Panel Analysis and Exploration of Data Relative to the Start of Crisis

```
# package and data importing
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
from linearmodels.panel import PanelOLS

wri_df = pd.read_excel('PS_WRI_data_nonlag_TRIMMED.xlsx')
```

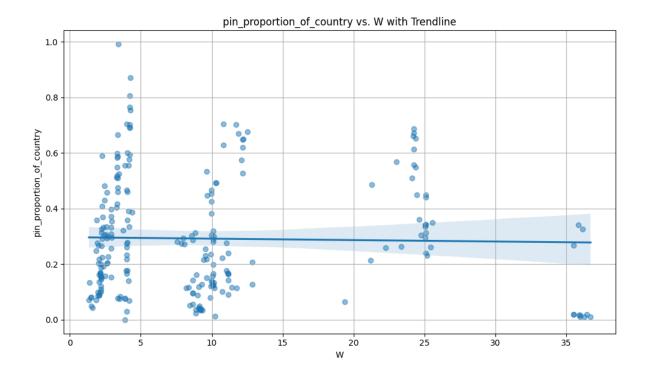
```
# converting the R-based approach from the nd-gain analysis
import pandas as pd
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
# Load data
ocha = pd.read_csv("GHO 2025 Development Needs.xlsx - Weighted averages.csv")
un_pop = pd.read_excel("Total Population by Sex data_v2.xlsx")
wri_reload_df = pd.read_excel("WRI_maunal_clean_W.xlsx")
# Clean and transform ocha
ocha['people_in_need'] = ocha['people_in_need'].str.replace(",", "").str.strip() # Remove con
ocha['people_in_need'] = ocha['people_in_need'].replace(' - ', np.nan) # Replace "-" with I
ocha['numeric_pin'] = pd.to_numeric(ocha['people_in_need'], errors='coerce')
ocha = ocha[["country", "calendar_year", "year_of_crisis", "numeric_pin", "years_since_crisis"
ocha['country_year'] = ocha['country'] + ocha['calendar_year'].astype(str)
# Clean and transform un_pop
```

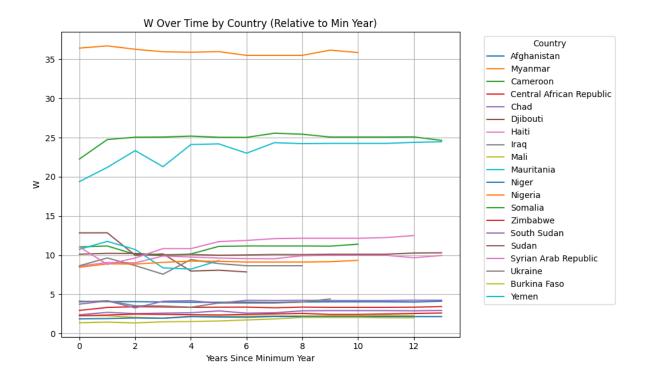
```
un_pop['country_year'] = un_pop['Country'] + un_pop['Time'].astype(str)
un_pop['total_country_population'] = pd.to_numeric(un_pop['Value'], errors='coerce') # Handle
# Merge ocha and un_pop
merged_ocha_un = pd.merge(un_pop, ocha, on="country_year")
merged_ocha_un = merged_ocha_un[["country_year", "Country", "total_country_population", "cale
merged_ocha_un['pin_proportion_of_country'] = merged_ocha_un['numeric_pin'] / merged_ocha_un
merged_ocha_un = merged_ocha_un.rename(columns={'calendar_year': 'Year'})
# Clean and transform wri_reload_df
wri_reload_df_melted = pd.melt(wri_reload_df, id_vars=['Country'], var_name='Year_Variable',
wri_reload_df_melted['Year'] = wri_reload_df_melted['Year_Variable'].str[:4].astype(int)
wri_reload_df_melted = wri_reload_df_melted[['Country', 'Year', 'W']] # Keep only necessary
# Merge WRI, OCHA, UN Pop Data
combined_data = pd.merge(merged_ocha_un, wri_reload_df_melted, on=['Country', 'Year'], how='.
combined_data['pin_proportion_of_country'] = combined_data['pin_proportion_of_country'].fill:
combined_data['years_since_min_year'] = combined_data.groupby('Country')['Year'].transform(learning)
## --- Analysis Views --- ##
# Scatter plot with regression line
plt.figure(figsize=(10, 6))
sns.regplot(x='W', y='pin_proportion_of_country', data=combined_data, scatter_kws={'alpha':0
plt.xlabel("W")
plt.ylabel("pin_proportion_of_country")
plt.title("pin_proportion_of_country vs. W with Trendline")
plt.grid(True)
plt.tight_layout()
plt.show()
# Line plot for each country (using years since min year [crisis year zero])
plt.figure(figsize=(10, 6))
for country in combined_data['Country'].unique():
    country_data = combined_data[combined_data['Country'] == country]
    plt.plot(country_data['years_since_min_year'], country_data['W'], label=country)
plt.xlabel("Years Since Minimum Year")
plt.ylabel("W")
plt.title("W Over Time by Country (Relative to Min Year)")
plt.legend(title="Country", bbox_to_anchor=(1.05, 1), loc='upper left')
```

```
plt.grid(True)
plt.tight_layout()
plt.show()

# Regressing W to predict PiN
X = combined_data['W']
X = sm.add_constant(X)
y = combined_data['pin_proportion_of_country']
model = sm.OLS(y, X).fit()
print("\nRegression Results (pin_proportion_of_country vs. W):")
print(model.summary())

# Correlation between W and PiN to confirm usability
correlation = combined_data['pin_proportion_of_country'].corr(combined_data['W'])
print(f"Correlation between pin_proportion_of_country and W: {correlation}")
```





Regression Results (pin_proportion_of_country vs. W):

OLS Regression Results

Dep. Variable:	pin_proportion_of_country	R-squared:	0.000
Model:	OLS	Adj. R-squared:	-0.004
Method:	Least Squares	F-statistic:	0.1160
Date:	Thu, 20 Feb 2025	<pre>Prob (F-statistic):</pre>	0.734
Time:	02:06:22	Log-Likelihood:	37.942
No. Observations:	236	AIC:	-71.88
Df Residuals:	234	BIC:	-64.96

Df Model: 1
Covariance Type: nonrobust

========	========			========	========	========
	coef	std err	t	P> t	[0.025	0.975]
const	0.2967	0.020	15.057	0.000	0.258	0.336
W ======	-0.0005	0.002 =======	-0.341 ======	0.734 =======	-0.003 =======	0.002
Omnibus:		19.	104 Durbi	n-Watson:		0.388
Prob(Omnib	us):	0.0	000 Jarqu	e-Bera (JB):		22.181
Skew:		0.	745 Prob(JB):		1.53e-05

Kurtosis: 2.809 Cond. No. 19.2

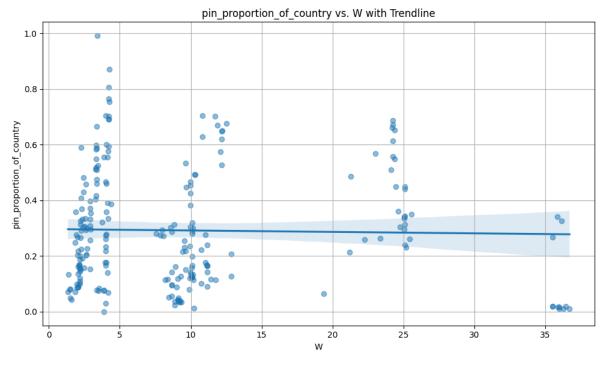
Notes:

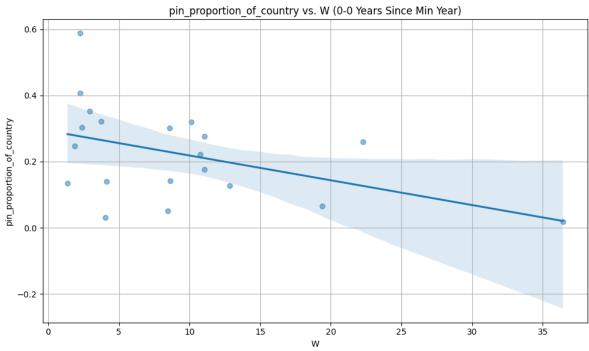
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. Correlation between pin_proportion_of_country and W: -0.022254929769720422

```
# time lagged approach -- building on the R-based approach from Steph
import pandas as pd
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
# Load data
ocha = pd.read_csv("GHO 2025 Development Needs.xlsx - Weighted averages.csv")
un_pop = pd.read_excel("Total Population by Sex data_v2.xlsx")
wri_reload_df = pd.read_excel("WRI_maunal_clean_W.xlsx")
# Clean and transform ocha
ocha['people_in_need'] = ocha['people_in_need'].str.replace(",", "").str.strip() # Remove con
ocha['people_in_need'] = ocha['people_in_need'].replace(' - ', np.nan) # Replace "-" with I
ocha['numeric_pin'] = pd.to_numeric(ocha['people_in_need'], errors='coerce')
ocha = ocha[["country", "calendar_year", "year_of_crisis", "numeric_pin", "years_since_crisis
ocha['country_year'] = ocha['country'] + ocha['calendar_year'].astype(str)
# Clean and transform un_pop
un_pop['country_year'] = un_pop['Country'] + un_pop['Time'].astype(str)
un_pop['total_country_population'] = pd.to_numeric(un_pop['Value'], errors='coerce') # Handle
# Merge ocha and un_pop
merged_ocha_un = pd.merge(un_pop, ocha, on="country_year")
merged_ocha_un = merged_ocha_un[["country_year", "Country", "total_country_population", "cal-
merged_ocha_un['pin_proportion_of_country'] = merged_ocha_un['numeric_pin'] / merged_ocha_un
merged_ocha_un = merged_ocha_un.rename(columns={'calendar_year': 'Year'})
# Clean and transform wri_reload_df
wri_reload_df_melted = pd.melt(wri_reload_df, id_vars=['Country'], var_name='Year_Variable',
wri_reload_df_melted['Year'] = wri_reload_df_melted['Year_Variable'].str[:4].astype(int)
wri_reload_df_melted = wri_reload_df_melted[['Country', 'Year', 'W']] # Keep only necessary
```

```
# Merge with nd_gain
combined_data = pd.merge(merged_ocha_un, wri_reload_df_melted, on=['Country', 'Year'], how='
combined_data['pin_proportion_of_country'] = combined_data['pin_proportion_of_country'].fill:
combined_data['years_since_min_year'] = combined_data.groupby('Country')['Year'].transform(1)
# --- Analysis ---
# Scatter plot with regression line (Corrected x and y axes)
plt.figure(figsize=(10, 6))
sns.regplot(x='W', y='pin_proportion_of_country', data=combined_data, scatter_kws={'alpha':0
plt.xlabel("W") # Corrected label
plt.ylabel("pin_proportion_of_country") # Corrected label
plt.title("pin_proportion_of_country vs. W with Trendline") # Corrected title
plt.grid(True)
plt.tight_layout()
plt.show()
# Define time periods (adjust as needed)
time_periods = [0, 1, 2, 3, 5]
for i in range(len(time_periods)):
    start_year = time_periods[i]
    if i < len(time_periods) - 1:</pre>
        end_year = time_periods[i+1]
        subset = combined_data[(combined_data['years_since_min_year'] >= start_year) & (comb
        title = f"pin_proportion_of_country vs. W ({start_year}-{end_year-1} Years Since Min
    else:
        subset = combined_data[combined_data['years_since_min_year'] >= start_year]
        title = f"pin_proportion_of_country vs. W ({start_year}+ Years Since Min Year)"
    if len(subset) > 0: # Check if the subset is not empty
        plt.figure(figsize=(10, 6))
        sns.regplot(x='W', y='pin_proportion_of_country', data=subset, scatter_kws={'alpha':
        plt.xlabel("W")
        plt.ylabel("pin_proportion_of_country")
        plt.title(title)
        plt.grid(True)
        plt.tight_layout()
        plt.show()
        # Regression for this time period
        X = subset['W']
        X = sm.add_constant(X)
```

```
y = subset['pin_proportion_of_country']
        model = sm.OLS(y, X).fit()
        print(f"\nRegression Results ({title}):")
        print(model.summary())
        # Correlation for this time period
        correlation = subset['pin_proportion_of_country'].corr(subset['W'])
        print(f"Correlation between pin_proportion_of_country and W ({title}): {correlation}
    else:
        print(f"No data for time period {start_year}+")
# Line plot for each country (using years since min year)
plt.figure(figsize=(10, 6))
for country in combined_data['Country'].unique():
    country_data = combined_data[combined_data['Country'] == country]
    plt.plot(country_data['years_since_min_year'], country_data['W'], label=country)
plt.xlabel("Years Since Year Zero of Crisis")
plt.ylabel("WRI Score for W Index")
plt.title("W Index Values Over Time by Country (Plotted Relative to Crisis Start)")
plt.legend(title="Country", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
plt.tight_layout()
plt.show()
# Regression - Corrected
X = combined_data['W'] # Independent variable is W
X = sm.add_constant(X)
y = combined_data['pin_proportion_of_country'] # Dependent variable is pin_proportion_of_co
model = sm.OLS(y, X).fit()
print("\nRegression Results (pin_proportion_of_country vs. W):")
print(model.summary())
# Correlation - Corrected
correlation = combined_data['pin_proportion_of_country'].corr(combined_data['W'])
print(f"Correlation between pin_proportion_of_country and W: {correlation}")
```





Regression Results (pin_proportion_of_country vs. W (0-0 Years Since Min Year)): OLS Regression Results

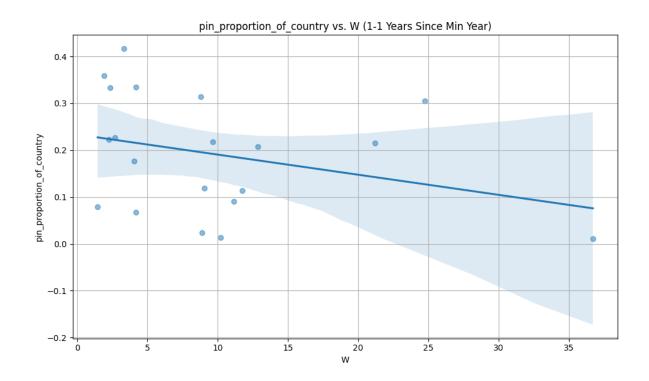
Dep. Variable:	pin_proportion_of_country	R-squared:	0.205
Model:	OLS	Adj. R-squared:	0.161
Method:	Least Squares	F-statistic:	4.655
Date:	Thu, 20 Feb 2025	Prob (F-statistic):	0.0447
Time:	02:06:22	Log-Likelihood:	13.356
No. Observations:	20	AIC:	-22.71
Df Residuals:	18	BIC:	-20.72

Df Model: 1
Covariance Type: nonrobust

========	=========		========	========	========	
	coef	std err	t	P> t	[0.025	0.975]
const W	0.2934 -0.0075	0.043 0.003	6.762 -2.158	0.000 0.045	0.202 -0.015	0.385 -0.000
Omnibus: Prob(Omnibu Skew: Kurtosis:	ns):	0.			:	1.394 0.373 0.830 18.6

Notes:

^[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. Correlation between pin_proportion_of_country and W (pin_proportion_of_country vs. W (0-0 Yes.)



Regression Results (pin_proportion_of_country vs. \mathbb{W} (1-1 Years Since Min Year)): OLS Regression Results

Dep. Variable:	pin_proportion_of_country	R-squared:	0.096
Model:	OLS	Adj. R-squared:	0.046
Method:	Least Squares	F-statistic:	1.916
Date:	Thu, 20 Feb 2025	Prob (F-statistic):	0.183
Time:	02:06:22	Log-Likelihood:	14.881
No. Observations:	20	AIC:	-25.76
Df Residuals:	18	BIC:	-23.77

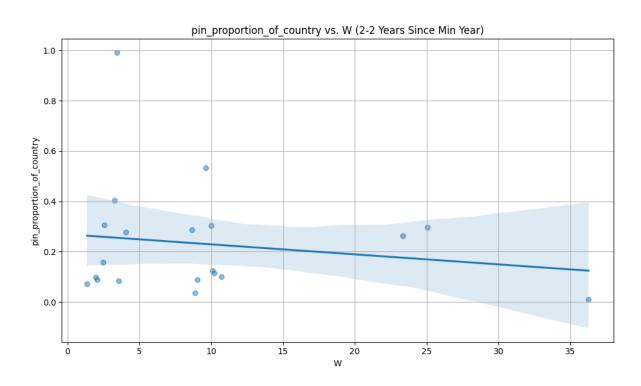
Df Model: 1
Covariance Type: nonrobust

========	========					=======
	coef	std err	t	P> t	[0.025	0.975]
const W	0.2335 -0.0043	0.040 0.003	5.807 -1.384	0.000 0.183	0.149 -0.011	0.318
Omnibus: Prob(Omnibu Skew:	s):	2.7 0.2 0.0	252 Jarque	n-Watson: e-Bera (JB): MB):		2.662 1.192 0.551

Kurtosis: 1.810 Cond. No. 19.3

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. Correlation between pin_proportion_of_country and W (pin_proportion_of_country vs. W (1-1 Yes.



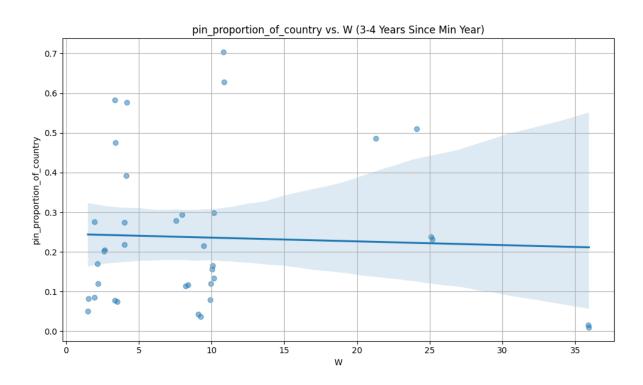
Regression Results (pin_proportion_of_country vs. W (2-2 Years Since Min Year)): OLS Regression Results

			==========
Dep. Variable:	pin_proportion_of_country	R-squared:	0.026
Model:	OLS	Adj. R-squared:	-0.028
Method:	Least Squares	F-statistic:	0.4798
Date:	Thu, 20 Feb 2025	Prob (F-statistic):	0.497
Time:	02:06:22	Log-Likelihood:	2.2593
No. Observations:	20	AIC:	-0.5187
Df Residuals:	18	BIC:	1.473
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const W	0.2688 -0.0040	0.074 0.006	3.634 -0.693	0.002 0.497	0.113 -0.016	0.424 0.008
Omnibus: Prob(Omnibus) Skew: Kurtosis:	ıs):	0	.000 Jaro .947 Prob	oin-Watson: que-Bera (JB) o(JB): l. No.):	2.253 26.463 1.79e-06 18.7
========		========				========

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. Correlation between pin_proportion_of_country and W (pin_proportion_of_country vs. W (2-2 Year)



Regression Results (pin_proportion_of_country vs. W (3-4 Years Since Min Year)): OLS Regression Results

Dep. Variable: pin_proportion_of_country R-squared: 0.002 Model: OLS Adj. R-squared: -0.026

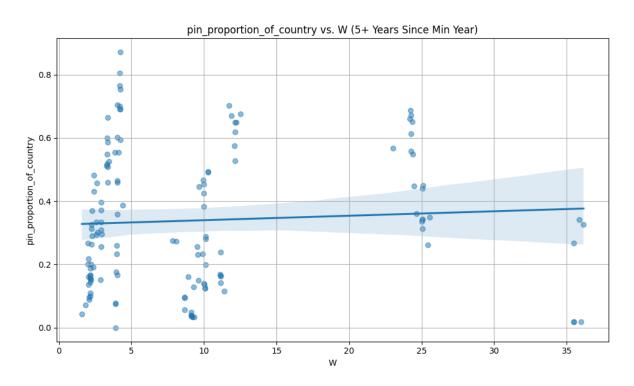
Method:	Least Squares	F-statistic:	0.07292
Date:	Thu, 20 Feb 2025	Prob (F-statistic):	0.789
Time:	02:06:22	Log-Likelihood:	10.103
No. Observations:	37	AIC:	-16.21
Df Residuals:	35	BIC:	-12.98
Df Model:	1		

Covariance Type: nonrobust

========	========	========		========	========	
	coef	std err	t	P> t	[0.025	0.975]
const	0.2454	0.046	5.369	0.000	0.153	0.338
W	-0.0009	0.003	-0.270	0.789	-0.008	0.006
========	========	========		========	========	
Omnibus:		6.	520 Durb	in-Watson:		1.241
Prob(Omnib	us):	0.	038 Jarq	ue-Bera (JB)	:	6.113
Skew:		0.	995 Prob	(JB):		0.0471
Kurtosis:		2.	936 Cond	. No.		19.3
========	========	========	:=======		========	========

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. Correlation between pin_proportion_of_country and W (pin_proportion_of_country vs. W (3-4 Year)



Regression Results (pin_proportion_of_country vs. W (5+ Years Since Min Year)):

OLS Regression Results

=======================================	=====		=======		========		======
Dep. Variable:	pin_p	proportion_o	f_country	R-squared:			0.004
Model:			OLS	Adj. R-squ	ared:		-0.004
Method:		Leas	t Squares	F-statisti	c:		0.4873
Date:		Thu, 20	Feb 2025	Prob (F-st	atistic):		0.486
Time:			02:06:22	Log-Likeli	hood:		17.612
No. Observations:			139	AIC:			-31.22
Df Residuals:			137	BIC:			-25.36
Df Model:			1				
Covariance Type:			nonrobust				
	====== coef	std err	t	P> t	[0.025	0.975]	
const 0.	3257	0.027	12.269	0.000	0.273	0.378	
W O.	0014	0.002	0.698	0.486	-0.003	0.005	
Omnibus:		14.2	:39 Durbi:	======= n-Watson:		0.450	
<pre>Prob(Omnibus):</pre>		0.0	01 Jarque	e-Bera (JB):		7.370	

Notes:

Skew:

Kurtosis:

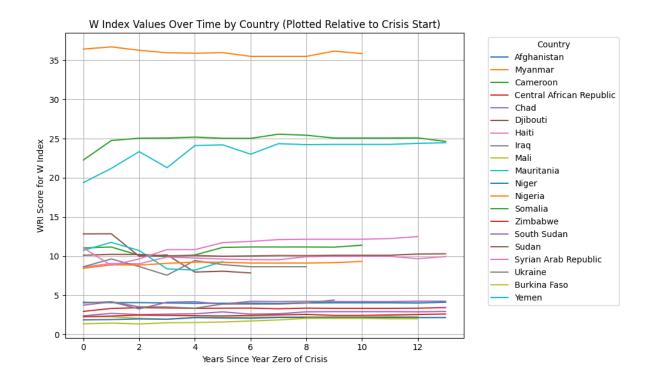
0.373 Prob(JB):

2.154 Cond. No.

0.0251

19.2

^[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. Correlation between pin_proportion_of_country and W (pin_proportion_of_country vs. W (5+ Year



Regression Results (pin_proportion_of_country vs. W): $\hbox{OLS Regression Results}$

Dep. Variable:	pin_proportion_of_country	R-squared:	0.000
Model:	OLS	Adj. R-squared:	-0.004
Method:	Least Squares	F-statistic:	0.1160
Date:	Thu, 20 Feb 2025	Prob (F-statistic):	0.734
Time:	02:06:22	Log-Likelihood:	37.942
No. Observations:	236	AIC:	-71.88
Df Residuals:	234	BIC:	-64.96

Df Model: 1
Covariance Type: nonrobust

========	=========		========			
	coef	std err	t	P> t	[0.025	0.975]
const	0.2967	0.020	15.057	0.000	0.258	0.336
W	-0.0005	0.002	-0.341	0.734	-0.003	0.002
=======	========		=======	========	=======	=======
Omnibus:		19.	104 Durbi	n-Watson:		0.388
Prob(Omnib	us):	0.	000 Jarqu	e-Bera (JB):		22.181
Skew:		0.	745 Prob(JB):		1.53e-05

Kurtosis: 2.809 Cond. No. 19.2

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. Correlation between pin_proportion_of_country and W: -0.022254929769720422

```
# Panel approach
# --- Ensure consistent data types for 'Country' and 'Year' ---
panel_df = combined_data.copy().reset_index()
panel_df['Country'] = panel_df['Country'].astype(str)
panel_df['Year'] = panel_df['Year'].astype(int)
1 1 1
# plot checking step
for country in panel_df['Country'].unique():
    plt.figure() # New figure for each country
    country_data = panel_df[panel_df['Country'] == country]
    plt.plot(country_data['Year'], country_data['W'], label='W')
    plt.plot(country_data['Year'], country_data['pin_proportion_of_country'], label='PiN')
    plt.title(f"Time Series for {country}")
    plt.xlabel("Year")
    plt.ylabel("Value")
    plt.legend()
    plt.show()
    print(f"Descriptive Statistics for W in {country}:\n{country_data['W'].describe()}")
    print(f"Number of unique W values for {country}:\n{country_data['W'].nunique()}")
1 1 1
# --- Panel Data Analysis for each time period ---
time_periods = [0, 1, 2, 3, 5]
for i in range(len(time_periods)):
    start_year = time_periods[i]
    if i < len(time_periods) - 1:</pre>
        end_year = time_periods[i + 1]
        title = f"Panel Regression Results ({start_year}-{end_year-1} Years Since Crisis Year
    else:
        end_year = panel_df['years_since_min_year'].max() + 1
        title = f"Panel Regression Results ({start_year}+ Years Since Crisis Year Zero)"
```

```
subset = panel_df[
        (panel_df['years_since_min_year'] >= start_year) & (panel_df['years_since_min_year']
    1
    if len(subset) > 0:
        print(f"\n--- {title} ---") #Separator for clarity
        print(f"Number of observations in subset: {len(subset['Country'].unique())}")
        print(f"Countries present in subset: {subset['Country'].unique()}") # Confirming countries
        print(f"Years present in subset: {subset['Year'].unique()}") # explicitly indicating
        subset = subset.set_index(['Country', 'Year'])
        y = subset[['pin_proportion_of_country']]
        X = subset[['W']]
        X = sm.add_constant(X)
        try:
            model = PanelOLS(y, X, entity_effects=True).fit()
            print(model)
            # --- Adjusted R-squared calculation ---
            n = len(subset) # Number of observations in the subset
            k = X.shape[1] + len(subset.index.get_level_values('Country').unique()) -1 # Nu
            r_squared = model.rsquared
            adjusted_r_squared = 1 - ((1 - r_squared) * (n - 1) / (n - k - 1))
            print(f"Adjusted R-squared for {title}: {adjusted_r_squared}")
        except Exception as e: # Catch any exception for diagnosis
            print(f"Error in {title}: {e}")
        subset = subset.reset_index()
    else:
        print(f"No data for time period {start_year}+")
--- Panel Regression Results (0-0 Years Since Crisis Year Zero) ---
Number of observations in subset: 20
Countries present in subset: ['Afghanistan' 'Myanmar' 'Cameroon' 'Central African Republic'
 'Djibouti' 'Haiti' 'Iraq' 'Mali' 'Mauritania' 'Niger' 'Nigeria' 'Somalia'
```

'Zimbabwe' 'South Sudan' 'Sudan' 'Syrian Arab Republic' 'Ukraine'

'Burkina Faso' 'Yemen']

Years present in subset: [2011 2014 2012 2015]

Error in Panel Regression Results (0-0 Years Since Crisis Year Zero): The model cannot be estimated. The included effects have fully absorbed one or more of the variables. This occurs when one or more of the dependent variable is perfectly explained using the effects included in the model.

The following variables or variable combinations have been fully absorbed or have become perfectly collinear after effects are removed:

const, W

Set drop_absorbed=True to automatically drop absorbed variables.

--- Panel Regression Results (1-1 Years Since Crisis Year Zero) ---

Number of observations in subset: 20

Countries present in subset: ['Afghanistan' 'Myanmar' 'Cameroon' 'Central African Republic'

'Djibouti' 'Haiti' 'Iraq' 'Mali' 'Mauritania' 'Niger' 'Nigeria' 'Somalia'

'Zimbabwe' 'South Sudan' 'Sudan' 'Syrian Arab Republic' 'Ukraine'

'Burkina Faso' 'Yemen']

Years present in subset: [2012 2015 2013 2016]

Error in Panel Regression Results (1-1 Years Since Crisis Year Zero): The model cannot be estimated. The included effects have fully absorbed one or more of the variables. This occurs when one or more of the dependent variable is perfectly explained using the effects included in the model.

The following variables or variable combinations have been fully absorbed or have become perfectly collinear after effects are removed:

const, W

Set drop_absorbed=True to automatically drop absorbed variables.

--- Panel Regression Results (2-2 Years Since Crisis Year Zero) ---

Number of observations in subset: 20

Countries present in subset: ['Afghanistan' 'Myanmar' 'Cameroon' 'Central African Republic'

'Djibouti' 'Haiti' 'Iraq' 'Mali' 'Mauritania' 'Niger' 'Nigeria' 'Somalia'

'Zimbabwe' 'South Sudan' 'Sudan' 'Syrian Arab Republic' 'Ukraine'

'Burkina Faso' 'Yemen']

Years present in subset: [2013 2016 2014 2017]

Error in Panel Regression Results (2-2 Years Since Crisis Year Zero):

The model cannot be estimated. The included effects have fully absorbed one or more of the variables. This occurs when one or more of the dependent variable is perfectly explained using the effects included in the model.

The following variables or variable combinations have been fully absorbed or have become perfectly collinear after effects are removed:

const, W

Set drop_absorbed=True to automatically drop absorbed variables.

--- Panel Regression Results (3-4 Years Since Crisis Year Zero) ---

Number of observations in subset: 19

Countries present in subset: ['Afghanistan' 'Myanmar' 'Cameroon' 'Central African Republic'

- 'Djibouti' 'Haiti' 'Iraq' 'Mali' 'Mauritania' 'Niger' 'Nigeria' 'Somalia'
- 'South Sudan' 'Sudan' 'Syrian Arab Republic' 'Ukraine' 'Burkina Faso'
- 'Yemen']

Years present in subset: [2014 2015 2017 2018 2016 2019]
PanelOLS Estimation Summary

Dep. Variable: pin_proportion_of_country R-squared: 0.0016 Estimator: PanelOLS R-squared (Between): -0.0051 No. Observations: R-squared (Within): 0.0016 Date: Thu, Feb 20 2025 R-squared (Overall): -0.0046 02:06:23 Log-likelihood Time: 75.660 Cov. Estimator: Unadjusted F-statistic: 0.0267 P-value 0.8722 Entities: Avg Obs: 1.9474 Distribution: F(1,17)Min Obs: 1.0000 Max Obs: 2.0000 F-statistic (robust): 0.0267 P-value 0.8722 Distribution: F(1,17)Time periods: 6

Avg Obs: 6.1667
Min Obs: 1.0000
Max Obs: 13.000

Parameter Estimates

=======		========	=======			
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	0.2616	0.1549	1.6889	0.1095	-0.0652	0.5884

W -0.0026 0.0161 -0.1633 0.8722 -0.0366 0.0313

F-test for Poolability: 31.726

P-value: 0.0000

Distribution: F(18,17)

Included effects: Entity

Adjusted R-squared for Panel Regression Results (3-4 Years Since Crisis Year Zero): -1.24647

--- Panel Regression Results (5+ Years Since Crisis Year Zero) ---

Number of observations in subset: 20

Countries present in subset: ['Afghanistan' 'Myanmar' 'Cameroon' 'Central African Republic'

'Djibouti' 'Haiti' 'Iraq' 'Mali' 'Mauritania' 'Niger' 'Nigeria' 'Somalia'

'Zimbabwe' 'South Sudan' 'Sudan' 'Syrian Arab Republic' 'Ukraine'

'Burkina Faso' 'Yemen']

Years present in subset: [2016 2017 2018 2019 2020 2021 2022 2023 2024]

PanelOLS Estimation Summary

=======================================			=========
Dep. Variable:	pin_proportion_of_country	R-squared:	0.0701
Estimator:	PanelOLS	R-squared (Between):	-49.188
No. Observations:	139	R-squared (Within):	0.0701
Date:	Thu, Feb 20 2025	R-squared (Overall):	-38.718
Time:	02:06:23	Log-likelihood	131.54
Cov. Estimator:	Unadjusted		
		F-statistic:	8.8899
Entities:	20	P-value	0.0035
Avg Obs:	6.9500	Distribution:	F(1,118)
Min Obs:	1.0000		
Max Obs:	9.0000	F-statistic (robust):	8.8899
		P-value	0.0035
Time periods:	9	Distribution:	F(1,118)
Avg Obs:	15.444		
Min Obs:	11.000		
Max Obs:	18.000		

Parameter Estimates

rai allie	eter Std. Er	r. T-sta [.]	t P-value 	Lower CI	Upper CI
	0838 0.47 1487 0.04			-2.0291 0.0499	-0.1385 0.2475

F-test for Poolability: 25.781

P-value: 0.0000

Distribution: F(19,118)

Included effects: Entity

Adjusted R-squared for Panel Regression Results (5+ Years Since Crisis Year Zero): -0.096852

```
# building our data for panel format application -- WRI specific -- OLD
# --- Data Preparation ---
# Melt to long format
country_col = [col for col in wri_df.columns if 'country' in col.lower()][0] #Find the country
long_data = pd.melt(wri_df,
                    id_vars=[country_col],
                    var_name='year_category',
                    value_name='score')
# Extract year and category
long_data[['year', 'category']] = long_data['year_category'].str.split('_', expand=True)
long_data['year'] = long_data['year'].astype(int)
long_data.drop(columns=['year_category'], inplace=True)
long_data.rename(columns={country_col: 'country'}, inplace=True)
## --- Panel Regression --- ##
long_data = long_data.set_index(['country', 'year'])
regressors = pd.get_dummies(long_data['category'], drop_first=True)
model_fe_panel = PanelOLS(long_data['score'], regressors, entity_effects=True, time_effects='
print("Panel Regression Results:")
print(model_fe_panel)
print("\nRobust standard errors:")
print(model_fe_panel.std_errors)
## --- Exporting Results to a Table --- ##
# Dictionary to store the results
results_dict = {
```

```
'Coefficient': model_fe_panel.params,
    'Std. Error': model_fe_panel.std_errors,
    't-statistic': model_fe_panel.tstats,
    'p-value': model_fe_panel.pvalues
}
# Convert the dictionary to a Pandas DataFrame
results_df = pd.DataFrame(results_dict)
# Format the table
results_df = results_df.round(3)
results_df.index.name = "Variable"
# Export to CSV, check quality
results_df.to_csv('panel_regression_results.csv')
print(results_df)
## --- Key Statistical Measures --- ##
# R-squared
r_squared = model_fe_panel.rsquared
print(f"R-squared: {r_squared:.3f}")
# Number of observations
nobs = model fe panel.nobs
print(f"Number of Observations: {nobs}")
# Entity and Time Effects included
def effects_status(model_result, effect_type):
    """Checks and returns the status of entity or time effects."""
    try:
        if effect_type == "entity":
            included = model_result.params.index.str.startswith("entity").any()
        elif effect_type == "time":
            included = model_result.params.index.str.startswith("time").any()
        else:
            return "Unknown effect type"
        return "Included" if included else "Not Included"
    except AttributeError:
      return "Not Applicable"
entity_effects_status = effects_status(model_fe_panel, "entity")
```

```
time_effects_status = effects_status(model_fe_panel, "time")
print(f"Entity Effects: {entity_effects_status}")
print(f"Time Effects: {time_effects_status}")
```

'\n# building our data for panel format application -- WRI specific -- OLD\n\n# --- Data Pre

```
# Cross-sectional regression approach -- OLD
import statsmodels.formula.api as smf
# setting up the year zero data
year_zero_df = pd.read_csv('developmentneeds_GHO2025.csv')
year_zero_df.rename(columns={'country':'country', 'calendar_year':'year'}, inplace=True)
year_zero_df['year'] = year_zero_df['year'].astype(int)
# creating a merged stream
cross_copy = long_data.reset_index()
wri_merged_df = pd.merge(cross_copy, year_zero_df, on= ['country', 'year'], how= 'left')
for country in wri_merged_df['country'].unique():
    # 3. Filter data for the current country and its crisis year:
    country_data = wri_merged_df[wri_merged_df['country'] == country]
    year_of_crisis = country_data['year_of_crisis'].iloc[0] #Get the year of crisis for the
    cross_sectional_data = country_data[country_data['year'] == year_of_crisis].copy()
    # 4. Handle Missing Values (Important - same as before, but inside the loop):
    cross_sectional_data.dropna(subset=['people_in_need', 'number_of_refugees', 'number_of_I
    # 5. Cross-sectional Regression:
    if not cross_sectional_data.empty: # Check if there's any data for the country
        model = smf.ols("score ~ people_in_need + number_of_refugees + number_of_IDPs", data
        print(f"\n--- Results for {country} (Year: {year_of_crisis}) ---")
        print(model.summary())
    else:
        print(f"\n--- No data for {country} in their year of crisis ({year_of_crisis}) ---")
# filtering to target year:
cross_sectional_data = cross_copy[cross_copy['year'] == year_to_analyze].copy()
```

```
# aggregating our multiple observations per country
cross_sectional_data = cross_sectional_data.groupby('country')['score'].sum().reset_index()

# --- Cross-Sectional Regression ---
csr_model = smf.ols("score ~ 1", data=cross_sectional_data).fit() #The 1 represents the inter
print(csr_model.summary())
'''
```

'\n# Cross-sectional regression approach -- OLD\nimport statsmodels.formula.api as smf \n\n#