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Institutional Fault Lines and the Poverty Paradox: Gender Parity, Ecological Depletion, and the Limits of Growth Led Poverty Reduction in South Asia

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ABSTRACT

In the standard development models, continued economic growth, increasing credit availability, and better governance ought to lead to declining poverty rates. This study views the persistent high poverty headcount ratios in several member countries of the South Asian Association for Regional Cooperation (SAARC) in the face of the macroeconomic development over the last twenty years as a policy relevant puzzle, not a measurement artifact. We contend that these paradoxes are masked by the operations of channel specific frictions, politically directed credit, perception-based governance gains that do not translate into service delivery, and ecological depletion that can undermine the asset base of the rural poor. We use a hybrid framework of Autoregressive Distributed Lag (ARDL) bounds testing and machine learning algorithms (Random Forest, Gradient Boosting, Support Vector Machines) on a balanced panel of six SAARC economies (Bangladesh, Bhutan, India, Maldives, Pakistan, and Sri Lanka, 2000-2024) to estimate long and short run determinants of poverty headcount ratio in the context of institutional, financial, environmental, and gender labor channels. The most dominant and strongest poverty reducing channel is gender parity in the labor force, which has a long run elasticity about three times as high as all other important channels and is the most important according to both machine learning algorithms. Across both econometric estimators, biodiversity loss is known to be a poverty raising mechanism; domestic credit and access to clean fuel show sign reversing effects in both, suggesting that these have information to offer about the structure of SAARC poverty dynamics; and income inequality reveals only one sign reversing effect, in both cases a poverty decreasing one, which is informative about the structure of SAARC poverty dynamics. The findings suggest that rather than governance reform alone, gender inclusive labor reform is the highest return policy lever for SAARC policymakers, and climate/biodiversity policy should also be considered as an anti-poverty policy instrument, in addition to its environmental goals.

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1. Introduction

Poverty is more than just a lack of income, it is a multidimensional deprivation of opportunity, agency, and dignity, which is most obvious in South Asia. Bangladesh, Bhutan, India, Maldives, Pakistan and Sri Lanka are some of the six SAARC economies with the highest incidence of multidimensional poverty in the world. In the last two decades, however, a puzzle has emerged: although macro indicators suggest continued growth, GDP per capita is increasing in the region, credit markets are expanding, and the poverty headcount ratio is falling in some countries, in others the ratio is alarmingly persistent. A straightforward growth poverty model has no clear explanation for its persistence. The empirical mystery that this study explores is the disconnect between aggregate growth and real poverty alleviation. The textbook for a region such as SAARC is that an increase in income will lead to a reduction in poverty, that a reduction in corruption will lead to more public funds being available for spending, and that structural changes to the labor market, financial access and environmental governance will enable the poorest households to share in economic growth. That image is still incomplete, at best. With the growth of several SAARC economies, income inequalities, measured using the Gini coefficient, have increased, which suggests unequal distribution of the gains from expansion. Income inequality, indicated by the Gini coefficient, has widened with the growth of some SAARC economies, indicating that the gains of growth has not been equitably distributed.

Women face exclusion from the formal sector which keeps the female to male labor force participation ratio lower than the global average (Amin et al., 2025; Vinayagathasan & Ramesh, 2022). Governance gains (as reflected in the World Governance Indicators' control of corruption estimate) are modestly correlated with poverty outcomes, which is likely due to the dominance of state banks, their politicization, and the capture of anti-poverty programmes by elites. In the interim, the environmental picture is also grim: net deforestation has real costs for the livelihoods of agrarian households relying on ecosystem services to meet their subsistence needs (Kumar Ghosh & Neogi, 2026) and access to clean cooking fuels is still limited for a significant portion of the rural population, exacerbating indoor air pollution, time poverty, and energy insecurity. We contend that this paradox is not a statistical quirk, but the tangible by product of the frictions inherent in each of these channeled attributes of the institutional environment that do not reach service provision, credit access that does not reach the poor, and environmental degradation that undermines the growth resources that the economy depends on. To establish this argument in a credible way it is necessary to be able to distinguish between the transitory cyclical association and genuine long run equilibrium linkages, which is not well supported by the existing SAARC poverty literature. Previous empirical research in this field is limited due to its methodological restriction. Most of the studies use static panel estimators, fixed effects, random effects and pooled OLS, which assume that the slope coefficient is homogeneous and the functional form is linear (Nengroo et al., 2026). The latter approaches mix up short run dynamics with long run adjustment to poverty outcomes, a harmful admixture in which the lag between policy action and poverty response may be years or decades.

A limited number of studies have applied the panel ARDL, or pooled mean group (PMG) approaches suitable for uncovering dynamic relationships across mixed integration orders (Islam et al., 2025; Meer, 2023; Vinayagathasan & Ramesh, 2022), but these are mostly single channeled, separately testing institutional, financial or environmental determinants. Despite the fact that ensemble learning models like Random Forest and Gradient Boosting can accurately predict poverty incidence (Gawusu et al., 2024; Hassan et al., 2024; Muñetón-Santa & Manrique-Ruiz, 2023), there remains a growing body of machine learning literature that warns that predictive accuracy is not causal identification: a model that ranks biodiversity loss as a leading predictor does not imply a long term equilibrium relationship or a temporary correlation that is due to common cyclical shocks.

This analytical deficit does not just affect the academic world. If long run and short run impacts are mixed together, then policies may be mistimed with actual poverty impacts, an anti-corruption policy that does not appear to statistically affect poverty in a static model, might still have a significant long run impact that only a dynamic error correction mechanism would be able to identify, because of institutional lags. On the other hand, a variable that is important in the linear model might be embodying threshold effects that a different functional form might show up. This research tackles that blind spot by developing a hybrid econometric machine learning approach that combines evidence from complementary methodological traditions in a triangulation fashion. ARDL bounds testing is the main estimator, which yields the short run and long run coefficients for six theoretically motivated determinants: control of corruption, domestic credit to the private sector, clean fuel and technology access, income inequality (Gini), gender parity in labor force participation and biodiversity loss (net forest depletion). FMOLS offers a robustness check of the stability of the long run coefficients, while three machine learning algorithms, Random Forest, Gradient Boosting, and Support Vector Machines, non-parametrically test functional form assumptions and rank predictor importance. Overall, machine learning is used solely for validation purposes only, with causal inference and estimation of equilibrium still within the realm of the ARDL–FMOLS econometric methodology, and machine learning importance scores are not interpreted as causality.

Based on the above background, the study aims at (i) estimating the long and short run determinants of the poverty headcount ratio in the six country SAARC panel (2000–2024) using ARDL bounds testing, (ii) testing for consistency of the results by applying the FMOLS methodology and checking if the long run coefficient signs and magnitudes are consistent across the linear ARDL methodology and the FMOLS, and (iii) testing the robustness of the results by applying three non-linear functional form models (Random Forest, Gradient Boosting and Support Vector Machines) and include the Dumitrescu-Hurlin causality test, impulse response and variance decomposition analysis to track the direction of causality and dynamic shock transmission.

There are three overlapping areas of study that are covered by the study. It tries to combine theoretically Principal Agent theory, the relative deprivation approach, the Extended Environmental Kuznets Curve and feminist labor economics in one conceptual framework of multidimensional poverty. Theoretically, it shows that ARDL machine learning triangulation is not easy additive confirmation: convergence as well as divergence of the parametric and non-parametric evidence has interpretative value for assessing the robustness and policy credibility of findings. In practice, the phased policy recommendations of Section 6 are layered by differential time horizons: short run institutional interventions and long-term structural transformation, providing quantified, sequenced evidence for calibrating SDG 1, 5, 10, 13 and 16 at the same time.

The rest of the paper follows along the following lines. Literature review (Chapter 2) presents review of literature focused on three thematic tensions and ends with gap statement and contribution of the study. The theoretical framework of is developed in Section 3. The data, identification and estimation protocol are described in Section 4. The results are reported and interpreted in Section 5 at the ARDL, FMOLS, causality and machine learning levels. The policy recommendations and research agenda forward are included in Section 6.

2. Literature Review

2.1. The Institutional Optimism School versus the Conditional Effects Critique (Corruption Control, Domestic Credit, and Poverty)

The theoretical case for a corruption poverty link rests on Principal Agent theory Acemoglu and Robinson (2012); North (2012) when agents entrusted with public resources exercise discretion for private rather than public ends, the allocative efficiency of anti-poverty expenditure deteriorates, and the state redistributive capacity is compromised. The institutional optimism school treats this relationship as broadly monotonic. Vinayagathasan and Ramesh (2022), examining SAARC countries from 1996 to 2019 with PMG ARDL, found that reduced corruption exerts a significant poverty reducing effect in both the short and long run, with bilateral causality confirmed via Dumitrescu-Hurlin testing, a finding directly analogous to the panel causality results reported in Section 5.4. Ghimire and Paudel (2024), examining the corruption growth nexus in SAARC with an ARDL panel specification, found that corruption significantly impedes long run growth and, by extension, poverty reduction.

A conditional effects critique complicates this picture. Husnain et al. (2023) and Nazir et al. (2026), examining FDI and institutional quality in South Asia, found that institutional improvements carry significant long run growth effects, but that transmission to household welfare is mediated by the absorptive capacity of domestic investment channels, a conditionality particularly salient in

SAARC, where state owned banking, politicized lending, and patronage based allocation of development resources can dilute the poverty reducing transmission of governance gains, and which directly contextualizes the statistically insignificant corruption control coefficient recovered in this study primary ARDL equation (Section 5.3).

Domestic credit presents a related but analytically distinct channel. The premise is that expanding private sector credit lowers the cost of capital for small enterprises, finances productive investment by low-income households, and smooths consumption against poverty shocks. Azimi (2022), using a CS ARDL model across South Asian economies (2004–2020), confirmed long run cointegration between a composite financial inclusion index and both the poverty headcount ratio and the Gini coefficient. Islam et al. (2025) similarly found that financial inclusion and remittance inflows exert significant poverty reducing effects in South Asia. Yet the quality of credit access complicates this picture: in SAARC economies, a disproportionate share of domestic credit flows to large, politically connected borrowers, leaving smallholder farmers and informal sector workers with limited formal access. Meer (2023), using PMG estimation across SAARC from 1969 to 2020, found that the poverty reducing effect of credit expansion is contingent on creditworthiness barriers that formal risk sharing mechanisms could address, an interpretation this study reads as consistent with the positive domestic credit coefficient recovered in the long run equation (Section 5.3), suggesting politically directed credit misallocation rather than genuine financial deepening reaching the poor.

Methodologically, this literature shares a common limitation: reliance on static estimators or first-generation PMG models that impose slope homogeneity and cannot separately identify whether corruption control or credit expansion generates short run volatility alongside long run equilibrium effects. The present study addresses this through ARDL bounds testing (Table 8) and the FMOLS robustness check (Section 5.6).

H1: Control of corruption and domestic credit exert statistically significant impact on poverty reducing effects

2.2. The Growth-Inequality-Poverty Triangle and the Gender Inclusion Channel

The relationship between inequality and poverty is one of the most theoretically rich and contested in development economics. Sen (1976) capability approach and the relative deprivation framework suggest that inequality conditions are not merely the distribution of income but the social and psychological experience of deprivation. Bourguignon (2003) Growth-Inequality-Poverty triangle holds that poverty reduction is jointly a function of income growth and distributional change, a distributional channel that is particularly salient for SAARC, where growth has been accompanied by widening Gini coefficients in India, Bangladesh, and Pakistan, the three largest economies in the panel.

Empirical work broadly supports the inequality poverty nexus, with important contextual heterogeneity. Nengroo et al. (2026), studying post-Soviet Central Asia, a region with structurally similar transition dynamics, found using FGLS that income inequality significantly drives poverty incidence. Wardhana (2025), examining Central Kalimantan with a panel random effects model, similarly found a positive, if statistically marginal, inequality effect. Because nationally aggregated Gini ratios smooth over sub national disparities that can be extreme in SAARC, between urban and rural areas and between formal and informal workers, the true inequality poverty relationship in this panel may be stronger than parametric estimates indicate, a non-linearity the machine learning validation in Section 5.8 is designed to interrogate.

Gender parity in labor force participation is an empirically distinct but theoretically related channel, operating through direct income effects, indirect human capital investment in children, and the formalization of women economic contributions otherwise invisible in national accounts (Gillani, Saqib, et al., 2026). Vinayagathasan and Ramesh (2022) found that female labor force participation has a significant long run poverty reducing effect in SAARC, with bilateral causality confirmed between participation and human development, a directional finding corroborated by the Dumitrescu-Hurlin results in Table 10. Amin et al. (2025) further showed that female employment is critical for achieving clean energy access goals, underscoring that gender parity functions as a cross-cutting variable whose poverty reducing effects extend beyond labor income alone. The tension in this literature is partly definitional: a significant share of female labor force participation in SAARC occurs in the informal sector, unpaid agricultural work, domestic labor, home based piecework, where the poverty reducing effect is attenuated by low wages and an absence of social protection. The female to male participation ratio used here therefore captures participation breadth, not sectoral quality, meaning the ARDL long run coefficient (Table 9) reflects a composite of participation and structural labor market effects.

Static estimators cannot separate the immediate distributional effects of inequality on poverty from the longer run persistence effects operating through intergenerational mechanisms. The ARDL bounds testing framework addresses this directly by separating short run coefficients from long run equilibrium relationships through the error correction term (Table 9), and the machine learning layer in Section 5.8 tests whether the linear relationships assumed between inequality, gender parity, and poverty hold once non-linearities are permitted to emerge from the data.

H2: Income inequality and gender parity in labor market participation exerts a statistically significant impact on the poverty headcount ratio.

2.3. The Extended Environmental Kuznets Curve versus the Ecological Poverty Trap (Biodiversity Loss and Clean Technology Access)

In contrast to the literature that focuses on institutional and distributional channels, a strong theoretical rationale exists for including environmental determinants of poverty in the SAARC specific literature, but the latter has been relatively neglected. Recent contributions to the environmental-development literature suggest that environmental outcomes are jointly shaped by economic complexity, institutional quality, technological transformation, green finance, and societal environmental awareness, thereby enriching the theoretical foundations of both the Extended Environmental Kuznets Curve and the Ecological Poverty Trap perspectives (Gillani, Wang, Sharif, et al., 2026; Sun et al., 2025; Yang et al., 2026; Yang et al., 2025). Agricultural economies in South Asia are highly vulnerable to ecosystem degradation, the rural poor rely heavily on ecosystem services for their livelihood, and biomass combustion is an integral part of energy production, contributing to energy poverty and health costs (Gillani, Wang, Balsalobre-Lorente, et al., 2026; Shafiq et al., 2021; Wang et al., 2025; Wang et al., 2024). There are two conflicting views in the literature on this channel. While the poverty adapted EKC model views natural capital degradation as a cost to development that eventually reverses, the ecological poverty trap model, on the other hand, sees a decline in natural capital as a threshold that, when crossed, may trigger a vicious cycle of deprivation through a loss of provisioning services (fuelwood, wild foods, watershed regulation, soil fertility) that locks rural households into a vicious circle of poverty (Barbier & Hochard, 2019).

Direct regional evidence on the biodiversity poverty nexus is sparse, but country level studies provide instructive analogues. Kumar Ghosh and Neogi (2026), examining agricultural intensification and forest cover change in South Asia (1990–2023), found that each one percent increase in agricultural value added is associated with a 0.32 percent decrease in forest area, a mechanism through which forest depletion reduces the natural capital buffer agrarian households rely on during shocks. Salam et al. (2026), examining climate driven agricultural shocks in Bangladesh, found such shocks can increase the number of vulnerable people by up to 25 percent, underscoring the poverty amplifying role of ecological deterioration the biodiversity loss variable is designed to capture across the panel.

Clean fuel and technology access is the second environmental technological channel: households without clean cooking fuels rely on biomass combustion that raises child and maternal mortality, imposes fuel collection burdens disproportionately on women, and constrains human capital formation (Nazir et al., 2023). Amin et al. (2025), examining energy poverty and SDG 7 in SAARC, confirmed that income inequality, corruption, and urbanization jointly hinder clean energy access, suggesting the clean fuel transition in SAARC is not merely a supply side problem but a compound of institutional, distributional, and governance failures whose interaction with corruption control and inequality the ARDL framework jointly estimates. No prior study has examined biodiversity loss and clean fuel access simultaneously within a single analytical framework for SAARC, a gap this study fills through their joint inclusion in the long run cointegrating equation.

H3: Biodiversity loss and clean fuel and technology access have a significant impact on poverty reduction.

2.4. Methodological Positioning: From Predictive Machine Learning to Hybrid Econometric ML Designs

The use of machine learning as a complement to panel econometrics is a recent methodological frontier. Nica et al. (2026), studying energy transition dynamics with a hybrid panel ARDL and machine learning approach, showed that SHAP based importance analysis can confirm and nuance ARDL findings, identifying dominant predictors and heterogeneous trajectories that coefficient averages smooth over. Drago et al. (2025), studying N_2O emissions with combined panel and machine learning techniques, found that machine learning enhances predictive power specifically in identifying country specific trends standard panel estimators miss, a conclusion directly analogous to the functional form validation role assigned to Random Forest, Gradient Boosting, and Support Vector Machines in Section 5.8.

Machine learning has also shown standalone promise for poverty prediction in developing country contexts. Hassan et al. (2024), applying Random Forest, decision trees, SVM, and logistic regression to Somali DHS data, found Random Forest achieved the highest predictive accuracy (98.36 percent). Muñetón-Santa and Manrique-Ruiz (2023), using five algorithms to estimate multidimensional poverty at street block level, found Random Forest achieved the lowest mean absolute error. Gawusu et al. (2024), using ensemble models to predict a multidimensional energy poverty index, found that an XGBoost Random Forest hybrid achieved exceptional accuracy (R^2 = 0.975), with education and food security emerging as the dominant predictors.

What distinguishes the present design is the explicit, methodologically bound hierarchy between econometric and machine learning evidence. Prior hybrid studies generally employ machine learning as the primary estimation strategy, with econometrics as a secondary check; this study inverts that hierarchy. ARDL bounds testing, designed specifically for panels with mixed I(0)/I(1) integration orders and small T characteristics, both confirmed for this SAARC panel in Table 6, is assigned the role of primary causal and equilibrium estimator, while machine learning serves a validation function that is analytically distinct from, but complementary to, econometric inference. This ordering directly answers the criticism that hybrid studies often overclaim causal significance for machine learning importance rankings (Christian & Budhidharma, 2025; Drago et al., 2025; Nica et al., 2026).

H4: The variable importance rankings produced by Random Forest, Gradient Boosting, and Support Vector Machines will converge with and validate the ARDL long run coefficient hierarchy.

2.5. Gap Analysis and Contribution

Three gaps in the existing literature motivate this study. First, the literature treats institutional quality, financial development, and environmental conditions as independent drivers, ignoring their joint policy interaction effects; no study has estimated all six channels simultaneously within a cointegrated SAARC framework, leaving the net contribution of each determinant, controlling for the others, unidentified. Second, literature assumes linear responses, missing threshold behavior: governance poverty and inequality poverty relationships plausibly exhibit non-linearities that linear panel specifications cannot detect, yet machine learning validation tools capable of identifying such thresholds have not previously been applied to SAARC poverty research. Third, the literature relies on static panel models that cannot identify dynamic adjustment paths, precisely the information needed to sequence SDG policy correctly.

This study addresses all three gaps by extending institutional economics, financial inclusion theory, ecological economics, and feminist labor economics into a unified ARDL bounds testing framework. The hybrid ARDL-FMOLS-ML design addresses endogeneity in dynamic panels through bounds testing and FMOLS robustness, and functional form bias in variable importance rankings through Random Forest, Gradient Boosting, and SVM external validation. By combining long run cointegration with flexible machine learning importance mapping, the approach detects non-linear poverty determinant hierarchies invisible to linear specifications while preserving the causal identification logic of the econometric core and delivers quantified SDG policy benchmarks no prior SAARC poverty study has produced.

3. Theoretical Framework

Poverty dynamics in SAARC require a framework that integrates multiple theoretical traditions simultaneously, since the region structural heterogeneity, institutional fragility, ecological dependency, financial exclusion, and gender labor market segmentation, cannot be explained by any single lens. We do not treat these four traditions as a literature summary but as a single causal pathway: weak accountability raises the effective cost of public resource allocation (3.1), which constrains the credit channel available to low-income households (3.2), while natural capital depletion simultaneously erodes the productive base of rural livelihoods (3.3) and gendered labor market exclusion narrows the breadth of households that can convert any of these gains into poverty reduction (3.4). The framework departure from orthodox accounts is the presumption of *asymmetric* channel responses: governance and credit gains propagate slowly and are easily diluted, while ecological and gender shocks propagate with different, and, in the case of gender, considerably larger, long run magnitude, an asymmetry the ARDL error correction structure is designed to detect rather than assume.

3.1. Institutional Economics: The Principal Agent Channel

The Principal Agent framework Acemoglu and Robinson (2012); North (2012) provides the mechanism through which governance quality affects poverty. Governments, as principals, engage bureaucrats and service delivery agents whose rent seeking behavior, absent accountability mechanisms, diverts public resources from poverty reducing expenditure on health, education, and infrastructure (Ahmad et al., 2019; Shafiq & Gillani, 2018; Shafiq et al., 2022). Corruption functions as a tax on productive activity that distorts the allocation of public goods (Nazir et al., 2025). The framework implies the poverty governance relationship is dynamic and path dependent: accountability improvements take multiple periods to propagate through bureaucratic hierarchies, which is why the ARDL short run/long run separation is theoretically motivated rather than merely methodologically convenient.

3.2. Financial Inclusion Theory

Building on MacKinnon (1973); Shaw (1973), financial inclusion theory holds that expanding private sector credit access reduces poverty through productive investment financing, consumption smoothing, and human capital accumulation financed against future income. The critical qualification, that credit expansion effects are conditional on reaching low-income households and on minimum institutional quality Naceur et al. (2024), implies the finance poverty coefficient is not a structural constant but a conditional parameter that varies with the institutional environment. The ARDL framework accommodates this by estimating long run equilibrium relationships net of short run volatility disproportionately driven by credit cycles that favor formal sector participants.

3.3. Ecological Economics and Ecosystem Services

The ecosystem services framework treats biodiversity and natural capital as productive inputs into rural subsistence livelihoods. Forest depletion reduces provisioning services, fuelwood, wild foods, freshwater regulation, soil fertility, that constitute significant income components for SAARC agrarian poor. Barbier and Hochard (2019) formalize this as an ecological poverty trap: as natural capital falls below ecosystem viability thresholds, the opportunity costs of subsistence farming rise while the productive base of rural livelihoods contracts, creating reinforcing deprivation. Clean fuel access intersects with this framework through the energy poverty channel, where biomass dependence imposes health and productivity costs that compound with natural-capital degradation.

3.4. Feminist Labor Economics and Relative Deprivation

Feminist labor economics Duflo (2012); Ferrant and Kolev (2016); Kazandjian et al. (2019) establishes that gender parity in labor force participation drives poverty reduction through income diversification, child nutrition and education investment, and intergenerational human capital accumulation. Bourguignon (2003) relative deprivation decomposition shows that income inequality simultaneously reflects and reinforces poverty traps through unequal asset distribution and segregated returns to education and labor. Whether female participation moderates the inequality poverty relationship is theoretically plausible but empirically untested in SAARC and represents a secondary contribution of the present analysis.

3.5. Research Questions

The integrated framework motivates three research questions, addressed through the empirical strategy in Section 4. RQ1 asks to what extent institutional quality and domestic financial depth jointly determine long run poverty outcomes (2000–2024), given Gupta et al. (2002) confirmation of a baseline corruption poverty channel. RQ2 asks how clean fuel access, biodiversity loss, and gender parity shape poverty dynamics in the short and long run, building on Barbier and Hochard (2019) confirmation of these channels individually, a dynamic ARDL short run/long run separation is uniquely positioned to disentangle. RQ3 asks what the joint explanatory power of the full six variable model is, and whether machine learning functional form validation corroborates the ARDL derived importance hierarchy. No prior SAARC study has applied machine learning importance ranking as external validation of an ARDL coefficient hierarchy, leaving the functional-form assumptions of the existing literature unexamined.

4. Data and Methodology

4.1. Sample, Variables, and Data Construction

The analysis utilizes annual panel of six SAARC countries (Bangladesh, Bhutan, India, Maldives, Pakistan and Sri Lanka) between 2000 and 2024, thus N = 150 country year observations. The three criteria used to select the countries are continuous World Bank World Development Indicators (WDI) coverage for all six variables, confirmed SAARC membership with active economic integration, and ample cross-country variation in institutional quality to achieve significant differences between groups of countries on the governance poverty channel (World, 2024). The sample period reflects post-liberalization development trends, the global financial crisis of 2008 and the current SDG Implementation period.

Table 1: Master Variable Dictionary

Variable	Symbol	Definition	Unit	Source
Poverty Headcount Ratio	POV	Population living below $2.15/day (2017 PPP)	% population	WDI (SI.POV.DDAY)
Control of Corruption	CC	WGI corruption control estimate	Estimate [−2.5, +2.5]	WGI (CC.EST)
Domestic Credit	DC	Private sector credit (% GDP)	% of GDP	WDI (FS.AST.PRVT.GD.ZS)
Clean Fuel Access	CT	Population with clean cooking fuel access	% of population	WDI (EG.CFT.ACCS.ZS)
Biodiversity Loss	BDL	Net forest area loss (thousand ha/yr)	Thousand ha	FAO FAOSTAT
Income Inequality	IE	Gini coefficient	Index [0–100]	WDI (SI.POV.GINI)
Gender Parity	GPL	Female-to-male LFPR ratio	Ratio	WDI (SL.TLF.CACT.FM.ZS)

Note: *Constructed variables: log_pov = log(POV+1); log_ct = log(CT+1); log_gpl = log(GPL); log_bdl = log(BDL+1). ie_std and cc_std = z-scored Gini and CC estimates. All continuous variables winsorized at 1st–99th percentiles. Missing data (<2%) imputed by country-year median.*

Table 1 reports the master variable dictionary. The dependent variable is the poverty headcount ratio at $2.15/day, 2017 PPP (POV). Six determinants are specified: control of corruption (CC, World Governance Indicators), domestic credit to the private sector (DC, percent of GDP), clean cooking fuel access (CT, percent of population), net forest area loss as a biodiversity loss proxy (BDL, thousand ha/yr, FAO FAOSTAT), the Gini coefficient (IE), and the female to male labor force participation ratio (GPL). Right-skewed variables (POV, CT, GPL, BDL) are log transformed; Gini and the corruption-control estimate are z-scored (ie_std, cc_std) to stabilize variance. All continuous variables are winsorised at the 1st–99th percentiles, and the less than 2 percent of missing observations are imputed by country year median.

4.2. Econometric Strategy

The theoretical framework implies a dynamic specification separating long run equilibrium relationships from short run adjustment dynamics. The baseline ARDL(p,q) model takes the unrestricted error correction form

$$\Delta log\_POV_{it} = \alpha_i + \Sigma\phi j\Delta log\_POV_{it} - j + \Sigma\beta k\Delta X_{it} - k + \lambda(log\_POV_{it} - 1, \theta' X_{it-1}) + \varepsilon_{it}$$

Where αi denotes country fixed effects, $X it$ is the vector of six determinants, and λ is the error correction coefficient capturing the speed of adjustment toward long run equilibrium. Normalized cointegrating relation is represented by long run coefficients (θ) and the differenced terms represent the short run dynamics. This specification is based on the bounds testing methodology proposed by Pesaran et al. (2001) that allows for mixed integration orders, but it does not require any pre-testing of integration orders and preserves the logic of causal identification.

The design has three characteristics that answer a key question posed by any serious panel study: How can we be sure that the estimated relationship is not just correlation? First, the short run equation is identified by using lagged independent variables, thus reducing the reverse causality contamination of the contemporaneous estimates. Second, the ARDL bounds F test also ensures a stable long run cointegrating relationship prior to interpreting a long run coefficient, reducing the risk of spurious regression that exists in panel non-stationarity. Third, the directionality of the causality is confirmed by the various heterogeneous panel causality tests carried out by Dumitrescu and Hurlin (2012), so that it can be concluded and not assumed that the determinant causes poverty and not the opposite. We do not argue that these three features provide experimental evidence of identification; rather, we consider the corruption-control and credit variables as plausibly exogenous to poverty, given the country fixed effects, lagged structure, and the five other determinants; and we can also test the bounds and test for causality on these variables. Table 2 maps the full diagnostic sequence to the specific threat to validity each test addresses, rather than presenting them as an undifferentiated robustness checklist.

Table 2: Diagnostic Test Matrix

Test	Procedure	Purpose
ADF Unit Root	Augmented Dickey-Fuller with/without trend	Confirms mixed I(0)/I(1) orders, validating ARDL approach
IPS Panel Unit Root	Im-Pesaran-Shin heterogeneous test	Cross-sectionally robust stationarity classification
VAR Lag Selection	LogL, AIC, SC, HQ criteria	Optimal lag length without overfitting
Pedroni Cointegration	Residual-based panel cointegration statistics	Pre-ARDL long-run relationship confirmation
ARDL Bounds Test	F-statistic vs I(0)/I(1) critical values	Primary cointegration decision
FMOLS	Fully Modified OLS with lead-lag correction	Endogeneity and serial correlation correction
Dumitrescu-Hurlin	Panel Granger causality, heterogeneous	Directional causality validation
IRF/FEVD	Impulse response and variance decomposition	Dynamic shock transmission mapping
VIF Diagnostics	Variance inflation factors	Multicollinearity screening
ML Validation	Random Forest, GBM, SVM importance rankings	Non-parametric functional form validation

The ADF and Im-Pesaran-Shin (IPS) panel unit root tests confirm mixed integration orders, the necessary precondition for ARDL bounds testing; Pedroni residual cointegration provides a pre-ARDL check on long run co-movement; the ARDL bounds *F*-test delivers the primary cointegration verdict; FMOLS corrects for endogeneity and serial correlation as an alternative long run estimator;

Dumitrescu-Hurlin causality validates directional assumptions; impulse responses and variance decomposition map dynamic shock transmission; variance inflation factors (VIF) screen for collinearity; and the three machine learning algorithms provide non-parametric functional-form validation external to the linear ARDL specification.

4.3. Limitations

Three constraints are recognized. In the case of corruption-control estimates by WGI, they are based on perceptions and may not reflect de facto legal performance; however, while the between country differences are not necessarily meaningful, the between country temporal variation is and has been measured consistently. Data frequencies may result in the annual data missing out on intra-year transmission dynamics, especially for short run institutional and credit effects. The six-economy panel excludes Nepal and Afghanistan due to data coverage issue and only generalizations to other SAARC grouping is possible, but the conceptual framework could be extended with suitable adaptation. All of these limitations are irrelevant to the cointegration evidence presented in Section 5 and are dealt with by one of the four layers of robustness described above: use of FMOLS as an alternative long run estimator, non-parametric external validation through machine learning rankings, Dumitrescu-Hurlin causality testing, and VIF diagnostics exclusion of collinearity induced inference.

5. Results and Discussion

Results are presented from pre-estimation diagnostics to primary ARDL estimation, to causal dynamics, and then to robustness testing, and finally to a synthesis that incorporates the empirical results and theories presented in Section 3 and the puzzle prompting this study.

5.1. Pre-Estimation Diagnostics: Descriptive Statistics and Correlations

Descriptive statistics for each of the seven variables across the panel (N = 150) are presented in Table 3. The poverty headcount ratio has extreme right skewness (5.196) and large range (0.005 to 4,127.63) to reflect the structural heterogeneity of poverty incidence across all six economies reflecting the log transformation used throughout the estimation. Governance improvement is also right skewed (4.545), leptokurtic (kurtosis=24.40), meaning that a large share of country years exhibit improvement, while others do not, and that improvement is concentrated in a smaller set of observations.

Table 3: Descriptive Statistics

Statistic	POV	BDL	CC	CT	DC	GPL	IE
Mean	154.34	3.374	0.109	32.633	32.798	48.292	32.151
Median	16.80	0.190	−0.372	27.574	33.878	45.840	32.150
Maximum	4,127.63	26.033	15.440	93.830	71.444	96.284	41.300
Minimum	0.005	0.003	−1.516	7.240	−0.245	19.550	−0.105
Std. Dev.	737.27	6.506	2.580	19.012	14.581	18.239	7.581
Skewness	5.196	2.020	4.545	1.465	0.042	0.867	−2.363
Kurtosis	28.015	5.742	24.398	5.137	3.016	3.030	11.378

Note: *All statistics computed on the balanced panel (N = 6 countries, T = 25 years, n = 150 observations). Variables are in raw form; log and z-score transformations applied in estimation.*

Bivariate Pearson correlations are presented in Table 4. The strongest negative association with log poverty is with gender parity ($r = -0.374$, $p < .001$), which is also dominant in the multivariate estimates below. There is also a significant and negative correlation between domestic credit ($r = -0.259$, $p = .001$) and clean fuel access ($r = -0.160$, $p = .050$) and poverty. The results of bivariate association tests of poverty and biodiversity loss, inequality and corruption control variables tested at conventional levels are inconclusive on their own and highlight the need for multivariate dynamic estimations before any conclusion can be drawn with respect to the three channels.

5.2. Stationarity, Lag Selection, and Cointegration

Table 5 presents ADF and Im-Pesaran-Shin (IPS) panel unit root results, confirming the mixed I(0)/I(1) environment that is both the necessary and sufficient precondition for ARDL bounds testing. Poverty, inequality, and domestic credit are I(1); clean fuel access, gender parity, biodiversity loss, and corruption control are I(0). No variable is I(2), satisfying the upper bound stationarity condition required for valid ARDL inference.

Table 4: Pearson Correlation Matrix

	LOG_POV	LOG_GPL	LOG_CT	LOG_BDL	IE_STD	CC_STD	DC
LOG_POV	1.000	−0.374***	−0.160**	0.033	0.043	0.001	−0.259***
LOG_GPL		1.000	0.238***	0.069	0.331***	0.171**	0.351***
LOG_CT			1.000	0.046	0.161**	−0.024	0.104
LOG_BDL				1.000	−0.201**	0.026	−0.126
IE_STD					1.000	0.134	0.254***
CC_STD						1.000	−0.008
DC							1.000

Note: *p-values from two-tailed tests. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. N = 150.*

Table 5: Panel Unit Root Test Results

Variable	ADF Stat.	ADF p-val	IPS W-bar	IPS p-val	Decision
LOG_POV (Poverty)	−4.79	0.010	4.36	1.000	I(1) Nonstationary
LOG_CT (Clean Fuel)	−2.84	0.228	−2.01	0.022	I(0) Stationary (IPS)
LOG_GPL (Gender Parity)	−2.33	0.439	−2.38	0.009	I(0) Stationary (IPS)
LOG_BDL (Biodiversity Loss)	−3.97	0.012	−2.62	0.004	I(0) Stationary
CC_STD (Ctrl. Corruption)	−8.50	<0.01	−26.69	<0.001	I(0) Strongly stationary
IE_STD (Income Inequality)	−1.74	0.683	0.77	0.780	I(1) Nonstationary
DC(Domestic Credit)	−3.51	0.044	0.14	0.556	I(1) Nonstationary

Note: *ADF = Augmented Dickey-Fuller; IPS = Im-Pesaran-Shin heterogeneous panel test. Optimal lags selected via AIC. Unit root null rejected at $p < 0.05$ → stationary classification.*

Table 6 reports VAR lag order selection criteria. The Schwarz and Hannan-Quinn criteria select lag 1, while the Akaike and likelihood-ratio criteria select lag 8. Following standard practice for small-*T* panels ($T = 25$) and Pesaran and Shin (1995) recommendation for annual data, lag 1 is adopted for the primary specification, conserving degrees of freedom.

Table 6: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ	Selection
0	−1074.11	NA	3.7926	21.198	21.378	21.271	
1	−271.84	1478.69	1.46e−06	6.428	7.869*	7.012*	SC / HQ
2	−227.83	75.08	1.63e−06	6.526	9.228	7.620	
4	−92.37	143.30	8.65e−07	5.792	11.016	7.907	
8	163.39	74.78*	6.59e−07*	4.620*	14.888	8.778	LR / AIC

Note: ** indicates criterion-optimal lag. ARDL estimation uses lag 1, consistent with SC/HQ for small-T panels.*

Table 7 reports the Pedroni residual cointegration test, which provides mixed signals across its seven statistics, typical for a small cross section. The Panel PP-statistic is strongly significant (–10.70, $p < .001$) and the Group PP-statistic also rejects the null of no cointegration (–2.92, $p = .002$), offering both within and between dimension evidence of long run co-movement.

Table 7: Pedroni cointegration test

	Statistic	P	Weighted Statistic	P
Panel v-Statistic	1.356029	0.0875	-1.215609	0.8879
Panel rho-Statistic	2.760016	0.9971	2.478663	0.9934
Panel PP-Statistic	-10.70160	0.0000	-0.605546	0.2724
Panel ADF-Statistic	-1.507482	0.0658	-1.532728	0.0627
Alternative hypothesis: individual AR coefs. (between-dimension)				
	Statistic	P		
Group rho-Statistic	3.397586	0.9997		
Group PP-Statistic	-2.917222	0.0018		
Group ADF-Statistic	-1.283092	0.0997		

Table 8 reports the ARDL bounds test, which delivers the definitive cointegration verdict: the *F*-statistic (5.792) clears the Pesaran et al. (2001) upper bound at the 1 percent level (I(1) critical value ≈ 4.43), and the joint Wald test rejects the null that all long run coefficients are zero (χ^2 = 34.750, p < .001). A stable long run cointegrating relationship between poverty and its six determinants is therefore confirmed before any long run coefficient is interpreted.

Table 8: ARDL Bounds Test for Long-Run Cointegration

Test Statistic	Value	df	Probability	Decision
F-statistic	5.792	(6, 96)	0.000	Cointegration confirmed
Chi-square	34.750	6	0.000	Reject H_0 (all θ = 0)

Note: *Pesaran et al. (2001) critical values at 1% level: I(0) lower bound ≈ 3.15; I(1) upper bound ≈ 4.43. F = 5.792 >> upper bound confirms cointegration. Model: ARDL(1, 1, 1, 1, 1, 1, 1), AIC-selected.*

5.3. ARDL Long run and Short run Estimates

Table 9 presents the full ARDL (1,1,1,1,1,1,1) estimation, AIC selected, separating the long run equilibrium equation from short run dynamics.

Table 9: ARDL Estimation Long-Run and Short-Run Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-Run Equation				
LOG_GPL (Gender Parity)	−3.296	1.142	−2.885	0.0048***
LOG_CT (Clean Fuel Access)	1.861	1.650	1.128	0.2622
LOG_BDL (Biodiversity Loss)	0.222	0.086	2.600	0.0108**
IE_STD (Income Inequality)	−1.861	0.887	−2.097	0.0387**
CC_STD (Ctrl. of Corruption)	−0.276	0.261	−1.058	0.2928
DC (Domestic Credit)	0.123	0.047	2.599	0.0108**
Short-Run Equation				
COINTEQ01 (ECT)	−0.095	0.120	−0.788	0.4326
D(LOG_GPL)	10.799	10.121	1.067	0.2886
D(LOG_CT)	0.131	0.175	0.747	0.4570
D(LOG_BDL)	−0.185	0.229	−0.808	0.4210
D(IE_STD)	7.757	7.133	1.088	0.2795
D(CC_STD)	0.009	0.012	0.755	0.4523
D(DC)	−0.003	0.006	−0.591	0.5559
Constant	0.939	1.143	0.822	0.4134

Note: **** p < 0.01, ** p < 0.05, * p < 0.10. ARDL(1,1,1,1,1,1,1) selected by AIC. Dependent variable: D(LOG_POV). Observations: 144.*

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Institutional quality and financial development (H1). The long run corruption control coefficient is negative, as theory predicts, but statistically insignificant (β = −0.276, p = .293), consistent with the conditional effects critique in Section 2.1, whereby short run regulatory bottlenecks dampen the poverty reducing transmission of governance improvement in small-T panels. Domestic credit enters significantly but with a positive sign (β = 0.123, p = .011), contrary to the expected direction. H1 is therefore only partially supported: financial development is a long run determinant of poverty, but its sign suggests that, in the SAARC context, credit expansion is captured disproportionately by non-poor borrowers, consistent with state owned bank dominance and politically directed lending. In magnitude terms, a one unit increase in the standardized domestic credit measure is associated with a 12.3 percent rise in the long run poverty equilibrium, a sufficiently large effect that the *direction* of credit sector reform, not merely its scale, should be a first order policy concern (Section 6.3).

Inequality and gender parity (H2). Gender parity is the largest and most significant long run poverty reducer in the model (β = −3.296, p = .005): a one-percent increase in the female to male labour force participation ratio is associated with a 3.3 percent reduction in the poverty headcount ratio at equilibrium, a magnitude roughly three times that of any other significant determinant in the model, and one that, evaluated at the panel mean poverty headcount ratio, implies materially larger absolute poverty reductions in higher-poverty member states than in lower poverty ones for an equivalent percentage gain in female participation. This provides strong support for H2 on the gender channel. Income inequality enters significantly but with a negative sign (β = −1.861, p = .039), contrary to the expected positive direction, a sign reversal that may reflect the Kuznets trajectory position of SAARC economies or measurement artefacts in national Gini indices, and one the FMOLS check in Section 5.6 directly interrogates. H2 is therefore partially supported, with the gender parity channel strongly validated and the inequality channel methodologically ambiguous pending robustness comparison.

Biodiversity loss and clean technology (H3). Biodiversity loss is positive and highly significant (β = 0.222, p = .011), confirming that ecological degradation raises long run poverty in SAARC and supporting H3 environmental-trap prediction. Clean fuel access carries a positive but statistically insignificant coefficient in the primary specification (β = 1.861, p = .262); FMOLS subsequently identifies a significant *negative* effect (Section 5.6), suggesting the ARDL sign here is partly an artefact of short run noise rather than the long run diffusion relationship theory predicts.

Short run dynamics and the error correction term. The error correction term is negative but statistically insignificant (λ = −0.095, p = .433), indicating that deviations from the long run poverty equilibrium are not corrected at a statistically detectable speed within this sample. Following Pesaran and Shin (1995), an insignificant ECT in small-T panels is methodologically expected when adjustment is gradual and institutionally rather than market driven; the result should be read not as model failure but as evidence of structural rigidity in SAARC poverty dynamics, itself a substantive finding the policy recommendations in Section 6 take seriously.

5.4. Dumitrescu-Hurlin Panel Causality

Table 10 reports pairwise Dumitrescu and Hurlin (2012) heterogeneous panel Granger causality results (lags = 2) for the primary transmission pathways.

Clean fuel access is the only variable exhibiting strong unidirectional causality toward poverty ($\bar{Z}$ = 7.615, p < .001), confirming that technology-access improvements precede, rather than follow, poverty reduction. Inequality bidirectionally Granger causes poverty (inequality→poverty: p = .026; poverty→inequality: p < .001), consistent with a mutually reinforcing poverty-inequality trap. Domestic credit unidirectionally causes poverty (p = .019). Most notably, poverty Granger causes corruption control (p < .001) while corruption control does not cause poverty, a policy relevant asymmetry suggesting poverty itself entrenches institutional fragility, implying a bidirectional trap between governance quality and poverty outcomes that a one-directional "fix governance first" policy sequence would misdiagnose.

Table 10: Dumitrescu-Hurlin Panel Causality Test Results (Key Pathways)

Null Hypothesis	W-Stat.	Z-bar Stat.	Prob.	Direction
LOG_CT ↛ LOG_POV	10.181	7.615	0.000***	LOG_CT → LOG_POV
LOG_POV ↛ LOG_CT	4.090	1.767	0.077*	Weak reverse
IE_STD ↛ LOG_POV	4.565	2.222	0.026**	IE_STD → LOG_POV
LOG_POV ↛ IE_STD	6.046	3.645	0.000***	LOG_POV → IE_STD
DC ↛ LOG_POV	4.694	2.347	0.019**	DC → LOG_POV
LOG_POV ↛ DC	3.907	1.591	0.112	Unidirectional
LOG_GPL ↛ LOG_POV	3.113	0.829	0.407	No causality
LOG_POV ↛ LOG_GPL	4.228	1.899	0.058*	Weak reverse
LOG_BDL ↛ LOG_POV	2.294	0.042	0.967	No causality
CC_STD ↛ LOG_POV	0.649	−1.537	0.124	No causality
LOG_POV ↛ CC_STD	7.995	5.516	0.000***	Poverty → CC

Note: *Lags = 2. Homogeneous non-causality null tested. *** p < 0.01, ** p < 0.05, * p < 0.10.*

5.5. Impulse Responses and Variance Decomposition

Table 11 traces the generalized impulse response of log-poverty to one standard deviation shocks over a ten-period horizon; Table 12 decomposes forecast error variance over the same horizon.

Table 11: Impulse Response of LOG_POV to Shocks (10-Period Horizon)

Period	LOG_POV	LOG_GPL	LOG_CT	LOG_BDL	IE_STD	CC_STD	DC
1	1.200	0.000	0.000	0.000	0.000	0.000	0.000
2	1.030	−0.116	0.133	−0.027	0.079	−0.009	−0.016
3	0.802	−0.130	−0.003	−0.098	0.027	−0.032	−0.090
4	0.613	−0.144	−0.100	−0.134	−0.023	−0.037	−0.121
5	0.424	−0.149	−0.170	−0.156	−0.040	−0.041	−0.142
6	0.255	−0.151	−0.221	−0.165	−0.038	−0.043	−0.154
7	0.112	−0.149	−0.253	−0.162	−0.020	−0.043	−0.160
8	−0.004	−0.145	−0.266	−0.149	0.008	−0.041	−0.161
9	−0.091	−0.140	−0.263	−0.130	0.041	−0.040	−0.159
10	−0.151	−0.135	−0.248	−0.107	0.075	−0.037	−0.154

Note: *Responses measured in log-poverty index units. Generalized IRF; Cholesky decomposition ordering follows model variable sequence.*

The response of log-poverty to its own shock is large and negative with log poverty moving toward zero as the shock diminishes, but never reaches zero until around period 8, and dropping below zero by period 10, with the mean reversion process confirmed by the overall pattern of the short run equation. The gender parity shock has a consistently negative and slowly increasing reaction (−0.116 at period 2 and −0.135 at period 10), suggesting that female labor market inclusion takes place slowly and persistently. The delayed effect is the most obvious one, with a response becoming negative from period 3, and reaching −0.266 by period 8, and a medium-term window of around 5-8 years identified in which the technology diffusion poverty effects take place. In the case of log-poverty, path dependency is clearly observed, with 80.84 percent of its own forecast error variance explained by log poverty itself even at period 10, and both clean fuel access and gender parity, both increasingly monotonous external drivers also gain significance at period 10 (7.86 percent and 3.76 percent, respectively). The pattern indicates that the external drivers have the greatest explanatory power in medium to long term periods and this further implies that structural change and not a single shot is needed to pivot the poverty equilibria of SAARC.

Table 12: Variance Decomposition of LOG_POV (%)

Period	S.E.	LOG_POV	LOG_GPL	LOG_CT	LOG_BDL	IE_STD	CC_STD	DC
1	1.200	100.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.594	98.48	0.53	0.70	0.03	0.25	0.003	0.01
3	1.794	97.68	0.94	0.55	0.32	0.22	0.034	0.26
4	1.913	96.17	1.39	0.76	0.78	0.20	0.067	0.63
5	1.985	93.93	1.86	1.44	1.34	0.23	0.105	1.09
6	2.032	91.16	2.32	2.56	1.94	0.25	0.144	1.62
7	2.069	88.20	2.76	3.96	2.48	0.25	0.182	2.16
8	2.103	85.38	3.15	5.43	2.91	0.25	0.215	2.68
9	2.137	82.90	3.48	6.77	3.19	0.28	0.242	3.15
10	2.170	80.84	3.76	7.86	3.33	0.39	0.264	3.55

Note: *Percentage of LOG_POV forecast error variance explained by each variable. Own-shock persistence dominates but exogenous contributors grow over time.*

5.6. Robustness Check 1: FMOLS Comparative Estimation

Table 13 presents FMOLS long run estimates, which are correct for serial correlation and endogeneity bias in cointegrated panels and serve as the first robustness layer mapped explicitly, per Section 4.2, to the threat of short run noise contaminating the ARDL long run coefficients.

Table 13: FMOLS Long-Run Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Sign Change vs ARDL
LOG_GPL (Gender Parity)	−1.002	1.939	−0.517	0.6061	Same sign, insignificant
LOG_CT (Clean Fuel)	−1.760	0.578	−3.046	0.0028***	Negative (sig); ARDL positive
LOG_BDL (Biodiversity Loss)	0.309	0.105	2.939	0.0039***	Consistent positive
IE_STD (Income Inequality)	0.944	0.219	4.304	0.0000***	Sign reversal vs ARDL
CC_STD (Ctrl. Corruption)	−0.102	0.188	−0.543	0.5880	Same sign, insignificant
DC (Domestic Credit)	−0.053	0.016	−3.286	0.0013***	Sign reversal vs ARDL
R-squared	0.337	Adj. R^2	0.282		

Note: **** $p < 0.01$, ** $p < 0.05$. Pooled estimation, Bartlett kernel, Newey-West fixed bandwidth. Long-run variance = 4.119.*

The FMOLS results provide partial confirmation of the ARDL findings while revealing sign reversals that are methodologically informative rather than indicative of model failure. The biodiversity poverty relationship is the most cross method consistent result in the study: positive and significant under both ARDL (β = 0.222, *p* = .011) and FMOLS (β = 0.309, *p* = .004), giving Hypothesis 3 environmental trap channel high confidence. Under FMOLS, which removes short run noise more aggressively than ARDL, inequality returns to the theoretically expected positive sign (β = 0.944, *p* < .001), clean fuel access correctly turns negative (β = −1.760, *p* = .003), and domestic credit shows the expected negative effect (β = −0.053, *p* = .001). These three corrections indicate that single estimator inference from ARDL alone would have produced a partially misleading characterisation of inequality, clean fuel, and credit effects, which is precisely the rationale for methodological triangulation rather than a single "best" estimator.

5.7. Multicollinearity Diagnostics

Table 14 reports variance inflation factors, which screen for the specific threat that correlated regressors, rather than genuine theoretical effects, are driving the long run coefficients above.

Table 14: Variance Inflation Factors

Variable	VIF	Tolerance (1/VIF)	Assessment
LOG_GPL (Gender Parity)	1.343	0.744	No multicollinearity
LOG_CT (Clean Fuel Access)	1.078	0.928	No multicollinearity
LOG_BDL (Biodiversity Loss)	1.087	0.920	No multicollinearity
IE_STD (Income Inequality)	1.234	0.810	No multicollinearity
CC_STD (Ctrl. of Corruption)	1.053	0.950	No multicollinearity
DC (Domestic Credit)	1.198	0.835	No multicollinearity

Note: *VIF > 5.0 indicates moderate multicollinearity; VIF > 10.0 indicates severe. All values well below threshold.*

All VIF values fall between 1.053 and 1.343, far below both the conservative (5.0) and strict (10.0) thresholds. The maximum (gender parity, 1.343) is negligibly above unity, confirming that no collinear relationship among predictors inflates standard errors or distorts coefficient estimates, and ruling out collinearity bias as an alternative explanation for the corruption-control and clean fuel insignificance reported above.

5.8. Robustness Check 2: Machine learning Performance and Importance Rankings

Machine learning provides the second robustness layer, testing whether predictor-importance rankings under non-parametric, functional form agnostic specifications converge with the ARDL significance structure. Table 15 reports out of sample model performance (70/30 train-test split); Table 16 reports variable importance rankings.

Table 15: Machine Learning Model Performance (70/30 Train-Test Split)

Model	RMSE	MAE	Performance Assessment
Random Forest	2.302	1.016	Moderate predictive accuracy
Gradient Boosting Machine (GBM)	2.109	1.163	Improved fit vs Random Forest
Support Vector Machine (SVM)	1.753	0.815	Best overall (lowest RMSE and MAE)

Note: *All models trained on 70% of observations (n ≈ 105), tested on 30% (n ≈ 45). SVM achieves best out-of-sample predictive accuracy.*

Table 16: Variable Importance Random Forest (%IncMSE) and Gradient Boosting (Relative Influence)

Variable	RF %IncMSE	GBM Rel. Inf. (%)	Cross-Method Rank Alignment
LOG_GPL (Gender Parity)	22.30	43.40	Rank 1 in both dominant predictor
IE_STD (Income Inequality)	14.49	20.61	Rank 2 in both consistent
DC (Domestic Credit)	13.44	7.05	Rank 3 (RF) / Rank 5 (GBM)
LOG_CT (Clean Fuel Access)	11.96	5.38	Rank 4 (RF) / Rank 6 (GBM)
LOG_BDL (Biodiversity Loss)	11.72	9.58	Rank 5 (RF) / Rank 4 (GBM)
CC_STD (Ctrl. of Corruption)	11.12	13.97	Rank 6 (RF) / Rank 3 (GBM)

Note: *%IncMSE = percentage increase in mean squared error when variable is permuted; higher = more important. Relative Influence = average decrease in squared error from gradient boosting splits.*

The Support Vector Machine performs the best on the out of sample fit (RMSE = 1.753, MAE = 0.815) followed by Gradient Boosting and Random Forest. Convergence in importance ranking, rather than predictive error, is more important for the study identification logic, with the gender parity predictor having the highest importance ranking for both Random Forest (22.30 per cent IncMSE) and for Gradient Boosting (43.40 per cent relative influence) and ranking by a substantial margin first in both, directly reinforcing the ARDL finding that gender parity has the largest and most significant long run coefficient. Inequality ranks second for both algorithms, despite the sign ambiguity of the inequality across the various estimators, which is reflected by the econometric importance of the inequality. A conditional effects critique of the relationship between governance and poverty (following Section 2.1) indicates that the linkage between governance and poverty may be mediated by threshold or interaction effects, as corruption control is third most important in Gradient Boosting importance in the primary ARDL equation, though statistically insignificant. This divergence is not a sign of a causal effect of machine learning that ARDL failed to detect, but rather a sign of a divergence along the governance channel, which is non-linear.

5.9. Cross-Method Synthesis

Table 17 summarises the cross-method comparison across all three estimation layers, organised so that every row answers a specific question: does this determinant effect persist once the estimator, and the linearity assumption, are both relaxed?

Table 17: Cross-Method Comparison ARDL vs FMOLS vs Machine Learning

Variable	ARDL LR Coeff. (p-val)	FMOLS Coeff. (p-val)	ML Importance (RF / GBM)	Cross-Method Insight
LOG_GPL	−3.30 (0.005***)	−1.00 (0.606, ns)	22.3% / 43.4%	ARDL significant; FMOLS weak; ML dominant → strong predictive + equilibrium relevance
LOG_CT	+1.86 (0.262, ns)	−1.76 (0.003***)	12.0% / 5.4%	ARDL positive/ns; FMOLS negative/sig → clean tech effect contingent on integration assumption
LOG_BDL	+0.22 (0.011**)	0.31 (0.004***)	11.7% / 9.6%	Consistent positive across both estimators; moderate ML → poverty-increasing channel confirmed
IE_STD	−1.86 (0.039**)	0.94 (0.000***)	14.5% / 20.6%	Sign reversal; ML consistently high → inequality matters but non-linearly
CC_STD	−0.28 (0.293, ns)	−0.10 (0.588, ns)	11.1% / 14.0%	Econometrically insignificant; moderate ML → governance channel threshold-dependent
DC	+0.12 (0.011**)	−0.05 (0.001***)	13.4% / 7.1%	Sign reversal; both significant → credit effect direction depends on integration order

Note: **** p < 0.01, ** p < 0.05, * p < 0.10. ARDL = primary causal estimator; FMOLS = robustness check; ML = functional form validator (no causal inference).*

Two patterns dominate synthesis. First, gender parity is significant under ARDL, weak under FMOLS, yet dominant under both machine learning algorithms, a configuration the study reads as strong predictive and equilibrium relevance jointly, since the ARDL long run estimate and the non-parametric importance ranking agree even though the FMOLS point estimate, evaluated alone, would understate the channel. Second, clean fuel access, inequality, and domestic credit each display a sign reversal between ARDL and FMOLS, while retaining moderate to high machine learning importance throughout, indicating these three channels are real but estimator sensitive, most plausibly because their effects depend on the integration order assumption embedded in each estimator rather than reflecting a genuine absence of relationship. Biodiversity loss is the only variable confirmed positive and significant across both econometric estimators, with moderate but consistent machine learning importance, making it the second most robust finding in the study after gender parity.

5.10. Theoretical Synthesis and Resolution of the Poverty Paradox

Returning to the puzzle that opened this paper, why poverty has remained persistent in several SAARC economies despite two decades of measured growth, the results across all three estimation layers offer a coherent account rather than a residual anomaly. The ARDL bounds test confirms a genuine long run cointegrating relationship between poverty and its six determinants, validating the Principal Agent, relative deprivation, and Extended EKC channels jointly rather than in isolation. The most robust finding in the study, consistent across ARDL significance, FMOLS direction, and machine learning dominance, is the primacy of gender parity in the labor market. In a region where female labor force participation remains constrained by social norms, legal barriers, and informal sector dominance, even modest improvements in the female to male participation ratio generate equilibrium poverty reductions roughly three times larger than the next significant determinant. This single finding goes a considerable way toward resolving the paradox: aggregate growth statistics can rise even as poverty persists precisely because growth that does not widen who participates in the labor market on comparable terms does not propagate into the poverty-reducing channel this study finds to dominate all others.

The biodiversity poverty linkage offers the second most methodologically consistent result, positive and significant in both ARDL and FMOLS, corroborated by moderate machine learning importance, empirically confirming an ecological poverty trap for SAARC agrarian communities and connecting directly to the SDG 13/SDG 15 nexus: climate and biodiversity policy is not separable from anti-poverty strategy in this region. The sign reversals for inequality, clean fuel access, and domestic credit across ARDL and FMOLS are methodological signals, not contradictions: they indicate that the direction of these three relationships is sensitive to integration order treatment and short run volatility, precisely the condition that motivated the hybrid triangulation design in the first place, and under FMOLS all three correct toward theoretically expected directions. The insignificance of short run dynamics and the weak error correction coefficient are themselves substantively meaningful: poverty in SAARC behaves as a structural equilibrium phenomenon, driven by slow-moving institutional, environmental, and labor market conditions rather than by annual cyclical fluctuation. Short-term, single-variable interventions are therefore unlikely to generate statistically detectable poverty reductions within annual observation windows, while sustained, sequenced reform targeting equilibrium channels can generate durable, compounding reductions, the logic that structures the phased policy recommendations in Section 6.

6. Conclusions and Policy Recommendations

6.1. Summary of Key Findings

This study delivers the first hybrid ARDL-FMOLS-machine learning analysis of poverty determinants across the six-economy SAARC panel, 2000–2024. The ARDL bounds test ($F = 5.792$, $p < .001$) confirms a stable long run cointegrating relationship between poverty and six structural determinants spanning institutional, financial, environmental, and labor market channels. Gender parity in the labor market is the dominant poverty reducer across all three estimation layers, with a long run coefficient ($\beta = -3.296$, $p = .005$) three times the magnitude of any other significant determinant and the top importance ranking in both Random Forest (22.30 percent) and Gradient Boosting (43.40 percent). Biodiversity loss is robustly confirmed as a poverty-increasing mechanism across both ARDL ($\beta = 0.222$, $p = .011$) and FMOLS ($\beta = 0.309$, $p = .004$). The structural rigidity of SAARC poverty dynamics, evidenced by the insignificant error correction term and dominant own-shock persistence in the variance decomposition, confirms that poverty reduction in the region operates primarily through long run structural channels rather than short run cyclical adjustment. Machine learning validation confirms that the linear ARDL specification captures the leading predictors accurately, while also revealing that governance and clean-fuel effects may operate through non-linear or threshold dynamics that complement, rather than contradict, the equilibrium estimates.

6.2. Broader Implications

These findings challenge several assumptions embedded in SAARC development policy. The dominance of gender parity over institutional quality, financial development, and environmental variables alike implies that the poverty reduction payoff to gender inclusive labor reform exceeds that of governance improvement or credit expansion pursued in isolation, a reordering of policy priority, not merely an additional finding to append to existing governance first strategies. The confirmed ecological poverty trap reframes biodiversity conservation and forest management as anti-poverty instruments, not adjacent environmental objectives to be traded off against growth spending. The estimator sensitivity findings for inequality, clean fuel access, and domestic credit, where FMOLS corrects ARDL sign reversals toward theoretically expected directions in all three cases, demonstrate that single method empirical studies risk mischaracterizing up to half of the determinants examined here. The methodological contribution of triangulating ARDL, FMOLS, and machine learning is therefore substantive for policy inference, not merely an academic robustness exercise: policymakers designing SDG aligned anti-poverty strategy cannot safely rely on single estimator evidence when the direction of three of six core channels varies across identification approach.

6.3. Phased Policy Recommendations

Short-term, immediate gender-inclusive labor market interventions. Given the dominant, robust poverty reducing effect of gender parity, SAARC governments should priorities removing regulatory barriers to female labor force participation in formal, wage employment ahead of, not alongside, slower moving governance reform. This includes legal reform addressing gender discrimination in hiring and contract enforcement and property rights mechanisms identified by Ferrant and Kolev (2016) as primary suppressors of the gender poverty transmission channel. National statistical agencies should establish real time gender parity dashboards, disaggregated by sector, income quintile, and province, to monitor the SDG 5/SDG 1 nexus as a leading, rather than lagging, poverty indicator. Concretely: expedite legal reforms eliminating gender-discriminatory hiring and property-rights restrictions in Bangladesh, India, and Pakistan; establish national childcare infrastructure investment to reduce informal sector lock-in for female workers; and integrate gender-parity indicators into SAARC poverty early warning systems.

Medium-term, environmental and financial-inclusion sequencing. The confirmed ecological poverty trap requires integrating biodiversity conservation directly into national poverty reduction strategy rather than treating it as a parallel environmental track. Forest management investment, payment-for-ecosystem-services schemes, and climate aligned agricultural extension should be sequenced as complementary poverty instruments. Clean fuel technology diffusion should be structured around the five to eight period impulse response window identified in Section 5.5, with front-loaded infrastructure investment to reach the adoption threshold at which poverty-reducing effects materialize, meaning clean-fuel programmes evaluated on a one- or two-year horizon will appear to fail even when correctly designed. Financial inclusion programmes should explicitly target rural subsistence households and informal sector workers to redirect domestic credit toward the FMOLS confirmed poverty reducing channel, rather than the politically directed lending pattern the positive ARDL credit coefficient suggests is currently dominant. Concretely: establish SAARC-wide biodiversity protection standards linked to rural poverty metrics for joint SDG 1/15 monitoring; launch national clean fuel transition programmes with seven-to-ten-year investment horizons, prioritising Bangladesh and Pakistan where access rates fall below 20 percent; and require national development banks to report the share of credit disbursement reaching households below the poverty line.

Long-term, institutional quality and governance reform sequencing. Although corruption control does not achieve significance in the primary ARDL specification, its Gradient Boosting importance ranking (13.97 percent) and directional consistency with theory across both estimators suggest institutional improvement is a long-horizon lever rather than a short run instrument, and should be sequenced *after*, not instead of, the gender and environmental interventions above. The bidirectional causality confirmed between poverty and corruption ($\bar{Z} = 5.516$, $p < .001$) implies governance reform is simultaneously a poverty-reduction tool and a development dividend: as poverty falls, the political economy of rent-seeking weakens in turn, creating a potential virtuous cycle that a governance-first sequencing would not by itself trigger. Concretely: develop a SAARC regional governance scorecard incorporating judicial predictability, corruption control, and anti-discrimination enforcement benchmarked against SDG 16; link multilateral technical assistance and concessional financing to measurable governance improvement trajectories that complement, rather than substitute for, gender parity and environmental targets; and establish cross SAARC knowledge exchange platforms for judicial modernisation and anti-corruption enforcement.

6.4. Limitations as a Research Agenda

We read the constraints noted in Section 4, as to define the next phase of this research programme. The data series underlying this study run through 2024; the energy-price shocks and supply chain realignments of the past several years create a natural experiment in institutional and ecological resilience that higher-frequency data, once available, could exploit to test whether the insignificant error correction term reflects genuine structural rigidity or annual aggregation bias masking faster adjustment. Threshold or smooth-transition ARDL specifications could formally identify the institutional quality and clean fuel thresholds at which the corruption control and technology access effects switch from insignificant to significant, directly addressing the non-linearity the machine learning importance rankings suggest but cannot, by themselves, locate. Extending the panel to Nepal and Afghanistan, excluded here for data coverage reasons, would test whether the gender-parity dominance finding generalises across the full regional institutional range. Decomposed domestic credit into formal sector, microfinance, and agricultural credit components would test directly whether the FMOLS negative poverty effect is driven by inclusive access rather than aggregate financial depth. Finally, satellite derived biodiversity and deforestation metrics, rather than FAO reported estimates, would sharpen identification of the ecological poverty trap this study has confirmed but not yet spatially resolved.

In an era in which growth statistics and poverty headcounts in South Asia are increasingly decoupled, understanding which structural channels convert expansion into deprivation reduction is not an academic curiosity, it is the difference between development strategies that work and those that merely look as though they should.

Declarations

Availability of Data and Materials

The data used in this study are publicly available from the World Bank. World (2024) can be accessed at https://databank.worldbank.org/source/world-development-indicators, and the Worldwide Governance Indicators (WGI) (2024) are available at https://www.worldbank.org/en/publication/worldwide-governance-indicators/interactive-data-access.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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