

Time series - Li2Co3 zeroes calculations and statistics

```
In [51]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import statsmodels.api as sm
from tabulate import tabulate
from statsmodels.stats.diagnostic import acorr_ljungbox
from statsmodels.tsa.stattools import acf
from google.colab import files
from sklearn.metrics import mean_squared_error
```

P1. Data Preprocess

```
In [2]: # Data from 2017-05-10 to 2024-04-19
li2co3 = pd.read_csv(r'/content/Lithium Carbonate 99%Min China Spot Historical Data')
li2co3['Date'] = pd.to_datetime(li2co3['Date'])
# The date order need to be inverted (from early to late)
li2co3 = li2co3.sort_values('Date')
li2co3.set_index('Date', inplace=True)
li2co3 = pd.DataFrame(li2co3["Price"])

li2co3['Price'] = (li2co3['Price'].str.replace(",", "").astype(float))
na_count = li2co3['Price'].isna().sum()
print("Number of missing values:", na_count)
if na_count > 0:
    li2co3 = li2co3.dropna(subset=['Price'])

# daily log returns
li2co3['log_ret'] = np.log(li2co3['Price']).diff()
li2co3 = li2co3.dropna(subset=['log_ret'])
```

Number of missing values: 0

```
In [3]: li2co3.head(10)
```

Out[3]:

	Price	log_ret
Date		
2017-05-11	123000.0	0.000000
2017-05-12	123000.0	0.000000
2017-05-15	123000.0	0.000000
2017-05-16	123000.0	0.000000
2017-05-17	123000.0	0.000000
2017-05-18	123000.0	0.000000
2017-05-19	124000.0	0.008097
2017-05-22	124000.0	0.000000
2017-05-23	124000.0	0.000000
2017-05-24	124000.0	0.000000

In [4]: `li2co3.tail(10)`

Out[4]:

	Price	log_ret
Date		
2024-04-08	109500.0	0.027780
2024-04-09	109500.0	0.000000
2024-04-10	110500.0	0.009091
2024-04-11	109500.0	-0.009091
2024-04-12	109500.0	0.000000
2024-04-15	109500.0	0.000000
2024-04-16	109500.0	0.000000
2024-04-17	109500.0	0.000000
2024-04-18	109500.0	0.000000
2024-04-19	109500.0	0.000000

P2. Weekly log return series and zero count series

In [5]: `Fridays = pd.DataFrame()
Thursdays = pd.DataFrame()
Wednesdays = pd.DataFrame()
Tuesdays = pd.DataFrame()
Mondays = pd.DataFrame()`

In [6]: `def weekly_returns(data, chosen_day):
 # chosen_day = ['W-MON', 'W-TUE', 'W-WED', 'W-THU', 'W-FRI']
 weekly_log_return = data.groupby(pd.Grouper(freq=chosen_day))['log_ret'].sum()`

```
weekly_log_return = weekly_log_return.dropna()
return weekly_log_return
```

```
In [7]: def count_zero(df, chosen_day):
# chosen_day = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday']
# Create a zero dummy series: 1 if 'log_ret' is zero, 0 otherwise
data = df.copy()
data['zero_dummy'] = (data['log_ret'] == 0).astype(int)
# Compute the sum of past 22 days and past 5 days for zero_dummy
data['zero_count_22'] = data['zero_dummy'].rolling(window=22).sum()
data['zero_count_5'] = data['zero_dummy'].rolling(window=5).sum()
data = data.dropna()
# Extract chosen day
data['day_of_week'] = data.index.day_name()
chosendays_data = data[data['day_of_week'] == chosen_day]

# Select only the zero count columns and the index for Fridays
chosendays_data = chosendays_data[['zero_count_22', 'zero_count_5']]
chosendays_data['zero_count_22'] = chosendays_data['zero_count_22'].astype(int)
chosendays_data['zero_count_5'] = chosendays_data['zero_count_5'].astype(int)
return chosendays_data
```

```
In [8]: # Friday to Friday
Fridays['Log_Return'] = weekly_returns(li2co3, 'W-FRI')
Fridays['Zero_Count_22'] = count_zero(li2co3, 'Friday')['zero_count_22']
Fridays['Zero_Count_5'] = count_zero(li2co3, 'Friday')['zero_count_5']
Fridays = Fridays.dropna()

# Thursday to Thursday
Thursdays['Log_Return'] = weekly_returns(li2co3, 'W-THU')
Thursdays['Zero_Count_22'] = count_zero(li2co3, 'Thursday')['zero_count_22']
Thursdays['Zero_Count_5'] = count_zero(li2co3, 'Thursday')['zero_count_5']
Thursdays = Thursdays.dropna()

# Wednesday to Wednesday
Wednesdays['Log_Return'] = weekly_returns(li2co3, 'W-WED')
Wednesdays['Zero_Count_22'] = count_zero(li2co3, 'Wednesday')['zero_count_22']
Wednesdays['Zero_Count_5'] = count_zero(li2co3, 'Wednesday')['zero_count_5']
Wednesdays = Wednesdays.dropna()

# Tuesday to Tuesday
Tuesdays['Log_Return'] = weekly_returns(li2co3, 'W-TUE')
Tuesdays['Zero_Count_22'] = count_zero(li2co3, 'Tuesday')['zero_count_22']
Tuesdays['Zero_Count_5'] = count_zero(li2co3, 'Tuesday')['zero_count_5']
Tuesdays = Tuesdays.dropna()

# Monday to Monday
Mondays['Log_Return'] = weekly_returns(li2co3, 'W-MON')
Mondays['Zero_Count_22'] = count_zero(li2co3, 'Monday')['zero_count_22']
Mondays['Zero_Count_5'] = count_zero(li2co3, 'Monday')['zero_count_5']
Mondays = Mondays.dropna()
```

```
In [9]: print("Friday to Friday")
print(Fridays.tail(10))
print("Thursday to Thursday")
print(Thursdays.tail(10))
print("Wednesday to Wednesday")
print(Wednesdays.tail(10))
print("Tuesday to Tuesday")
print(Tuesdays.tail(10))
print("Monday to Monday")
print(Mondays.tail(10))
```

Friday to Firday

	Log_Return	Zero_Count_22	Zero_Count_5
Date			
2024-01-26	0.000000	22.0	5.0
2024-02-02	0.000000	22.0	5.0
2024-02-23	-0.005666	20.0	4.0
2024-03-01	0.092206	16.0	1.0
2024-03-08	0.050516	14.0	3.0
2024-03-15	0.038652	10.0	0.0
2024-03-22	0.028039	8.0	2.0
2024-03-29	-0.037563	7.0	2.0
2024-04-12	0.027780	7.0	2.0
2024-04-19	0.000000	12.0	5.0

Thursday to Thursday

	Log_Return	Zero_Count_22	Zero_Count_5
Date			
2024-01-25	0.000000	22.0	5.0
2024-02-01	0.000000	22.0	5.0
2024-02-22	-0.005666	20.0	4.0
2024-02-29	0.071263	17.0	2.0
2024-03-07	0.071459	14.0	2.0
2024-03-14	0.066691	10.0	1.0
2024-03-21	0.000000	8.0	1.0
2024-03-28	-0.037563	6.0	2.0
2024-04-11	0.027780	6.0	1.0
2024-04-18	0.000000	11.0	5.0

Wednesday to Wednesday

	Log_Return	Zero_Count_22	Zero_Count_5
Date			
2024-02-07	0.022858	21.0	4.0
2024-02-21	-0.005666	20.0	4.0
2024-02-28	0.039002	18.0	3.0
2024-03-06	0.103720	14.0	1.0
2024-03-13	0.057432	11.0	2.0
2024-03-20	0.000000	8.0	1.0
2024-03-27	-0.028304	5.0	1.0
2024-04-03	0.018958	8.0	3.0
2024-04-10	0.036871	7.0	1.0
2024-04-17	-0.009091	10.0	4.0

Tuesday to Tuesday

	Log_Return	Zero_Count_22	Zero_Count_5
Date			
2024-02-06	0.022858	21.0	4.0
2024-02-20	-0.005666	20.0	3.0
2024-02-27	0.016902	19.0	4.0
2024-03-05	0.125820	14.0	0.0
2024-03-12	0.029128	12.0	3.0
2024-03-19	0.028304	8.0	0.0
2024-03-26	-0.018780	6.0	2.0
2024-04-02	0.000000	8.0	3.0
2024-04-09	0.037214	8.0	2.0
2024-04-16	0.000000	9.0	3.0

Monday to Monday

	Log_Return	Zero_Count_22	Zero_Count_5
Date			
2024-02-05	0.022858	21.0	4.0
2024-02-19	0.000000	21.0	4.0
2024-02-26	-0.005666	20.0	4.0
2024-03-04	0.122821	15.0	0.0
2024-03-11	0.029705	13.0	3.0
2024-03-18	0.038282	9.0	0.0
2024-03-25	0.009346	7.0	2.0
2024-04-01	-0.028304	8.0	3.0

2024-04-08	0.046737	8.0	2.0
2024-04-15	0.000000	8.0	3.0

P3. Summary statistics

```
In [10]: summary_statistics_Fridays = Fridays.describe().loc[['mean', 'min', 'max', 'std']]
summary_statistics_Thursdays = Thursdays.describe().loc[['mean', 'min', 'max', 'std']]
summary_statistics_Wednesdays = Wednesdays.describe().loc[['mean', 'min', 'max', 'std']]
summary_statistics_Tuesdays = Tuesdays.describe().loc[['mean', 'min', 'max', 'std']]
summary_statistics_Mondays = Mondays.describe().loc[['mean', 'min', 'max', 'std']]

print("Friday to Friday")
print(summary_statistics_Fridays)
print("Thursday to Thursday")
print(summary_statistics_Thursdays)
print("Wednesday to Wednesday")
print(summary_statistics_Wednesdays)
print("Tuesday to Tuesday")
print(summary_statistics_Tuesdays)
print("Monday to Monday")
print(summary_statistics_Mondays)
```

```
Friday to Friday
      Log_Return  Zero_Count_22  Zero_Count_5
mean   -0.000397      15.089783      3.421053
min    -0.152469       0.000000      0.000000
max     0.267022      22.000000      5.000000
std     0.044616       5.608998      1.584804

Thursday to Thursday
      Log_Return  Zero_Count_22  Zero_Count_5
mean   -0.000692      15.096386      3.418675
min    -0.172141       0.000000      0.000000
max     0.204501      22.000000      5.000000
std     0.044082       5.556335      1.576646

Wednesday to Wednesday
      Log_Return  Zero_Count_22  Zero_Count_5
mean   -0.000154      15.036145      3.418675
min    -0.190575       0.000000      0.000000
max     0.252326      22.000000      5.000000
std     0.044743       5.529806      1.533911

Tuesday to Tuesday
      Log_Return  Zero_Count_22  Zero_Count_5
mean   -0.000803      15.026946      3.410180
min    -0.163827       0.000000      0.000000
max     0.298955      22.000000      5.000000
std     0.045178       5.532529      1.552684

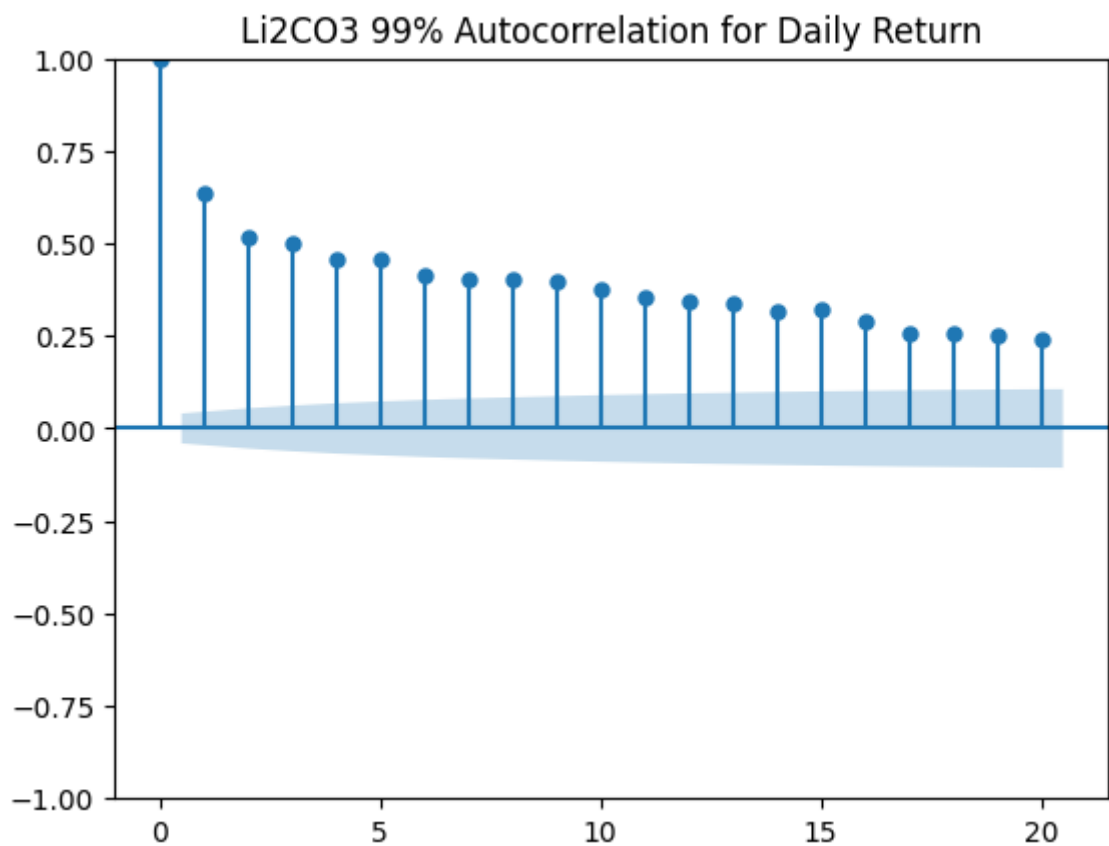
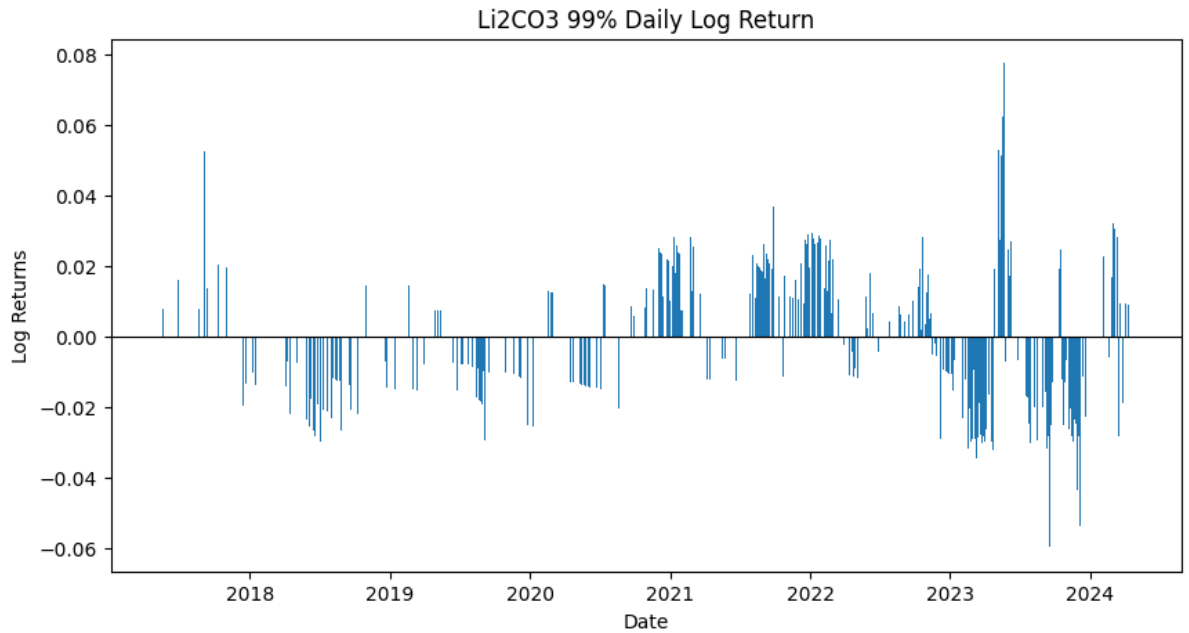
Monday to Monday
      Log_Return  Zero_Count_22  Zero_Count_5
mean   -0.000810      15.090062      3.403727
min    -0.171980       0.000000      0.000000
max     0.293305      22.000000      5.000000
std     0.045656       5.598839      1.576221
```

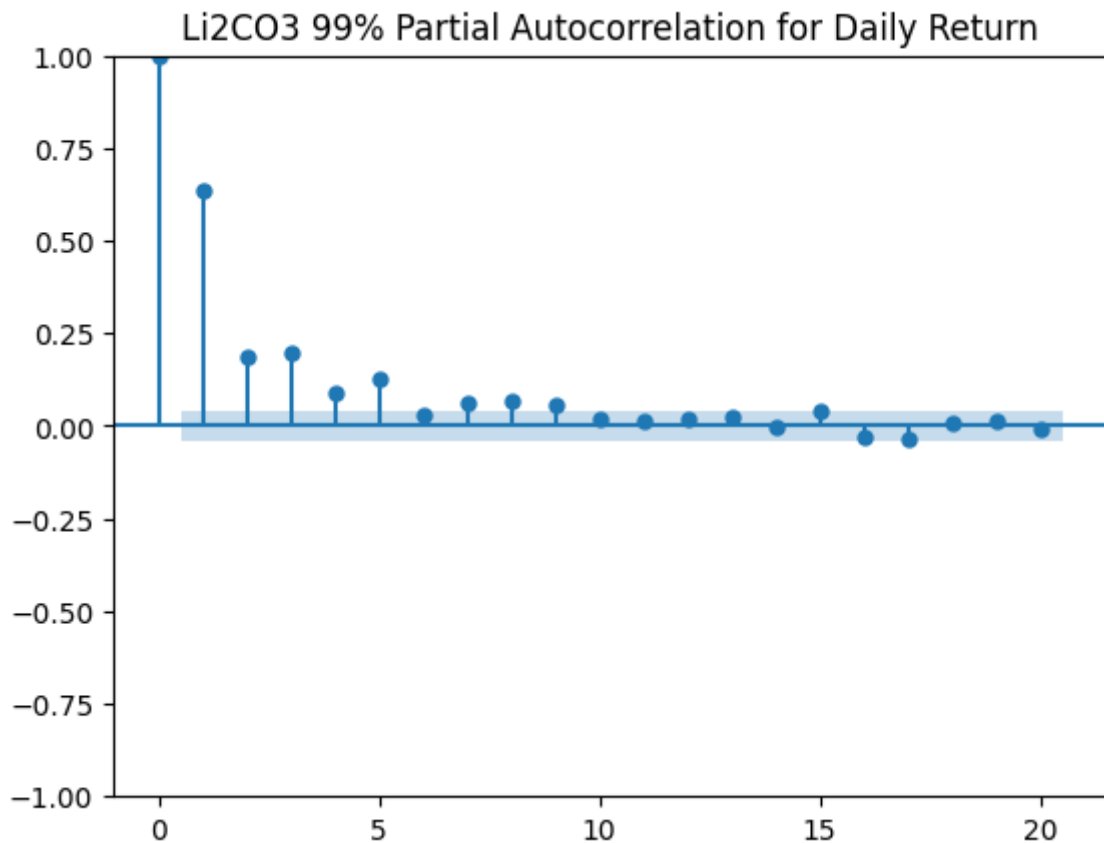
P4. Autocorrelogram and partial autocorrelogram for daily return

```
In [11]: # Daily return
fig, axs = plt.subplots(1, 1, figsize=(10, 5))
axs.bar(l12co3.index, l12co3['log_ret'], width=2.5)
```

```
plt.axhline(0, linewidth=0.8, color='k')
plt.xlabel('Date')
plt.ylabel('Log Returns')
plt.title('Li2CO3 99% Daily Log Return')
plt.show()

# Plot autocorrelation and partial autocorrelation
acf = plot_acf(li2co3['log_ret'], lags=20, alpha=0.1, title='Li2CO3 99% Autocorrelat
pacf = plot_pacf(li2co3['log_ret'], lags=20, alpha=0.1, method='ywm', title='Li2CO3
```





P5. Autocorrelogram and partial autocorrelogram for weekly return

```
In [12]: def plot_returns_acf_pacf(df, df_name):
    """
    Plots the log returns, autocorrelation, and partial autocorrelation for a given DataFrame.

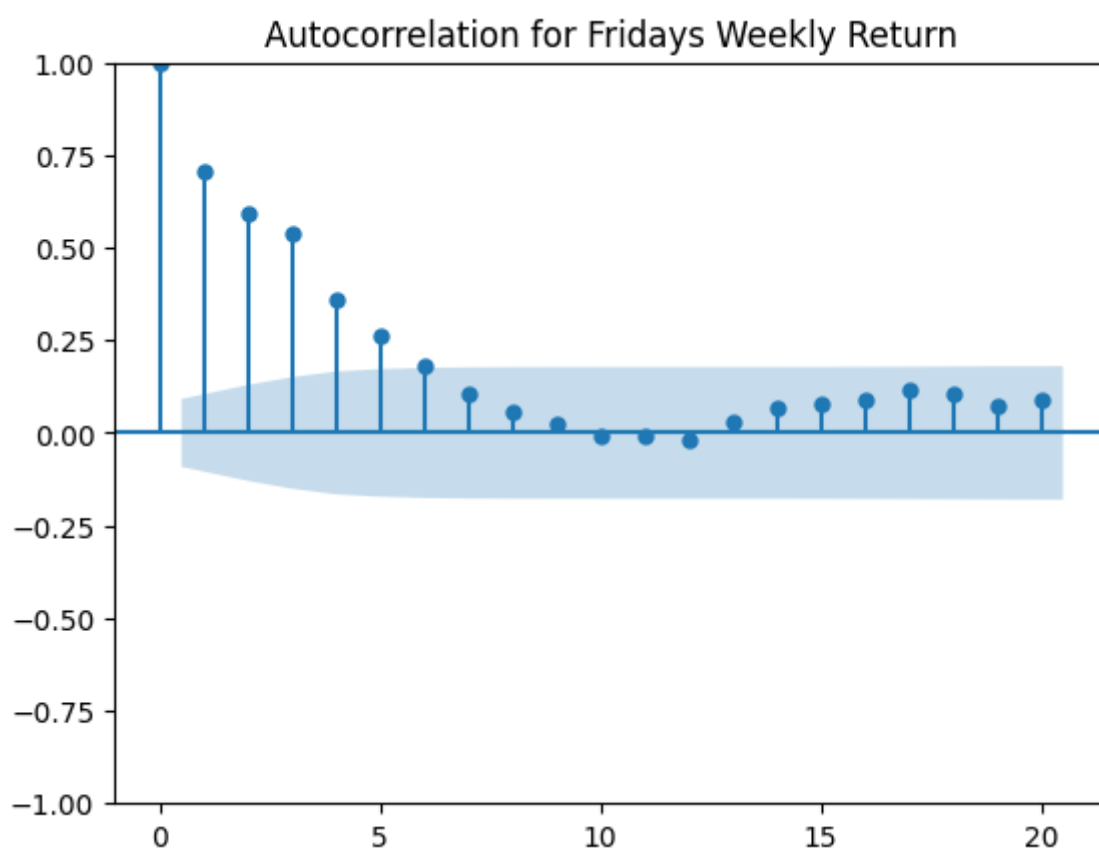
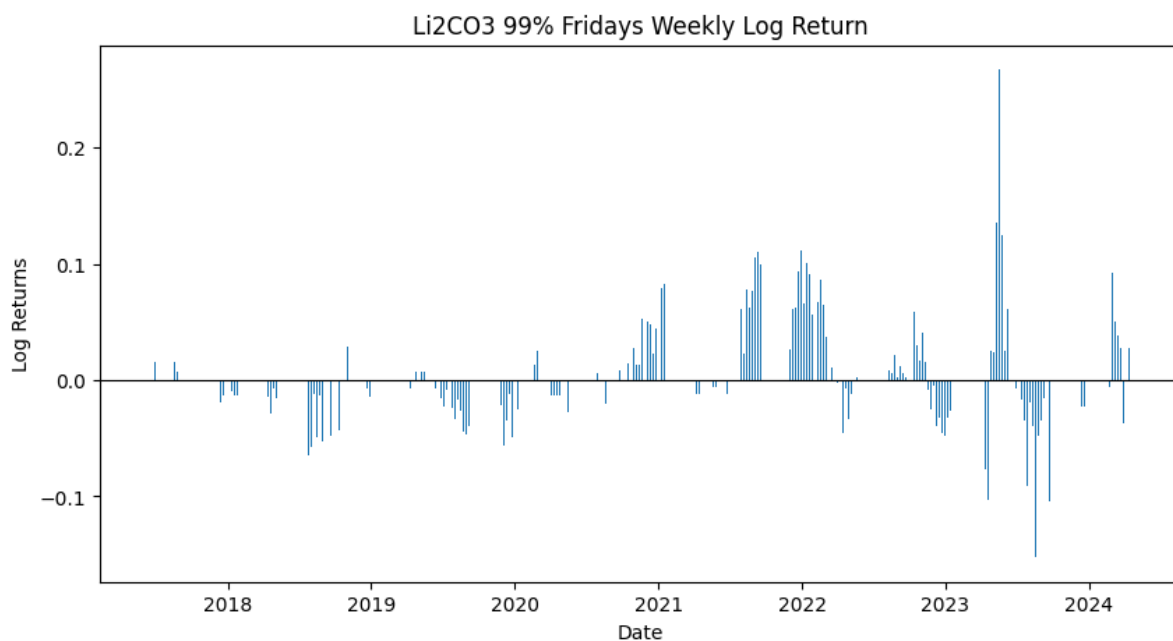
    Parameters:
    - df: The DataFrame containing the log returns data.
    - df_name: Name of the DataFrame to use in plot titles to indicate the data source.
    """
    data = df.copy()

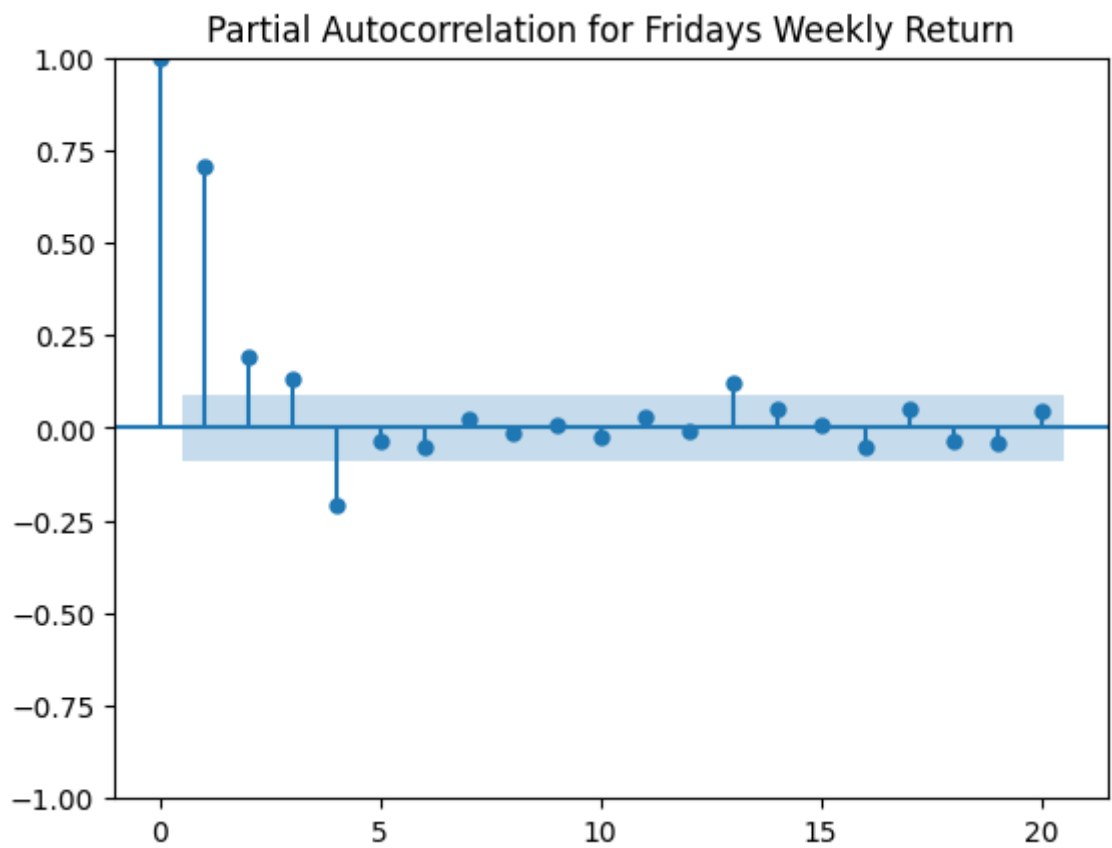
    # Plotting the log returns
    fig, axs = plt.subplots(1, 1, figsize=(10, 5))
    axs.bar(data.index, data['Log_Return'], width=2.5)
    plt.axhline(0, linewidth=0.8, color='k')
    plt.xlabel('Date')
    plt.ylabel('Log Returns')
    plt.title(f'Li2CO3 99% {df_name} Weekly Log Return')
    plt.show()

    # Plotting the autocorrelation
    fig_acf = plot_acf(data['Log_Return'], lags=20, alpha=0.1, title=f'Autocorrelation for {df_name}')

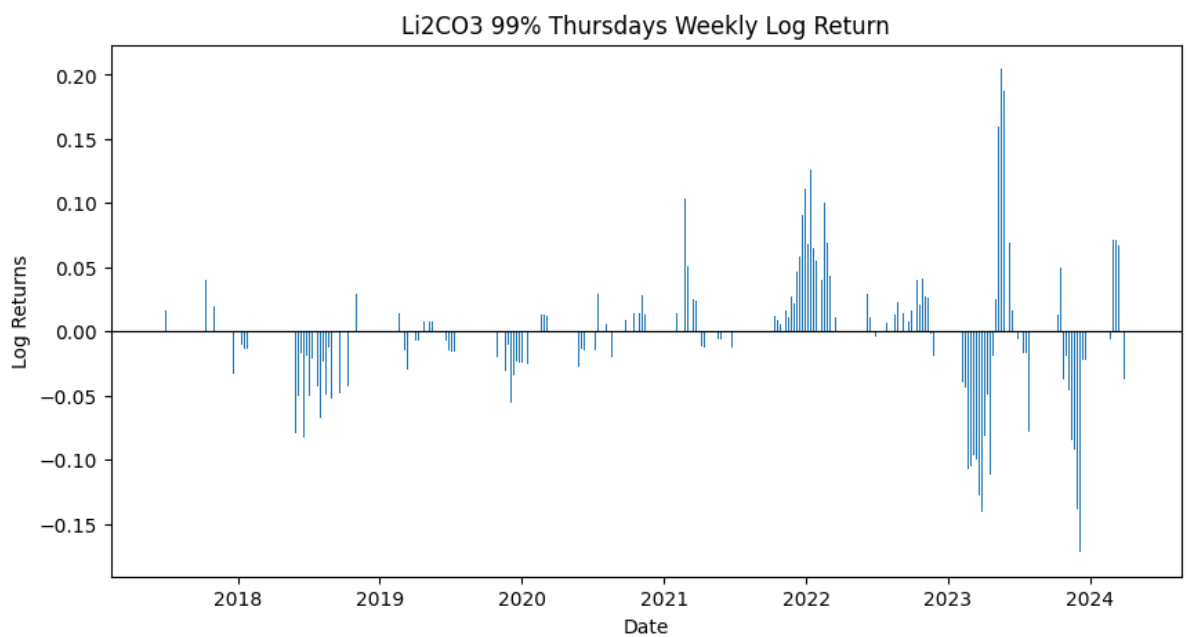
    # Plotting the partial autocorrelation
    fig_pacf = plot_pacf(data['Log_Return'], lags=20, alpha=0.1, method='yw', title=f'Partial Autocorrelation for {df_name}')
    plt.show()
```

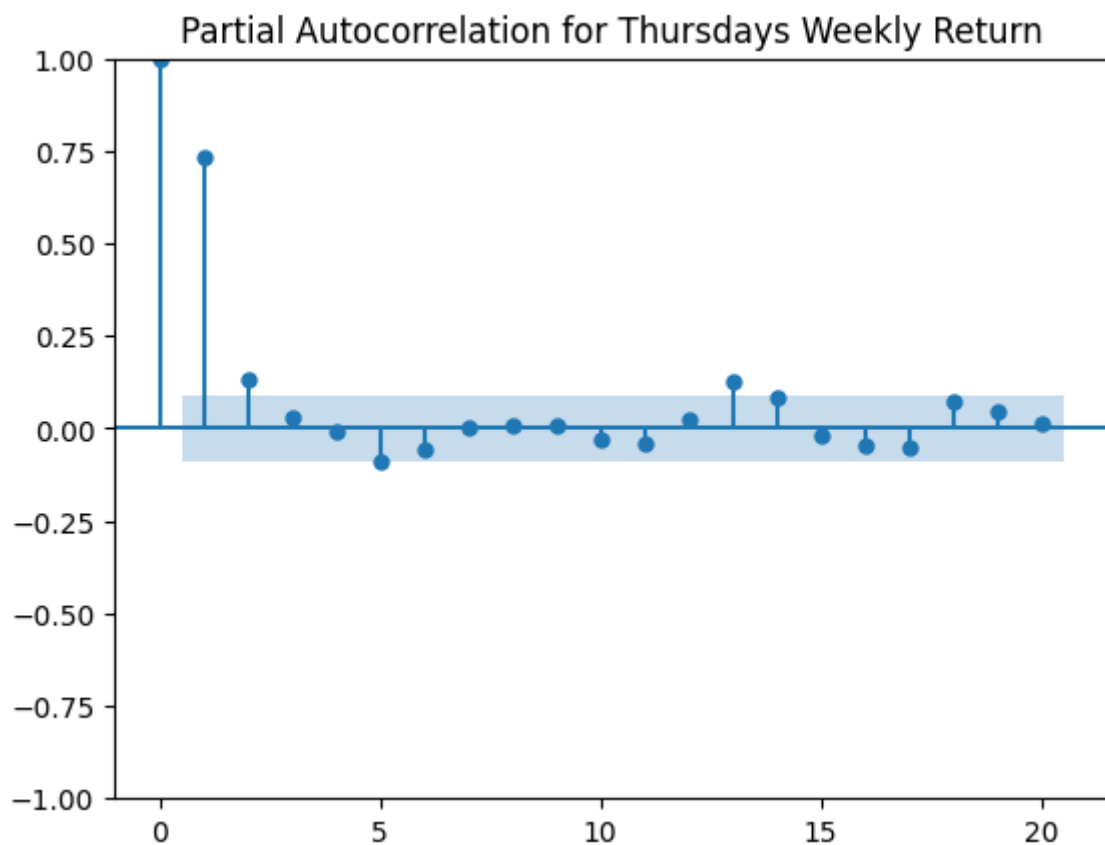
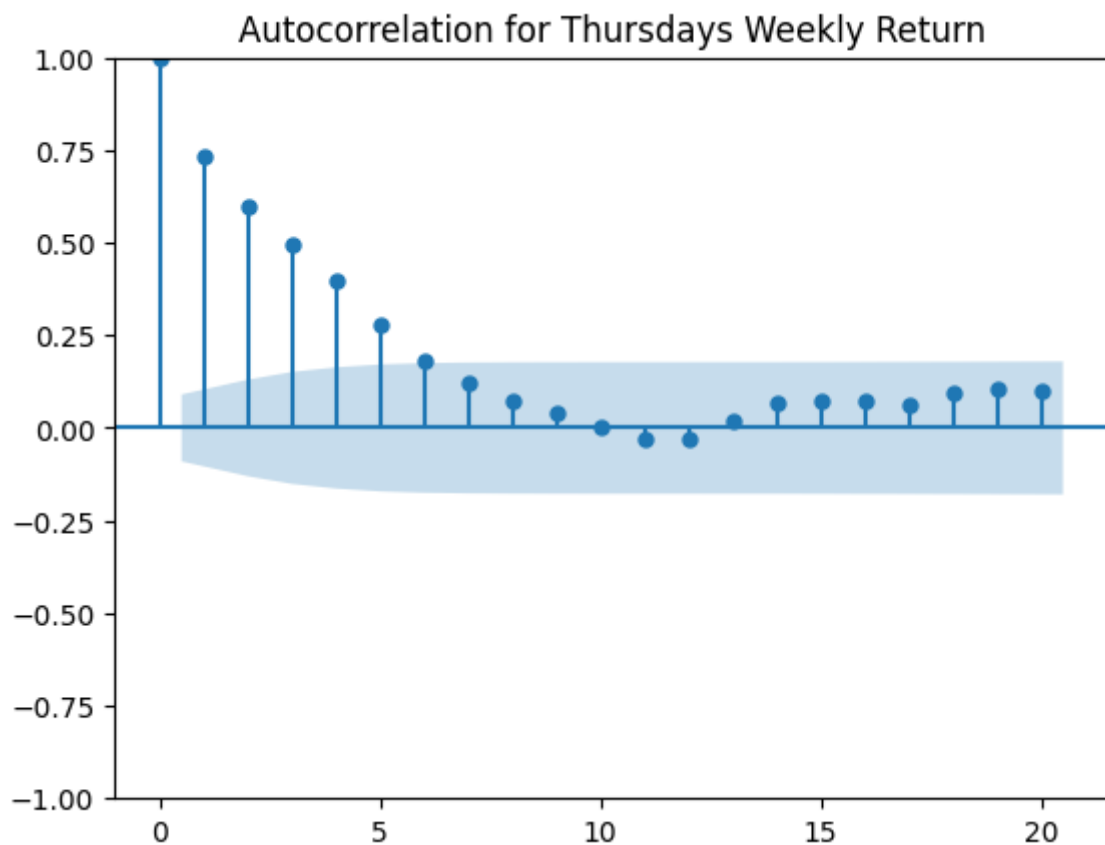
```
In [13]: # Fridays
plot_returns_acf_pacf(Fridays, 'Fridays')
```



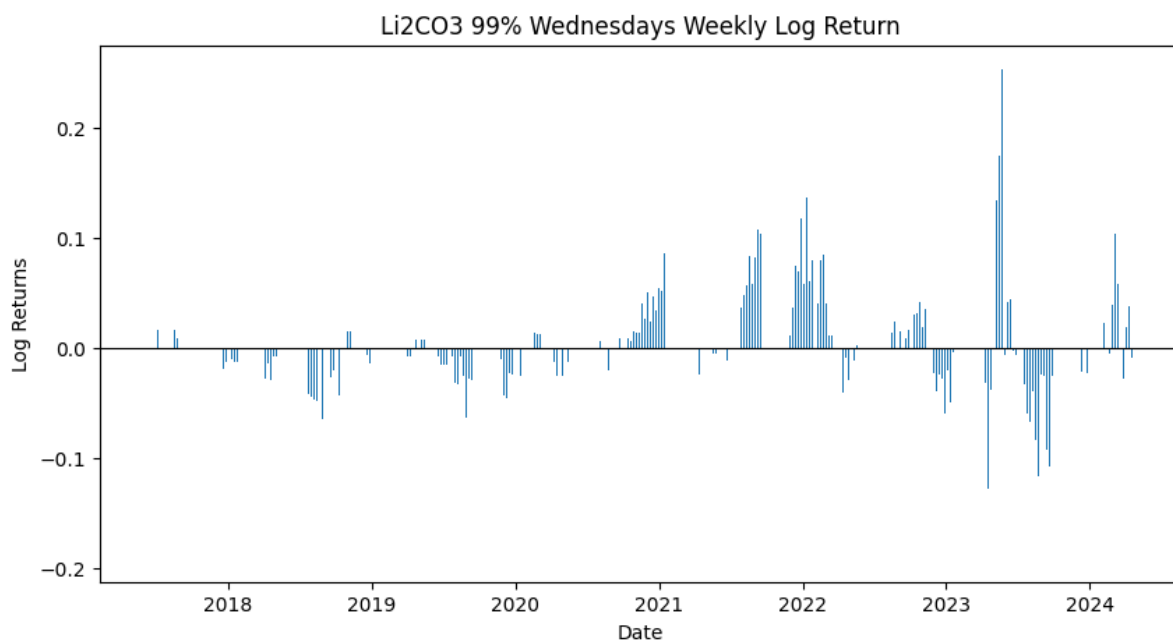


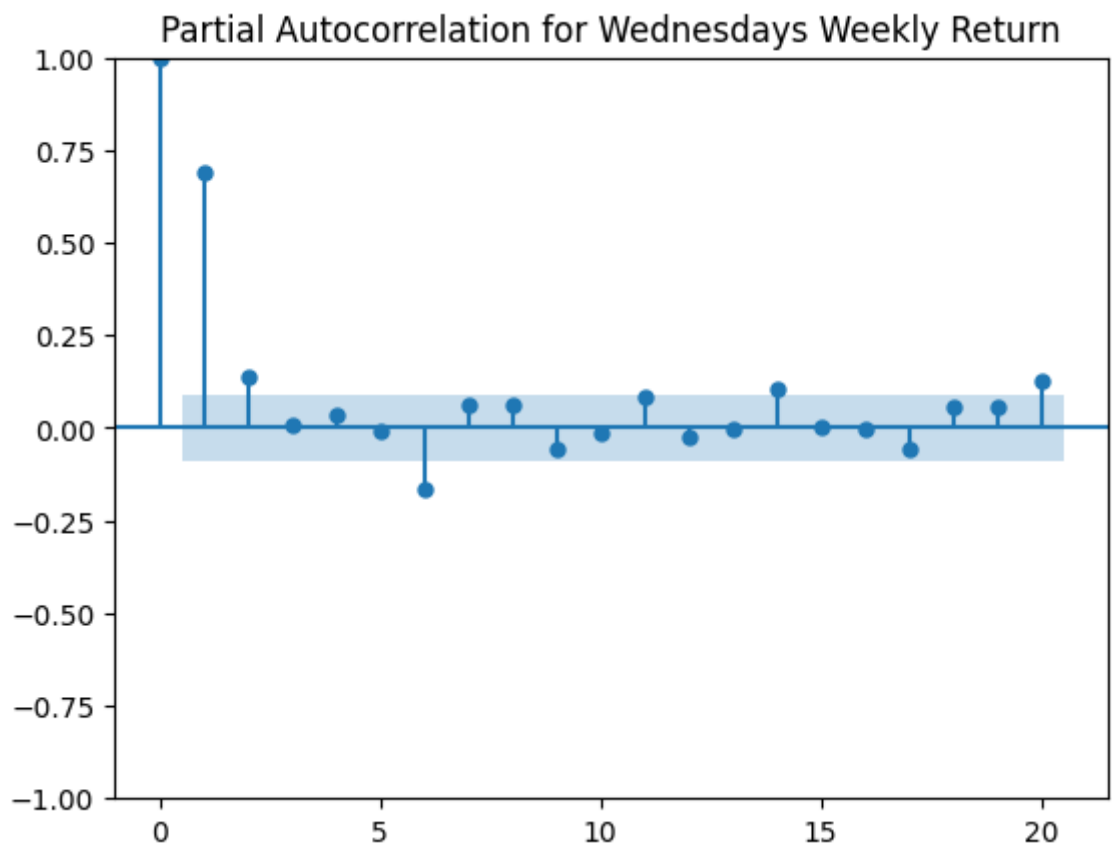
```
In [14]: # Thursdays  
plot_returns_acf_pacf(Thursdays, 'Thursdays')
```



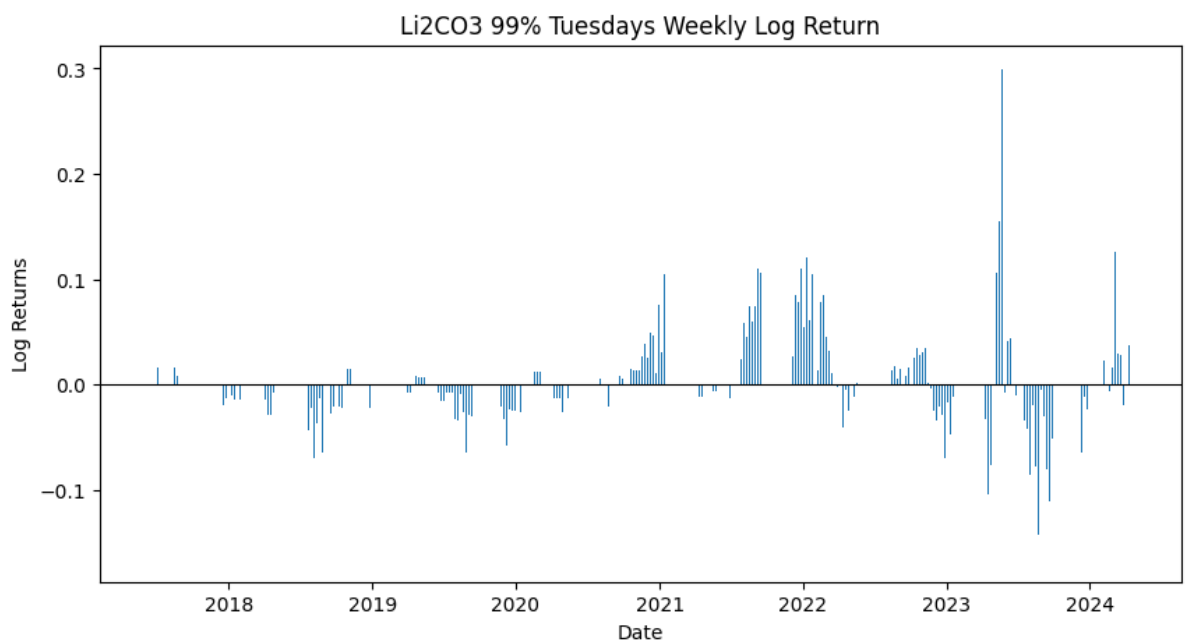


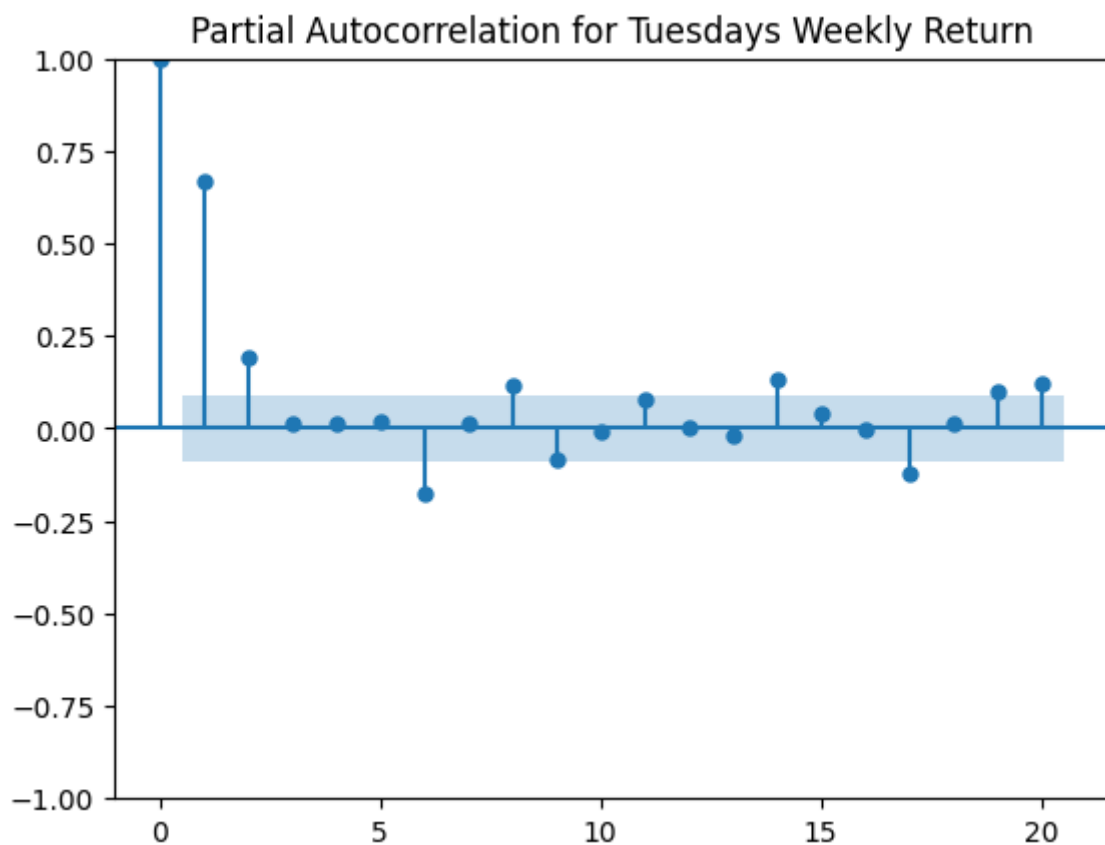
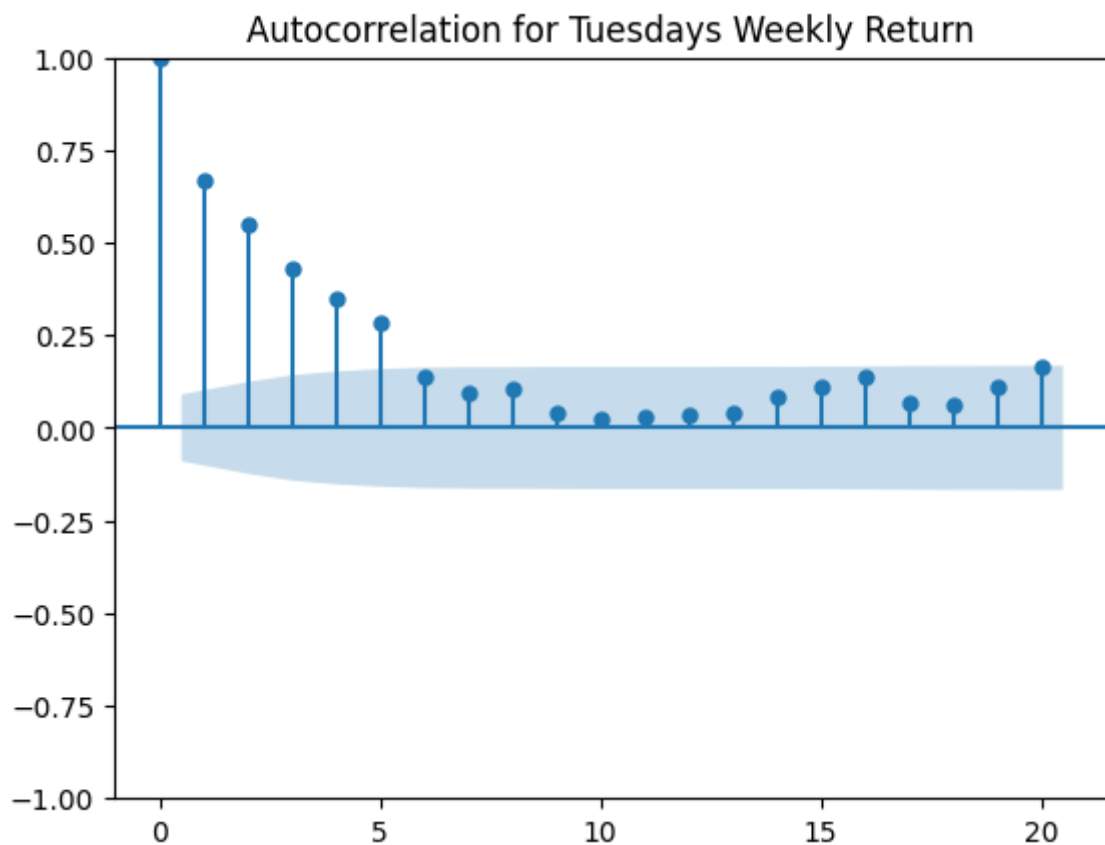
```
In [15]: # Wednesdays
plot_returns_acf_pacf(Wednesdays, 'Wednesdays')
```



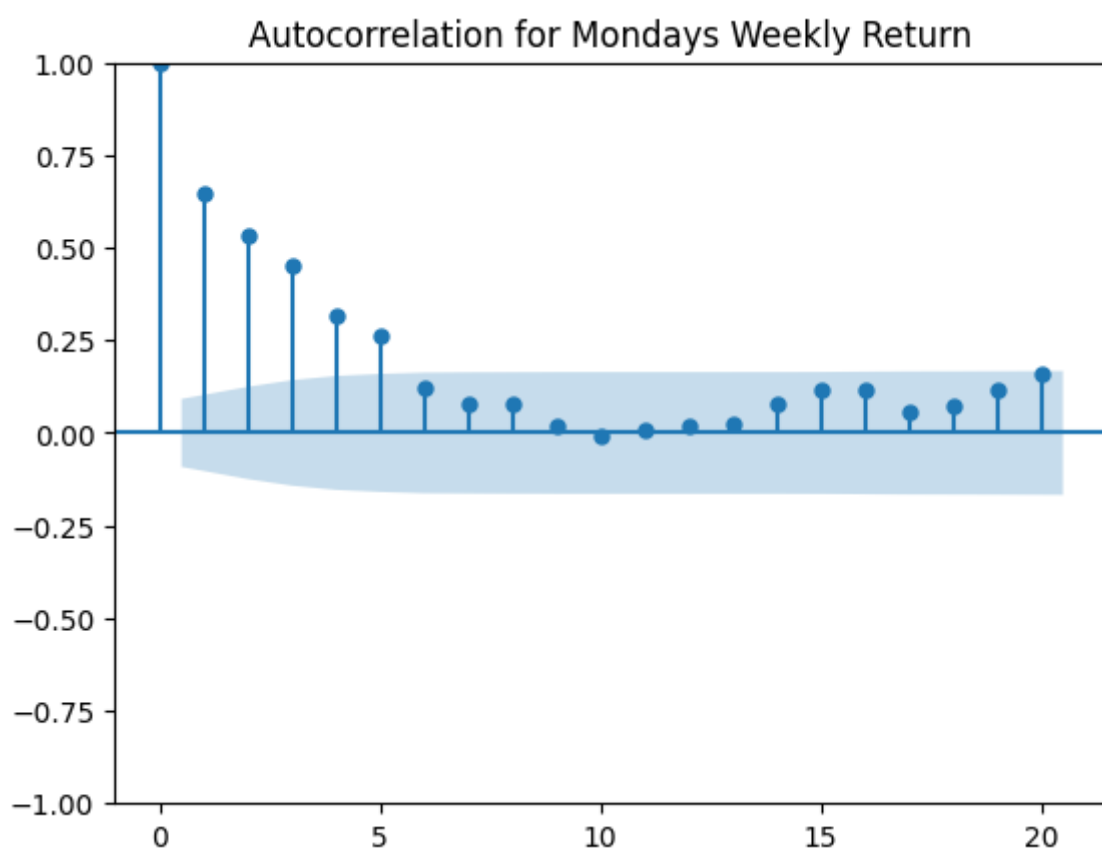
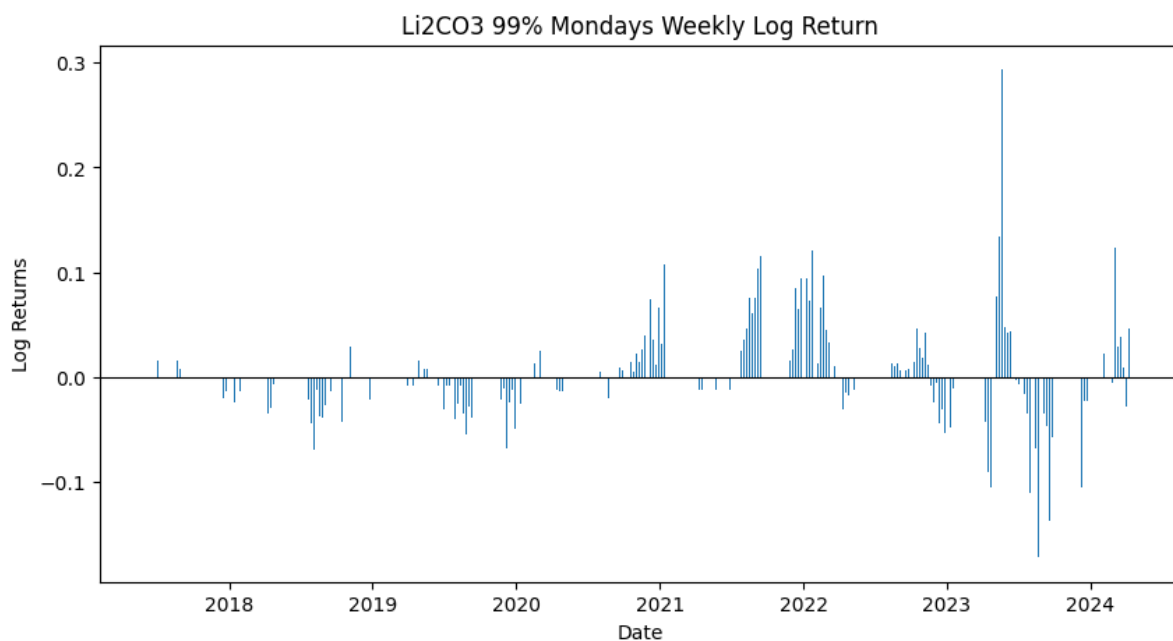


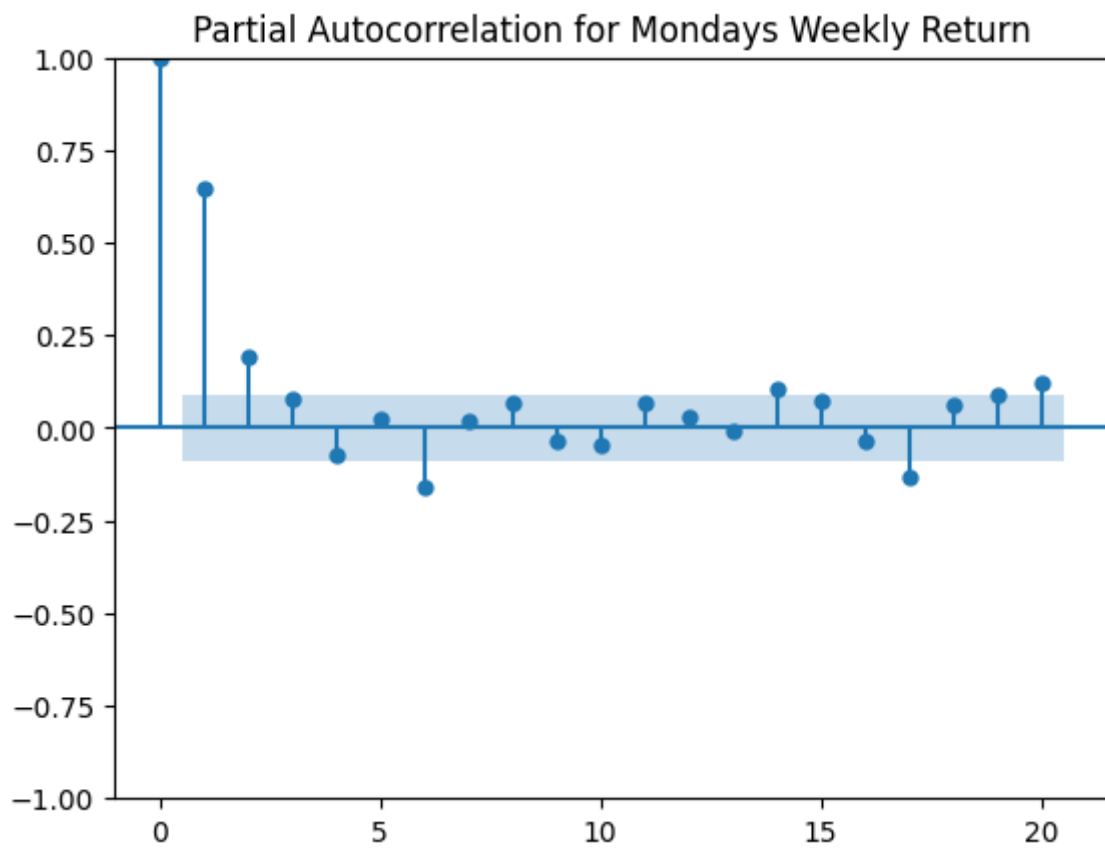
```
In [16]: # Tuesdays
plot_returns_acf_pacf(Tuesdays, 'Tuesdays')
```





```
In [17]: # Mondays
plot_returns_acf_pacf(Mondays, 'Mondays')
```





maxlags = 4 for Fridays

maxlags = 2 for others

P6. Two AR(2) models for daily return

```
In [18]: def estimate_ar2_model(df, lags):
        """
        Estimate a basic AR(2) model for returns.

        Parameters:
        - df: DataFrame containing the log returns series under 'log_ret'.
        - lags: Number of lags to use for HAC standard errors.

        Returns:
        - model: OLS regression results containing the fitted model.
        """

        data = df.copy()
        data['log_ret_lag1'] = data['log_ret'].shift(1)
        data['log_ret_lag2'] = data['log_ret'].shift(2)

        data.dropna(inplace=True)

        # Define the variables and add a constant term for the intercept (alpha)
        X = data[['log_ret_lag1', 'log_ret_lag2']]
        X = sm.add_constant(X) # Adds a constant column to input data set
        Y = data['log_ret']

        # Fit the AR(2) model
        model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kws={'maxlags': lags})

        return model
```

```
In [19]: # lags=5 according to the daily pacf
        daily_return_ar2_model = estimate_ar2_model(li2co3, lags=5)
```

```
In [20]: print(daily_return_ar2_model.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  log_ret      R-squared:                 0.424
Model:                            OLS       Adj. R-squared:                0.423
Method:                 Least Squares      F-statistic:                 188.0
Date:                  Wed, 22 May 2024    Prob (F-statistic):          2.62e-74
Time:                  07:43:05           Log-Likelihood:              5540.0
No. Observations:        1662            AIC:                       -1.107e+04
Df Residuals:            1659            BIC:                       -1.106e+04
Df Model:                  2
Covariance Type:          HAC
=====

```

	coef	std err	z	P> z	[0.025	0.975]
const	-2.075e-05	0.000	-0.104	0.917	-0.000	0.000
log_ret_lag1	0.5158	0.036	14.302	0.000	0.445	0.586
log_ret_lag2	0.1876	0.038	4.933	0.000	0.113	0.262

```

=====
Omnibus:                  177.765    Durbin-Watson:                2.075
Prob(Omnibus):             0.000    Jarque-Bera (JB):             1463.753
Skew:                      -0.004    Prob(JB):                     0.00
Kurtosis:                  7.598    Cond. No.                     145.
=====

```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 5 lags and without small sample correction

```
In [21]: def estimate_ar2_model_with_zero_dummy(df, lags):
        """
```



```

Estimate an AR(2) model for log returns with modifications to account for zero du

Parameters:
- df: DataFrame containing the log returns 'log_ret'.
- lags: Number of lags to use for HAC standard errors.

Returns:
- model: OLS regression results containing the fitted model.
"""

data = df.copy()
data['zero_dummy'] = (data['log_ret'] == 0).astype(int)

# Generate lagged return series
data['log_ret_lag1'] = data['log_ret'].shift(1)
data['log_ret_lag2'] = data['log_ret'].shift(2)

# Generate interaction terms
data['log_ret_lag1_zero'] = data['log_ret_lag1'] * data['zero_dummy']
data['log_ret_lag2_zero'] = data['log_ret_lag2'] * data['zero_dummy']

data.dropna(inplace=True)

# Define the new model with additional interaction terms
X = data[['zero_dummy', 'log_ret_lag1', 'log_ret_lag2', 'log_ret_lag1_zero', 'lo
X = sm.add_constant(X)
Y = data['log_ret']

# Fit the AR(2) model
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kwds={'maxlags': lags})

return model

```

```

In [22]: # lags=5 according to the daily pacf
daily_return_ar2_model_with_zero_dummy = estimate_ar2_model_with_zero_dummy(li2co3,

```

```

In [23]: print(daily_return_ar2_model_with_zero_dummy.summary())

```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          log_ret      R-squared:                 0.607
Model:                  OLS          Adj. R-squared:            0.605
Method:                 Least Squares   F-statistic:              442.3
Date:                  Wed, 22 May 2024   Prob (F-statistic):       5.35e-211
Time:                  07:43:05         Log-Likelihood:           5856.5
No. Observations:      1662            AIC:                     -1.170e+04
Df Residuals:          1656            BIC:                     -1.167e+04
Df Model:              5
Covariance Type:       HAC
=====
=

```

	coef	std err	z	P> z	[0.025	0.97
const	-0.0010	0.001	-1.594	0.111	-0.002	0.00
zero_dummy	0.0010	0.001	1.594	0.111	-0.000	0.00
log_ret_lag1	0.6606	0.045	14.796	0.000	0.573	0.74
log_ret_lag2	0.3622	0.048	7.575	0.000	0.268	0.45
log_ret_lag1_zero	-0.6606	0.045	-14.796	0.000	-0.748	-0.57
log_ret_lag2_zero	-0.3622	0.048	-7.575	0.000	-0.456	-0.26

```

=====
Omnibus:                 304.524    Durbin-Watson:              1.918
Prob(Omnibus):           0.000     Jarque-Bera (JB):           5065.128
Skew:                    0.339     Prob(JB):                   0.00
Kurtosis:                11.526    Cond. No.                   413.
=====

```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 5 lags and without small sample correction

/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:1894: ValueWarning: covariance of constraints does not have full rank. The number of constraints is 5, but rank is 3

warnings.warn('covariance of constraints does not have full ')

P7. Four AR(2) models for returns with zero count series (use Fridays as example)

Model1: Standard AR(2) model

```

In [24]: def estimate_ar2_model(df, lags):
          """
          Estimate a basic AR(2) model for returns.

          Parameters:
          - df: DataFrame containing the log returns series under 'Log_Return'.
          - lags: Number of lags to use for HAC standard errors.

          Returns:
          - model: OLS regression results containing the fitted model.

```

```

"""

data = df.copy()
data['log_ret_lag1'] = data['Log_Return'].shift(1)
data['log_ret_lag2'] = data['Log_Return'].shift(2)

data.dropna(inplace=True)

# Define the variables and add a constant term for the intercept (alpha)
X = data[['log_ret_lag1', 'log_ret_lag2']]
X = sm.add_constant(X) # Adds a constant column to input data set
Y = data['Log_Return']

# Fit the AR(2) model
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kwds={'maxlags': lags})

return model

```

```

In [25]: # lags=4 according to the weekly pacf
weekly_return_ar2_model = estimate_ar2_model(Fridays, lags=4)

print(weekly_return_ar2_model.summary())

```

```

OLS Regression Results
=====
Dep. Variable:          Log_Return      R-squared:                0.516
Model:                  OLS             Adj. R-squared:           0.513
Method:                 Least Squares    F-statistic:              84.51
Date:                   Wed, 22 May 2024  Prob (F-statistic):      3.69e-30
Time:                   07:43:06         Log-Likelihood:           658.66
No. Observations:       321             AIC:                     -1311.
Df Residuals:           318             BIC:                     -1300.
Df Model:               2
Covariance Type:        HAC
=====

```

	coef	std err	z	P> z	[0.025	0.975]
const	-7.831e-05	0.002	-0.044	0.965	-0.004	0.003
log_ret_lag1	0.5691	0.079	7.160	0.000	0.413	0.725
log_ret_lag2	0.1929	0.088	2.188	0.029	0.020	0.366

```

=====
Omnibus:                73.893      Durbin-Watson:           2.050
Prob(Omnibus):          0.000      Jarque-Bera (JB):        539.301
Skew:                   0.713      Prob(JB):                7.80e-118
Kurtosis:               9.188      Cond. No.                41.3
=====

```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Model2: AR(2) model using interaction with the weekly zero count series

```

In [26]: def estimate_ar2_model_with_weekly_zero(df, lags):
        """
        Estimate an AR(2) model for weekly log returns, incorporating
        weekly zero count series as interaction effect,
        and allowing for specification of lags for HAC standard errors.

        Parameters:
        - df: DataFrame containing the weekly log returns under 'Log_Return',

```

```

        and the weekly zero count series 'Zero_Count_5'.
    - lags: Maximum number of lags to use for HAC standard errors.

Returns:
- model: OLS regression results containing the fitted model with HAC standard errors
"""

data = df.copy()
# Generate lagged return series
data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
data['Log_Return_Lag2'] = data['Log_Return'].shift(2)

# Generate interaction terms for lagged returns and 'Zero_Count_5'
data['Log_Return_Lag1_Zero5'] = data['Log_Return_Lag1'] * data['Zero_Count_5']
data['Log_Return_Lag2_Zero5'] = data['Log_Return_Lag2'] * data['Zero_Count_5']

# Drop any rows with NaN values that were created by lagging
data.dropna(inplace=True)

# Define the model with additional interaction terms
X = data[['Zero_Count_5', 'Log_Return_Lag1', 'Log_Return_Lag2',
          'Log_Return_Lag1_Zero5', 'Log_Return_Lag2_Zero5']]
X = sm.add_constant(X)
Y = data['Log_Return']

# Fit the model with HAC standard errors
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kwds={'maxlags': lags})

return model

```

```

In [27]: # lags=4 according to the weekly pacf
ar2_model_with_weekly_zero = estimate_ar2_model_with_weekly_zero(Fridays, lags=4)

print(ar2_model_with_weekly_zero.summary())

```

OLS Regression Results					
=====					
Dep. Variable:	Log_Return	R-squared:	0.656		
Model:	OLS	Adj. R-squared:	0.650		
Method:	Least Squares	F-statistic:	61.77		
Date:	Wed, 22 May 2024	Prob (F-statistic):	9.64e-45		
Time:	07:43:06	Log-Likelihood:	713.29		
No. Observations:	321	AIC:	-1415.		
Df Residuals:	315	BIC:	-1392.		
Df Model:	5				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	-0.0015	0.007	-0.202	0.840	-0.016
0.013					
Zero_Count_5	6.781e-05	0.002	0.041	0.967	-0.003
0.003					
Log_Return_Lag1	0.9768	0.188	5.203	0.000	0.609
1.345					
Log_Return_Lag2	0.3009	0.179	1.680	0.093	-0.050
0.652					
Log_Return_Lag1_Zero5	-0.2143	0.058	-3.664	0.000	-0.329
0.100					
Log_Return_Lag2_Zero5	-0.0485	0.047	-1.022	0.307	-0.141
0.045					
=====					
Omnibus:	88.859	Durbin-Watson:	1.738		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	614.566		
Skew:	0.938	Prob(JB):	3.54e-134		
Kurtosis:	9.514	Cond. No.	340.		
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Model3: AR(2) model using interaction with the monthly zero count series

```
In [28]: def estimate_ar2_model_with_monthly_zero(df, lags):
    """
    Estimate an AR(2) model for weekly log returns, incorporating
    monthly zero count series as interaction effect,
    and allowing for specification of lags for HAC standard errors.

    Parameters:
    - df: DataFrame containing the weekly log returns under 'Log_Return',
      and the monthly zero count series 'Zero_Count_22'.
    - lags: Maximum number of lags to use for HAC standard errors.

    Returns:
    - model: OLS regression results containing the fitted model with HAC standard errors
    """

    data = df.copy()
    # Generate lagged return series
    data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
    data['Log_Return_Lag2'] = data['Log_Return'].shift(2)
```

```

# Generate interaction terms for lagged returns and 'Zero_Count_22'
data['Log_Return_Lag1_Zero22'] = data['Log_Return_Lag1'] * data['Zero_Count_22']
data['Log_Return_Lag2_Zero22'] = data['Log_Return_Lag2'] * data['Zero_Count_22']

# Drop any rows with NaN values that were created by lagging
data.dropna(inplace=True)

# Define the model with additional interaction terms
X = data[['Zero_Count_22', 'Log_Return_Lag1', 'Log_Return_Lag2',
          'Log_Return_Lag1_Zero22', 'Log_Return_Lag2_Zero22']]
X = sm.add_constant(X)
Y = data['Log_Return']

# Fit the model with HAC standard errors
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kwds={'maxlags': lags})

return model

```

```

In [29]: # lags=4 according to the weekly pacf
ar2_model_with_monthly_zero = estimate_ar2_model_with_monthly_zero(Fridays, lags=4)

print(ar2_model_with_monthly_zero.summary())

```

OLS Regression Results					
=====					
Dep. Variable:	Log_Return	R-squared:	0.540		
Model:	OLS	Adj. R-squared:	0.533		
Method:	Least Squares	F-statistic:	43.84		
Date:	Wed, 22 May 2024	Prob (F-statistic):	2.99e-34		
Time:	07:43:06	Log-Likelihood:	666.79		
No. Observations:	321	AIC:	-1322.		
Df Residuals:	315	BIC:	-1299.		
Df Model:	5				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	0.0009	0.008	0.122	0.903	-0.014
0.016					
Zero_Count_22	-0.0001	0.000	-0.266	0.790	-0.001
0.001					
Log_Return_Lag1	0.9183	0.177	5.179	0.000	0.571
1.266					
Log_Return_Lag2	0.0360	0.206	0.175	0.861	-0.368
0.440					
Log_Return_Lag1_Zero22	-0.0396	0.013	-3.042	0.002	-0.065
-0.014					
Log_Return_Lag2_Zero22	0.0109	0.014	0.766	0.444	-0.017
0.039					
=====					
Omnibus:	62.191	Durbin-Watson:	1.967		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	422.402		
Skew:	0.568	Prob(JB):	1.89e-92		
Kurtosis:	8.504	Cond. No.	1.60e+03		

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

[2] The condition number is large, 1.6e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Model4: AR(2) model separately using interactions with the short-term illiquidity and long-term illiquidity variable

```
In [30]: def estimate_ar2_model_separate_illiquidity(df, lags):
    """
    Estimate a complex AR(2) model for log returns, incorporating
    separate interactions with two types of zero counts.
    The formula incorporates separate interactions for different lags
    with different term-length zero count measures.

    Parameters:
    - df: DataFrame containing the log returns under 'Log_Return',
        two zero count series 'Zero_Count_5' and 'Zero_Count_22'.
    - lags: Maximum number of lags to use for HAC standard errors.

    Returns:
    - model: OLS regression results containing the fitted model with HAC standard errors
    """
```

```

data = df.copy()
# Generate lagged return series
data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
data['Log_Return_Lag2'] = data['Log_Return'].shift(2)

# Generate separate interaction terms for lagged returns and zero counts
data['Log_Return_Lag1_Zero5'] = data['Log_Return_Lag1'] * data['Zero_Count_5']
data['Log_Return_Lag2_Zero22'] = data['Log_Return_Lag2'] * data['Zero_Count_22']

# Drop any rows with NaN values that were created by lagging
data.dropna(inplace=True)

# Define the model with additional interaction terms
X = data[['Zero_Count_5', 'Zero_Count_22', 'Log_Return_Lag1', 'Log_Return_Lag2',
          'Log_Return_Lag1_Zero5', 'Log_Return_Lag2_Zero22']]
X = sm.add_constant(X)
Y = data['Log_Return']

# Fit the model with HAC standard errors
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kwds={'maxlags': lags})

return model

```

```

In [31]: # lags=4 according to the weekly pacf
ar2_model_with_separate_illiquidity = estimate_ar2_model_separate_illiquidity(Friday)

print(ar2_model_with_separate_illiquidity.summary())

```


OLS Regression Results					
=====					
Dep. Variable:	Log_Return	R-squared:	0.665		
Model:	OLS	Adj. R-squared:	0.659		
Method:	Least Squares	F-statistic:	89.29		
Date:	Wed, 22 May 2024	Prob (F-statistic):	6.64e-65		
Time:	07:43:06	Log-Likelihood:	717.72		
No. Observations:	321	AIC:	-1421.		
Df Residuals:	314	BIC:	-1395.		
Df Model:	6				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	-0.0006	0.006	-0.089	0.929	-0.013
0.012					
Zero_Count_5	0.0010	0.002	0.410	0.682	-0.004
0.006					
Zero_Count_22	-0.0003	0.001	-0.447	0.655	-0.001
0.001					
Log_Return_Lag1	1.2167	0.127	9.596	0.000	0.968
1.465					
Log_Return_Lag2	-0.1038	0.133	-0.782	0.434	-0.364
0.156					
Log_Return_Lag1_Zero5	-0.2886	0.036	-8.052	0.000	-0.359
-0.218					
Log_Return_Lag2_Zero22	0.0286	0.011	2.618	0.009	0.007
0.050					
=====					
Omnibus:	87.066	Durbin-Watson:	1.952		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	525.799		
Skew:	0.960	Prob(JB):	6.67e-115		
Kurtosis:	8.969	Cond. No.	1.27e+03		
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

[2] The condition number is large, 1.27e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Comparsion among last three models

```
In [32]: model1_results = ar2_model_with_weekly_zero
model2_results = ar2_model_with_monthly_zero
model3_results = ar2_model_with_separate_illiquidity

# Create a DataFrame to summarize the fit statistics
summary_stats = pd.DataFrame({
    'Model': ['Model with Weekly Zero', 'Model with Monthly Zero', 'Model with Separate Illiquidity'],
    'R-squared': [model1_results.rsquared, model2_results.rsquared, model3_results.rsquared],
    'Adj. R-squared': [model1_results.rsquared_adj, model2_results.rsquared_adj, model3_results.rsquared_adj],
    'AIC': [model1_results.aic, model2_results.aic, model3_results.aic],
    'BIC': [model1_results.bic, model2_results.bic, model3_results.bic],
    'F-statistic': [model1_results.fvalue, model2_results.fvalue, model3_results.fvalue]
})

# Print the summary statistics using tabulate
print(tabulate(summary_stats, headers='keys', tablefmt='pretty', showindex=False))
```

Model		R-squared	Adj. R-squared
AIC	BIC	F-statistic	
Model with Weekly Zero	0.6555624644924585	0.6500952020240849	-1414.5814877806774
Model with Monthly Zero	0.5398221716814222	0.5325177617081115	-1321.587709665845
Model with Separate Illiquidity	0.6649370501762542	0.6585345734280297	-1421.4392679155076

Interpretation

R-squared & Adj. R-squared: The proportion of the variance in the dependent variable that is predictable from the independent variables. The higher these values, the better the model explains the variability of the response variable. From the table, the *Model with Separate Illiquidity* has both the highest R-squared and the highest Adjusted R-squared, which means it is the best model that explains the highest proportion of variance in the weekly log return series among the last three models.

AIC & BIC: Both criteria help in model selection where lower values generally indicate a better model. AIC shows the goodness of fit with a penalty for the number of parameters to avoid overfitting, and BIC considers a larger penalty for models with more parameters. The *Model with Separate Illiquidity* has both the lowest AIC and the lowest BIC, which means it is the best model from a complexity-fit trade-off perspective.

F-statistic: Indicates the overall significance of the regression AR(2) model. The higher the F-statistic, the more significant the model is. The *Model with Separate Illiquidity* has the highest F-statistic, which means it is statistically the most significant model in terms of the contribution of the explanatory variables used in the model.

Conclusion

Model with Separate Illiquidity has advantages on all three aspects: explaining the variance in the weekly log return; balance between model complexity and fit; and also, the prediction ability, because the statistical significance of this model's explanatory variables is highest, making it potentially more reliable when making predictions or inferences.

Besides, *Model with Weekly Zero* is the second best model, where its variance explaining ability and complexity-fit balance are all very close to the *Model with Separate Illiquidity*.

The conclusion is just for Friday to Friday return series, it might be different for other days.

P8: Rescale zero count series to zero fraction series

```
In [33]: # Rescale the zero counts to be fractions of their respective periods
Fridays['Zero_Fraction_5'] = Fridays['Zero_Count_5'] / 5
Fridays['Zero_Fraction_22'] = Fridays['Zero_Count_22'] / 22

print(Fridays[['Zero_Count_5', 'Zero_Fraction_5', 'Zero_Count_22', 'Zero_Fraction_22']])
# Double check the range
print(Fridays[['Zero_Count_5', 'Zero_Fraction_5', 'Zero_Count_22', 'Zero_Fraction_22']])
```

	Zero_Count_5	Zero_Fraction_5	Zero_Count_22	Zero_Fraction_22
Date				
2017-06-16	5.0	1.0	21.0	0.954545
2017-06-23	5.0	1.0	22.0	1.000000
2017-06-30	4.0	0.8	21.0	0.954545
2017-07-07	5.0	1.0	21.0	0.954545
2017-07-14	5.0	1.0	21.0	0.954545
	Zero_Count_5	Zero_Fraction_5	Zero_Count_22	Zero_Fraction_22
count	323.000000	323.000000	323.000000	323.000000
mean	3.421053	0.684211	15.089783	0.685899
std	1.584804	0.316961	5.608998	0.254954
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	0.400000	11.500000	0.522727
50%	4.000000	0.800000	17.000000	0.772727
75%	5.000000	1.000000	20.000000	0.909091
max	5.000000	1.000000	22.000000	1.000000

```
In [34]: Thursdays['Zero_Fraction_5'] = Thursdays['Zero_Count_5'] / 5
Thursdays['Zero_Fraction_22'] = Thursdays['Zero_Count_22'] / 22
print(Thursdays[['Zero_Count_5', 'Zero_Fraction_5', 'Zero_Count_22', 'Zero_Fraction_22']])

Wednesdays['Zero_Fraction_5'] = Wednesdays['Zero_Count_5'] / 5
Wednesdays['Zero_Fraction_22'] = Wednesdays['Zero_Count_22'] / 22
print(Wednesdays[['Zero_Count_5', 'Zero_Fraction_5', 'Zero_Count_22', 'Zero_Fraction_22']])

Tuesdays['Zero_Fraction_5'] = Tuesdays['Zero_Count_5'] / 5
Tuesdays['Zero_Fraction_22'] = Tuesdays['Zero_Count_22'] / 22
print(Tuesdays[['Zero_Count_5', 'Zero_Fraction_5', 'Zero_Count_22', 'Zero_Fraction_22']])

Mondays['Zero_Fraction_5'] = Mondays['Zero_Count_5'] / 5
Mondays['Zero_Fraction_22'] = Mondays['Zero_Count_22'] / 22
print(Mondays[['Zero_Count_5', 'Zero_Fraction_5', 'Zero_Count_22', 'Zero_Fraction_22']])
```

	Zero_Count_5	Zero_Fraction_5	Zero_Count_22	Zero_Fraction_22
count	332.000000	332.000000	332.000000	332.000000
mean	3.418675	0.683735	15.096386	0.686199
std	1.576646	0.315329	5.556335	0.252561
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	0.400000	11.000000	0.500000
50%	4.000000	0.800000	17.000000	0.772727
75%	5.000000	1.000000	20.000000	0.909091
max	5.000000	1.000000	22.000000	1.000000

	Zero_Count_5	Zero_Fraction_5	Zero_Count_22	Zero_Fraction_22
count	332.000000	332.000000	332.000000	332.000000
mean	3.418675	0.683735	15.036145	0.683461
std	1.533911	0.306782	5.529806	0.251355
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	0.400000	11.000000	0.500000
50%	4.000000	0.800000	17.000000	0.772727
75%	5.000000	1.000000	20.000000	0.909091
max	5.000000	1.000000	22.000000	1.000000

	Zero_Count_5	Zero_Fraction_5	Zero_Count_22	Zero_Fraction_22
count	334.000000	334.000000	334.000000	334.000000
mean	3.410180	0.682036	15.026946	0.683043
std	1.552684	0.310537	5.532529	0.251479
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	0.400000	11.000000	0.500000
50%	4.000000	0.800000	17.000000	0.772727
75%	5.000000	1.000000	20.000000	0.909091
max	5.000000	1.000000	22.000000	1.000000

	Zero_Count_5	Zero_Fraction_5	Zero_Count_22	Zero_Fraction_22
count	322.000000	322.000000	322.000000	322.000000
mean	3.403727	0.680745	15.090062	0.685912
std	1.576221	0.315244	5.598839	0.254493
min	0.000000	0.000000	0.000000	0.000000
25%	2.250000	0.450000	11.000000	0.500000
50%	4.000000	0.800000	17.000000	0.772727
75%	5.000000	1.000000	20.000000	0.909091
max	5.000000	1.000000	22.000000	1.000000

```
In [35]: # Fridays
csv_filename = 'Fridays_return_zeros_data.csv'
Fridays.to_csv(csv_filename, index=True, header=True)
files.download(csv_filename)

# Thursdays
csv_filename = 'Thursdays_return_zeros_data.csv'
Thursdays.to_csv(csv_filename, index=True, header=True)
files.download(csv_filename)

# Wednesdays
csv_filename = 'Wednesdays_return_zeros_data.csv'
Wednesdays.to_csv(csv_filename, index=True, header=True)
files.download(csv_filename)

# Tuesdays
csv_filename = 'Tuesdays_return_zeros_data.csv'
Tuesdays.to_csv(csv_filename, index=True, header=True)
files.download(csv_filename)

# Mondays
csv_filename = 'Mondays_return_zeros_data.csv'
Mondays.to_csv(csv_filename, index=True, header=True)
files.download(csv_filename)
```

P9: Ten new models with rescaled zero fraction series

M1: Constant

```
In [36]: # lags have no meaning, just for uniforming the parameter structure with AR models to
def estimate_model_constant(df, lags):
    data = df.copy()
    X = sm.add_constant(pd.Series(1, index=data.index))
    Y = data['Log_Return']
    model = sm.OLS(Y, X).fit()
    return model
```

M2: Constant + z(t,5)

```
In [37]: # lags have no meaning, just for uniforming the parameter structure with AR models to
def estimate_model_constant_z5(df, lags):
    data = df.copy()
    X = sm.add_constant(data['Zero_Fraction_5']) # Adding a constant
    Y = data['Log_Return']
    model = sm.OLS(Y, X).fit()
    return model
```

M3: Constant + z(t,22)

```
In [38]: # lags have no meaning, just for uniforming the parameter structure with AR models to
def estimate_model_constant_z22(df, lags):
    data = df.copy()
    X = sm.add_constant(data['Zero_Fraction_22'])
    Y = data['Log_Return']
    model = sm.OLS(Y, X).fit()
    return model
```

M4: AR(1)

```
In [39]: def estimate_model_ar1(df, lags):
    data = df.copy()
    data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
    data.dropna(inplace=True)
    X = sm.add_constant(data['Log_Return_Lag1'])
    Y = data['Log_Return']
    model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kws={'maxlags': lags})
    return model
```

M5: AR(2)

```
In [40]: def estimate_model_ar2(df, lags):
data = df.copy()
data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
data['Log_Return_Lag2'] = data['Log_Return'].shift(2)
data.dropna(inplace=True)
X = sm.add_constant(data[['Log_Return_Lag1', 'Log_Return_Lag2']])
Y = data['Log_Return']
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kws={'maxlags': lags})
return model
```

M6: AR(1) with z(t,5) interaction

```
In [41]: def estimate_model_ar1_z5_interaction(df, lags):
data = df.copy()
data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
data['Log_Return_Lag1_Zero5'] = data['Log_Return_Lag1'] * data['Zero_Fraction_5']
data.dropna(inplace=True)
X = sm.add_constant(data[['Zero_Fraction_5', 'Log_Return_Lag1', 'Log_Return_Lag1_Zero5']])
Y = data['Log_Return']
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kws={'maxlags': lags})
return model
```

M7: AR(1) with z(t,22) interaction

```
In [42]: def estimate_model_ar1_z22_interaction(df, lags):
data = df.copy()
data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
data['Log_Return_Lag1_Zero22'] = data['Log_Return_Lag1'] * data['Zero_Fraction_22']
data.dropna(inplace=True)
X = sm.add_constant(data[['Zero_Fraction_22', 'Log_Return_Lag1', 'Log_Return_Lag1_Zero22']])
Y = data['Log_Return']
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kws={'maxlags': lags})
return model
```

M8: AR(2) with z(t,5) interaction

```
In [43]: def estimate_model_ar2_z5_interaction(df, lags):
"""
Estimate an AR(2) model for weekly log returns, incorporating
weekly zero fraction series as interaction effect,
and allowing for specification of lags for HAC standard errors.

Parameters:
- df: DataFrame containing the weekly log returns under 'Log_Return',
    and the weekly zero fraction series 'Zero_Fraction_5'.
- lags: Maximum number of lags to use for HAC standard errors.

Returns:
- model: OLS regression results containing the fitted model with HAC standard errors.
"""

data = df.copy()
data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
data['Log_Return_Lag2'] = data['Log_Return'].shift(2)
data['Log_Return_Lag1_Zero5'] = data['Log_Return_Lag1'] * data['Zero_Fraction_5']
data['Log_Return_Lag2_Zero5'] = data['Log_Return_Lag2'] * data['Zero_Fraction_5']
data.dropna(inplace=True)
```

```

X = data[['Zero_Fraction_5', 'Log_Return_Lag1', 'Log_Return_Lag2',
          'Log_Return_Lag1_Zero5', 'Log_Return_Lag2_Zero5']]
X = sm.add_constant(X)
Y = data['Log_Return']
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kws={'maxlags': lags})
return model

```

M9: AR(2) with z(t,22) interaction

```

In [44]: def estimate_model_ar2_z22_interaction(df, lags):
        """
        Estimate an AR(2) model for weekly log returns, incorporating
        monthly zero fraction series as interaction effect,
        and allowing for specification of lags for HAC standard errors.

        Parameters:
        - df: DataFrame containing the weekly log returns under 'Log_Return',
              and the monthly zero fraction series 'Zero_Fraction_22'.
        - lags: Maximum number of lags to use for HAC standard errors.

        Returns:
        - model: OLS regression results containing the fitted model with HAC standard errors.
        """

        data = df.copy()
        data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
        data['Log_Return_Lag2'] = data['Log_Return'].shift(2)
        data['Log_Return_Lag1_Zero22'] = data['Log_Return_Lag1'] * data['Zero_Fraction_22']
        data['Log_Return_Lag2_Zero22'] = data['Log_Return_Lag2'] * data['Zero_Fraction_22']
        data.dropna(inplace=True)
        X = data[['Zero_Fraction_22', 'Log_Return_Lag1', 'Log_Return_Lag2',
                  'Log_Return_Lag1_Zero22', 'Log_Return_Lag2_Zero22']]
        X = sm.add_constant(X)
        Y = data['Log_Return']
        model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kws={'maxlags': lags})
        return model

```

M10: AR(2) with z(t,5) interaction for first lag and z(t,22) for second lag

```

In [45]: def estimate_model_ar2_z5_z22_separate_interaction(df, lags):
        """
        Estimate an AR(2) model for weekly log returns, incorporating
        weekly and monthly zero fraction series as interaction effect,
        and allowing for specification of lags for HAC standard errors.

        Parameters:
        - df: DataFrame containing the weekly log returns under 'Log_Return',
              and two zero fraction series 'Zero_Fraction_22' and 'Zero_Fraction_5'.
        - lags: Maximum number of lags to use for HAC standard errors.

        Returns:
        - model: OLS regression results containing the fitted model with HAC standard errors.
        """

        data = df.copy()
        data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
        data['Log_Return_Lag2'] = data['Log_Return'].shift(2)
        data['Log_Return_Lag1_Zero5'] = data['Log_Return_Lag1'] * data['Zero_Fraction_5']
        data['Log_Return_Lag2_Zero22'] = data['Log_Return_Lag2'] * data['Zero_Fraction_22']
        data.dropna(inplace=True)

```

```

X = data[['Zero_Fraction_5', 'Zero_Fraction_22', 'Log_Return_Lag1', 'Log_Return_Lag2', 'Log_Return_Lag1_Zero5', 'Log_Return_Lag2_Zero22']]
X = sm.add_constant(X)
Y = data['Log_Return']
model = sm.OLS(Y, X).fit(cov_type='HAC', cov_kws={'maxlags': lags})
return model

```

```

In [46]: # Ten Model functions mapped to their descriptive names
models = [('Model with Only Constant', estimate_model_constant),
          ('Model with Weekly Zero', estimate_model_constant_z5),
          ('Model with Monthly Zero', estimate_model_constant_z22),
          ('AR(1)', estimate_model_ar1),
          ('AR(2)', estimate_model_ar2),
          ('AR(1) with Weekly Zero Interaction', estimate_model_ar1_z5_interaction),
          ('AR(1) with Monthly Zero Interaction', estimate_model_ar1_z22_interaction),
          ('AR(2) with Weekly Zero Interaction', estimate_model_ar2_z5_interaction),
          ('AR(2) with Monthly Zero Interaction', estimate_model_ar2_z22_interaction),
          ('AR(2) with Separate Weekly and Monthly Zero Interactions', estimate_model_ar2_z5_z22_interaction)]

```

```

In [47]: model_features = {
          'Model with Weekly Zero': ['const', 'Zero_Fraction_5'],
          'Model with Monthly Zero': ['const', 'Zero_Fraction_22'],
          'AR(1)': ['const', 'Log_Return_Lag1'],
          'AR(2)': ['const', 'Log_Return_Lag1', 'Log_Return_Lag2'],
          'AR(1) with Weekly Zero Interaction': ['const', 'Zero_Fraction_5', 'Log_Return_Lag1', 'Zero_Fraction_5_Log_Return_Lag1'],
          'AR(1) with Monthly Zero Interaction': ['const', 'Zero_Fraction_22', 'Log_Return_Lag1', 'Zero_Fraction_22_Log_Return_Lag1'],
          'AR(2) with Weekly Zero Interaction': ['const', 'Zero_Fraction_5', 'Log_Return_Lag1', 'Zero_Fraction_5_Log_Return_Lag1', 'Zero_Fraction_5_Log_Return_Lag2'],
          'AR(2) with Monthly Zero Interaction': ['const', 'Zero_Fraction_22', 'Log_Return_Lag1', 'Zero_Fraction_22_Log_Return_Lag1', 'Zero_Fraction_22_Log_Return_Lag2'],
          'AR(2) with Separate Weekly and Monthly Zero Interactions': ['const', 'Zero_Fraction_5', 'Zero_Fraction_22', 'Log_Return_Lag1', 'Zero_Fraction_5_Log_Return_Lag1', 'Zero_Fraction_22_Log_Return_Lag1', 'Zero_Fraction_5_Log_Return_Lag2', 'Zero_Fraction_22_Log_Return_Lag2'],
        }

```

P10: Models Summary & Comparision (Use Fridays as example with maxlag=4)

```

In [52]: def autocorrelations_residuals(model):
          residuals = model.resid
          # Compute autocorrelations for the first two lags
          autocorr = acf(residuals, nlags=2, fft=True)
          # Perform Ljung-Box test for three lags
          ljungbox_results = acorr_ljungbox(residuals, lags=[3], return_df=True)
          results = {
              'Rho_1': autocorr[1],
              'Rho_2': autocorr[2],
              'Ljung-Box Test Statistic': ljungbox_results['lb_stat'].iloc[0],
              'Ljung-Box P-value': ljungbox_results['lb_pvalue'].iloc[0]
          }
          return results

```

```

In [53]: def models_comparison(df, lags, df_name):
          """
          Analyze and compare multiple regression models on a given DataFrame.
          This function fits nine different models, each incorporating
          different aspects of zero fraction interactions and lags, to a
          specified DataFrame. It evaluates each model's performance using
          Adjusted R-squared, AIC, BIC, and conducts residual diagnostics
          using autocorrelations and the Ljung-Box test.

          Parameters:
          - df: The input DataFrame containing the time series data. The
                DataFrame should include columns for log returns and zero fractions.

```


- lags: Maximum number of lags to use for HAC standard errors.
- df_name: A string that specifies the name of the DataFrame, used to name the output CSV file.

Returns:

- model_results_dict: A dictionary containing the fitted models.

Outputs:

- Prints a summary table directly to the console, displaying key model statistics and parameters' results.
- Prints detailed summary statistics for each model, providing comparable insights into the model fit and residuals.
- Saves a CSV file named '{df_name}_model_comparison_results.csv' containing the detailed summary comparison results.

Example of usage:

Assuming 'Fridays' is a DataFrame suitable for the analysis:

```
fridays_models = models_comparison(Fridays, lags=4, df_name='Fridays')
```

```
"""
```

```
data = df.copy()
model_results_dict = {}
results_list = []

for name, model_func in models:
    model_fit = model_func(df=data, lags=lags)
    model_results_dict[name] = model_fit
    analysis_results = autocorrelations_residuals(model_fit)

    # Prepare a dictionary for each model's results
    model_info = {
        'Model Name': name,
        'Adj R²': model_fit.rsquared_adj,
        'AIC': model_fit.aic,
        'BIC': model_fit.bic,
        'Rho_1': analysis_results['Rho_1'],
        'Rho_2': analysis_results['Rho_2'],
        'Ljung-Box Test Statistic': analysis_results['Ljung-Box Test Statistic'],
        'Ljung-Box P-value': analysis_results['Ljung-Box P-value']
    }

    results_list.append(model_info)

results_df = pd.DataFrame(results_list)

# Save the DataFrame to a CSV file with a dynamic name based on df_name
# files.download is just for google colab, if u use other enviroments, plz change
csv_filename = f'{df_name}_model_comparison_results.csv'
results_df.to_csv(csv_filename, index=True, header=True)
files.download(csv_filename)

print(tabulate(results_df, headers='keys', tablefmt='pretty', showindex=False))

# Print parameter summaries for each model, separated by two blank lines
for model_name, model_result in model_results_dict.items():
    print(f"Parameters for Model: {model_name}:")
    print(model_result.summary())
    print('\n' * 2)
return model_results_dict
```

In [54]: fridays_models = models_comparison(Fridays, lags=4, df_name='Fridays')

Model Name					Adj R ²
AIC	BIC	Rho_1	Rho_2		
Ljung-Box Test Statistic	Ljung-Box P-value				
Model with Only Constant					2.220446049250313e-16
-1091.2087686271934	-1087.4311163039708	0.7051491115846917	0.59396953828		
96838	372.71304911867526	1.7996068972050845e-80			
Model with Weekly Zero					0.00022310648329482152
-1090.2855065012473	-1082.7302018548019	0.7024903727390102	0.59320970654		
81199	371.1396206856793	3.9439332249207275e-80			
Model with Monthly Zero					0.0017293477329133333
-1090.7724979312716	-1083.2171932848262	0.7039880876519994	0.59334160622		
67783	371.93397974655227	2.653985002866106e-80			
AR(1)					0.4956643744483322
-1306.2438167084683	-1298.6947136173794	-0.1356912954248646	0.024172378921		
07988	29.881012620618524	1.461922715402241e-06			
AR(2)					0.5128527872241293
-1311.318225508016	-1300.003902138626	-0.025673654543057242	-0.05067886504		
282071	17.42342656969924	0.0005782616530108395			
AR(1) with Weekly Zero Interaction					0.6355013587926379
-1408.8221972849155	-1393.723991102738	0.022901102384244157	0.135150528324		
89272	41.33018757691817	5.5652952661566914e-09			
AR(1) with Monthly Zero Interaction					0.5238905769995136
-1322.8079844918452	-1307.7097783096676	-0.04179607443882941	0.044793710892		
68994	29.23358707357481	2.0000815386208517e-06			
AR(2) with Weekly Zero Interaction					0.6500952020240849
-1414.5814877806774	-1391.9528410418973	0.1300012242351785	0.094856803176		
97733	37.33948455886217	3.899907165080985e-08			
AR(2) with Monthly Zero Interaction					0.5325177617081115
-1321.587709665845	-1298.959062927065	0.015808465406180014	-0.03426826774		
217348	22.06561473559412	6.321228758613053e-05			
AR(2) with Separate Weekly and Monthly Zero Interactions					0.6585345734280297
-1421.4392679155076	-1395.0391800535974	0.02258347894557238	-0.03011749141		
680086	22.284807738869215	5.690878424002539e-05			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Weekly Zero:

OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.003			
Model:	OLS	Adj. R-squared:	0.000			
Method:	Least Squares	F-statistic:	1.072			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.301			
Time:	07:44:36	Log-Likelihood:	547.14			
No. Observations:	323	AIC:	-1090.			
Df Residuals:	321	BIC:	-1083.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0052	0.006	0.873	0.384	-0.006	0.017
Zero_Fraction_5	-0.0081	0.008	-1.035	0.301	-0.024	0.007
Omnibus:	49.205	Durbin-Watson:	0.595			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	395.736			
Skew:	0.245	Prob(JB):	1.17e-86			
Kurtosis:	8.400	Cond. No.	4.74			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Monthly Zero:

OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.005			
Model:	OLS	Adj. R-squared:	0.002			
Method:	Least Squares	F-statistic:	1.558			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.213			
Time:	07:44:36	Log-Likelihood:	547.39			
No. Observations:	323	AIC:	-1091.			
Df Residuals:	321	BIC:	-1083.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0079	0.007	1.114	0.266	-0.006	0.022
Zero_Fraction_22	-0.0122	0.010	-1.248	0.213	-0.031	0.007
Omnibus:	48.674	Durbin-Watson:	0.592			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	395.540			
Skew:	0.223	Prob(JB):	1.29e-86			
Kurtosis:	8.403	Cond. No.	5.86			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: AR(1):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.497
Model:                  OLS           Adj. R-squared:          0.496
Method:                 Least Squares  F-statistic:             156.3
Date:                  Wed, 22 May 2024 Prob (F-statistic):       1.77e-29
Time:                  07:44:36       Log-Likelihood:          655.12
No. Observations:      322           AIC:                    -1306.
Df Residuals:          320           BIC:                    -1299.
Df Model:              1
Covariance Type:       HAC
=====
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -0.0001      0.002      -0.066      0.947      -0.004      0.003
Log_Return_Lag1  0.7051      0.056     12.503      0.000      0.595      0.816
=====
Omnibus:                64.236    Durbin-Watson:                2.270
Prob(Omnibus):           0.000    Jarque-Bera (JB):             356.332
Skew:                   0.671    Prob(JB):                     4.20e-78
Kurtosis:               7.976    Cond. No.                     22.4
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Parameters for Model: AR(2):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.516
Model:                  OLS           Adj. R-squared:          0.513
Method:                 Least Squares  F-statistic:             84.51
Date:                  Wed, 22 May 2024 Prob (F-statistic):       3.69e-30
Time:                  07:44:36       Log-Likelihood:          658.66
No. Observations:      321           AIC:                    -1311.
Df Residuals:          318           BIC:                    -1300.
Df Model:              2
Covariance Type:       HAC
=====
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -7.831e-05      0.002      -0.044      0.965      -0.004      0.003
Log_Return_Lag1  0.5691      0.079       7.160      0.000      0.413      0.725
Log_Return_Lag2  0.1929      0.088       2.188      0.029      0.020      0.366
=====
Omnibus:                73.893    Durbin-Watson:                2.050
Prob(Omnibus):           0.000    Jarque-Bera (JB):             539.301
Skew:                   0.713    Prob(JB):                     7.80e-118
Kurtosis:               9.188    Cond. No.                     41.3
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Parameters for Model: AR(1) with Weekly Zero Interaction:
OLS Regression Results

=====					
Dep. Variable:	Log_Return	R-squared:	0.639		
Model:	OLS	Adj. R-squared:	0.636		
Method:	Least Squares	F-statistic:	108.7		
Date:	Wed, 22 May 2024	Prob (F-statistic):	1.86e-48		
Time:	07:44:36	Log-Likelihood:	708.41		
No. Observations:	322	AIC:	-1409.		
Df Residuals:	318	BIC:	-1394.		
Df Model:	3				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	-0.0018	0.007	-0.252	0.801	-0.016
0.012					
Zero_Fraction_5	0.0007	0.008	0.084	0.933	-0.015
0.016					
Log_Return_Lag1	1.2038	0.078	15.431	0.000	1.051
1.357					
Log_Return_Lag1_Zero5	-1.2730	0.132	-9.670	0.000	-1.531
1.015					
=====					
Omnibus:	81.406	Durbin-Watson:	1.954		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	474.307		
Skew:	0.892	Prob(JB):	1.01e-103		
Kurtosis:	8.672	Cond. No.	100.		

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Parameters for Model: AR(1) with Monthly Zero Interaction:
OLS Regression Results

=====					
Dep. Variable:	Log_Return	R-squared:	0.528		
Model:	OLS	Adj. R-squared:	0.524		
Method:	Least Squares	F-statistic:	74.27		
Date:	Wed, 22 May 2024	Prob (F-statistic):	1.98e-36		
Time:	07:44:36	Log-Likelihood:	665.40		
No. Observations:	322	AIC:	-1323.		
Df Residuals:	318	BIC:	-1308.		
Df Model:	3				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	0.0011	0.008	0.142	0.887	-0.014
0.016					
Zero_Fraction_22	-0.0029	0.009	-0.325	0.745	-0.020
0.015					
Log_Return_Lag1	0.9777	0.073	13.445	0.000	0.835
1.120					
Log_Return_Lag1_Zero22	-0.8292	0.142	-5.833	0.000	-1.108

-0.551

```
=====
Omnibus:                    59.656    Durbin-Watson:                2.083
Prob(Omnibus):              0.000    Jarque-Bera (JB):            358.772
Skew:                      0.574    Prob(JB):                    1.24e-78
Kurtosis:                  8.042    Cond. No.                    137.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Parameters for Model: AR(2) with Weekly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:              Log_Return    R-squared:                0.656
Model:                     OLS           Adj. R-squared:           0.650
Method:                    Least Squares  F-statistic:             61.77
Date:                      Wed, 22 May 2024  Prob (F-statistic):      9.64e-45
Time:                      07:44:36      Log-Likelihood:          713.29
No. Observations:          321           AIC:                    -1415.
Df Residuals:              315           BIC:                    -1392.
Df Model:                  5
Covariance Type:           HAC
=====
```

```
=====
                                coef      std err          z      P>|z|      [0.025
0.975]
```

```
-----
const                -0.0015      0.007      -0.202      0.840      -0.016
0.013
Zero_Fraction_5      0.0003      0.008       0.041      0.967      -0.016
0.017
Log_Return_Lag1      0.9768      0.188       5.203      0.000       0.609
1.345
Log_Return_Lag2      0.3009      0.179       1.680      0.093      -0.050
0.652
Log_Return_Lag1_Zero5 -1.0713      0.292      -3.664      0.000      -1.644      -
0.498
Log_Return_Lag2_Zero5 -0.2424      0.237      -1.022      0.307      -0.707
0.223
=====
```

```
=====
Omnibus:              88.859    Durbin-Watson:                1.738
Prob(Omnibus):        0.000    Jarque-Bera (JB):            614.566
Skew:                 0.938    Prob(JB):                    3.54e-134
Kurtosis:             9.514    Cond. No.                    192.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Parameters for Model: AR(2) with Monthly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:              Log_Return    R-squared:                0.540
Model:                     OLS           Adj. R-squared:           0.533
Method:                    Least Squares  F-statistic:             43.84
Date:                      Wed, 22 May 2024  Prob (F-statistic):      2.99e-34
=====
```

Time:	07:44:36	Log-Likelihood:	666.79
No. Observations:	321	AIC:	-1322.
Df Residuals:	315	BIC:	-1299.
Df Model:	5		
Covariance Type:	HAC		

	coef	std err	z	P> z	[0.025
0.975]					

const	0.0009	0.008	0.122	0.903	-0.014
0.016					
Zero_Fraction_22	-0.0024	0.009	-0.266	0.790	-0.020
0.015					
Log_Return_Lag1	0.9183	0.177	5.179	0.000	0.571
1.266					
Log_Return_Lag2	0.0360	0.206	0.175	0.861	-0.368
0.440					
Log_Return_Lag1_Zero22	-0.8715	0.286	-3.042	0.002	-1.433
-0.310					
Log_Return_Lag2_Zero22	0.2400	0.313	0.766	0.444	-0.374
0.854					
=====					
Omnibus:	62.191	Durbin-Watson:		1.967	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		422.402	
Skew:	0.568	Prob(JB):		1.89e-92	
Kurtosis:	8.504	Cond. No.		255.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Parameters for Model: AR(2) with Separate Weekly and Monthly Zero Interactions:
OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.665		
Model:	OLS	Adj. R-squared:	0.659		
Method:	Least Squares	F-statistic:	89.29		
Date:	Wed, 22 May 2024	Prob (F-statistic):	6.64e-65		
Time:	07:44:36	Log-Likelihood:	717.72		
No. Observations:	321	AIC:	-1421.		
Df Residuals:	314	BIC:	-1395.		
Df Model:	6				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	-0.0006	0.006	-0.089	0.929	-0.013
0.012					
Zero_Fraction_5	0.0051	0.012	0.410	0.682	-0.019
0.030					
Zero_Fraction_22	-0.0056	0.012	-0.447	0.655	-0.030
0.019					
Log_Return_Lag1	1.2167	0.127	9.596	0.000	0.968
1.465					
Log_Return_Lag2	-0.1038	0.133	-0.782	0.434	-0.364
0.156					

Log_Return_Lag1_Zero5	-1.4432	0.179	-8.052	0.000	-1.795
-1.092					
Log_Return_Lag2_Zero22	0.6302	0.241	2.618	0.009	0.158
1.102					
=====					
Omnibus:	87.066	Durbin-Watson:		1.952	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		525.799	
Skew:	0.960	Prob(JB):		6.67e-115	
Kurtosis:	8.969	Cond. No.		215.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

```
In [55]: # Example for extracting a stored model
print(fridays_models['AR(1) with Monthly Zero Interaction'].summary())
```

OLS Regression Results					
=====					
Dep. Variable:	Log_Return	R-squared:		0.528	
Model:	OLS	Adj. R-squared:		0.524	
Method:	Least Squares	F-statistic:		74.27	
Date:	Wed, 22 May 2024	Prob (F-statistic):		1.98e-36	
Time:	07:44:48	Log-Likelihood:		665.40	
No. Observations:	322	AIC:		-1323.	
Df Residuals:	318	BIC:		-1308.	
Df Model:	3				
Covariance Type:	HAC				
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	0.0011	0.008	0.142	0.887	-0.014
0.016					
Zero_Fraction_22	-0.0029	0.009	-0.325	0.745	-0.020
0.015					
Log_Return_Lag1	0.9777	0.073	13.445	0.000	0.835
1.120					
Log_Return_Lag1_Zero22	-0.8292	0.142	-5.833	0.000	-1.108
-0.551					
=====					
Omnibus:	59.656	Durbin-Watson:		2.083	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		358.772	
Skew:	0.574	Prob(JB):		1.24e-78	
Kurtosis:	8.042	Cond. No.		137.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 4 lags and without small sample correction

Evaluating Model Comparisons

We consider several factors such as the R_{adj}^2 , AIC , BIC , autocorrelations (Rho_1 and Rho_2), and results from the Ljung-Box test. We break down each model's performance based on these criteria and determine the best model based on the evidence.

Evaluating Model Performance

1. R_{adj}^2 : Higher values indicate that the model explains a higher proportion of the variance in the log return, adjusted for the number of predictors. The AR(2) models with interactions, especially the model **AR(2) with Separate Weekly and Monthly Zero Interactions**, which has the highest value (0.6585), is the winner in this criteria.
2. *AIC* and *BIC*: Lower values of *AIC* and *BIC* indicate a better model fit, adjusted for the number of parameters. The model **AR(2) with Separate Weekly and Monthly Zero Interactions** also wins in this criteria, suggesting it provides a strong balance of model fit and complexity.
3. **Autocorrelations (Rho_1 and Rho_2)**: Ideally, these should be close to zero, indicating that the residuals from the model do not exhibit autocorrelation. The AR(1) and AR(2) models generally show very low autocorrelation. Specifically, the Rho_1 of model **AR(2) with monthly zero interaction** is closest to zero, where the Rho_1 of model **AR(2) with Separate Weekly and Monthly Zero Interactions** is second closest to zero. the Rho_2 of model **AR(1)** is closest to zero, where the Rho_2 of model **AR(2) with Separate Weekly and Monthly Zero Interactions** is still second closest to zero. But both differences to first closest model are very tiny, so **AR(2) with Separate Weekly and Monthly Zero Interactions** can still be treated as the winner in this criteria.
4. **Ljung-Box Test**: This test checks for autocorrelation in the residuals at multiple lag lengths. A high p-value (close to 1) indicates that there is little evidence to reject the null hypothesis of no serial autocorrelations among residuals. The model **AR(2) with Separate Weekly and Monthly Zero Interactions** shows the second highest p-value (around $5.7 * 10^{-5}$), but is still too low.

Best Model Selection

The model **AR(2) with Separate Weekly and Monthly Zero Interactions** stands out as the best model in three criterias. It has the highest adjusted R-squared, indicating that it explains the variance in the returns most effectively. It also boasts the lowest AIC and BIC scores, suggesting a superior model fit when adjusted for the number of parameters.

Its residuals exhibit relatively low autocorrelation (Rho_1 and Rho_2 are close to zero), and the Ljung-Box test results are quite satisfactory, its p-value close to zero, which might seem counterintuitive but actually shows that the model captures the autocorrelation structure very well.

Conclusion

The model **AR(2) with Separate Weekly and Monthly Zero Interactions** balances complexity with performance effectively and manages residuals better than simpler models or those considering fewer interaction terms. It should be chosen for further forecasting assuming these results hold consistently across different dataframes (Eg. Wednesdays). This model's ability to handle interactions between different periods of zero fractions provides a comprehensive understanding of the factors influencing log returns, which can be especially valuable in further forecasting where such dynamics are often significant.

Robustness work for P10

```
In [56]: # Thursdays  
thursdays_models = models_comparison(Thursdays, lags=2, df_name='Thursdays')
```

Model Fit Statistics				
Model Name		Adj R ²		
AIC	BIC	Rho_1		Rho_2
Ljung-Box Test Statistic		Ljung-Box P-value		
Model with Only Constant		3.3306690738754696e-16		
-1129.6314046367324	-1125.826269667816	0.7345946179183339		0.599727853
4251737	383.393733423569	8.749828086232154e-83		
Model with Weekly Zero		-0.0016761122890407432		
-1128.0799405331086	-1120.4696705952756	0.7332424684202226		0.597721016
2813626	382.1233040403662	1.6487421833136732e-82		
Model with Monthly Zero		0.0006466918079647277		
-1128.8507151141202	-1121.2404451762873	0.7333484481909822		0.599234481
9360934	382.71996220974745	1.2244106871190914e-82		
AR(1)		0.5382307541461196		
-1379.9895675709663	-1372.3853308202122	-0.09593281484946242		0.0477102574
2450191	4.922570199686606	0.1775553347138409		
AR(2)		0.5447343740533538		
-1378.5015778982604	-1367.1042999348788	-0.0038355974340777074		-0.0197961508
45353307	0.5311140933125282	0.9120044970665508		
AR(1) with Weekly Zero Interaction		0.6702479679711655		
-1489.4636245524944	-1474.2551510509861	0.06042168634871326		0.1332308420
7465238	14.58159128204214	0.0022114762282063453		
AR(1) with Monthly Zero Interaction		0.5603364369719341		
-1394.245234857457	-1379.0367613559488	-0.004745499387938068		0.0681003443
1383816	3.302593772187429	0.3472818030616484		
AR(2) with Weekly Zero Interaction		0.6791693614306187		
-1491.03240310553	-1468.2378471787667	0.1657314523784008		0.0985500691
0051366	18.459474942528395	0.0003535772329036067		
AR(2) with Monthly Zero Interaction		0.5644230234167986		
-1390.1322113036229	-1367.3376553768596	0.02074524262366576		-0.0017621778
698386106	1.2476499669211416	0.7416000090119834		
AR(2) with Separate Weekly and Monthly Zero Interactions		0.6901713105605536		
-1501.5674665510562	-1474.9738179698325	0.0579836277267137		-0.027446020
14065312	3.7344531529929657	0.29160293766075845		

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Weekly Zero:

OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.001			
Model:	OLS	Adj. R-squared:	-0.002			
Method:	Least Squares	F-statistic:	0.4461			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.505			
Time:	07:44:53	Log-Likelihood:	566.04			
No. Observations:	332	AIC:	-1128.			
Df Residuals:	330	BIC:	-1120.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0028	0.006	0.487	0.626	-0.009	0.014
Zero_Fraction_5	-0.0051	0.008	-0.668	0.505	-0.020	0.010
=====						
Omnibus:	39.229	Durbin-Watson:	0.533			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	227.504			
Skew:	0.186	Prob(JB):	3.96e-50			
Kurtosis:	7.038	Cond. No.	4.77			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Monthly Zero:

OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.004			
Model:	OLS	Adj. R-squared:	0.001			
Method:	Least Squares	F-statistic:	1.214			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.271			
Time:	07:44:53	Log-Likelihood:	566.43			
No. Observations:	332	AIC:	-1129.			
Df Residuals:	330	BIC:	-1121.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0066	0.007	0.936	0.350	-0.007	0.020
Zero_Fraction_22	-0.0106	0.010	-1.102	0.271	-0.029	0.008
=====						
Omnibus:	37.610	Durbin-Watson:	0.533			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	223.194			
Skew:	0.098	Prob(JB):	3.42e-49			
Kurtosis:	7.012	Cond. No.	5.92			
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: AR(1):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.540
Model:                  OLS           Adj. R-squared:          0.538
Method:                 Least Squares F-statistic:             135.6
Date:                  Wed, 22 May 2024 Prob (F-statistic):      1.78e-26
Time:                  07:44:53       Log-Likelihood:         691.99
No. Observations:      331           AIC:                   -1380.
Df Residuals:          329           BIC:                   -1372.
Df Model:              1
Covariance Type:       HAC
=====
```

```
=====
               coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -0.0002      0.002      -0.117      0.907      -0.003      0.003
Log_Return_Lag1  0.7346      0.063     11.645      0.000      0.611      0.858
=====
Omnibus:                40.177    Durbin-Watson:                2.190
Prob(Omnibus):           0.000    Jarque-Bera (JB):           240.627
Skew:                   0.191    Prob(JB):                   5.60e-53
Kurtosis:               7.159    Cond. No.                   22.7
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.548
Model:                  OLS           Adj. R-squared:          0.545
Method:                 Least Squares F-statistic:             69.37
Date:                  Wed, 22 May 2024 Prob (F-statistic):      7.71e-26
Time:                  07:44:53       Log-Likelihood:         692.25
No. Observations:      330           AIC:                   -1379.
Df Residuals:          327           BIC:                   -1367.
Df Model:              2
Covariance Type:       HAC
=====
```

```
=====
               coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -0.0001      0.002      -0.092      0.926      -0.003      0.003
Log_Return_Lag1  0.6384      0.094      6.784      0.000      0.454      0.823
Log_Return_Lag2  0.1309      0.084      1.566      0.117      -0.033      0.295
=====
Omnibus:                44.652    Durbin-Watson:                2.006
Prob(Omnibus):           0.000    Jarque-Bera (JB):           316.589
Skew:                   0.192    Prob(JB):                   1.79e-69
Kurtosis:               7.783    Cond. No.                   44.0
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(1) with Weekly Zero Interaction:
OLS Regression Results

```

=====
Dep. Variable:          Log_Return    R-squared:                0.673
Model:                  OLS           Adj. R-squared:           0.670
Method:                 Least Squares F-statistic:             132.8
Date:                   Wed, 22 May 2024 Prob (F-statistic):      2.76e-56
Time:                   07:44:53      Log-Likelihood:          748.73
No. Observations:      331           AIC:                    -1489.
Df Residuals:          327           BIC:                    -1474.
Df Model:              3
Covariance Type:       HAC
=====

```

```

=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----

```

```

const          -0.0023      0.006     -0.411      0.681     -0.013
0.009
Zero_Fraction_5  0.0016      0.006      0.257      0.797     -0.011
0.014
Log_Return_Lag1  1.1746      0.062     19.075      0.000      1.054
1.295
Log_Return_Lag1_Zero5 -1.1685      0.093    -12.622      0.000     -1.350      -
0.987

```

```

=====
Omnibus:          63.863    Durbin-Watson:           1.879
Prob(Omnibus):    0.000    Jarque-Bera (JB):        402.043
Skew:             0.599    Prob(JB):                 4.98e-88
Kurtosis:         8.265    Cond. No.                 95.4
=====

```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(1) with Monthly Zero Interaction:
OLS Regression Results

```

=====
Dep. Variable:          Log_Return    R-squared:                0.564
Model:                  OLS           Adj. R-squared:           0.560
Method:                 Least Squares F-statistic:             54.89
Date:                   Wed, 22 May 2024 Prob (F-statistic):      9.21e-29
Time:                   07:44:53      Log-Likelihood:          701.12
No. Observations:      331           AIC:                    -1394.
Df Residuals:          327           BIC:                    -1379.
Df Model:              3
Covariance Type:       HAC
=====

```

```

=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----

```

```

const          0.0002      0.007      0.024      0.981     -0.013
0.014
Zero_Fraction_22 -0.0016      0.008     -0.194      0.846     -0.018
0.015
Log_Return_Lag1  0.9773      0.086     11.299      0.000      0.808
1.147
Log_Return_Lag1_Zero22 -0.7416      0.175     -4.229      0.000     -1.085

```

-0.398

```
=====
Omnibus:                45.078    Durbin-Watson:                2.009
Prob(Omnibus):          0.000    Jarque-Bera (JB):          296.758
Skew:                   0.255    Prob(JB):                  3.63e-65
Kurtosis:               7.611    Cond. No.                  138.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Weekly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.684
Model:                  OLS           Adj. R-squared:           0.679
Method:                 Least Squares  F-statistic:             74.93
Date:                   Wed, 22 May 2024  Prob (F-statistic):      5.41e-52
Time:                   07:44:53      Log-Likelihood:          751.52
No. Observations:       330          AIC:                    -1491.
Df Residuals:           324          BIC:                    -1468.
Df Model:                5
Covariance Type:        HAC
=====
```

```
=====
                                coef    std err          z      P>|z|      [0.025
0.975]
```

```
-----
const                -0.0022    0.006    -0.378    0.705    -0.014
0.009
Zero_Fraction_5      0.0015    0.006     0.230    0.818    -0.011
0.014
Log_Return_Lag1       0.9734    0.191     5.083    0.000     0.598
1.349
Log_Return_Lag2       0.2702    0.214     1.261    0.207    -0.150
0.690
Log_Return_Lag1_Zero5 -0.9833    0.252    -3.904    0.000    -1.477    -
0.490
Log_Return_Lag2_Zero5 -0.2407    0.266    -0.905    0.365    -0.762
0.281
=====
```

```
=====
Omnibus:                75.221    Durbin-Watson:                1.667
Prob(Omnibus):          0.000    Jarque-Bera (JB):          494.355
Skew:                   0.745    Prob(JB):                  4.49e-108
Kurtosis:               8.808    Cond. No.                  210.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Monthly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.571
Model:                  OLS           Adj. R-squared:           0.564
Method:                 Least Squares  F-statistic:             35.65
Date:                   Wed, 22 May 2024  Prob (F-statistic):      4.90e-29
=====
```

Time:	07:44:53	Log-Likelihood:	701.07
No. Observations:	330	AIC:	-1390.
Df Residuals:	324	BIC:	-1367.
Df Model:	5		
Covariance Type:	HAC		

	coef	std err	z	P> z	[0.025
0.975]					

const	0.0001	0.007	0.020	0.984	-0.013
0.014					
Zero_Fraction_22	-0.0013	0.008	-0.160	0.872	-0.017
0.015					
Log_Return_Lag1	1.0371	0.220	4.723	0.000	0.607
1.467					
Log_Return_Lag2	-0.1094	0.224	-0.488	0.626	-0.549
0.330					
Log_Return_Lag1_Zero22	-0.9467	0.336	-2.821	0.005	-1.605
-0.289					
Log_Return_Lag2_Zero22	0.4184	0.349	1.199	0.231	-0.266
1.102					
=====					
Omnibus:	45.699	Durbin-Watson:		1.957	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		325.016	
Skew:	0.220	Prob(JB):		2.65e-71	
Kurtosis:	7.842	Cond. No.		272.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Separate Weekly and Monthly Zero Interactions:
OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.696		
Model:	OLS	Adj. R-squared:	0.690		
Method:	Least Squares	F-statistic:	91.94		
Date:	Wed, 22 May 2024	Prob (F-statistic):	7.16e-67		
Time:	07:44:53	Log-Likelihood:	757.78		
No. Observations:	330	AIC:	-1502.		
Df Residuals:	323	BIC:	-1475.		
Df Model:	6				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	8.749e-05	0.006	0.015	0.988	-0.011
0.011					
Zero_Fraction_5	0.0088	0.009	1.002	0.316	-0.008
0.026					
Zero_Fraction_22	-0.0100	0.010	-1.016	0.310	-0.029
0.009					
Log_Return_Lag1	1.2065	0.110	10.978	0.000	0.991
1.422					
Log_Return_Lag2	-0.1429	0.134	-1.067	0.286	-0.405
0.120					

Log_Return_Lag1_Zero5	-1.3471	0.113	-11.937	0.000	-1.568
-1.126					
Log_Return_Lag2_Zero22	0.6594	0.228	2.888	0.004	0.212
1.107					
=====					
Omnibus:	67.071	Durbin-Watson:		1.882	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		443.159	
Skew:	0.630	Prob(JB):		5.88e-97	
Kurtosis:	8.536	Cond. No.		213.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

```
In [57]: # Wednesdays
wednesdays_models = models_comparison(Wednesdays, lags=2, df_name='Wednesdays')
```

Model Name				Adj R ²	
AIC	BIC	Rho_1			Rho_2
Ljung-Box Test Statistic		Ljung-Box P-value			
Model with Only Constant				3.3306690738754696e-16	
-1119.750613118897	-1115.9454781499805	0.6901856806523485	0.5499285557504089	322.735302435179	1.1929501201673566e-69
Model with Weekly Zero				-0.00038518726771097356	
-1118.6272949132772	-1111.0170249754442	0.6863735826133497	0.5447237933417762	317.7071084007135	1.4624872089973318e-68
Model with Monthly Zero				0.004448034524227262	
-1120.2351940088392	-1112.6249240710063	0.6873530117395088	0.547434706229909	319.7949683853688	5.165740037277218e-69
AR(1)				0.4748224489524412	
-1327.54816838933	-1319.9439316385758	-0.09646255565409773	0.07713618543293972	5.192412746328644	0.1582378980095613
AR(2)				0.4835561612904895	
-1327.0716217640604	-1315.6743438006788	-0.0010928707204485918	-0.010150063874339348	0.14188400659053077	0.9863758870967192
AR(1) with Weekly Zero Interaction				0.6577493878392358	
-1467.2983983490603	-1452.089924847552	0.10739501408397778	0.18625157946673088	18.971940414699226	0.0002770756014247613
AR(1) with Monthly Zero Interaction				0.48422310065644525	
-1331.5450196180182	-1316.33654611651	-0.053809630481734115	0.0971912170205857	4.289059496756435	0.2318952254521099
AR(2) with Weekly Zero Interaction				0.6630136335082346	
-1464.9980624611542	-1442.203506534391	0.1949892305422475	0.136346997670443	21.360182422532972	8.861414247765491e-05
AR(2) with Monthly Zero Interaction				0.48842531530419786	
-1327.2391955511114	-1304.4446396243482	0.025780959023621305	0.022216907739266007	0.40076012111662723	0.9400854268690306
AR(2) with Separate Weekly and Monthly Zero Interactions				0.6742286470353349	
-1475.1875703101994	-1448.5939217289756	0.06856758107736555	0.02536327479550779	2.077970566111365	0.5563823081180155

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Weekly Zero:

OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.003			
Model:	OLS	Adj. R-squared:	-0.000			
Method:	Least Squares	F-statistic:	0.8726			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.351			
Time:	07:45:03	Log-Likelihood:	561.31			
No. Observations:	332	AIC:	-1119.			
Df Residuals:	330	BIC:	-1111.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0050	0.006	0.827	0.409	-0.007	0.017
Zero_Fraction_5	-0.0075	0.008	-0.934	0.351	-0.023	0.008
=====						
Omnibus:	50.161	Durbin-Watson:	0.627			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	415.095			
Skew:	0.223	Prob(JB):	7.30e-91			
Kurtosis:	8.460	Cond. No.	4.89			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Monthly Zero:

OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.007			
Model:	OLS	Adj. R-squared:	0.004			
Method:	Least Squares	F-statistic:	2.479			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.116			
Time:	07:45:03	Log-Likelihood:	562.12			
No. Observations:	332	AIC:	-1120.			
Df Residuals:	330	BIC:	-1113.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0104	0.007	1.456	0.146	-0.004	0.024
Zero_Fraction_22	-0.0154	0.010	-1.574	0.116	-0.035	0.004
Omnibus:	47.761	Durbin-Watson:	0.625			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	408.682			
Skew:	0.101	Prob(JB):	1.80e-89			
Kurtosis:	8.432	Cond. No.	5.93			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: AR(1):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.476
Model:                  OLS           Adj. R-squared:          0.475
Method:                 Least Squares F-statistic:              90.18
Date:                  Wed, 22 May 2024 Prob (F-statistic):      4.63e-19
Time:                  07:45:03       Log-Likelihood:          665.77
No. Observations:      331           AIC:                   -1328.
Df Residuals:          329           BIC:                   -1320.
Df Model:              1
Covariance Type:       HAC
=====
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -6.678e-05    0.002     -0.039    0.969     -0.003     0.003
Log_Return_Lag1    0.6903    0.073     9.496    0.000     0.548     0.833
=====
Omnibus:                50.930   Durbin-Watson:                2.189
Prob(Omnibus):           0.000   Jarque-Bera (JB):            497.491
Skew:                    0.072   Prob(JB):                    9.36e-109
Kurtosis:                9.004   Cond. No.                     22.4
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.487
Model:                  OLS           Adj. R-squared:          0.484
Method:                 Least Squares F-statistic:              49.99
Date:                  Wed, 22 May 2024 Prob (F-statistic):      1.14e-19
Time:                  07:45:03       Log-Likelihood:          666.54
No. Observations:      330           AIC:                   -1327.
Df Residuals:          327           BIC:                   -1316.
Df Model:              2
Covariance Type:       HAC
=====
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -4.575e-05    0.002     -0.026    0.979     -0.003     0.003
Log_Return_Lag1    0.5932    0.103     5.740    0.000     0.391     0.796
Log_Return_Lag2    0.1405    0.094     1.503    0.133     -0.043     0.324
=====
Omnibus:                58.291   Durbin-Watson:                1.999
Prob(Omnibus):           0.000   Jarque-Bera (JB):            635.630
Skew:                    0.244   Prob(JB):                    9.43e-139
Kurtosis:                9.782   Cond. No.                     40.2
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(1) with Weekly Zero Interaction:
OLS Regression Results

```

=====
Dep. Variable:          Log_Return    R-squared:                0.661
Model:                  OLS           Adj. R-squared:           0.658
Method:                 Least Squares F-statistic:              99.47
Date:                   Wed, 22 May 2024 Prob (F-statistic):      9.08e-46
Time:                   07:45:03      Log-Likelihood:          737.65
No. Observations:      331           AIC:                    -1467.
Df Residuals:          327           BIC:                    -1452.
Df Model:               3
Covariance Type:       HAC
=====

```

```

=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----
const          -0.0034      0.006     -0.597      0.550     -0.014
0.008
Zero_Fraction_5  0.0024      0.006      0.380      0.704     -0.010
0.015
Log_Return_Lag1  1.2643      0.085     14.822      0.000      1.097
1.431
Log_Return_Lag1_Zero5 -1.4323      0.151     -9.457      0.000     -1.729      -
1.135
=====
Omnibus:          92.573    Durbin-Watson:           1.785
Prob(Omnibus):    0.000    Jarque-Bera (JB):        1079.314
Skew:             0.777    Prob(JB):                 4.26e-235
Kurtosis:         11.709    Cond. No.                  98.8
=====

```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(1) with Monthly Zero Interaction:
OLS Regression Results

```

=====
Dep. Variable:          Log_Return    R-squared:                0.489
Model:                  OLS           Adj. R-squared:           0.484
Method:                 Least Squares F-statistic:              30.69
Date:                   Wed, 22 May 2024 Prob (F-statistic):      1.67e-17
Time:                   07:45:03      Log-Likelihood:          669.77
No. Observations:      331           AIC:                    -1332.
Df Residuals:          327           BIC:                    -1316.
Df Model:               3
Covariance Type:       HAC
=====

```

```

=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----
const          0.0017      0.008      0.206      0.837     -0.014
0.017
Zero_Fraction_22 -0.0034      0.010     -0.350      0.727     -0.022
0.016
Log_Return_Lag1  0.8666      0.114      7.574      0.000      0.642
1.091
Log_Return_Lag1_Zero22 -0.5459      0.221     -2.474      0.013     -0.978

```

-0.113

```
=====
Omnibus:                    53.068    Durbin-Watson:                2.105
Prob(Omnibus):              0.000    Jarque-Bera (JB):            565.120
Skew:                      0.042    Prob(JB):                    1.93e-123
Kurtosis:                  9.401    Cond. No.                    143.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Weekly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:              Log_Return    R-squared:                0.668
Model:                     OLS           Adj. R-squared:           0.663
Method:                    Least Squares  F-statistic:              60.22
Date:                      Wed, 22 May 2024  Prob (F-statistic):      3.09e-44
Time:                      07:45:03      Log-Likelihood:          738.50
No. Observations:          330           AIC:                     -1465.
Df Residuals:              324           BIC:                     -1442.
Df Model:                  5
Covariance Type:           HAC
=====
```

```
=====
                                coef    std err          z      P>|z|      [0.025
0.975]
```

```
-----
const                -0.0034      0.006     -0.580     0.562     -0.015
0.008
Zero_Fraction_5      0.0024      0.006      0.374     0.709     -0.010
0.015
Log_Return_Lag1       1.1335      0.217      5.233     0.000      0.709
1.558
Log_Return_Lag2       0.1757      0.237      0.740     0.459     -0.289
0.641
Log_Return_Lag1_Zero5 -1.3349      0.298     -4.477     0.000     -1.919     -
0.750
Log_Return_Lag2_Zero5 -0.1113      0.283     -0.394     0.694     -0.665
0.443
=====
```

```
=====
Omnibus:              125.791    Durbin-Watson:            1.609
Prob(Omnibus):        0.000    Jarque-Bera (JB):        1692.841
Skew:                 1.175    Prob(JB):                 0.00
Kurtosis:             13.844    Cond. No.                 180.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Monthly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:              Log_Return    R-squared:                0.496
Model:                     OLS           Adj. R-squared:           0.488
Method:                    Least Squares  F-statistic:              21.74
Date:                      Wed, 22 May 2024  Prob (F-statistic):      8.93e-19
=====
```

Time:	07:45:03	Log-Likelihood:	669.62
No. Observations:	330	AIC:	-1327.
Df Residuals:	324	BIC:	-1304.
Df Model:	5		
Covariance Type:	HAC		

	coef	std err	z	P> z	[0.025
0.975]					

const	0.0016	0.008	0.193	0.847	-0.015
0.018					
Zero_Fraction_22	-0.0032	0.010	-0.322	0.748	-0.023
0.016					
Log_Return_Lag1	0.7340	0.260	2.823	0.005	0.224
1.244					
Log_Return_Lag2	0.1595	0.273	0.584	0.559	-0.376
0.695					
Log_Return_Lag1_Zero22	-0.4169	0.428	-0.974	0.330	-1.256
0.422					
Log_Return_Lag2_Zero22	-0.0972	0.449	-0.217	0.829	-0.977
0.783					
=====					
Omnibus:	58.729	Durbin-Watson:		1.945	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		686.047	
Skew:	0.202	Prob(JB):		1.06e-149	
Kurtosis:	10.052	Cond. No.		254.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Separate Weekly and Monthly Zero Interactions:
OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.680		
Model:	OLS	Adj. R-squared:	0.674		
Method:	Least Squares	F-statistic:	62.73		
Date:	Wed, 22 May 2024	Prob (F-statistic):	2.55e-51		
Time:	07:45:03	Log-Likelihood:	744.59		
No. Observations:	330	AIC:	-1475.		
Df Residuals:	323	BIC:	-1449.		
Df Model:	6				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	-0.0021	0.006	-0.336	0.737	-0.014
0.010					
Zero_Fraction_5	0.0059	0.008	0.742	0.458	-0.010
0.021					
Zero_Fraction_22	-0.0047	0.009	-0.495	0.620	-0.023
0.014					
Log_Return_Lag1	1.2954	0.133	9.719	0.000	1.034
1.557					
Log_Return_Lag2	-0.1476	0.170	-0.867	0.386	-0.481
0.186					

Log_Return_Lag1_Zero5	-1.5820	0.167	-9.483	0.000	-1.909
-1.255					
Log_Return_Lag2_Zero22	0.6466	0.279	2.318	0.020	0.100
1.193					
=====					
Omnibus:	103.307	Durbin-Watson:		1.862	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		1517.576	
Skew:	0.845	Prob(JB):		0.00	
Kurtosis:	13.369	Cond. No.		209.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

```
In [58]: # Tuesdays
tuesdays_models = models_comparison(Tuesdays, lags=2, df_name='Tuesdays')
```


Model Name					Adj R ²
AIC	BIC		Rho_1	Rho_2	
Ljung-Box Test Statistic		Ljung-Box P-value			
Model with Only Constant					4.440892098500626e-16
-1120.0482104914004	-1116.2370694984236	0.6662548458224645	0.5498091033		
843614	314.5186833119641	7.165941752616387e-68			
Model with Weekly Zero					-1.1187337564999567e-05
-1119.048985976916	-1111.4267039909626	0.6663684172207335	0.5470806169		
291975	313.5534914848556	1.1593079726098431e-67			
Model with Monthly Zero					0.00047332969827085236
-1119.2108520726424	-1111.588570086689	0.6659031915516898	0.549412311		
126432	314.32366766858763	7.897443881395843e-68			
AR(1)					0.44221628864425344
-1309.095199471638	-1301.478914491677	-0.12692869813086013	0.1139968538		
880168	10.397345606056946	0.015473677649263303			
AR(2)					0.4608973245266801
-1314.4740652539508	-1303.0586603472013	-0.002327121756879495	-0.0101467210		
29427166	0.04215333467183039	0.9977270952194889			
AR(1) with Weekly Zero Interaction					0.6397049321725019
-1452.650353016808	-1437.417783056886	0.051606429811643866	0.2483583351		
2121724	27.3948706744289	4.8653971446982565e-06			
AR(1) with Monthly Zero Interaction					0.4506298798857473
-1312.1746169699295	-1296.9420470100076	-0.08786852316957235	0.1316902097		
2684173	9.17651799578683	0.027033752967145667			
AR(2) with Weekly Zero Interaction					0.6502198530775722
-1455.1389195190632	-1432.3081097055642	0.1554979055162424	0.1661700084		
429255	21.682379886804345	7.594916831227399e-05			
AR(2) with Monthly Zero Interaction					0.46482449585413876
-1313.9426618394	-1291.111852025901	0.029356139090624987	0.01760915791		
9125807	0.40900268841602766	0.9383765352599154			
AR(2) with Separate Weekly and Monthly Zero Interactions					0.6667421419818788
-1470.2237941547537	-1443.5878493723383	-0.0060668329669526355	0.0698299493		
6368837	2.5793865303526005	0.46111482000108095			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Weekly Zero:

OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.003			
Model:	OLS	Adj. R-squared:	-0.000			
Method:	Least Squares	F-statistic:	0.9963			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.319			
Time:	07:45:11	Log-Likelihood:	561.52			
No. Observations:	334	AIC:	-1119.			
Df Residuals:	332	BIC:	-1111.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0046	0.006	0.774	0.439	-0.007	0.016
Zero_Fraction_5	-0.0080	0.008	-0.998	0.319	-0.024	0.008
Omnibus:	70.359	Durbin-Watson:	0.667			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	744.999			
Skew:	0.483	Prob(JB):	1.68e-162			
Kurtosis:	10.253	Cond. No.	4.83			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Monthly Zero:

OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.003			
Model:	OLS	Adj. R-squared:	0.000			
Method:	Least Squares	F-statistic:	1.158			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.283			
Time:	07:45:11	Log-Likelihood:	561.61			
No. Observations:	334	AIC:	-1119.			
Df Residuals:	332	BIC:	-1112.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0064	0.007	0.898	0.370	-0.008	0.021
Zero_Fraction_22	-0.0106	0.010	-1.076	0.283	-0.030	0.009
Omnibus:	71.142	Durbin-Watson:	0.668			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	747.870			
Skew:	0.499	Prob(JB):	4.00e-163			
Kurtosis:	10.263	Cond. No.	5.92			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: AR(1):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.444
Model:                  OLS           Adj. R-squared:           0.442
Method:                 Least Squares F-statistic:              66.37
Date:                  Wed, 22 May 2024 Prob (F-statistic):      7.73e-15
Time:                  07:45:11       Log-Likelihood:          656.55
No. Observations:      333           AIC:                    -1309.
Df Residuals:          331           BIC:                    -1301.
Df Model:              1
Covariance Type:       HAC
=====
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -0.0003      0.002     -0.152      0.879     -0.004      0.003
Log_Return_Lag1  0.6663      0.082      8.147      0.000      0.506      0.827
=====
Omnibus:                68.206   Durbin-Watson:                2.252
Prob(Omnibus):           0.000   Jarque-Bera (JB):           1086.804
Skew:                    0.214   Prob(JB):                   1.01e-236
Kurtosis:                11.840   Cond. No.                   22.1
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.464
Model:                  OLS           Adj. R-squared:           0.461
Method:                 Least Squares F-statistic:              42.85
Date:                  Wed, 22 May 2024 Prob (F-statistic):      2.89e-17
Time:                  07:45:11       Log-Likelihood:          660.24
No. Observations:      332           AIC:                    -1314.
Df Residuals:          329           BIC:                    -1303.
Df Model:              2
Covariance Type:       HAC
=====
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -0.0002      0.002     -0.109      0.913     -0.004      0.003
Log_Return_Lag1  0.5389      0.098      5.493      0.000      0.347      0.731
Log_Return_Lag2  0.1912      0.076      2.518      0.012      0.042      0.340
=====
Omnibus:                79.052   Durbin-Watson:                2.004
Prob(Omnibus):           0.000   Jarque-Bera (JB):           1219.009
Skew:                    0.465   Prob(JB):                   1.97e-265
Kurtosis:                12.341   Cond. No.                   38.3
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(1) with Weekly Zero Interaction:
OLS Regression Results

```

=====
Dep. Variable:          Log_Return    R-squared:                0.643
Model:                  OLS           Adj. R-squared:           0.640
Method:                 Least Squares F-statistic:              77.71
Date:                   Wed, 22 May 2024 Prob (F-statistic):      5.03e-38
Time:                   07:45:11      Log-Likelihood:          730.33
No. Observations:      333           AIC:                    -1453.
Df Residuals:          329           BIC:                    -1437.
Df Model:               3
Covariance Type:       HAC
=====

```

```

=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----

```

```

const              0.0015      0.006      0.247      0.805      -0.011
0.014
Zero_Fraction_5    -0.0042      0.007     -0.595      0.552      -0.018
0.010
Log_Return_Lag1     1.2301      0.102     12.009      0.000      1.029
1.431
Log_Return_Lag1_Zero5 -1.3795      0.181     -7.605      0.000      -1.735      -
1.024
=====

```

```

=====
Omnibus:            85.940    Durbin-Watson:           1.896
Prob(Omnibus):      0.000    Jarque-Bera (JB):        1007.035
Skew:               0.678    Prob(JB):                2.11e-219
Kurtosis:           11.411    Cond. No.                91.3
=====

```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(1) with Monthly Zero Interaction:
OLS Regression Results

```

=====
Dep. Variable:          Log_Return    R-squared:                0.456
Model:                  OLS           Adj. R-squared:           0.451
Method:                 Least Squares F-statistic:              21.64
Date:                   Wed, 22 May 2024 Prob (F-statistic):      8.17e-13
Time:                   07:45:11      Log-Likelihood:          660.09
No. Observations:      333           AIC:                    -1312.
Df Residuals:          329           BIC:                    -1297.
Df Model:               3
Covariance Type:       HAC
=====

```

```

=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----

```

```

const              0.0014      0.008      0.166      0.868      -0.015
0.017
Zero_Fraction_22    -0.0031      0.010     -0.317      0.751      -0.022
0.016
Log_Return_Lag1     0.8338      0.125      6.696      0.000      0.590
1.078
Log_Return_Lag1_Zero22 -0.5250      0.218     -2.411      0.016      -0.952

```

-0.098

```
=====
Omnibus:                67.786    Durbin-Watson:                2.174
Prob(Omnibus):          0.000    Jarque-Bera (JB):          1204.642
Skew:                   -0.037    Prob(JB):                   2.60e-262
Kurtosis:               12.317    Cond. No.                   140.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Weekly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.656
Model:                  OLS           Adj. R-squared:           0.650
Method:                 Least Squares  F-statistic:             46.30
Date:                   Wed, 22 May 2024  Prob (F-statistic):      4.46e-36
Time:                   07:45:11      Log-Likelihood:          733.57
No. Observations:       332          AIC:                     -1455.
Df Residuals:           326          BIC:                     -1432.
Df Model:                5
Covariance Type:        HAC
=====
```

```
=====
                                coef    std err          z      P>|z|      [0.025
0.975]
```

```
-----
const                0.0013    0.007    0.188    0.851    -0.012
0.014
Zero_Fraction_5     -0.0038    0.008   -0.486    0.627    -0.019
0.011
Log_Return_Lag1      1.0806    0.203    5.314    0.000    0.682
1.479
Log_Return_Lag2      0.2033    0.189    1.076    0.282    -0.167
0.574
Log_Return_Lag1_Zero5 -1.2771    0.313   -4.077    0.000    -1.891    -
0.663
Log_Return_Lag2_Zero5 -0.1084    0.251   -0.432    0.666    -0.601
0.384
=====
```

```
=====
Omnibus:                115.235    Durbin-Watson:                1.688
Prob(Omnibus):          0.000    Jarque-Bera (JB):          1540.908
Skew:                   1.029    Prob(JB):                   0.00
Kurtosis:               13.352    Cond. No.                   181.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Monthly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.473
Model:                  OLS           Adj. R-squared:           0.465
Method:                 Least Squares  F-statistic:             18.25
Date:                   Wed, 22 May 2024  Prob (F-statistic):      5.64e-16
=====
```

Time:	07:45:11	Log-Likelihood:	662.97
No. Observations:	332	AIC:	-1314.
Df Residuals:	326	BIC:	-1291.
Df Model:	5		
Covariance Type:	HAC		

	coef	std err	z	P> z	[0.025
0.975]					
const	0.0013	0.009	0.157	0.876	-0.015
0.018					
Zero_Fraction_22	-0.0030	0.010	-0.287	0.774	-0.023
0.017					
Log_Return_Lag1	0.6216	0.233	2.670	0.008	0.165
1.078					
Log_Return_Lag2	0.2676	0.219	1.223	0.221	-0.161
0.696					
Log_Return_Lag1_Zero22	-0.2796	0.390	-0.716	0.474	-1.045
0.485					
Log_Return_Lag2_Zero22	-0.2342	0.386	-0.606	0.544	-0.991
0.523					
Omnibus:	73.378	Durbin-Watson:	1.940		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1280.143		
Skew:	0.289	Prob(JB):	1.05e-278		
Kurtosis:	12.602	Cond. No.	265.		

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Separate Weekly and Monthly Zero Interactions:
OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.673
Model:	OLS	Adj. R-squared:	0.667
Method:	Least Squares	F-statistic:	54.85
Date:	Wed, 22 May 2024	Prob (F-statistic):	1.49e-46
Time:	07:45:11	Log-Likelihood:	742.11
No. Observations:	332	AIC:	-1470.
Df Residuals:	325	BIC:	-1444.
Df Model:	6		
Covariance Type:	HAC		

	coef	std err	z	P> z	[0.025
0.975]					
const	0.0015	0.006	0.233	0.816	-0.011
0.014					
Zero_Fraction_5	-0.0047	0.009	-0.551	0.582	-0.022
0.012					
Zero_Fraction_22	0.0015	0.009	0.156	0.876	-0.017
0.020					
Log_Return_Lag1	1.2624	0.133	9.484	0.000	1.001
1.523					
Log_Return_Lag2	-0.1597	0.134	-1.189	0.234	-0.423
0.104					

Log_Return_Lag1_Zero5	-1.5699	0.176	-8.922	0.000	-1.915
-1.225					
Log_Return_Lag2_Zero22	0.7974	0.246	3.242	0.001	0.315
1.279					
=====					
Omnibus:	108.881	Durbin-Watson:		2.012	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		1523.817	
Skew:	0.930	Prob(JB):		0.00	
Kurtosis:	13.330	Cond. No.		213.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

```
In [59]: # Mondays
mondays_models = models_comparison(Mondays, lags=2, df_name='Mondays')
```

Model Name				Adj R ²
AIC	BIC	Rho_1	Rho_2	
Ljung-Box Test Statistic		Ljung-Box P-value		
Model with Only Constant				1.1102230246251565e-16
-1072.9949067216508	-1069.2203551761063	0.6485785132468169	0.53265564400	
54085	295.15763921355324	1.1111279373154317e-63		
Model with Weekly Zero				-0.0013642233682962246
-1071.5606071650618	-1064.011504073973	0.6480396176913513	0.5303938643	
05114	293.6864814259133	2.3128325060110028e-63		
Model with Monthly Zero				-0.0009601028270205259
-1071.6905829280845	-1064.1414798369956	0.6478161168849362	0.53188351163	
61448	294.54437907639203	1.5082842725604658e-63		
AR(1)				0.4188387831233582
-1241.8783715514755	-1234.3354893052156	-0.125428185903783	0.07747961535	
798127	14.154821894854246	0.0027018115793091355		
AR(2)				0.43892848337180257
-1247.2675692410312	-1235.96260625365	-0.015422930053294053	-0.03477978750	
6850623	3.305239746236195	0.3469140351821625		
AR(1) with Weekly Zero Interaction				0.5965349149049617
-1357.0424231719608	-1341.9566586794408	0.07622468836713626	0.20659773890	
744296	25.00169788862177	1.542788201211415e-05		
AR(1) with Monthly Zero Interaction				0.4490982825589066
-1257.0616868956981	-1241.9759224031782	-0.03388237253119526	0.10406670866	
775199	11.545775520866492	0.009112736978480765		
AR(2) with Weekly Zero Interaction				0.604503175290116
-1356.2161795957159	-1333.6062536209533	0.15480873916245083	0.13287133048	
486352	20.45510996278377	0.000136592546067836		
AR(2) with Monthly Zero Interaction				0.45974285447753893
-1256.4073914369355	-1233.797465462173	0.012894971051207562	0.000734765467	
8739172	4.315220497958294	0.229376328766992		
AR(2) with Separate Weekly and Monthly Zero Interactions				0.6228941722918944
-1370.4743222644406	-1344.0960752938843	0.011265292103581532	0.02770651322	
372761	4.235255008758069	0.2371558080663643		

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Weekly Zero:

OLS Regression Results

=====						
Dep. Variable:	Log_Return	R-squared:	0.002			
Model:	OLS	Adj. R-squared:	-0.001			
Method:	Least Squares	F-statistic:	0.5627			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.454			
Time:	07:45:20	Log-Likelihood:	537.78			
No. Observations:	322	AIC:	-1072.			
Df Residuals:	320	BIC:	-1064.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0033	0.006	0.547	0.585	-0.009	0.015
Zero_Fraction_5	-0.0061	0.008	-0.750	0.454	-0.022	0.010
=====						
Omnibus:	62.377	Durbin-Watson:	0.704			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	651.135			
Skew:	0.383	Prob(JB):	4.05e-142			
Kurtosis:	9.924	Cond. No.	4.75			
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: Model with Monthly Zero:

OLS Regression Results

=====						
Dep. Variable:	Log_Return	R-squared:	0.002			
Model:	OLS	Adj. R-squared:	-0.001			
Method:	Least Squares	F-statistic:	0.6921			
Date:	Wed, 22 May 2024	Prob (F-statistic):	0.406			
Time:	07:45:20	Log-Likelihood:	537.85			
No. Observations:	322	AIC:	-1072.			
Df Residuals:	320	BIC:	-1064.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.0049	0.007	0.670	0.504	-0.010	0.019
Zero_Fraction_22	-0.0083	0.010	-0.832	0.406	-0.028	0.011
=====						
Omnibus:	62.920	Durbin-Watson:	0.704			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	651.615			
Skew:	0.398	Prob(JB) :	3.19e-142			
Kurtosis:	9.924	Cond. No.	5.87			
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Parameters for Model: AR(1):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.421
Model:                  OLS           Adj. R-squared:          0.419
Method:                 Least Squares F-statistic:              91.99
Date:                   Wed, 22 May 2024 Prob (F-statistic):      2.62e-19
Time:                   07:45:20      Log-Likelihood:          622.94
No. Observations:      321           AIC:                    -1242.
Df Residuals:          319           BIC:                    -1234.
Df Model:               1
Covariance Type:       HAC
=====
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -0.0003      0.002     -0.156      0.876     -0.004      0.003
Log_Return_Lag1  0.6486      0.068      9.591      0.000      0.516      0.781
=====
Omnibus:                81.877    Durbin-Watson:                2.249
Prob(Omnibus):           0.000    Jarque-Bera (JB):            641.468
Skew:                    0.800    Prob(JB):                     5.09e-140
Kurtosis:                9.738    Cond. No.                     21.9
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2):

OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.442
Model:                  OLS           Adj. R-squared:          0.439
Method:                 Least Squares F-statistic:              53.35
Date:                   Wed, 22 May 2024 Prob (F-statistic):      1.07e-20
Time:                   07:45:20      Log-Likelihood:          626.63
No. Observations:      320           AIC:                    -1247.
Df Residuals:          317           BIC:                    -1236.
Df Model:               2
Covariance Type:       HAC
=====
```

```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
const          -0.0002      0.002     -0.109      0.913     -0.004      0.003
Log_Return_Lag1  0.5224      0.077      6.792      0.000      0.372      0.673
Log_Return_Lag2  0.1945      0.070      2.791      0.005      0.058      0.331
=====
Omnibus:                95.002    Durbin-Watson:                2.030
Prob(Omnibus):           0.000    Jarque-Bera (JB):            788.916
Skew:                    0.963    Prob(JB):                     4.89e-172
Kurtosis:               10.447    Cond. No.                     37.0
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(1) with Weekly Zero Interaction:
OLS Regression Results

```

=====
Dep. Variable:          Log_Return    R-squared:                0.600
Model:                  OLS           Adj. R-squared:           0.597
Method:                 Least Squares F-statistic:              66.88
Date:                   Wed, 22 May 2024 Prob (F-statistic):      1.56e-33
Time:                   07:45:20      Log-Likelihood:          682.52
No. Observations:      321           AIC:                    -1357.
Df Residuals:          317           BIC:                    -1342.
Df Model:               3
Covariance Type:       HAC
=====

```

```

=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----

```

```

const              0.0019      0.007      0.259      0.796      -0.013
0.016
Zero_Fraction_5    -0.0046      0.009     -0.540      0.589      -0.021
0.012
Log_Return_Lag1     1.1773      0.103     11.422      0.000      0.975
1.379
Log_Return_Lag1_Zero5 -1.2719      0.182     -6.969      0.000      -1.630      -
0.914

```

```

=====
Omnibus:            105.213    Durbin-Watson:           1.846
Prob(Omnibus):      0.000    Jarque-Bera (JB):        990.319
Skew:               1.055    Prob(JB):                9.02e-216
Kurtosis:           11.342    Cond. No.                87.8
=====

```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(1) with Monthly Zero Interaction:
OLS Regression Results

```

=====
Dep. Variable:          Log_Return    R-squared:                0.454
Model:                  OLS           Adj. R-squared:           0.449
Method:                 Least Squares F-statistic:              35.52
Date:                   Wed, 22 May 2024 Prob (F-statistic):      8.09e-20
Time:                   07:45:20      Log-Likelihood:          632.53
No. Observations:      321           AIC:                    -1257.
Df Residuals:          317           BIC:                    -1242.
Df Model:               3
Covariance Type:       HAC
=====

```

```

=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----

```

```

const              -0.0002      0.008     -0.028      0.978      -0.016
0.016
Zero_Fraction_22    -0.0012      0.010     -0.126      0.900      -0.020
0.018
Log_Return_Lag1     0.9371      0.107      8.727      0.000      0.727
1.148
Log_Return_Lag1_Zero22 -0.8609      0.217     -3.967      0.000      -1.286

```

-0.436

```
=====
Omnibus:                                71.199    Durbin-Watson:                2.066
Prob(Omnibus):                          0.000    Jarque-Bera (JB):             690.368
Skew:                                   0.568    Prob(JB):                     1.23e-150
Kurtosis:                               10.094    Cond. No.                     133.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Weekly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.611
Model:                  OLS           Adj. R-squared:           0.605
Method:                Least Squares  F-statistic:             38.05
Date:                  Wed, 22 May 2024  Prob (F-statistic):      1.77e-30
Time:                  07:45:20       Log-Likelihood:          684.11
No. Observations:      320           AIC:                    -1356.
Df Residuals:          314           BIC:                    -1334.
Df Model:              5
Covariance Type:      HAC
=====
```

```
=====
                                coef    std err          z      P>|z|      [0.025
0.975]
```

```
-----
const                0.0017    0.008      0.218    0.827    -0.013
0.017
Zero_Fraction_5     -0.0042    0.009    -0.465    0.642    -0.022
0.014
Log_Return_Lag1      1.0356    0.187     5.551    0.000     0.670
1.401
Log_Return_Lag2      0.1905    0.187     1.020    0.308    -0.176
0.557
Log_Return_Lag1_Zero5 -1.1651    0.289    -4.030    0.000    -1.732    -
0.599
Log_Return_Lag2_Zero5 -0.1091    0.251    -0.435    0.663    -0.601
0.382
=====
```

```
=====
Omnibus:            116.273    Durbin-Watson:            1.690
Prob(Omnibus):      0.000    Jarque-Bera (JB):         1281.701
Skew:               1.156    Prob(JB):                 4.81e-279
Kurtosis:           12.528    Cond. No.                 176.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Monthly Zero Interaction:
OLS Regression Results

```
=====
Dep. Variable:          Log_Return    R-squared:                0.468
Model:                  OLS           Adj. R-squared:           0.460
Method:                Least Squares  F-statistic:             23.54
Date:                  Wed, 22 May 2024  Prob (F-statistic):      4.29e-20
=====
```

Time:	07:45:20	Log-Likelihood:	634.20
No. Observations:	320	AIC:	-1256.
Df Residuals:	314	BIC:	-1234.
Df Model:	5		
Covariance Type:	HAC		

	coef	std err	z	P> z	[0.025
0.975]					
const	-0.0002	0.008	-0.018	0.985	-0.016
0.016					
Zero_Fraction_22	-0.0009	0.010	-0.094	0.925	-0.020
0.019					
Log_Return_Lag1	0.8894	0.187	4.756	0.000	0.523
1.256					
Log_Return_Lag2	0.0208	0.182	0.114	0.909	-0.336
0.378					
Log_Return_Lag1_Zero22	-0.9164	0.316	-2.898	0.004	-1.536
-0.297					
Log_Return_Lag2_Zero22	0.2921	0.312	0.937	0.349	-0.319
0.903					
Omnibus:	77.096	Durbin-Watson:	1.973		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	771.186		
Skew:	0.647	Prob(JB):	3.46e-168		
Kurtosis:	10.494	Cond. No.	235.		

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

Parameters for Model: AR(2) with Separate Weekly and Monthly Zero Interactions:
OLS Regression Results

Dep. Variable:	Log_Return	R-squared:	0.630		
Model:	OLS	Adj. R-squared:	0.623		
Method:	Least Squares	F-statistic:	44.75		
Date:	Wed, 22 May 2024	Prob (F-statistic):	2.16e-39		
Time:	07:45:20	Log-Likelihood:	692.24		
No. Observations:	320	AIC:	-1370.		
Df Residuals:	313	BIC:	-1344.		
Df Model:	6				
Covariance Type:	HAC				
=====					
=====					
	coef	std err	z	P> z	[0.025
0.975]					

const	0.0006	0.007	0.087	0.931	-0.013
0.014					
Zero_Fraction_5	-0.0091	0.011	-0.796	0.426	-0.031
0.013					
Zero_Fraction_22	0.0072	0.011	0.644	0.519	-0.015
0.029					
Log_Return_Lag1	1.2330	0.130	9.493	0.000	0.978
1.488					
Log_Return_Lag2	-0.1863	0.138	-1.354	0.176	-0.456
0.083					

Log_Return_Lag1_Zero5	-1.4512	0.201	-7.228	0.000	-1.845
-1.058					
Log_Return_Lag2_Zero22	0.7774	0.289	2.689	0.007	0.211
1.344					
=====					
Omnibus:	121.275	Durbin-Watson:		1.977	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		1199.366	
Skew:	1.262	Prob(JB):		3.64e-261	
Kurtosis:	12.142	Cond. No.		201.	
=====					

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 2 lags and without small sample correction

The model **AR(2) with Separate Weekly and Monthly Zero Interactions** is still the best model for other 4 dataframes in almost all criterias. Furthurmore, not like Fridays, the mix model shows high enough Ljung-Box p-values (0.24, 0.29, 0.46, 0.56) based on these four dataframes, supports there not exist serial correlations of residuals.

P11: Plot rolling average of SQUARED residuals of the best model (Use fridays_models as the example)

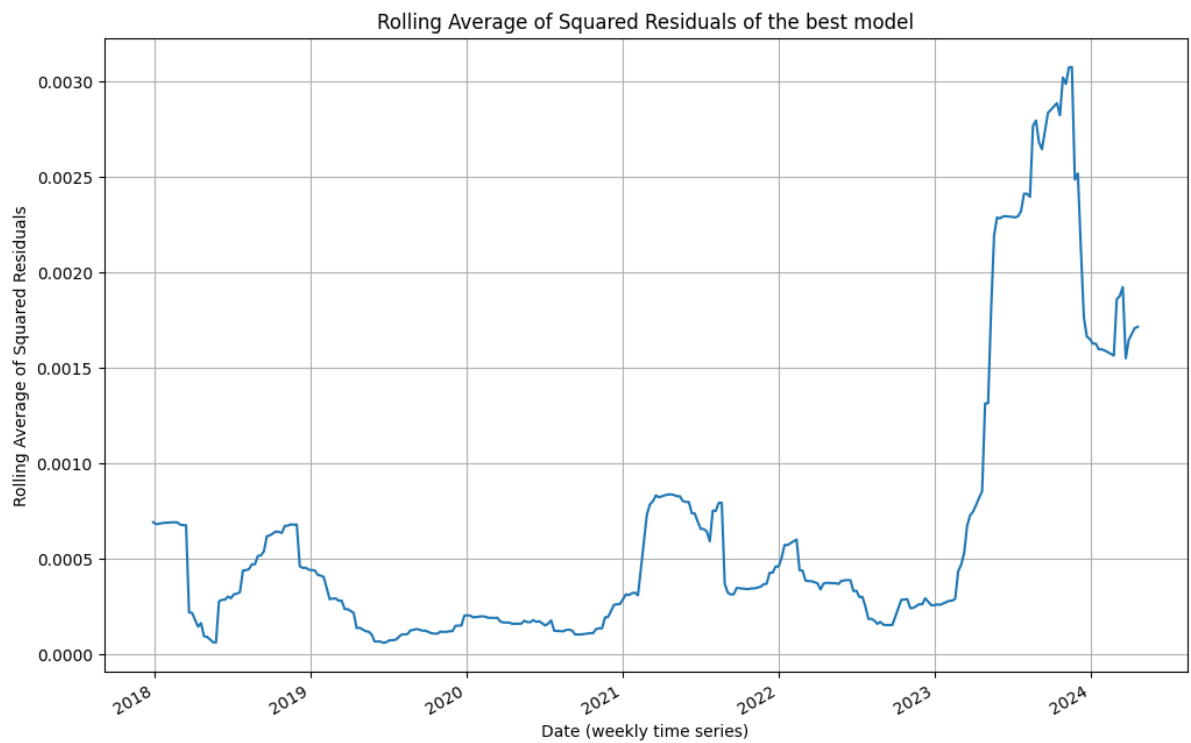
```
In [60]: def plot_rolling_average_of_squared_residuals(model_results):
        """
        Plots the rolling average of squared residuals for a given model.

        Parameters:
        - model_results (RegressionResultsWrapper): The fitted model result.

        Outputs:
        - A plot showing the rolling average of squared residuals.
        """
        residuals = model_results.resid
        squared_residuals = residuals ** 2
        rolling_average = squared_residuals.rolling(window=26).mean()

        plt.figure(figsize=(12, 8))
        rolling_average.plot(title='Rolling Average of Squared Residuals of the best mod
        plt.xlabel('Date (weekly time series)')
        plt.ylabel('Rolling Average of Squared Residuals')
        plt.grid(True)
        plt.show()
```

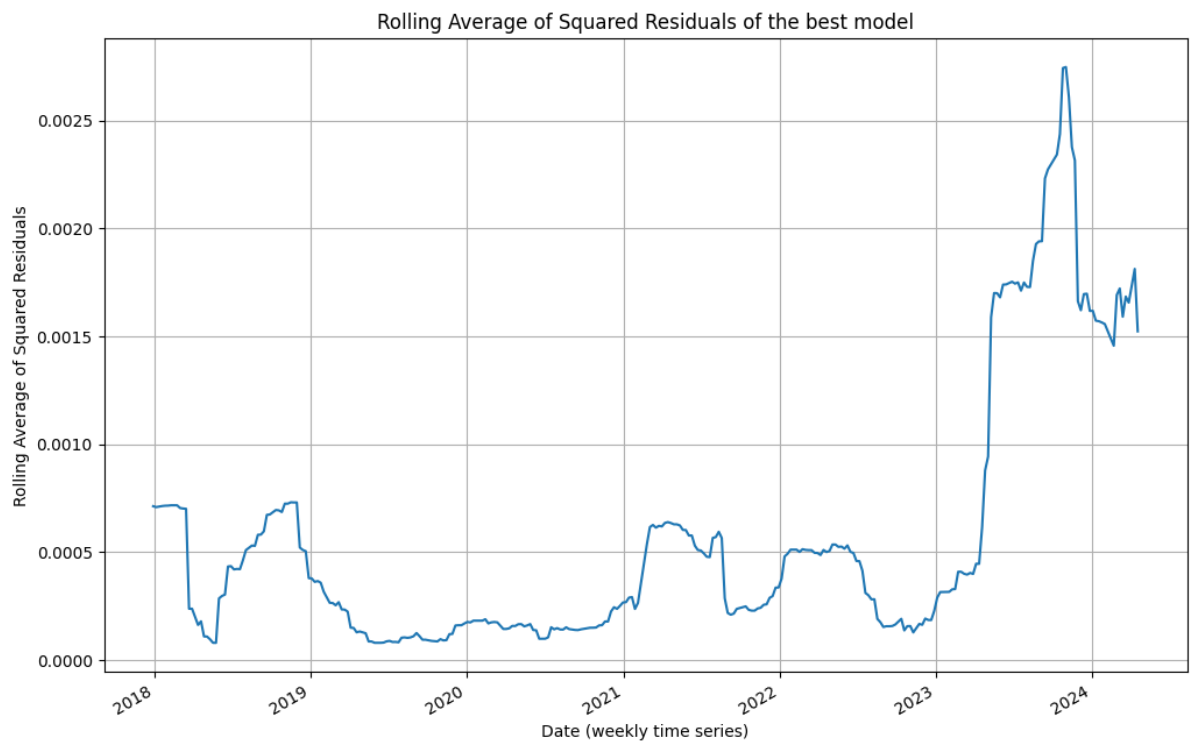
```
In [61]: plot_rolling_average_of_squared_residuals(model_results=fridays_models['AR(2) with S
```



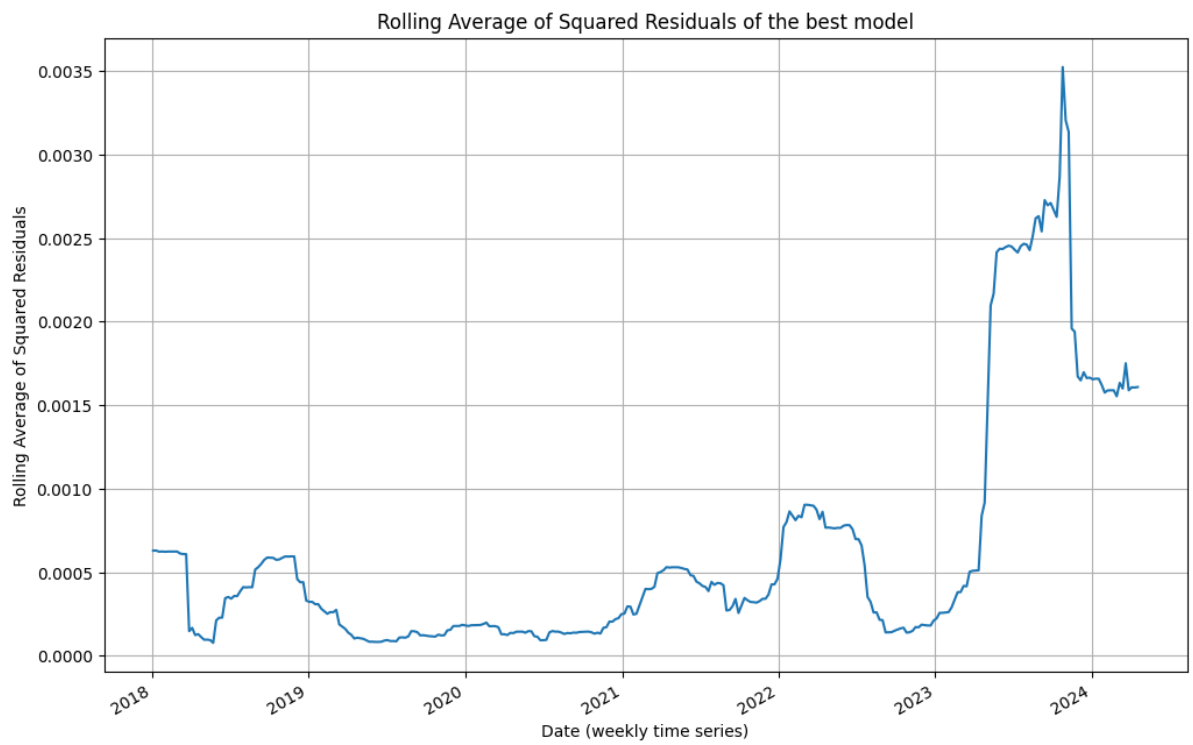
The rolling average follows a totally increasing trend, this indicates a rising volatility, but there also exists a sharp decreasing near the end of year 2023.

Robustness work for P11

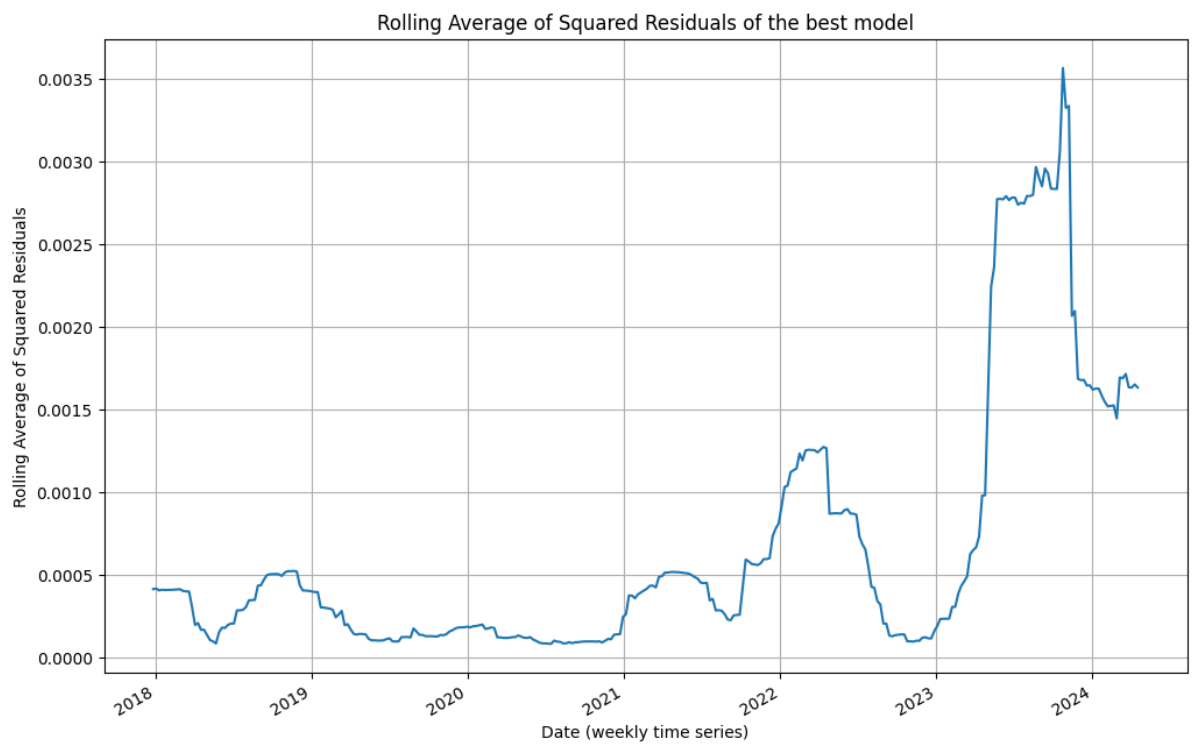
```
In [62]: # Thursdays
plot_rolling_average_of_squared_residuals(model_results=thursdays_models['AR(2) with
```



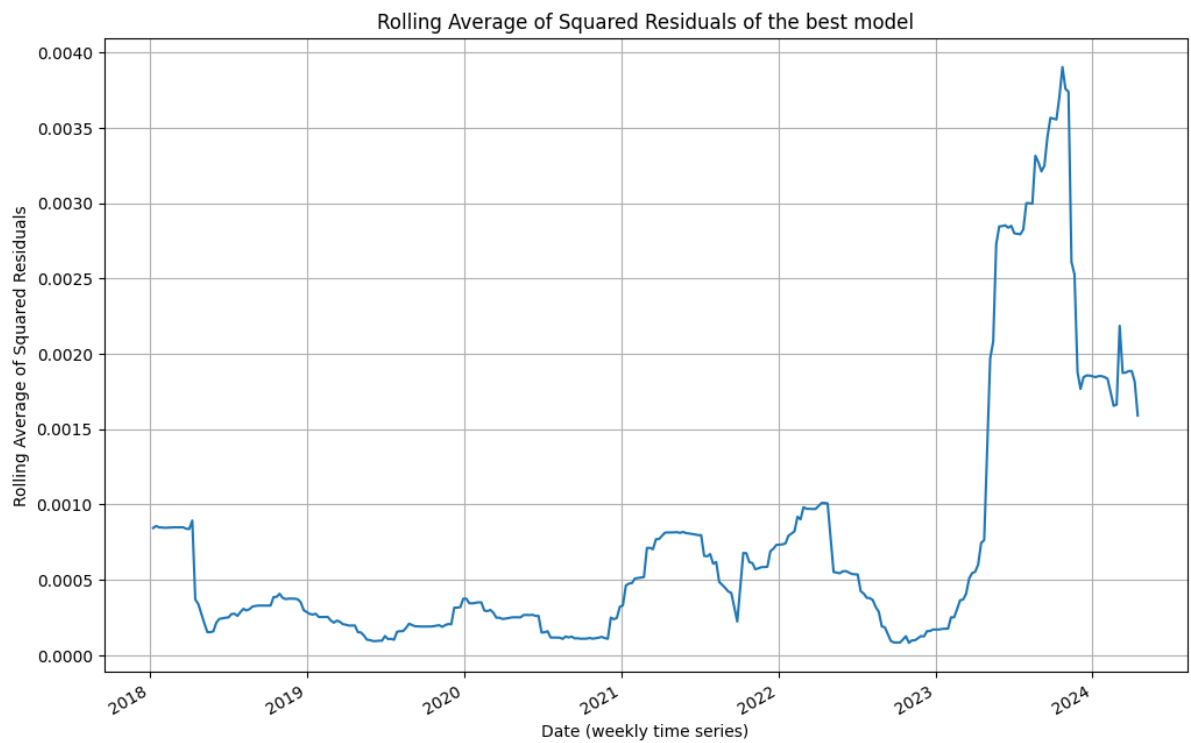
```
In [63]: # Wednesdays
plot_rolling_average_of_squared_residuals(model_results=wednesdays_models['AR(2) with
```



```
In [64]: # Tuesdays
plot_rolling_average_of_squared_residuals(model_results=tuesdays_models['AR(2) with S
```



```
In [65]: # Mondays
plot_rolling_average_of_squared_residuals(model_results=mondays_models['AR(2) with S
```

P12: Perform Out-of-Sample Forecasting and Compute RMSE (Use Fridays as an example)

```
In [66]: def prepare_input_data(df):
    """
    Prepares input data for out-of-sample predictions by creating necessary lagged
    variables and interactions based on the specified models. The function safely
    operates on a copy of the input DataFrame to avoid modifying the original data.

    Parameters:
    - df: Original DataFrame containing the columns ['Log_Return',
        'Zero_Count_22', 'Zero_Count_5', 'Zero_Fraction_5', 'Zero_Fraction_22'].

    Returns:
    - input_data: A new DataFrame with original and derived columns
        necessary for making predictions with all ten models.
    """
    data = df.copy()

    input_data = pd.DataFrame(index=data.index)
    input_data['Log_Return'] = data['Log_Return']
    input_data['Zero_Fraction_5'] = data['Zero_Fraction_5']
    input_data['Zero_Fraction_22'] = data['Zero_Fraction_22']

    # Create lagged features for Log_Return
    input_data['Log_Return_Lag1'] = data['Log_Return'].shift(1)
    input_data['Log_Return_Lag2'] = data['Log_Return'].shift(2)

    # Create interactions for lagged Log_Return with Zero Fractions
    input_data['Log_Return_Lag1_Zero5'] = input_data['Log_Return_Lag1'] * data['Zero_Fraction_5']
    input_data['Log_Return_Lag1_Zero22'] = input_data['Log_Return_Lag1'] * data['Zero_Fraction_22']
    input_data['Log_Return_Lag2_Zero5'] = input_data['Log_Return_Lag2'] * data['Zero_Fraction_5']
    input_data['Log_Return_Lag2_Zero22'] = input_data['Log_Return_Lag2'] * data['Zero_Fraction_22']

    input_data.dropna(inplace=True)
```

```
# Add constant term for regression
input_data = sm.add_constant(input_data)

return input_data
```

```
In [67]: def calculate_rmse(errors):
        """
        Calculate the root mean squared error for a list of errors.
        """
        mse = np.mean([e**2 for e in errors])
        return np.sqrt(mse)
```

```
In [161... def forecast_and_compute_RMSE(df, lags, df_name):
        """
        Performs out-of-sample forecasting using a list of predefined
        models on an expanding window basis. Starting with the first
        52 observations, this function forecasts the 53rd observation
        and continues expanding the sample one observation at a time,
        re-estimating models and forecasting the next observation.
        The forecast errors are calculated for each model and used to
        compute the Root Mean Squared Error (RMSE) for each model's
        predictions. The results are then ranked by RMSE and saved to
        a csv file.

        Parameters:
        - df: A DataFrame containing the time series data, specifically
              a column 'Log_Return' which is used for the forecasting.
        - lags: Maximum number of lags to use for HAC standard errors.
        - df_name: A string that specifies the name of the DataFrame,
                  used to name the output CSV file.

        Returns:
        - rmse_df: a DataFrame containing the model names and their
                  corresponding RMSE, sorted by RMSE.

        Outputs:
        - Prints a sorted table of the RMSE results for each model.
        - Saves a CSV file named '{df_name}_forecast_rmse_results.csv'
          containing the RMSE results for each model based on input
          dataframe.
        """
        data = df.copy()
        perpared_data = prepare_input_data(data)
        forecast_errors = {name: [] for name, _ in models}

        # Start forecasting from the 53rd observation, using the first 52 observations in
        for i in range(52, len(perpared_data)):
            current_sample = perpared_data[['Log_Return', 'Zero_Fraction_5', 'Zero_Fraction_10']]

            for name, model_func in models:

                if name == 'Model with Only Constant': # Special case for constant model
                    forecast = current_sample['Log_Return'].mean()
                else:
                    features = model_features[name]
                    model = model_func(current_sample, lags)
                    input_data = perpared_data.iloc[i][features]
                    forecast = model.predict(input_data)

                # Actual return for the next time point (i)
                actual_return = perpared_data['Log_Return'].iloc[i]
                forecast_error = actual_return - forecast
```

```

forecast_errors[name].append(forecast_error)

# Compute RMSE for each model
rmse = {name: calculate_rmse(errors) for name, errors in forecast_errors.items}
rmse_df = pd.DataFrame(list(rmse.items()), columns=['Model', 'RMSE'])

# Sort by RMSE
rmse_df.sort_values(by='RMSE', inplace=True)

# Print the RMSE table
print(tabulate(rmse_df, headers='keys', tablefmt='pretty', showindex=False))

# Save the RMSE results to CSV
# files.download is just for google colab, if u use other environments, plz change
csv_filename = f'{df_name}_forecast_rmse_results.csv'
rmse_df.to_csv(csv_filename, index=True, header=True)
files.download(csv_filename)

return rmse_df

```

In [162...

```
fridays_forecast = forecast_and_compute_RMSE(df=Fraturdays, lags=4, df_name='Fraturdays')
```

Model	RMSE
AR(2) with Separate Weekly and Monthly Zero Interactions	0.028574111727738244
AR(1) with Weekly Zero Interaction	0.028699248262294284
AR(2) with Weekly Zero Interaction	0.028750511204274645
AR(1) with Monthly Zero Interaction	0.033110236042147606
AR(2)	0.03319323376216553
AR(1)	0.03347683497575105
AR(2) with Monthly Zero Interaction	0.0337186149256691
Model with Only Constant	0.047601851591042715
Model with Weekly Zero	0.048232338814404634
Model with Monthly Zero	0.048241569860663525

The model **AR(2) with Separate Weekly and Monthly Zero Interactions** still wins in *RMSE* criteria. This mix model has the lowest RMSE, which signifies highest accuracy in predictive performance. It means that the mix model's predictions are, on average, closer to the actual observed weekly log return.

AR(1) with Weekly Zero Interaction and **AR(2) with Weekly Zero Interaction** also have very lose *RMSE* to the mixed model.

Robustness work for P12

In [70]:

```
# Thursdays
thursdays_forecast = forecast_and_compute_RMSE(df=Thursdays, lags=2, df_name='Thursdays')
```

Model	RMSE
AR(1) with Weekly Zero Interaction	0.02644831863828377
AR(2) with Separate Weekly and Monthly Zero Interactions	0.02645577475084485
AR(2) with Weekly Zero Interaction	0.026687454429006337
AR(1) with Monthly Zero Interaction	0.03100346819508346
AR(1)	0.031228836428829586
AR(2)	0.03131017690997134
AR(2) with Monthly Zero Interaction	0.03152634740024679
Model with Only Constant	0.04684102151231067
Model with Weekly Zero	0.047454280581655434
Model with Monthly Zero	0.04748348409918562

```
In [71]: # Wednesdays
wednesdays_forecast = forecast_and_compute_RMSE(df=Wednesdays, lags=2, df_name='Wedn
```

Model	RMSE
AR(1) with Weekly Zero Interaction	0.027619063383236837
AR(2) with Separate Weekly and Monthly Zero Interactions	0.028173505929623775
AR(2) with Weekly Zero Interaction	0.028430185568081297
AR(1)	0.0344754974330957
AR(2)	0.034532832194297196
AR(1) with Monthly Zero Interaction	0.03482136156950505
AR(2) with Monthly Zero Interaction	0.03567962652680273
Model with Only Constant	0.047647999920785465
Model with Monthly Zero	0.048149164570744966
Model with Weekly Zero	0.04824941542810454

```
In [72]: # Tuesdays
tuesdays_forecast = forecast_and_compute_RMSE(df=Tuesdays, lags=2, df_name='Tuesdays
```

Model	RMSE
AR(2) with Separate Weekly and Monthly Zero Interactions	0.029554669343551537
AR(2) with Weekly Zero Interaction	0.029972662026528443
AR(1) with Weekly Zero Interaction	0.030109608823150988
AR(2)	0.0363193179205231
AR(1)	0.03668898286049331
AR(1) with Monthly Zero Interaction	0.03711598115118176
AR(2) with Monthly Zero Interaction	0.0373343424740437
Model with Only Constant	0.048320938820529416
Model with Weekly Zero	0.04892653471571601
Model with Monthly Zero	0.04893450220541475

```
In [73]: # Mondays
mondays_forecast = forecast_and_compute_RMSE(df=Mondays, lags=2, df_name='Mondays')
```

Model	RMSE
AR(2) with Separate Weekly and Monthly Zero Interactions	0.031247302347774532
AR(1) with Weekly Zero Interaction	0.03165887030234597
AR(2) with Weekly Zero Interaction	0.03215754992225925
AR(2)	0.03668184362733399
AR(1) with Monthly Zero Interaction	0.0368788773003294
AR(1)	0.037050763630292645
AR(2) with Monthly Zero Interaction	0.037297806583013175
Model with Only Constant	0.04851899399219849
Model with Weekly Zero	0.0491806017065333
Model with Monthly Zero	0.04926107862652646

The mix model **AR(2) with Separate Weekly and Monthly Zero Interactions** has second lowest *RMSE* for Thursdays dataframe and Wednesdays dataframe.

The mix model has first lowest *RMSE* for Fridays, Tuesdays, Mondays dataframe.

Source of the weirdly lowh Ljung Box p-values for the Fridays series

```
In [74]: model_test = fridays_models['AR(2) with Separate Weekly and Monthly Zero Interaction']
residuals = model_test.resid
ljung_box_results = acorr_ljungbox(residuals, lags=[3], return_df=True)

print("Ljung-Box test results for the first three lags:")
print(ljung_box_results)
```

```
Ljung-Box test results for the first three lags:
   lb_stat  lb_pvalue
3    22.284808    0.000057
```

large 'lb_stat' and low 'lb_pvalue'

Compute the autocorrelations of the residuals at the first three lags

```
In [75]: # Fridays
model_test = fridays_models['AR(2) with Separate Weekly and Monthly Zero Interaction']
residuals = model_test.resid
autocorrs = acf(residuals, nlags=3, fft=True)
print("Autocorrelations at the first three lags:", autocorrs[1:])
print("Fridays' third autocorrelation:", autocorrs[3])
```

```
Autocorrelations at the first three lags: [ 0.02258348 -0.03011749  0.25872257]
Fridays' third autocorrelation: 0.25872257471076554
```

```
In [76]: # Mondays
model_test = mondays_models['AR(2) with Separate Weekly and Monthly Zero Interaction']
residuals = model_test.resid
autocorrs = acf(residuals, nlags=3, fft=True)
print("Autocorrelations at the first three lags:", autocorrs[1:])
print("Mondays' third autocorrelation:", autocorrs[3])
```

Autocorrelations at the first three lags: [0.01126529 0.02770651 0.11017399]
Mondays' third autocorrelation: 0.11017399321047239

```
In [77]: # Tuesdays
model_test = tuesdays_models['AR(2) with Separate Weekly and Monthly Zero Interactions']
residuals = model_test.resid
autocorrs = acf(residuals, nlags=3, fft=True)
print("Autocorrelations at the first three lags:", autocorrs[1:])
print("Tuesdays' third autocorrelation:", autocorrs[3])
```

Autocorrelations at the first three lags: [-0.00606683 0.06982995 0.05248715]
Tuesdays' third autocorrelation: 0.05248715210374084

```
In [78]: # Wednesdays
model_test = wednesdays_models['AR(2) with Separate Weekly and Monthly Zero Interactions']
residuals = model_test.resid
autocorrs = acf(residuals, nlags=3, fft=True)
print("Autocorrelations at the first three lags:", autocorrs[1:])
print("Wednesdays' third autocorrelation:", autocorrs[3])
```

Autocorrelations at the first three lags: [0.06856758 0.02536327 0.02979565]
Wednesdays' third autocorrelation: 0.029795653661547118

```
In [79]: # Thursdays
model_test = thursdays_models['AR(2) with Separate Weekly and Monthly Zero Interactions']
residuals = model_test.resid
autocorrs = acf(residuals, nlags=3, fft=True)
print("Autocorrelations at the first three lags:", autocorrs[1:])
print("Thursdays' third autocorrelation:", autocorrs[3])
```

Autocorrelations at the first three lags: [0.05798363 -0.02744602 0.08398479]
Thursdays' third autocorrelation: 0.08398478977334237

Comparing Fridays and other four data, it is obvious that the reason for the Ljung-Box test rejecting the null hypothesis of no autocorrelation for models based on Fridays is the unusually higher third autocorrelation (0.258) than other four data (0.11, 0.052, 0.03, 0.084), where first two autocorrelations have no significant difference between these five data.

New P13: Forecast Graph

```
In [179... def generate_forecast_plot(df, lags, df_name):
    """
    Generates a plot showing the actual observed returns and the out-of-sample
    forecasted returns for the given DataFrame using the AR(2) model with
    separate interactions for zero fractions

    Parameters:
    - df: The input DataFrame containing the data. It must
      include the following columns: 'Log_Return',
      'Zero_Fraction_5', and 'Zero_Fraction_22'.
    - lags: Maximum number of lags to use for HAC standard errors.
    - df_name: A string that specifies the name of the DataFrame,
      used to name the plot titles.

    Returns:
    - None: This function generates and displays a plot, but does not return any value
    """
    data = df.copy()
    prepared_data = prepare_input_data(data)
    forecasted_returns = []
```

```

for i in range(52, len(perpared_data)):
    train_data = perpared_data[['Log_Return', 'Zero_Fraction_5', 'Zero_Fraction_10', 'Zero_Fraction_15', 'Zero_Fraction_20', 'Zero_Fraction_25', 'Zero_Fraction_30', 'Zero_Fraction_35', 'Zero_Fraction_40', 'Zero_Fraction_45', 'Zero_Fraction_50', 'Zero_Fraction_55', 'Zero_Fraction_60', 'Zero_Fraction_65', 'Zero_Fraction_70', 'Zero_Fraction_75', 'Zero_Fraction_80', 'Zero_Fraction_85', 'Zero_Fraction_90', 'Zero_Fraction_95', 'Zero_Fraction_100'])
    features = model_features['AR(2) with Separate Weekly and Monthly Zero Interaction']
    model = estimate_model_ar2_z5_z22_separate_interaction(train_data, lags)
    input_data = perpared_data.iloc[i][features]
    forecast = model.predict(input_data)
    forecasted_returns.append(forecast[0])

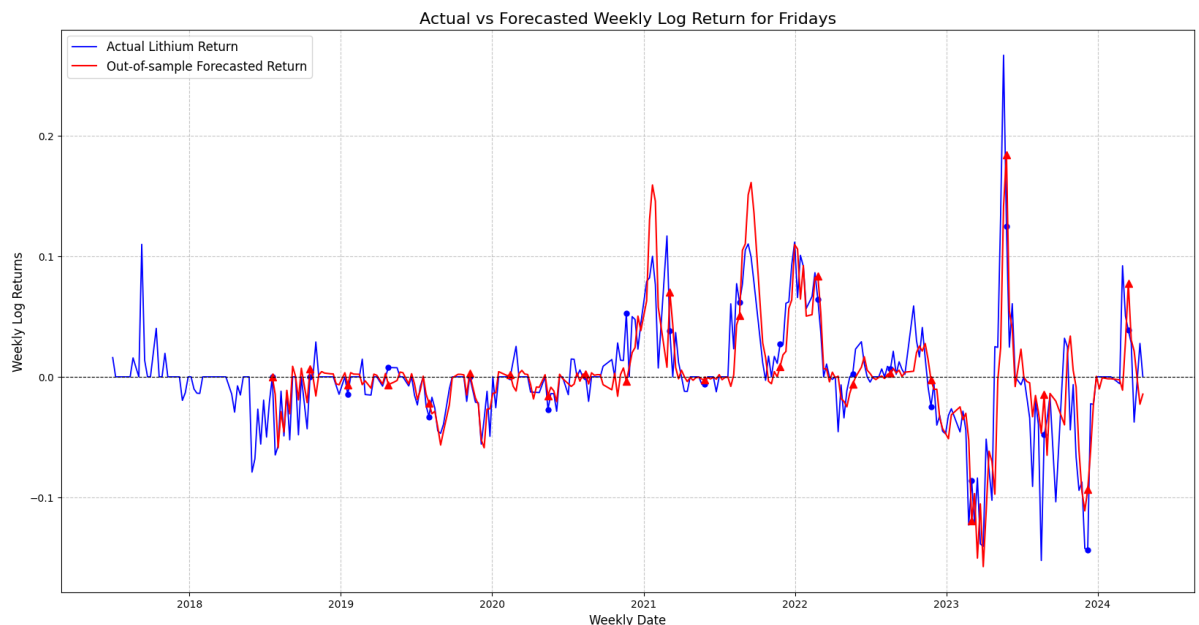
# Adjust the index for forecasted returns
forecasted_index = perpared_data.index[52:]
forecasted_series = pd.Series(forecasted_returns, index=forecasted_index)

marker_positions = forecasted_index[::12]

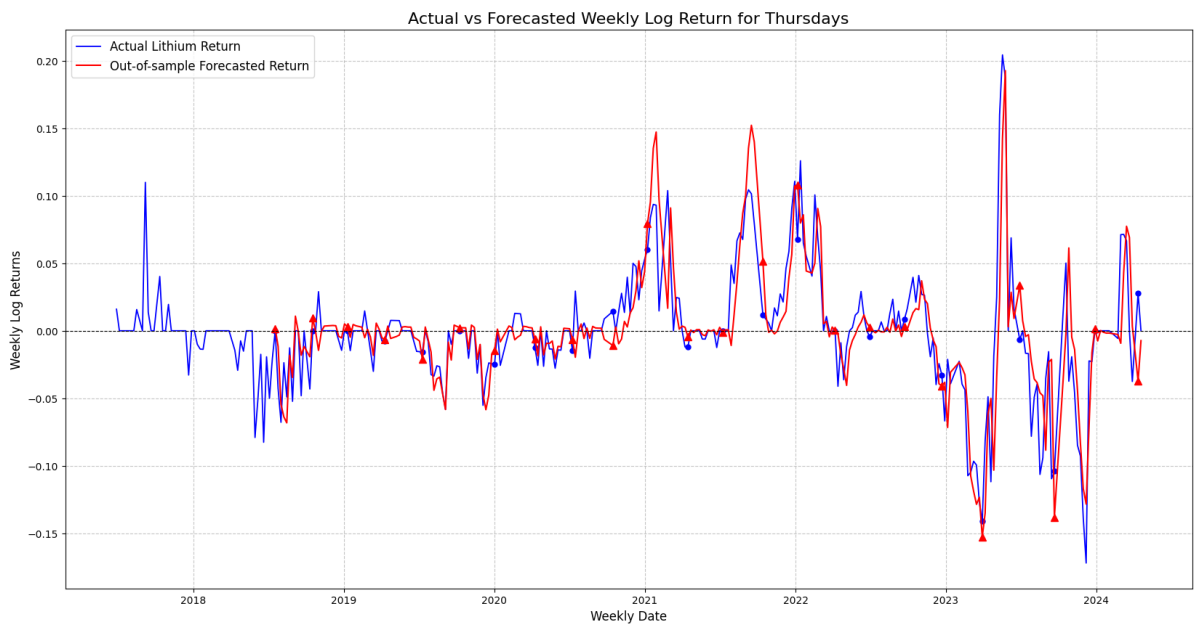
# Plot the actual vs forecasted returns
plt.figure(figsize=(20, 10))
plt.plot(perpared_data.index, perpared_data['Log_Return'], label='Actual Lithium')
plt.plot(marker_positions, perpared_data.loc[marker_positions, 'Log_Return'], 'bo')
plt.plot(forecasted_series.index, forecasted_series, label='Out-of-sample Forecast')
plt.plot(marker_positions, forecasted_series.loc[marker_positions], 'r^', markersize=10)
plt.axhline(0, color='k', linestyle='--', linewidth=0.8)
plt.xlabel('Weekly Date', fontsize=12)
plt.ylabel('Weekly Log Returns', fontsize=12)
plt.title(f'Actual vs Forecasted Weekly Log Return for {df_name}', fontsize=16)
plt.legend(loc='upper left', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.show()

```

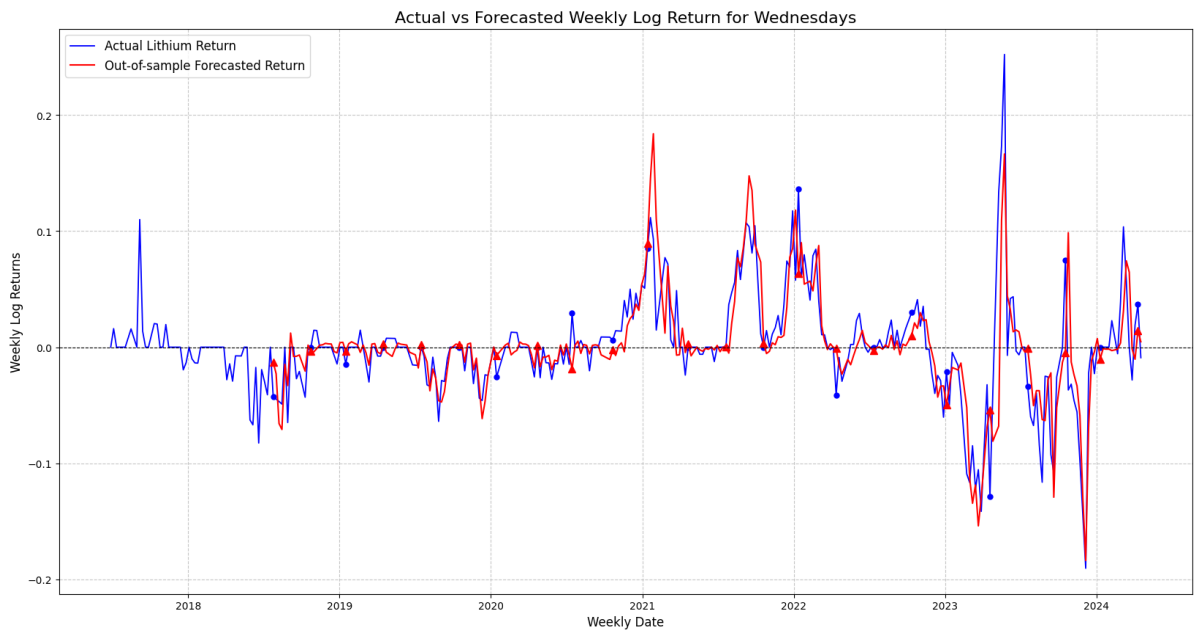
In [180... generate_forecast_plot(Fridays, lags=4, df_name='Fridays')



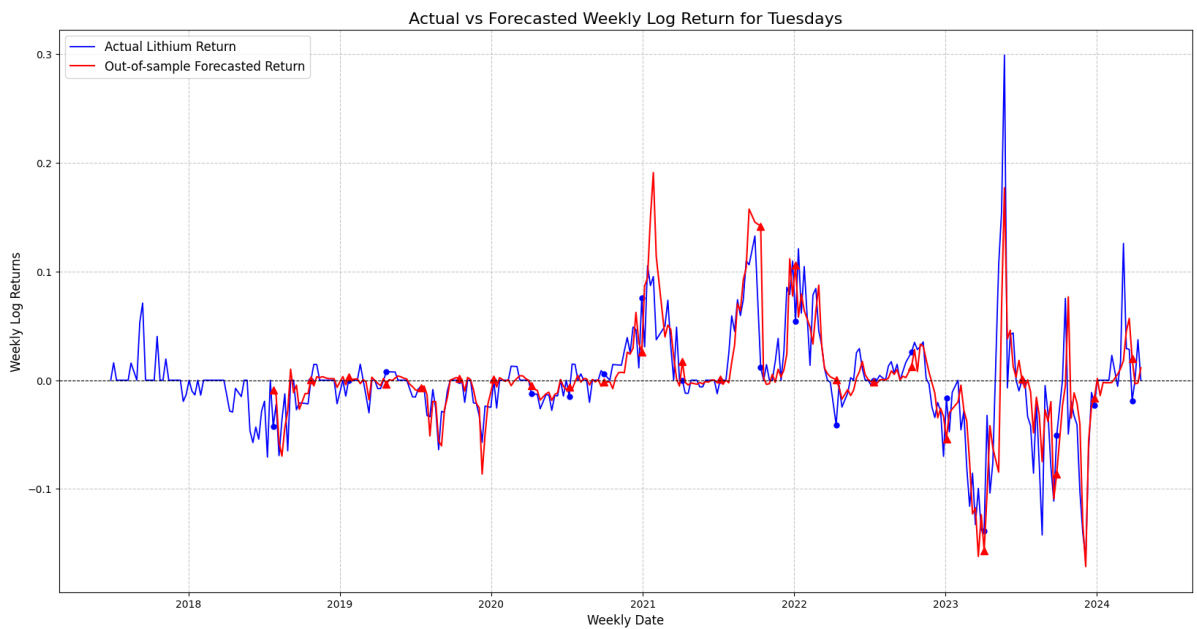
In [181... generate_forecast_plot(Thursdays, lags=2, df_name='Thursdays')



```
In [182...] generate_forecast_plot(Wednesdays, lags=2, df_name='Wednesdays')
```



```
In [183...] generate_forecast_plot(Tuesdays, lags=2, df_name='Tuesdays')
```



In [184...

```
generate_forecast_plot(Mondays, lags=2, df_name='Mondays')
```

