Problem set 4

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패키지 로드

In [407...

```
# 기본적인 패키지 로드
import pandas as pd
import numpy as np

# 시각화 패키지 로드
import matplotlib.pyplot as plt
import statsmodels.api as sm
from matplotlib import rc
rc('font', family='AppleGothic')
plt.rcParams['axes.unicode_minus'] = False

# 분석 패키지 로드
from statsmodels.tsa.stattools import coint
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import grangercausalitytests
from statsmodels.tsa.vector_ar.vecm import VECM
from statsmodels.tsa.api import VAR

# ignore warning
import warnings
warnings.filterwarnings('ignore')
```

1. The file COINT PPP.csv contains monthly values of the Japanese, Canadian, and Swiss consumer price levels and the bilateral exchange rates with the United States. The file also contains the U.S. consumer price level. The starting date for all variables is January 1974 while the availability of the variables is such that most end near the end of 2013. The price indices have been normalized to equal 100 in January 1973 and only the U.S. price index is seasonally adjusted.

Data Load

In [408...

```
df = pd.read_csv('COINT_PPP.csv')
df.set_index(keys='DATE',drop=True, inplace = True)

df.dropna(inplace = True)
```

Check columns

In [409…
```
df.columns
```
Out[409]:
```
Index(['ENTRY', 'USCPI', 'CANEX', 'CANCPI', 'JAPANEX', 'JAPANCPI', 'SWEX',
       'SWCPI'],
      dtype='object')
```

In [410…
```
df
```
Out[410]:

DATE	ENTRY	USCPI	CANEX	CANCPI	JAPANEX	JAPANCPI	SWEX	SWCPI
01-Jan-74	22-Mar-00	117.293	0.992	121.077	299.685	135.294	3.364	127.774
01-Feb-74	22-Mar-00	118.546	0.977	122.057	291.658	139.706	3.176	126.836
01-Mar-74	22-Mar-00	119.799	0.972	123.528	287.949	140.294	3.079	127.431
01-Apr-74	22-Mar-00	120.551	0.968	124.508	292.197	144.118	3.027	126.662
01-May-74	22-Mar-00	121.805	0.962	126.959	291.430	144.706	2.917	128.886
...	...	...	...	...	...	...	...	...
01-Aug-12	23-Mar-00	576.506	0.992	597.050	97.812	292.353	0.968	286.416
01-Sep-12	23-Mar-00	579.516	0.978	598.030	99.210	292.941	0.939	287.309
01-Oct-12	23-Mar-00	580.509	0.987	599.011	97.770	292.941	0.932	287.664
01-Nov-12	23-Mar-00	579.125	0.997	597.540	100.074	291.765	0.939	286.720
01-Dec-12	23-Mar-00	579.291	0.990	594.109	103.285	292.059	0.921	286.108

468 rows × 8 columns

Visualization Variables

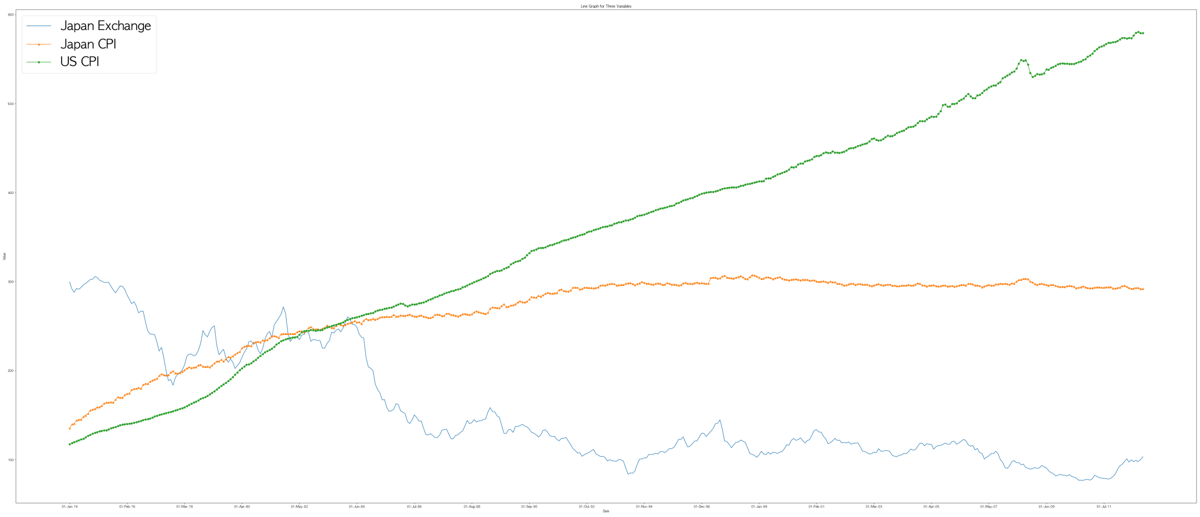
In [411…
```
# 사이즈 설정
plt.rcParams['figure.figsize'] = [70, 30]

# 제목 설정
plt.xlabel('Date')
plt.ylabel('Value')
plt.title('Line Graph for Three Variables')

# x축 간격 설정
plt.xticks(np.arange(0,468,25))

# 그래프 그리기
plt.plot(df.index,df.JAPANEX, label='Japan Exchange')
plt.plot(df.index,df.JAPANCPI, marker='^', label='Japan CPI')
plt.plot(df.index,df.USCPI, marker='o', label='US CPI')
```

```
# legend 폰트사이즈 설정
plt.legend(fontsize='40')
plt.show()
```



ADF test

Null Hypotesis : Stationarity하지 않다. (단위근이 존재)
Alternative Hypotesis : Stationarity하다. (단위근 존재 X)

관심 변수가 Stationary process인지 확인하기 위해 ADF test를 진행한다.

In [412…

```
def adf_test(df):
    result  = adfuller(df.values)
    print('ADF Statistics: %f' % result[0])
    print('p-value: %f' % result[1])
    print('Critical value:')
    for key, value in result[4].items():
        print('\t%s: %.3f' % (key,value))
```

JAPANEX ADF test

In [413…

```
adf_test(df['JAPANEX'])
```

```
ADF Statistics: -2.155502
p-value: 0.222790
Critical value:
        1%: -3.445
        5%: -2.868
        10%: -2.570
```

- p-value가 0.22로 유의수준 0.05보다 커 귀무가설을 기각하지 못한다.
- 따라서 stationary process가 아니다.

JAPANCPI ADF test

In [414…

```
adf_test(df['JAPANCPI'])
```

```
ADF Statistics: -3.601891
p-value: 0.005725
Critical value:
        1%: -3.445
        5%: -2.868
        10%: -2.570
```

- p-value가 0.005로 유의수준 0.05보다 작아 귀무가설을 기각한다.
- 따라서 stationary process이다.

USCPI ADF test

In [415…

```
adf_test(df['USCPI'])
```

```
ADF Statistics: -0.733380
p-value: 0.837913
Critical value:
        1%: -3.445
        5%: -2.868
        10%: -2.570
```

- p-value가 0.83로 유의수준 0.05보다 작아 귀무가설을 기각하지 못한다.
- 따라서 stationary process가 아니다.

JAPANEX와 USCPI가 stationary process가 아니기 때문에 OLS를 실시하면 해당 결과가 spurious regression일 가능성이 있다.

a. Form the log of each variable. Estimate the long-run relationship between Japan and the U.S. as (1)

Create DataFrame

In [416…

```
# 관심변수만 추출
df_a = df[['JAPANEX', 'JAPANCPI', 'USCPI']]

# 관심변수 로그 변환
df_a['L_JAPANEX'] = np.log(df_a['JAPANEX'])
df_a['L_JAPANCPI'] = np.log(df_a['JAPANCPI'])
df_a['L_USCPI'] = np.log(df_a['USCPI'])

df_a
```

Out[416]:

	JAPANEX	JAPANCPI	USCPI	L_JAPANEX	L_JAPANCPI	L_USCPI
DATE						
01-Jan-74	299.685	135.294	117.293	5.702732	4.907450	4.764675
01-Feb-74	291.658	139.706	118.546	5.675582	4.939540	4.775301
01-Mar-74	287.949	140.294	119.799	5.662783	4.943740	4.785815
01-Apr-74	292.197	144.118	120.551	5.677428	4.970632	4.792073
01-May-74	291.430	144.706	121.805	5.674800	4.974704	4.802421
...	...	...	...	...	...	...
01-Aug-12	97.812	292.353	576.506	4.583047	5.677962	6.356986
01-Sep-12	99.210	292.941	579.516	4.597239	5.679971	6.362193
01-Oct-12	97.770	292.941	580.509	4.582618	5.679971	6.363905
01-Nov-12	100.074	291.765	579.125	4.605910	5.675949	6.361518
01-Dec-12	103.285	292.059	579.291	4.637492	5.676956	6.361805

468 rows × 6 columns

Visualization log variables

In [417…

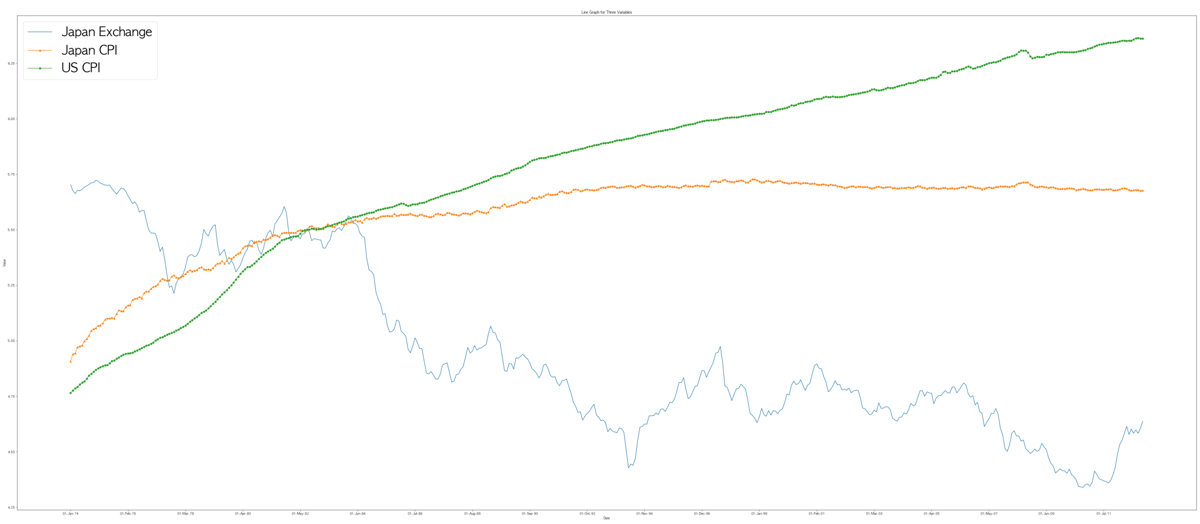
```
# 사이즈 설정
plt.rcParams['figure.figsize'] = [70, 30]

# 제목 설정
plt.xlabel('Date')
plt.ylabel('Value')
plt.title('Line Graph for Three Variables')

# x축 간격 설정
plt.xticks(np.arange(0,468,25))

# 그래프 그리기
plt.plot(df.index,df_a.L_JAPANEX, label='Japan Exchange')
plt.plot(df.index,df_a.L_JAPANCPI, marker='^', label='Japan CPI')
plt.plot(df.index,df_a.L_USCPI, marker='o', label='US CPI')

# legend 폰트사이즈 설정
plt.legend(fontsize='40')
plt.show()
```



Split Independent Data and Target Data

In [418…

```
X = df_a.loc[:,['L_JAPANCPI','L_USCPI']]
Y = df_a.loc[:,['L_JAPANEX']]

# 상수항 추가
X = sm.add_constant(X, has_constant = "add")
```

Multi Linear Regression

In [419…

```
model = sm.OLS(Y, X)
results = model.fit()
results.summary()
```

Out[419]:

OLS Regression Results

Dep. Variable:	L_JAPANEX	**R-squared:**	0.834
Model:	OLS	**Adj. R-squared:**	0.833
Method:	Least Squares	**F-statistic:**	1165.
Date:	Wed, 14 Jun 2023	**Prob (F-statistic):**	8.13e-182
Time:	01:58:44	**Log-Likelihood:**	206.95
No. Observations:	468	**AIC:**	-407.9
Df Residuals:	465	**BIC:**	-395.5
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	9.9746	0.366	27.258	0.000	9.256	10.694
L_JAPANCPI	-0.1042	0.107	-0.977	0.329	-0.314	0.105
L_USCPI	-0.7682	0.045	-17.054	0.000	-0.857	-0.680

Omnibus:	10.594	**Durbin-Watson:**	0.031
Prob(Omnibus):	0.005	**Jarque-Bera (JB):**	10.689
Skew:	0.363	**Prob(JB):**	0.00477
Kurtosis:	3.145	**Cond. No.**	429.

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

i. Do the point estimates of the slope coefficients seem to be consistent with long-run PPP?

- USCPI의 t-statistics 값은 -17.054이고 p-value가 0으로 매우 작으므로 귀무가설을 기각한다.
- USCPI의 coefficient의 값이 음수이다.
- USCPI가 JAPANEX에 음의 영향을 미친다.

ii. From the t-statistics, can you conclude that the Japanese CPI is not significant at the 5% level?

- Japan CPI의 t-statistics 값은 -0.977이고, p-value가 0.329로 매우 크므로 유의수준 0.05하에서 귀무가설을 기각하지 못한다.
- 따라서 not significant하다.

b. Let ut denote the residuals from the long-run relationship. Use these residuals to perform the Engle-Granger test for cointegration. If you use eleven lagged changes, you should find (2)

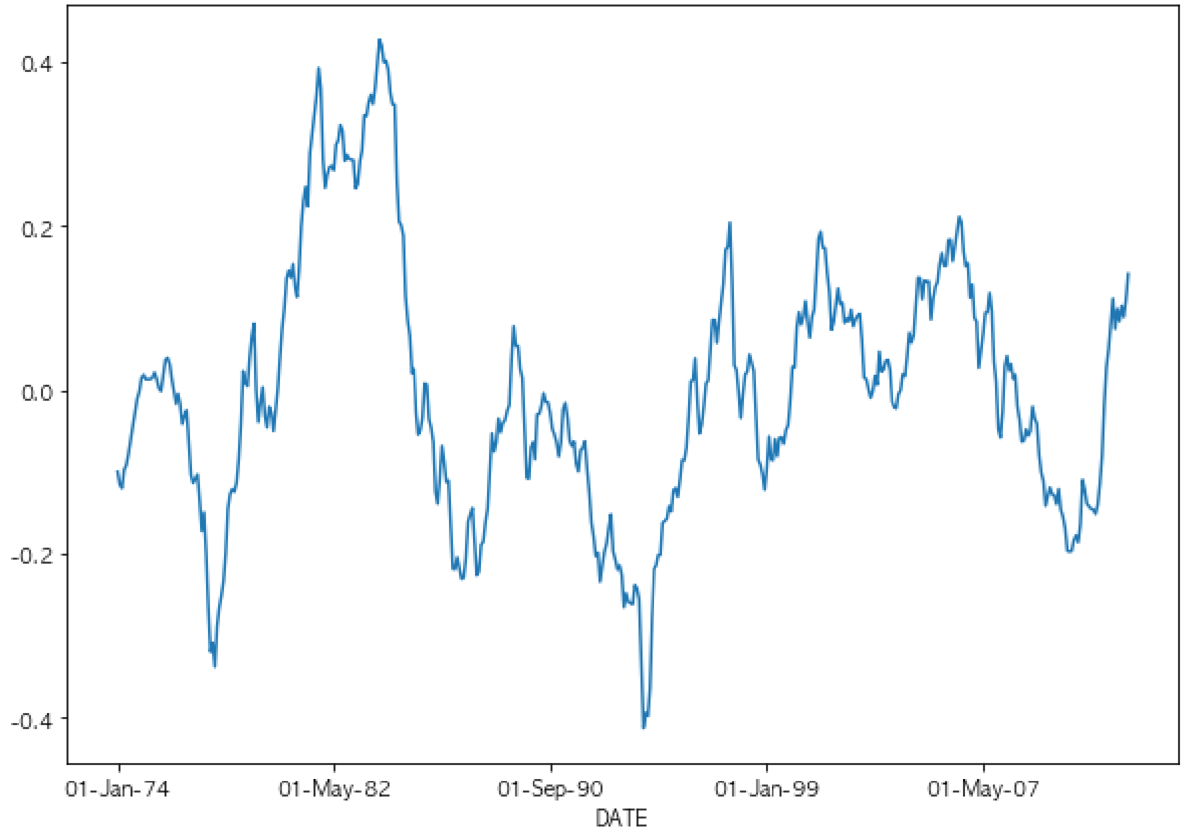
The t-statistic on the coefficient for ut−1 is -3.44. With three variables and 457 usable observations, the 5% and 10% critical values are about -3.760 and -3.464, respectively. Do you conclude that long-run PPP fails?

Residual 구하기

In [420…
```
resid = results.resid
```

Visualization Residual

In [421…
```
plt.figure(figsize=(10,7))
resid.plot()
plt.show()
```



Residual에 대한 ADF test 진행

In [422…

```
adf_test = adfuller(resid,regression='n',maxlag=11, store = False)
adf_test
```

Out[422]:

```
(-3.4305204799132403,
 0.0006200994091774181,
 11,
 456,
 {'1%': -2.5706605130424744,
  '5%': -1.9416048886604955,
  '10%': -1.6162503284529517},
 -2039.4183172706953)
```

- p-value가 0.0006이므로 유의수준 0.05하에서 귀무가설을 기각한다.
- 따라서 정상성을 만족해 공적분 관계이다. 따라서 장기적인 관계를 가진다.

c. Although (at conventional significance levels) we reject the null hypothesis of long-run PPP between Japan and the United States, estimate the error-correction model for ljapanext. If you use 11 lagged changes of each variable, you should find (3)

where ebt−1 is the residual from the equilibrium relationship above and eleven lagged changes are used for each variable. The t-statistic on the error correction term is -3.54. Which of the variable(s) can be said to be weakly exogenous?

In [423…

```
df_coint = df[['JAPANEX', 'JAPANCPI', 'USCPI']]
```

coint_johansen test 진행

In [424…
```
from statsmodels.tsa.vector_ar.vecm import coint_johansen

def joh_output(res):
    output = pd.DataFrame([res.lr2,res.lr1],
                          index=['max_eig_stat',"trace_stat"])
    print(output.T,'\n')
    print("Critical values(90%, 95%, 99%) of max_eig_stat\n",res.cvm,'\n')
    print("Critical values(90%, 95%, 99%) of trace_stat\n",res.cvt,'\n')

joh_model = coint_johansen(df_coint,0,1)
joh_output(joh_model)
```

```
   max_eig_stat  trace_stat
0     46.305986   55.173621
1      8.867009    8.867635
2      0.000626    0.000626

Critical values(90%, 95%, 99%) of max_eig_stat
 [[18.8928 21.1314 25.865 ]
 [12.2971 14.2639 18.52  ]
 [ 2.7055  3.8415  6.6349]]

Critical values(90%, 95%, 99%) of trace_stat
 [[27.0669 29.7961 35.4628]
 [13.4294 15.4943 19.9349]
 [ 2.7055  3.8415  6.6349]]
```

- coint rank는 1로 확인되었다.

VECM 모델 추정

In [425…
```
vecm = VECM(endog = df_a[['L_JAPANEX','L_JAPANCPI','L_USCPI']], k_ar_diff =
vecm_fit = vecm.fit()
```

In [426…
```
vecm_fit.summary()
```

Out[426]:

Det. terms outside the coint. relation & lagged endog. parameters for equation L_JAPANEX

	coef	std err	z	P>|z|	[0.025	0.975]
L1.L_JAPANEX	0.3055	0.046	6.584	0.000	0.215	0.396
L1.L_JAPANCPI	0.0692	0.288	0.240	0.810	-0.495	0.634
L1.L_USCPI	0.3041	0.526	0.579	0.563	-0.726	1.334
L2.L_JAPANEX	-0.0456	0.049	-0.938	0.348	-0.141	0.050
L2.L_JAPANCPI	-0.0578	0.276	-0.209	0.834	-0.600	0.484
L2.L_USCPI	-0.5296	0.591	-0.896	0.370	-1.688	0.629
L3.L_JAPANEX	0.0446	0.048	0.920	0.357	-0.050	0.140
L3.L_JAPANCPI	-0.3443	0.287	-1.198	0.231	-0.908	0.219
L3.L_USCPI	-0.0157	0.590	-0.027	0.979	-1.173	1.142
L4.L_JAPANEX	0.0172	0.048	0.355	0.723	-0.078	0.112
L4.L_JAPANCPI	-0.2129	0.288	-0.738	0.460	-0.778	0.352
L4.L_USCPI	0.0541	0.589	0.092	0.927	-1.100	1.209
L5.L_JAPANEX	-0.0637	0.049	-1.303	0.192	-0.160	0.032
L5.L_JAPANCPI	-0.5337	0.285	-1.872	0.061	-1.092	0.025
L5.L_USCPI	0.2121	0.589	0.360	0.719	-0.942	1.366
L6.L_JAPANEX	-0.0630	0.049	-1.284	0.199	-0.159	0.033
L6.L_JAPANCPI	-0.9029	0.287	-3.147	0.002	-1.465	-0.341
L6.L_USCPI	-0.0646	0.586	-0.110	0.912	-1.213	1.084
L7.L_JAPANEX	-0.0093	0.049	-0.188	0.851	-0.106	0.087
L7.L_JAPANCPI	-0.2901	0.286	-1.013	0.311	-0.851	0.271
L7.L_USCPI	0.5887	0.588	1.001	0.317	-0.564	1.742
L8.L_JAPANEX	0.1098	0.050	2.218	0.027	0.013	0.207
L8.L_JAPANCPI	-0.1577	0.293	-0.539	0.590	-0.732	0.416
L8.L_USCPI	-0.3217	0.585	-0.550	0.582	-1.468	0.825
L9.L_JAPANEX	0.0507	0.050	1.017	0.309	-0.047	0.148
L9.L_JAPANCPI	-0.0473	0.280	-0.169	0.866	-0.596	0.502
L9.L_USCPI	1.0391	0.582	1.786	0.074	-0.101	2.179
L10.L_JAPANEX	0.0028	0.050	0.056	0.955	-0.095	0.101
L10.L_JAPANCPI	0.0345	0.268	0.129	0.898	-0.491	0.560
L10.L_USCPI	-0.4942	0.582	-0.850	0.395	-1.634	0.646
L11.L_JAPANEX	0.1042	0.048	2.188	0.029	0.011	0.198
L11.L_JAPANCPI	0.5031	0.270	1.864	0.062	-0.026	1.032
L11.L_USCPI	-0.2934	0.516	-0.569	0.569	-1.304	0.717

Det. terms outside the coint. relation & lagged endog. parameters for equation L_JAPANCPI

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

L1.L_JAPANEX	0.0060	0.008	0.794	0.427	-0.009	0.021
L1.L_JAPANCPI	-0.0480	0.047	-1.032	0.302	-0.139	0.043
L1.L_USCPI	0.0356	0.085	0.418	0.676	-0.131	0.202
L2.L_JAPANEX	-0.0009	0.008	-0.118	0.906	-0.016	0.014
L2.L_JAPANCPI	-0.3115	0.045	-6.969	0.000	-0.399	-0.224
L2.L_USCPI	0.1329	0.096	1.390	0.165	-0.054	0.320
L3.L_JAPANEX	0.0114	0.008	1.452	0.147	-0.004	0.027
L3.L_JAPANCPI	-0.0571	0.046	-1.229	0.219	-0.148	0.034
L3.L_USCPI	0.2361	0.095	2.472	0.013	0.049	0.423
L4.L_JAPANEX	0.0027	0.008	0.340	0.734	-0.013	0.018
L4.L_JAPANCPI	-0.0391	0.047	-0.838	0.402	-0.131	0.052
L4.L_USCPI	-0.0045	0.095	-0.048	0.962	-0.191	0.182
L5.L_JAPANEX	-0.0049	0.008	-0.617	0.537	-0.020	0.011
L5.L_JAPANCPI	0.1761	0.046	3.821	0.000	0.086	0.266
L5.L_USCPI	-0.0706	0.095	-0.742	0.458	-0.257	0.116
L6.L_JAPANEX	-0.0053	0.008	-0.662	0.508	-0.021	0.010
L6.L_JAPANCPI	0.1152	0.046	2.484	0.013	0.024	0.206
L6.L_USCPI	-0.1033	0.095	-1.091	0.275	-0.289	0.082
L7.L_JAPANEX	-0.0006	0.008	-0.074	0.941	-0.016	0.015
L7.L_JAPANCPI	0.1625	0.046	3.509	0.000	0.072	0.253
L7.L_USCPI	0.0464	0.095	0.487	0.626	-0.140	0.233
L8.L_JAPANEX	-0.0035	0.008	-0.439	0.661	-0.019	0.012
L8.L_JAPANCPI	-0.0063	0.047	-0.134	0.893	-0.099	0.086
L8.L_USCPI	-0.1239	0.095	-1.310	0.190	-0.309	0.062
L9.L_JAPANEX	-0.0109	0.008	-1.350	0.177	-0.027	0.005
L9.L_JAPANCPI	0.0092	0.045	0.203	0.840	-0.080	0.098
L9.L_USCPI	0.0685	0.094	0.728	0.466	-0.116	0.253
L10.L_JAPANEX	0.0003	0.008	0.036	0.971	-0.016	0.016
L10.L_JAPANCPI	-0.2917	0.043	-6.724	0.000	-0.377	-0.207
L10.L_USCPI	-0.0464	0.094	-0.493	0.622	-0.231	0.138
L11.L_JAPANEX	-0.0058	0.008	-0.754	0.451	-0.021	0.009
L11.L_JAPANCPI	-0.0096	0.044	-0.219	0.826	-0.095	0.076
L11.L_USCPI	0.1253	0.083	1.503	0.133	-0.038	0.289

Det. terms outside the coint. relation & lagged endog. parameters for equation L_USCPI

	coef	std err	z	P>|z|	[0.025	0.975]
L1.L_JAPANEX	-0.0024	0.004	-0.572	0.568	-0.010	0.006
L1.L_JAPANCPI	-1.984e-05	0.026	-0.001	0.999	-0.050	0.050

L1.L_USCPI	0.5307	0.047	11.302	0.000	0.439	0.623
L2.L_JAPANEX	0.0011	0.004	0.254	0.800	-0.007	0.010
L2.L_JAPANCPI	-0.0521	0.025	-2.109	0.035	-0.100	-0.004
L2.L_USCPI	-0.0986	0.053	-1.868	0.062	-0.202	0.005
L3.L_JAPANEX	0.0035	0.004	0.815	0.415	-0.005	0.012
L3.L_JAPANCPI	-0.0505	0.026	-1.967	0.049	-0.101	-0.000
L3.L_USCPI	0.0473	0.053	0.897	0.370	-0.056	0.151
L4.L_JAPANEX	-0.0121	0.004	-2.809	0.005	-0.021	-0.004
L4.L_JAPANCPI	-0.0389	0.026	-1.509	0.131	-0.089	0.012
L4.L_USCPI	0.0597	0.053	1.135	0.256	-0.043	0.163
L5.L_JAPANEX	0.0043	0.004	0.991	0.322	-0.004	0.013
L5.L_JAPANCPI	-0.0566	0.025	-2.224	0.026	-0.107	-0.007
L5.L_USCPI	0.0079	0.053	0.150	0.880	-0.095	0.111
L6.L_JAPANEX	0.0007	0.004	0.164	0.870	-0.008	0.009
L6.L_JAPANCPI	-0.0629	0.026	-2.455	0.014	-0.113	-0.013
L6.L_USCPI	0.0866	0.052	1.654	0.098	-0.016	0.189
L7.L_JAPANEX	0.0035	0.004	0.785	0.432	-0.005	0.012
L7.L_JAPANCPI	-0.0766	0.026	-2.996	0.003	-0.127	-0.026
L7.L_USCPI	0.0622	0.053	1.185	0.236	-0.041	0.165
L8.L_JAPANEX	-0.0108	0.004	-2.433	0.015	-0.019	-0.002
L8.L_JAPANCPI	-0.0058	0.026	-0.223	0.824	-0.057	0.045
L8.L_USCPI	0.0206	0.052	0.395	0.693	-0.082	0.123
L9.L_JAPANEX	-0.0022	0.004	-0.488	0.625	-0.011	0.007
L9.L_JAPANCPI	-0.0311	0.025	-1.244	0.213	-0.080	0.018
L9.L_USCPI	0.1003	0.052	1.929	0.054	-0.002	0.202
L10.L_JAPANEX	0.0049	0.004	1.099	0.272	-0.004	0.014
L10.L_JAPANCPI	-0.0327	0.024	-1.364	0.173	-0.080	0.014
L10.L_USCPI	0.1173	0.052	2.259	0.024	0.016	0.219
L11.L_JAPANEX	0.0022	0.004	0.511	0.609	-0.006	0.011
L11.L_JAPANCPI	-0.0047	0.024	-0.195	0.845	-0.052	0.043
L11.L_USCPI	0.0668	0.046	1.450	0.147	-0.024	0.157

Loading coefficients (alpha) for equation L_JAPANEX

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-0.0012	0.001	-0.874	0.382	-0.004	0.002

Loading coefficients (alpha) for equation L_JAPANCPI

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-0.0012	0.000	-5.214	0.000	-0.002	-0.001

Loading coefficients (alpha) for equation L_USCPI

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-0.0005	0.000	-4.141	0.000	-0.001	-0.000

Cointegration relations for loading-coefficients-column 1

	coef	std err	z	P>|z|	[0.025	0.975]
beta.1	1.0000	0	0	0.000	1.000	1.000
beta.2	9.6772	2.493	3.881	0.000	4.791	14.564
beta.3	1.1893	0.877	1.356	0.175	-0.529	2.908
const	-66.6831	10.894	-6.121	0.000	-88.036	-45.331

- USCPI가 JAPANCPI보다 coef가 더 0에 가깝기 때문에 weakly exogenous하다.

In [427…

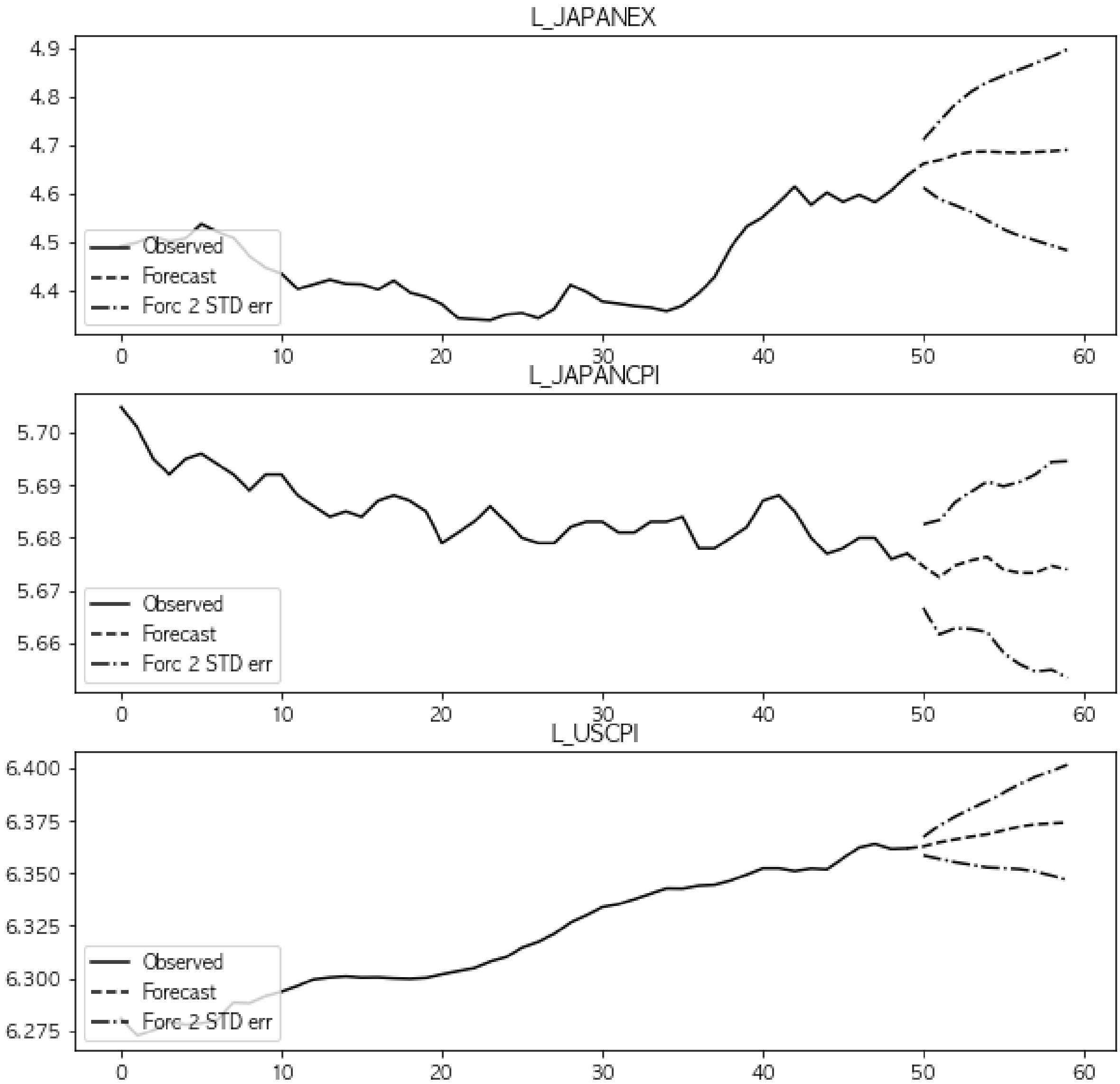
```
vecm_fit.predict(steps=10)
```

Out[427]:

```
array([[4.66136952, 5.67460501, 6.36271879],
       [4.66874643, 5.67248349, 6.36465089],
       [4.68011191, 5.67474735, 6.36601257],
       [4.68626299, 5.67571907, 6.36731066],
       [4.68692998, 5.67636216, 6.36843291],
       [4.68527616, 5.67394599, 6.37029937],
       [4.68437726, 5.67330096, 6.37208659],
       [4.68584948, 5.67329134, 6.37326186],
       [4.68767919, 5.67467267, 6.37374712],
       [4.6903311 , 5.67395607, 6.37409486]])
```

In [428…

```
vecm_fit.plot_forecast(steps=10, n_last_obs=50);
```

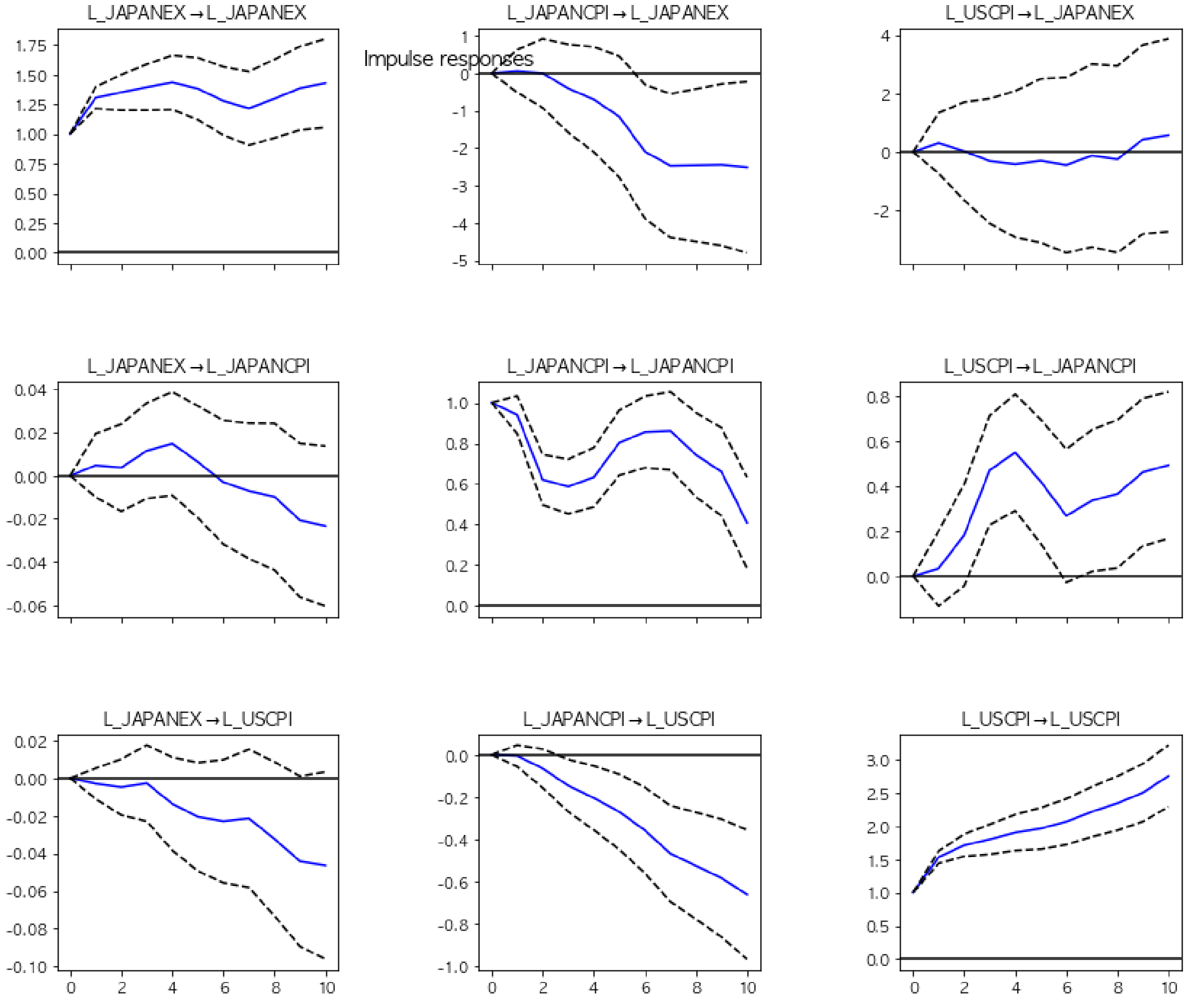


d. [BONUS POINTS] Obtain the impulse functions using the ordering luscpii → ljapancpit → ljapanext. You should find that the U.S. price shock has little effect on the exchange rate but that a shock to the Japanese price level causes the yen to depreciate. The response of the exchange rate to its own shock is immediate and permanent.

In [429…

```
vecm_fit.irf(10).plot()
plt.tight_layout()
plt.subplots_adjust(left=0.125, bottom=0.1, right=1.2, top=1, wspace=0.5, hs

plt.show()
```



- US CPI의 충격이 JAPAN Exchange에 거의 영향을 미치지 않는다.
- JAPAN CPI의 충격은 JAPAN Exchange에 큰 음의 영향을 미친다.
- JAPAN Exchange의 자체 충격은 즉각적이고 0으로 수렴하지 않아 영구적이다.

2. Now, I assume that you have set your objective (theme) of your term paper. By now, you must have your data on two (X and Y , at least) or more variables in your hands. You have already held some statistical analyses based on your problem sets.

Case (i): If your variables are ALL stationary, please estimate the VAR system and interpret the results. Does this system explains your hypothesis? If so, can you make relevant prediction on your variables based on the system? Please show the predicted values of YT +1 based on the parameters of the VAR system and your data at YT .

KRX리츠TOP10지수

In [430…

```
KRX_REITs = pd.read_excel('KRX_리츠TOP10지수.xlsx')
```

In [431…

```
KRX_REITs = KRX_REITs.sort_index(ascending=False)
KRX_REITs.reset_index(drop = True, inplace = True)
```

```
KRX_REITs.set_index('일자',drop=True, inplace = True)

KRX_REITs_df = KRX_REITs[['종가']]
```

In [432…
```
KRX_REITs_df
```

Out[432]:

	종가
일자	
2022/05/23	1187.49
2022/05/24	1194.48
2022/05/25	1205.65
2022/05/26	1215.53
2022/05/27	1220.22
...	...
2023/05/17	855.59
2023/05/18	857.98
2023/05/19	862.43
2023/05/22	864.23
2023/05/23	861.18

249 rows × 1 columns

KRX 건설 지수

In [433…
```
KRX건설지수 = pd.read_excel('KRX건설지수.xlsx')
```

In [434…
```
KRX건설지수 = KRX건설지수.sort_index(ascending=False)
KRX건설지수.reset_index(drop = True, inplace = True)
KRX건설지수.set_index('일자',drop=True, inplace = True)

KRX건설지수_df = KRX건설지수[['종가']]
```

In [435…
```
KRX건설지수_df
```

Out[435]:

	종가
일자	
2022/05/23	627.13
2022/05/24	622.74
2022/05/25	632.37
2022/05/26	634.68
2022/05/27	632.63
...	...
2023/05/17	680.59
2023/05/18	686.32
2023/05/19	694.64
2023/05/22	712.69
2023/05/23	719.90

249 rows × 1 columns

장단기금리차

In [436…

```
KRX장단기금리차 = pd.read_excel('KRX시장금리.xlsx')
KRX장단기금리차.reset_index(drop = True, inplace = True)
KRX장단기금리차.set_index('일자',drop=True, inplace = True)

KRX장단기금리차['KRX장단기금리차'] = KRX장단기금리차['국고채(10년)'] - KRX장단기금리차['국고
KRX장단기금리차_df = KRX장단기금리차[['KRX장단기금리차']]
```

In [437…

```
KRX장단기금리차_df
```

Out[437]:

	KRX장단기금리차
일자	
2022/05/24	0.495
2022/05/25	0.477
2022/05/26	0.519
2022/05/27	0.519
2022/05/30	0.524
...	...
2023/05/17	-0.056
2023/05/18	-0.046
2023/05/19	-0.023
2023/05/22	-0.015
2023/05/23	0.021

249 rows × 1 columns

한국은행 뉴스심리지수

In [438...
```
BOK뉴스심리지수 = pd.read_excel('BOK뉴스심리지수.xlsx')
```

In [439...
```
BOK뉴스심리지수_df = BOK뉴스심리지수.sort_index(ascending=False)
BOK뉴스심리지수_df.reset_index(drop = True, inplace = True)
BOK뉴스심리지수_df.set_index('일자',drop=True, inplace = True)
```

In [440...
```
BOK뉴스심리지수_df
```

Out[440]:

	지수
일자	
2022/05/23	108.47
2022/05/24	107.77
2022/05/25	108.64
2022/05/26	109.47
2022/05/27	111.67
...	...
2023/05/16	94.64
2023/05/17	95.60
2023/05/18	96.50
2023/05/19	99.54
2023/05/22	103.73

249 rows × 1 columns

Merge Data

In [441...
```
KRX_REITs_df.reset_index(inplace = True)
KRX건설지수_df.reset_index(inplace = True)
KRX장단기금리차_df.reset_index(inplace = True)
BOK뉴스심리지수_df.reset_index(inplace = True)
```

In [442...
```
KRX_REITs_df.columns = ['Date', 'KRX리츠TOP10지수']
KRX건설지수_df.columns = ['Date', 'KRX건설지수']
KRX장단기금리차_df.columns = ['Date', 'KRX장단기금리차']
BOK뉴스심리지수_df.columns = ['Date', 'BOK뉴스심리지수']
```

In [443...
```
df_final = pd.DataFrame()
df_final = pd.merge(KRX_REITs_df, KRX건설지수_df, how='inner',on=['Date'])
df_final = pd.merge(df_final, KRX장단기금리차_df, how='inner',on=['Date'])
df_final = pd.merge(df_final, BOK뉴스심리지수_df, how='inner',on=['Date'])
```

In [444...
```
df_final.set_index(keys='Date',drop=True, inplace = True)
```

최종 데이터셋

In [445...
```
df_final
```

Out[445]:

Date	KRX리츠TOP10지수	KRX건설지수	KRX장단기금리차	BOK뉴스심리지수
2022/05/24	1194.48	622.74	0.495	107.77
2022/05/25	1205.65	632.37	0.477	108.64
2022/05/26	1215.53	634.68	0.519	109.47
2022/05/27	1220.22	632.63	0.519	111.67
2022/05/30	1209.95	640.66	0.524	107.97
...	...	...	...	...
2023/05/16	859.21	680.88	-0.043	94.64
2023/05/17	855.59	680.59	-0.056	95.60
2023/05/18	857.98	686.32	-0.046	96.50
2023/05/19	862.43	694.64	-0.023	99.54
2023/05/22	864.23	712.69	-0.015	103.73

247 rows × 4 columns

In [446…

```
df_final.describe()
```

Out[446]:

	KRX리츠TOP10지수	KRX건설지수	KRX장단기금리차	BOK뉴스심리지수
count	247.000000	247.000000	247.000000	247.000000
mean	919.848421	596.505628	-0.002445	91.787530
std	112.020337	52.086684	0.164817	7.297894
min	761.870000	510.850000	-0.327000	74.650000
25%	831.915000	554.515000	-0.112000	86.505000
50%	872.630000	596.500000	-0.015000	92.810000
75%	1007.915000	621.385000	0.058000	96.550000
max	1220.220000	750.410000	0.601000	111.670000

Visualization Variables

In [447…

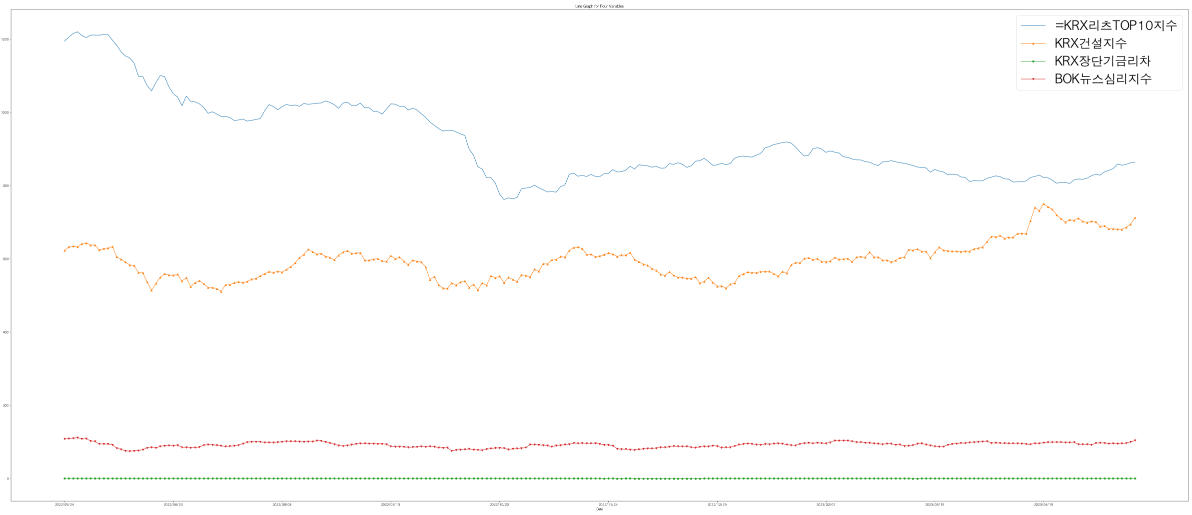
```
# 사이즈 설정
plt.rcParams['figure.figsize'] = [70, 30]

# 제목 설정
plt.xlabel('Date')
plt.ylabel('Value')
plt.title('Line Graph for Four Variables')

# x축 간격 설정
plt.xticks(np.arange(0,247,25))

# 그래프 그리기
plt.plot(df_final.index,df_final.KRX리츠TOP10지수, label='=KRX리츠TOP10지수')
plt.plot(df_final.index,df_final.KRX건설지수, marker='^', label='KRX건설지수')
plt.plot(df_final.index,df_final.KRX장단기금리차, marker='o', label='KRX장단기금리
plt.plot(df_final.index,df_final.BOK뉴스심리지수, marker='v', label='BOK뉴스심리지
```

```
# legend 폰트사이즈 설정
plt.legend(fontsize='40')
plt.show()
```



ADF test 진행

In [448…

```
def adf_test(df):
    result  = adfuller(df.values)
    print('ADF Statistics: %f' % result[0])
    print('p-value: %f' % result[1])
    print('Critical value:')
    for key, value in result[4].items():
        print('\t%s: %.3f' % (key,value))
```

In [449…

```
adf_test(df_final['KRX리츠TOP10지수'])
```

```
ADF Statistics: -3.160391
p-value: 0.022395
Critical value:
	1%: -3.458
	5%: -2.874
	10%: -2.573
```

In [450…

```
adf_test(df_final['KRX건설지수'])
```

```
ADF Statistics: -1.183600
p-value: 0.680610
Critical value:
	1%: -3.457
	5%: -2.873
	10%: -2.573
```

In [451…

```
adf_test(df_final['KRX장단기금리차'])
```

```
ADF Statistics: -3.097665
p-value: 0.026726
Critical value:
	1%: -3.457
	5%: -2.873
	10%: -2.573
```

In [452…

```
adf_test(df_final['BOK뉴스심리지수'])
```

```
ADF Statistics: -2.773405
p-value: 0.062174
Critical value:
        1%: -3.458
        5%: -2.874
        10%: -2.573
```

- 4가지 변수 모두 좀 더 강한 가정인 유의수준 0.01 하에서 귀무가설을 기각하지 못한다.
- 따라서 모두 non-stationary process이다.

Non-stationary process에 대한 차분 실시

KRX리츠TOP10지수 로그수익률

In [453…

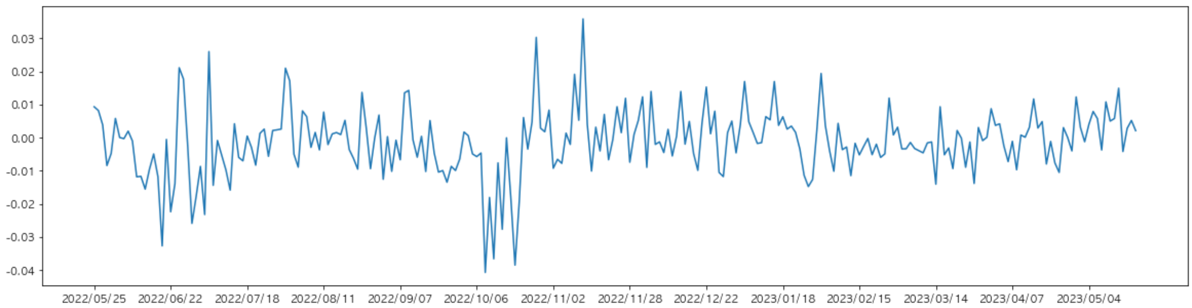
```
df_final['KRX리츠TOP10지수_로그수익률'] = np.log(df_final['KRX리츠TOP10지수']) - np

df_final.dropna(inplace = True)

plt.figure(figsize=(20,5))
plt.xticks(np.arange(0,249,18))
plt.plot(df_final['KRX리츠TOP10지수_로그수익률'])
```

Out[453]:

```
[<matplotlib.lines.Line2D at 0x7fb7d49ea910>]
```



In [454…

```
adf_test(df_final['KRX리츠TOP10지수_로그수익률'])
```

```
ADF Statistics: -3.988336
p-value: 0.001473
Critical value:
        1%: -3.458
        5%: -2.874
        10%: -2.573
```

차분 결과 stationary process로 나타났다.

KRX건설지수 로그수익률

In [455…

```
df_final['KRX건설지수_로그수익률'] = np.log(df_final['KRX건설지수']) - np.log(df_fi
```

In [456…

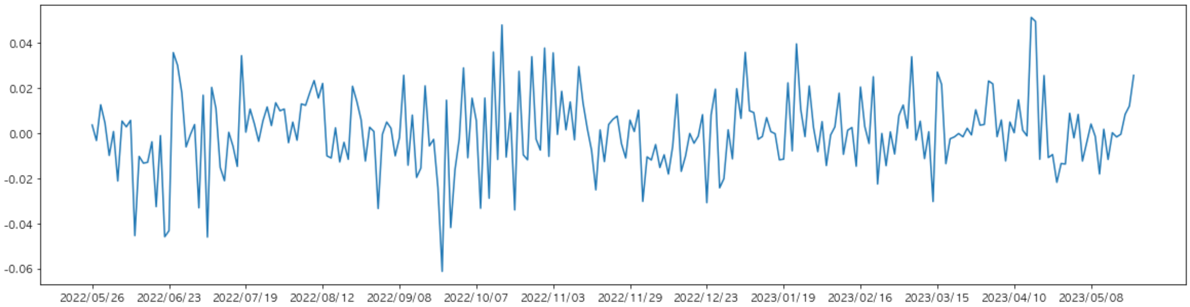
```
df_final.dropna(inplace = True)
```

In [457…

```
plt.figure(figsize=(20,5))
plt.xticks(np.arange(0,248,18))
plt.plot(df_final['KRX건설지수_로그수익률'])
```

Out[457]:

```
[<matplotlib.lines.Line2D at 0x7fb7d4e78460>]
```



In [458…
```
adf_test(df_final['KRX건설지수_로그수익률'])
```

```
ADF Statistics: -9.153187
p-value: 0.000000
Critical value:
        1%: -3.458
        5%: -2.874
        10%: -2.573
```

차분 결과 stationary process로 나타났다.

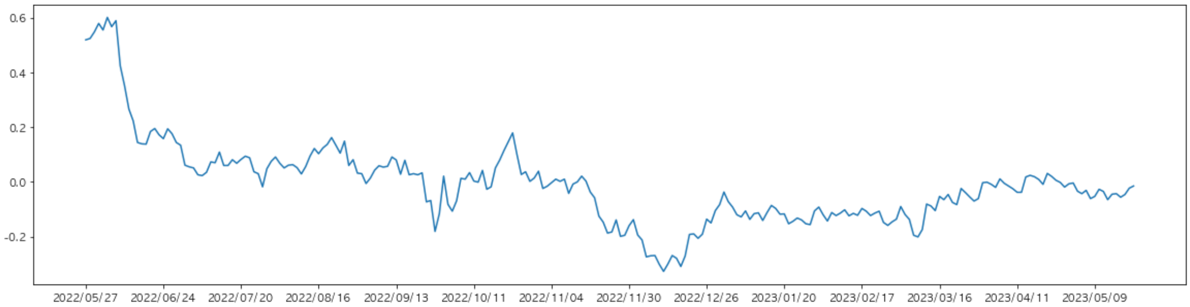
장단기금리차 차분

In [459…
```
df_final['KRX장단기금리차_차분'] = df_final['KRX장단기금리차'] - df_final['KRX장단기금

df_final.dropna(inplace = True)
```

In [460…
```
plt.figure(figsize=(20,5))
plt.xticks(np.arange(0,250,18))
plt.plot(df_final['KRX장단기금리차'])
```

Out[460]:
```
[<matplotlib.lines.Line2D at 0x7fb7d418ac40>]
```



In [461…
```
adf_test(df_final['KRX장단기금리차_차분'])
```

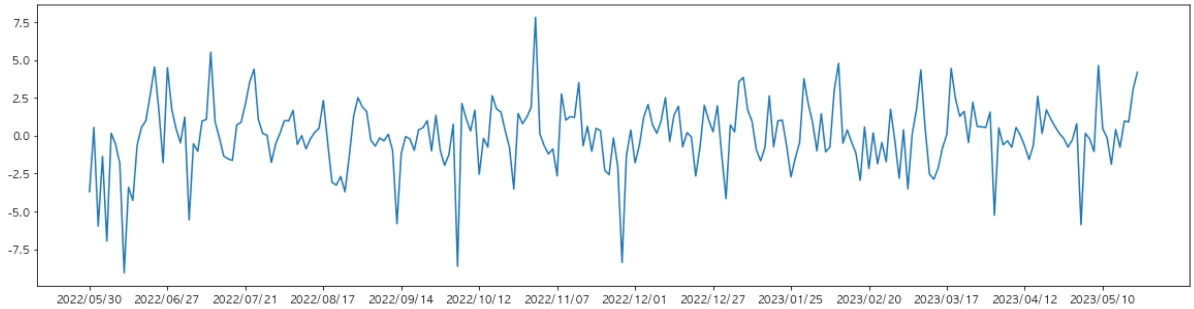
```
ADF Statistics: -11.050630
p-value: 0.000000
Critical value:
        1%: -3.458
        5%: -2.874
        10%: -2.573
```

차분 결과 stationary process로 나타났다.

BOK뉴스심리지수 차분

In [462…
```
df_final['BOK뉴스심리지수_차분'] = df_final['BOK뉴스심리지수'] - df_final['BOK뉴스심리

df_final.dropna(inplace = True)
```

In [463…
```
plt.figure(figsize=(20,5))
plt.xticks(np.arange(0,249,18))
plt.plot(df_final['BOK뉴스심리지수_차분'])
```
Out[463]:
```
[<matplotlib.lines.Line2D at 0x7fb7f3972cd0>]
```


In [464…
```
adf_test(df_final['BOK뉴스심리지수_차분'])
```
```
ADF Statistics: -6.832234
p-value: 0.000000
Critical value:
        1%: -3.459
        5%: -2.874
        10%: -2.573
```
차분 결과 stationary process로 나타났다.

In [465…
```
df_final = df_final[['KRX리츠TOP10지수_로그수익률','KRX건설지수_로그수익률','BOK뉴스심리
```
In [466…
```
df_final
```
Out[466]:

Date	KRX리츠TOP10지수_로그수익률	KRX건설지수_로그수익률	BOK뉴스심리지수_차분	KRX장단기금리차_차분
2022/05/30	-0.008452	0.012613	-3.70	0.005
2022/05/31	-0.004797	0.004532	0.55	0.024
2022/06/02	0.005788	-0.009853	-5.97	0.031
2022/06/03	0.000025	0.000753	-1.36	-0.024
2022/06/07	-0.000322	-0.021172	-6.96	0.046
...	...	...	...	...
2023/05/16	0.014927	-0.001658	-0.77	0.002
2023/05/17	-0.004222	-0.000426	0.96	-0.013
2023/05/18	0.002789	0.008384	0.90	0.010
2023/05/19	0.005173	0.012050	3.04	0.023
2023/05/22	0.002085	0.025653	4.19	0.008

243 rows × 4 columns

VAR 모형 추정

lag 선정

In [467…

```
var = VAR(df_final[['KRX리츠TOP10지수_로그수익률','KRX건설지수_로그수익률','BOK뉴스심리지
var.select_order(maxlags=10).summary()
```

Out[467]:

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	-22.69	-22.63*	1.405e-10	-22.66
1	-22.80*	-22.50	1.253e-10*	-22.68*
2	-22.80	-22.27	1.255e-10	-22.58
3	-22.69	-21.92	1.394e-10	-22.38
4	-22.64	-21.63	1.475e-10	-22.23
5	-22.69	-21.44	1.404e-10	-22.19
6	-22.63	-21.15	1.487e-10	-22.03
7	-22.59	-20.87	1.558e-10	-21.89
8	-22.56	-20.61	1.603e-10	-21.77
9	-22.54	-20.35	1.646e-10	-21.65
10	-22.55	-20.12	1.639e-10	-21.57

criteria를 기준으로 lag 1로 선정했다.

Granger Causality 분석

KRX건설지수_로그수익률 -> KRX리츠TOP10지수_로그수익률

In [481…

```
sample_outs1 = grangercausalitytests(df_final[['KRX리츠TOP10지수_로그수익률','KRX
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=9.0342  , p=0.0029  , df_denom=239, df_num=1
ssr based chi2 test:   chi2=9.1476  , p=0.0025  , df=1
likelihood ratio test: chi2=8.9790  , p=0.0027  , df=1
parameter F test:         F=9.0342  , p=0.0029  , df_denom=239, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=5.1187  , p=0.0067  , df_denom=236, df_num=2
ssr based chi2 test:   chi2=10.4544 , p=0.0054  , df=2
likelihood ratio test: chi2=10.2340 , p=0.0060  , df=2
parameter F test:         F=5.1187  , p=0.0067  , df_denom=236, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=3.6043  , p=0.0141  , df_denom=233, df_num=3
ssr based chi2 test:   chi2=11.1378 , p=0.0110  , df=3
likelihood ratio test: chi2=10.8871 , p=0.0124  , df=3
parameter F test:         F=3.6043  , p=0.0141  , df_denom=233, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=2.8344  , p=0.0253  , df_denom=230, df_num=4
ssr based chi2 test:   chi2=11.7812 , p=0.0191  , df=4
likelihood ratio test: chi2=11.5001 , p=0.0215  , df=4
parameter F test:         F=2.8344  , p=0.0253  , df_denom=230, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=2.3686  , p=0.0404  , df_denom=227, df_num=5
ssr based chi2 test:   chi2=12.4168 , p=0.0295  , df=5
likelihood ratio test: chi2=12.1038 , p=0.0334  , df=5
parameter F test:         F=2.3686  , p=0.0404  , df_denom=227, df_num=5
```

KRX리츠TOP10지수_로그수익률 -> KRX건설지수_로그수익률

In [487…

```
sample_outs2 = grangercausalitytests(df_final[['KRX건설지수_로그수익률','KRX리츠TO
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.8573  , p=0.3554  , df_denom=239, df_num=1
ssr based chi2 test:   chi2=0.8680  , p=0.3515  , df=1
likelihood ratio test: chi2=0.8665  , p=0.3519  , df=1
parameter F test:         F=0.8573  , p=0.3554  , df_denom=239, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.5859  , p=0.5574  , df_denom=236, df_num=2
ssr based chi2 test:   chi2=1.1967  , p=0.5497  , df=2
likelihood ratio test: chi2=1.1937  , p=0.5505  , df=2
parameter F test:         F=0.5859  , p=0.5574  , df_denom=236, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.4782  , p=0.6978  , df_denom=233, df_num=3
ssr based chi2 test:   chi2=1.4777  , p=0.6874  , df=3
likelihood ratio test: chi2=1.4731  , p=0.6885  , df=3
parameter F test:         F=0.4782  , p=0.6978  , df_denom=233, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.3464  , p=0.8464  , df_denom=230, df_num=4
ssr based chi2 test:   chi2=1.4398  , p=0.8373  , df=4
likelihood ratio test: chi2=1.4355  , p=0.8380  , df=4
parameter F test:         F=0.3464  , p=0.8464  , df_denom=230, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=1.1206  , p=0.3502  , df_denom=227, df_num=5
ssr based chi2 test:   chi2=5.8746  , p=0.3186  , df=5
likelihood ratio test: chi2=5.8033  , p=0.3258  , df=5
parameter F test:         F=1.1206  , p=0.3502  , df_denom=227, df_num=5
```

BOK뉴스심리지수_차분 -> KRX리츠TOP10지수_로그수익률

In [483…

```
sample_outs_3 = grangercausalitytests(df_final[['KRX리츠TOP10지수_로그수익률','BC
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.0838  , p=0.7725  , df_denom=239, df_num=1
ssr based chi2 test:   chi2=0.0848  , p=0.7709  , df=1
likelihood ratio test: chi2=0.0848  , p=0.7709  , df=1
parameter F test:         F=0.0838  , p=0.7725  , df_denom=239, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.1683  , p=0.8452  , df_denom=236, df_num=2
ssr based chi2 test:   chi2=0.3438  , p=0.8421  , df=2
likelihood ratio test: chi2=0.3436  , p=0.8422  , df=2
parameter F test:         F=0.1683  , p=0.8452  , df_denom=236, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.1386  , p=0.9368  , df_denom=233, df_num=3
ssr based chi2 test:   chi2=0.4283  , p=0.9343  , df=3
likelihood ratio test: chi2=0.4279  , p=0.9344  , df=3
parameter F test:         F=0.1386  , p=0.9368  , df_denom=233, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.7647  , p=0.5492  , df_denom=230, df_num=4
ssr based chi2 test:   chi2=3.1785  , p=0.5284  , df=4
likelihood ratio test: chi2=3.1575  , p=0.5318  , df=4
parameter F test:         F=0.7647  , p=0.5492  , df_denom=230, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=0.9328  , p=0.4605  , df_denom=227, df_num=5
ssr based chi2 test:   chi2=4.8897  , p=0.4295  , df=5
likelihood ratio test: chi2=4.8402  , p=0.4357  , df=5
parameter F test:         F=0.9328  , p=0.4605  , df_denom=227, df_num=5
```

KRX리츠TOP10지수_로그수익률 -> BOK뉴스심리지수_차분

In [484…

```
sample_outs_4 = grangercausalitytests(df_final[['BOK뉴스심리지수_차분','KRX리츠TOI
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=3.0844  , p=0.0803  , df_denom=239, df_num=1
ssr based chi2 test:   chi2=3.1231  , p=0.0772  , df=1
likelihood ratio test: chi2=3.1032  , p=0.0781  , df=1
parameter F test:         F=3.0844  , p=0.0803  , df_denom=239, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=1.8348  , p=0.1619  , df_denom=236, df_num=2
ssr based chi2 test:   chi2=3.7474  , p=0.1536  , df=2
likelihood ratio test: chi2=3.7186  , p=0.1558  , df=2
parameter F test:         F=1.8348  , p=0.1619  , df_denom=236, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=1.4522  , p=0.2284  , df_denom=233, df_num=3
ssr based chi2 test:   chi2=4.4874  , p=0.2134  , df=3
likelihood ratio test: chi2=4.4460  , p=0.2172  , df=3
parameter F test:         F=1.4522  , p=0.2284  , df_denom=233, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=1.0957  , p=0.3594  , df_denom=230, df_num=4
ssr based chi2 test:   chi2=4.5543  , p=0.3362  , df=4
likelihood ratio test: chi2=4.5115  , p=0.3412  , df=4
parameter F test:         F=1.0957  , p=0.3594  , df_denom=230, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=1.3753  , p=0.2345  , df_denom=227, df_num=5
ssr based chi2 test:   chi2=7.2097  , p=0.2055  , df=5
likelihood ratio test: chi2=7.1027  , p=0.2131  , df=5
parameter F test:         F=1.3753  , p=0.2345  , df_denom=227, df_num=5
```

KRX장단기금리차_차분 -> KRX리츠TOP10지수_로그수익률

In [485…

```
sample_outs_5 = grangercausalitytests(df_final[['KRX리츠TOP10지수_로그수익률','KR
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.0284  , p=0.8662  , df_denom=239, df_num=1
ssr based chi2 test:   chi2=0.0288  , p=0.8653  , df=1
likelihood ratio test: chi2=0.0288  , p=0.8653  , df=1
parameter F test:         F=0.0284  , p=0.8662  , df_denom=239, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.6484  , p=0.5238  , df_denom=236, df_num=2
ssr based chi2 test:   chi2=1.3242  , p=0.5158  , df=2
likelihood ratio test: chi2=1.3206  , p=0.5167  , df=2
parameter F test:         F=0.6484  , p=0.5238  , df_denom=236, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.7889  , p=0.5011  , df_denom=233, df_num=3
ssr based chi2 test:   chi2=2.4379  , p=0.4866  , df=3
likelihood ratio test: chi2=2.4257  , p=0.4889  , df=3
parameter F test:         F=0.7889  , p=0.5011  , df_denom=233, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=1.4969  , p=0.2039  , df_denom=230, df_num=4
ssr based chi2 test:   chi2=6.2218  , p=0.1832  , df=4
likelihood ratio test: chi2=6.1422  , p=0.1888  , df=4
parameter F test:         F=1.4969  , p=0.2039  , df_denom=230, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=1.1932  , p=0.3133  , df_denom=227, df_num=5
ssr based chi2 test:   chi2=6.2551  , p=0.2822  , df=5
likelihood ratio test: chi2=6.1743  , p=0.2896  , df=5
parameter F test:         F=1.1932  , p=0.3133  , df_denom=227, df_num=5
```

KRX리츠TOP10지수_로그수익률 -> KRX장단기금리차_차분

In [486…

```
sample_outs_6 = grangercausalitytests(df_final[['KRX장단기금리차_차분','KRX리츠TOI
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.5809  , p=0.4467  , df_denom=239, df_num=1
ssr based chi2 test:   chi2=0.5882  , p=0.4431  , df=1
likelihood ratio test: chi2=0.5875  , p=0.4434  , df=1
parameter F test:         F=0.5809  , p=0.4467  , df_denom=239, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.3271  , p=0.7214  , df_denom=236, df_num=2
ssr based chi2 test:   chi2=0.6680  , p=0.7160  , df=2
likelihood ratio test: chi2=0.6671  , p=0.7164  , df=2
parameter F test:         F=0.3271  , p=0.7214  , df_denom=236, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.2328  , p=0.8734  , df_denom=233, df_num=3
ssr based chi2 test:   chi2=0.7195  , p=0.8686  , df=3
likelihood ratio test: chi2=0.7184  , p=0.8689  , df=3
parameter F test:         F=0.2328  , p=0.8734  , df_denom=233, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.3716  , p=0.8288  , df_denom=230, df_num=4
ssr based chi2 test:   chi2=1.5446  , p=0.8187  , df=4
likelihood ratio test: chi2=1.5396  , p=0.8196  , df=4
parameter F test:         F=0.3716  , p=0.8288  , df_denom=230, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=0.5070  , p=0.7708  , df_denom=227, df_num=5
ssr based chi2 test:   chi2=2.6579  , p=0.7526  , df=5
likelihood ratio test: chi2=2.6432  , p=0.7548  , df=5
parameter F test:         F=0.5070  , p=0.7708  , df_denom=227, df_num=5
```

VAR 모형

In [474…

```
VAR_model = sm.tsa.VAR(df_final[['KRX리츠TOP10지수_로그수익률','KRX건설지수_로그수익률
display(VAR_model.summary())
```

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Wed, 14, Jun, 2023
Time:                     01:58:46
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                   -22.2901
Nobs:                     242.000    HQIC:                  -22.4623
Log likelihood:           1378.46    FPE:                1.56425e-10
AIC:                     -22.5785    Det(Omega_mle):     1.44138e-10
--------------------------------------------------------------------
Results for equation KRX리츠TOP10지수_로그수익률
============================================================================
============
                           coefficient       std. error           t-stat
prob
----------------------------------------------------------------------------
------------
const                        -0.000843         0.000634           -1.329
0.184
L1.KRX리츠TOP10지수_로그수익률         0.344752         0.068069            5.065
0.000
L1.KRX건설지수_로그수익률           -0.119549         0.039979           -2.990
0.003
L1.BOK뉴스심리지수_차분            -0.000053         0.000277           -0.193
0.847
L1.KRX장단기금리차_차분             0.004153         0.017351            0.239
0.811
============================================================================
============

Results for equation KRX건설지수_로그수익률
============================================================================
============
                           coefficient       std. error           t-stat
prob
----------------------------------------------------------------------------
------------
const                         0.000658         0.001150            0.572
0.567
L1.KRX리츠TOP10지수_로그수익률         0.114075         0.123409            0.924
0.355
L1.KRX건설지수_로그수익률           -0.078195         0.072483           -1.079
0.281
L1.BOK뉴스심리지수_차분             0.000207         0.000503            0.411
0.681
L1.KRX장단기금리차_차분             0.006074         0.031458            0.193
0.847
============================================================================
============

Results for equation BOK뉴스심리지수_차분
============================================================================
============
                           coefficient       std. error           t-stat
prob
----------------------------------------------------------------------------
------------
const                         0.004022         0.142012            0.028
0.977
L1.KRX리츠TOP10지수_로그수익률        11.927422        15.236348            0.783
0.434
L1.KRX건설지수_로그수익률           17.244244         8.948906            1.927
```

```
0.054
L1.BOK뉴스심리지수_차분                0.255799         0.062078           4.121
0.000
L1.KRX장단기금리차_차분               -0.767841         3.883817          -0.198
0.843
============================================================================
============

Results for equation KRX장단기금리차_차분
============================================================================
============
                           coefficient       std. error           t-stat
prob
----------------------------------------------------------------------------
------------
const                        -0.002645         0.002383           -1.110
0.267
L1.KRX리츠TOP10지수_로그수익률        -0.294025         0.255623           -1.150
0.250
L1.KRX건설지수_로그수익률              0.170706         0.150138            1.137
0.256
L1.BOK뉴스심리지수_차분                0.002000         0.001041           1.920
0.055
L1.KRX장단기금리차_차분               -0.013478         0.065160          -0.207
0.836
============================================================================
============

Correlation matrix of residuals
                      KRX리츠TOP10지수_로그수익률  KRX건설지수_로그수익률  BOK뉴스심리지
수_차분   KRX장단기금리차_차분
KRX리츠TOP10지수_로그수익률              1.000000        0.431644     -0.011757
0.138012
KRX건설지수_로그수익률                  0.431644        1.000000      0.046680
0.169723
BOK뉴스심리지수_차분                  -0.011757        0.046680      1.000000
0.014474
KRX장단기금리차_차분                   0.138012        0.169723      0.014474
1.000000
```

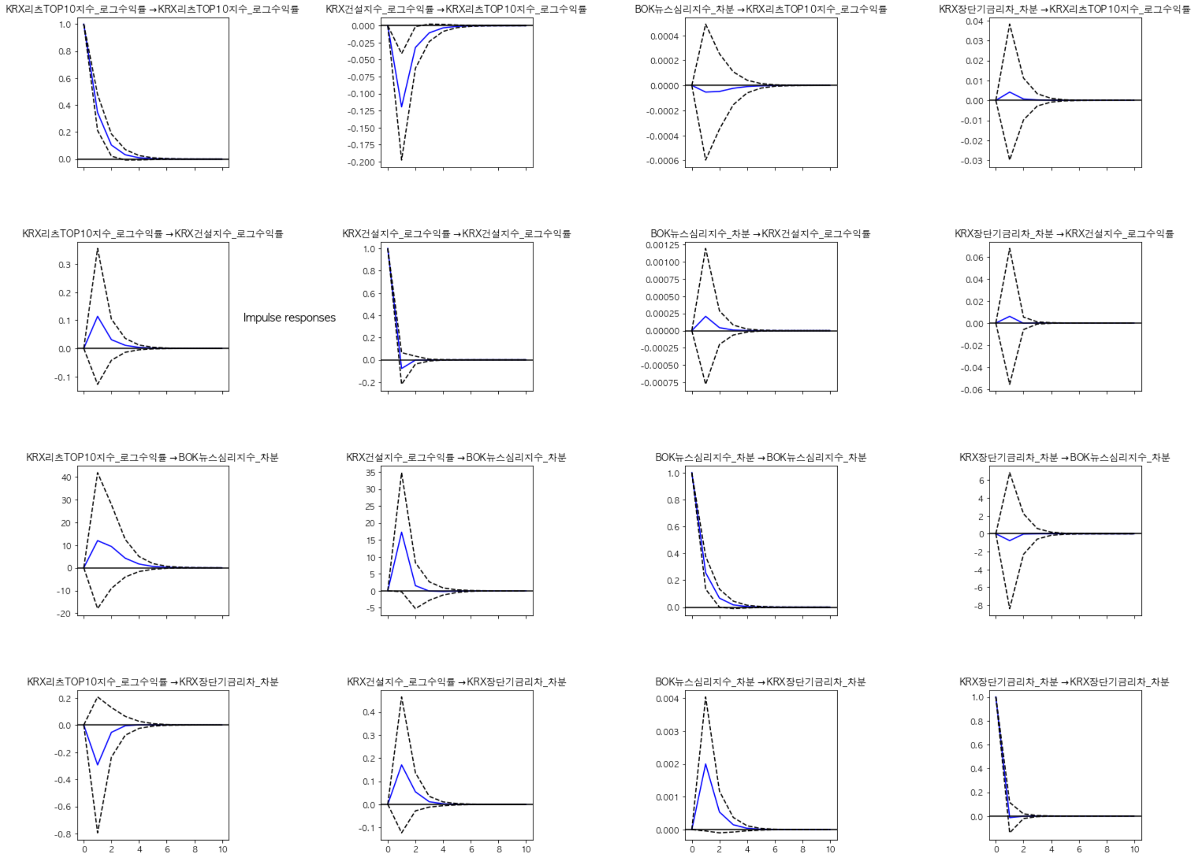
충격반응함수 추정

In [475…

```
irf = VAR_model.irf(10)

irf.plot()
plt.tight_layout()
plt.subplots_adjust(left=0.125, bottom=0.05, right=2, top=1.5, wspace=1, hsp

plt.show()
```



In [476…
```
var_decomp = VAR_model.fevd(periods=10, var_decomp=None)
```

In [477…
```
var_decomp.summary()
```

FEVD for KRX리츠TOP10지수_로그수익률

	KRX리츠TOP10지수_로그수익률	KRX건설지수_로그수익률	BOK뉴스심리지수_차분	KRX장단기금리차_차분
0	1.000000	0.000000	0.000000	0.000000
1	0.965416	0.034244	0.000126	0.000213
2	0.963083	0.036469	0.000230	0.000217
3	0.962813	0.036714	0.000254	0.000218
4	0.962786	0.036738	0.000258	0.000218
5	0.962783	0.036740	0.000259	0.000218
6	0.962783	0.036741	0.000259	0.000218
7	0.962783	0.036741	0.000259	0.000218
8	0.962783	0.036741	0.000259	0.000218
9	0.962783	0.036741	0.000259	0.000218

FEVD for KRX건설지수_로그수익률

	KRX리츠TOP10지수_로그수익률	KRX건설지수_로그수익률	BOK뉴스심리지수_차분	KRX장단기금리차_차분
0	0.186317	0.813683	0.000000	0.000000
1	0.186080	0.813117	0.000651	0.000152
2	0.186274	0.812895	0.000679	0.000152
3	0.186292	0.812876	0.000680	0.000152
4	0.186294	0.812874	0.000680	0.000152
5	0.186294	0.812874	0.000680	0.000152
6	0.186294	0.812874	0.000680	0.000152
7	0.186294	0.812874	0.000680	0.000152
8	0.186294	0.812874	0.000680	0.000152
9	0.186294	0.812874	0.000680	0.000152

FEVD for BOK뉴스심리지수_차분

	KRX리츠TOP10지수_로그수익률	KRX건설지수_로그수익률	BOK뉴스심리지수_차분	KRX장단기금리차_차분
0	0.000138	0.003292	0.996570	0.000000
1	0.010920	0.020647	0.968287	0.000146
2	0.012787	0.020717	0.966350	0.000146
3	0.013082	0.020706	0.966067	0.000145
4	0.013121	0.020706	0.966028	0.000145
5	0.013125	0.020706	0.966023	0.000145
6	0.013126	0.020706	0.966023	0.000145
7	0.013126	0.020706	0.966022	0.000145
8	0.013126	0.020706	0.966022	0.000145
9	0.013126	0.020706	0.966022	0.000145

FEVD for KRX장단기금리차_차분

	KRX리츠TOP10지수_로그수익률	KRX건설지수_로그수익률	BOK뉴스심리지수_차분	KRX장단기금리차_차분
0	0.019047	0.014911	0.000083	0.965958
1	0.020691	0.020765	0.013900	0.944644
2	0.020671	0.021349	0.014868	0.943112
3	0.020669	0.021375	0.014942	0.943014
4	0.020670	0.021376	0.014948	0.943007
5	0.020670	0.021376	0.014948	0.943007
6	0.020670	0.021376	0.014948	0.943007
7	0.020670	0.021376	0.014948	0.943007
8	0.020670	0.021376	0.014948	0.943007
9	0.020670	0.021376	0.014948	0.943007