BTC price analysis

In [55]:

```
#!pip install yfinance
import yfinance as yf
import datetime as dt
import pandas as pd

start = dt.datetime(2010,3,1)
end = dt.datetime(2024,3,2)

df = yf.download('BTC-AUD', start, end)
```

```
[*********************100%%**********************]  1 of 1 completed
```

In [56]:

```
df.tail()
```

Out[56]:

Date	Open	High	Low	Close	Adj Close	V
2024-02-26	78665.468750	79180.101562	78279.570312	78820.445312	78820.445312	23483
2024-02-27	78816.343750	84033.539062	77795.875000	83375.875000	83375.875000	52106
2024-02-28	83371.226562	87965.406250	83398.804688	87236.039062	87236.039062	76036
2024-02-29	87214.226562	98355.726562	86821.304688	96242.187500	96242.187500	128168
2024-03-01	96233.554688	97557.101562	93069.312500	94151.382812	94151.382812	100764

In [57]:

```
# df.describe()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3454 entries, 2014-09-17 to 2024-03-01
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Open       3454 non-null   float64
 1   High       3454 non-null   float64
 2   Low        3454 non-null   float64
 3   Close      3454 non-null   float64
 4   Adj Close  3454 non-null   float64
 5   Volume     3454 non-null   int64
dtypes: float64(5), int64(1)
memory usage: 188.9 KB
```

Simple BTC graphing

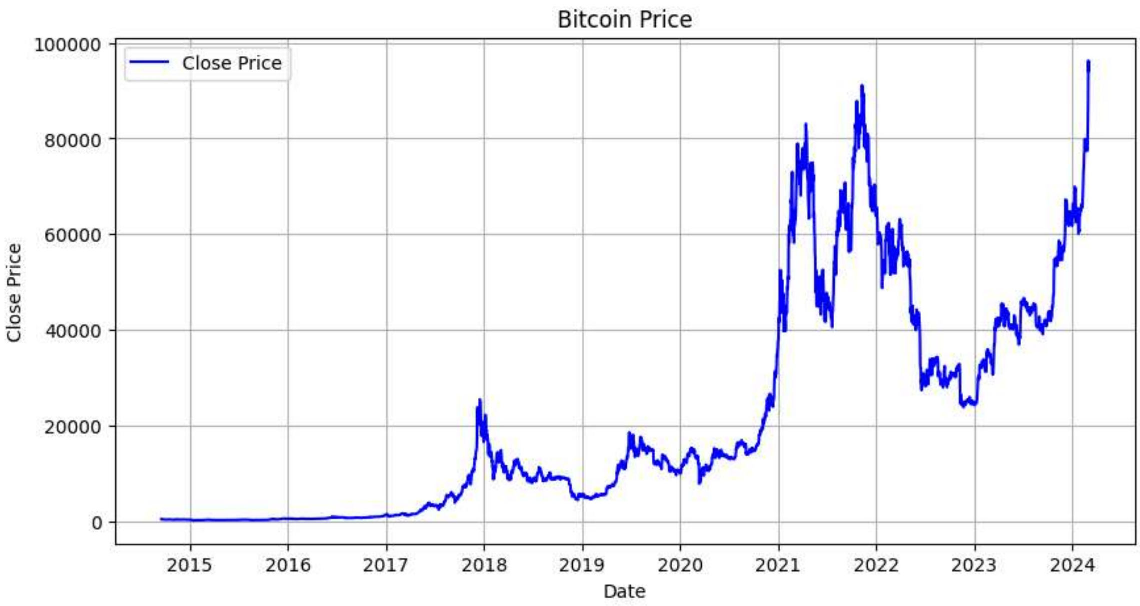
BTC Price

BTC Price

In [58]:

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
plt.plot(df.index, df['Close'], linestyle='-', color='b', label='Close Price'
plt.title('Bitcoin Price')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.grid(True)
plt.show()
```



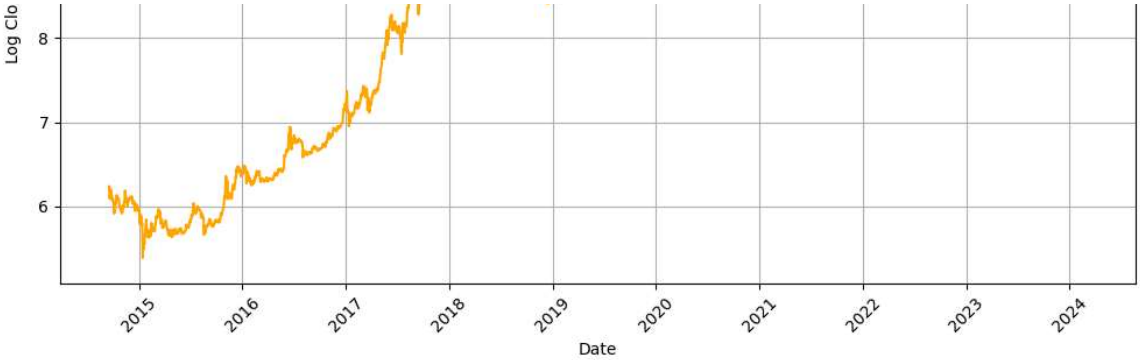
BTC logged price

In [59]:

```python
import numpy as np

df['Log_Close'] = np.log(df['Close'])

# Plotting the logarithm of the close price
plt.figure(figsize=(10, 6))
plt.plot(df.index, df['Log_Close'], label='Log Close Price', color='orange')
plt.title('Logarithm of Close Price Over Time')
plt.xlabel('Date')
plt.ylabel('Log Close Price')
plt.legend()
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Checking for autocorrelation

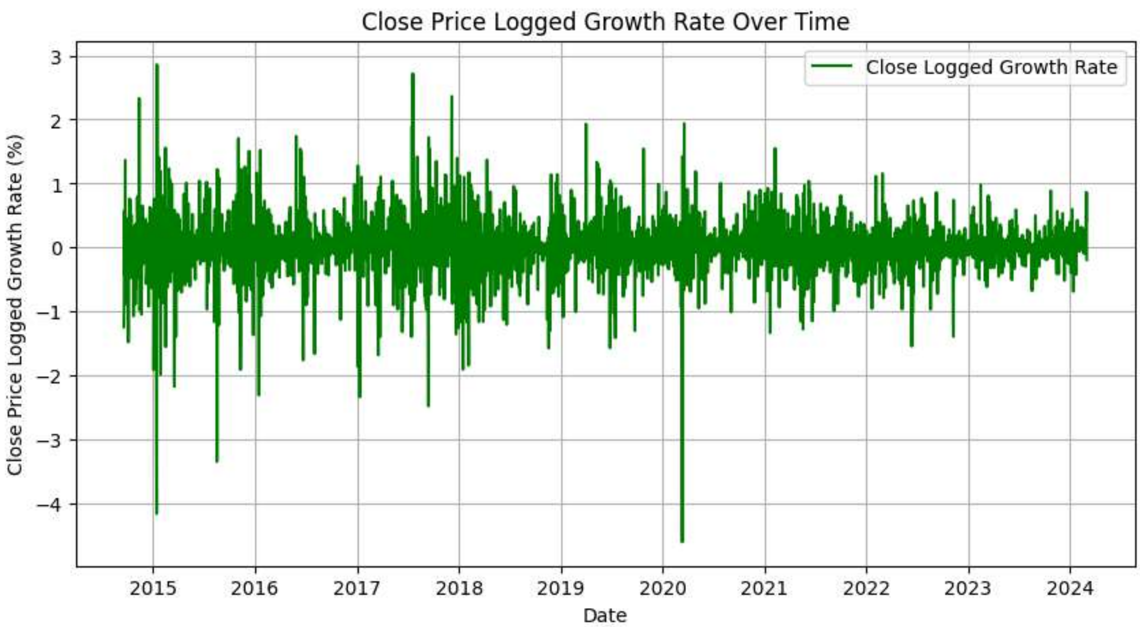
Making data stationary for unbiased estimates

We take the I(1) (intergrated to the first order) approach by differencing (i.e. taking the growth rate of logged prices).

In [60]:

```
# Calculate the daily percentage change (growth rate)
df['Close_Log_Growth_Rate'] = df['Log_Close'].pct_change() * 100
# Also make just the growth rate for later analysis
df['Close_Growth_Rate'] = df['Close'].pct_change() * 100


# Plotting growth rate on its own
plt.figure(figsize=(10, 5))
plt.plot(df.index, df['Close_Log_Growth_Rate'], linestyle='-', color='g', lab
plt.title('Close Price Logged Growth Rate Over Time')
plt.xlabel('Date')
plt.ylabel('Close Price Logged Growth Rate (%)')
plt.legend()
plt.grid(True)
plt.show()
```



In [61]:

```
import pandas as pd
from statsmodels.tsa.stattools import adfuller
```

```python
# Assuming df is your DataFrame and 'Close_Log_Growth_Rate' is the column you
# Perform Augmented Dickey-Fuller test
result = adfuller(df['Close_Log_Growth_Rate'].dropna())

# Output the results
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))

# Interpretation
if result[1] > 0.05:
    print("The series is not stationary")
else:
    print("The series is stationary")
```

```
ADF Statistic: -18.433370
p-value: 0.000000
Critical Values:
	1%: -3.432
	5%: -2.862
	10%: -2.567
The series is stationary
```

Deciding upon sample

We decide to try 2 different samples to test for any autocorrelation in BTC price (as it is difficult to test daily prices over a decade of time):

1. Daily data over 1 year: for short term fluctuation analysis
2. Monthly data for 5 years: for long term trend analysis
3. Intraday data over 1 week (recorded at 5 minute intervals): for extremely short-term analysis

In [69]:

```python
#!pip install yfinance
import yfinance as yf
import datetime as dt
import pandas as pd

# 1. Daily data over 1 year

daily_data_1yr = df.last('365D')

# 2. Monthly data for 5 years

monthly_data_5yr = df.last('5Y').resample('M').mean()

# 3. Intra-day data for 1 week

start_forIntraDay = dt.datetime(2024,2,24)
end_forIntraDay = dt.datetime(2024,3,2)
minute_data_1wk = yf.download('BTC-AUD', start_forIntraDay, end_forIntraDay,
# Calculate logged price
minute_data_1wk['Log_Close'] = np.log(minute_data_1wk['Close'])
# Calculate the daily percentage change (growth rate)
minute_data_1wk['Close_Log_Growth_Rate'] = minute_data_1wk['Log_Close'].pct_c
# Also make just the growth rate alone
minute_data_1wk['Close_Growth_Rate'] = minute_data_1wk['Close'].pct_change()
```

```python
# Drop all rows with NaN values
minute_data_1wk.dropna(inplace=True)

daily_data_1yr.head(), monthly_data_5yr.head(), minute_data_1wk.head()
```

```
/var/folders/1c/xdsm7htj4334pn2n9vx5kz900000gn/T/ipykernel_1757/2681600539.py:
8: FutureWarning: last is deprecated and will be removed in a future version. P
lease create a mask and filter using `.loc` instead
  daily_data_1yr = df.last('365D')
/var/folders/1c/xdsm7htj4334pn2n9vx5kz900000gn/T/ipykernel_1757/2681600539.py:1
2: FutureWarning: last is deprecated and will be removed in a future version. P
lease create a mask and filter using `.loc` instead
  monthly_data_5yr = df.last('5Y').resample('M').mean()
[*********************100%%**********************]  1 of 1 completed
```

Out[69]:

```
(                    Open          High           Low         Close  \
 Date
 2023-03-03  34875.359375  34879.886719  32809.906250  33041.796875
 2023-03-04  33042.156250  33102.437500  32797.796875  33025.867188
 2023-03-05  33027.039062  33410.500000  32957.601562  33217.597656
 2023-03-06  33219.523438  33526.722656  33073.078125  33317.765625
 2023-03-07  33315.636719  33416.160156  33403.851562  33722.808594

                Adj Close       Volume  Log_Close  Close_Log_Growth_Rate  \
 Date
 2023-03-03  33041.796875  38508297433  10.405529              -0.515872
 2023-03-04  33025.867188  16497181114  10.405046              -0.004634
 2023-03-05  33217.597656  19716899742  10.410835               0.055633
 2023-03-06  33317.765625  25776901263  10.413846               0.028922
 2023-03-07  33722.808594  34550990217  10.425930               0.116035

             Close_Growth_Rate
 Date
 2023-03-03          -5.252771
 2023-03-04          -0.048211
 2023-03-05           0.580546
 2023-03-06           0.301551
 2023-03-07           1.215697  ,
                     Open          High           Low         Close  \
 Date
 2020-01-31  12107.797915  12369.311460  11944.036920  12228.686114
 2020-02-29  14475.996633  14676.984813  14208.783574  14450.521518
 2020-03-31  11088.148374  11463.077589  10589.622102  10995.810342
 2020-04-30  11363.521647  11663.056380  11206.143978  11458.122363
 2020-05-31  14190.745432  14515.087922  13897.235383  14217.975334

                Adj Close        Volume  Log_Close  Close_Log_Growth_Rate  \
 Date
 2020-01-31  12228.686114  4.010258e+10   9.407679               0.106693
 2020-02-29  14450.521518  6.023657e+10   9.577553              -0.019830
 2020-03-31  10995.810342  6.723576e+10   9.292311              -0.073974
 2020-04-30  11458.122363  6.113336e+10   9.344805               0.085897
 2020-05-31  14217.975334  6.379741e+10   9.561507               0.021925

             Close_Growth_Rate
 Date
 2020-01-31           1.041995
 2020-02-29          -0.161160
 2020-03-31          -0.319569
 2020-04-30           0.854873
 2020-05-31           0.256802  ,
                                    Open          High           Low  \
 Datetime
 2024-02-24 00:02:00+00:00  77425.343750  77425.343750  77425.343750
```

```
2024-02-24 00:04:00+00:00  77469.875000  77469.875000  77450.648438
2024-02-24 00:05:00+00:00  77422.781250  77422.781250  77422.781250
2024-02-24 00:06:00+00:00  77422.781250  77422.781250  77406.968750
2024-02-24 00:07:00+00:00  77390.695312  77390.695312  77390.695312

                                  Close     Adj Close    Volume  Log_Close
\
Datetime
2024-02-24 00:02:00+00:00  77425.343750  77425.343750         0  11.257069
2024-02-24 00:04:00+00:00  77450.648438  77450.648438   8751104  11.257396
2024-02-24 00:05:00+00:00  77422.781250  77422.781250  14110720  11.257036
2024-02-24 00:06:00+00:00  77406.968750  77406.968750    487424  11.256832
2024-02-24 00:07:00+00:00  77390.695312  77390.695312         0  11.256622

                           Close_Log_Growth_Rate  Close_Growth_Rate
Datetime
2024-02-24 00:02:00+00:00               0.003017           0.033966
2024-02-24 00:04:00+00:00               0.002903           0.032683
2024-02-24 00:05:00+00:00              -0.003197          -0.035981
2024-02-24 00:06:00+00:00              -0.001814          -0.020424
2024-02-24 00:07:00+00:00              -0.001868          -0.021023  )
```

Testing for autocorrelation and modelling

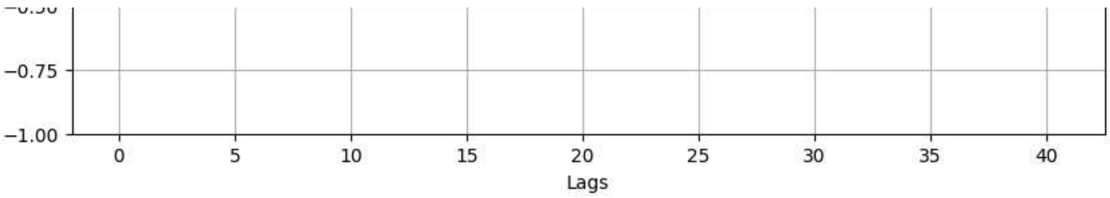
Short term (daily data over 1 year)

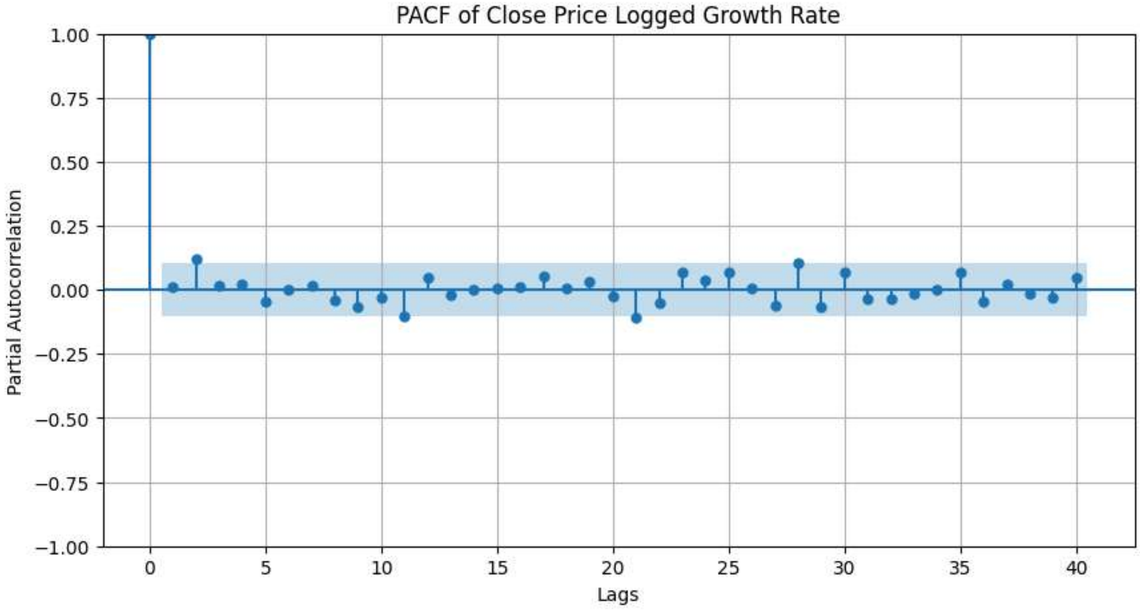
In [63]:

```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# ACF plot
plt.figure(figsize=(10, 5))
plot_acf(daily_data_1yr['Close_Log_Growth_Rate'].dropna(), ax=plt.gca(), lags
plt.title('ACF of Close Price Logged Growth Rate')
plt.xlabel('Lags')
plt.ylabel('Autocorrelation')
plt.grid(True)
plt.show()

# PACF plot
plt.figure(figsize=(10, 5))
plot_pacf(daily_data_1yr['Close_Log_Growth_Rate'].dropna(), ax=plt.gca(), lag
plt.title('PACF of Close Price Logged Growth Rate')
plt.xlabel('Lags')
plt.ylabel('Partial Autocorrelation')
plt.grid(True)
plt.show()
```





The fact that both ACF and PACF truncate after the second lag might suggest that a mixed ARMA model is not necessary, and a simpler AR(p) or MA(q) model might be adequate for modeling the time series.

As the second lag is significant in the ACF and PACF, we test for autocorrelation using an AR(2) and MA(2) and test for which has a lower AIC to measure model suitability.

Testing AR(2)

In [64]:

```
import pandas as pd
from statsmodels.tsa.arima.model import ARIMA

# Initialise and fit the ARIMA model with order (2,0,0) for AR(2) process
model = ARIMA(daily_data_1yr['Close_Log_Growth_Rate'].dropna(), order=(2,0,0)
model_fit = model.fit()

# Print out the summary of the model
print(model_fit.summary())

# You can also make predictions
# For example, to forecast the next 5 values:
forecast = model_fit.forecast(steps=5)
print(forecast)
```

```
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-package
s/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information
was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-package
s/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information
was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-package
s/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information
```

```
was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
                                 SARIMAX Results
================================================================================
==
Dep. Variable:     Close_Log_Growth_Rate   No. Observations:                  3
65
Model:                    ARIMA(2, 0, 0)   Log Likelihood                  48.7
24
Date:                   Sun, 03 Mar 2024   AIC                            -89.4
48
Time:                           16:07:52   BIC                            -73.8
48
Sample:                       03-03-2023   HQIC                           -83.2
48
                            - 03-01-2024
Covariance Type:                     opg
===============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
const          0.0251      0.013      1.902      0.057      -0.001       0.051
ar.L1          0.0095      0.047      0.201      0.840      -0.083       0.102
ar.L2          0.1275      0.055      2.338      0.019       0.021       0.234
sigma2         0.0448      0.002     18.888      0.000       0.040       0.049
================================================================================
====
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                10
6.84
Prob(Q):                              0.97   Prob(JB):
0.00
Heteroskedasticity (H):               0.94   Skew:
0.41
Prob(H) (two-sided):                  0.73   Kurtosis:
5.52
================================================================================
====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
2024-03-02    0.129966
2024-03-03   -0.001538
2024-03-04    0.038201
2024-03-05    0.021807
2024-03-06    0.026720
Freq: D, Name: predicted_mean, dtype: float64
```

The first lag is insignificant, but the second lag is significant. To exclude the first lag, we'd have to include the second lag as basically an exogenous variable. This is difficult to interpret in a model, so I will refrain from doing so.

Testing MA(2)

In [65]:

```python
import pandas as pd
from statsmodels.tsa.arima.model import ARIMA

# Initialise and fit the ARIMA model with order (2,0,0) for AR(2) process
model = ARIMA(daily_data_1yr['Close_Log_Growth_Rate'].dropna(), order=(0,0,2)
model_fit = model.fit()

# Print out the summary of the model
print(model_fit.summary())
```

```
# You can also make predictions
# For example, to forecast the next 5 values:
forecast = model_fit.forecast(steps=5)
print(forecast)
```

```
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-package
s/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information
was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-package
s/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information
was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-package
s/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information
was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
                                 SARIMAX Results
================================================================================
==
Dep. Variable:     Close_Log_Growth_Rate   No. Observations:                   3
65
Model:                    ARIMA(0, 0, 2)   Log Likelihood                   48.5
48
Date:                   Sun, 03 Mar 2024   AIC                             -89.0
97
Time:                           16:07:53   BIC                             -73.4
97
Sample:                       03-03-2023   HQIC                            -82.8
97
                            - 03-01-2024
Covariance Type:                     opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0251      0.013      1.963      0.050    3.95e-05       0.050
ma.L1          0.0041      0.047      0.089      0.929      -0.087       0.095
ma.L2          0.1201      0.053      2.245      0.025       0.015       0.225
sigma2         0.0449      0.002     19.087      0.000       0.040       0.049
================================================================================
====
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                  11
0.32
Prob(Q):                              0.95   Prob(JB):
0.00
Heteroskedasticity (H):               0.94   Skew:
0.42
Prob(H) (two-sided):                  0.71   Kurtosis:
5.56
================================================================================
====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
2024-03-02    0.117883
2024-03-03   -0.006695
2024-03-04    0.025051
2024-03-05    0.025051
2024-03-06    0.025051
Freq: D, Name: predicted_mean, dtype: float64
```

Similar results as with AR(2). Modelling an ARMA(2,2) doesnt help either

Similar results as with AR(2). Modelling an ARMA(2,2) doesn't help either.

In sum, AR and MA modelling is not appropriate for residuals of BTC growth rate.

Long term (monthly data over 5 years)

In [66]:

```
# Plotting growth rate on its own
plt.figure(figsize=(10, 5))
plt.plot(monthly_data_5yr.index, monthly_data_5yr['Close_Log_Growth_Rate'], l
plt.title('Close Price Logged Growth Rate Over Time')
plt.xlabel('Date')
plt.ylabel('Close Price Logged Growth Rate (%)')
plt.legend()
plt.grid(True)
plt.show()
```

In [67]:

```
## Test for stationarity in this new df first:

import pandas as pd
from statsmodels.tsa.stattools import adfuller

# Perform Augmented Dickey-Fuller test
result = adfuller(monthly_data_5yr['Close_Log_Growth_Rate'].dropna())

# Output the results
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))

# Interpretation
if result[1] > 0.05:
    print("The series is not stationary")
else:
    print("The series is stationary")
```

```
ADF Statistic: -6.075511
p-value: 0.000000
Critical Values:
	1%: -3.568
```

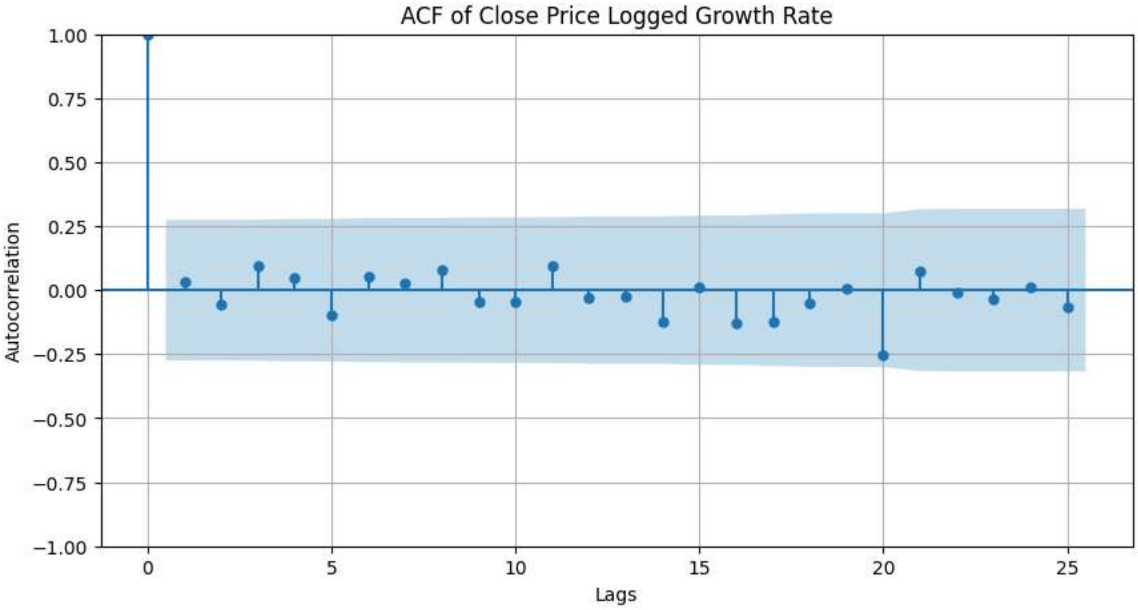
```
    5%: -2.921
    10%: -2.599
The series is stationary
```

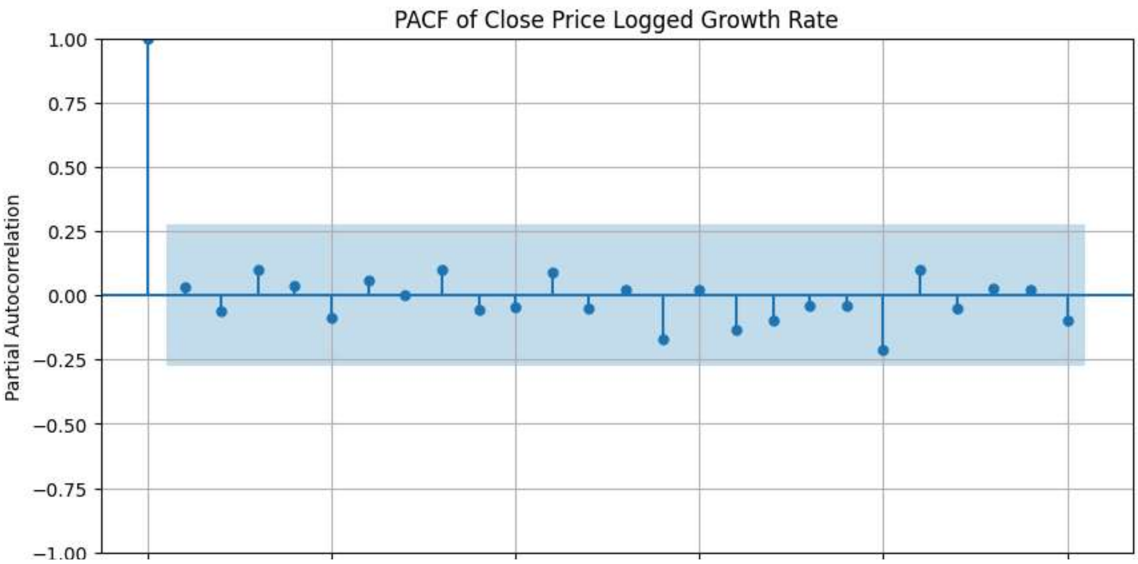
In [68]:

```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# ACF plot
plt.figure(figsize=(10, 5))
plot_acf(monthly_data_5yr['Close_Log_Growth_Rate'].dropna(), ax=plt.gca(), la
plt.title('ACF of Close Price Logged Growth Rate')
plt.xlabel('Lags')
plt.ylabel('Autocorrelation')
plt.grid(True)
plt.show()

# PACF plot
plt.figure(figsize=(10, 5))
plot_pacf(monthly_data_5yr['Close_Log_Growth_Rate'].dropna(), ax=plt.gca(), l
plt.title('PACF of Close Price Logged Growth Rate')
plt.xlabel('Lags')
plt.ylabel('Partial Autocorrelation')
plt.grid(True)
plt.show()
```



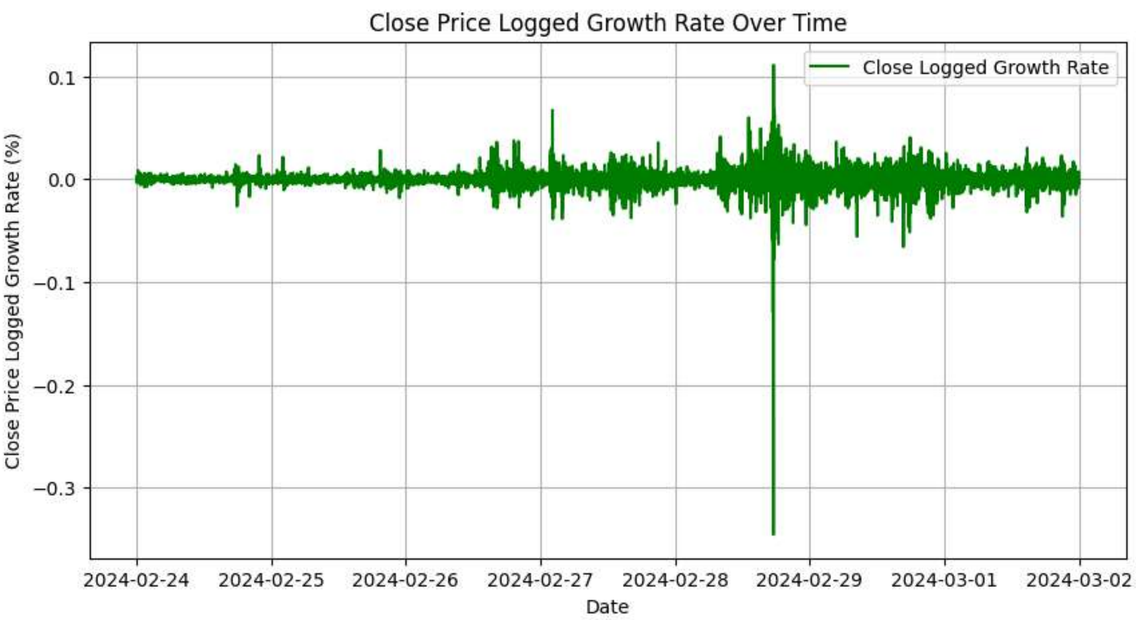


There is no autocorrelation at any of the lags. No autocorrelation modelling of the error term is required.

Extreme short term (intra-day minute-by-minute)

In [70]:

```
# Plotting growth rate on its own
plt.figure(figsize=(10, 5))
plt.plot(minute_data_1wk.index, minute_data_1wk['Close_Log_Growth_Rate'], lin
plt.title('Close Price Logged Growth Rate Over Time')
plt.xlabel('Date')
plt.ylabel('Close Price Logged Growth Rate (%)')
plt.legend()
plt.grid(True)
plt.show()
```



In [71]:

```
## Test for stationarity in this new df first:

import pandas as pd
from statsmodels.tsa.stattools import adfuller

# Perform Augmented Dickey-Fuller test
result = adfuller(minute_data_1wk['Close_Log_Growth_Rate'].dropna())

# Output the results
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))

# Interpretation
if result[1] > 0.05:
    print("The series is not stationary")
else:
    print("The series is stationary")
```

```
ADF Statistic: -15.502151
```

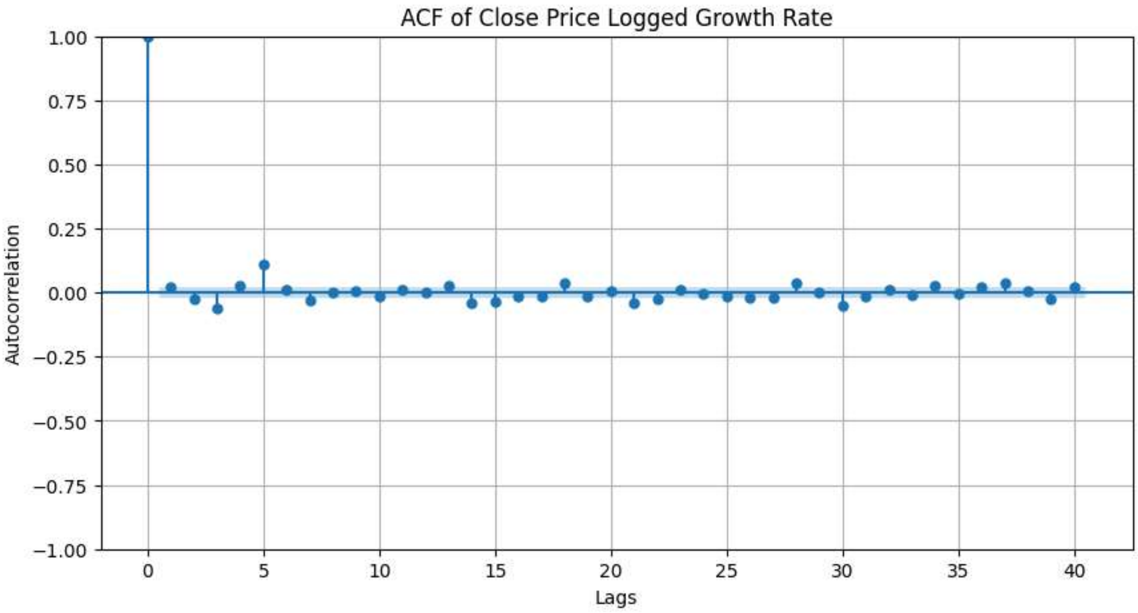
```
p-value: 0.000000
Critical Values:
        1%: -3.431
        5%: -2.862
        10%: -2.567
The series is stationary
```

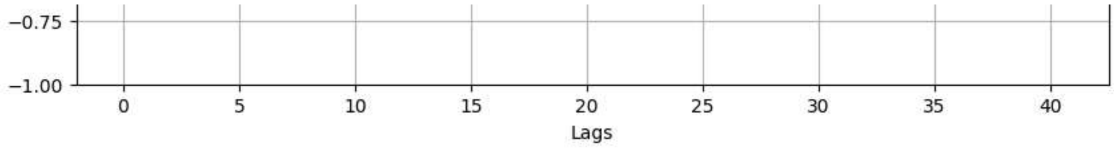
In [73]:

```python
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# ACF plot
plt.figure(figsize=(10, 5))
plot_acf(minute_data_1wk['Close_Log_Growth_Rate'].dropna(), ax=plt.gca(), lag
plt.title('ACF of Close Price Logged Growth Rate')
plt.xlabel('Lags')
plt.ylabel('Autocorrelation')
plt.grid(True)
plt.show()

# PACF plot
plt.figure(figsize=(10, 5))
plot_pacf(minute_data_1wk['Close_Log_Growth_Rate'].dropna(), ax=plt.gca(), la
plt.title('PACF of Close Price Logged Growth Rate')
plt.xlabel('Lags')
plt.ylabel('Partial Autocorrelation')
plt.grid(True)
plt.show()
```





Both ACF and PACF are truncated and both have 5 lags that are significant. Both graphs exhibit a sine wave pattern.

What actually affects the price of BTC if not its past values?