Predicting the Quarterly Net Income for Walmart

In [1]:
```python
# Importing Packages
import itertools
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import matplotlib
import itertools
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import matplotlib
import sklearn.preprocessing
from sklearn.metrics import r2_score
import keras

from keras.layers import Dense,Dropout,SimpleRNN,GRU, Bidirectional,LSTM
from tensorflow.keras.optimizers import SGD
from keras.models import Sequential
from sklearn.preprocessing import MinMaxScaler, StandardScaler

plt.style.use('fivethirtyeight')
matplotlib.rcParams['axes.labelsize'] = 14
matplotlib.rcParams['xtick.labelsize'] = 12
matplotlib.rcParams['ytick.labelsize'] = 12
matplotlib.rcParams['text.color'] = 'k'
```

In [2]:
```python
# Reading the Data
df=pd.read_excel('Walmart Quarterly Net Income.xlsx')
df.head()
```

Out[2]:

	Date	Quarterly Net Income
0	2009-01-31	3772
1	2009-04-30	3022
2	2009-07-31	3472
3	2009-10-31	3144
4	2010-01-31	4732

In [3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56 entries, 0 to 55
Data columns (total 2 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Date                  56 non-null     datetime64[ns]
 1   Quarterly Net Income  56 non-null     int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 1.0 KB
```

In [4]:
```python
# Setting Date as Index
df = df.set_index('Date')
df.head()
```

Out[4]:

Date	Quarterly Net Income
2009-01-31	3772
2009-04-30	3022
2009-07-31	3472
2009-10-31	3144
2010-01-31	4732

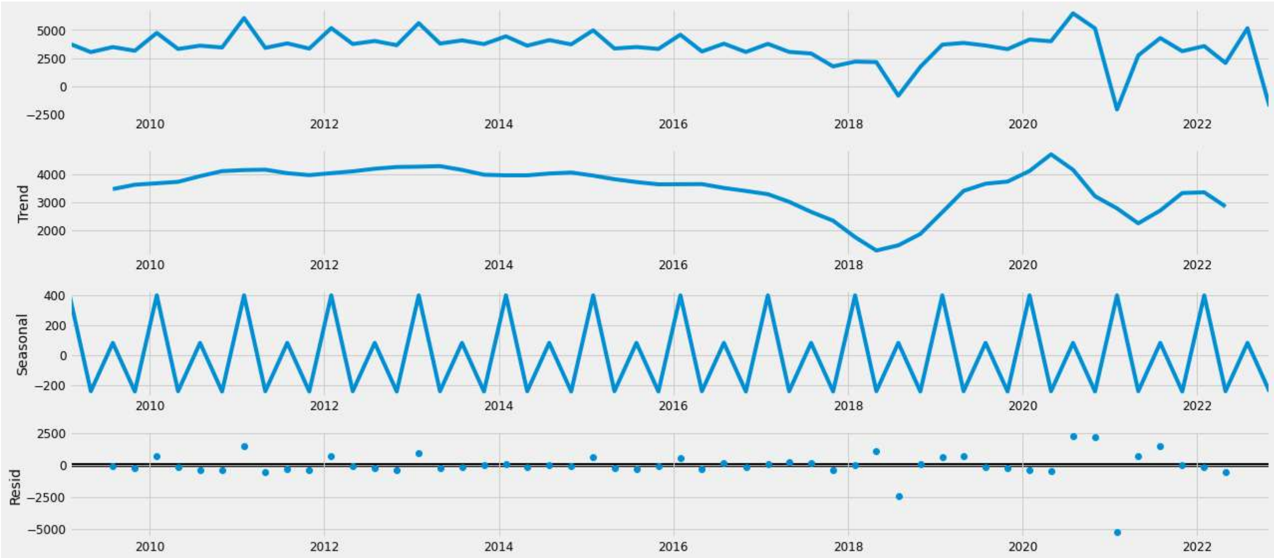
In [5]:

```python
# Plotting the data
df.plot(figsize=(16,4),legend=True)
plt.title('Walmart Quarterly Revenue')
plt.show()
```

In [6]:

```python
# Decomposition the data
from pylab import rcParams
rcParams['figure.figsize'] = 18, 8

decomposition = sm.tsa.seasonal_decompose(df, model = 'additive')
fig = decomposition.plot()
plt.show()
```



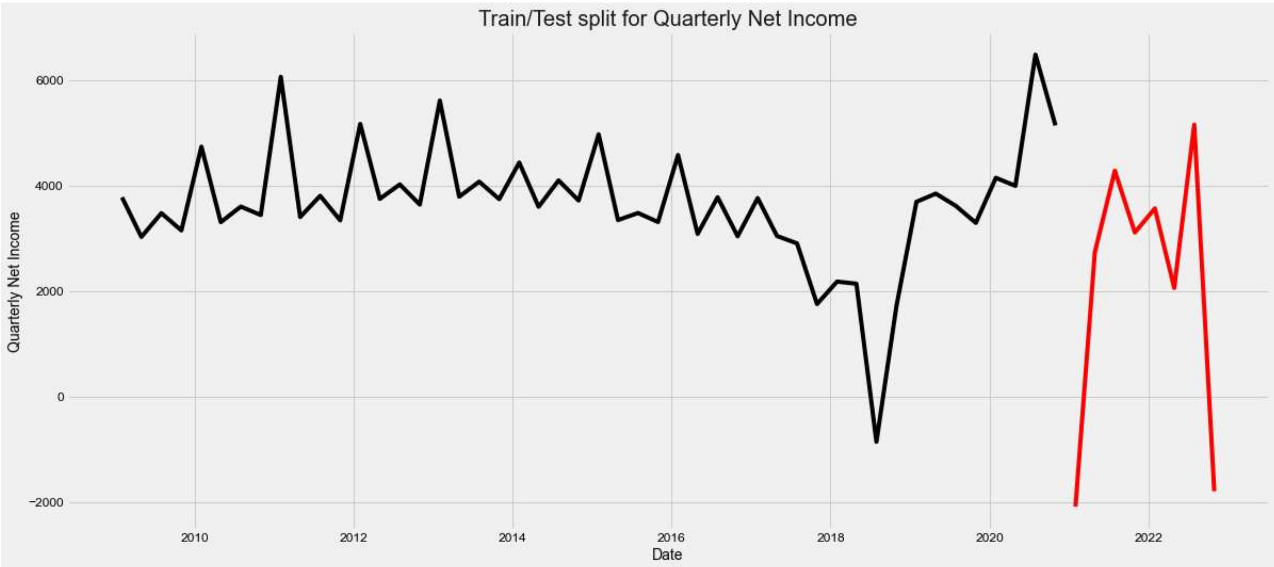
In [7]:

```python
# Dividing the data into training and testing
# Ploting the data
import seaborn as sns
df['Date'] = df.index
train = df[df['Date'] < pd.to_datetime("2020-12", format='%Y-%m')]
train['train'] = train['Quarterly Net Income']
del train['Date']
del train['Quarterly Net Income']
test = df[df['Date'] >= pd.to_datetime("2020-12", format='%Y-%m')]
del test['Date']
test['test'] = test['Quarterly Net Income']
del test['Quarterly Net Income']
plt.plot(train, color = "black")
plt.plot(test, color = "red")
plt.title("Train/Test split for Quarterly Net Income")
plt.ylabel("Quarterly Net Income")
plt.xlabel('Date')
sns.set()
plt.show()
```

```
C:\Users\ravit\AppData\Local\Temp\ipykernel_20844\2151717043.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-vers
us-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  train['train'] = train['Quarterly Net Income']
C:\Users\ravit\AppData\Local\Temp\ipykernel_20844\2151717043.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-vers
us-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  test['test'] = test['Quarterly Net Income']
```



Arima Model

In [8]:

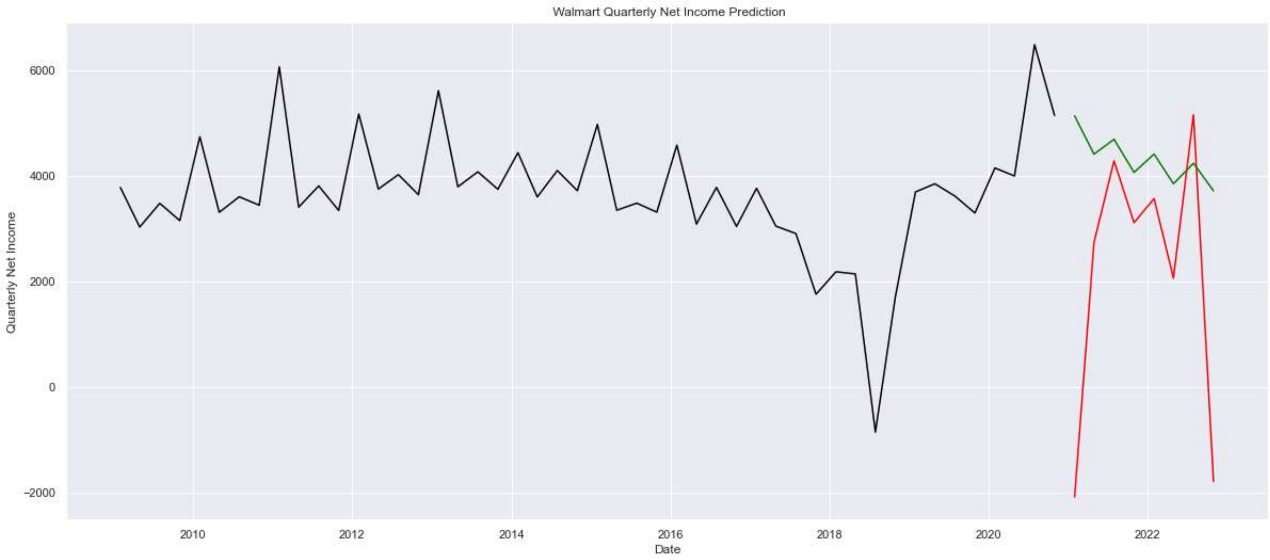
```python
# Applying ARIMA Model
from pmdarima.arima import auto_arima
model = auto_arima(train, trace=True, error_action='ignore', suppress_warnings=True)
model.fit(train)
forecast = model.predict(n_periods=len(test))
forecast = pd.DataFrame(forecast,index = test.index,columns=['Prediction'])
```

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=806.808, Time=0.44 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=816.188, Time=0.02 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=810.220, Time=0.02 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=813.280, Time=0.09 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=930.029, Time=0.01 sec
 ARIMA(1,0,2)(0,0,0)[0] intercept   : AIC=813.033, Time=0.06 sec
 ARIMA(2,0,1)(0,0,0)[0] intercept   : AIC=807.215, Time=0.28 sec
 ARIMA(3,0,2)(0,0,0)[0] intercept   : AIC=808.238, Time=0.37 sec
 ARIMA(2,0,3)(0,0,0)[0] intercept   : AIC=807.490, Time=0.28 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=810.846, Time=0.04 sec
 ARIMA(1,0,3)(0,0,0)[0] intercept   : AIC=814.300, Time=0.10 sec
 ARIMA(3,0,1)(0,0,0)[0] intercept   : AIC=808.793, Time=0.39 sec
 ARIMA(3,0,3)(0,0,0)[0] intercept   : AIC=808.855, Time=0.40 sec
 ARIMA(2,0,2)(0,0,0)[0]             : AIC=812.069, Time=0.21 sec

Best model:  ARIMA(2,0,2)(0,0,0)[0] intercept
Total fit time: 2.739 seconds
```

In [9]:

```
# Plotting the prediction
plt.plot(train, color = "black")
plt.plot(test, color = "red")
plt.plot(forecast, color = "green")
plt.title(" Walmart Quarterly Net Income Prediction")
plt.ylabel("Quarterly Net Income")
plt.xlabel('Date')
sns.set()
plt.show()
```



In [10]:

```
from math import sqrt
from sklearn.metrics import mean_squared_error
rms = sqrt(mean_squared_error(test,forecast))
print("RMSE: ", rms)
```

```
RMSE:  3373.786162000279
```

SARIMA Model

In [11]:

```
df=pd.read_excel('Walmart Quarterly Net Income.xlsx')
df = df.set_index('Date')
```

In [12]:

```
# set the typical ranges for p, d, q
p = d = q = range(0, 2)

#take all possible combination for p, d and q
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

print('Examples of parameter combinations for Seasonal ARIMA...')
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[2]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[3]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[4]))
```

```
Examples of parameter combinations for Seasonal ARIMA...
SARIMAX: (0, 0, 1) x (0, 0, 1, 12)
SARIMAX: (0, 0, 1) x (0, 1, 0, 12)
SARIMAX: (0, 1, 0) x (0, 1, 1, 12)
SARIMAX: (0, 1, 0) x (1, 0, 0, 12)
```

In [13]:

```
# Using Grid Search find the optimal set of parameters that yields the best performance
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(df, order = param, seasonal_order = param_seasonal, enforce_stationary = False,enf
            result = mod.fit()
            print('SARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, result.aic))
        except:
            continue
```

```
R:\Anaconda\envs\general\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was p
rovided, so inferred frequency Q-OCT will be used.
  self._init_dates(dates, freq)
R:\Anaconda\envs\general\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was p
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R:\Anaconda\envs\general\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was p
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R:\Anaconda\envs\general\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was p
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  self._init_dates(dates, freq)
R:\Anaconda\envs\general\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was p
```

In [14]:

```
#Fitting the SARIMA model using above optimal combination of p, d, q (optimal means combination at which we got lowest AIC sco

model = sm.tsa.statespace.SARIMAX(df, order = (1, 1, 1),
                                  seasonal_order = (1, 1, 0, 12)
                                 )
result = model.fit()
print(result.summary().tables[1])
```

```
R:\Anaconda\envs\general\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was prov
ided, so inferred frequency Q-OCT will be used.
  self._init_dates(dates, freq)
R:\Anaconda\envs\general\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was prov
ided, so inferred frequency Q-OCT will be used.
  self._init_dates(dates, freq)
R:\Anaconda\envs\general\lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible starting MA par
ameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0253      0.307      0.082      0.934      -0.575       0.626
ma.L1         -0.7526      0.141     -5.332      0.000      -1.029      -0.476
ar.S.L12      -0.5014      0.218     -2.300      0.021      -0.929      -0.074
sigma2      3.299e+06   6.54e+05      5.045      0.000    2.02e+06    4.58e+06
==============================================================================
```

In [15]:

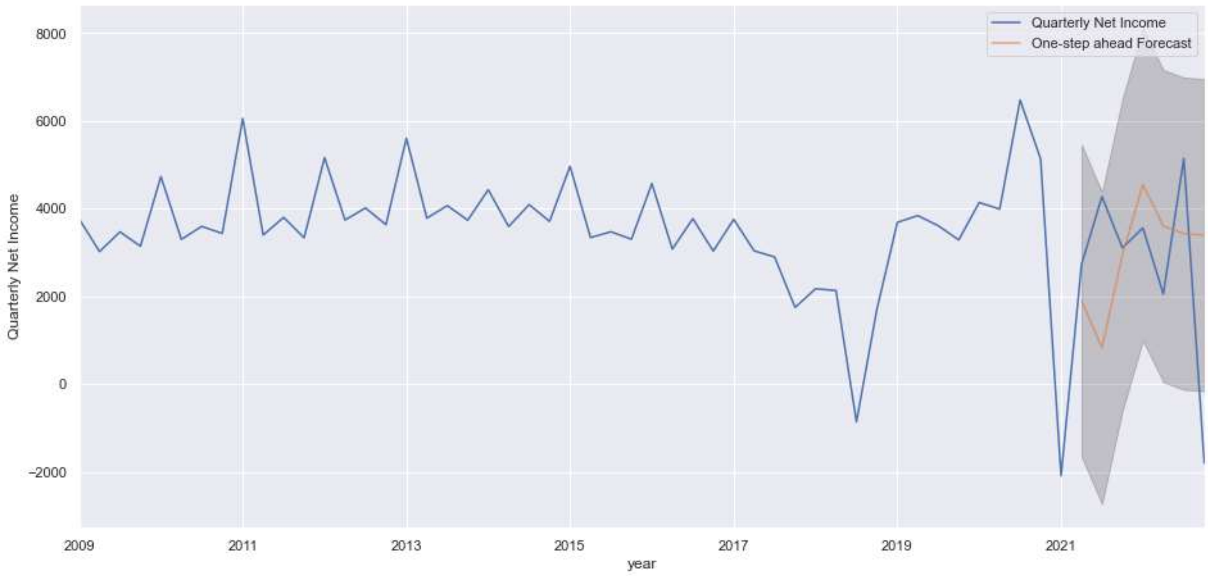
```
prediction = result.get_prediction(start = pd.to_datetime('2021-04-30'), dynamic = False)
prediction_ci = prediction.conf_int()
prediction_ci
```

Out[15]:

	lower Quarterly Net Income	upper Quarterly Net Income
2021-04-30	-1654.421889	5465.365348
2021-07-31	-2733.527648	4386.259526
2021-10-31	-608.785230	6511.001910
2022-01-31	991.979169	8111.766289
2022-04-30	45.244418	7165.031526
2022-07-31	-127.355867	6992.431234
2022-10-31	-161.408001	6958.379097

In [16]:

```python
#Visualize the forecasting
ax = df['2009':].plot(label = 'observed')
prediction.predicted_mean.plot(ax = ax, label = 'One-step ahead Forecast', alpha = 0.7, figsize = (14, 7))
ax.fill_between(prediction_ci.index, prediction_ci.iloc[:, 0], prediction_ci.iloc[:, 1], color = 'k', alpha = 0.2)
ax.set_xlabel("year")
ax.set_ylabel('Quarterly Net Income')
plt.legend()
plt.show()
```



In [17]:

```python
# Evaluation metrics are Squared Mean Error(SME) and Root Mean Squared Error(RMSE)

from sklearn.metrics import mean_squared_error

y_hat = prediction.predicted_mean
y_truth = df['2021-04-30':]
mse = mean_squared_error(y_truth,y_hat)
rmse = np.sqrt(mse)

print('The Mean Squared Error of our forecasts is', mse)
print('The Root Mean Squared Error of our forecasts is', rmse)
```

```
The Mean Squared Error of our forecasts is 6562726.660534659
The Root Mean Squared Error of our forecasts is 2561.7819307143727
```

In [18]:

```python
# forcasting for out of sample data
pred_uc = result.get_forecast(steps = 10)
pred_ci = pred_uc.conf_int()

ax = df.plot(label = 'observed', figsize = (14, 7))
pred_uc.predicted_mean.plot(ax = ax, label = 'forecast')
ax.fill_between(pred_ci.index, pred_ci.iloc[:, 0], pred_ci.iloc[:, 1], color = 'k', alpha = 0.25)
ax.set_xlabel('Date')
ax.set_ylabel('Quarterly Net Income')

plt.legend()
plt.show()

```

DNN MODEL

In [19]:

```
def convert2matrix(data_arr, look_back):
    X, Y =[], []
    for i in range(len(data_arr)-look_back):
        d=i+look_back
        X.append(data_arr[i:d,0])
        Y.append(data_arr[d,0])
    return np.array(X).astype('int'), np.array(Y).astype('int')
```

In [20]:

```
df=pd.read_excel('Walmart Quarterly Net Income.xlsx')

df = df.set_index('Date')

```

In [21]:

```
df1 = df
#Split data set into testing dataset and train dataset
train_size = 49
train, test =df1.values[0:train_size,:],df1.values[train_size:len(df1.values),:]
# setup look_back window
look_back = 4
#convert dataset into right shape in order to input into the DNN
trainX, trainY = convert2matrix(train, look_back)
testX, testY = convert2matrix(test, look_back)
```

In [22]:

```
from keras.models import Sequential
from keras.layers import Dense
def model_dnn(look_back):
    model=Sequential()
    model.add(Dense(units=32, input_dim=look_back, activation='relu'))
    model.add(Dense(8, activation='relu'))
    model.add(Dense(1))
    model.compile(loss='mean_squared_error',  optimizer='adam',metrics = ['mse', 'mae'])
    return model
```

In [23]:

```
model=model_dnn(look_back)
history=model.fit(trainX,trainY, epochs=500, batch_size=4, verbose=1, validation_data=(testX,testY),shuffle=False)
```

```
Epoch 1/500
12/12 [==============================] - 1s 21ms/step - loss: 10397825.0000 - mse: 10397825.0000 - mae: 3072.6726 - val_loss: 7986049.5000 - val_mse: 7986049.5000 - val_mae: 2522.6152
Epoch 2/500
12/12 [==============================] - 0s 5ms/step - loss: 6700009.0000 - mse: 6700009.0000 - mae: 2413.0437 - val_loss: 8489033.0000 - val_mse: 8489033.0000 - val_mae: 2491.5454
Epoch 3/500
12/12 [==============================] - 0s 4ms/step - loss: 5305328.5000 - mse: 5305328.5000 - mae: 2086.3992 - val_loss: 8537176.0000 - val_mse: 8537176.0000 - val_mae: 2424.1121
Epoch 4/500
12/12 [==============================] - 0s 4ms/step - loss: 4452226.5000 - mse: 4452226.5000 - mae: 1854.4752 - val_loss: 8702546.0000 - val_mse: 8702546.0000 - val_mae: 2435.6445
Epoch 5/500
12/12 [==============================] - 0s 5ms/step - loss: 3831167.2500 - mse: 3831167.2500 - mae: 1662.9531 - val_loss: 9023541.0000 - val_mse: 9023541.0000 - val_mae: 2541.0049
Epoch 6/500
12/12 [==============================] - 0s 5ms/step - loss: 3359253.7500 - mse: 3359253.7500 - mae: 1490.4729 - val_loss: 9525285.0000 - val_mse: 9525285.0000 - val_mae: 2646.3252
Epoch 7/500
```

In [24]:

```
def model_loss(history):
    plt.figure(figsize=(8,4))
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Test Loss')
    plt.title('model loss')
    plt.ylabel('loss')
    plt.xlabel('epochs')
    plt.legend(loc='upper right')
    plt.show();
```

In [25]:

```
train_score = model.evaluate(trainX, trainY, verbose=0)
print('Train Root Mean Squared Error(RMSE): %.2f; Train Mean Absolute Error(MAE) : %.2f '
% (np.sqrt(train_score[1]), train_score[2]))
test_score = model.evaluate(testX, testY, verbose=0)
print(train_score)
print(test_score)
print('Test Root Mean Squared Error(RMSE): %.2f; Test Mean Absolute Error(MAE) : %.2f '
% (np.sqrt(test_score[1]), test_score[2]))
```

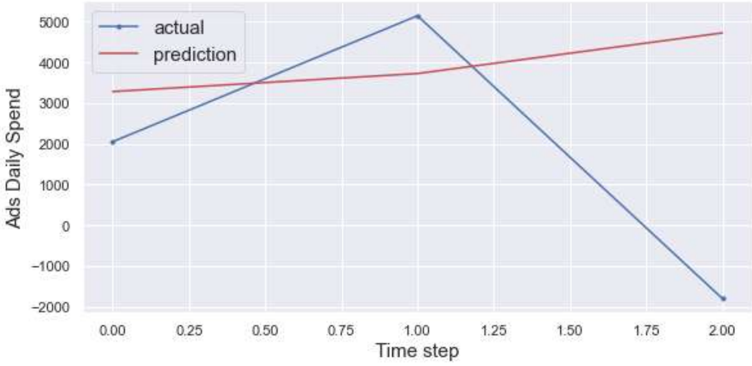
```
Train Root Mean Squared Error(RMSE): 919.19; Train Mean Absolute Error(MAE) : 580.17
[844912.1875, 844912.1875, 580.17041015625]
[15373329.0, 15373329.0, 3059.468017578125]
Test Root Mean Squared Error(RMSE): 3920.88; Test Mean Absolute Error(MAE) : 3059.47
```

In [26]:

```
def prediction_plot(testY, test_predict):
     len_prediction=[x for x in range(len(testY))]
     plt.figure(figsize=(8,4))
     plt.plot(len_prediction, testY[:8], marker='.', label="actual")
     plt.plot(len_prediction, test_predict[:8], 'r', label="prediction")
     plt.tight_layout()
     sns.despine(top=True)
     plt.subplots_adjust(left=0.07)
     plt.ylabel('Ads Daily Spend', size=15)
     plt.xlabel('Time step', size=15)
     plt.legend(fontsize=15)
     plt.show();
```

In [27]:

```
test_predict = model.predict(testX)
prediction_plot(testY, test_predict)
```



GRU and BiLSTM Models

In [28]:

```
df=pd.read_excel('Walmart Quarterly Net Income.xlsx')
df.head()
```

Out[28]:

	Date	Quarterly Net Income
0	2009-01-31	3772
1	2009-04-30	3022
2	2009-07-31	3472
3	2009-10-31	3144
4	2010-01-31	4732

In [29]:

```
df = df.set_index('Date')
df.head()
```

Out[29]:

Date	Quarterly Net Income
2009-01-31	3772
2009-04-30	3022
2009-07-31	3472
2009-10-31	3144
2010-01-31	4732

In [30]:

```
# Split train data and test data
train_size = int(len(df)*0.8)

train_data = df.iloc[:train_size]
test_data = df.iloc[train_size:]
```

In [31]:

```
scaler = MinMaxScaler().fit(train_data)
train_scaled = scaler.transform(train_data)
test_scaled = scaler.transform(test_data)
```

In [32]:

```
# Create input dataset
def create_dataset (X, look_back = 1):
    Xs, ys = [], []

    for i in range(len(X)-look_back):
        v = X[i:i+look_back]
        Xs.append(v)
        ys.append(X[i+look_back])

    return np.array(Xs), np.array(ys)
LOOK_BACK = 4
X_train, y_train = create_dataset(train_scaled,LOOK_BACK)
X_test, y_test = create_dataset(test_scaled,LOOK_BACK)
# Print data shape
print('X_train.shape: ', X_train.shape)
print('y_train.shape: ', y_train.shape)
print('X_test.shape: ', X_test.shape)
print('y_test.shape: ', y_test.shape)
```

```
X_train.shape:  (40, 4, 1)
y_train.shape:  (40, 1)
X_test.shape:  (8, 4, 1)
y_test.shape:  (8, 1)
```

In [33]:

```
# Create BiLSTM model
def create_bilstm(units):
    model = Sequential()
    # Input layer
    model.add(Bidirectional(
              LSTM(units = units, return_sequences=True),
              input_shape=(X_train.shape[1], X_train.shape[2])))
    # Hidden layer
    model.add(Bidirectional(LSTM(units = units)))
    model.add(Dense(1))
    #Compile model
    model.compile(optimizer='adam',loss='mse')
    return model
model_bilstm = create_bilstm(64)
# Create GRU model
def create_gru(units):
    model = Sequential()
    # Input layer
    model.add(GRU (units = units, return_sequences = True,
    input_shape = [X_train.shape[1], X_train.shape[2]]))
    model.add(Dropout(0.2))
    # Hidden layer
    model.add(GRU(units = units))
    model.add(Dropout(0.2))
    model.add(Dense(units = 1))
    #Compile model
    model.compile(optimizer='adam',loss='mse')
    return model
model_gru = create_gru(64)
```

In [34]:

```
def fit_model(model):
    early_stop = keras.callbacks.EarlyStopping(monitor = 'val_loss',
                                               patience = 10)
    history = model.fit(X_train, y_train, epochs = 100,
                        validation_split = 0.2,
                        batch_size = 16, shuffle = False,
                        callbacks = [early_stop])
    return history
history_gru = fit_model(model_gru)
```

```
Epoch 1/100
2/2 [==============================] - 3s 606ms/step - loss: 0.3822 - val_loss: 0.1531
Epoch 2/100
2/2 [==============================] - 0s 26ms/step - loss: 0.2012 - val_loss: 0.0856
Epoch 3/100
2/2 [==============================] - 0s 39ms/step - loss: 0.0839 - val_loss: 0.0544
Epoch 4/100
2/2 [==============================] - 0s 37ms/step - loss: 0.0290 - val_loss: 0.0613
Epoch 5/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0308 - val_loss: 0.0841
Epoch 6/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0540 - val_loss: 0.0916
Epoch 7/100
2/2 [==============================] - 0s 32ms/step - loss: 0.0573 - val_loss: 0.0821
Epoch 8/100
2/2 [==============================] - 0s 32ms/step - loss: 0.0433 - val_loss: 0.0669
Epoch 9/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0237 - val_loss: 0.0566
Epoch 10/100
2/2 [==============================] - 0s 31ms/step - loss: 0.0199 - val_loss: 0.0526
Epoch 11/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0151 - val_loss: 0.0526
Epoch 12/100
2/2 [==============================] - 0s 31ms/step - loss: 0.0209 - val_loss: 0.0540
Epoch 13/100
2/2 [==============================] - 0s 28ms/step - loss: 0.0273 - val_loss: 0.0545
Epoch 14/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0256 - val_loss: 0.0538
Epoch 15/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0297 - val_loss: 0.0526
Epoch 16/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0165 - val_loss: 0.0521
Epoch 17/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0167 - val_loss: 0.0527
Epoch 18/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0165 - val_loss: 0.0544
Epoch 19/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0188 - val_loss: 0.0559
Epoch 20/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0198 - val_loss: 0.0565
Epoch 21/100
2/2 [==============================] - 0s 31ms/step - loss: 0.0237 - val_loss: 0.0563
Epoch 22/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0207 - val_loss: 0.0556
Epoch 23/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0147 - val_loss: 0.0542
Epoch 24/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0170 - val_loss: 0.0531
Epoch 25/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0161 - val_loss: 0.0525
Epoch 26/100
2/2 [==============================] - 0s 38ms/step - loss: 0.0141 - val_loss: 0.0522
```

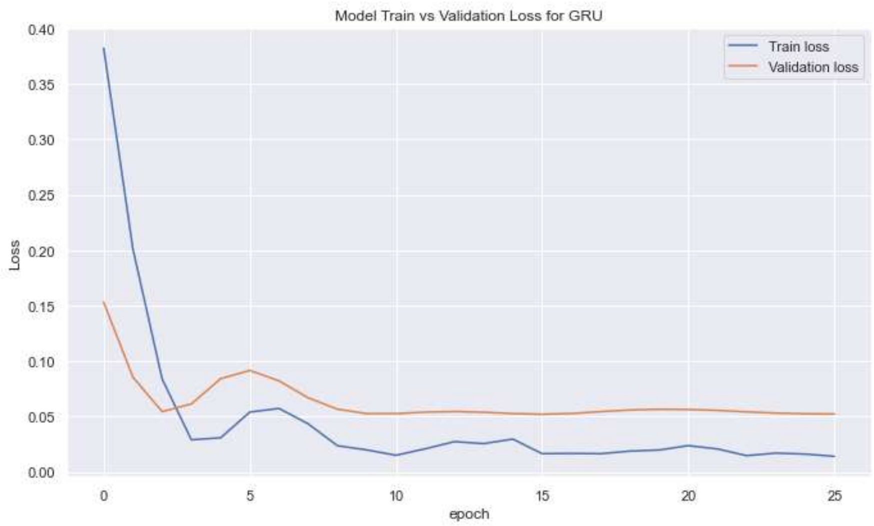
In [35]:

```
history_bilstm = fit_model(model_bilstm)
```

```
Epoch 1/100
2/2 [==============================] - 5s 1s/step - loss: 0.4587 - val_loss: 0.2108
Epoch 2/100
2/2 [==============================] - 0s 33ms/step - loss: 0.3189 - val_loss: 0.1503
Epoch 3/100
2/2 [==============================] - 0s 33ms/step - loss: 0.2007 - val_loss: 0.1008
Epoch 4/100
2/2 [==============================] - 0s 34ms/step - loss: 0.1039 - val_loss: 0.0658
Epoch 5/100
2/2 [==============================] - 0s 32ms/step - loss: 0.0374 - val_loss: 0.0535
Epoch 6/100
2/2 [==============================] - 0s 32ms/step - loss: 0.0169 - val_loss: 0.0676
Epoch 7/100
2/2 [==============================] - 0s 31ms/step - loss: 0.0407 - val_loss: 0.0840
Epoch 8/100
2/2 [==============================] - 0s 31ms/step - loss: 0.0583 - val_loss: 0.0802
Epoch 9/100
2/2 [==============================] - 0s 35ms/step - loss: 0.0450 - val_loss: 0.0669
Epoch 10/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0238 - val_loss: 0.0570
Epoch 11/100
2/2 [==============================] - 0s 31ms/step - loss: 0.0129 - val_loss: 0.0537
Epoch 12/100
2/2 [==============================] - 0s 30ms/step - loss: 0.0129 - val_loss: 0.0542
Epoch 13/100
2/2 [==============================] - 0s 32ms/step - loss: 0.0177 - val_loss: 0.0556
Epoch 14/100
2/2 [==============================] - 0s 29ms/step - loss: 0.0217 - val_loss: 0.0561
Epoch 15/100
2/2 [==============================] - 0s 31ms/step - loss: 0.0228 - val_loss: 0.0555
```

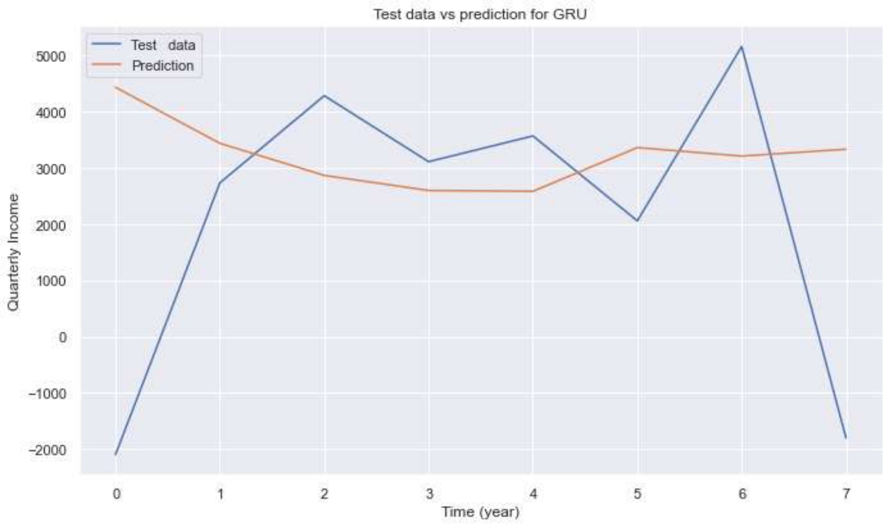
In [36]:

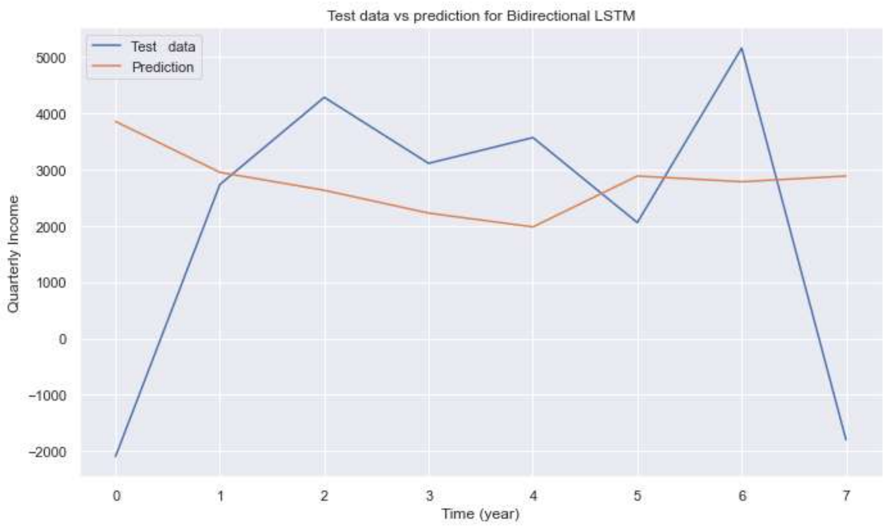
```
def plot_loss (history, model_name):
    plt.figure(figsize = (10, 6))
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model Train vs Validation Loss for ' + model_name)
    plt.ylabel('Loss')
    plt.xlabel('epoch')
    plt.legend(['Train loss', 'Validation loss'], loc='upper right')

plot_loss (history_gru, 'GRU')
plot_loss (history_bilstm, 'Bidirectional LSTM')
```



In [37]:

```
# Make prediction
def prediction(model):
    prediction = model.predict(X_test)
    prediction = scaler.inverse_transform(prediction)
    return prediction
prediction_gru = prediction(model_gru)
prediction_bilstm = prediction(model_bilstm)
# Plot test data vs prediction
def plot_future(prediction, model_name, y_test):
    plt.figure(figsize=(10, 6))
    range_future = len(prediction)
    plt.plot(np.arange(range_future), np.array(scaler.inverse_transform(y_test)),
             label='Test   data')
    plt.plot(np.arange(range_future),
             np.array(prediction),label='Prediction')
    plt.title('Test data vs prediction for ' + model_name)
    plt.legend(loc='upper left')
    plt.xlabel('Time (year)')
    plt.ylabel('Quarterly Income')

plot_future(prediction_gru, 'GRU', y_test)
plot_future(prediction_bilstm, 'Bidirectional LSTM', y_test)
```





In [38]:

```
def evaluate_prediction(predictions, actual, model_name):
    errors = predictions - actual
    mse = np.square(errors).mean()
    rmse = np.sqrt(mse)
    mae = np.abs(errors).mean()
    print(model_name + ':')
    print('Mean Absolute Error: {:.4f}'.format(mae))
    print('Root Mean Square Error: {:.4f}'.format(rmse))
    print('')
evaluate_prediction(prediction_gru, scaler.inverse_transform(y_test), 'GRU')
evaluate_prediction(prediction_bilstm, scaler.inverse_transform(y_test), 'Bidirectional LSTM')
```

```
GRU:
Mean Absolute Error: 2311.8309
Root Mean Square Error: 3120.6002

Bidirectional LSTM:
Mean Absolute Error: 2268.0282
Root Mean Square Error: 2947.6046
```

In [39]:

```
def evaluate_prediction(predictions, actual, model_name):
    errors = predictions - actual
    mse = np.square(errors).mean()
    rmse = np.sqrt(mse)
    mae = np.abs(errors).mean()
    print(model_name + ':')
    print('Mean Absolute Error: {:.4f}'.format(mae))
    print('Root Mean Square Error: {:.4f}'.format(rmse))
    print('')
evaluate_prediction(scaler.transform(prediction_gru), y_test, 'GRU')
evaluate_prediction(scaler.transform(prediction_bilstm), y_test, 'Bidirectional LSTM')
```

```
GRU:
Mean Absolute Error: 0.3342
Root Mean Square Error: 0.4511

Bidirectional LSTM:
Mean Absolute Error: 0.3279
Root Mean Square Error: 0.4261


R:\Anaconda\envs\general\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but MinMaxScale
r was fitted with feature names
  warnings.warn(
R:\Anaconda\envs\general\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but MinMaxScale
r was fitted with feature names
  warnings.warn(
```

In [ ]:

```

```