In [1]:
```python
import pandas as pd
import numpy as np
from statsmodels.tsa.arima_process import ArmaProcess
import matplotlib.pyplot as plt
import datetime
import io
import datetime
import matplotlib.lines as mlines
import statsmodels.formula.api as smf
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import adfuller
from pmdarima.arima import auto_arima
from statsmodels.tsa.arima.model import ARIMA
import scipy.stats as st
import pmdarima as pm
```

1

In [2]:
```python
df = pd.read_csv("desktop/JPYUSD.csv",parse_dates = True, index_col
```

In [3]:
```python
df
```

Out[3]:

	Japan
1985-01-01	0.003927
1985-02-01	0.003854
1985-03-01	0.003960
1985-04-01	0.003964
1985-05-01	0.003971
...	...
2022-07-01	0.007519
2022-08-01	0.007214
2022-09-01	0.006909
2022-10-01	0.006746
2022-11-01	0.007205

455 rows × 1 columns

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 455 entries, 1985-01-01 to 2022-11-01
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Japan   455 non-null    float64
dtypes: float64(1)
memory usage: 7.1 KB
```

In [5]:
```
df80 = df.iloc[:int(len(df)*0.8)]
```

In [6]:
```
df80
```

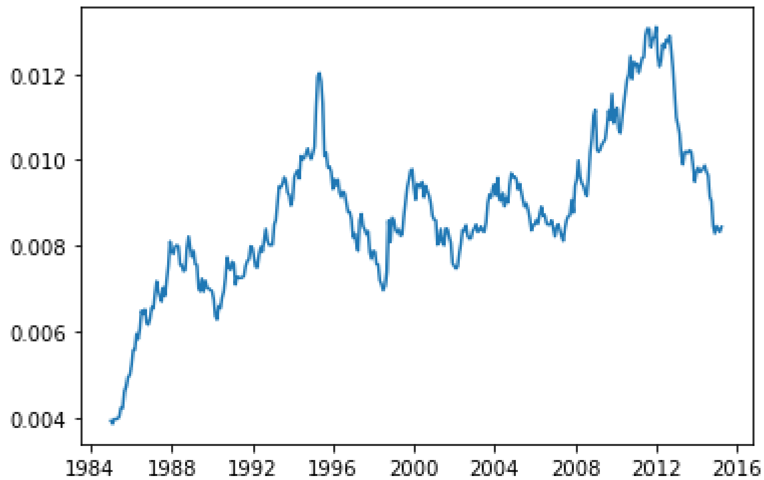
Out[6]:

	Japan
1985-01-01	0.003927
1985-02-01	0.003854
1985-03-01	0.003960
1985-04-01	0.003964
1985-05-01	0.003971
...	...
2014-12-01	0.008289
2015-01-01	0.008459
2015-02-01	0.008385
2015-03-01	0.008326
2015-04-01	0.008438

364 rows × 1 columns

In [7]:
```
plt.plot(df80)
```

Out[7]: [<matplotlib.lines.Line2D at 0x7fc2c4e20d30>]



In [8]:
```
df80.diff()
```

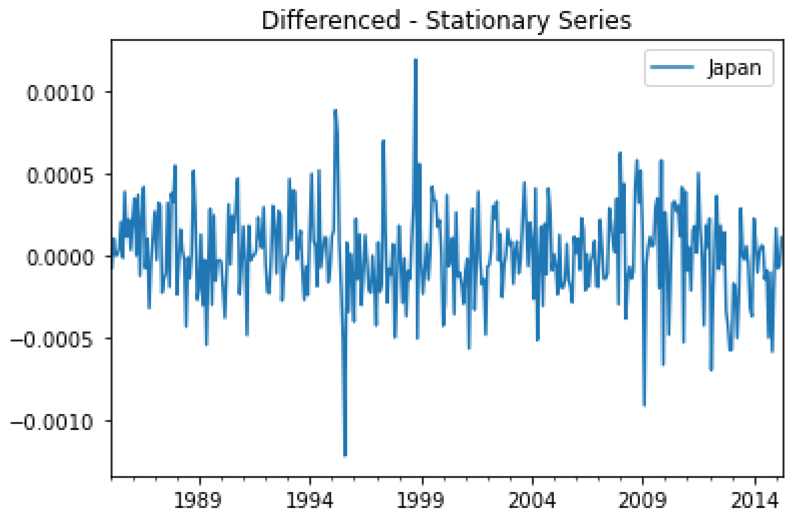
Out[8]:

	Japan
1985-01-01	NaN
1985-02-01	-0.000073
1985-03-01	0.000107
1985-04-01	0.000004
1985-05-01	0.000006
...	...
2014-12-01	-0.000170
2015-01-01	0.000170
2015-02-01	-0.000074
2015-03-01	-0.000059
2015-04-01	0.000112

364 rows × 1 columns

In [9]:
```
df80.diff().plot()
plt.title("Differenced - Stationary Series")
```

Out[9]: Text(0.5, 1.0, 'Differenced - Stationary Series')

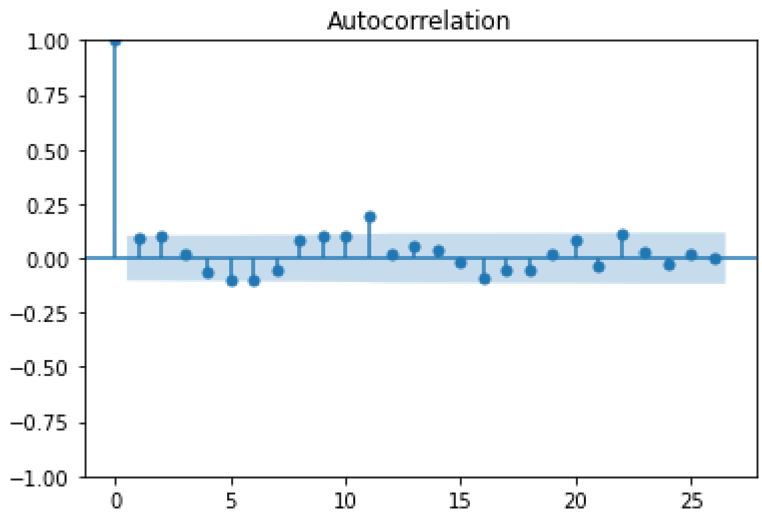


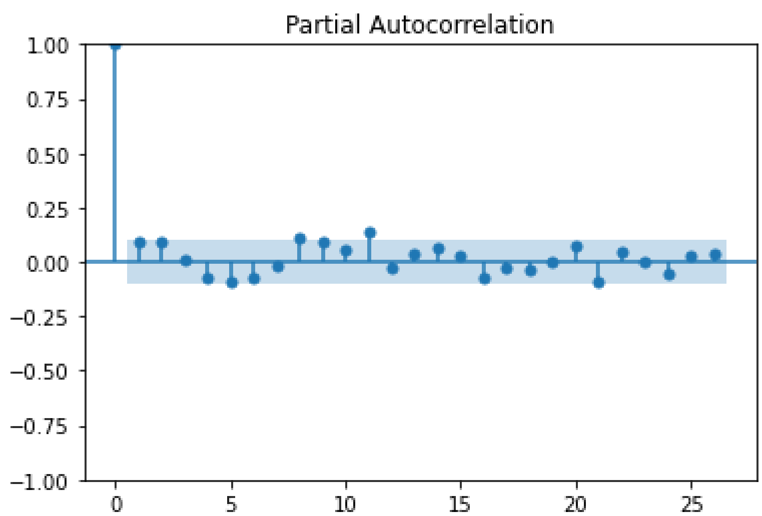
The differenced training data looks stationary as it is mean converting.

In [10]:

```
plot_acf(df80['Japan'].diff().dropna())
plot_pacf(df80['Japan'].diff().dropna(), method='ywm')
plt.plot()
```

Out[10]: []





In [ ]:

```

```

In [11]:
```
model3 = ARIMA(df80.dropna(), order=(1,1,0)).fit()
model3.summary()
```

```
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/stats
models/tsa/base/tsa_model.py:471: ValueWarning: No frequency informat
ion was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/stats
models/tsa/base/tsa_model.py:471: ValueWarning: No frequency informat
ion was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/stats
models/tsa/base/tsa_model.py:471: ValueWarning: No frequency informat
ion was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/stats
models/base/model.py:604: ConvergenceWarning: Maximum Likelihood opti
mization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

Out[11]:

SARIMAX Results

Dep. Variable:	Japan	**No. Observations:**	364
Model:	ARIMA(1, 1, 0)	**Log Likelihood**	2461.065
Date:	Fri, 27 Jan 2023	**AIC**	-4918.130
Time:	16:19:55	**BIC**	-4910.341
Sample:	01-01-1985	**HQIC**	-4915.034
	- 04-01-2015		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.0991	0.044	2.267	0.023	0.013	0.185
sigma2	7.537e-08	4.21e-09	17.901	0.000	6.71e-08	8.36e-08

Ljung-Box (L1) (Q):	0.04	**Jarque-Bera (JB):**	41.03
Prob(Q):	0.83	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.49	**Skew:**	-0.09
Prob(H) (two-sided):	0.03	**Kurtosis:**	4.64

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

In [12]:

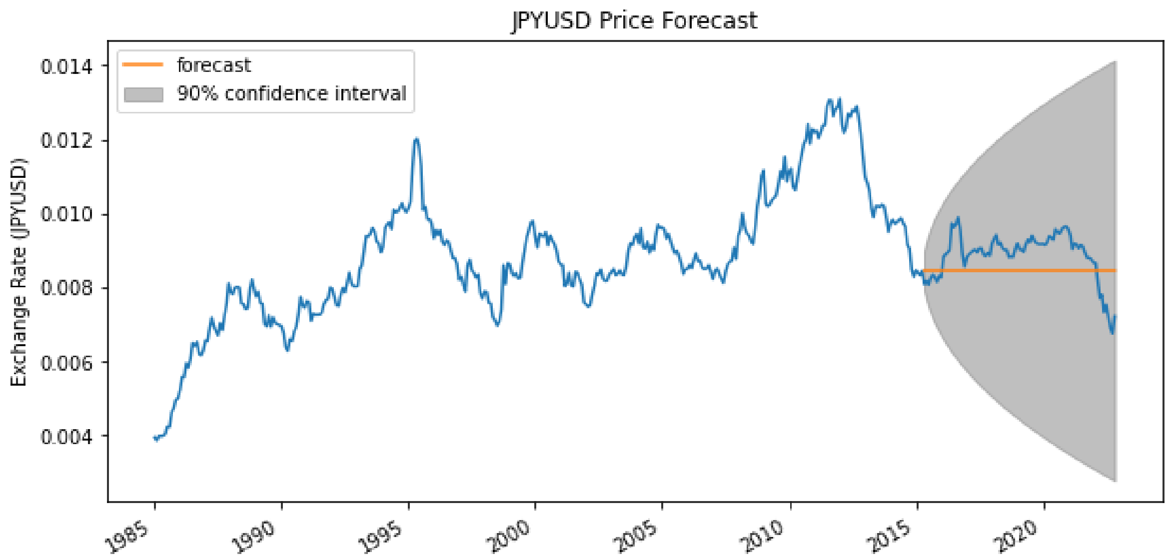
```
forecast2 = model3.get_forecast(12)

# get the 90% confidence interval for the forecast
yhat_conf_int2 = forecast2.conf_int(alpha=0.1)
yhat_conf_int2["mean"] = forecast2.predicted_mean
yhat_conf_int2
```

Out[12]:

	lower Japan	upper Japan	mean
2015-05-01	0.007998	0.008901	0.008449
2015-06-01	0.007779	0.009121	0.008450
2015-07-01	0.007613	0.009288	0.008450
2015-08-01	0.007475	0.009426	0.008450
2015-09-01	0.007353	0.009548	0.008450
2015-10-01	0.007244	0.009657	0.008450
2015-11-01	0.007144	0.009757	0.008450
2015-12-01	0.007051	0.009850	0.008450
2016-01-01	0.006964	0.009937	0.008450
2016-02-01	0.006882	0.010019	0.008450
2016-03-01	0.006804	0.010097	0.008450
2016-04-01	0.006729	0.010172	0.008450

In [13]:

```
from statsmodels.graphics.tsaplots import plot_predict

# Plot the data and the forecast
fig, ax = plt.subplots(figsize = (10, 5))
plt.title("JPYUSD Price Forecast")
plt.plot(df['Japan'])
plt.ylabel("Exchange Rate (JPYUSD)")
plot_predict(model3, ax=ax, start = "2015-05-01", end = "2022-11-01
plt.legend()
plt.show()
```



In [14]:

```
def evaluate_arima_model(X, arima_order):
    # prepare training dataset
    train_size = int(len(X) * 0.8)
    train, test = X[0:train_size], X[train_size:]
    history = [x for x in train]
    # make predictions
    predictions = list()
    for t in range(len(test)):
        model = ARIMA(history, order=arima_order)
        model_fit = model.fit()
        yhat = model_fit.forecast()[0]
        predictions.append(yhat)
        history.append(test[t])
    # calculate out of sample error
    test = pd.DataFrame(test)
    test["predictions"] = predictions
    return test
y = evaluate_arima_model(df['Japan'], (1,1,0))
```

```
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/st
atsmodels/base/model.py:604: ConvergenceWarning: Maximum Likelihoo
d optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/st
atsmodels/base/model.py:604: ConvergenceWarning: Maximum Likelihoo
d optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/st
atsmodels/base/model.py:604: ConvergenceWarning: Maximum Likelihoo
d optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/st
atsmodels/base/model.py:604: ConvergenceWarning: Maximum Likelihoo
d optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
/Users/youssefmahmoud/opt/anaconda3/lib/python3.9/site-packages/st
atsmodels/base/model.py:604: ConvergenceWarning: Maximum Likelihoo
d optimization failed to converge. Check mle_retvals
```

In [15]:
```
y
```

Out[15]:

	Japan	predictions
2015-05-01	0.008081	0.008449
2015-06-01	0.008167	0.008046
2015-07-01	0.008066	0.008175
2015-08-01	0.008251	0.008057
2015-09-01	0.008337	0.008268
...	...	...
2022-07-01	0.007519	0.007272
2022-08-01	0.007214	0.007538
2022-09-01	0.006909	0.007186
2022-10-01	0.006746	0.006880
2022-11-01	0.007205	0.006730

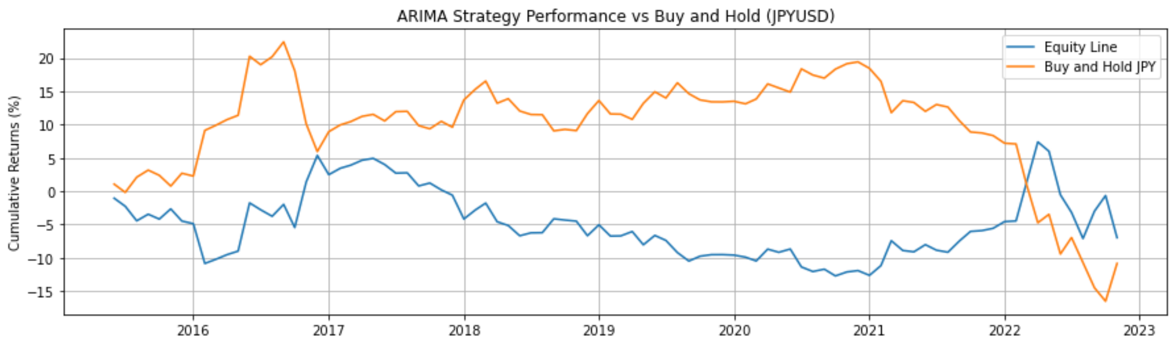
91 rows × 2 columns

In [16]:
```
y["Signals"] = np.where(y["predictions"]>y['Japan'].shift(), 1,-1)


y["returns"] = np.log(y["Japan"]/y["Japan"].shift())


y["strategy returns"] = y["Signals"]*y["returns"]


y["Cumulative Returns"] = (np.exp(y["strategy returns"].cumsum())-1
```

In [17]:
```
y["Cumulative Returns"]
```

Out[17]:
```
2015-05-01          NaN
2015-06-01    -1.050505
2015-07-01    -2.263728
2015-08-01    -4.447558
2015-09-01    -3.451806
                 ...
2022-07-01    -3.187663
2022-08-01    -7.105975
2022-09-01    -2.997755
2022-10-01    -0.652115
2022-11-01    -6.978640
Name: Cumulative Returns, Length: 91, dtype: float64
```

In [18]:
```
plt.figure(figsize = (15, 4))
plt.plot(y["Cumulative Returns"])
plt.plot((np.exp(y["returns"].cumsum())-1)*100)
plt.ylabel("Cumulative Returns (%)")
plt.title("ARIMA Strategy Performance vs Buy and Hold (JPYUSD)")
plt.legend(["Equity Line", "Buy and Hold JPY"])
plt.grid()
```



In [19]:
```
y["Cumulative Returns"]/(100+1)
```

Out[19]:
```
2015-05-01         NaN
2015-06-01   -0.010401
2015-07-01   -0.022413
2015-08-01   -0.044035
2015-09-01   -0.034176
                 ...
2022-07-01   -0.031561
2022-08-01   -0.070356
2022-09-01   -0.029681
2022-10-01   -0.006457
2022-11-01   -0.069095
Name: Cumulative Returns, Length: 91, dtype: float64
```

In [20]:
```
P = 1000000
A = (((y["Cumulative Returns"]/100)+1)*P)[-1]
t = (len(y)/12)
CCROR = np.log(A/P)/t
print(CCROR*100)
```

```
-0.9539477975994095
```

In [21]:
```
((A/P)**(1/t)-1)*100 # Annualized
```

Out[21]:
```
-0.9494121496260166
```

2

In [22]:
```
y['error'] =y['Japan']- y['predictions']
y
```

Out[22]:

	Japan	predictions	Signals	returns	strategy returns	Cumulative Returns	error
2015-05-01	0.008081	0.008449	-1	NaN	NaN	NaN	-0.000368
2015-06-01	0.008167	0.008046	-1	0.010561	-0.010561	-1.050505	0.000121
2015-07-01	0.008066	0.008175	1	-0.012337	-0.012337	-2.263728	-0.000108
2015-08-01	0.008251	0.008057	-1	0.022598	-0.022598	-4.447558	0.000194
2015-09-01	0.008337	0.008268	1	0.010367	0.010367	-3.451806	0.000068
...	...	...	...	...	...	...	...
2022-07-01	0.007519	0.007272	-1	0.026927	-0.026927	-3.187663	0.000247
2022-08-01	0.007214	0.007538	1	-0.041315	-0.041315	-7.105975	-0.000323
2022-09-01	0.006909	0.007186	-1	-0.043275	0.043275	-2.997755	-0.000277
2022-10-01	0.006746	0.006880	-1	-0.023894	0.023894	-0.652115	-0.000134
2022-11-01	0.007205	0.006730	-1	0.065799	-0.065799	-6.978640	0.000475

91 rows × 7 columns

In [23]:
```
s_current = np.log(y["Japan"]).reset_index(drop=True)
s_current = s_current.rename('s_current')
s_current
```

Out[23]:
```
0     -4.818263
1     -4.807703
2     -4.820040
3     -4.797442
4     -4.787075
         ...
86    -4.890349
87    -4.931664
88    -4.974939
89    -4.998833
90    -4.933034
Name: s_current, Length: 91, dtype: float64
```

In [24]:
```
df3 = pd.DataFrame(s_current, columns = ['s_current'])

```

In [25]:
```
df3
```

Out[25]:

	s_current
0	-4.818263
1	-4.807703
2	-4.820040
3	-4.797442
4	-4.787075
...	...
86	-4.890349
87	-4.931664
88	-4.974939
89	-4.998833
90	-4.933034

In [26]:
```
s_future = s_current.shift(1)
```

In [27]:
```
s_future.fillna(0)
```

Out[27]:
```
0      0.000000
1     -4.818263
2     -4.807703
3     -4.820040
4     -4.797442
         ...
86    -4.917277
87    -4.890349
88    -4.931664
89    -4.974939
90    -4.998833
Name: s_current, Length: 91, dtype: float64
```

In [28]:
```
s_future1 = s_future.fillna(0)
```

In [29]:
```
s_future1
```

Out[29]:
```
0     0.000000
1    -4.818263
2    -4.807703
3    -4.820040
4    -4.797442
        ...
86   -4.917277
87   -4.890349
88   -4.931664
89   -4.974939
90   -4.998833
Name: s_current, Length: 91, dtype: float64
```

In [30]:
```
s_change = s_future - s_current
s_change = s_change.rename('s_change')
s_change
```

Out[30]:
```
0          NaN
1    -0.010561
2     0.012337
3    -0.022598
4    -0.010367
        ...
86   -0.026927
87    0.041315
88    0.043275
89    0.023894
90   -0.065799
Name: s_change, Length: 91, dtype: float64
```

In [42]:
```
s_change_fitted = np.log(np.abs(s_change)).fillna(0)
```

In [43]:
```
s_change_fitted
```

Out[43]:
```
0     0.000000
1    -4.550623
2    -4.395167
3    -3.789915
4    -4.569119
        ...
86   -3.614610
87   -3.186527
88   -3.140185
89   -3.734147
90   -2.721158
Name: s_change, Length: 91, dtype: float64
```

In [31]:
```
df6 = pd.DataFrame(s_change.fillna(0), columns = ['s_change'])
```

In [32]:
```
df6
```

Out[32]:

	s_change
0	0.000000
1	-0.010561
2	0.012337
3	-0.022598
4	-0.010367
...	...
86	-0.026927
87	0.041315
88	0.043275
89	0.023894
90	-0.065799

91 rows × 1 columns

In [33]:
```
P1 = len(y['error'])
MSE_T = np.sum(np.square(y['error']))/P1
MSE_T
```

Out[33]: 4.368784909818687e-08

In [34]:
```
MSE_R = np.sum(np.square([df6['s_change']]))/P1
MSE_R
```

Out[34]: 0.0005809296335330899

In [35]:

```
error_R = df6['s_change'].reset_index(drop=True)
error_T = y['error'].reset_index(drop=True)
tmp = np.square(error_R) - np.square(error_T) - (MSE_R - MSE_T)
V_hat = np.sum(np.square(tmp))/P1

## Statistic
DMW = (MSE_R - MSE_T)/np.sqrt(V_hat/P1)

print('Since the DMW statitsic is equal to ' + str(DMW) + ',' + ' w
print('we reject the null hypothesis that the MP model does not out
```

```
Since the DMW statitsic is equal to 4.734497242845056, which is more
than the critical value (1.28),
we reject the null hypothesis that the MP model does not outperform t
he random walk model.
```

In [44]:

```
tmp2 = np.sum(np.square(s_change_fitted))/P1
CW = (MSE_R - MSE_T + tmp2)/np.sqrt(V_hat/P1)

print('Since the CW statitsic is equal to ' + str(CW) + ',' + ' whi
print('we reject the null hypothesis that the MP model does not out
```

```
Since the CW statitsic is equal to 187938.73511034384, which is more
than the critical value (1.28),
we reject the null hypothesis that the MP model does not outperform t
he random walk model.
```

In [ ]:

```
 
```