

```
In [1]: #Crimes Against Women 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/crimes against women new.csv')
#df['L_ipc'] = np.log(df['ipc_cr'])
df.head()
```

```
Out[3]:   s.no. districts year type crimes_against_women pop_in_lak craw_cr avg_temp
```

0	1	ariyalur	2011	crimes against women	99	7.52	13.2	28.312353	11
1	1	ariyalur	2012	crimes against women	117	7.63	15.3	28.777312	9
2	1	ariyalur	2013	crime against women	63	7.76	8.1	28.730311	8
3	1	ariyalur	2014	crime against women	61	7.88	7.7	28.536042	10
4	1	ariyalur	2015	crime against women	32	8.00	4.0	28.565911	15

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

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

## PanelOLS Estimation Summary

Dep. Variable:	craw_cr	R-squared:	0.0272
Estimator:	PanelOLS	R-squared (Between):	0.0752
No. Observations:	384	R-squared (Within):	0.0011
Date:	Wed, Nov 12 2025	R-squared (Overall):	0.0272
Time:	18:22:47	Log-likelihood	-1063.2
Cov. Estimator:	Unadjusted	F-statistic:	5.3354
Entities:	32	P-value	0.0052
Avg Obs:	12.000	Distribution:	F(2, 381)
Min Obs:	12.000		
Max Obs:	12.000	F-statistic (robust):	5.3354
		P-value	0.0052
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	10.588	1.9657	5.3863	0.0000	6.7230	14.453
avg_temp	-0.0992	0.0625	-1.5877	0.1132	-0.2220	0.0237
tot_rf	-0.0015	0.0005	-3.2535	0.0012	-0.0024	-0.0006

```
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:	craw_cr	R-squared:	0.0083
Estimator:	PanelOLS	R-squared (Between):	0.0043
No. Observations:	384	R-squared (Within):	0.0083
Date:	Wed, Nov 12 2025	R-squared (Overall):	0.0069
Time:	18:22:47	Log-likelihood	-983.39
Cov. Estimator:	Unadjusted	F-statistic:	1.4639
Entities:	32	P-value	0.2327
Avg Obs:	12.000	Distribution:	F(2, 350)
Min Obs:	12.000		
Max Obs:	12.000	F-statistic (robust):	1.4639
		P-value	0.2327
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	5.0647	7.9375	0.6381	0.5238	-10.546	20.676
avg_temp	0.0722	0.2843	0.2540	0.7996	-0.4869	0.6313
tot_rf	-0.0007	0.0005	-1.4059	0.1606	-0.0017	0.0003

F-test for Poolability: 5.8183

P-value: 0.0000

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:	craw_cr	R-squared:	0.0112			
Estimator:	RandomEffects	R-squared (Between):	0.0526			
No. Observations:	384	R-squared (Within):	0.0075			
Date:	Wed, Nov 12 2025	R-squared (Overall):	0.0234			
Time:	18:22:47	Log-likelihood	-999.66			
Cov. Estimator:	Unadjusted	F-statistic:	2.1663			
Entities:	32	P-value	0.1160			
Avg Obs:	12.000	Distribution:	F(2,381)			
Min Obs:	12.000	F-statistic (robust):	2.1663			
Max Obs:	12.000	P-value	0.1160			
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	8.7975	3.3428	2.6318	0.0088	2.2248	15.370
avg_temp	-0.0562	0.1153	-0.4875	0.6262	-0.2829	0.1705
tot_rf	-0.0009	0.0005	-2.0703	0.0391	-0.0018	-4.717e-05

In [8]: #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: 1.947

Degrees of Freedom: 2

p-value: 0.3777

In [9]: *#Diagnostic Checks*

```
from statsmodels.stats.diagnostic import het_breushpagan, 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 = reresult.resids
```

```
bp_test = het_breushpagan(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(10.555337591621296), 'p-value': np.float64(0.005104316136896624), 'f-value': np.float64(5.384443837638701), 'f p-value': np.float64(0.004943148107568016)}
```

White Test

```
{'LM stat': np.float64(11.496469341991258), 'LM p-value': np.float64(0.042378147203781594), 'F p-value': np.float64(2.333221058923278)}
```

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: 1.096

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: 1764.881
p-value: 0.0000
```

```
Pearson CD Test
Pesaran CD statistic: 10.167
p-value: 0.0000
```

```
In [13]: #Re-estimate RE Model
```

```
In [14]: #RE with cov.type 'clustered'
re_model_robust1 = REmodel.fit(cov_type='clustered', cluster_entity=True)
print(re_model_robust1.summary)
```

## RandomEffects Estimation Summary

Dep. Variable:	craw_cr	R-squared:	0.0112
Estimator:	RandomEffects	R-squared (Between):	0.0526
No. Observations:	384	R-squared (Within):	0.0075
Date:	Wed, Nov 12 2025	R-squared (Overall):	0.0234
Time:	18:22:47	Log-likelihood	-999.66
Cov. Estimator:	Clustered	F-statistic:	2.1663
Entities:	32	P-value	0.1160
Avg Obs:	12.000	Distribution:	F(2,381)
Min Obs:	12.000		
Max Obs:	12.000	F-statistic (robust):	2.9307
		P-value	0.0546
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	8.7975	3.3391	2.6347	0.0088	2.2321	15.363
avg_temp	-0.0562	0.1164	-0.4829	0.6294	-0.2850	0.1726
tot_rf	-0.0009	0.0004	-2.3546	0.0191	-0.0017	-0.0002

```
In [15]: #RE with cov.type 'kernel' (Driscoll-Kraay Method)
re_model_robust2 = REmodel.fit(cov_type='kernel')
print(re_model_robust2.summary)
```

RandomEffects Estimation Summary						
Dep. Variable:	craw_cr	R-squared:	0.0112			
Estimator:	RandomEffects	R-squared (Between):	0.0526			
No. Observations:	384	R-squared (Within):	0.0075			
Date:	Wed, Nov 12 2025	R-squared (Overall):	0.0234			
Time:	18:22:48	Log-likelihood	-999.66			
Cov. Estimator:	Driscoll-Kraay					
		F-statistic:	2.1663			
Entities:	32	P-value	0.1160			
Avg Obs:	12.000	Distribution:	$F(2, 381)$			
Min Obs:	12.000					
Max Obs:	12.000	F-statistic (robust):	0.8908			
		P-value	0.4112			
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	8.7975	4.0931	2.1493	0.0322	0.7496	16.845
avg_temp	-0.0562	0.0718	-0.7825	0.4344	-0.1974	0.0850
tot_rf	-0.0009	0.0008	-1.2011	0.2304	-0.0025	0.0006

```
In [16]: # Check residuals and fitted values
df['residuals1'] = re_model_robust1.resids
df['fitted1'] = re_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 (RE 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 (RE model)')
plt.show()

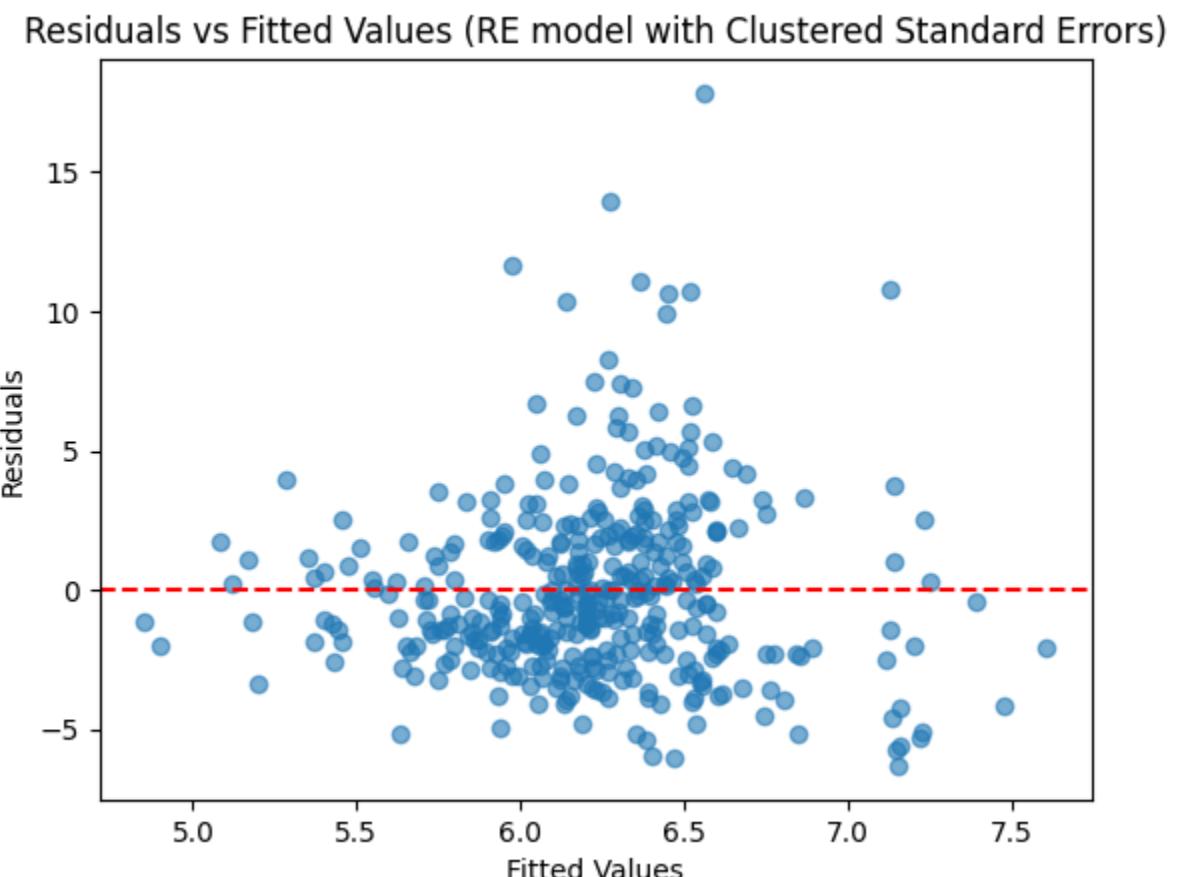
resid_df = df['residuals1'].unstack(level=0)
plt.plot(resid_df.mean(axis=1))
plt.title('Average Residuals over Time')
plt.xlabel('Year')
plt.ylabel('Mean Residual')
```

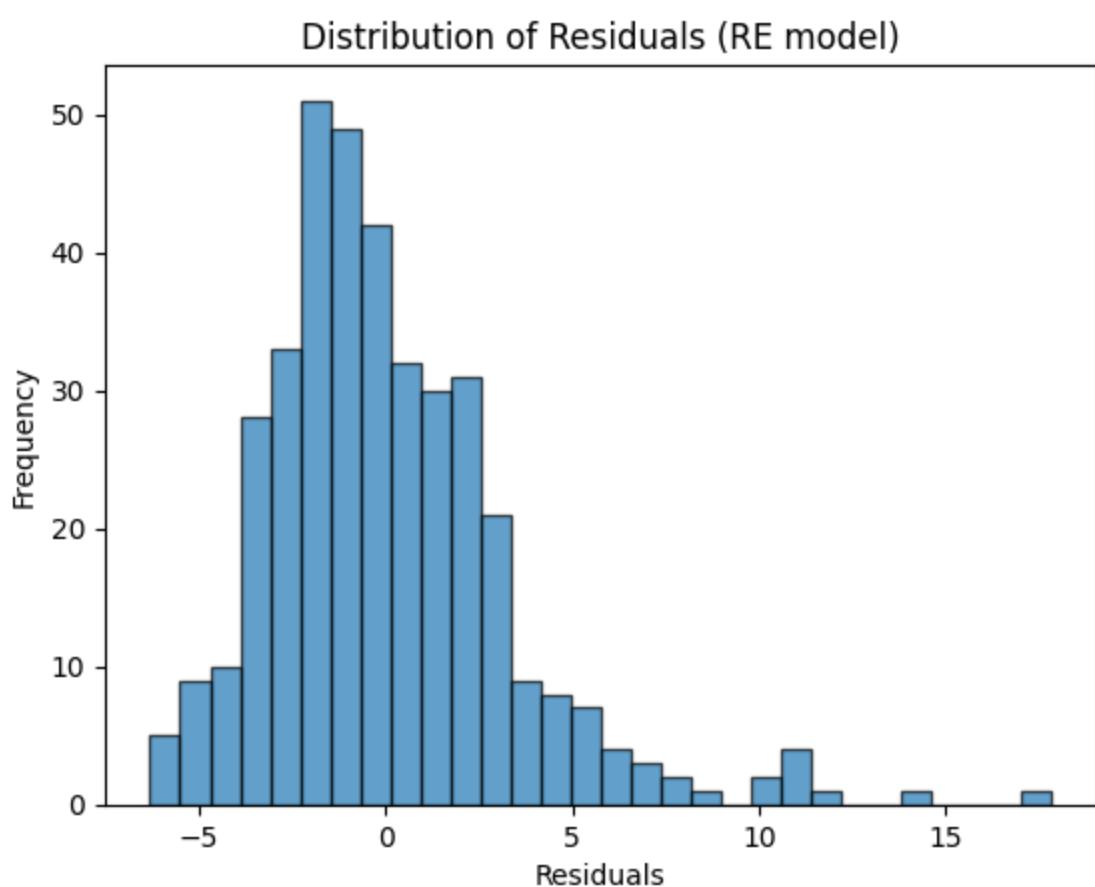
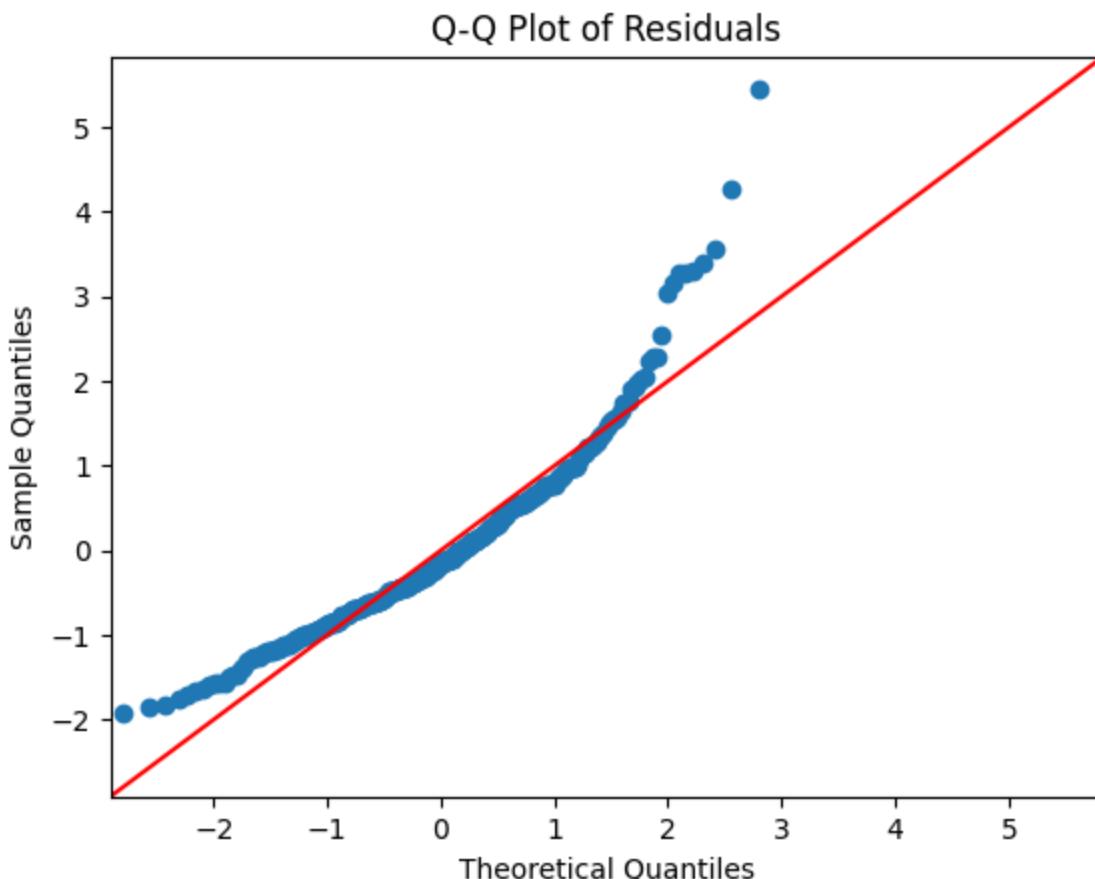
```
plt.show()

from scipy.stats import shapiro

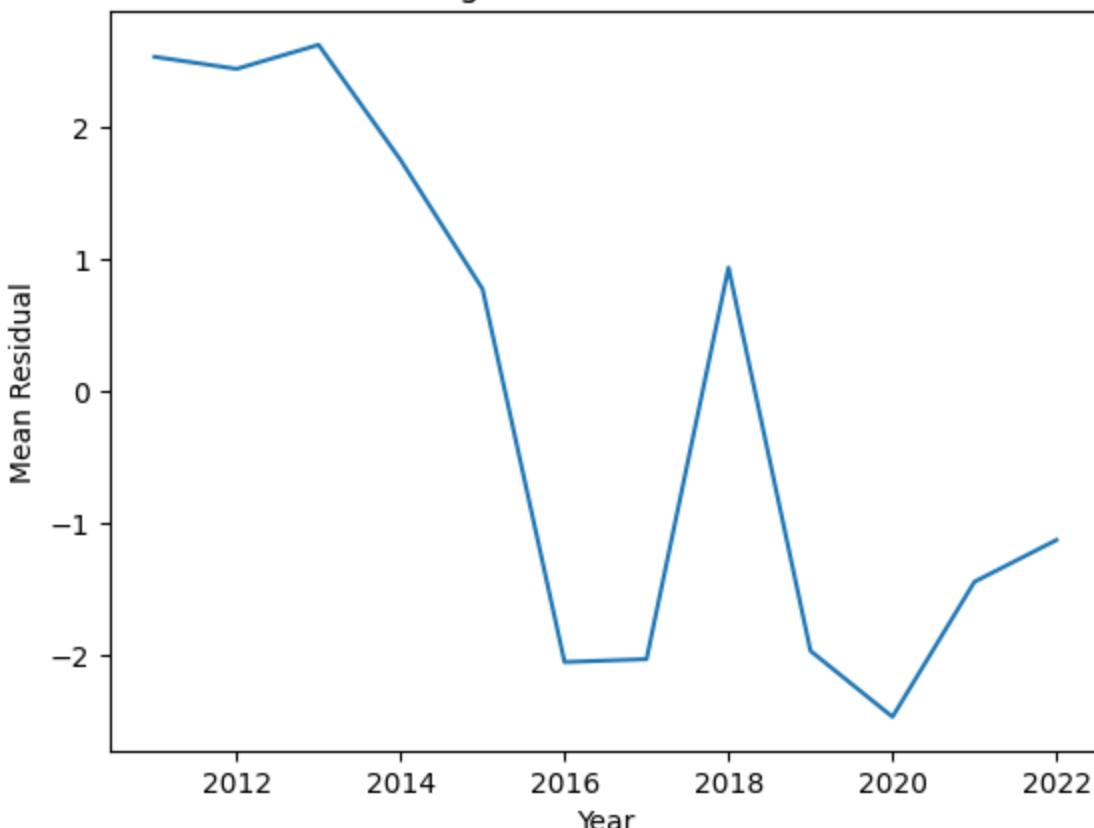
#Test for normality

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





### Average Residuals over Time



Shapiro-Wilk Test: Statistic=0.921, p-value=0.0000

```
In [17]: # Check residuals and fitted values
df['residuals2'] = re_model_robust2.resids
df['fitted2'] = re_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 (RE 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 (RE model)')
plt.show()

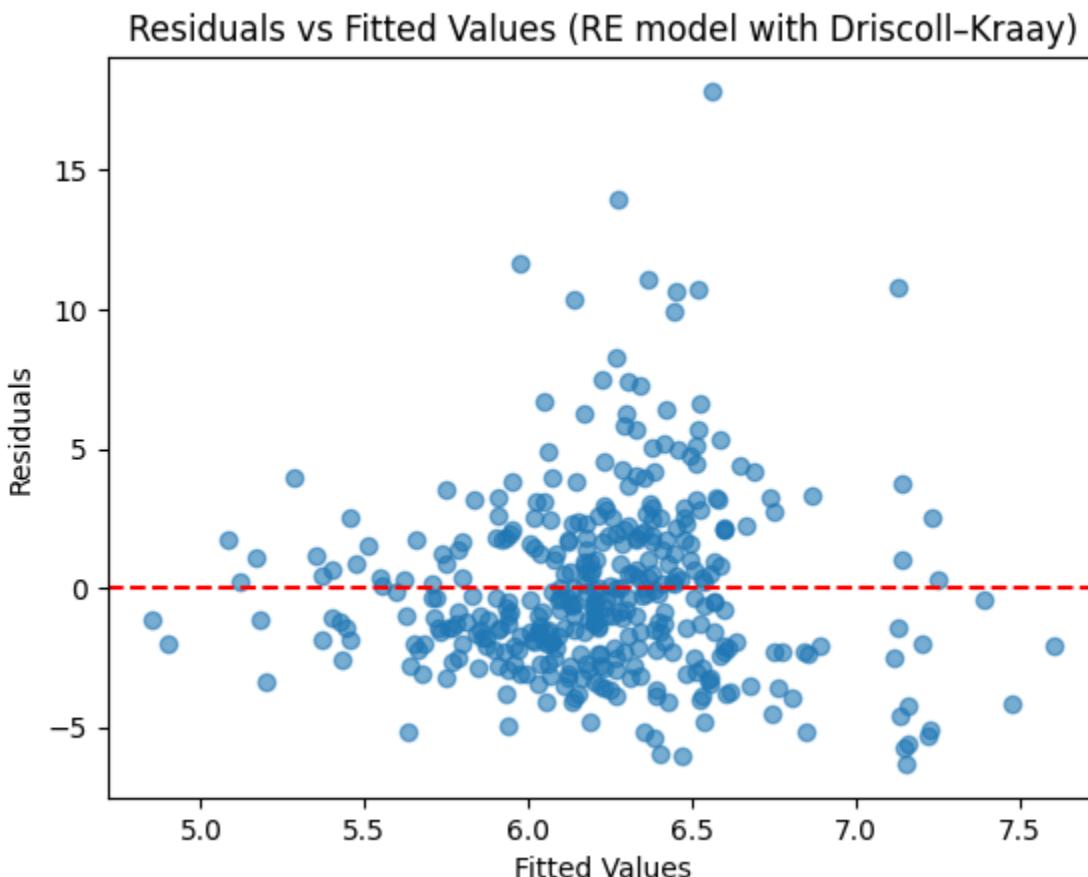
resid_df = df['residuals2'].unstack(level=0)
plt.plot(resid_df.mean(axis=1))
plt.title('Average Residuals over Time')
plt.xlabel('Year')
```

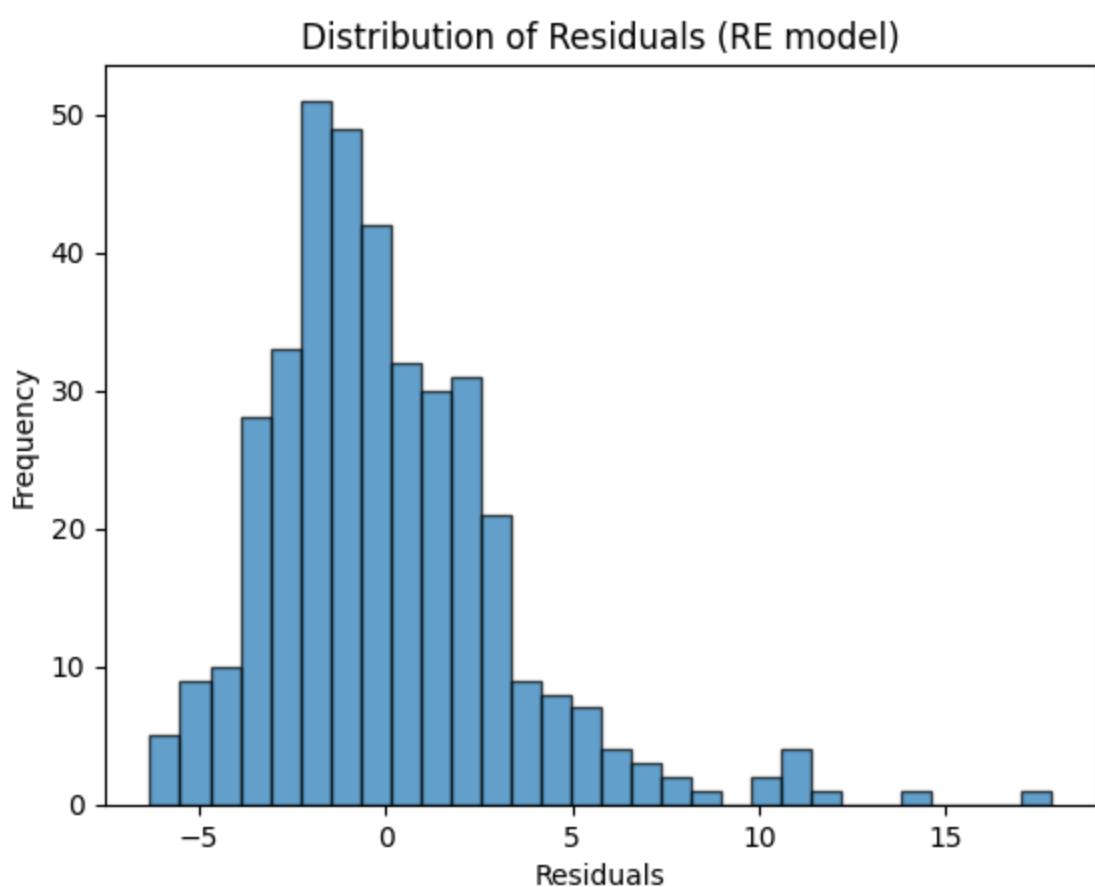
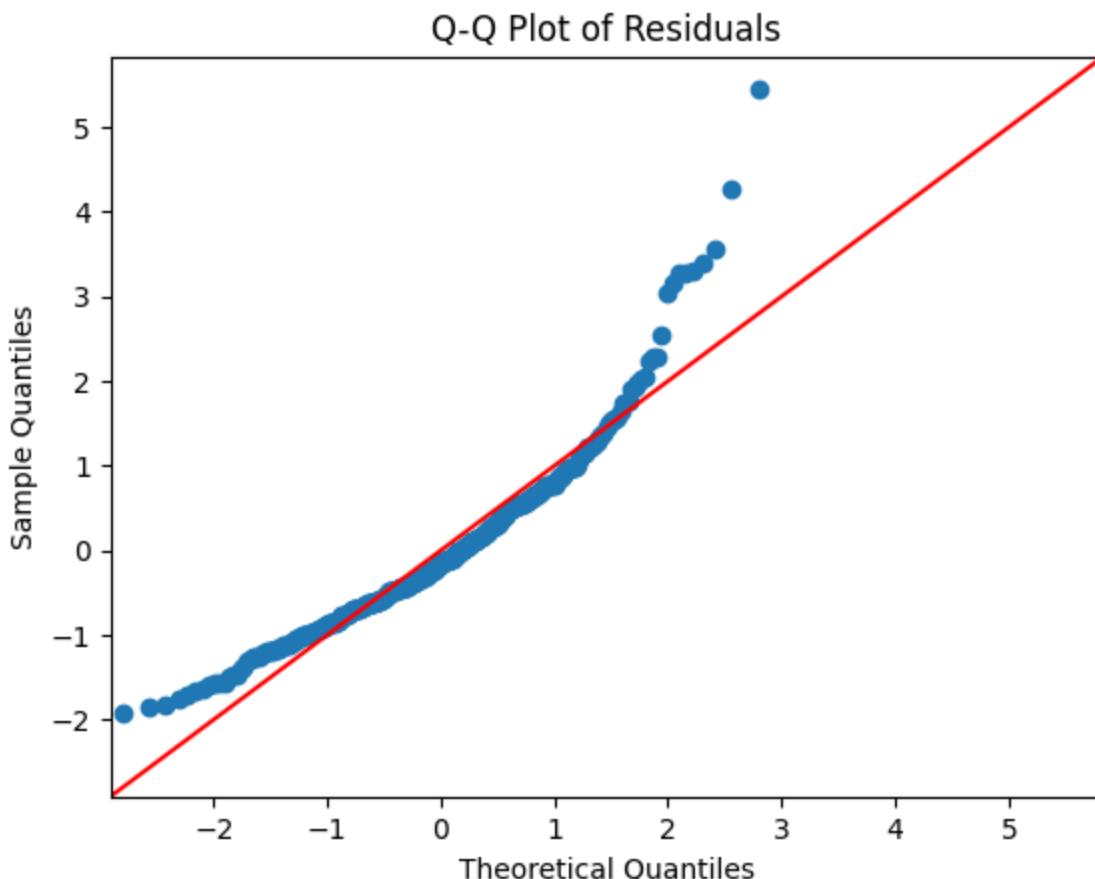
```
plt.ylabel('Mean Residual')
plt.show()

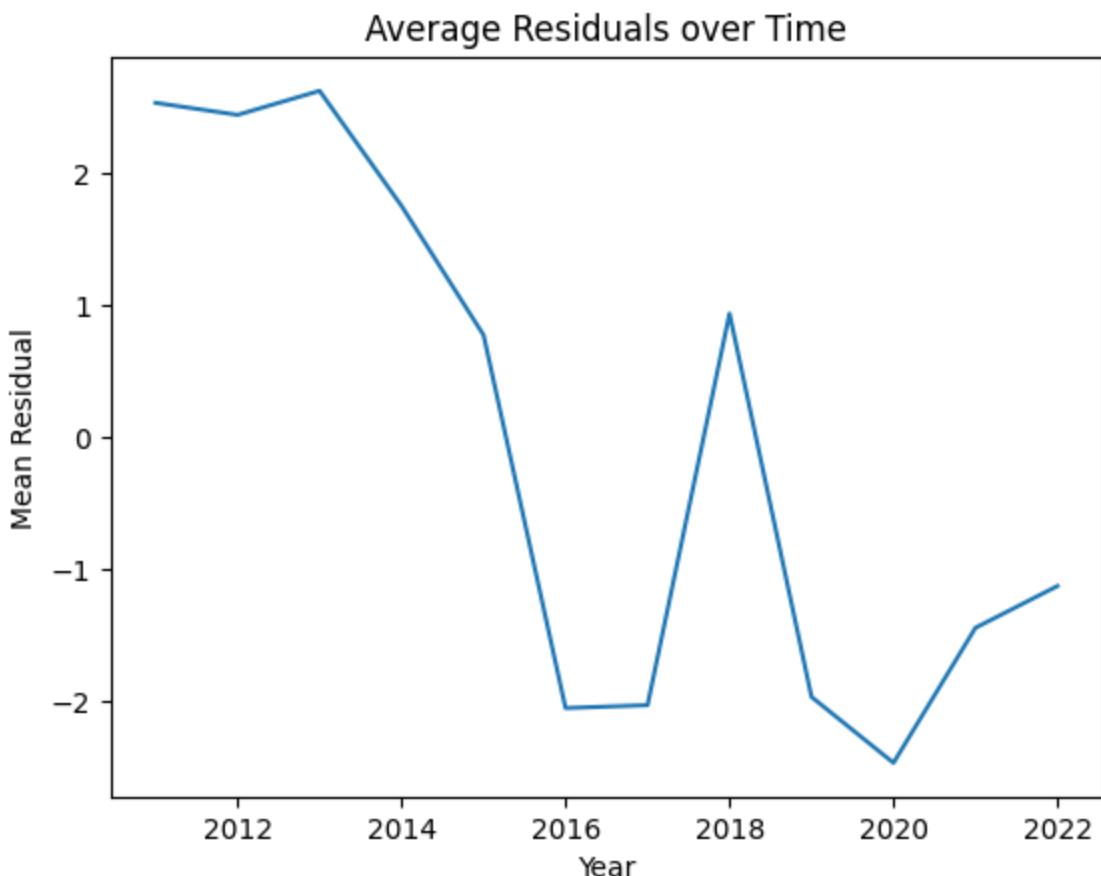
from scipy.stats import shapiro

#Test for normality

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







Shapiro-Wilk Test: Statistic=0.921, p-value=0.0000

In [ ]: