The Impact of Solar Photovoltaic Energy on Greenhouse Gas Emissions: Evidence from Selected Countries Using a Panel ARDL Approach (2013-2022)

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Summary: The objective of this study is to investigate the influence of solar photovoltaic energy production on greenhouse gas emissions reduction in a selected group of countries from 2013 to 2022. Countries' selection was based on their geographical locations between 45°N and 45°S latitude, ensuring high solar energy potential due to year-round sunlight exposure. To reach its objective, the study employs the panel ARDL model. The model involves four variables: greenhouse gas emissions as the dependent variable, solar photovoltaic energy production, industrial added value, and electricity generation from oil, gas, and coal as independent variables. The study concludes that solar photovoltaic energy production contributes to greenhouse gas reduction in the studied countries.

Keywords: Solar photovoltaic energy; greenhouse gas emissions; renewable energy; panel ARDL.
Jel Classification Codes : P48; Q42; Q51; Q54.

I- Introduction :

Climate change is one of the most significant challenges facing the world. One of the primary factors causing global warming is the release of greenhouse gases resulting from the use of fossil fuels as an essential energy source. Consequently, the resulting disruptions to ecosystems and Earth's climate regulation pose a comprehensive socio-economic and environmental threat to human well-being and societies.

In response, renewable energy has emerged as a strategic option to reduce emissions, as it is a clean and reliable source that does not rely on fossil fuels, the primary source of anthropogenic carbon emissions. Moreover, investment in renewable energy, in addition to its role in environmental protection and enhancement of life quality for current generations, reflects a commitment to sustainable development that balances economic growth with the preservation of natural resources for future generations. Therefore, Numerous countries are pursuing investment in renewable energy as a strategy to lower greenhouse gas emissions and promote sustainable development.

To examine the influence of investment in solar energy, as a renewable energy source, on reducing greenhouse gas emissions in selected countries, the study addresses the following research question:

What is the impact of solar photovoltaic energy production on greenhouse gas emissions in the selected countries?

Research hypothesis: The study hypothesizes that the production of solar photovoltaic energy leads to reduced greenhouse gas emissions in the selected countries.

1. **Previous Studies:** Several empirical studies have examined the contribution of renewable energy, particularly solar energy, to the reduction of greenhouse gas emissions.

– Sharif et al. (2021) in their research, "Role of solar energy in reducing ecological footprints: An empirical analysis," analyzed data from 1990 to 2017 for the top ten solar-energy-consuming countries using Quantile-on-Quantile regression. The study found that solar energy generally reduces ecological footprints, with stronger effects at higher quantiles of solar power and lower quantiles of ecological footprint levels; however, the results were mixed in India and the UK. Evidence of bidirectional causality indicated that ecological conditions also shape solar adoption.

– H. Darwish and W. Darwish (2023) examined the solar energy effects on reducing GHG emissions in Jordan. They discussed the effectiveness of a proposed 100 kW grid-connected solar PV (photovoltaic) station in Ma'an, Jordan. The authors compared this project to an oil-based system. They found that solar energy adoption would reduce greenhouse gas emissions by 89%, equivalent to 49.9 MMT tons of CO_2 annually. The study revealed Jordan's vast solar potential, especially in Ma'an. It demonstrated that solar PV can significantly lower emissions and contribute to sustainable energy development.

– Al-Ismail et al. (2023) reviewed the influence of renewable energy on GHG emissions in Saudi Arabia, focusing on how renewable energy can lower the high reliance on non-renewable electricity, which contributes approximately one-third of national GHG emissions. Based on a systematic review of data and policies, the study highlighted the potential of solar and wind energy while noting challenges such as high temperatures and sandstorms. With renewable capacity only slightly above 400 MW in 2020, Saudi Arabia's Vision 2030 aims for 58.7 GW, which is expected to significantly decrease emissions. The study concluded that large-scale renewable energy is crucial for reducing emissions and promoting sustainable development.

– Saaidia Fouzia and Dahmani Smail (2024) examined the relationship between economic growth and CO_2 emissions, considered as an environmental quality indicator, in Algeria over the period

1990–2020. In their study titled "The Relationship between Economic Growth and Environmental Quality: The Role of Renewable Energies in Algeria," the authors employed the ARDL model and the Granger causality test. The research paper concluded that there is a positive relationship between economic growth and CO_2 emissions in both the long and short term. Furthermore, the authors revealed that there is a unidirectional causality running from the consumption of renewable energy to CO_2 emissions, indicating that higher renewable energy use contributes to reducing emissions in Algeria.

– Biswas et al (2025) examined in their study "Quantifying effects of solar power adoption on CO2 emissions reduction" how solar power generation reduces U.S. electricity sector CO_2 emissions using hourly EIA data (2018–2023) and a distributed lag nonlinear model. Simulating 5–20% increases in solar output, the authors found both immediate and delayed reductions in emissions, with large effects in regions like California, Texas, and the Midwest, and minimal impact in low-fossil fuel regions like New England. A 15% increase in solar energy production is estimated to result in a yearly CO_2 reduction of 8.54 MMT, accounting for approximately 12.38% of the EPA's annual target of 69 MMT CO_2 reductions requested to cut 1,380 MMT of CO_2 in twenty (20) years, while also generating cross-regional spillover benefits.

– Mishra et al. (2025), in their research "Case Study on Role of Solar Energy in Greenhouse Gas Emissions Reduction in India," analyzed a 100 KW photovoltaic installation in a Pune educational institution. By quantitative analysis, the main findings of the paper were that the adoption of solar decreased CO_2 emissions by 146.24 MT, or 27.75% of the reference level, and presented noticeable environmental and economic benefits. The authors concluded that the adoption of solar energy, with the assistance of the National Solar Mission, is a realistic method for reducing emissions and developing clean energy in India.

2. Key Variable Definitions:

2.1. Solar photovoltaic energy: It is a renewable form of energy that produces electricity by converting sunlight through photovoltaic cells. It is considered sustainable because sunlight is constantly available and replenishes itself, unlike fossil fuels, which are finite and non-renewable. (Sartzetakis, 2024, p.13)

2.2. Greenhouse gas emissions: Greenhouse gas (GHG) emissions are the release of gases mainly composed of carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases into the Earth’s atmosphere. Since the 19th century, human activities have been the primary cause of these emissions, especially through the fossil fuels such as coal, oil, and gas, used in industrial processes, electricity generation, transportation, and home heating. Other important sources include agriculture, buildings, land use, and waste management. These emissions create a heat-trapping layer around the Earth, producing the greenhouse effect that raises temperatures. Deforestation also releases carbon into the atmosphere, increasing GHG concentrations and raising global warming. The rising concentration of these gases is already harming the environment, human health, and the economy, and without concerted action, these effects will become more severe. (Climate Action (UN), 2025; Aji & Dadzie, 2024, p.281)

II– Data and Methodology:

1. Data Sources and Variables Description: This study examines the influence of producing solar PV energy on reducing GHG emissions across the selected countries (Algeria, Australia, Chile, Egypt, Morocco, Namibia, Saudi Arabia, United Arab Emirates, Mexico, Brazil, South Africa, Pakistan, and Spain). The countries' selection was based on two considerations: their geographical locations between 45°N and 45°S latitude, which ensures high solar energy potential due to year-round sunlight exposure; and second, the availability of comprehensive data for all study variables from the World Bank's 2025 database, and the International Renewable Energy Agency (IRENA) reports. The study period spanned 10 years, from 2013 to 2022, across 13 countries, resulting in 130 observations. The variables employed in the econometric study include:

Table (1): Study Variables Presentation

The variable	Interpretation	Unit
GRE	The greenhouse gas emissions	Mt CO2e
SOL	The solar energy photovoltaic production	GWh
IND	The industry value added	Current US$
ELC	Electricity production from oil, gas, and coal	% of total

The source: Prepared by the researcher

2. **The Econometric Model:**

2.1. Econometric Model Definition: The study employs a panel data methodology. A panel dataset refers to a cross-sectional time-series data that typically provides frequent measurements of several variables over a period of time on observed units, such as individuals, firms, or countries. A cross-sectional dataset includes observations on a certain number of variables at a single point in time. In contrast, a time-series dataset consists of observations on a certain number of variables over several periods. (Eom et al, 2007, p.572)

2.2. Advantages of Panel Data: the main advantages of using panel data modeling are: (Gujarati & Porter, 2009, pp.592-593)

– Panel data relate to firms, individuals, countries, and other entities over time, so heterogeneity is inevitable. Panel data estimation techniques explicitly account for this by allowing subject-specific variables.

– By combining time series with cross-sectional observations, panel data provide more informative data, greater variability, reduced collinearity, higher degrees of freedom, and greater efficiency. They are more appropriate for studying the dynamics of change.

– Panel data also detect and measure effects that are unobservable in pure cross-sectional or time-series data. They enable more complex behavioral models, which handle phenomena such as technological development and economies of scale more effectively.

– Moreover, with data available for thousands of units, panel data minimizes bias from aggregation**.**

2.3. Model Specification: For examining the relationship between solar energy production and greenhouse gas emissions reduction, a panel data model was applied, which is more appropriate for cross-sectional time-series data. The general formula is specified as:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots\ldots + \varepsilon_{it}$$

$$i = 1, 2, ..., N;\ t = 1, 2, ..., T$$

The specific analytical model for this study is formulated as:

$$GRE_{it} = \beta_0 + \beta_1 SOL_{it} + \beta_2 IND_{it} + \beta_3 ELC_{it} + \varepsilon_{it}$$

$$i = 1,2...N;\ t = 1,2...T$$

Where:

i represents the country (N = 13 countries)

t represents the time period (T = 10 years, from 2013 to 2022)
GRE_{it}: greenhouse gas emissions in country i at time t as a dependent variable.
Sol_{it}: solar photovoltaic energy production in country i at time t as an independent variable.
IND_{it}: industry added value in country i at time t as an independent variable.
ELC_{it}: electricity production from oil, gas, and coal sources in country i at time t as an independent variable.

ε_{it}: the error term.

3. Summary Statistics of Study Variables:

Table (2): Descriptive statistics of the study variables (GRE, SOL, IND, and ELC)

Statistic	GRE	SOL	IND	ELC
Mean	5.666722	6.558078	20.50215	8.890372
Maximum	7.168957	10.45398	27.21284	26.43622
Minimum	2.391081	1.098612	3.463228	0.076816
Std. Dev.	1.154196	2.342382	9.10882	9.17223
Sum	736.6738	852.5501	2665.279	1155.748
Observations	130	130	130	130

The source: Prepared by the researcher based on the Eviews 13 outputs

As the table above presents, the descriptive statistics provide a statistical overview of the study variables: GRE, SOL, IND, and ELC. The mean values reveal that IND has the highest average (20.50), followed by ELC (8.89), while SOL (6.56) and GRE (5.67) have lower averages. The range between the maximum and minimum values indicates that ELC (26.44 to 0.08) and IND (27.21 to 3.46) exhibit the widest variations, indicating significant volatility. The sums reflect the accumulated values over 130 observations. Overall, the results indicate that IND and ELC are highly dispersed, whereas GRE and SOL remain steadier.

4. Model Selection and Estimation: In this section, the regression equation introduced earlier will be estimated based on the study's longitudinal data characteristics. Three alternative panel data models are considered: the pooled, the fixed effects, and the random effects models. The pooled and fixed effects models are estimated using "Ordinary Least Squares" (OLS), while the random effects model is estimated using Generalized Least Squares (GLS). The results of these estimations are shown in the following tables.

Table (3): The Pooled Model Estimation

Dependent Variable: GRE
Method: Panel Least Squares
Date: 08/31/25 Time: 13:47
Sample: 2013 2022
Periods included: 10
Cross-sections included: 13
Total panel (balanced) observations: 130

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SOL	0.012830	0.022818	0.562254	0.5749
IND	0.464555	0.024609	18.87713	0.0000
ELC	0.482355	0.024845	19.41431	0.0000
C	-8.230108	0.705297	-11.66899	0.0000

R-squared	0.767217	Mean dependent var	5.666722
Adjusted R-squared	0.761674	S.D. dependent var	1.154196
S.E. of regression	0.563463	Akaike info criterion	1.720854
Sum squared resid	40.00374	Schwarz criterion	1.809086
Log likelihood	-107.8555	Hannan-Quinn criter.	1.756706
F-statistic	138.4253	Durbin-Watson stat	0.049871
Prob(F-statistic)	0.000000		

Source: from Eviews 13 outputs

Table (4): Lagrange Multiplier Tests

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided (all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	543.1851 (0.0000)	4.645729 (0.0311)	547.8309 (0.0000)
Honda	23.30633 (0.0000)	-2.155395 (0.9844)	14.95597 (0.0000)
King-Wu	23.30633 (0.0000)	-2.155395 (0.9844)	13.62825 (0.0000)
Standardized Honda	27.15978 (0.0000)	-2.007929 (0.9777)	13.67246 (0.0000)
Standardized King-Wu	27.15978 (0.0000)	-2.007929 (0.9777)	12.11619 (0.0000)
Gourieroux, et al.	--	--	543.1851 (0.0000)

Source: from Eviews 13 outputs

After estimating the pooled model (Table 3) and implementing Lagrange Multiplier Tests (Table 4), it is noted that the statistical value of most tests is less than 0.05, i.e., p-value < 0.05. Focusing on the Breusch-Pagan test, the p-value < 0.05, which leads to reject the H_0: No effect, which states that there is no effect of the cross-sectional or time data, and that the pooled model is the most appropriate one, as opposed to the alternative hypothesis, which proves the existence of the effect and also tests whether this effect is at the cross-sectional level only, at the time level, or at the level of both. As noted, the Breusch-Pagan test indicated the existence of the effect at both the cross-sectional and time levels, as the statistical value is less than 0.05 for both. Therefore, the model will be two-sided or two-way. The estimation results of the fixed effects and random effects models are presented as follows:

Table (5): Fixed Effects Model

Dependent Variable: GRE
Method: Panel Least Squares
Date: 08/31/25 Time: 13:54
Sample: 2013 2022
Periods included: 10
Cross-sections included: 13
Total panel (balanced) observations: 130

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SOL	-0.002115	0.004924	-0.429647	0.6683
IND	0.060552	0.039736	1.523836	0.1306
ELC	0.011223	0.029457	0.380992	0.7040
C	4.339376	0.879139	4.935940	0.0000

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.998499	Mean dependent var	5.666722
Adjusted R-squared	0.998155	S.D. dependent var	1.154196
S.E. of regression	0.049572	Akaike info criterion	-2.999733
Sum squared resid	0.258027	Schwarz criterion	-2.448284
Log likelihood	219.9826	Hannan-Quinn criter.	-2.775661
F-statistic	2909.438	Durbin-Watson stat	0.542910
Prob(F-statistic)	0.000000		

Source: from Eviews 13 outputs

Table (6): Random Effects Model

Dependent Variable: GRE
Method: Panel EGLS (Cross-section random effects)
Date: 08/31/25 Time: 14:38
Sample: 2013 2022
Periods included: 10
Cross-sections included: 13
Total panel (balanced) observations: 130
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SOL	0.009459	0.002732	3.462268	0.0007
IND	0.054003	0.024814	2.176286	0.0314
ELC	0.067553	0.024062	2.807447	0.0058
C	3.896931	0.707228	5.510146	0.0000

Effects Specification

	S.D.	Rho
Cross-section random	0.655069	0.9936
Idiosyncratic random	0.052533	0.0064

Weighted Statistics

R-squared	0.101606	Mean dependent var	0.143661
Adjusted R-squared	0.080216	S.D. dependent var	0.059289
S.E. of regression	0.056862	Sum squared resid	0.407390
F-statistic	4.750102	Durbin-Watson stat	0.563667
Prob(F-statistic)	0.003581		

Source: from Eviews 13 outputs

Table (7): Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	24.618530	3	0.0000

The source: from Eviews 13 outputs

H_0: Random effect is appropriate
H_1: Fixed effect is appropriate

As the table above shows, the Hausman Test statistic result is significant, as the p-value is less than 0.05, which guides the rejection of H_0, that the random model is appropriate, and the acceptance of the alternative hypothesis that the fixed effects model is more suitable.

4.1. Fixed Effects Model Estimation: According to the previous tests, the most appropriate model for our study is the fixed effects model. Based on the estimation results shown in Table 4, the parameters of the fixed effects model are expressed as follows:

$$GRE_{it} = 4.339 - 0.002SOL_{it} + 0.060IND_{it} + 0.011ELC_{it} + \varepsilon_{it}$$

4.2. Fixed Effects Model Interpretation and Evaluation:

– **Economic Interpretation:**

As can be seen from Table 4, the estimated coefficients vary from one variable to another; solar photovoltaic energy carries a negative sign, while industrial added value, as well as electricity generated from oil, gas, and coal, carry positive signs. The value of the coefficient for solar PV energy is negative, indicating that a one-unit increase in the production level of solar PV energy results in a decrease of 0.002 units in GHG emissions, as expected from an economic perspective, given the substitutive effect that renewables can have on reducing emissions. By contrast, increases in industrial added value and non-renewable electricity generation are associated with rises in GHG emissions, by 0.06 and 0.01 units, respectively. These results are consistent with economic logic, as higher industrial activity and reliance on fossil-fuel-based electricity are key contributors to increased emissions.

– **Statistical Evaluation:**

Although the F-statistic equals 0.0000, which confirms the model's overall significance, the individual estimated parameters are not statistically significant at the 5% level as the p-value is greater than 0.05. Furthermore, the Durbin–Watson (DW) statistic is relatively low and falls below the coefficient of determination (R^2). This pattern indicates potential autocorrelation in the residuals, which may lead to spurious regression and unreliable parameter estimates. However, for panel data, the DW test is not considered effective in detecting autocorrelation. Instead, cross-sectional dependence and autocorrelation tests for panel residuals are more appropriate. The results of these tests are presented as follows:

Table (8): Residual Cross-Section Dependence Test

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in residuals
Equation: Untitled
Periods included: 10
Cross-sections included: 13
Total panel observations: 130
Cross-section effects were removed during estimation

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	188.5098	78	0.0000
Pesaran scaled LM	8.847862		0.0000
Bias-corrected scaled LM	8.125640		0.0000
Pesaran CD	2.529492		0.0114

The source: from Eviews 13 outputs

From the table above, it is evident that all test statistics results are significant at the 5% level (p-value < 0.05). Therefore, the H_0 of no cross-section dependence (correlation) in residuals is rejected. This result directs the analysis towards estimating a dynamic relationship.

5. Estimation of the Relationship between Solar PV Production and GHG Emissions:

Before estimating the relationship, it is essential to examine the stationarity properties of the panel time series variables included in the model. The panel unit root test results are reported in the following table.

5.1. Stationarity of Panel Time Series Variables: The tests provide evidence on whether the series is stationary or requires differencing. This step is crucial, as the integration order of the variables determines the appropriate cointegration approach to estimate the long-run relationship.

Table (9): Time Series Stationarity Results

Series	Tests	At level		1st difference		Results
		Ind Int &Trend	Ind Int	Ind Int &Trend	Ind Int	
GRE	ADF	0.4258	0.7205	0.0000	0.0000	Stationary I(1)
	PP – F. Chi-square	0.3095	0.4127	0.0000	0.0000	
SOL	ADF	0.0394	0.0001			Stationary I(0)
	PP – F. Chi-square	0.0032	0.0000			
IND	ADF	0.2266	0.0131	0.0023	0.0000	Stationary I(1)
	PP – F.Chi-square	0.7088	0.8866	0.0000	0.0001	
ELC	ADF	0.0170	0.6281	0.0003	0.0001	Stationary I(1)
	PP – F. Chi-square	0.3361	0.8700	0.0000	0.0001	

The source: Prepared by the researcher based on the Eviews 13 outputs

From the above table, the SOL time series is stationary at the level, and the others are differenced stationary (DS). Therefore, the first difference was applied to them to become stationary.

5.2. Long-run Relationship Estimation: Before estimating the long-run relationship, as a precondition for valid long-run estimation, it is necessary to test for cointegration among the variables. For panel data, one of the most common cointegration tests is the Pedroni test:

Table (10): Pedroni Cointegration Test

Pedroni Residual Cointegration Test
Series: GRE SOL IND ELC
Date: 08/31/25 Time: 14:44
Sample: 2013 2022
Included observations: 130
Cross-sections included: 13
Null Hypothesis: No cointegration
Trend assumption: Deterministic intercept and trend
Automatic lag length selection based on SIC with a max lag of 0
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	0.488537	0.3126	-1.121646	0.8690
Panel rho-Statistic	3.111255	0.9991	3.104556	0.9990
Panel PP-Statistic	-3.644362	0.0001	-5.205348	0.0000
Panel ADF-Statistic	-2.962480	0.0015	-3.703449	0.0001

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	4.393351	1.0000
Group PP-Statistic	-6.714396	0.0000
Group ADF-Statistic	-4.262360	0.0000

The source: from Eviews 13 outputs

H_0: No cointegration among variables

H_1: Cointegration exists

From the table above, it is observed that the p-values of the Pedroni cointegration test (most of them) are below 0.05, indicating significance at the 5% level. This result leads to rejecting the null hypothesis of no cointegration and accepting the alternative hypothesis, confirming the cointegration among the variables studied.

The stationarity test results reveal a mixture of integration orders: the SOL series is stationary at the level I(0), whereas the GRE, IND, and ELC series are stationary at the first difference I(1). Based on this combination of integration orders and the evidence of cointegration, the Autoregressive Distributed Lag (ARDL) approach is a suitable modeling framework for this analysis. Accordingly, the long-run and short-run dynamics are estimated using the panel ARDL–PMG estimator within an Error Correction Model (ECM) specification.

Table (11): ARDL-PMG model Estimation

Dependent Variable: D(GRE)
Method: ARDL
Date: 09/01/25 Time: 21:37
Sample: 2014 2022
Included observations: 117
Number of cross-sections: 13
Dependent lags: 2 (Automatic)
Automatic-lag linear regressors (0 max. lags): SOL IND ELC
Deterministics: Restricted constant and no trend (Case 2)
Model selection method: Akaike info criterion (AIC)
Number of models evaluated: 2
Selected model: PMG(1,0,0,0)

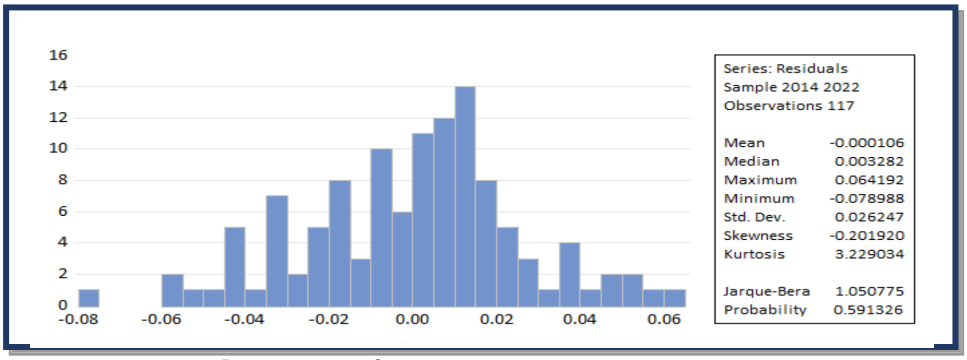
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-run (Pooled) Coefficients				
SOL	-0.049759	0.020515	-2.425495	0.0169
IND	0.595779	0.061181	9.738006	0.0000
ELC	0.598584	0.062308	9.606863	0.0000
C	-11.67722	1.883689	-6.199127	0.0000
Short-run (Mean-Group) Coefficients				
COINTEQ	-0.092035	0.049890	-1.844758	0.0676
Log-Likelihood:	238.7296			

The source: from Eviews 13 outputs

5.3. Model Diagnostics:

– **Normality Test:**

Figure (1): Residuals Normality Distribution Test



The source: from Eviews 13 outputs

As shown in the above table, the Jarque-Bera test assesses whether residuals are normally distributed. Here, the test results are a statistic of 1.0508 and a probability of 0.5913, exceeding 0.05. Thus, the null hypothesis cannot be rejected, indicating that the residuals are consistent with normality.

– **Causality Test of Panel Data:**

Since establishing a long-run equilibrium relationship between a set of cointegrated variables requires at least one directional causality within the estimated model, we conducted a Granger causality test.

Table (12): Pairwise Granger Causality Tests

Pairwise Granger Causality Tests
Date: 09/02/25 Time: 15:17
Sample: 2013 2022
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
SOL does not Granger Cause GRE	117	2.44308	0.1208
GRE does not Granger Cause SOL		3.35212	0.0577
IND does not Granger Cause GRE	117	0.38518	0.5361
GRE does not Granger Cause IND		0.00754	0.9310
ELC does not Granger Cause GRE	117	0.43753	0.5097
GRE does not Granger Cause ELC		0.41177	0.5224
IND does not Granger Cause SOL	117	0.43997	0.5085
SOL does not Granger Cause IND		8.20586	0.0050
ELC does not Granger Cause SOL	117	0.09188	0.7624
SOL does not Granger Cause ELC		0.20942	0.6481
ELC does not Granger Cause IND	117	0.01980	0.8883
IND does not Granger Cause ELC		0.25180	0.6168

The source: from Eviews 13 outputs

The results, presented in the table above, indicate a unidirectional causality running from the dependent variable GHG (greenhouse gas emissions) to the independent variable SOL (solar photovoltaic energy production) at the 5% significance level.

III- Results and discussion :

1. Long-term Relationship Interpretation

The results (Table 11) indicate a long-term relationship between greenhouse gas emissions (GRE) and solar photovoltaic (SOL), industrial added value (IND), and electricity generation from oil, gas, and coal (ELC). Estimation results show that the solar photovoltaic energy coefficient is negative (-0.0497) and statistically significant (p-value less than 0.05), indicating that increased reliance on solar energy contributes to reducing GHG emissions. This is consistent with economic logic and literature that emphasizes the important role of renewable energy in reducing emissions and environmental sustainability. In contrast, both industry and electricity showed positive and high coefficients (0.5957 and 0.5986, respectively), which were statistically significant, with p-values less than 0.05. This suggests that the expansion of industrial activity and increased non-renewable electricity generation have led to a significant increase in emissions. This reflects the reliance of the economies studied on fossil energy sources for industry and electricity generation.

2. Short-term Relationship Interpretation

In the short term, the correction coefficient (COINTEQ) (Table 11) showed a negative sign (-0.0920), indicating the existence of a mechanism to correct short-term imbalances toward equilibrium. However, its statistical significance is weak (p = 0.0676, significant at 10%), and the pace of correction is relatively slow, with the rate of adjustment toward equilibrium not exceeding approximately 9.2% of the imbalance in each period. Therefore, the economy is moving toward equilibrium in the long term, but this correction is occurring slowly and with limited force in the short term.

The results confirm that continued reliance on fossil fuels in the studied economies, whether for non-renewable electricity production or industrial activity, will lead to increased greenhouse gas emissions. In contrast, expanding solar photovoltaic energy production will gradually reduce emissions.

Therefore, these countries should decrease their dependence on fossil fuel-based energy and replace it gradually with renewable sources, particularly solar energy. Their favorable geographical location enables them to become leaders in solar energy production and use, similar to Australia, which records high photovoltaic energy output compared to the other countries under study.

IV- Conclusion:

This paper examined the impact of solar photovoltaic (PV) energy production on greenhouse gas (GHG) emissions reduction in a selected group of countries, during the period 2013-2022. To achieve its objective, the study employed the panel ARDL model using EViews 13 software. The model incorporated four variables: greenhouse gas emissions as the dependent variable, and solar photovoltaic energy production, industrial added value, and electricity generation from oil, gas, and coal as independent variables.

Following the estimation of the model, analysis of the outputs, and implementation of the necessary diagnostic tests, the central hypothesis -that solar photovoltaic energy production contributes to reducing GHG emissions in the studied countries- is accepted.

The study's key findings are as follows:

– Solar photovoltaic energy production significantly reduced greenhouse gas emissions in the studied countries during the period (2013–2022). This result is consistent with the findings of Mishra et al. (2025), H. Darwish and W. Darwish (2023), Biswas et al. (2025), and Sharif et al. (2021).

– Electricity generation from oil, gas, and coal increased greenhouse gas emissions in the studied countries during the period of study.

– Industrial added value also contributed to higher greenhouse gas emissions in the studied countries during the period of study.

The Recommendations:

It is recommended that the studied countries:

– Promote the renewable energy generation and use, especially solar and wind energy, to reduce emissions in the long term.

– Reduce reliance on fossil fuels in industry and electricity generation by investing in clean alternatives.

– Develop clean energy infrastructure and encourage research and development in sustainable production technologies.

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