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The Impact of Militarisation on Environmental Degradation in the E7 Countries: Panel CS-ARDL Approach

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ABSTRACT

This paper, within the framework of the Environmental Kuznets Curve (EKC), investigates the impact of militarisation on environmental degradation, including the role of renewable energy. Military expenditure and burden are used as proxies for militarisation, and models are estimated to quantify their relationship with carbon dioxide (CO_2) emissions. The study utilizes the CS-ARDL approach to analyse data from Brazil, China, India, Indonesia, Mexico, Russia, and Turkey collectively known as the E7 nations from 1992 to 2022. The method employs both fixed-effect and random-effect models, taking into account short-run and long-run coefficients while accounting for cross-sectional dependencies and heterogeneities. The study puts forward four hypotheses for investigation, and a notable finding is that military expenditure, contradicting prevalent sustainability assumptions, has a substantial impact on the reduction of CO_2 emissions over both short and long-run periods. This suggests that within the E7 context, militarisation may paradoxically function as a catalyst for environmental conservation rather than a detrimental impact. The findings further corroborate the inverted U-shaped EKC hypothesis by demonstrating that while economic growth initially increases emission levels, these levels begin to decline once a certain income threshold is reached. The study also underscores the long-run benefits of renewable energy in reducing CO_2 emissions and advocates for investment in green energy projects, complemented by implementing viable environmental policies. These insights offer actionable guidance for policymakers seeking to harmonize economic development with environmental protection and sustainability objectives.

Keywords: E7 Countries, Militarisation, Military Expenditure, Environmental Degradation, EKC, Renewable Energy, Panel CS-ARDL
JEL Classifications: O50, S52, H56, P48, R11, Q51, C23

1. INTRODUCTION

The interaction between economic growth and environmental conservation is a pivotal issue, given that production processes depend on limited resources and generate waste, thereby intensifying ecological crises (Jorgenson et al., 2012, p. 316; Junejo et al., 2023). In order to stimulate growth, states employ a variety of strategies, including trade agreements and industrial expansion. However, these strategies frequently conflict with sustainability objectives. The urgency for harmonising economic and environmental priorities is highlighted by climate change, which is driven significantly by CO_2 emissions. Among these challenges, militarisation emerges as a paradoxical contributor to ecological degradation, with the potential to both exacerbate and mitigate environmental harm through innovation spillovers.

Military activities have been shown to exert a detrimental effect on ecosystems, both directly and indirectly, through a variety of mechanisms including, but not limited to, fossil fuel consumption, nuclear testing, armed conflicts, and large-scale infrastructure

(Clark and Jorgenson, 2012, p. 57; Ullah et al., 2021, pp. 94-95). In addition to the impact of warfare, the presence of the military in peacetime also perpetuates environmental harm through resource-intensive operations, weapons testing, and global troop deployments. The seminal work of Schnaiberg (1980) pioneered the concept of the "treadmill of production," which established a nexus between capitalist expansion and environmental exploitation (Devall, 1980, p. 162). Building on this foundation, Hooks and Smith (2004, 2005) advanced the "treadmill of destruction" theory, asserting that militarisation functions as an autonomous process driven by state power objectives rather than solely economic factors. Their work highlights how military institutions prioritise geopolitical influence over emissions reduction, perpetuating reliance on fossil fuels (Jorgenson and Clark, 2016, p. 507; Givens, 2014, p. 13; Brauer, 2002; Kennedy, 2023).

However, emerging research suggests that the environmental impact of militarisation is not monolithic but rather has dual implications. Technological innovation within military systems, including the adoption of renewable energy sources and the implementation of energy-efficient infrastructure, has the potential to mitigate environmental damage (Erdogan et al., 2022, pp. 31612-31613; Uddin et al., 2024, p. 3; Zhu et al., 2023; Uddin et al., 2022). For instance, investments in digital infrastructure and clean energy have been shown to reduce CO_2 emissions while enhancing operational efficiency (Özcan and Apergis, 2018; Atlason and Gerstlberger, 2017, p. 231). This paradox underscores the need to reevaluate militarisation's role in sustainability transitions.

Despite the ongoing global discourse on climate security, the reciprocal effects of militarisation particularly military expenditures and conflicts on environmental degradation remain underexplored (IEA, 2021; Jamil and Wahyuni, 2025; CCPI, 2024). This gap is critical for the E7 (Emerging 7) nations (Brazil, China, India, Indonesia, Mexico, Russia, and Turkey), which collectively account for over 40% of global CO_2 emissions. These economies face dual pressures: the need to balance growth with sustainability and the challenge of navigating the environmental costs of militarisation in the context of rising carbon pricing policies, which are projected to reach \$200 per tonne by 2050 in E7 sectors (IEA, 2021; Eurosatory, 2024).

This study, which covers the E7 countries (1992-2022) and is based on the EKC and militarisation frameworks, tests four hypotheses that address the dual role of militarisation, the EKC validity, renewable energy efficiency, and military burden efficiency. In doing so, the study addresses cross-sectional dependence and heterogeneity when analysing military expenditures and burdens as separate indicators using panel CS-ARDL techniques.

The present study makes three contributions to the existing literature on militarisation and environmental research. Firstly, it introduces novel methodological rigor in the form of advanced econometric models, which resolve data limitations and account for structural breaks and non-linear dynamics. Secondly, it employs indicator disaggregation to reveal nuanced insights by separating military expenditure and burden, demonstrating the superior efficacy of burden in emission mitigation. Thirdly, it demonstrates policy relevance by providing practical recommendations for E7 countries to align their defense priorities with sustainability and to standardise green defense integration (e.g., renewable energy military bases) and decarbonisation practices. The findings include strategies for E7 countries to align their defense priorities with sustainability and to standardise green defense integration (e.g., renewable energy military bases) and decarbonisation practices. By linking militarisation and environmental sociology, this research aims to provide a framework for reconciling national security with ecological protection and advancing discussions on sustainable development in an era of climate uncertainty.

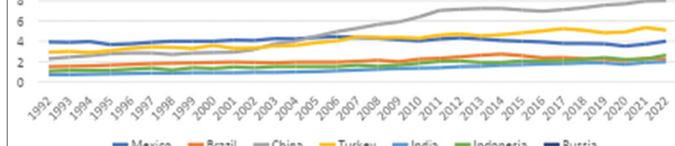
2. THE RELATIONSHIP BETWEEN MILITARIZATION AND THE ENVIRONMENT IN THE E7 COUNTRIES

The term "E7" introduced by economists John Hawksworth and Gordon Cookson in 2006, refers to seven major developing economies Brazil, Russia, India, China, Mexico, Indonesia, and Turkey with significant growth potential compared to advanced economies (Hawksworth and Cookson, 2006; Weir, 2024). Though not a formal alliance, the E7's collective GDP, which was half that of the G7 in the 1990s, is projected to double the G7's output by 2040 due to sustained higher growth rates over the past two decades (PwC, 2017). Environmentally, the E7 plays a pivotal role in global climate dynamics. In 2022, their CO_2 intensity measured as emissions per unit of GDP was 312 units, 30% higher than the global average of 240 units, reflecting their heavy reliance on carbon-intensive industries (IEA, 2023). While per capita emissions in E7 nations remain near the global average, these countries face disproportionate impacts from climate change, including extreme weather events and agricultural disruptions. Additionally, they are the world's largest net importers of carbon emissions (Global Carbon Project, 2022), underscoring their responsibility and influence in global sustainability efforts through supply chain and energy policy reforms.

2.1. CO_2 Emissions and Economic Structures

As depicted in Figure 1, per capita CO_2 emissions in the E7 countries have followed divergent trajectories since 1992. Russia's emissions remain the highest, driven by its fossil fuel dependent energy system, where renewables account for less than 5% of its energy mix (IEA, 2024; UN, 2024). China and India, despite lower per capita emissions, contribute significantly to global totals due to their large populations and carbon-intensive industrialization

Figure 1: CO_2 Emissions per Capita in E7 Countries (1992-2022)



Source: (Authors' calculations using data from Our World in Data)

(Wolde-Rufael and Idowu, 2017). These trends align with the EKC hypothesis, where early industrialization phases exacerbate emissions, but subsequent technological adoption may reverse this trend a relationship tested in this study.

The per capita emissions of carbon dioxide (CO_2) related to energy are significantly influenced by the economic structure and energy systems of a nation. Countries that are reliant on carbon-intensive industries, such as the production of electricity from fossil fuels and steel production, or transportation, including personal vehicles and aviation, demonstrate higher per capita emissions (IEA, 2024). Among the E7 nations, Russia has the highest per capita CO_2 emissions, driven by the fact that fossil fuels constitute over 95% of its energy mix (IEA, 2024; USAFacts, 2024). As a top global producer of oil, gas, and coal, Russia's plans to expand fossil fuel production by 2030 starkly conflict with the goals of the Paris Agreement (IEA, 2024; World Bank, 2023). In contrast, populous economies like China and India face rising emissions due to unsustainable consumption patterns. Wolde-Rufael and Idowu (2017) attribute this to rapid urbanisation and consumerism, which intensify resource overuse and ecological strain.

2.2. Military Expenditure Trends

As demonstrated in Figure 2, there is a marked difference in E7 defence spending from 1992 to 2022: China is the most significant player, with military expenditures rising from 1% to 14% of global totals (1990-2018), peaking in 2022. This is indicative of ambitions to secure global resources and geopolitical dominance (Kartal, 2023; SIPRI, 2023a; Wezeman, 2024). In contrast, Russia has prioritised defence spending amid regional tensions, with volatile spending peaks during the 2010s and the aftermath of the Ukraine crisis in 2014. India, in third position, has doubled its investments since 2010 to boost domestic arms production and reduce import dependency (Behera, 2024). Turkey, Brazil, Mexico and Indonesia have demonstrated stable and lower spending, reflecting divergent strategic priorities (Behera, 2024).

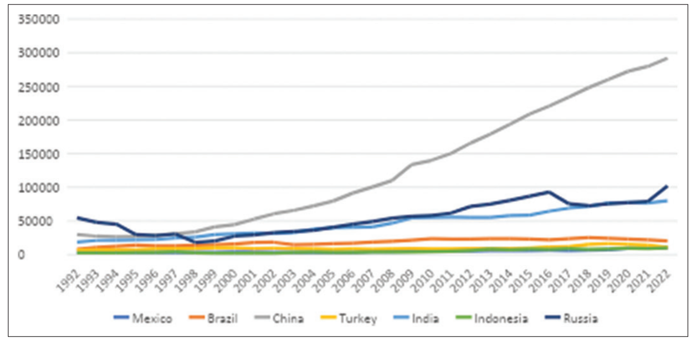
2.3. Military Burden Dynamics

As demonstrated in Figure 3, a clear discrepancy exists between the levels of absolute spending and the economic priorities of the respective nations. The military expenditure of China, for instance, remains relatively low (1.7% of GDP in 2022), due to the country's expansive economy. However, Russia's military expenditure increased significantly to 4.1% in the post-2014 period, resulting in a diversion of funds from social services to defence (Luzin and Prokopenko, 2023; SIPRI, 2023b; ART, 2024). India and Turkey maintain moderate burdens (2.4% and 2.6%, respectively), balancing modernisation with economic goals. Brazil, Mexico, and Indonesia prioritise non-defence sectors, with burdens below 1.5%.

3. LITERATURE REVIEW

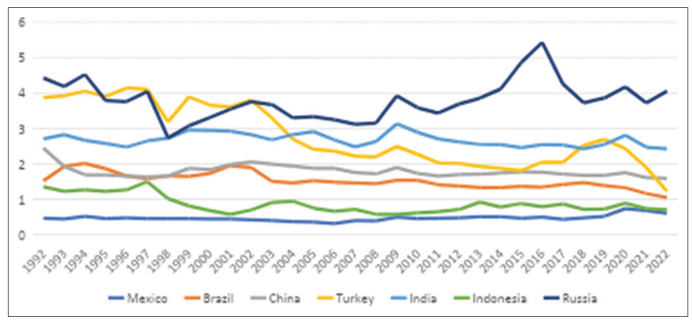
The EKC hypothesis has been a foundational concept in environmental economics, suggesting an inverted U-shaped relationship between environmental quality and income levels. Despite extensive research, scholars have yet to reach a consensus on its validity. Various indicators have been used to test the EKC hypothesis, with renewable energy consumption being among

Figure 2: Military expenditures (2022, Constant Prices $)



Source: (The authors created this dataset using data from the 2023, SIPRI database)

Figure 3: Military burden (Military Expenditure/GDP) in E7 Countries



Source: (Authors' calculations using 2023, SIPRI data)

the most common. While it is widely accepted that increased renewable energy use reduces environmental degradation, recent empirical studies have begun to challenge this assumption.

In addition to traditional indicators, military expenditure has become an increasingly significant variable in environmental studies, serving as a reliable measure of militarization. Military burden defined as military expenditure as a percentage of GDP has also gained prominence. Some studies have gone further, linking climate change and its associated environmental degradation to national security concerns, suggesting that technological advancements in the military sector might yield positive environmental outcomes.

Understanding the relationship between CO_2 emissions and militarisation is therefore crucial. Examining this interplay allows researchers to uncover underlying dynamics and generate empirical evidence that informs policy development, helping to balance environmental sustainability with national defence priorities.

3.1. CO_2 Emissions and Economic Growth

The EKC, as proposed by Grossman and Krueger (1991), hypothesises an inverted U-shaped relationship between income and environmental degradation. Empirical validations of the EKC vary across different contexts: Shahbaz et al. (2013) and Apergis and Ozturk (2015) validate the EKC in Romania and 14 Asian countries, respectively, while Dinçer et al. (2023), Ahmad et al. (2020) and Hao and Chen (2023) extend its applicability to the

E7 economies. However, critiques highlight methodological and contextual limitations. Murshed et al. (2021) advocate for the use of ecological footprint metrics over CO_2 emissions in South Asia, while Dong et al. (2020) limit the validity of the EKC to high- and upper-middle-income nations. The EU has yielded equivocal results; Ketenci (2021) validates the EKC in five EU-15 countries via DOLS, while Frodyma et al. (2022) report inconclusive findings for the EU28, emphasising regional heterogeneity.

3.2. CO_2 Emissions and Renewable Energy Consumption

The role of renewable energy in reducing emissions remains a subject of debate. Researchers have utilised both traditional and nonlinear panel data approaches to investigate this dynamic. A number of studies have been conducted on this issue, including those by Namahoro et al. (2021), which examined 50 African countries, and Cheng et al. (2019), which focused on BRICS economies. These studies indicated a negative correlation between renewable energy use and emissions, particularly when the consumption levels exceeded certain thresholds (Chen et al., 2022; Adebayo et al., 2023). However, Jebli and Youssef (2017) identify a paradoxical positive association in North Africa, attributed to outdated infrastructure and fossil fuel lock-ins. These disparities align with Dong et al.'s (2020) emphasis on developmental stages, suggesting decarbonisation efficacy depends on economic maturity and sectoral focus.

3.3. CO_2 Emissions and Militarization

The environmental impact of militarisation is indicative of methodological and contextual disparities. As asserted by Bildirici (2017) and Gökmenoğlu et al. (2021), there is a correlation between military expenditures and increased emissions, thereby reinforcing the "treadmill of destruction" hypothesis. Conversely, the findings of Konuk et al. (2023) report negative correlations in G7 nations, thereby suggesting the presence of innovation spillovers (e.g., energy-efficient military technologies). Regional studies, such as Erdogan et al. (2022) in Mediterranean Europe and Çolak et al. (2022) in NATO countries, highlight systemic harm from fossil-intensive practices. The methodological choices employed in these studies, such as the selection of metrics (e.g., $CO_{2\text{ vs.}}$ ecological footprint) or the measurement scope (e.g., payload vs. per capita spending), reflect the ongoing debates in the EKC literature (Murshed et al., 2021; Solarin et al., 2018; Kwakwa, 2022; Ullah et al., 2021).

3.4. Literature Review

The existing literature emphasises three interlinked drivers of emissions:

1. Economic Growth: The validity of the EKC depends on balancing industrialisation and sustainability depending on the stages of development (Dong et al., 2020)
2. Renewable Energy: Threshold effects (Chen et al., 2022) and infrastructure readiness determine the effectiveness of decarbonisation
3. Militarisation: Although fossil-intensive practices are dominant, innovation potential exists (Erdogan et al., 2022).

Methodological differences, such as variable selection (CO_2 and Ecological Footprint) and regional heterogeneity, explain the conflicting results. For example, the paradoxical results of Jebli and Youssef (2017) in North Africa may conflict with the global thresholds of Chen et al. (2022). Furthermore, Konuk et al. (2023) find negative correlations for militarisation.

4. HYPOTHESIS DEVELOPMENT, DATA AND MODEL

EKC posits that economic growth initially exacerbates environmental degradation but eventually promotes sustainability as nations prioritise cleaner technologies and regulatory frameworks (Grossman and Krueger, 1991). At the same time, the environmental impact of militarisation is theorised through the "treadmill of destruction" (Hooks and Smith, 2004), where defence activities accelerate resource exploitation. However, emerging evidence suggests that militarisation can also drive technological innovation that reduces emissions (Erdogan et al., 2022). Building on these frameworks, we propose:

4.1. H_1 (Militarisation-emissions Paradox Hypothesis)

Military expenditure and military burden are inversely correlated with CO_2 emissions due to technological spillovers (e.g., energy-efficient innovations in the defence sector).

4.2. H_2 (EKC Validation Hypothesis)

Economic growth in E7 countries has an inverted U-shaped relationship with CO_2 emissions, where emissions initially rise but decline after a certain income threshold is reached.

4.3. H_3 (Renewable Energy Mitigation Hypothesis)

Renewable energy consumption significantly reduces CO_2 emissions, offsetting carbon-intensive industrialisation in the E7 economies.

4.4. H_4 (Military Burden Efficacy Hypothesis)

Military burden (as % of GDP) has a stronger mitigating effect on CO_2 emissions than absolute military expenditure, reflecting efficiency gains in defence planning.

This study analyzes the impact of militarization (via military expenditures and burden) on CO_2 emissions in E7 countries (1992–2022) within the EKC framework, incorporating renewable energy consumption. Two panel models are estimated:

$$\text{Model 1: } \ln(CO2_{it})=\beta_0+\beta_1\ln(ME_{it})+\beta_2\ln(PCGDP_{it})+\beta_3\ln(PCGDPS_{it})^2+\beta_4\ln(REN_{it})+\varepsilon_{it} \quad (1)$$

$$\text{Model 2: } \ln(CO2_{it})=\beta_0+\beta_1\ln(MB_{it})+\beta_2\ln(PCGDP_{it})+\beta_3\ln(PCGDPS_{it})^2+\beta_4\ln(REN_{it})+\varepsilon_{it} \quad (2)$$

In the equations presented above, the variable i: represents countries, t: denotes periods, : refers to coefficients, and the parent represents the error term.

The models incorporate the following variables: $lnco_2$: CO_2 emissions (per capita, measured in metric tonnes), *lnme*: Military expenditures (expressed in 2022 constant prices, \$),: *lnmb*: Military burden (share of military spending as a percentage of GDP), *lnpcgdp*: GDP per capita (2015 constant prices, \$), *lnpcgpds*: The square of GDP per capita (to capture nonlinear effects), : Renewable energy consumption (per capita, measured in kWh).

The data for CO_2 emissions and renewable energy consumption were obtained from the Our World in Data database. GDP per capita figures were sourced from the World Bank's World Development Indicators database, while military expenditures and payload data were retrieved from the 2023, SIPRI database. To ensure linearity and enhance the interpretability of the coefficients, all variables were log-transformed prior to their inclusion in the models. The descriptive statistics for these variables are summarised in Table 1.

Table 1 summarizes the dataset (N = 217). Key observations include:

- CO_2 emissions (mean = 1.16) exhibit moderate variability (SD = 0.74)
- Military burden ranges widely (−1.17-1.69), reflecting divergent E7 priorities.

5. RESULTS

5.1. Cross-Sectionally Dependence and Homogeneity Test

First-generation panel data methods assume (1) no cross-sectional dependence (CSD) and (2) slope homogeneity. Violations of these assumptions yield biased estimates. We address this using two preliminary tests (Pesaran & Yamagata, 2008):

5.1.1. Cross-sectional dependence test

The Breusch-Pagan LM test (Breusch and Pagan, 1980), augmented by Pesaran (2004), evaluates CSD via pairwise residual correlations:

$$CD_{LM} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2$$

Where $\hat{\rho}_{ij}^2$: represents the squared correlation coefficient of the residuals. The null and alternative hypotheses of the test statistic are as follows(Chudik et al., 2015):

H_0:*cov*($u_{it}u_{jt}$) = *0 for all t* (*No cross-sectional dependence*)
H_1:*cov*(u_{it} u_{jt}) ≠ *0 for at least one pair of i≠j* (*Cross-sectional dependence exists*)

Results (Table 2): All variables and the full model reject H_0 at 1% significance (P = 0.000), confirming CSD.

5.1.2. The Swamy test (Swamy, 1970) assesses slope homogeneity

$$\hat{S} = \sum_{i=1}^{N}(\hat{\beta}_i - \hat{\beta}_{WFE})'\frac{X'_i M_\tau X_i}{\hat{\sigma}_i^2}(\hat{\beta}_i - \hat{\beta}_{WFE})$$

In the equation above; $\hat{\beta}_i$: heterogeneous coefficient for each cross-section, $\hat{\beta}_{WFE}$: is the weighted coefficient of the fixed effects estimator. The null and alternative hypotheses for the homogeneity test are as follows:

H_0: *β_i=β for all i,* (*Slope coefficients are homogeneous*)
H_1:*β_i≠β_j for a non-zero fraction of pairwise slopes for i≠j* (*Slope coefficients are heterogeneous*)

Results (Table 3): H_0 is rejected for both models (P = 0.000), confirming slope heterogeneity.

5.2. Unit Root Test

Given detected cross-sectional dependence and slope heterogeneity, this study employs the second-generation CIPS test (Pesaran, 2007; Ahmad et al., 2020) to assess stationarity. The CIPS statistic is computed as:

$$CIPS\left(N,T\right) = t-bar = N^{-1}\sum_{i=1}^{N}t_i(N,T)$$

Where t_i denotes the individual CADF statistic for cross-section *i*.
Hypotheses:

- H_0: Unit root exists (non-stationary).
- H_1: Stationarity.

Results (Table 4): All variables are non-stationary at levels but achieve stationarity at first differences (1% significance), justifying cointegration analysis.

5.3. Cointegration Test

To identify long-run equilibrium relationships, we apply the Westerlund (2007) ECM cointegration test, which accommodates cross-sectional dependence and slope heterogeneity. The test comprises four statistics:

- Group statistics (*Gt*, *Ga*): Assess cointegration in at least one cross-section.
- Panel statistics (*Pt*, *Pa*): Evaluate cointegration across the entire panel.

$$G_t = \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \text{ and } G_a = \frac{1}{N}\sum_{i=1}^{N}\frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)}$$

Table 1: Descriptive statistics

Variables	Number of observations	Mean	Standard deviation	Minimum	Maximum
lnco2	217	1.1614	0.7437385	0.3254577	2.58191
Inme	217	9.820119	1.202783	7.654763	12.58437
lnmb	217	0.47573	0.7059793	−1.16741	1.691045
lnpcgdp	217	8.442938	0.833818	6.303426	9.550741
lnpcgdps	217	71.97525	13.47449	39.73318	91.21665
lnren	217	7.143508	1.154437	4.808922	9.039678

Where G_t is the group test statistic based on individual error correction terms, G_a is the aggregate panel test statistic that combines information across all units, $\hat{\alpha}_i$ represents the estimated error correction term for each cross-sectional unit, $SE(\hat{\alpha}_i)$ is the standard error of the estimated error correction term, and T denotes the time dimension of the panel data. These test statistics enable the evaluation of integration by considering both group-specific and panel-wide relationships, providing robust insights into the long-run equilibrium dynamics of the series.

Hypotheses of group test statistics:

H_0: $\alpha_i = 0$ *for all i's* (*No cointegration*)

H_1: $\alpha_i < 0$ *for at least one i* (*Cointegration exists*)

$$P_\tau = \frac{\hat{\alpha}}{SE(\hat{\alpha})} \text{ and } P_\alpha = T\hat{\alpha}$$

Hypotheses of panel test statistics:

H_0: $\alpha_i = 0$ *for all i's* (*No cointegration*)

H_1: $\alpha_i = \alpha < 0$ *for at least one i* (*Cointegration exists*)

Results (Table 5):

- Panel statistics (Pt, Pa) reject H0 at 1-5% significance for both models, confirming cointegration
- Group statistics (Gt, Ga) further support this, although panel statistics are preferred due to slope heterogeneity (Yerdelen Tatoğlu, 2018).

5.4. Panel CS-ARDL Method

The Cross-Sectionally Augmented ARDL (CS-ARDL) method (Chudik and Pesaran, 2015; Brooks, 2019) addresses endogeneity, slope heterogeneity, and cross-sectional dependence, overcoming limitations of PMG/FMOLS. The model is robust to integration order (I(0)/I(1)) and estimates short- and long-run coefficients via:

Table 2: Cross-sectional dependence test

Tests	CD_{LM}	Probability value
lnco2	283.0267***	0.000
Inme	412.8602***	0.000
lnmb	92.89221***	0.000
lnpcgdp	523.4997***	0.000
lnpcgdps	522.4872***	0.000
lnren	339.4766***	0.000
Model	136.261***	0.000

*** indicates a 1% significance level

Table 3: Slope homogeneity test

Tests	Test statistic	Probability value
Model 1	22999.16***	0.000
Model 2	13872.86***	0.000

*** indicates a 1% significance level

Table 4: CIPS unit root test results

Variables	Level	Difference
lnco2	−2.179	−4.676***
Inme	−1.466	−4.163***
lnmb	−2.098	−4.540***
lnpcgdp	−2.026	−3.671***
lnpcgdps	−2.149	−3.648***
lnren	−2.038	−5.963***

*** indicates a 1% significance level.

Table 5: Westerlund cointegration test results

Tests	Model 1		Model 2	
	Test statistics	Bootstrap probability value	test Statistics	Bootstrap probability value
G_t	−2.651**	0.040	−2.552***	0.000
G_a	−11.038**	0.030	−10.757***	0.000
P_t	−6.569**	0.050	−6.209***	0.000
P_a	−12.429***	0.010	−11.468***	0.000

***** denote 1% and 5% significance levels, respectively

Table 6: Panel CS-ARDL short- and long-run estimates

Variables	Model 1		Model 2	
	Coefficient	Probability value	Coefficient	Probability value
Short run results				
ECT_{-1}	−0.6622***	0.000	−0.6654***	0.000
Δlnme	−0.0934**	0.036		
Δlnmb			−0.1031***	0.004
Δlnpcgdp	0.7729***	0.000	0.7011***	0.000
Δlnpcgdps	−0.0154***	0.002	−0.0151***	0.001
Δnren	−0.1103**	0.040	−0.1073**	0.033
Long run results				
Inme	−0.1588**	0.018		0.001
lnmb			−0.1791***	0.000
lnpcgdp	1.4043***	0.000	1.3120***	0.000
lnpcgdps	−0.0331***	0.005	−0.0329***	0.008
lnren	−0.1379**	0.030	−0.1408**	0.020
F Statistics	4.80***		4.85***	
CD test	0.94		1.28	
R^2	0.40		0.40	

$$y_{it} = c_{yi}^{*} + \sum_{\tilde{n}=1}^{p_y} \varphi_{i\ell} y_{i,t-\ell} + \sum_{\ell=0}^{p_x} \beta_{i\ell}^{'} x_{i,t-\ell} + \sum_{\ell=0}^{p_{\bar{z}}} \psi_{i\ell}^{'} \bar{z}_{t-\ell} + e_{it}^{*}$$

In the equation above, $\bar{z}_t = \left(\bar{y}_t, \bar{x}_t^{'}\right)^{'}$, $p_{\bar{z}} = \left[T^{1/3}\right]$ are the lagged values of the cross-sectional averages, and φ_{il} and $\beta_{i\ell}^{'}$ are the short-run coefficient estimates.

Furthermore, the terms $\hat{\varphi}_{i\ell}$ and $\hat{\beta}_{i\ell}$ illustrate the short-run coefficient estimates. The CS-ARDL estimation values for the unit average coefficient and the long-run coefficients of the Mean Group estimator are calculated using the following formulas:

$$\hat{\theta}_{CS-ARDL,i} = \frac{\sum_{\ell=0}^{p_x} \hat{\beta}_{i\ell}}{1 - \sum_{\ell=1}^{p_y} \hat{\varphi}_{i\ell}} \text{ and } \hat{\theta}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\theta}_i$$

In the aforementioned equations, $\hat{\beta}_{i\ell}$ and $\hat{\varphi}_{i\ell}$ represent the estimated short-run coefficient values, whereas $\hat{\theta}_i$ depicts the estimated long-run coefficient values.

Results (Table 6):

1. Error Correction: ECT_{-1} is significant (−0.66, P = 0.000), indicating 66% short-run disequilibrium correction
2. Militarization-Emissions Nexus:
   - Military expenditure reduces CO_2 by 9% (short-run-SR) and 15.8% (long run-LR)
   - Military burden amplifies reductions to 17.9% (LR), validating its policy efficacy
3. EKC Validation: Inverted U-shaped GDP-CO_2 relationship (β_{GDP}=1.40, $\beta_{GDP}{}^{2}$=−0.03)
4. Renewables: A 1% increase in renewable energy reduces emissions by 11% (SR) and 14% (LR**)**.

6. CONCLUSION

The EKC hypothesis, which posits an inverted U-shaped relationship between income and environmental degradation, remains central to debates on sustainable development. This study examines its validity for the E7 economies (1992-2022), while exploring the dual role of militarisation as both a driver and a mitigator of carbon emissions.

The main findings of the study are as follows:

- Militarisation-emissions nexus: Military expenditure reduces CO_2 emissions by 9% (short-run) and 15.8% (long-run), while military burden (expenditure to GDP ratio) amplifies the reduction to 17.9%. This is consistent with the expenditure-tax hypothesis (H_1) and underlines the effectiveness of strategic prioritisation of defence budgets (H_4). These findings contrast with previous studies linking militarisation to resource depletion (Jorgenson et al., 2019) but support claims of technological spillovers that improve energy efficiency (Solarin et al., 2018)
- EKC validation: A confirmed inverted U-shaped relationship (β_1 = 1.40, β_2 = -0.03) validates the EKC hypothesis (H_2). Early stages of industrialisation intensify emissions, but maturity promotes cleaner technologies, as evidenced by China's and India's investments in renewables, which reduce per capita emissions by 11-14% (IEA, 2023)
- The role of renewables: Consistent with hypothesis H_3, the adoption of renewable energy significantly reduces emissions, especially above consumption thresholds (Chen et al., 2022)

To capitalise on these findings, policymakers can:

- Integrate renewable energy into defence operations, such as solar-powered bases (DoD, 2022), and mandate carbon audits for military contracts
- E7 countries could standardise their green practices and climate strategies. The budgets they allocate to this issue can be aligned with the Paris Agreement targets
- R&D incentives and fossil fuel subsidies could be redirected towards energy-efficient military technologies (e.g., AI-driven logistics).

Future research should expand metrics beyond CO_2 to include methane and ecological footprints, while disaggregating renewable energy sources by type (e.g., hydropower and solar) to improve decarbonisation pathways (Murshed et al., 2021). By balancing security and sustainability, the E7 could transform militarisation from a planetary stressor to a driver of green innovation.

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