In [1]:
```
#Overall Cyber Crime Category
```

In [2]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from linearmodels.panel import PanelOLS
from linearmodels.panel import compare
```

In [3]:
```
df = pd.read_csv('panel_data/cyber new.csv')
df['l_cyber'] = np.log(df['cyber_cr'] + 1)
df.head()
```

Out[3]:

	s.no.	districts	year	type	cyber_crimes	pop_in_lak	cyber_cr	avg_temp	tot_rf
0	1	ariyalur	2011	cyber crime	0	7.52	0.0	28.312353	1103.207404
1	1	ariyalur	2012	cyber crimes	0	7.63	0.0	28.777312	973.207972
2	1	ariyalur	2013	cyber crime	0	7.76	0.0	28.730311	870.158045
3	1	ariyalur	2014	cyber crime	0	7.88	0.0	28.536042	1090.802339
4	1	ariyalur	2015	cyber crime	0	8.00	0.0	28.565911	1501.644532

In [4]:
```
df = df.set_index(['districts','year'])
y = df['l_cyber']
X = df[['avg_temp','tot_rf']]
```

In [5]:
```
#PooledOLS Estimation
X = sm.add_constant(X)
pols = PanelOLS(y,X)
pols_result = pols.fit()
print(pols_result.summary)
```

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:                l_cyber   R-squared:                        0.0441
Estimator:                   PanelOLS   R-squared (Between):             -0.1054
No. Observations:                 384   R-squared (Within):               0.0628
Date:                Wed, Nov 12 2025   R-squared (Overall):              0.0441
Time:                        18:23:29   Log-likelihood                   -231.70
Cov. Estimator:            Unadjusted
                                        F-statistic:                      8.7810
Entities:                          32   P-value                           0.0002
Avg Obs:                       12.000   Distribution:                   F(2,381)
Min Obs:                       12.000
Max Obs:                       12.000   F-statistic (robust):             8.7810
                                        P-value                           0.0002
Time periods:                      12   Distribution:                   F(2,381)
Avg Obs:                       32.000
Min Obs:                       32.000
Max Obs:                       32.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const         -0.2533     0.2255    -1.1233     0.2620     -0.6967      0.1901
avg_temp       0.0125     0.0072     1.7388     0.0829     -0.0016      0.0266
tot_rf         0.0002  5.271e-05     4.1905     0.0000      0.0001      0.0003
==============================================================================
```

In [6]:

```
#FE Model Estimation
X = sm.add_constant(X)
FEmodel = PanelOLS(y,X,entity_effects=True)
feresult = FEmodel.fit()
print(feresult.summary)
```

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:                l_cyber   R-squared:                        0.1097
Estimator:                   PanelOLS   R-squared (Between):             -10.891
No. Observations:                 384   R-squared (Within):               0.1097
Date:                Wed, Nov 12 2025   R-squared (Overall):             -1.1178
Time:                        18:23:29   Log-likelihood                   -195.33
Cov. Estimator:            Unadjusted
                                        F-statistic:                      21.561
Entities:                          32   P-value                           0.0000
Avg Obs:                       12.000   Distribution:                   F(2,350)
Min Obs:                       12.000
Max Obs:                       12.000   F-statistic (robust):             21.561
                                        P-value                           0.0000
Time periods:                      12   Distribution:                   F(2,350)
Avg Obs:                       32.000
Min Obs:                       32.000
Max Obs:                       32.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const          3.5550     1.0196     3.4868     0.0006      1.5498      5.5602
avg_temp      -0.1286     0.0365    -3.5220     0.0005     -0.2004     -0.0568
tot_rf         0.0002  6.409e-05     3.4167     0.0007   9.293e-05      0.0003
==============================================================================

F-test for Poolability: 2.3548
P-value: 0.0001
Distribution: F(31,350)

Included effects: Entity
```

In [7]:

```
#RE Model Estimation
from linearmodels.panel import RandomEffects
import statsmodels.api as sm
X = sm.add_constant(X)
REmodel = RandomEffects(y,X)
reresult = REmodel.fit()
print(reresult.summary)
```

```
                          RandomEffects Estimation Summary
================================================================================
Dep. Variable:                l_cyber   R-squared:                        0.0520
Estimator:              RandomEffects   R-squared (Between):             -0.1568
No. Observations:                 384   R-squared (Within):               0.0679
Date:                Wed, Nov 12 2025   R-squared (Overall):              0.0428
Time:                        18:23:29   Log-likelihood                   -221.39
Cov. Estimator:            Unadjusted
                                        F-statistic:                      10.458
Entities:                          32   P-value                           0.0000
Avg Obs:                       12.000   Distribution:                   F(2,381)
Min Obs:                       12.000
Max Obs:                       12.000   F-statistic (robust):             10.458
                                        P-value                           0.0000
Time periods:                      12   Distribution:                   F(2,381)
Avg Obs:                       32.000
Min Obs:                       32.000
Max Obs:                       32.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const         -0.2419     0.2671    -0.9058     0.3656     -0.7670     0.2832
avg_temp       0.0109     0.0088     1.2423     0.2149     -0.0063     0.0281
tot_rf         0.0002  5.471e-05     4.5469     0.0000      0.0001     0.0004
==============================================================================
```

In [8]:

```python
#Hausman Test
from numpy.linalg import inv
from scipy.stats import chi2

b_FE = feresult.params
b_RE = reresult.params

common_coef = list(set(b_FE.index) & set(b_RE.index))

if 'const' in common_coef:
    common_coef.remove('const')

b_FE = b_FE[common_coef]
b_RE = b_RE[common_coef]

V_FE = feresult.cov
V_RE = reresult.cov

diff = b_FE - b_RE
diff_var = V_FE.loc[common_coef, common_coef] - V_RE.loc[common_coef, common_coef]

hausman_stat = np.dot(np.dot(diff.T, inv(diff_var)), diff)

df_h = len(diff)
p_value = 1 - chi2.cdf(hausman_stat, df_h)

print("Hausman Test Statistic:", round(hausman_stat, 3))
print("Degrees of Freedom:", df_h)
```

```
print("p-value:", round(p_value, 4))
```

```
Hausman Test Statistic: 23.427
Degrees of Freedom: 2
p-value: 0.0
```

In [9]:
```
#Diagnostic Checks
from statsmodels.stats.diagnostic import het_breuschpagan, het_white
from statsmodels.stats.stattools import durbin_watson
```

In [10]:
```
#Test for Heteroskedasticity

#H0: No heteroskedasticity
#H1: Heteroskedasticity exists

#p-value <= 0.05 ---> Heteroskedasticity; p-value > 0.05 ---> Homoskedasticity

print('Breusch-Pagan Test')
residuals = feresult.resids
bp_test = het_breuschpagan(residuals, X)
bp_labels = ['Lagrange multiplier statistic','p-value','f-value','f p-value']
print(dict(zip(bp_labels, bp_test)))
print()
print('White Test')
white_test = het_white(residuals,X)
white_labels = ['LM stat','LM p-value','F p-value']
print(dict(zip(white_labels,white_test)))
```

```
Breusch-Pagan Test
{'Lagrange multiplier statistic': np.float64(5.423555035377646), 'p-value': np.float
64(0.06641864141569061), 'f-value': np.float64(2.7291376628992072), 'f p-value': n
p.float64(0.06655189051757221)}

White Test
{'LM stat': np.float64(15.07649151978812), 'LM p-value': np.float64(0.01004045305445
1835), 'F p-value': np.float64(3.089482596518018)}
```

In [11]:
```
#Test for serial correlation (autocorrelation)

#Durbin-Watson statistic ranges between 0 to 4

#DW statistic = 2 ---> No autocorrelation
#DW statistic < 2 ---> Positive autocorrelation
#DW statistic > 2 ---> Negative autocorrelation

print('Durbin-Watson Test')
dw_value = durbin_watson(residuals)
print("Durbin-Watson statistic: ", round(dw_value,3))
```

```
Durbin-Watson Test
Durbin-Watson statistic:  1.514
```

In [12]:
```
from scipy import stats

#Test for cross-section dependency

#H0: No cross-section dependency
```

```
#H1: Cross-section dependency exists

print('Breusch-Pagan LM Test')
resid_df = residuals.unstack(level=0)
T = resid_df.shape[0]
N = resid_df.shape[1]

rho = resid_df.corr().values
upper_tri_idx = np.triu_indices(N, k=1)
rho_upper = rho[upper_tri_idx]
LM_stat = T * np.sum(rho_upper**2)
p_value = 1 - stats.chi2.cdf(LM_stat, N*(N-1)/2)

print(f"Breusch-Pagan LM statistic: {LM_stat:.3f}")
print(f"p-value: {p_value:.4f}")
print()

print('Pesaran CD Test')
CD_stat = np.sqrt(2 / (N*(N-1))) * np.sum(rho_upper)
p_value_cd = 2 * (1 - stats.norm.cdf(abs(CD_stat)))

print(f"Pesaran CD statistic: {CD_stat:.3f}")
print(f"p-value: {p_value_cd:.4f}")
```

```
Breusch-Pagan LM Test
Breusch-Pagan LM statistic: 2311.733
p-value: 0.0000

Pearson CD Test
Pesaran CD statistic: 12.098
p-value: 0.0000
```

In [13]:

```
#Re-estimate FE Model
```

In [14]:

```
#FE with cov.type 'clustered'
fe_model_robust1 = FEmodel.fit(cov_type='clustered', cluster_entity=True)
print(fe_model_robust1.summary)
```

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:                l_cyber   R-squared:                        0.1097
Estimator:                   PanelOLS   R-squared (Between):             -10.891
No. Observations:                 384   R-squared (Within):               0.1097
Date:                Wed, Nov 12 2025   R-squared (Overall):             -1.1178
Time:                        18:23:29   Log-likelihood                   -195.33
Cov. Estimator:             Clustered
                                        F-statistic:                      21.561
Entities:                          32   P-value                           0.0000
Avg Obs:                       12.000   Distribution:                   F(2,350)
Min Obs:                       12.000
Max Obs:                       12.000   F-statistic (robust):             18.245
                                        P-value                           0.0000
Time periods:                      12   Distribution:                   F(2,350)
Avg Obs:                       32.000
Min Obs:                       32.000
Max Obs:                       32.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const          3.5550     2.2630     1.5709     0.1171     -0.8959      8.0058
avg_temp      -0.1286     0.0819    -1.5698     0.1174     -0.2897      0.0325
tot_rf         0.0002  6.773e-05     3.2335     0.0013   8.579e-05      0.0004
==============================================================================

F-test for Poolability: 2.3548
P-value: 0.0001
Distribution: F(31,350)

Included effects: Entity
```

In [15]:

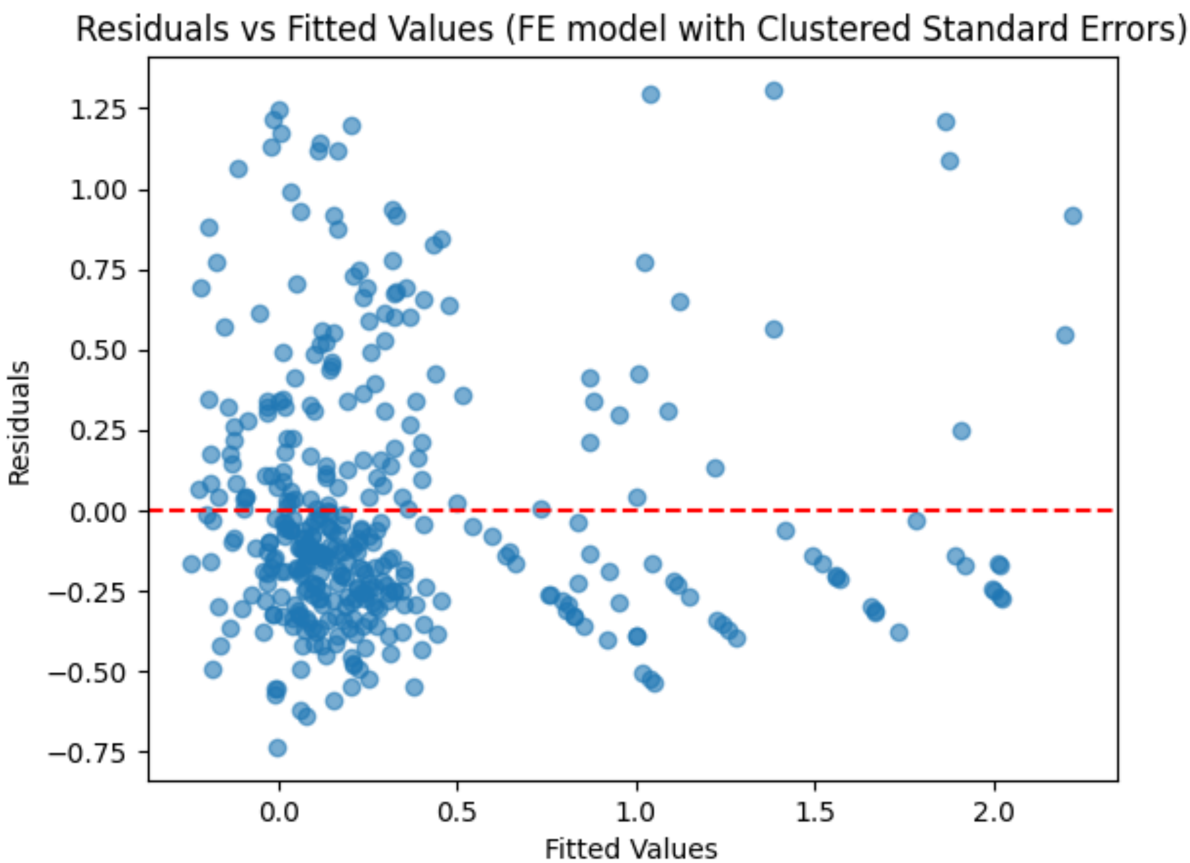
```
#FE with cov.type 'kernel' (Driscoll-Kraay Method)
fe_model_robust2 = FEmodel.fit(cov_type='kernel')
print(fe_model_robust2.summary)
```

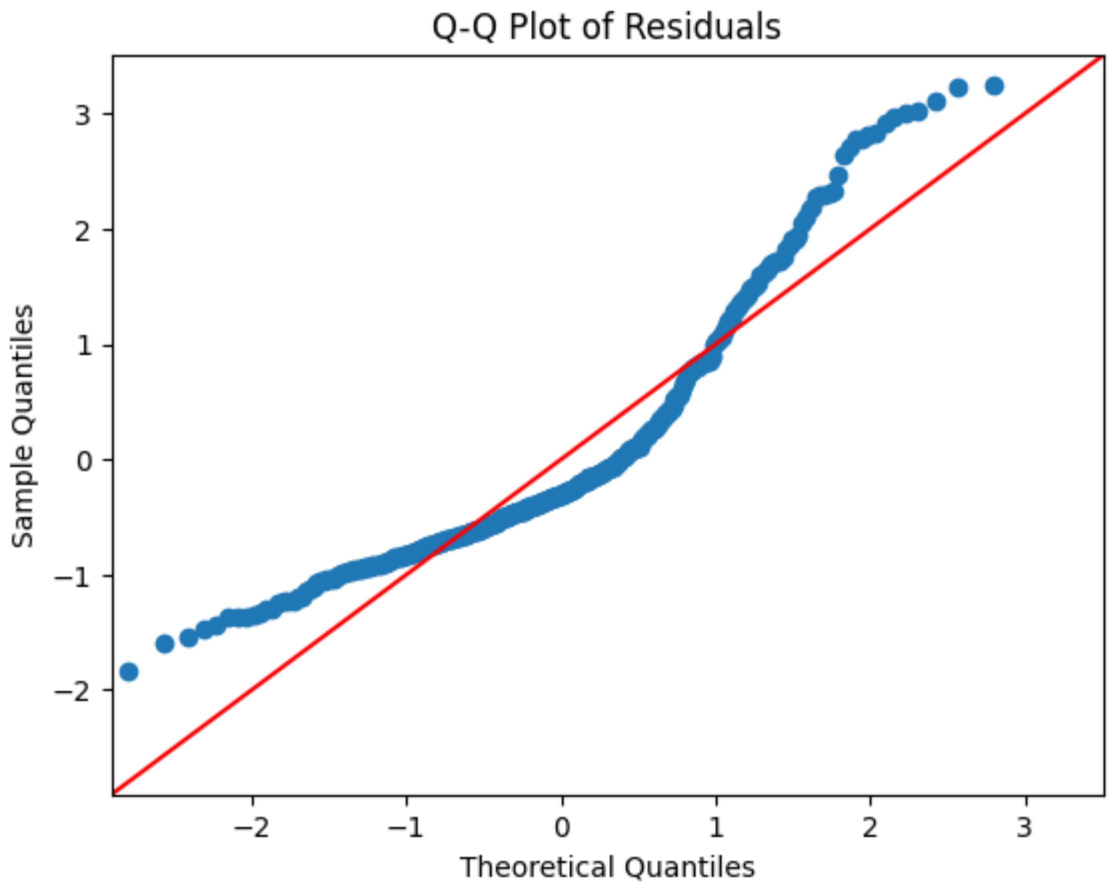
```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:                l_cyber   R-squared:                        0.1097
Estimator:                   PanelOLS   R-squared (Between):             -10.891
No. Observations:                 384   R-squared (Within):               0.1097
Date:                Wed, Nov 12 2025   R-squared (Overall):             -1.1178
Time:                        18:23:29   Log-likelihood                   -195.33
Cov. Estimator:         Driscoll-Kraay
                                        F-statistic:                      21.561
Entities:                          32   P-value                           0.0000
Avg Obs:                       12.000   Distribution:                   F(2,350)
Min Obs:                       12.000
Max Obs:                       12.000   F-statistic (robust):             5.9750
                                        P-value                           0.0028
Time periods:                      12   Distribution:                   F(2,350)
Avg Obs:                       32.000
Min Obs:                       32.000
Max Obs:                       32.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const          3.5550     1.1217     3.1692     0.0017      1.3488      5.7612
avg_temp      -0.1286     0.0391    -3.2882     0.0011     -0.2055     -0.0517
tot_rf         0.0002     0.0002     1.0647     0.2877     -0.0002      0.0006
==============================================================================

F-test for Poolability: 2.3548
P-value: 0.0001
Distribution: F(31,350)

Included effects: Entity
```

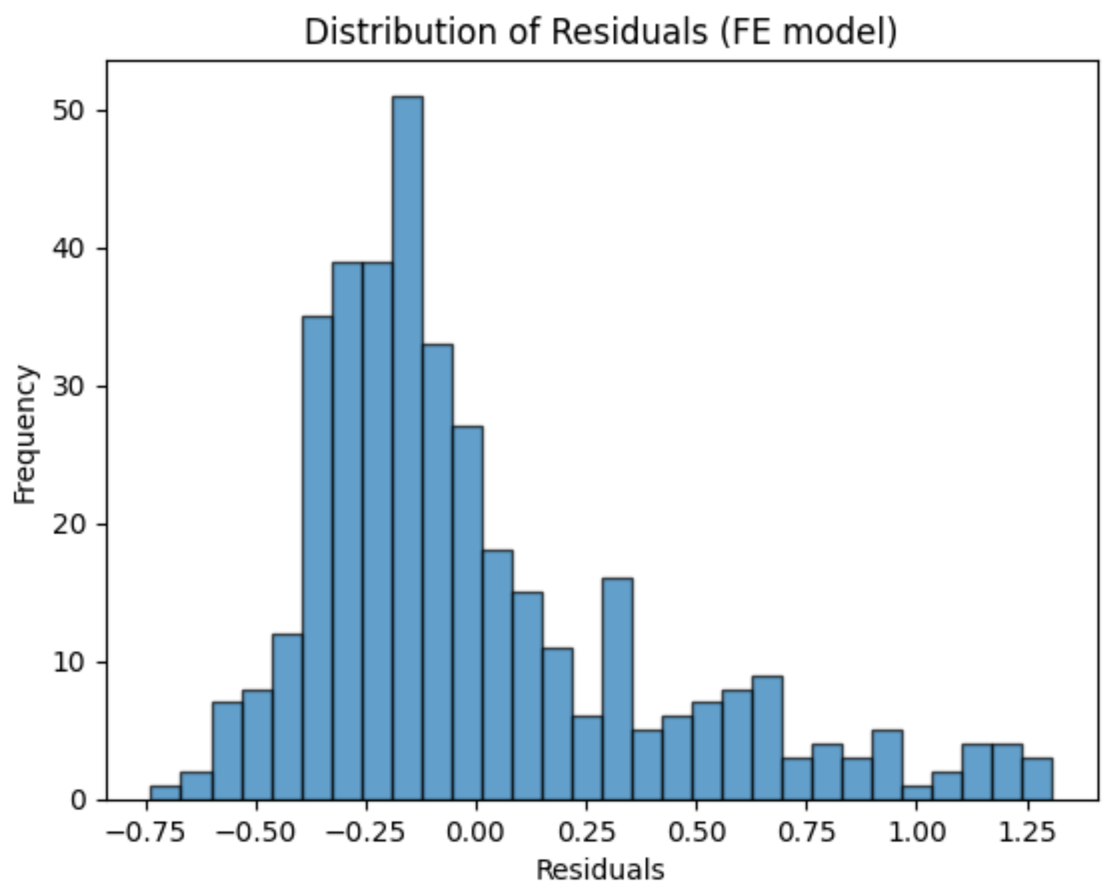
In [16]:

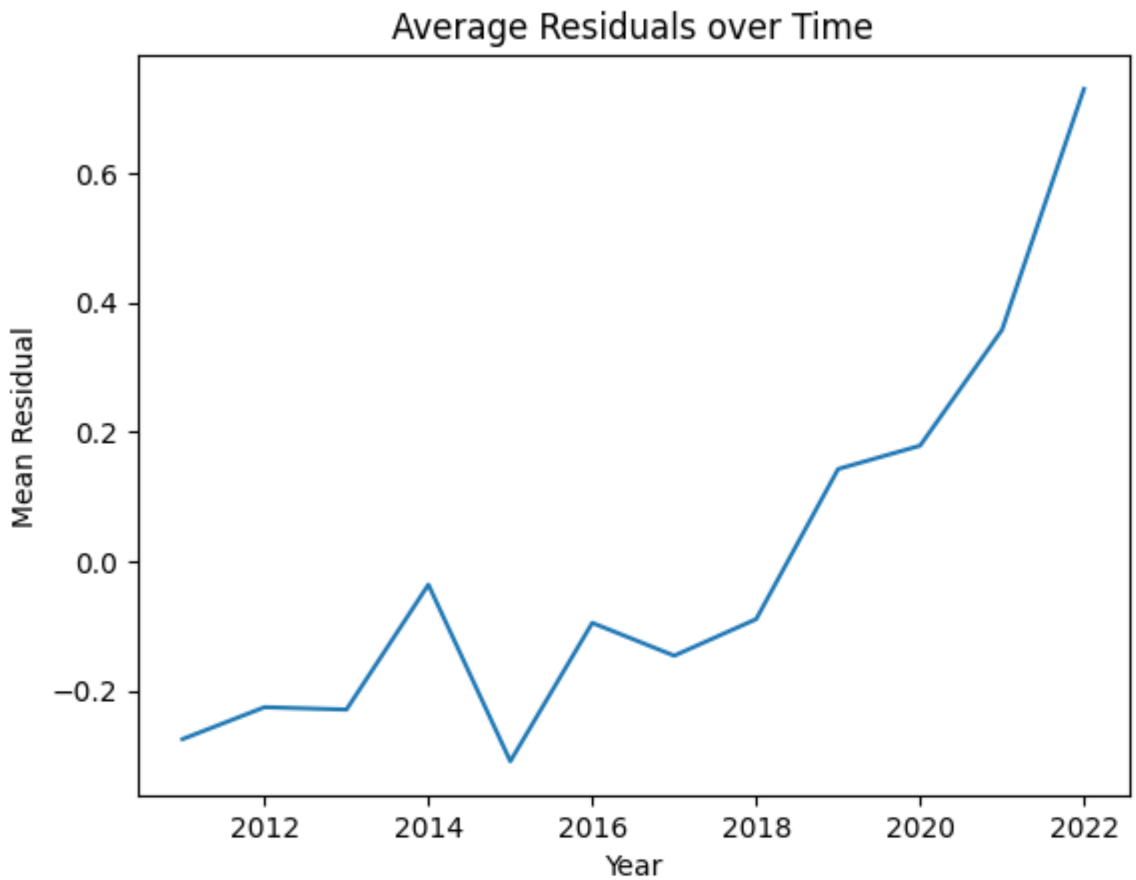
```python
# Check residuals and fitted values
df['residuals1'] = fe_model_robust1.resids
df['fitted1'] = fe_model_robust1.fitted_values

import matplotlib.pyplot as plt

plt.scatter(df['fitted1'], df['residuals1'], alpha=0.6)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
plt.title('Residuals vs Fitted Values (FE model with Clustered Standard Errors)')
plt.show()

sm.qqplot(df['residuals1'], line='45', fit=True)
plt.title('Q-Q Plot of Residuals')
plt.show()

plt.hist(df['residuals1'], bins=30, edgecolor='black', alpha=0.7)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Distribution of Residuals (FE model)')
plt.show()
```

```
resid_df = df['residuals1'].unstack(level=0)
plt.plot(resid_df.mean(axis=1))
plt.title('Average Residuals over Time')
plt.xlabel('Year')
plt.ylabel('Mean Residual')
plt.show()

from scipy.stats import shapiro

#Test for normality

stat, p = shapiro(df['residuals1'])
print(f"Shapiro-Wilk Test: Statistic={stat:.3f}, p-value={p:.4f}")
```




Q-Q Plot of Residuals
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−2
−1
0
1
2
3

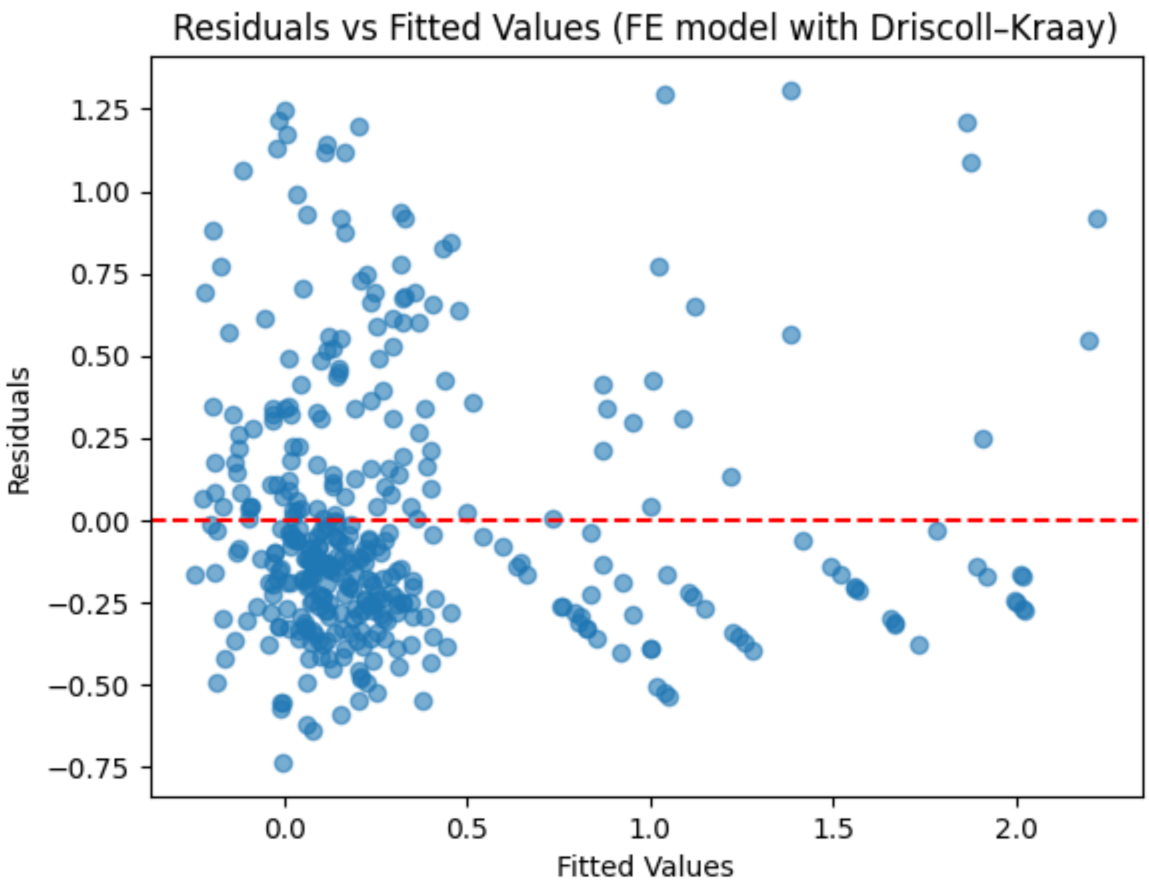

Distribution of Residuals (FE model)
Frequency
Residuals
50
40
30
20
10
0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25

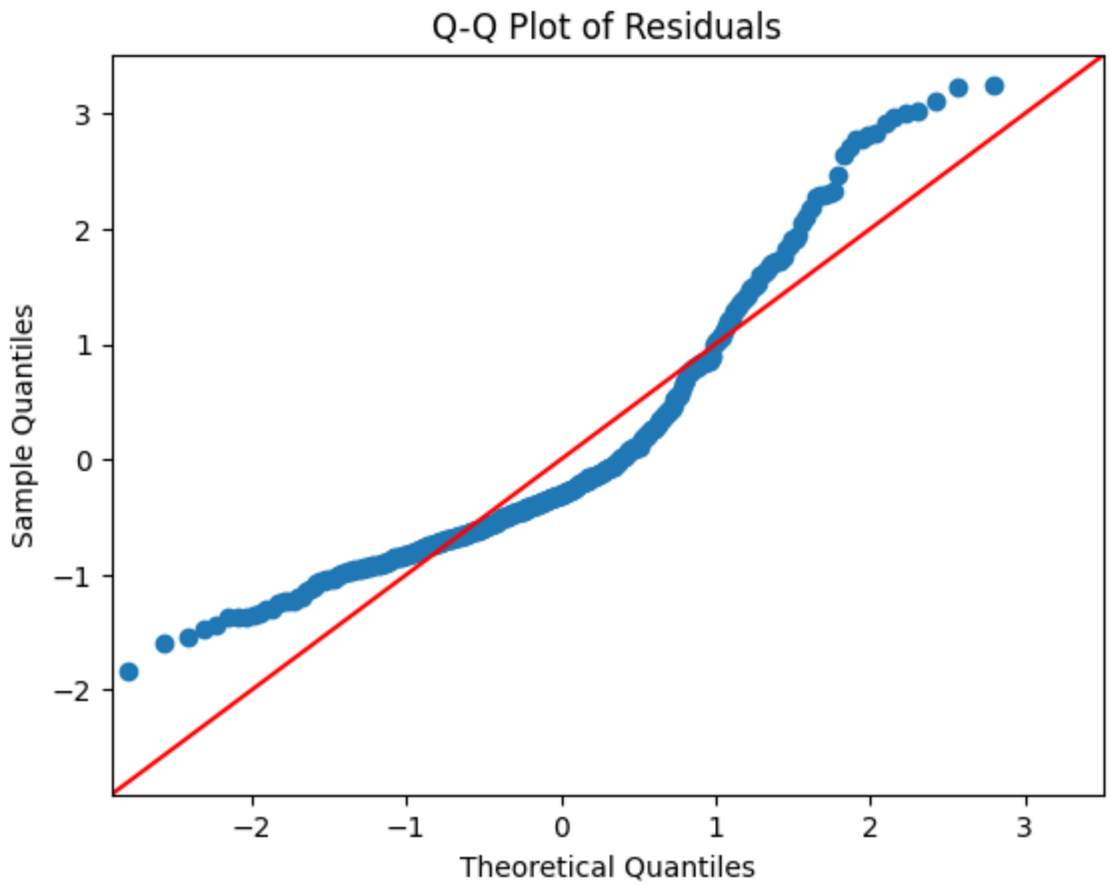


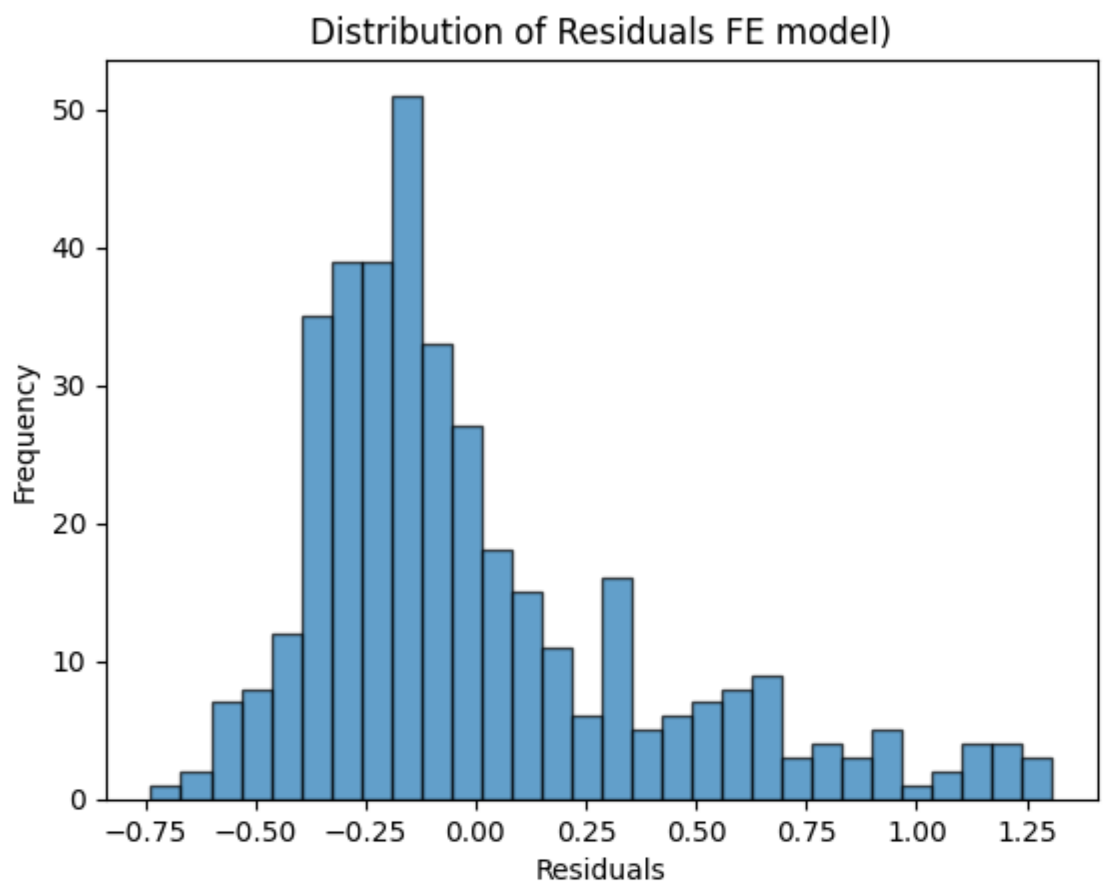

```
Shapiro-Wilk Test: Statistic=0.887, p-value=0.0000
```

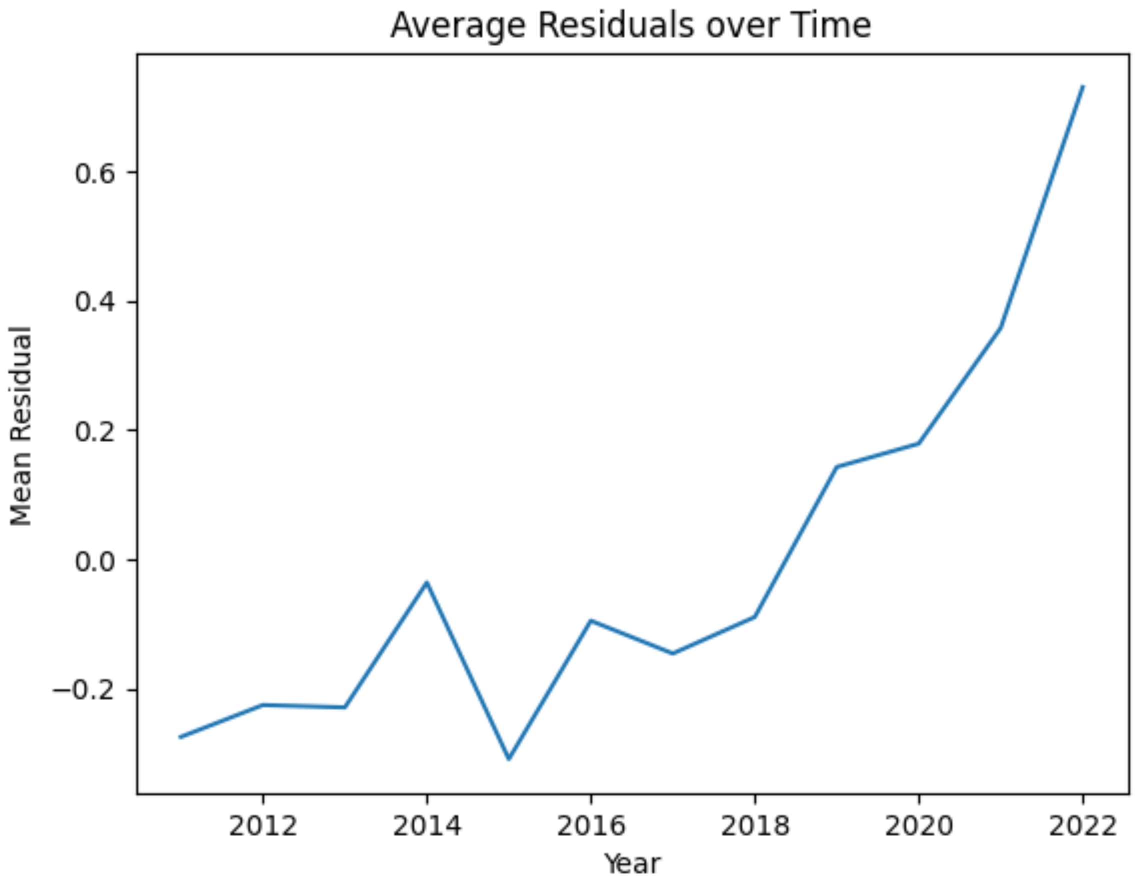
In [17]:
```
# Check residuals and fitted values
df['residuals2'] = fe_model_robust2.resids
df['fitted2'] = fe_model_robust2.fitted_values

import matplotlib.pyplot as plt

plt.scatter(df['fitted2'], df['residuals2'], alpha=0.6)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
plt.title('Residuals vs Fitted Values (FE model with Driscoll-Kraay)')
plt.show()

sm.qqplot(df['residuals2'], line='45', fit=True)
plt.title('Q-Q Plot of Residuals')
plt.show()

plt.hist(df['residuals2'], bins=30, edgecolor='black', alpha=0.7)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Distribution of Residuals FE model)')
plt.show()

resid_df = df['residuals2'].unstack(level=0)
plt.plot(resid_df.mean(axis=1))
plt.title('Average Residuals over Time')
plt.xlabel('Year')
```

```
plt.ylabel('Mean Residual')
plt.show()

from scipy.stats import shapiro

#Test for normality

stat, p = shapiro(df['residuals2'])
print(f"Shapiro-Wilk Test: Statistic={stat:.3f}, p-value={p:.4f}")
```




Q-Q Plot of Residuals
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−2
−1
0
1
2
3


Distribution of Residuals FE model)
Frequency
Residuals
50
40
30
20
10
0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25




```
Shapiro-Wilk Test: Statistic=0.887, p-value=0.0000
```

In [ ]: