Classic ARIMA Model - Baseline

We usd ARIMA as our baseline to forecast future stock prices.

In [19]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_pacf, plot_acf
from statsmodels.tsa.arima.model import ARIMA
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

Load and Preprocess Data

In [20]:
```
# Load and preprocess data
df = pd.read_csv('./berkshire_hathaway_data.csv', index_col=0, parse_dates=True)
df = df[df.index >= '2020-01-01']
df = df.asfreq('D').fillna(method='ffill')
df['log_Close'] = np.log(df['Close'])
df['date_ordinal'] = df.index.map(lambda date: date.toordinal())
print(df)
```

```
                  Open        High         Low       Close   Adj Close  \
Date
2020-01-02  227.509995  228.389999  226.710007  228.389999  228.389999
2020-01-03  225.690002  227.429993  225.479996  226.179993  226.179993
2020-01-04  225.690002  227.429993  225.479996  226.179993  226.179993
2020-01-05  225.690002  227.429993  225.479996  226.179993  226.179993
2020-01-06  224.990005  227.130005  224.699997  226.990005  226.990005
...                ...         ...         ...         ...         ...
2024-07-25  431.600006  439.630005  431.600006  433.290009  433.290009
2024-07-26  435.660004  439.000000  434.100006  437.660004  437.660004
2024-07-27  435.660004  439.000000  434.100006  437.660004  437.660004
2024-07-28  435.660004  439.000000  434.100006  437.660004  437.660004
2024-07-29  438.010010  439.440002  435.489990  438.309998  438.309998

               Volume  log_Close  date_ordinal
Date
2020-01-02  3764000.0   5.431055        737426
2020-01-03  3023900.0   5.421331        737427
2020-01-04  3023900.0   5.421331        737428
2020-01-05  3023900.0   5.421331        737429
2020-01-06  4263000.0   5.424906        737430
...               ...        ...           ...
2024-07-25  3334300.0   6.071407        739092
2024-07-26  2717600.0   6.081442        739093
2024-07-27  2717600.0   6.081442        739094
2024-07-28  2717600.0   6.081442        739095
2024-07-29  2620000.0   6.082926        739096

[1671 rows x 8 columns]
```

Stationarity Handler

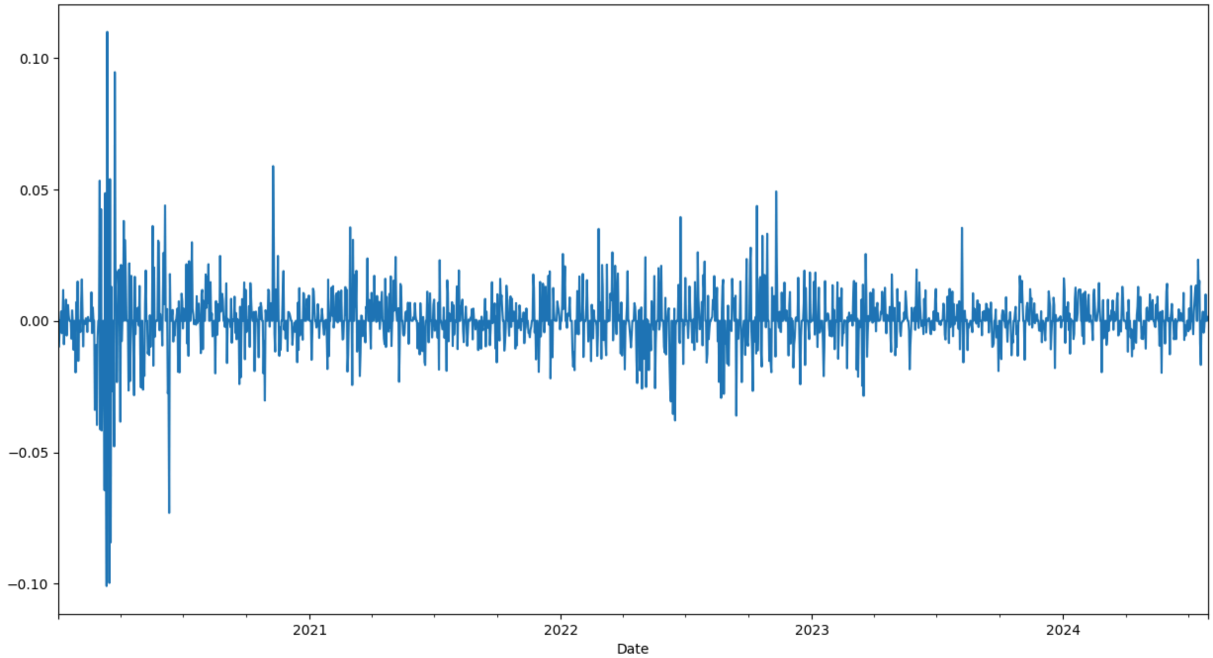
To make sure ARIMA works properly, we remove trends and make the data more stationary.

In [21]:

```
result = adfuller(df['log_Close'].dropna())

print("Test Statistic:", result[0])
print("P-Value:", result[1])

df['diff_log_Close'] = df['log_Close'].diff().dropna()
if(df['diff_log_Close'][1] < 0.05):
    print("Stationary | D=1")
else:
    print("Non-Stationary")

print(result)

# Plot
df['diff_log_Close'].plot(figsize=(15,8))
```

```
Test Statistic: -0.5218750340147723
P-Value: 0.8876765782218701
Stationary | D=1
(-0.5218750340147723, 0.8876765782218701, 11, 1659, {'1%': -3.4342978282123258,
'5%': -2.8632837412222885, '10%': -2.567698326213784}, -10057.536085265187)
```

Out[21]: <Axes: xlabel='Date'>

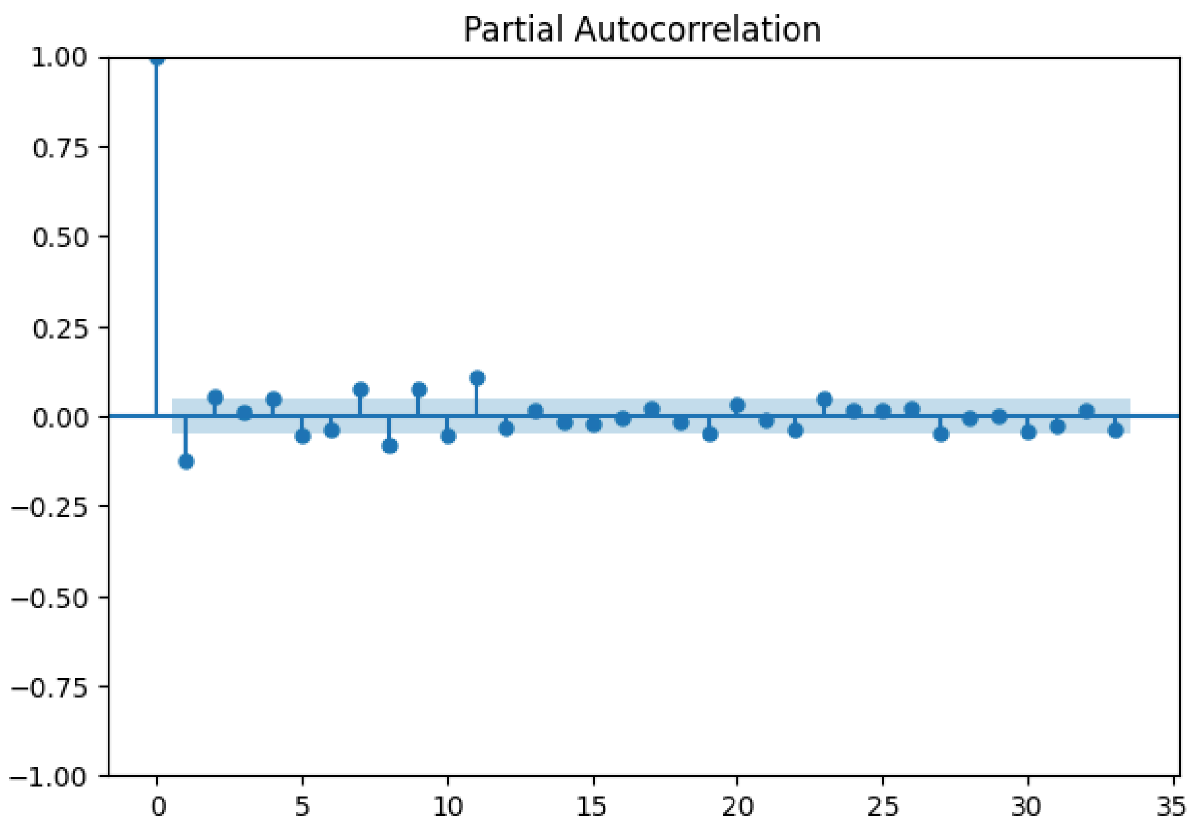


Plot PACF + ACF

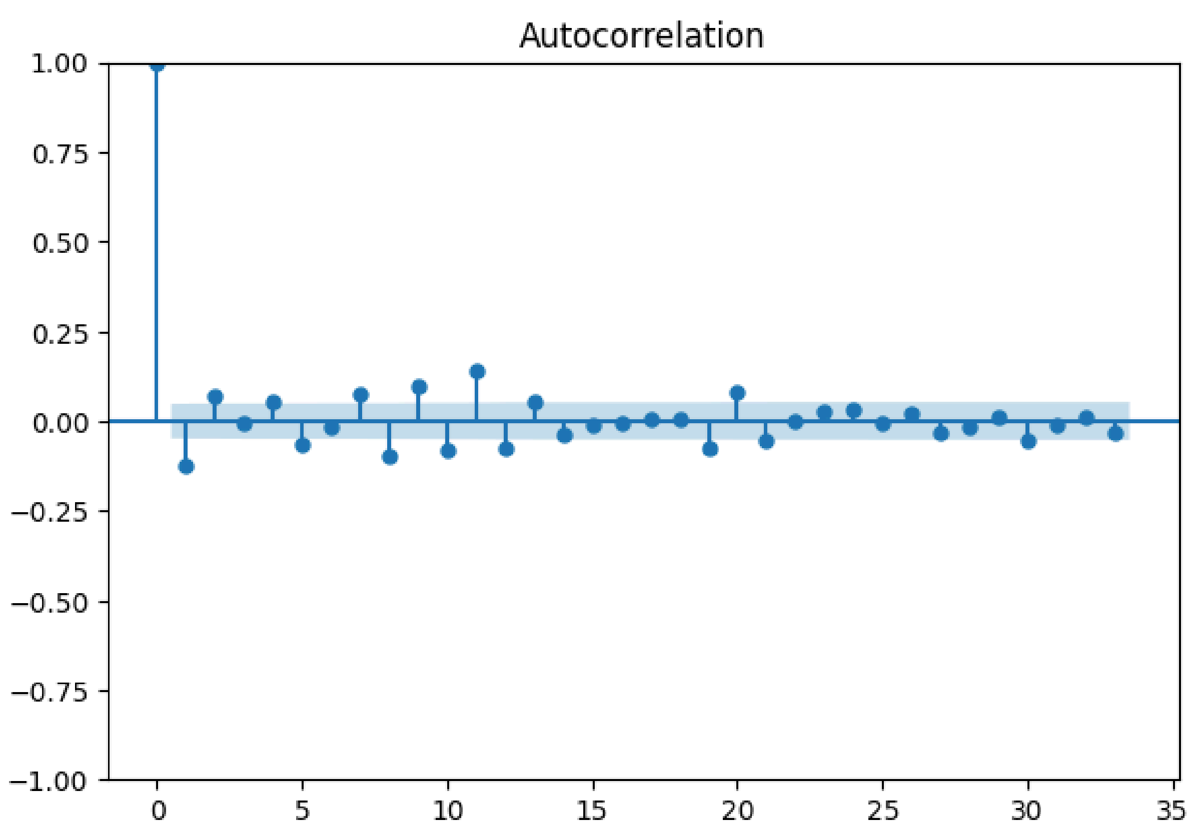
The purpose of this si to

In [22]:
```
# PACF
fig_pacf = plot_pacf(df['diff_log_Close'].dropna(), method='ywm')
fig_pacf.suptitle("PACF - Differenced log_Close")
fig_pacf.tight_layout()
plt.show()

# ACF
fig_acf = plot_acf(df['diff_log_Close'].dropna())
fig_acf.suptitle("ACF - Differenced log_Close")
fig_acf.tight_layout()
plt.show()
```

PACF - Differenced log_Close



ACF - Differenced log_Close



ARIMA Train Model

Using the information provided from the graphs, we are going to use this to train our model. For our testing, we decided to predict using the last 30 days to predict the next 30 days.

In [23]:
```
train = df.iloc[:-30]
test = df.iloc[-30:]

train_idx = df.index <= train.index[-1]
test_idx = df.index > train.index[-1]

arima = ARIMA(train['Close'], order=(0, 1, 0)).fit()
fig, ax= plt.subplots(figsize=(15,8))

# Plot the real values of stock prices
ax.plot(df['Close'], label='Actual Return')

# Plot fitted values of our model
train_pred = arima.fittedvalues
ax.plot(train.index, train_pred, color='green', label='fitted')

prediction_result = arima.get_forecast(30)
conf_int = prediction_result.conf_int()

# Plot lower and upper limits
lower = conf_int[conf_int.columns[0]]
upper = conf_int[conf_int.columns[1]]

forecast = prediction_result.predicted_mean

ax.plot(test.index, forecast, label='forecast')
ax.fill_between(test.index, lower, upper, color='red', alpha=0.3)
ax.legend()
```

Out[23]:
```
<matplotlib.legend.Legend at 0x2111892d650>
```

Evaluate Model

Using RMSE and MAE metrics to see the performance of our model

In [24]:
```
y_true = test['Close'].values
rmse = np.sqrt(mean_squared_error(y_true, forecast))
mae = mean_absolute_error(y_true, forecast)

print(f'RMSE: {rmse}')
print(f'MAE: {mae}')
```

```
RMSE: 22.248062804324675
MAE: 18.150012207031214
```

Linear Regression

In [25]:
```
lr_model = LinearRegression()
lr_model.fit(train[['date_ordinal']], train['Close'])
lr_forecast = lr_model.predict(test[['date_ordinal']])
```

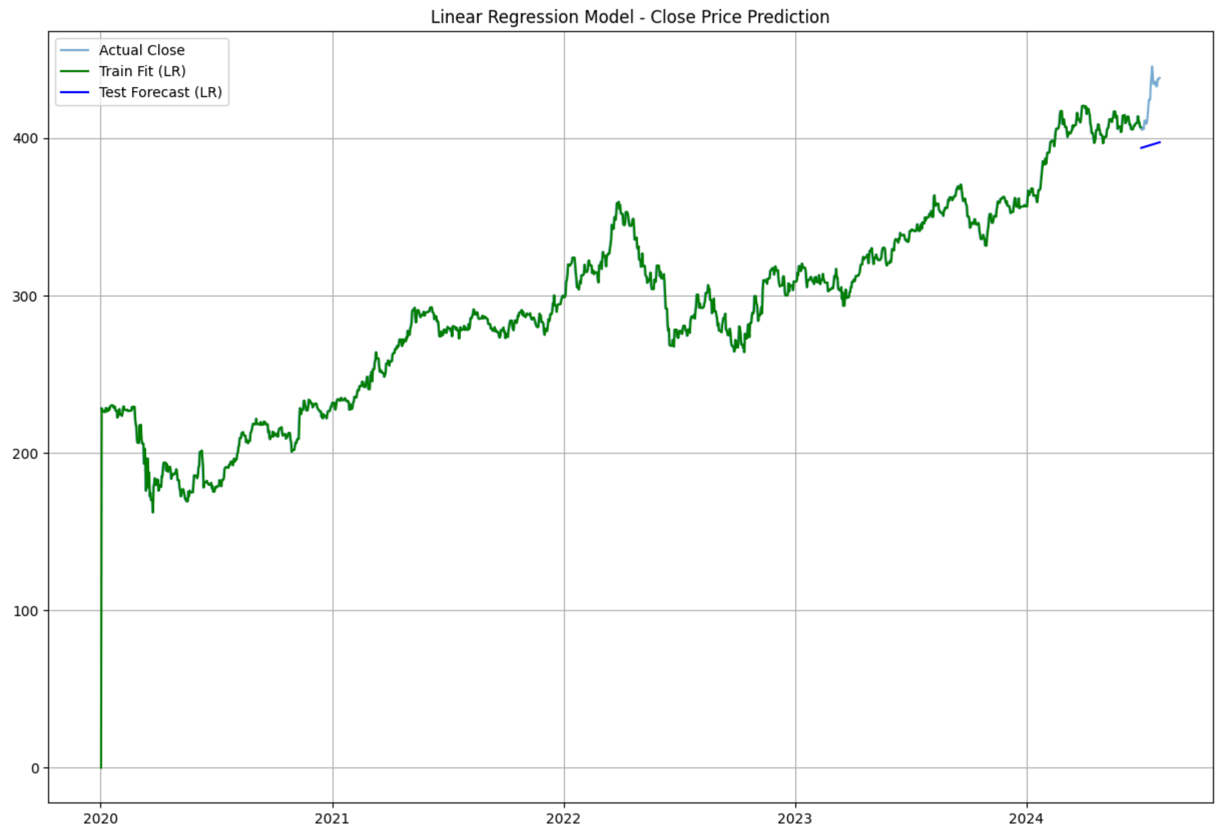
Compute RMSE and MAE

In [26]:
```
lr_rmse = np.sqrt(mean_squared_error(y_true, lr_forecast))
lr_mae = mean_absolute_error(y_true, lr_forecast)
print(f'RMSE: {lr_rmse}')
print(f'MAE: {lr_mae}')
```

```
RMSE: 31.580726027481326
MAE: 29.103639338446875
```

Plot Linear Regression

In [27]:
```
plt.figure(figsize=(15,10))
plt.plot(df.index, df['Close'], label='Actual Close', alpha=0.6)
plt.plot(train.index, train_pred, label='Train Fit (LR)', color='green')
plt.plot(test.index, lr_forecast, label='Test Forecast (LR)', color='blue')
plt.title('Linear Regression Model - Close Price Prediction')
plt.legend()
plt.grid(True)
```



Random Forest

In [28]:
```
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(train[['date_ordinal']], train['Close'])
rf_forecast = rf_model.predict(test[['date_ordinal']])

print(rf_forecast)
```

```
[406.98698975 406.98698975 406.98698975 406.98698975 406.98698975
 406.98698975 406.98698975 406.98698975 406.98698975 406.98698975
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 406.98698975 406.98698975 406.98698975 406.98698975 406.98698975]
```
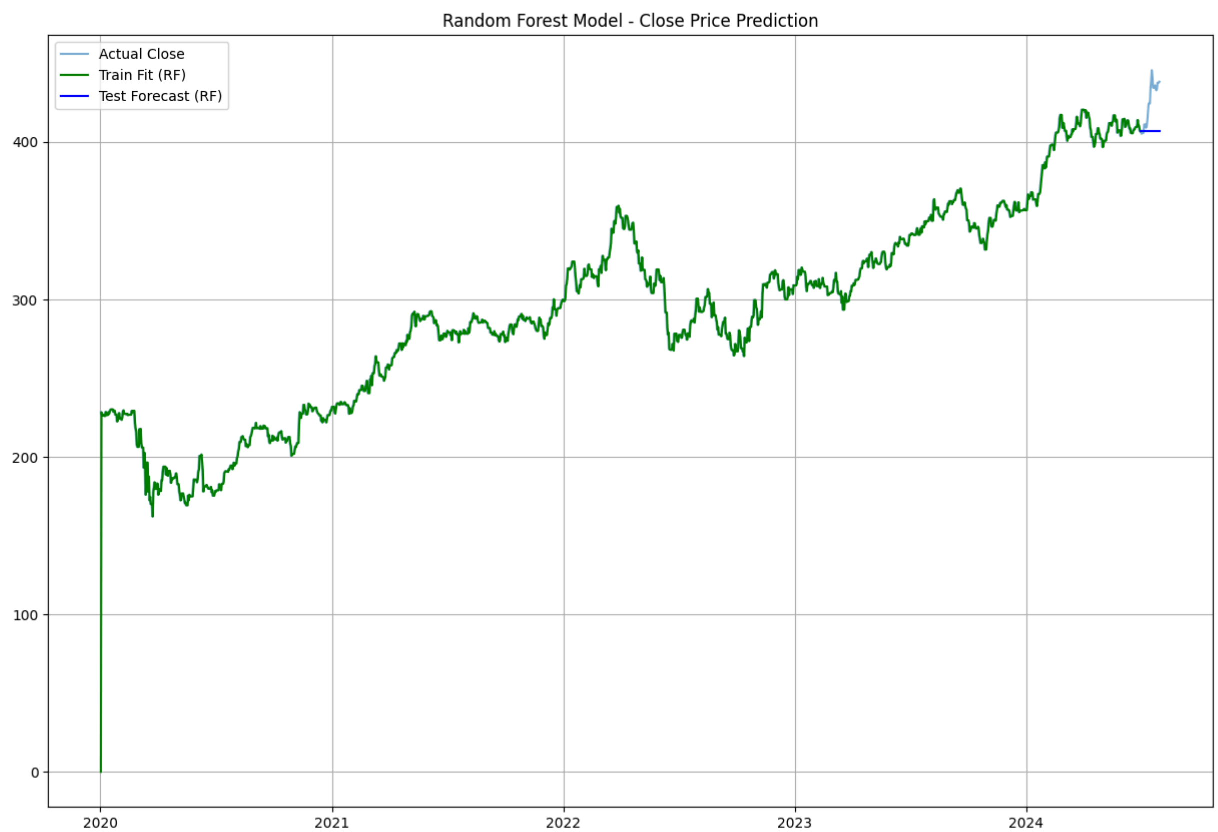

Compute RMSE + MAE

In [29]:
```
rf_rmse = np.sqrt(mean_squared_error(y_true, rf_forecast))
rf_mae = mean_absolute_error(y_true, rf_forecast)
print(f'RMSE: {rf_rmse}')
print(f'MAE: {rf_mae}')
```

```
RMSE: 22.097841493564125
MAE: 18.012877441406218
```

Plot Random Forest

In [30]:
```
plt.figure(figsize=(15,10))
plt.plot(df.index, df['Close'], label='Actual Close', alpha=0.6)
plt.plot(train.index, train_pred, label='Train Fit (RF)', color='green')
plt.plot(test.index, rf_forecast, label='Test Forecast (RF)', color='blue')
plt.title('Random Forest Model - Close Price Prediction')
plt.legend()
plt.grid(True)
```



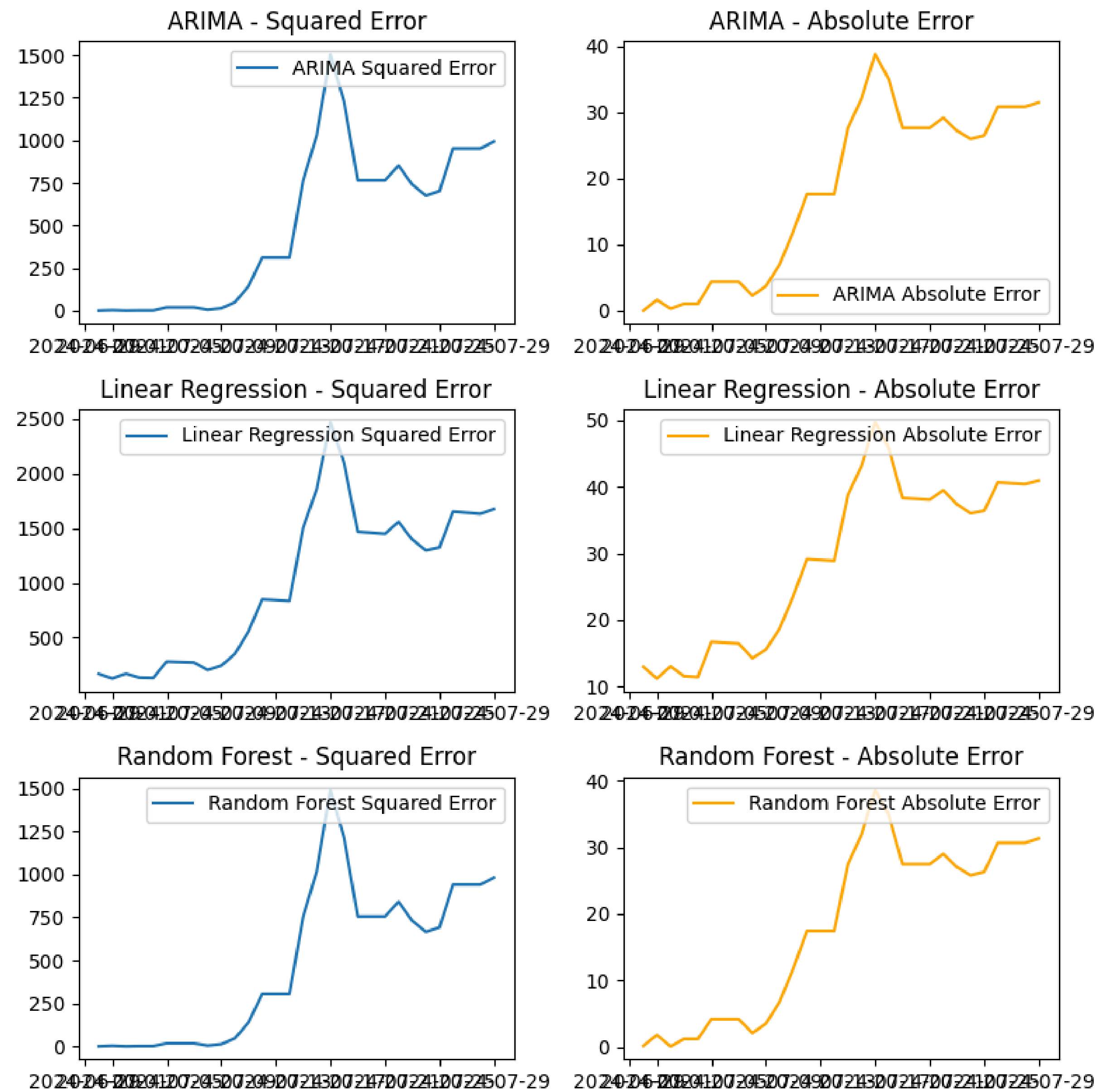
Compare Baseline Models

In [31]:
```
print("ARIMA")
print(f'RMSE: {rmse}')
print(f'MAE: {mae}\n')

print("Linear Regression")
print(f'RMSE: {lr_rmse}')
print(f'MAE: {lr_mae}\n')
```

```
print("Random Forest")
print(f'RMSE: {rf_rmse}')
print(f'MAE: {rf_mae}')
```

```
ARIMA
RMSE: 22.248062804324675
MAE: 18.150012207031214

Linear Regression
RMSE: 31.580726027481326
MAE: 29.103639338446875

Random Forest
RMSE: 22.097841493564125
MAE: 18.012877441406218
```

In [32]:
```
fig, axs = plt.subplots(3, 2, figsize=(8, 8))

# ARIMA Graph
arima_error = y_true - forecast
axs[0, 0].plot(test.index, arima_error**2, label='ARIMA Squared Error')
axs[0, 0].set_title('ARIMA - Squared Error')
axs[0, 0].legend()

axs[0, 1].plot(test.index, np.abs(arima_error), label='ARIMA Absolute Error', color
axs[0, 1].set_title('ARIMA - Absolute Error')
axs[0, 1].legend()

# Linear Regression Graph
lr_error = y_true - lr_forecast
axs[1, 0].plot(test.index, lr_error**2, label='Linear Regression Squared Error')
axs[1, 0].set_title('Linear Regression - Squared Error')
axs[1, 0].legend()

axs[1, 1].plot(test.index, np.abs(lr_error), label='Linear Regression Absolute Erro
axs[1, 1].set_title('Linear Regression - Absolute Error')
axs[1, 1].legend()

# Random Forest Graph
rf_error = y_true - rf_forecast
axs[2, 0].plot(test.index, rf_error**2, label='Random Forest Squared Error')
axs[2, 0].set_title('Random Forest - Squared Error')
axs[2, 0].legend()

axs[2, 1].plot(test.index, np.abs(rf_error), label='Random Forest Absolute Error',
axs[2, 1].set_title('Random Forest - Absolute Error')
axs[2, 1].legend()

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


ARIMA - Squared Error
ARIMA Squared Error
ARIMA - Absolute Error
ARIMA Absolute Error
Linear Regression - Squared Error
Linear Regression Squared Error
Linear Regression - Absolute Error
Linear Regression Absolute Error
Random Forest - Squared Error
Random Forest Squared Error
Random Forest - Absolute Error
Random Forest Absolute Error