_val_ba[['Close', 'Prediction']])
plt.plot(test_ba[['Close', 'Prediction']])
plt.legend(['Train_Close', 'Train_Prediction','Test_Close', 'Test_Prediction'], loc='upper right')
#plt.show()
plt.savefig("images/LSTM Model - Boeing (BA)")
```



In [119]:
```
# Visualize the data
plt.figure(figsize=(16,6))
plt.title('LSTM Model - Zoom (ZM)')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train_val_zm[['Close', 'Prediction']])
plt.plot(test_zm[['Close', 'Prediction']])
plt.legend(['Train_Close', 'Train_Prediction','Test_Close', 'Test_Prediction'], loc='upper right')
#plt.show()
plt.savefig("images/LSTM Model - Zoom (ZM)")
```