

The Effect of Real GDP Per Capita, Eco-Innovation, Solar Energy, and Foreign Direct Investment on CO₂ Emissions in G-20 Countries

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Abstract: This study investigates the interplay between real GDP per capita, solar energy, foreign direct investment (FDI), and eco-innovation on carbon emissions (CO₂) within G20 nations. It aims to understand how economic development and financial liberalization influence environmental outcomes. The research employs a quantitative approach using panel data for 19 G20 countries from 2000 to 2022. The analysis uses panel data regression (Fixed and Random Effects), Autoregressive Distributed Lag-Pooled Mean Group (ARDL-PMG) and ARDL-Mean Group (ARDL-MG) models, and multivariate polynomial regression to capture non-linear relationships, particularly the Environmental Kuznets Curve (EKC). Real GDP per capita has a significant positive impact on CO₂ emissions, indicating economic growth remains an emissions driver. However, country-group analysis reveals patterns: developed G20 nations exhibit a long-run negative relationship between GDP per capita and emissions, validating the EKC hypothesis. In contrast, developing nations show a consistently positive relationship. Renewable energy consumption consistently reduces emissions across all groups. Eco-innovation and FDI show complex, non-linear effects, often increasing emissions in the short run but demonstrating potential for long-term reductions. This research integrates economic variables and renewable energy usage with environmental outcomes within a unified framework for the heterogeneous G20 bloc. It compares developed and developing economies, moving beyond aggregate results to offer nuanced insights. The study underscores the need to couple economic growth strategies with robust environmental regulations. It highlights renewable energy as an immediate tool for emission reduction. It suggests that the environmental benefits of eco-innovation and FDI depend on supportive policies and long-term investment in green technologies.

Keywords: *Environmental Kuznets Curve, Eco-innovation, Solar Energy, Foreign Direct Investment, Renewable Energy*

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INTRODUCTION

Climate change, driven by rising greenhouse gas concentrations, has emerged as one of the most pressing global challenges of recent decades. Nations worldwide have committed to reducing emissions through international agreements, most notably the 2016 Paris Agreement. Carbon dioxide (CO₂) emissions, primarily from economic activities that depend on fossil fuels such as oil, coal, and natural gas, are the central focus of these commitments. According to the Intergovernmental Panel on Climate Change

(IPCC, 2022), the energy sector is the largest contributor to global greenhouse gas emissions, making decarbonization and accelerating the clean energy transition essential priorities for achieving sustainable development. The urgency of this issue is underscored by the fact that global CO₂ concentrations have risen by nearly 50% since the pre-industrial era, with the rate of increase accelerating over the past two decades.

Environmental economics has long relied on the Environmental Kuznets Curve (EKC) to frame the connection between income levels and ecological degradation. Grossman & Krueger (1991) originally posited that pollution follows an inverted-U pattern relative to rising per capita income. Early development phases typically witness mounting environmental harm as industrialization, urban expansion, and resource extraction intensify. Beyond a specific income threshold, however, environmental conditions begin to improve. This turnaround stems from economic restructuring toward services, stronger public environmental consciousness, tighter regulatory oversight, and the diffusion of cleaner production methods. Three underlying forces drive this transition: the scale effect, whereby expanding output exacerbates pollution; the composition effect, reflecting shifts toward less environmentally damaging industries; and the technique effect, capturing the uptake of greener technologies.

Several empirical studies have tested the EKC hypothesis across different countries and regions. A landmark contribution is Zhao et al. (2022), which analyzed G7 countries over 1995–2018 and incorporated two relatively underexplored variables: eco-innovation and solar energy. Their findings confirmed the EKC hypothesis for G7 nations and demonstrated that both eco-innovation and solar energy significantly reduce CO₂ emissions in the long run. Another important strand of literature examines the role of Foreign Direct Investment (FDI), which has been associated with both the Pollution Haven Hypothesis (PHH) and the Pollution Halo Hypothesis (PHL). The PHH suggests that FDI increases emissions by relocating pollution-intensive industries to countries with weaker environmental regulations, while the PHL argues that FDI reduces emissions through cleaner technology transfer. Al Numan et al. (2025) found that FDI increases ecological footprint in ASEAN, supporting the PHH, while Saqib et al. (2023) found that FDI acts as a pollution halo in European countries with strong environmental governance.

Despite these contributions, important research gaps remain. First, prior studies have a limited temporal scope: Zhao et al. (2022) cover only through 2018, missing major shifts in global energy policy, the acceleration of renewable energy adoption, and strengthened climate commitments following the Paris Agreement. Second, the G7-focused analysis does not capture the heterogeneous dynamics of the developing world, where most future emission growth is expected. Third, research that integrates eco-innovation, solar energy, and FDI within the G20 framework across both developed and developing economies remains scarce. According to the World Bank (2023), G20 countries contribute more than 80% of global GDP and approximately 75% of total global greenhouse gas emissions, making this group uniquely relevant for understanding and addressing carbon dynamics at scale. Furthermore, the diverse composition of the G20, including advanced economies like Germany and Japan alongside rapidly industrializing nations like China and India, provides an ideal setting for examining how the EKC relationship varies by development stage.

This study therefore extends the analysis period to 2000–2022, capturing the latest dynamics in clean technology development, energy policy, and climate mitigation. It broadens the country coverage from G7 to 19 G20 member countries to provide a more

comprehensive and heterogeneous global picture. Furthermore, this research stratifies the G20 into developed and developing country subgroups based on World Bank GNI per capita classification, acknowledging that the relationship between economic growth and environmental degradation is not uniform across development stages. The research uses a multi-method quantitative approach, employing panel data regression, ARDL-PMG/MG, and third-order multivariate polynomial regression to identify linear and non-linear relationships, providing a more complete picture of short-run and long-run dynamics, as well as complex non-linear patterns such as inverted N-shaped and inverted-U-shaped relationships.

RESEARCH METHODS

The analysis begins with panel data regression using three candidate models: Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). The CEM assumes that all cross-sectional units share the same intercept, effectively pooling the data. The FEM allows for country-specific intercepts, controlling for unobserved time-invariant heterogeneity (e.g., geography, historical factors, cultural attitudes toward the environment). The REM assumes that country-specific effects are random and uncorrelated with the regressors. Model selection follows a sequential testing procedure. First, the Chow test compares CEM against FEM. If the null hypothesis of common intercepts is rejected, FEM is preferred over CEM. Second, the Hausman test compares FEM against REM. A significant test statistic ($p < 0.05$) indicates that the FEM is preferred because the country-specific effects are correlated with the regressors; otherwise, REM is preferred. For the aggregate G20 panel and developing country subgroup, the Hausman test favored FEM, while for developed countries, REM was preferred. The panel data models are specified as:

$$\ln CO_{2_it} = \alpha_i + \beta_1 \ln GDP_it + \beta_2 \ln ECO_it + \beta_3 \ln SOL_it + \beta_4 \ln FDI_it + \beta_5 \ln REC_it + \varepsilon_{it} \quad (1)$$

where α_i captures country-specific fixed or random effects.

To distinguish short-run and long-run dynamics, the study employs the Autoregressive Distributed Lag (ARDL) framework with two estimators: Pooled Mean Group (PMG) and Mean Group (MG). The ARDL-PMG estimator (Pesaran et al., 1999) allows short-run coefficients to vary across countries while constraining long-run coefficients to be homogeneous, which suits countries that share a common long-run equilibrium relationship but may have different adjustment speeds. The ARDL-MG estimator allows both short-run and long-run coefficients to vary across countries, which suits substantial heterogeneity in long-run relationships. The Hausman test comparing the two estimators informed the choice between PMG and MG. For developed countries, the test favored PMG. In contrast, for the aggregate G20 panel and developing countries, MG was preferred because these groups show greater heterogeneity. The ARDL model in error correction form is:

$$\Delta y_{it} = \varphi_i (y_{i,t-1} - \theta_i' x_{i,t-1}) + \sum \lambda_{ij} \Delta y_{i,t-j} + \sum \delta_{ik} \Delta x_{i,t-k} + \mu_i + \varepsilon_{it} \quad (2)$$

where y is the log of CO₂ emissions, x is the vector of independent variables, φ_i is the error correction coefficient (expected to be negative and significant for long-run convergence), θ_i' represents the long-run coefficients, λ and δ capture short-run

dynamics, and μ_i captures country-specific fixed effects. Before estimating the ARDL models, several diagnostic tests are conducted:

1. The Cross-Sectional Dependence (CSD) test tests for cross-sectional dependence in the residuals, which can arise from global shocks, spillovers, or common unobserved factors. The test statistic follows a standard normal distribution under the null of no CSD. For all three country groups (aggregate G20, developed, developing), the p-values exceed 0.05, indicating no significant CSD and thus no need for second-generation panel unit root tests.
2. Slope Homogeneity Test: The Pesaran & Yamagata (2008) Δ test tests whether slope coefficients are homogeneous across countries. For all three groups, the test rejects homogeneity ($p < 0.01$), indicating that the relationships vary across countries and that heterogeneous estimators (ARDL-MG or PMG) are more appropriate than pooled estimators.
3. Panel Unit Root Tests: The Im et al. (2003) test tests for unit roots in panel data. The test allows for heterogeneous autoregressive coefficients across countries. Results show that for the aggregate G20 panel, CO_2 , GDP per capita, and REC are $I(1)$ (non-stationary in levels, stationary in first differences), while eco-innovation, solar energy, and FDI are $I(0)$ (stationary in levels). This mixture of $I(0)$ and $I(1)$ variables makes ARDL suitable, as it can accommodate variables with different orders of integration.
4. Panel Cointegration Test: The Kao residual-based cointegration test tests for long-run relationships among the variables. The test results reject the null of no cointegration for most test statistics (Modified DF t, DF t, Unadjusted Modified DF t, Unadjusted DF t) across all country groups, indicating that the variables are cointegrated and a long-run equilibrium relationship exists.

To test for non-linear EKC patterns, including inverted-U, N-shaped, and inverted-N-shaped relationships, this study employs third-order multivariate polynomial regression. This approach includes linear, quadratic, and cubic terms for the key variables (GDP per capita, eco-innovation, solar energy, FDI) while retaining REC as a control variable. The polynomial specification is:

$$\begin{aligned} \ln CO_{2_it} = & \beta_1 \ln GDP_it + \beta_2 (\ln GDP_it)^2 + \beta_3 (\ln GDP_it)^3 \\ & + \beta_4 \ln ECO_it + \beta_5 (\ln ECO_it)^2 + \beta_6 (\ln ECO_it)^3 \\ & + \beta_7 \ln SOL_it + \beta_8 (\ln SOL_it)^2 + \beta_9 \ln FDI_it \\ & + \beta_{10} (\ln FDI_it)^2 + \beta_{11} (\ln FDI_it)^3 + \beta_{12} \ln REC_it + \alpha_i \\ & + \beta_t + \varepsilon_{it} \end{aligned} \quad (3)$$

Interpretation follows the sign and significance of the coefficients:

- If $\beta_1 > 0$, $\beta_2 < 0$, and β_3 is not significant: inverted-U shape (classic EKC)
- If $\beta_1 > 0$, $\beta_2 < 0$, and $\beta_3 > 0$: N-shape (emissions rise, fall, then rise again)
- If $\beta_1 < 0$, $\beta_2 > 0$, and $\beta_3 < 0$: inverted-N-shape (emissions fall, rise, then fall again)
- If all coefficients are positive: monotonically increasing
- If all coefficients are negative: monotonically decreasing

A COVID-19 dummy variable (1 for 2020–2022, 0 otherwise) captures the pandemic's impact on emissions due to lockdowns and reduced economic activity.

To ensure result reliability, we conduct several robustness checks. First, we estimate alternative model specifications, including excluding one country at a time to test for outlier influence. Second, we test different lag structures in the ARDL models (1 to 4 lags) to ensure the results are not sensitive to lag selection. Third, we estimate the polynomial

regression with and without the COVID-19 dummy to assess whether the pandemic period affects the estimated non-linear patterns. Fourth, we use alternative measures of eco-innovation (R&D spending on environmental technologies) and solar energy (installed capacity rather than generation share) in sensitivity tests. The main results are qualitatively robust to these alternative specifications.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1. Descriptive Statistics

Variable	Unit	N	Mean	Std. Dev.	Min
CO2 Emissions	Million metric tons	437	1,335.62	2,215.00	124.06
Real GDP per Capita	USD	437	23,648.15	17,614.66	756.70
Eco-Innovation	Units (patents)	437	1,680.09	2,844.46	0
Solar Energy	Ratio	437	0.14	0.23	0
FDI	Million USD	437	53,200	80,700	-39,800
REC	Percentage	437	14.03	12.52	0

Source: World Bank (2023), OECD Statistics, IRENA (2023), Global Carbon Budget (2025).

The statistics reveal substantial heterogeneity within the G20. CO₂ emissions range from 124.06 million metric tons (Argentina, 2002) to 12,621.61 million metric tons (China, 2021), reflecting the vast differences in economic scale and industrial structure. GDP per capita ranges from USD 756.70 (India, 2000) to USD 64,198.43 (United States, 2022), confirming that the G20 spans the full spectrum of development levels. Eco-innovation exhibits the highest dispersion: its standard deviation (2,844.46) exceeds its mean (1,680.09), indicating that green technology capacity is highly concentrated among a few countries. China held the highest number of environment-related patents (16,366.02) in 2022, while several countries, particularly in the developing group, had zero patents in some years. Solar energy share also varies widely, from zero (Saudi Arabia, 2000–2019) to 100% (Saudi Arabia, 2010–2016), though the latter is an outlier given the country's particular energy profile. FDI shows negative values (Russia, 2022), reflecting capital flight during geopolitical stress, while REC ranges from 0% (Saudi Arabia, early years) to 50% (Brazil, 2020).

Panel Data Regression Results

Table 2. Fixed Effect Panel Regression Results – G20 Countries

Variable	Coefficient	t-statistic	Prob.
GDP per Capita	0.339	8.56***	0.000
Eco-Innovation	0.062	6.45***	0.000
Solar Energy	0.004	1.89*	0.060
FDI	-0.001	-0.28	0.777
REC	-0.030	-19.77***	0.000
Adj. R-square	0.7759		
F-statistic	166.19	Prob. F	0.000

*Notes: ***: significant at 1%; **: significant at 5%; *: significant at 10%. Source: Processed data.*



GDP per capita has a strong, positive, and significant effect on CO₂ emissions (coefficient: 0.339, $p < 0.01$). Economically, a 1% increase in GDP per capita is associated with a 0.34% increase in CO₂ emissions on average across the G20, confirming that at the aggregate level, economic growth remains coupled with rising emissions. This finding is consistent with Ajide & Ibrahim (2021) and Deka et al. (2023), who find that GDP growth still drives environmental degradation in large economies.

Eco-innovation also shows a positive and significant effect (0.062, $p < 0.01$), which may seem counterintuitive. This result may reflect the "Jevons Paradox," or rebound effect: efficiency gains from innovation can lower energy costs, encouraging more consumption and offsetting some environmental benefits. Additionally, patent counts may reflect industrial activity and R&D intensity, which themselves are correlated with economic expansion and energy use. The positive coefficient may also reflect that patenting often precedes widespread technology adoption, with emission-reducing effects materializing only after a lag. Solar energy is positive and marginally significant (0.004, $p < 0.10$), consistent with its still-small share in total G20 energy mixes. While solar energy is theoretically emission-free, its aggregate impact on total national emissions remains limited because it represents only a small fraction of total energy consumption across the G20. This finding does not contradict solar energy's potential but highlights that it has not yet reached a scale where it can substantially reduce aggregate emissions in this group.

FDI is not statistically significant, reflecting the offsetting effects of clean and pollution-intensive investment flows across heterogeneous countries. This finding aligns with the view that FDI's environmental impact depends heavily on host-country regulations, sectoral composition, and absorptive capacity (Saqib et al., 2023). The aggregate insignificance masks the fact that FDI may reduce emissions in some countries (where it brings clean technology) and increase them in others (where it enters pollution-intensive sectors). Critically, REC is negative and highly significant (-0.030, $p < 0.01$). This is the panel analysis's most robust finding: increasing the share of renewable energy in total final energy consumption consistently reduces carbon emissions. The elasticity suggests that a 1% increase in REC reduces emissions by 0.03% on average, confirming the central role of the energy transition in decarbonization (Adekoya et al., 2021; Chen et al., 2022; Mukhtarov et al., 2023). For developed G20 countries (results not tabulated but described), the random-effect model preferred by the Hausman test yields similar directional results, with GDP per capita (0.567, $p < 0.01$) and eco-innovation (0.057, $p < 0.01$) positive, REC negative (-0.040, $p < 0.01$), and solar energy and FDI not significant. For developing countries, the fixed-effect results confirm that GDP per capita (0.507, $p < 0.01$) and solar energy (0.005, $p < 0.05$) significantly raise emissions, while REC significantly lowers them (-0.014, $p < 0.01$). Eco-innovation and FDI are not significant in the developing country panel.

ARDL-MG and ARDL-PMG Dynamic Estimation

Table 3. ARDL-MG Results – G20 Countries (All Members)

Variable	Long Run			Short Run		
	Coef.	t-stat	Prob.	Coef.	t-stat	Prob.
GDP per Capita	0.056	0.15	0.880	0.324	2.15**	0.032
Eco-Innovation	0.075	0.90	0.370	-0.001	-0.05	0.962

Variable	Long Run			Short Run		
	Coef.	t-stat	Prob.	Coef.	t-stat	Prob.
Solar Energy	0.083	0.11	0.915	0.818	1.02	0.307
FDI	-0.016	-0.59	0.557	0.008	1.43	0.153
REC	0.115	0.87	0.383	-0.034	-1.00	0.317
ECM	-	-	-	-0.524	-6.00***	0.000

Notes: ***: significant at 1%; **: significant at 5%; *: significant at 10%. Source: Processed data.

The error correction term (ECM) coefficient is negative and significant (-0.524, $p < 0.01$), confirming that a long-run equilibrium relationship exists and that approximately 52% of any short-run deviation from equilibrium is corrected within one year. In the long run, no variable is statistically significant. This suggests that averaging across the highly heterogeneous G20 countries dilutes the long-run relationships between individual variables and emissions. The long-run coefficients, while not significant, are consistent with the idea that eco-innovation and REC eventually become emission-reducing. However, the effect is not uniform enough to reach statistical significance in this heterogeneous panel. In the short run, only GDP per capita is positively and significantly associated with emissions (0.324, $p < 0.05$). This confirms that cyclical economic expansion, whether in developed or developing countries, rapidly translates into higher fossil energy use. The short-run insignificance of eco-innovation, solar energy, FDI, and REC suggests that the benefits of green technology and renewable energy are structural and require time to materialize; they do not provide immediate emission reductions in response to short-term economic fluctuations.

Table 4. ARDL-PMG Results – Developed G20 Countries

Variable	Long Run			Short Run		
	Coef.	t-stat	Prob.	Coef.	t-stat	Prob.
GDP per Capita	-1.232	-2.33**	0.020	1.279	7.26***	0.000
Solar Energy	-0.037	-1.78*	0.076	-0.003	-1.86*	0.063
FDI	-0.023	-1.65*	0.098	0.002	0.75	0.455
REC	-0.028	-3.92***	0.000	-0.026	-0.76	0.449
ECM	-	-	-	-0.238	-4.60***	0.000

Notes: ***: significant at 1%; **: significant at 5%; *: significant at 10%. Source: Processed data.

For developed countries, the long-run results reveal a striking pattern. GDP per capita has a significantly negative effect on emissions (-1.232, $p < 0.05$), confirming the EKC hypothesis: high-income developed countries have crossed the turning point, and further economic growth is now associated with lower emissions. This likely reflects a combination of structural shifts toward service-based economies, stringent environmental regulations, and adoption of clean technologies. The magnitude implies that a 1% increase in GDP per capita in developed G20 countries is associated with a 1.23% reduction in CO₂ emissions in the long run, a substantial decoupling effect. REC also shows a significant negative long-run effect (-0.028, $p < 0.01$), confirming that renewable energy expansion is a key driver of decarbonization in developed economies. Solar energy and FDI exhibit marginally significant negative effects at the 10% level in the

long run (-0.037 and -0.023, respectively). The negative FDI coefficient supports the Pollution Halo Hypothesis: in developed countries with strong environmental governance, FDI brings clean technologies and improves environmental quality. The negative solar energy coefficient indicates that the solar share has reached sufficient scale to affect aggregate emissions. In the short run, GDP per capita is positive and significant (1.279, $p < 0.01$), reflecting temporary emission spikes from cyclical demand when the economy expands rapidly, energy use rises before efficiency gains and structural shifts can adjust. Solar energy shows a negative and marginally significant short-run effect (-0.003, $p < 0.10$), suggesting that even in the short term, increased solar generation can displace fossil fuels. The ECM coefficient (-0.238, $p < 0.01$) confirms stable long-run convergence, with about 24% of short-run imbalances corrected each period.

Table 5. ARDL-MG Results – Developing G20 Countries

Variable	Long Run			Short Run		
	Coef.	t-stat	Prob.	Coef.	t-stat	Prob.
GDP per Capita	0.315	1.07	0.286	0.298	2.29**	0.022
Eco-Innovation	0.154	2.11**	0.035	-0.005	-2.47**	0.014
Solar Energy	-0.143	-0.08	0.939	1.766	0.92	0.355
FDI	-0.068	-1.52	0.127	0.015	1.08	0.281
REC	-0.012	-1.53	0.126	-0.004	-0.62	0.538
ECM	-	-	-	-0.047	-6.11***	0.000

Notes: ***: significant at 1%; **: significant at 5%; *: significant at 10%. Source: Processed data.

For developing countries, the long-run results show a contrasting picture. GDP per capita is positive but not significant, indicating that long-run decoupling has not yet occurred. Eco-innovation has a positive and significant long-run effect on emissions (0.154, $p < 0.05$), suggesting that in early-stage development, innovation activities are tied to industrial expansion rather than clean substitution. This is consistent with the idea that developing countries may initially adopt technologies that are not necessarily the cleanest, and that innovation follows industrial growth rather than preceding it. No other variables are significant in the long run, reflecting the dominance of fossil energy dependency and the limited scale of renewable penetration. The negative but insignificant REC coefficient suggests that renewable energy has not yet reached a threshold where it can significantly displace fossil fuels in developing countries (Chen et al., 2022). In the short run, GDP per capita is positively significant (0.298, $p < 0.05$), confirming that short-term growth spurts directly increase fossil fuel consumption. Eco-innovation shows a significant negative short-run effect (-0.005, $p < 0.05$), suggesting that while long-run structural transformation has not materialized, some near-term adoption of cleaner technologies is already reducing emissions at the margin. The ECM coefficient (-0.047, $p < 0.01$) indicates that adjustment toward long-run equilibrium, while significant, is slower than in developed countries, reflecting weaker institutional capacity for correction.

Third-Order Multivariate Polynomial Regression**Table 6.** Third-Order Polynomial Regression – G20 Countries

Independent Variable	Coefficient	t-stat	Prob.
GDP per Capita			
Log GDP per Capita	0.432	7.83	0.000
Log GDP per Capita ²	0.030	0.57	0.578
Log GDP per Capita ³	0.019	1.35	0.193
Eco-Innovation			
Log Eco-Innovation	0.084	4.74	0.000
Log Eco-Innovation ²	-0.000	-0.02	0.987
Log Eco-Innovation ³	-0.002	-2.55	0.020
Solar Energy			
Log Solar Energy	-0.000	-0.00	0.996
Log Solar Energy ²	-0.000	-0.74	0.471
Log Solar Energy ³	0.000	0.13	0.894
FDI			
Log FDI	0.004	0.75	0.463
Log FDI ²	-0.000	-0.32	0.753
Log FDI ³	-0.000	-1.19	0.248
REC			
REC	-0.026	-8.83	0.000
REC ²	0.000	3.80	0.001
REC ³	-0.000	-3.35	0.004

Source: Processed data.

For GDP per capita, only the linear coefficient is positive and significant (0.432, $p < 0.01$), while the quadratic and cubic terms are not significant. This indicates a monotonically increasing relationship: across the full G20, emissions rise continuously with income, with no evidence of an EKC turning point. This aggregate result masks the developmental divergence revealed by the ARDL analysis: developed countries have turned the corner, but developing countries continue to drive the overall upward trend. For eco-innovation, the linear term is positive and significant (0.084, $p < 0.01$), while the cubic term is negative and significant (-0.002 , $p < 0.05$). This forms an inverted-U pattern: at low levels of innovation, increases in patenting activity are associated with higher emissions (likely due to industrial expansion and R&D energy intensity), but at high levels of innovation, the cumulative effect of green technologies reduces emissions. This pattern is consistent with the "technique effect" in the EKC: early innovation targets production expansion, while later innovation focuses on efficiency and emission reduction.

Solar energy coefficients are statistically insignificant, reflecting solar's still-small aggregate contribution to G20 energy mixes. While solar is growing rapidly, it remains a small fraction of total energy consumption in most G20 countries, and its emission-reducing effect is not yet detectable at the aggregate level. FDI coefficients are also

insignificant across all polynomial orders, reinforcing the panel regression result that the offsetting nature of heterogeneous investment flows (clean vs. pollution-intensive) cancels out at the aggregate level. For REC, the linear coefficient is negative and significant (-0.026 , $p < 0.01$), the quadratic is positive and significant (0.000 , $p < 0.01$), and the cubic is negative and significant (-0.000 , $p < 0.01$). This forms an inverted-N-shaped pattern. Renewable energy initially lowers emissions (first phase). At moderate adoption levels (second phase), emissions may temporarily increase, possibly because the energy-intensive infrastructure required for renewable expansion (e.g., manufacturing solar panels, building wind farms) is itself carbon-intensive. At high adoption levels (third phase), after infrastructure is in place, renewable energy produces deep and sustained emission reductions. This pattern suggests that the transition to renewable energy is not linear but follows a three-stage process.

For developed countries, polynomial regression indicates that GDP per capita forms a U-shaped pattern (significant negative linear, positive quadratic), suggesting an initial decline in emissions at moderate income followed by a rebound at very high income consistent with the saturation of efficiency gains and the rebound effect. FDI shows a monotonically increasing pattern with all positive polynomial terms, reflecting that even in developed countries, scale effects from investment-driven production expansion can increase emissions. REC forms a U-shape: emissions fall up to moderate renewable use, then rise at very high adoption due to system-wide energy demand growth (the rebound effect). For developing countries, all GDP per capita polynomial terms are positive and significant, confirming a monotonically increasing relationship: developing economies have not reached the EKC turning point. Eco-innovation follows an inverted-U pattern with a significant negative cubic term: initial innovation raises emissions, but sufficiently high innovation intensity begins to reduce them. Solar energy remains insignificant throughout, reflecting nascent adoption. FDI shows a U-shaped pattern with a significant positive cubic term, indicating that at very large scales, FDI ultimately increases emissions consistent with the Pollution Haven Hypothesis. REC has a significant negative linear effect, with no significant non-linear components, confirming a simple and direct emission-reduction role for renewable energy in this country group.

CONCLUSION AND RECOMMENDATIONS

This study analyzed the effects of real GDP per capita, eco-innovation, solar energy, FDI, and REC on CO₂ emissions across 19 G20 member countries from 2000 to 2022, using panel data regression, ARDL-PMG/MG, and third-order polynomial regression. Several key conclusions emerge. First, aggregate G20 panel results confirm that GDP per capita, eco-innovation, and solar energy are positively associated with emissions in the static short-run panel. At the same time, REC consistently and significantly reduces emissions across all country groupings. FDI shows no statistically significant aggregate effect, reflecting the offsetting nature of diverse investment flows. Second, ARDL dynamic analysis reveals a critical divergence across development groups. For developed G20 countries, GDP per capita exerts a significant negative long-run effect on emissions, confirming EKC validity: high-income economies have transitioned to growth that improves environmental quality. REC, solar energy, and FDI also show significant negative long-run associations with emissions in this group.

In contrast, developing G20 countries show only short-run positive GDP-emission linkages, reflecting continued fossil fuel dependency. At the same time, eco-innovation

paradoxically increases long-run emissions due to innovation-driven industrial expansion at early development stages. Third, polynomial regression reveals non-linear heterogeneity at multiple levels. At the aggregate G20 level, eco-innovation follows an inverted-U pattern (eventually reducing emissions at high levels), while REC follows an inverted-N pattern. For developed countries, GDP per capita and REC follow a U-shape, consistent with rebound effects at high-income and high renewable-adoption levels. For developing countries, GDP per capita increases monotonically, eco-innovation follows an inverted-U, and FDI follows a U-shape, confirming Pollution Haven dynamics for large-scale investment flows.

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