In [1]:
```
run __init__.py
```

In [2]:
```
import pandas as pd
import numpy as np
from joblib import load, dump
from finnhub_api import Finnhub
from datetime_util import timestamp2datetime, str2date, str2datetime
import matplotlib.pyplot as plt
# from pmdarima import auto_arima
from statsmodels.tsa.seasonal import seasonal_decompose
import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)
from time_series import TS
```

Stock Market TimeSeries

In [3]:
```
finnhub_key = load('./finnhub/finnhub_key.pkl', 'rb')
```

collect Apple stock prices history from finnhub using using a custom function we wrote to scrap the stock/asset candlestick. We use the 5 minutes time frame in order to forcast the stock price for the upcoming 30 minutes.

In [4]:
```
fin_5m = Finnhub(finnhub_key, "2021-05-15", "2021-06-16", "AAPL")
aapl_5m = fin_5m.stock_candles("5")

hist_cols = ['close', 'high', 'low', 'open', 'status','date', 'volume']
aapl_5m_df = pd.DataFrame(aapl_5m)
aapl_5m_df.columns = hist_cols
aapl_5m_df['date'] = aapl_5m_df['date'].apply(lambda x: timestamp2datetime(x))
aapl_5m_df['date'] = pd.to_datetime(aapl_5m_df['date'], format='%Y-%m-%d %H:%M:%S')#.dt.normalize()
aapl_5m_df.set_index('date', inplace=True)
```

In [5]:
```
aapl_5m_df.to_csv('./data/apple_5m.csv',index=True)
```

In [6]:
```
aapl_5m_df = pd.read_csv('./data/apple_5m.csv', parse_dates=['date'], date_parser=str2datetime)
aapl_5m_df.set_index('date', inplace=True)
```

In [7]:
```
aapl_5m_df.head()
```

Out[7]:

	close	high	low	open	status	volume
date						
2021-05-17 04:00:00	126.90	127.00	126.81	126.96	ok	3209
2021-05-17 04:15:00	126.83	126.83	126.83	126.83	ok	692
2021-05-17 04:40:00	127.19	127.19	127.10	127.10	ok	1527
2021-05-17 04:55:00	127.16	127.16	127.13	127.13	ok	1243
2021-05-17 05:15:00	127.06	127.07	127.06	127.07	ok	1002

In [8]:
```
date = pd.to_datetime("2021-06-15")
ts_origin = aapl_5m_df.loc[aapl_5m_df.index.date == date, 'close']
roll = 6
```

Dickey-Fuller Test

We start by investigating the statistical properties of our data by tracking the price movement in order to identify the sessionality, and allow us to prove our hypothesis by testing for stationarity.

In [9]:
```
ts = TS()
```

Check for Data Stationarity using Augmented Dickey-Fuller(ADF) test.

In [10]:
```
ts.adf_test(ts_origin)
```

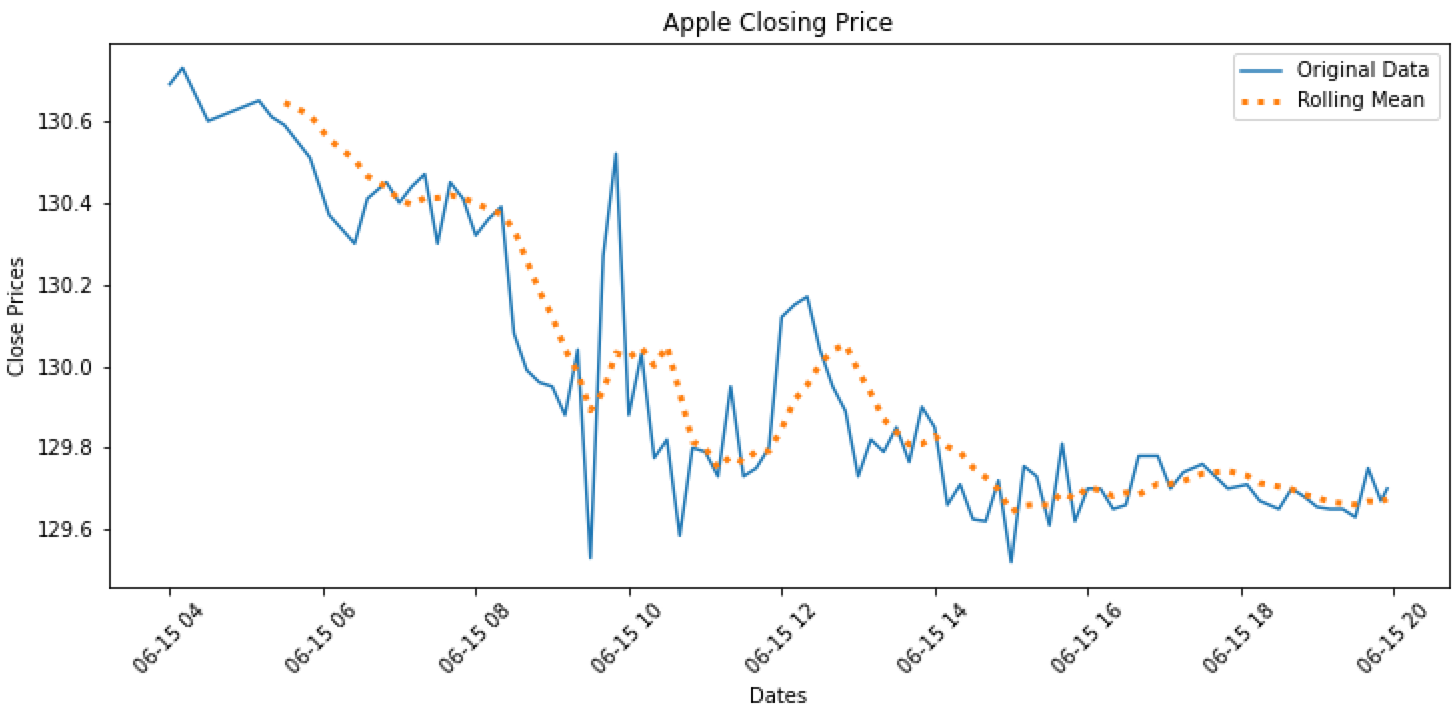
Out[10]:
```
Test Statistic                 -2.219934
p-value                         0.199090
#Lags Used                      2.000000
Number of Observations Used    84.000000
Critical Value (1%)            -3.510712
Critical Value (5%)            -2.896616
Critical Value (10%)           -2.585482
dtype: float64
```

Time Series Testing Trend

Rolling Statistics

In [11]:
```
ts_orig_roll_mean = ts_origin.rolling(roll).mean()
```

In [12]:
```
fig, ax1 = plt.subplots(figsize=(12,5))
ax1.set_xlabel('Dates')
ax1.set_ylabel('Close Prices')
ax1.set_title('Apple Closing Price')
ax1.tick_params(axis='x', labelrotation=45)
ax1.plot(ts_origin, label='Original Data')
ax1.plot(ts_orig_roll_mean, color='tab:orange', ls='dotted', linewidth=3, label='Rolling Mean')
# ax.legend()
plt.legend(loc='best')
plt.tight_layout
plt.show()
```

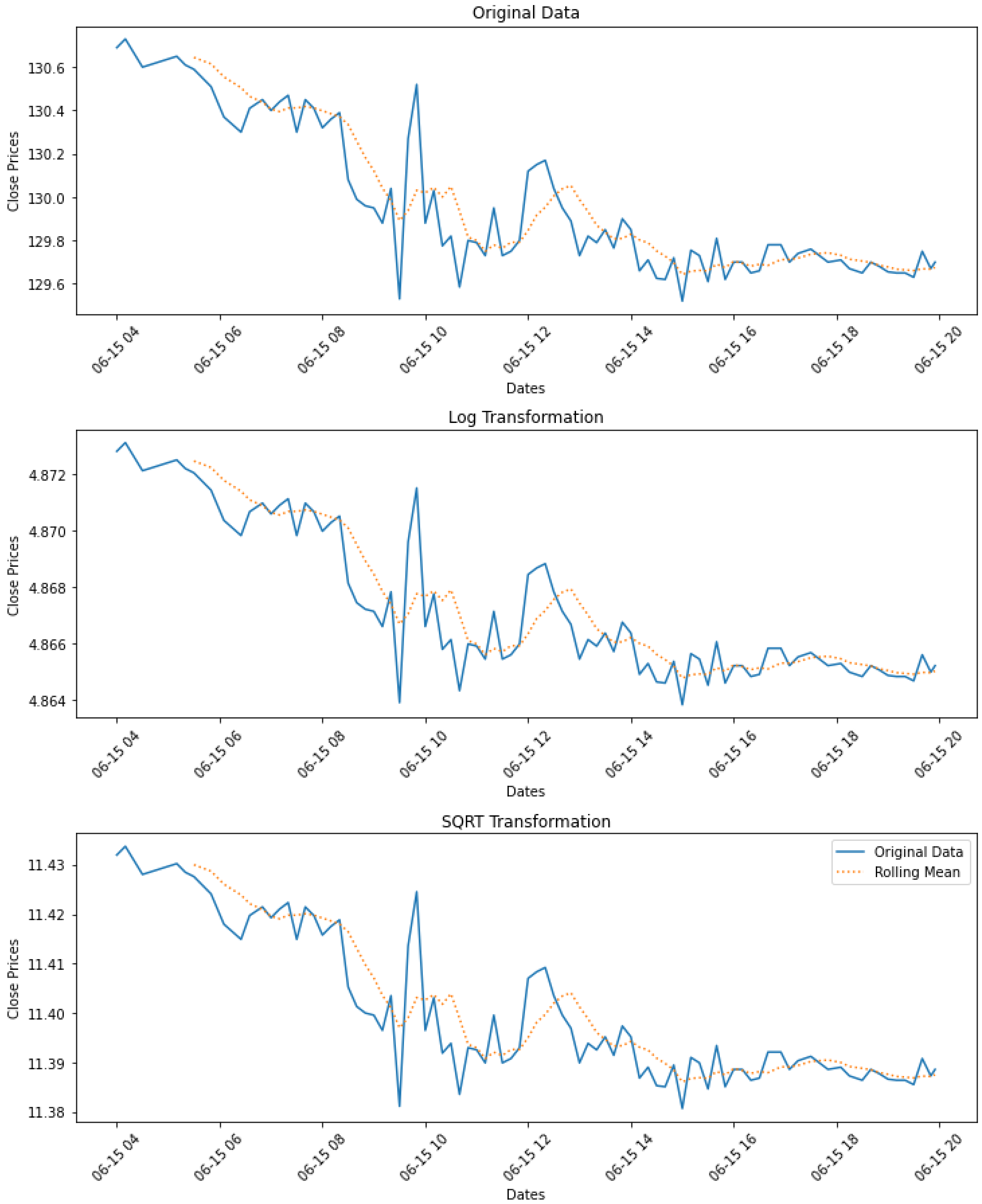


Removing Trends

The logarithmic transform takes the log of each point and changes the data into a logarithmic scale.

In [13]:
```
ts_log = np.log(ts_origin)
ts_sqrt = np.sqrt(ts_origin)
ts_log_roll_mean = ts_log.rolling(roll).mean()
ts_sqrt_roll_mean = ts_sqrt.rolling(roll).mean()
```

In [14]:
```
fig, (ax1,ax2,ax3) = plt.subplots(nrows=3, sharex=False, figsize=(12,15))
ax1.grid(False)
ax1.set_xlabel('Dates')
ax1.set_ylabel('Close Prices')
ax1.set_title('Original Data')
ax1.tick_params(axis='x', labelrotation=45)
ax1.plot(ts_origin, label='Original Data')
ax1.plot(ts_orig_roll_mean, color='tab:orange', ls='dotted', label='Rolling Mean')

ax2.grid(False)
ax2.set_xlabel('Dates')
ax2.set_ylabel('Close Prices')
ax2.set_title('Log Transformation')
ax2.tick_params(axis='x', labelrotation=45)
ax2.plot(ts_log, label='Original Data')
ax2.plot(ts_log_roll_mean, color='tab:orange', ls='dotted', label='Rolling Mean')

ax3.grid(False)
ax3.set_xlabel('Dates')
ax3.set_ylabel('Close Prices')
ax3.set_title('SQRT Transformation')
ax3.tick_params(axis='x', labelrotation=45)
ax3.plot(ts_sqrt, label='Original Data')
ax3.plot(ts_sqrt_roll_mean, color='tab:orange', ls='dotted', label='Rolling Mean')

plt.subplots_adjust(hspace = .4)
plt.legend(loc='best')
plt.tight_layout
plt.show()
```



Differencing the rolling mean

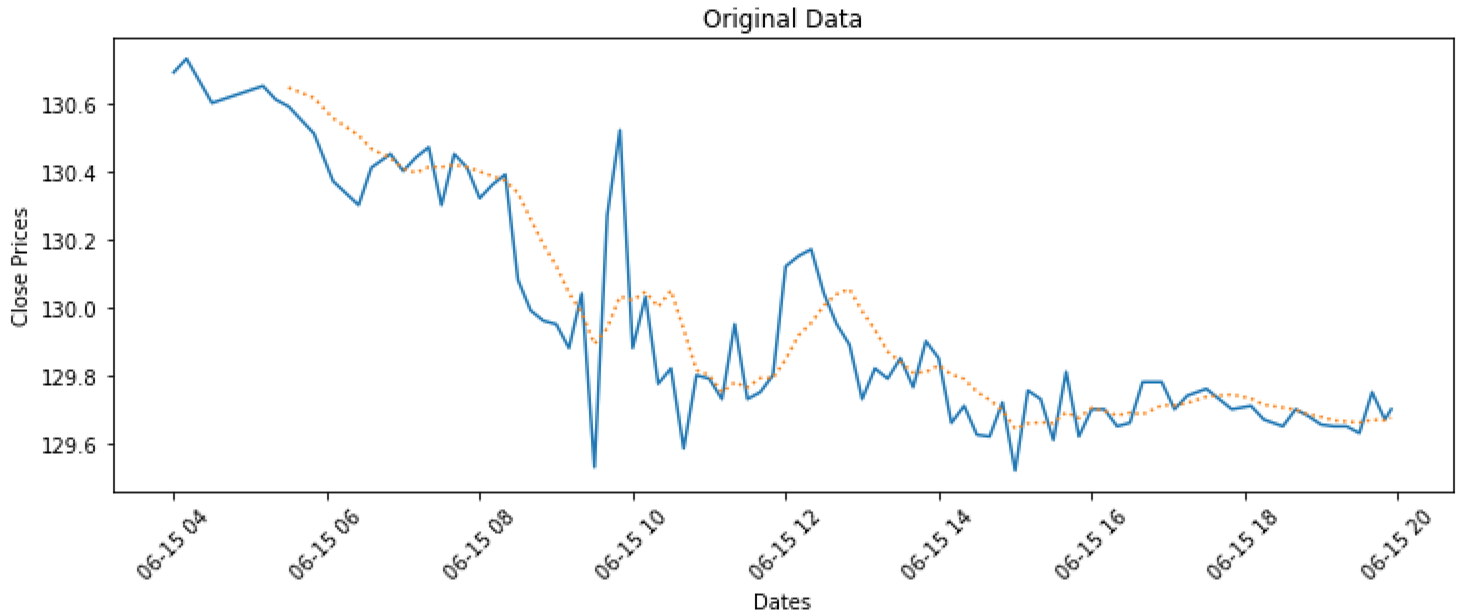
Differencing would helps stabilize the mean of the time series by removing changes in the level of a time series, which eliminates trend and seasonality. The first-order difference transform consists of taking the data point at the current time and subtracting it with the point before.

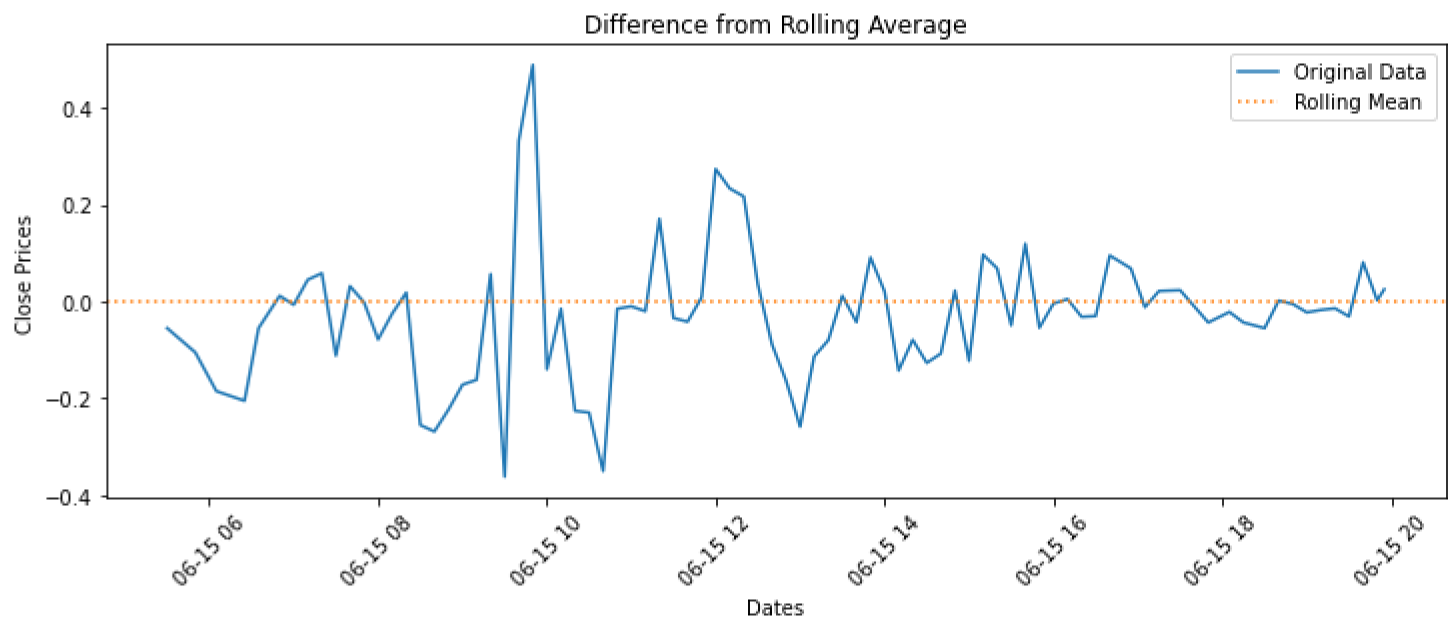
In [15]:

```
ts_origin_min_roll_mean = (ts_origin - ts_origin.rolling(roll).mean())
```

In [16]:

```
fig, (ax1,ax2) = plt.subplots(nrows=2, sharex=False, figsize=(12,10))
ax1.grid(False)
ax1.set_xlabel('Dates')
ax1.set_ylabel('Close Prices')
ax1.set_title('Original Data')
ax1.tick_params(axis='x', labelrotation=45)
ax1.plot(ts_origin, label='Original Data')
ax1.plot(ts_orig_roll_mean, color='tab:orange', ls='dotted', label='Rolling Mean')

ax2.grid(False)
ax2.set_xlabel('Dates')
ax2.set_ylabel('Close Prices')
ax2.set_title('Difference from Rolling Average')
ax2.tick_params(axis='x', labelrotation=45)
ax2.plot(ts_origin_min_roll_mean, label='Original Data')
ax2.axhline(ls='dotted', color='tab:orange',  label='Rolling Mean')

plt.subplots_adjust(hspace = .4)
plt.legend(loc='best')
plt.tight_layout
plt.show()
```





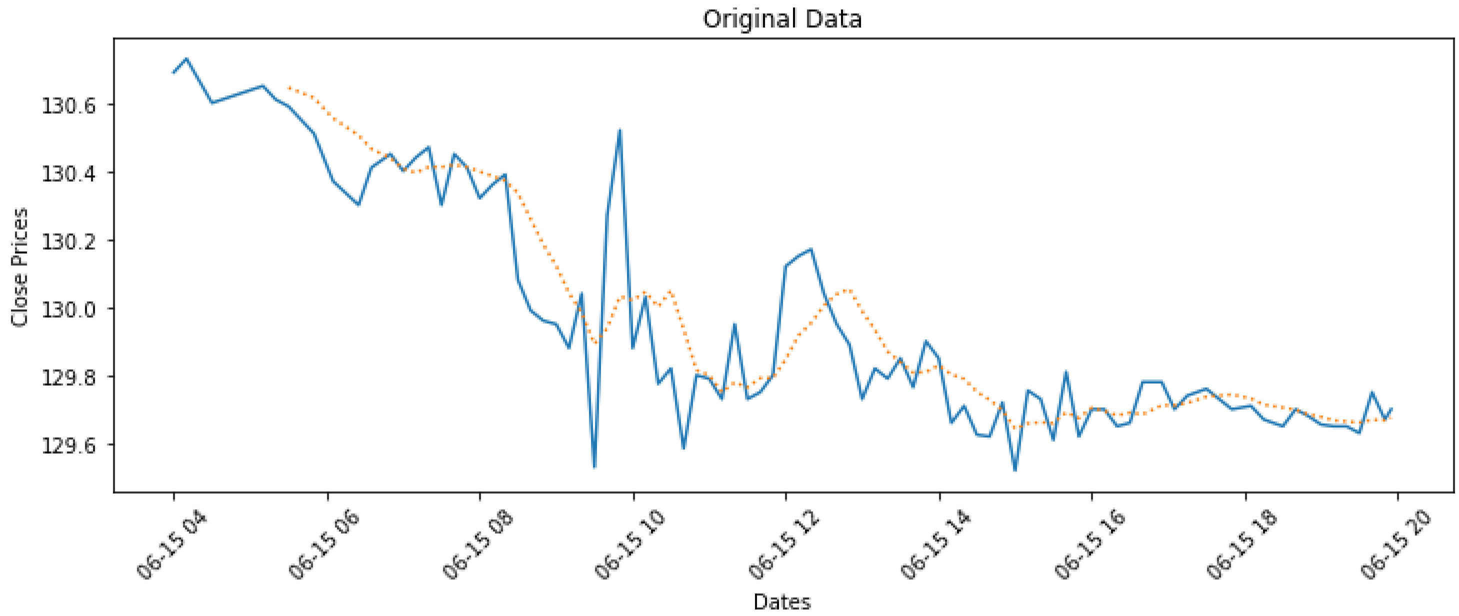
Differencing with the weighted rolling mean

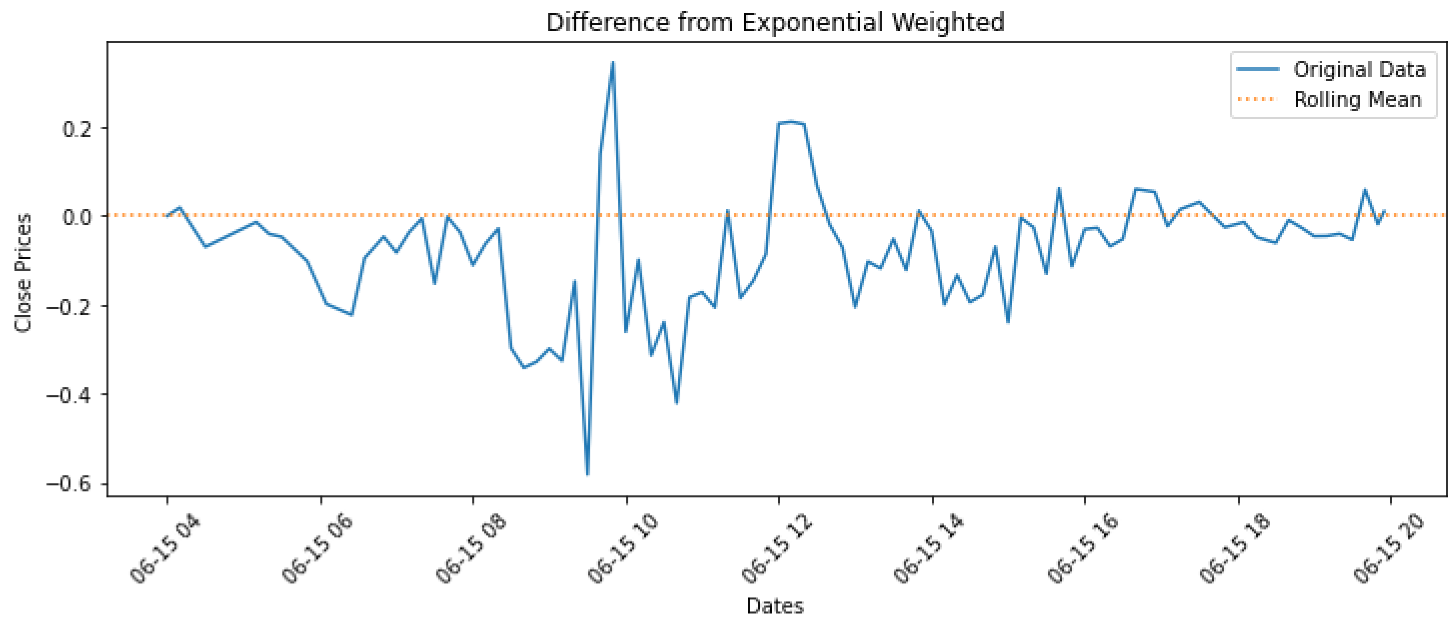
In [17]:

```
ts_ewm = ts_origin.ewm(halflife=6).mean()
```

In [18]:

```
fig, (ax1,ax2) = plt.subplots(nrows=2, sharex=False, figsize=(12,10))

ax1.grid(False)
ax1.set_xlabel('Dates')
ax1.set_ylabel('Close Prices')
ax1.set_title('Original Data')
ax1.tick_params(axis='x', labelrotation=45)
ax1.plot(ts_origin, label='Original Data')
ax1.plot(ts_orig_roll_mean, color='tab:orange', ls='dotted', label='Rolling Mean')

ax2.grid(False)
ax2.set_xlabel('Dates')
ax2.set_ylabel('Close Prices')
ax2.set_title('Difference from Exponential Weighted')
ax2.tick_params(axis='x', labelrotation=45)
ax2.plot(ts_origin - ts_ewm, label='Original Data')
ax2.axhline(ls='dotted', color='tab:orange',  label='Rolling Mean')

plt.subplots_adjust(hspace = .4)
plt.legend(loc='best')
plt.tight_layout
plt.show()
```



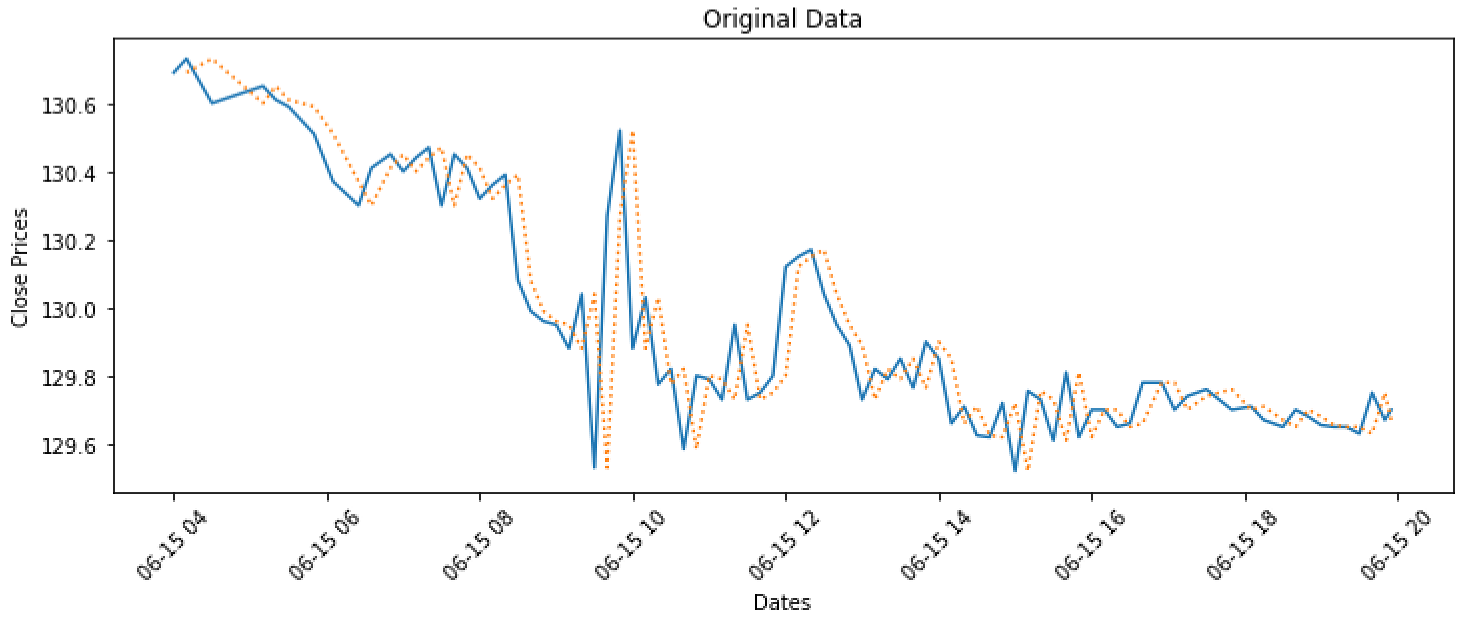


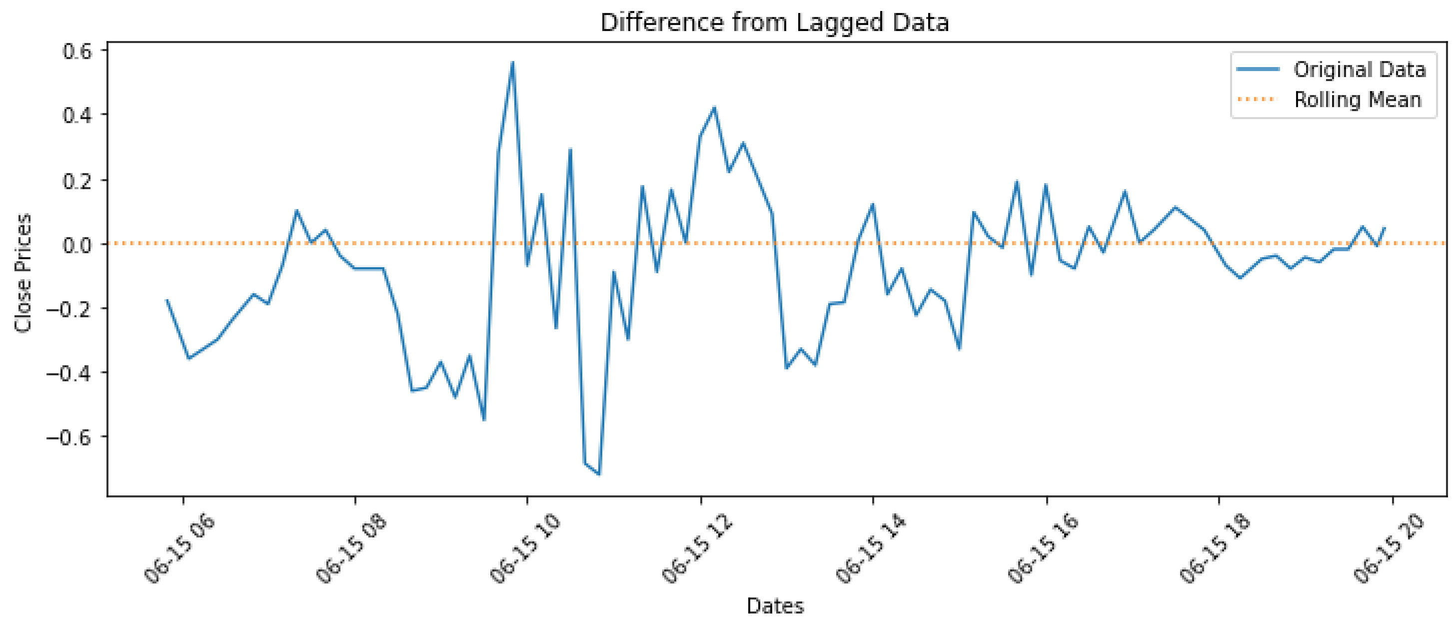
Differencing

Using differencing method to transform the time series by taking the difference of 6 lags between consecutive observations to remove the series dependence on time "temporal dependence"

In [19]:

```
fig, (ax1,ax2) = plt.subplots(nrows=2, sharex=False, figsize=(12,10))

ax1.set_xlabel('Dates')
ax1.set_ylabel('Close Prices')
ax1.set_title('Original Data')
ax1.tick_params(axis='x', labelrotation=45)
ax1.plot(ts_origin, label='Original Data')
ax1.plot(ts_origin.shift(1), color='tab:orange', ls='dotted', label='Original Data')

ax2.set_xlabel('Dates')
ax2.set_ylabel('Close Prices')
ax2.set_title('Difference from Lagged Data')
ax2.tick_params(axis='x', labelrotation=45)
ax2.plot(ts_origin.diff(roll), label='Original Data')
ax2.axhline(ls='dotted', color='tab:orange',  label='Rolling Mean')

plt.subplots_adjust(hspace = .4)
plt.legend(loc='best')
plt.tight_layout
plt.show()
```





In [20]:

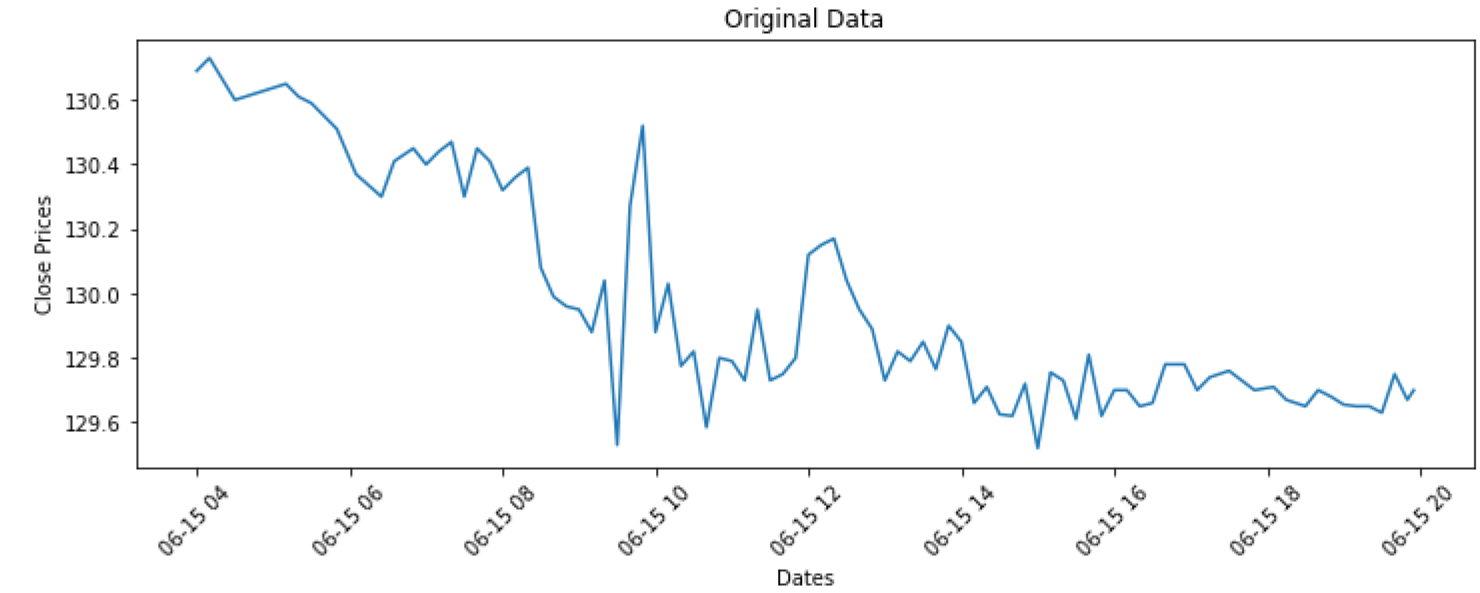
```
decomposition = seasonal_decompose(ts_log, period=3)
```

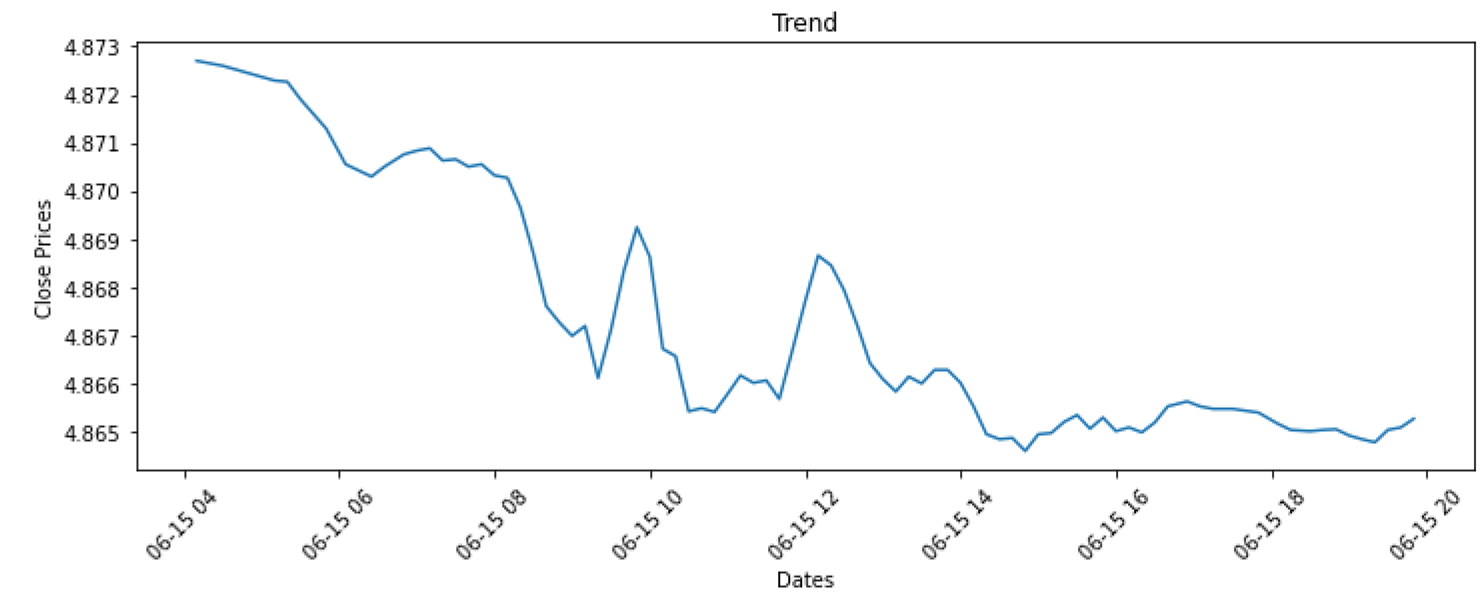
In [21]:

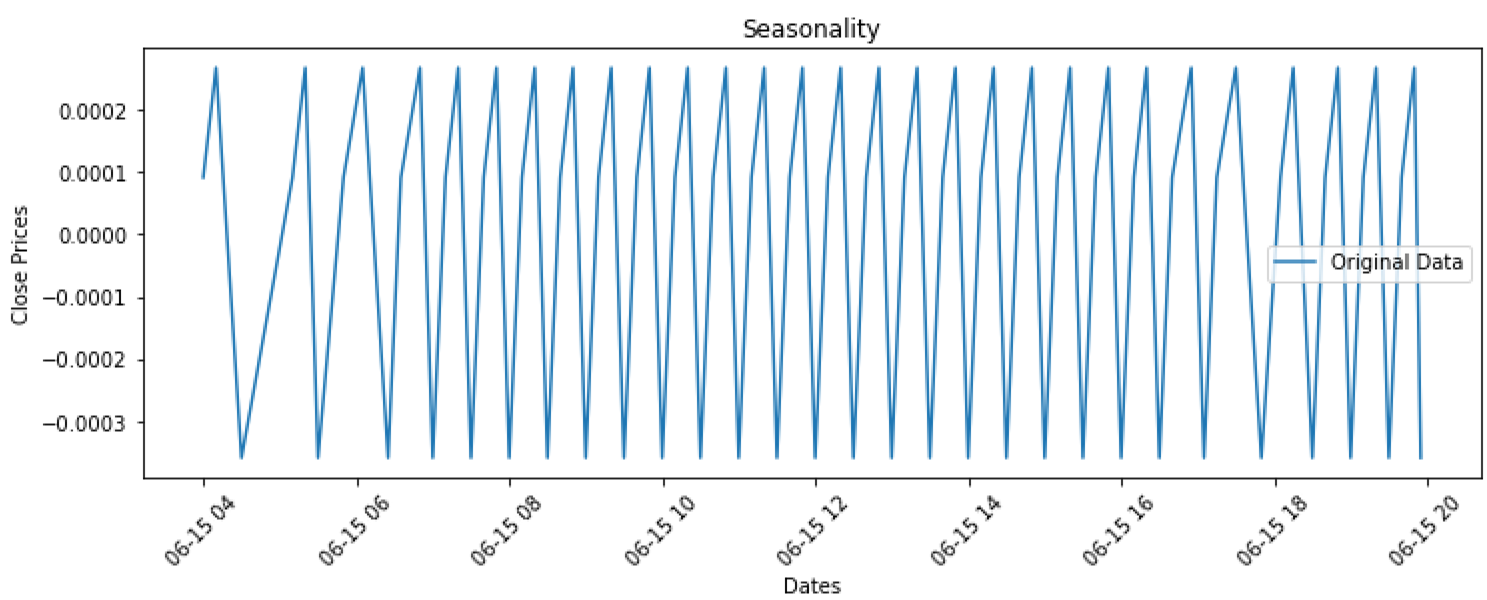
```
ts_trend = decomposition.trend
ts_seasonal = decomposition.seasonal
```

In [22]:

```
fig, (ax1, ax2, ax3) = plt.subplots(nrows=3, sharex=False, figsize=(12,15))
ax1.grid(False)
ax1.set_xlabel('Dates')
ax1.set_ylabel('Close Prices')
ax1.set_title('Original Data')
ax1.tick_params(axis='x', labelrotation=45)
ax1.plot(ts_origin, label='Original Data')

ax2.grid(False)
ax2.set_xlabel('Dates')
ax2.set_ylabel('Close Prices')
ax2.set_title('Trend')
ax2.tick_params(axis='x', labelrotation=45)
ax2.plot(ts_trend, label='Original Data')

ax3.grid(False)
ax3.set_xlabel('Dates')
ax3.set_ylabel('Close Prices')
ax3.set_title('Seasonality')
ax3.tick_params(axis='x', labelrotation=45)
ax3.plot(ts_seasonal, label='Original Data')

plt.subplots_adjust(hspace = .4)
plt.legend(loc='best')
plt.tight_layout
plt.show()
```







In [23]:

```
ts.adf_test(ts_seasonal)
```

Out[23]:

```
Test Statistic                -8.205088e+15
p-value                        0.000000e+00
#Lags Used                     1.100000e+01
Number of Observations Used    7.500000e+01
Critical Value (1%)           -3.520713e+00
Critical Value (5%)           -2.900925e+00
Critical Value (10%)          -2.587781e+00
dtype: float64
```

In [24]:

```
ts_diff = ts_origin.diff(roll).dropna()
ts.adf_test(ts_diff)
```

Out[24]:

```
Test Statistic                 -1.658787
p-value                         0.452462
#Lags Used                     12.000000
Number of Observations Used    68.000000
Critical Value (1%)            -3.530399
Critical Value (5%)            -2.905087
Critical Value (10%)           -2.590001
dtype: float64
```

In [25]:

```
ts = TS()
```

In [26]:

```
date_range = (aapl_5m_df.index <= pd.to_datetime("2021-06-15 12:00:00"))
train = aapl_5m_df.loc[date_range,'close'].to_period("5T")
# exog = aapl_5m_df.loc[date_range, 'close'].to_period("5T")
test_range = (
            (aapl_5m_df.index >= pd.to_datetime("2021-06-15 00:00:00"))
            &
            (aapl_5m_df.index <= pd.to_datetime("2021-06-15 23:59:00"))
            )
# test = aapl_5m_df.loc[test_range, 'open'].to_period("5T")
test = aapl_5m_df.loc[date_range,'open'].to_period("5T")
```

In [27]:

```
arima_model = auto_arima(train,m=6,start_p=1,d=1, max_d=6, start_P=1, max_p=6,
                         start_q=1,max_q=6, trace=True, error_action='ignore')
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(1,0,1)[6] intercept   : AIC=-615.001, Time=3.11 sec
 ARIMA(0,1,0)(0,0,0)[6] intercept   : AIC=-613.303, Time=0.13 sec
 ARIMA(1,1,0)(1,0,0)[6] intercept   : AIC=-616.638, Time=0.33 sec
 ARIMA(0,1,1)(0,0,1)[6] intercept   : AIC=-617.339, Time=0.64 sec
 ARIMA(0,1,0)(0,0,0)[6]             : AIC=-615.144, Time=0.07 sec
 ARIMA(0,1,1)(0,0,0)[6] intercept   : AIC=-615.837, Time=0.10 sec
 ARIMA(0,1,1)(1,0,1)[6] intercept   : AIC=-615.399, Time=1.58 sec
 ARIMA(0,1,1)(0,0,2)[6] intercept   : AIC=-615.461, Time=0.93 sec
 ARIMA(0,1,1)(1,0,0)[6] intercept   : AIC=-617.228, Time=0.34 sec
 ARIMA(0,1,1)(1,0,2)[6] intercept   : AIC=-616.038, Time=2.76 sec
 ARIMA(0,1,0)(0,0,1)[6] intercept   : AIC=-615.311, Time=0.28 sec
 ARIMA(1,1,1)(0,0,1)[6] intercept   : AIC=-616.957, Time=1.65 sec
 ARIMA(0,1,2)(0,0,1)[6] intercept   : AIC=-618.823, Time=0.65 sec
 ARIMA(0,1,2)(0,0,0)[6] intercept   : AIC=-618.086, Time=0.16 sec
 ARIMA(0,1,2)(1,0,1)[6] intercept   : AIC=-616.862, Time=1.23 sec
 ARIMA(0,1,2)(0,0,2)[6] intercept   : AIC=-616.910, Time=0.96 sec
 ARIMA(0,1,2)(1,0,0)[6] intercept   : AIC=-618.748, Time=0.52 sec
 ARIMA(0,1,2)(1,0,2)[6] intercept   : AIC=-617.071, Time=2.40 sec
 ARIMA(1,1,2)(0,0,1)[6] intercept   : AIC=-616.965, Time=1.96 sec
 ARIMA(0,1,3)(0,0,1)[6] intercept   : AIC=-617.204, Time=0.80 sec
 ARIMA(1,1,3)(0,0,1)[6] intercept   : AIC=-624.277, Time=2.92 sec
 ARIMA(1,1,3)(0,0,0)[6] intercept   : AIC=-619.080, Time=1.08 sec
 ARIMA(1,1,3)(1,0,1)[6] intercept   : AIC=-617.171, Time=4.83 sec
 ARIMA(1,1,3)(0,0,2)[6] intercept   : AIC=-622.320, Time=4.74 sec
 ARIMA(1,1,3)(1,0,0)[6] intercept   : AIC=-623.746, Time=2.62 sec
 ARIMA(1,1,3)(1,0,2)[6] intercept   : AIC=-623.368, Time=121.82 sec
 ARIMA(2,1,3)(0,0,1)[6] intercept   : AIC=-618.105, Time=3.77 sec
 ARIMA(1,1,4)(0,0,1)[6] intercept   : AIC=-623.832, Time=3.16 sec
 ARIMA(0,1,4)(0,0,1)[6] intercept   : AIC=-617.600, Time=0.93 sec
 ARIMA(2,1,2)(0,0,1)[6] intercept   : AIC=-620.102, Time=2.55 sec
 ARIMA(2,1,4)(0,0,1)[6] intercept   : AIC=-616.131, Time=3.57 sec
 ARIMA(1,1,3)(0,0,1)[6]             : AIC=-626.328, Time=0.99 sec
 ARIMA(1,1,3)(0,0,0)[6]             : AIC=-620.947, Time=0.37 sec
 ARIMA(1,1,3)(1,0,1)[6]             : AIC=inf, Time=2.39 sec
 ARIMA(1,1,3)(0,0,2)[6]             : AIC=-625.403, Time=1.97 sec
 ARIMA(1,1,3)(1,0,0)[6]             : AIC=-625.648, Time=0.74 sec
 ARIMA(1,1,3)(1,0,2)[6]             : AIC=-625.504, Time=2.82 sec
 ARIMA(0,1,3)(0,0,1)[6]             : AIC=-618.980, Time=0.33 sec
 ARIMA(1,1,2)(0,0,1)[6]             : AIC=-618.736, Time=0.52 sec
 ARIMA(2,1,3)(0,0,1)[6]             : AIC=-619.902, Time=1.58 sec
 ARIMA(1,1,4)(0,0,1)[6]             : AIC=-625.774, Time=1.23 sec
 ARIMA(0,1,2)(0,0,1)[6]             : AIC=-620.593, Time=0.30 sec
 ARIMA(0,1,4)(0,0,1)[6]             : AIC=-619.391, Time=0.57 sec
 ARIMA(2,1,2)(0,0,1)[6]             : AIC=-621.900, Time=1.19 sec
 ARIMA(2,1,4)(0,0,1)[6]             : AIC=-617.934, Time=1.79 sec

Best model:  ARIMA(1,1,3)(0,0,1)[6]
Total fit time: 189.467 seconds
```

In [28]:

```
arima_model.summary()
```

Out[28]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	813
Model:	SARIMAX(1, 1, 3)x(0, 0, [1], 6)	**Log Likelihood**	319.164
Date:	Mon, 14 Jun 2021	**AIC**	-626.328
Time:	01:44:18	**BIC**	-598.131
Sample:	0	**HQIC**	-615.503
	- 813		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.9151	0.061	14.933	0.000	0.795	1.035
ma.L1	-1.0004	0.068	-14.607	0.000	-1.135	-0.866
ma.L2	0.0008	0.042	0.018	0.986	-0.082	0.084
ma.L3	0.1140	0.031	3.641	0.000	0.053	0.175
ma.S.L6	-0.1075	0.034	-3.123	0.002	-0.175	-0.040
sigma2	0.0267	0.001	43.238	0.000	0.025	0.028

Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	1832.20
Prob(Q):	0.91	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.43	**Skew:**	0.18
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.35

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

In [27]:

```
sarimax_model = ts.sarimax_model(train, None, (1,1,3), (0,0,1,6))
```

In [28]:

```
sarimax_model.summary()
```

Out[28]:

SARIMAX Results

Dep. Variable:	close	**No. Observations:**	1767
Model:	SARIMAX(1, 1, 3)x(0, 0, [1], 6)	**Log Likelihood**	737.121
Date:	Wed, 16 Jun 2021	**AIC**	-1462.242

Time:	15:56:45	**BIC**	-1429.417
Sample:	05-17-2021	**HQIC**	-1450.110
	- 06-15-2021		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.8371	0.101	8.271	0.000	0.639	1.035
ma.L1	-0.9134	0.103	-8.880	0.000	-1.115	-0.712
ma.L2	-0.0312	0.025	-1.226	0.220	-0.081	0.019
ma.L3	0.1137	0.019	6.002	0.000	0.077	0.151
ma.S.L6	-0.0839	0.021	-3.947	0.000	-0.126	-0.042
sigma2	0.0253	0.000	69.280	0.000	0.025	0.026

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	6349.48
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.89	**Skew:**	0.42
Prob(H) (two-sided):	0.17	**Kurtosis:**	12.28

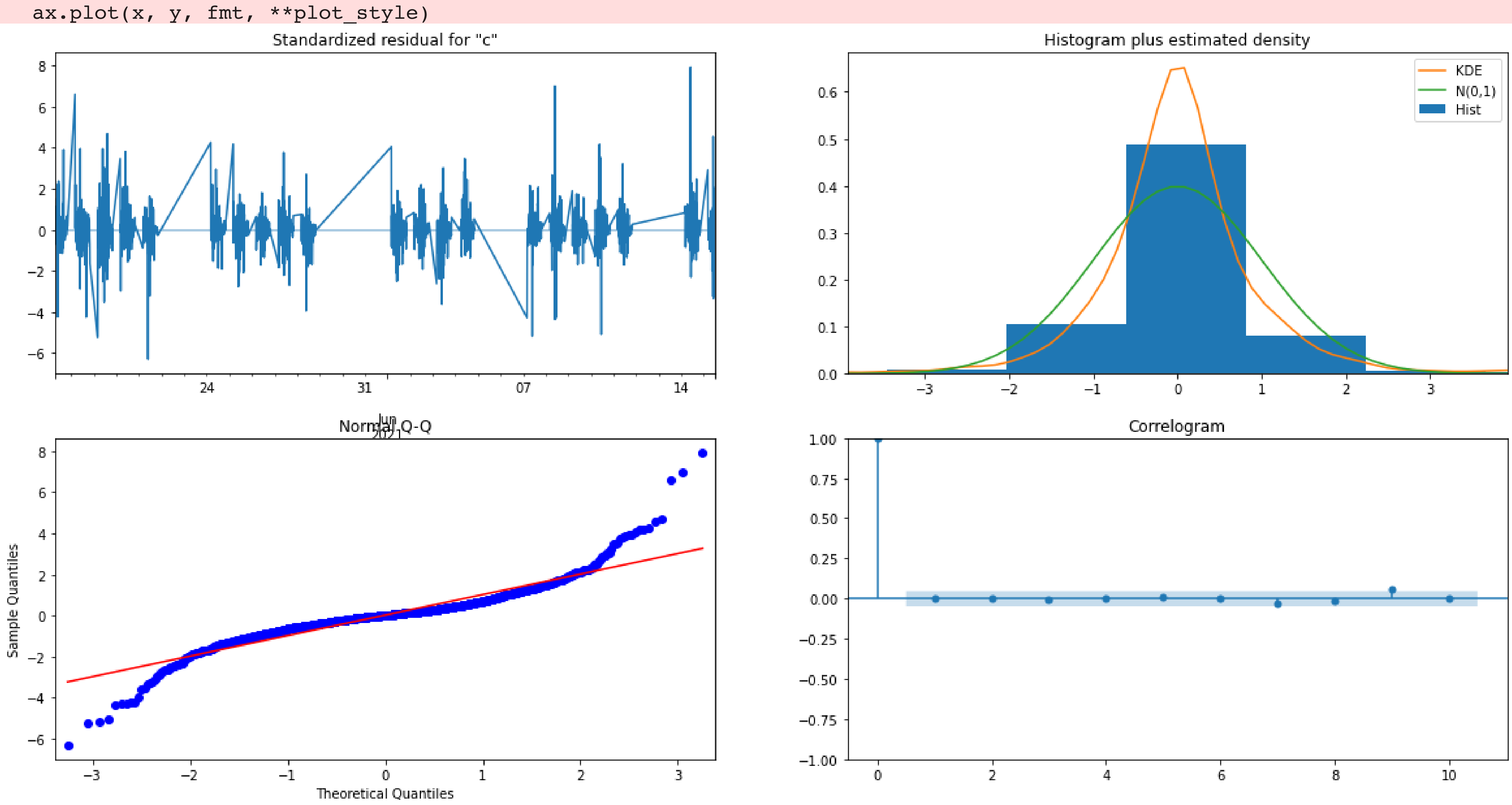
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

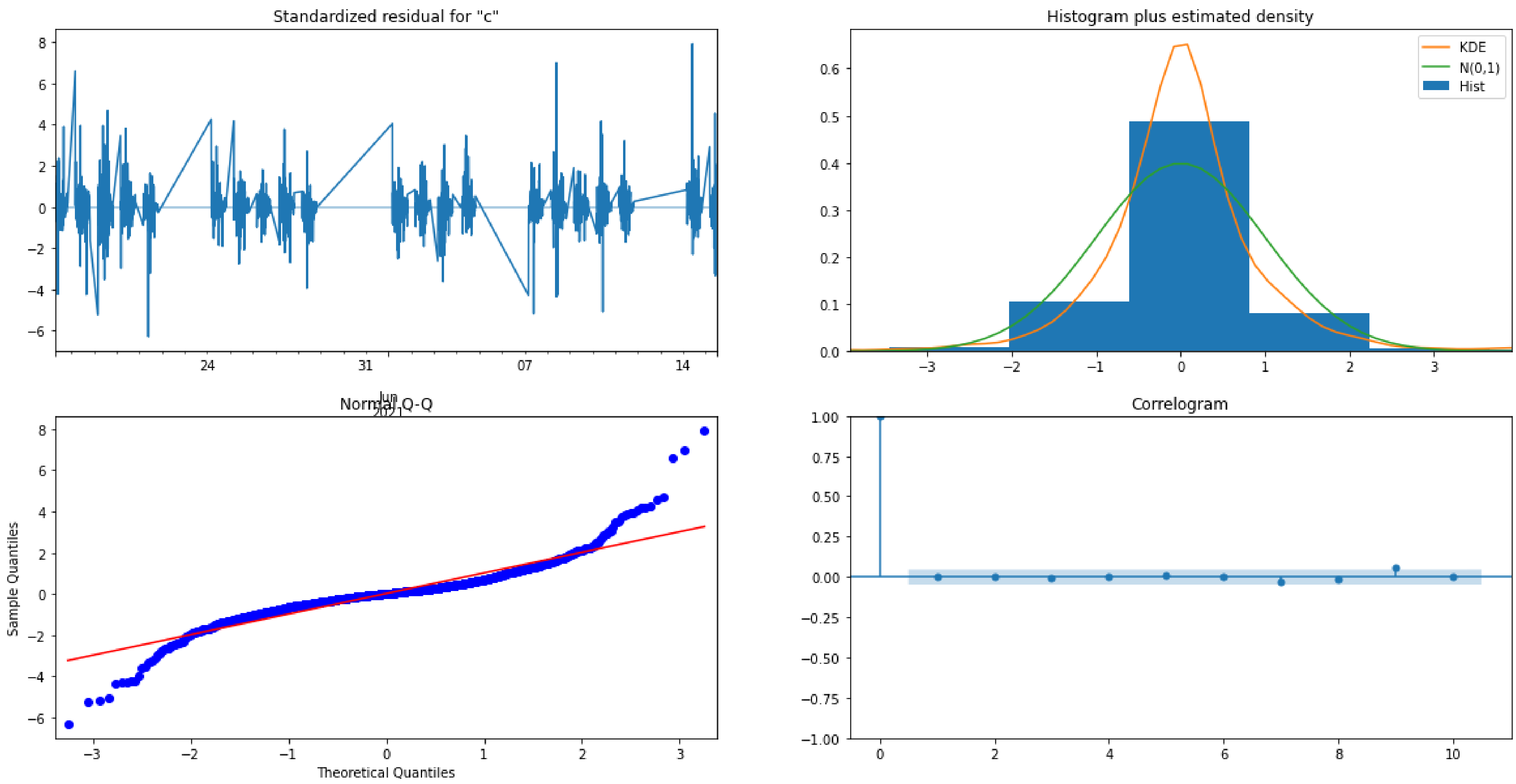
In [29]:

```
sarimax_model.plot_diagnostics(figsize=(20,10))
```

```
/Users/boula/miniforge3/envs/python394/lib/python3.9/site-packages/statsmodels/graphics/gofplots.py:993: UserWarning: marker is redundantly defined by the 'marker' keyword argument and the fmt string "bo" (-> marker='o'). The keyword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
```

Out[29]:





In [30]:
```
train.index = train.index.to_timestamp()
test.index = test.index.to_timestamp()
```

Time Series Prediction

In [31]:
```
pred = sarimax_model.get_prediction(
    start=pd.to_datetime("2021-06-15 12:00:00"),
    end=pd.to_datetime("2021-06-15 13:00:00"),
    dynamic=False)
```

In [32]:
```
prediction = pred.predicted_mean
prediction.index = prediction.index.to_timestamp()
Conf_interval = pred.conf_int()
```

In [33]:
```
fig, ax = plt.subplots(figsize=(12, 6))
ax.plot(train.loc["2021-06-15 07:00:00":,], label='Training Data')
ax.plot(prediction.loc["2021-06-15 12:00:00":,], label='One-Step Forecast', linewidth=4, ls=':')
ax.legend()
fig.tight_layout()
```