In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os

from sklearn.metrics import r2_score;
from sklearn.metrics import mean_squared_error

from statsmodels.tools import add_constant
from statsmodels.regression.linear_model import OLS;
from statsmodels.tsa.stattools import kpss;
from statsmodels.tsa.stattools import acf;
from statsmodels.tsa.stattools import pacf;
from statsmodels.graphics.tsaplots import plot_acf;
from statsmodels.graphics.tsaplots import plot_pacf;
from statsmodels.tsa.arima.model import ARIMA;


import warnings
warnings.filterwarnings('ignore')
data_dir = './data'
```

In [2]:
```
data = pd.read_csv(os.path.join(data_dir, 'DAAA.csv'), parse_dates=['observation_date'], index_col='observation_date')
data
```

Out[2]:

observation_date	DAAA
1995-01-03	8.53
1995-01-04	8.46
1995-01-05	8.51
1995-01-06	8.45
1995-01-09	8.49
...	...
2025-02-25	5.21
2025-02-26	5.17
2025-02-27	5.21
2025-02-28	5.21
2025-03-03	5.16

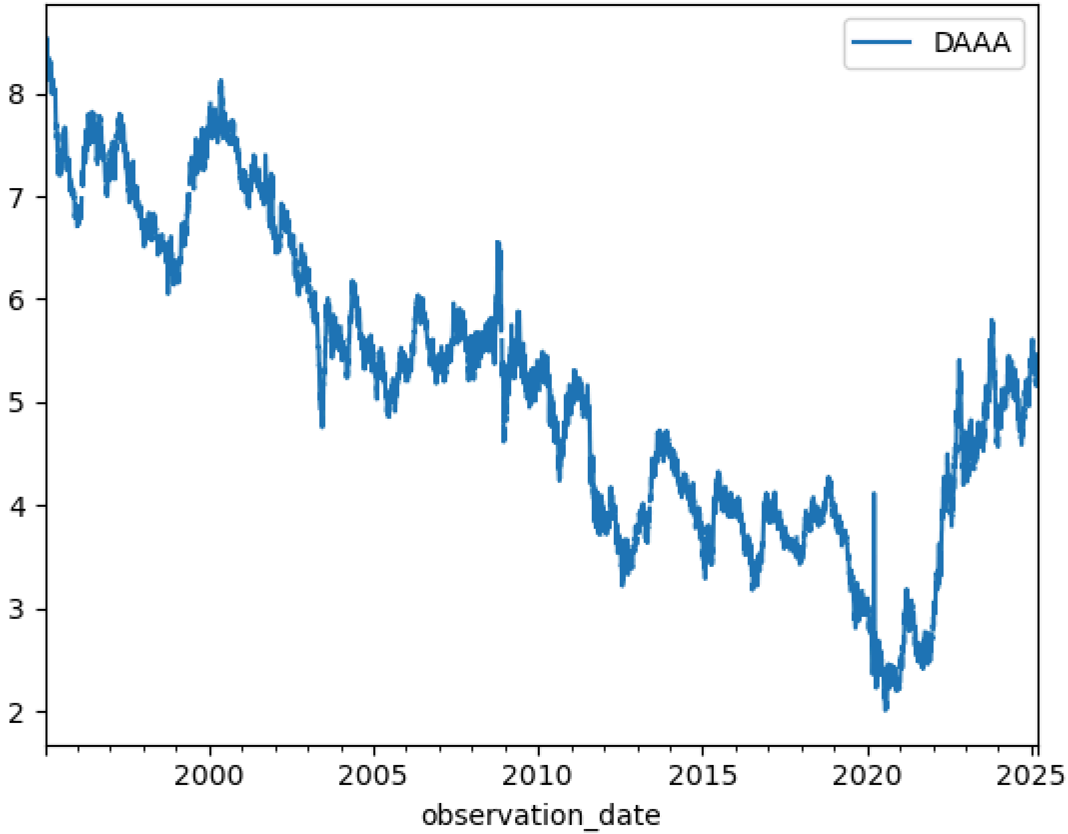
7870 rows × 1 columns

In [3]:

```
data.plot()
```

Out[3]:

```
<Axes: xlabel='observation_date'>
```



In [4]:
```
data = data.ffill()
data.isna().sum()
```

Out[4]:
```
DAAA    0
dtype: int64
```

In [5]:
```
t = np.arange(data.shape[0])

n = data.shape[0]
y = data.values.T.ravel()
```

In [6]:
```
model = OLS(y,add_constant(t)).fit()
model.summary()
```

Out[6]:

OLS Regression Results

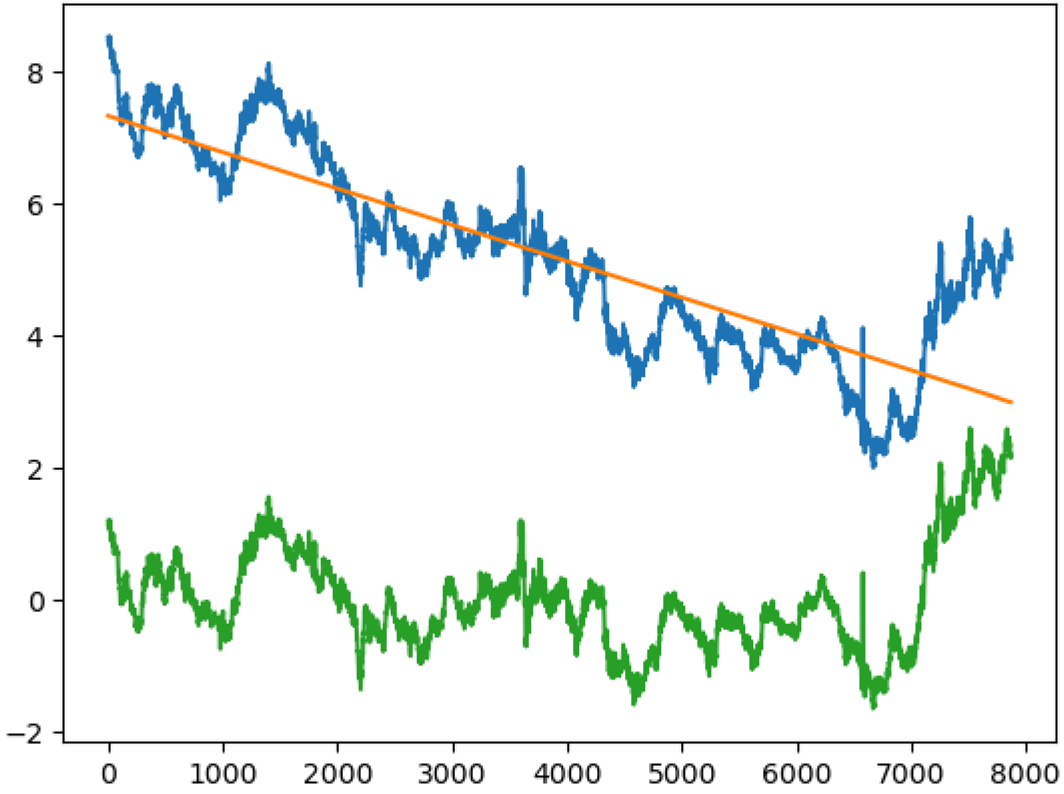
Dep. Variable:	y	**R-squared:**	0.722
Model:	OLS	**Adj. R-squared:**	0.722
Method:	Least Squares	**F-statistic:**	2.046e+04
Date:	Thu, 06 Mar 2025	**Prob (F-statistic):**	0.00
Time:	10:27:32	**Log-Likelihood:**	-9177.1
No. Observations:	7870	**AIC:**	1.836e+04
Df Residuals:	7868	**BIC:**	1.837e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	7.3352	0.018	418.955	0.000	7.301	7.370
x1	-0.0006	3.85e-06	-143.048	0.000	-0.001	-0.001

Omnibus:	821.405	**Durbin-Watson:**	0.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1124.300
Skew:	0.843	**Prob(JB):**	7.27e-245
Kurtosis:	3.764	**Cond. No.**	9.09e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.09e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [7]:
```
plt.plot(y)
plt.plot(model.predict(add_constant(t)))
plt.plot(y - model.predict(add_constant(t)))
#plt.xlabel()
plt.show()
```

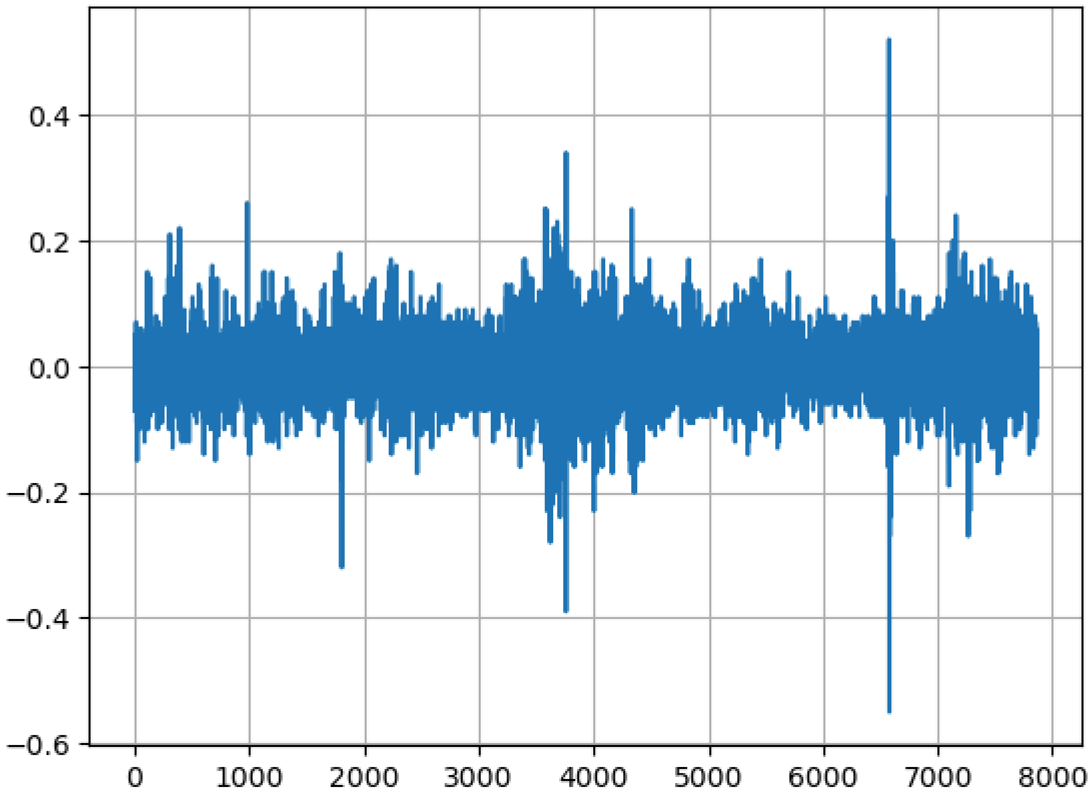


In [8]:
```
display(kpss(y,'ct',1))
```

```
(30.177107317567113,
 0.01,
 1,
 {'10%': 0.119, '5%': 0.146, '2.5%': 0.176, '1%': 0.216})
```

In [9]:
```
plt.grid()
x_t = y[1:] - y[:-1]
```

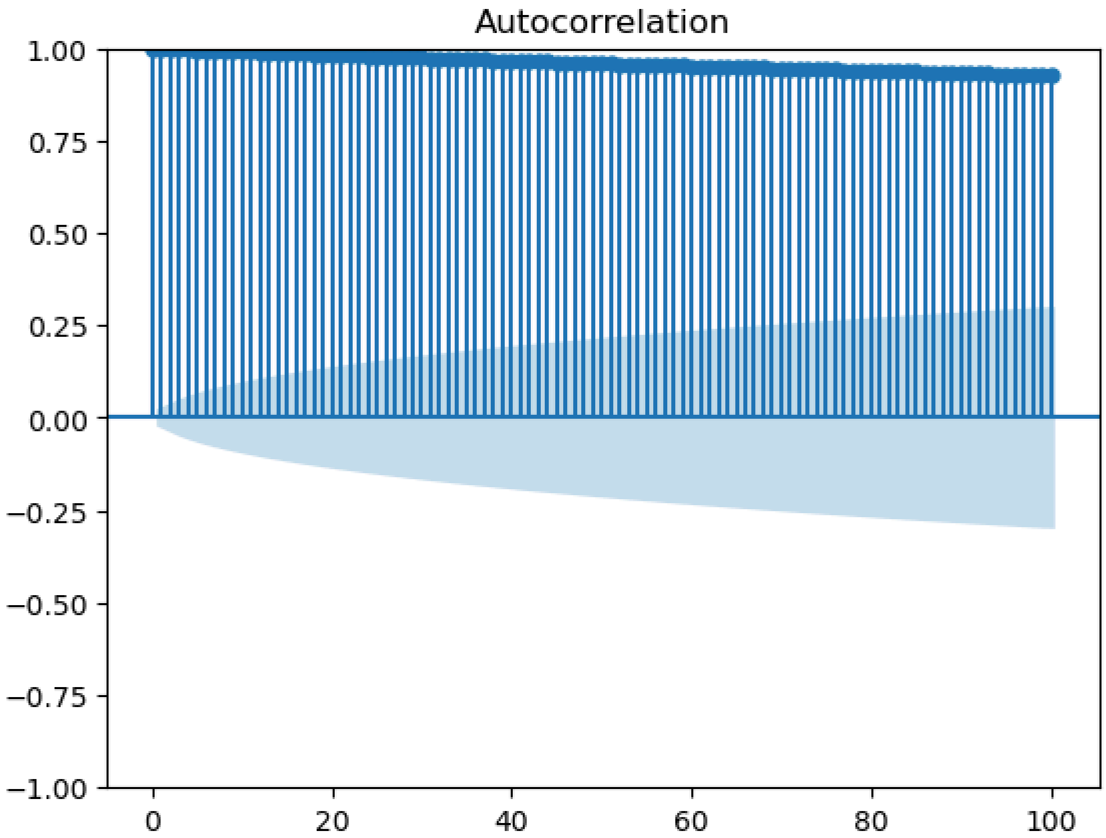
```
plt.plot(x_t)
plt.show()
display(kpss(x_t,'ct',1)[0])
```

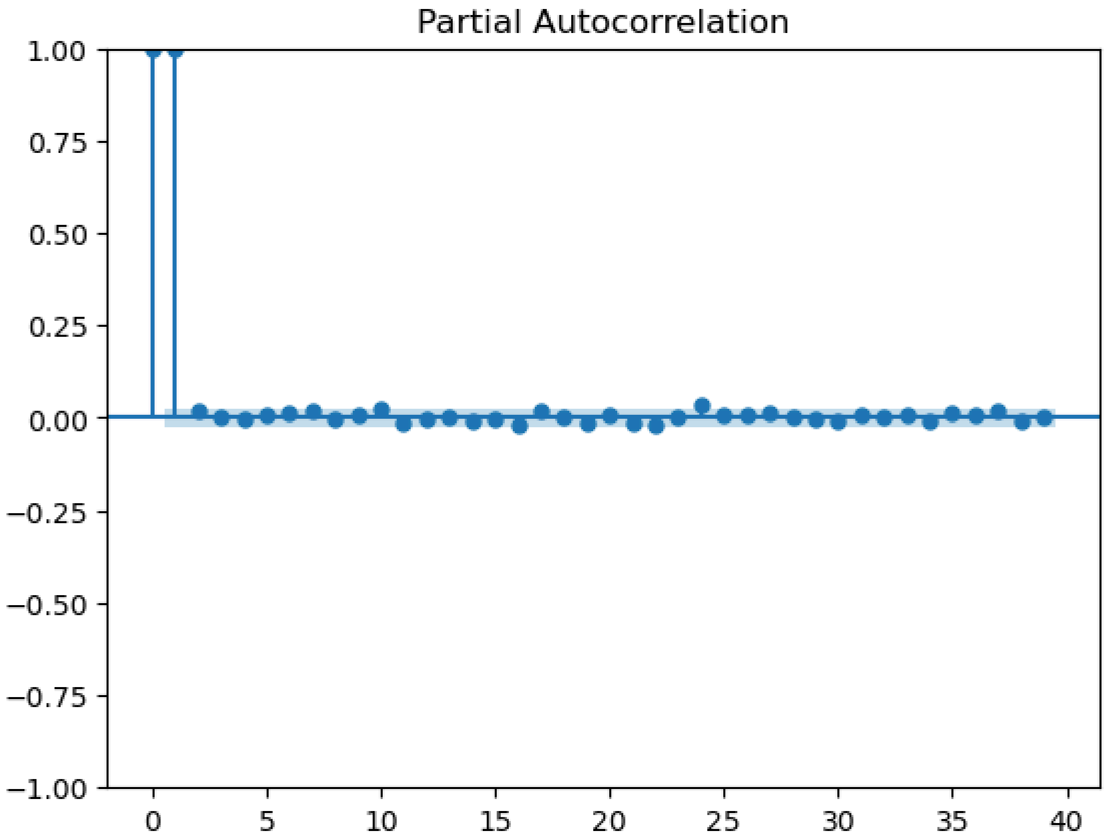



```
0.029595843295856076
```

2. Нарисуйте график ACF и PACF

In [10]:
```
fig = plot_acf(data,use_vlines=True,lags=100)
fig = plot_pacf(data)
```


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
20
40
60
80
100



3. Является ли $\rho(5)$ значимым?

In [11]:
```
r, conf = acf(data, alpha=0.05)

if conf[5][0] < r[5]<conf[5][1]:
  print('Значим')

else:
  print(f'Незначим')
```

Значим

In [12]:
```
kpss(data)
```

Out[12]:
```
(11.467924510039927,
 0.01,
 54,
 {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})
```

4. Постройте подходящую ARMA модель.

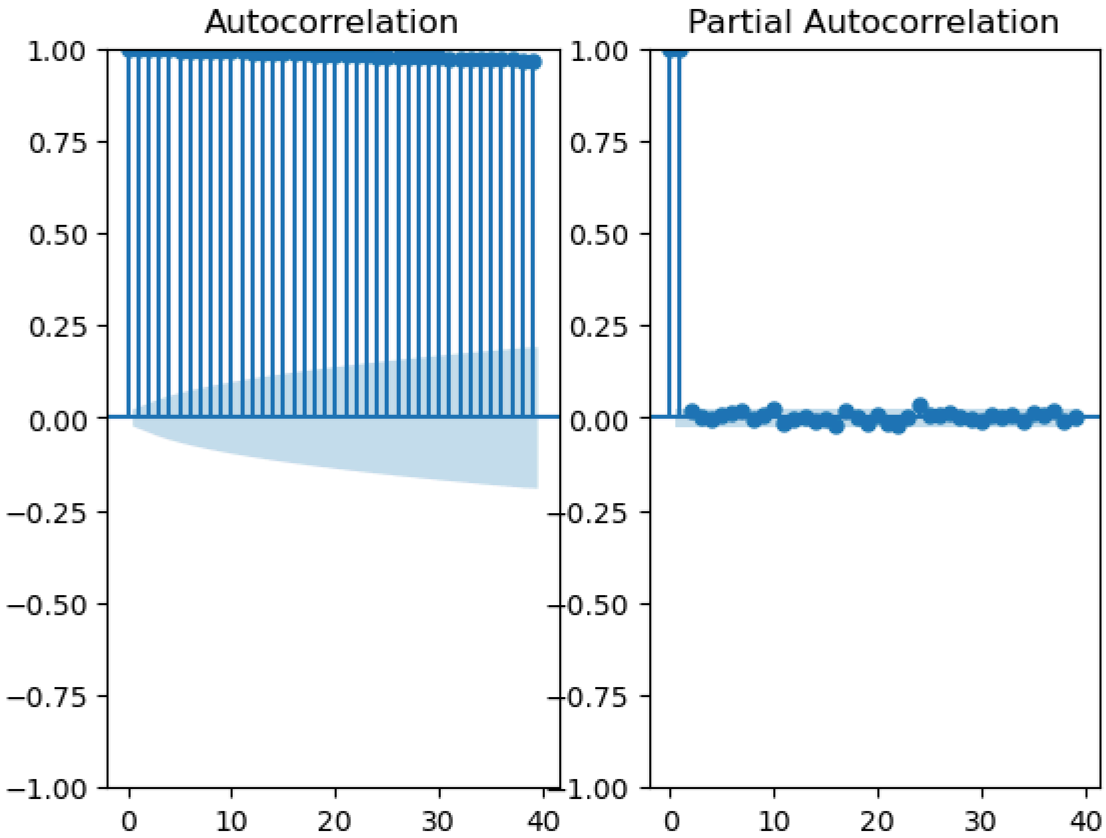
In [13]:
```
from statsmodels.tsa.stattools import adfuller

result = adfuller(data)
print(f'ADF Statistic: {result[0]}')
print(f'p-value: {result[1]}')
```

```
ADF Statistic: -2.2250525396248118
p-value: 0.1972787867912364
```

In [14]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import matplotlib.pyplot as plt

fig, (ax1, ax2) = plt.subplots(1, 2)
plot_acf(data, ax=ax1)
plot_pacf(data, ax=ax2)
plt.show()
```



In [19]:
```
from pmdarima import auto_arima

model = auto_arima(
    data,
    start_p=0, max_p=3,
    start_q=1, max_q=3,
    seasonal=True,  # Для ARMA seasonal=False
    trace=True
)
model.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=-23847.573, Time=1.96 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=-23846.334, Time=1.36 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=-23847.483, Time=0.94 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=-23847.824, Time=0.90 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=-23846.268, Time=4.61 sec

Best model:  ARIMA(0,1,0)(0,0,0)[0]
Total fit time: 9.782 seconds
```

Out[19]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	7870
Model:	SARIMAX(0, 1, 0)	**Log Likelihood**	11924.912
Date:	Thu, 06 Mar 2025	**AIC**	-23847.824
Time:	10:30:32	**BIC**	-23840.853
Sample:	01-03-1995	**HQIC**	-23845.436
	- 03-03-2025		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
sigma2	0.0028	2.26e-05	125.006	0.000	0.003	0.003

Ljung-Box (L1) (Q):	3.15	**Jarque-Bera (JB):**	11640.41
Prob(Q):	0.08	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.33	**Skew:**	0.18
Prob(H) (two-sided):	0.00	**Kurtosis:**	8.95

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

In [25]:
```
# Проверка с помощью Ljung-Box теста
from statsmodels.stats.diagnostic import acorr_ljungbox

lb_test = acorr_ljungbox(model.resid(), lags=[10])
print(f'Ljung-Box p-value: {lb_test.iloc[0, 1]}')  # p-value > 0.05 — остатки случайны
```

```
Ljung-Box p-value: 0.9844364560965213
```

5. Дайте прогноз на 10 месяцев вперед.

In [30]:
```
model.predict(int(365/12 * 10))
```

Out[30]:
```
2025-03-04    5.16
2025-03-05    5.16
2025-03-06    5.16
2025-03-07    5.16
2025-03-10    5.16
              ...
2026-04-27    5.16
2026-04-28    5.16
2026-04-29    5.16
2026-04-30    5.16
2026-05-01    5.16
Freq: B, Length: 304, dtype: float64
```