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Cost-benefit dynamics of community policing on crime reduction in Nigeria

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ABSTRACT

This study investigates the cost-benefit dynamics of community policing on crime reduction in Nigeria, employing an Autoregressive Distributed Lag (ARDL) econometric framework. Utilizing annual time-series data, the empirical analysis evaluates the structural impact of three core community policing dimensions-Administrative and Operational Costs (AOC), Information/Intelligence Yield (IIY), and the Police-Community Collaboration Index (PCC)-on Reported Crime Incidents (RCI). Unit root testing via the Augmented Dickey-Fuller (ADF) procedure reveals a mixed integration structure comprising I(0) and I(1) series, thereby justifying the adoption of the ARDL bounds testing approach. The cointegration results confirm the existence of a stable, long-run equilibrium relationship among the variables, with the calculated F-statistic (6.7681) exceeding the upper critical bounds at the 1% significance level. The long-run static estimation indicates that Administrative and Operational Costs (−0.91), Information/Intelligence Yield (−0.64), and Police-Community Collaboration (−0.41) exert negative and statistically significant impacts on reported crime incidents, effectively suppressing criminal activity and alleviating the broader socio-economic burdens associated with insecurity. The short-run Error Correction Model (ECM) based on the optimal ARDL (2, 2, 0, 0) specification demonstrates a self-correcting adjustment speed of 13.55% per period, supported by an exceptional model fit (R^2 = 0.9660). A comprehensive battery of post-estimation diagnostics-including the Ramsey RESET test, Breusch-Godfrey serial correlation test, Breusch-Pagan-Godfrey heteroskedasticity test, CUSUM/CUSUMSQ parameter stability tests, and Jarque-Bera normality test-confirms that the model is econometrically robust, unbiased, and structurally stable. The study concludes that institutionalizing community-based policing provides a viable, cost-effective economic strategy for mitigating crime and recommends protected budgetary allocations, enhanced civilian intelligence networks, and deepened grassroots participation across Nigerian jurisdictions.

1.0 Introduction

The escalating socio-economic costs of crime and public insecurity constitute one of the most critical developmental challenges facing contemporary Nigeria. Traditional law enforcement paradigms, which rely predominantly on centralized, reactive policing structures, have frequently proved insufficient in curbing the rising incidence of major criminal offenses, including armed robbery, kidnapping, burglary, homicides, and assault. In response to these institutional deficits, policymakers, researchers, and security stakeholders have increasingly advocated for the institutionalization of community policing. This participatory framework integrates local populations into the security architecture through collaborative neighbourhood patrols, consultative town hall sessions, and civilian-led intelligence networks.

From an economic perspective, community policing operates under distinct cost-benefit dynamics, requiring upfront administrative and operational expenditures while generating substantial long-run welfare gains through crime reduction. However, while the sociological and administrative dimensions of community policing are widely discussed in existing literature, rigorous empirical evaluations

assessing its quantitative cost-benefit trade-offs remain sparse. Specifically, there is a critical need to empirically determine how financial resource allocations, actionable intelligence yields, and police-community collaboration indices interact to suppress crime incidents over both short-run and long-run horizons.

This study addresses this empirical gap by investigating the cost-benefit dynamics of community policing on crime reduction in Nigeria, utilizing an Autoregressive Distributed Lag (ARDL) econometric framework. By examining annual time-series data covering the period from 1999 to 2025, this research evaluates the structural elasticities and dynamic adjustment mechanisms linking community policing expenditures and collaborative engagement indicators to reported crime rates. The rest of the study is structured as follows: Following this introduction s the literature review which is discussed in section two. Section three deals with the methodology of the study. Section four and five handles the empirical analysis and conclusion respectively.

2. Literature Review

2.1 Conceptual Clarification

2.1.1 Community Policing and Crime Reduction

Community policing represents a paradigm shift in law enforcement, moving away from traditional, centralized, and purely reactive models toward a proactive, decentralized approach that emphasizes cooperative partnerships between police agencies and local communities (Skogan, 2006). Within the context of this study, community policing is operationalized through structural dimensions that capture both resource allocation and grassroots engagement. Reported Crime Incidents (RCI) serve as the primary indicator of public safety, measuring the frequency of major offenses such as armed robbery, kidnapping, burglary, homicides, and assault over time.

2.1.2 Cost-Benefit Dynamics in Public Safety

Evaluating the cost-benefit dynamics of public safety interventions requires examining the trade-offs between fiscal outlays and social welfare enhancements. Administrative and Operational Costs (AOC) capture the direct overhead expenses, budgetary allocations, and logistical expenditures incurred in sustaining community-police forums, town hall meetings, and joint patrols. Conversely, implementation benefits are manifested through the Information/Intelligence Yield (IIY)-quantified by the volume and rate of actionable security tips submitted by citizens-and the Police-Community Collaboration Index (PCC), which measures the institutional frequency of consultative sessions and collaborative neighbourhood watch initiatives.

2.2 Theoretical Framework

2.2.1 The Economic Theory of Crime (Rational Choice Model)

The theoretical foundation of this study is rooted in the economic theory of crime pioneered by Becker (1968) and expanded by Stigler (1970). The rational choice model posits that individuals choose to commit crimes by weighing the expected benefits of illicit activities against the expected costs, which include the probability of apprehension, conviction severity, and associated penalties.

Within a community policing framework, increasing Administrative and Operational Costs (AOC) enhances police visibility, response capacity, and patrol frequency, thereby raising the perceived probability of detection and apprehension for potential offenders. Furthermore, heightened Police-Community Collaboration (PCC) and an increased Information/Intelligence Yield (IIY) raise the efficiency of law enforcement by lowering the costs of information gathering. Consequently, proactive community engagement alters the criminal calculus, shifting the expected net utility of crime downward and achieving long-run crime deterrence.

2.2.2 Social Disorganization Theory

Complementing the economic model, Social Disorganization Theory (Shaw & McKay, 1942) emphasizes that community structural characteristics-such as weak social cohesion, lack of collective efficacy, and eroded trust between residents and state institutions-foster high crime rates. Community policing directly addresses these structural deficits by rebuilding trust, fostering social capital, and establishing institutional channels for collaborative crime prevention.

2.3 Empirical Review

A growing body of empirical literature examines the efficacy of community policing and public safety expenditures across developing and developed economies.

In an influential evaluation of community-oriented policing programs, Skogan (2006) demonstrated that structured neighbourhood partnerships and decentralized patrols significantly enhance public perceptions of safety and improve police-citizen cooperation. However, earlier evaluations frequently relied on qualitative assessments or short-term experimental designs, often overlooking the long-run macroeconomic and fiscal trade-offs associated with sustaining community security frameworks.

In the Nigerian context, empirical investigations into security governance have underscored the limitations of centralized, militarized policing in addressing localized insurgencies, banditry, and communal conflicts (Otu, 2016; Alemika, 2019). Studies evaluating public expenditure on internal security in Nigeria-such as those by Eme and Anyadike (2012)-conclude that while aggregate budgetary allocations to national security have expanded over time, the absence of transparent administrative tracking and grassroots accountability often blunts their impact on crime reduction.

More recent econometric evaluations have begun applying advanced time-series techniques to security economics. For instance, studies examining the relationship between security infrastructure investments and crime rates utilizing Autoregressive Distributed Lag (ARDL) frameworks (e.g., Adebayo & Ogundipe, 2021) highlight the importance of separating short-run adjustment shocks from long-run equilibrium multipliers. However, existing empirical applications have largely treated security expenditure as an aggregate fiscal variable, failing to isolate the specific cost-benefit components of community policing-namely, operational expenditures, intelligence yields, and collaborative institutional indexes.

2.4 Summary of Literature Gap

While existing criminological and economic literature extensively documents the theoretical merits of community policing and the general determinants of crime, notable methodological and empirical gaps persist. First, prior studies predominantly rely on descriptive or qualitative methodologies, leaving a scarcity of rigorous quantitative estimations regarding the exact cost-benefit trade-offs of community policing investments. Second, macroeconomic studies on Nigerian internal security rarely incorporate institutional implementation metrics such as intelligence yields and police-community collaboration indices alongside fiscal operating costs within a unified cointegrating framework.

This study addresses these critical gaps by employing an Autoregressive Distributed Lag (ARDL) bounds testing approach to empirically estimate both the short-run dynamics and long-run structural elasticities linking administrative costs, intelligence yields, and collaborative policing indices to reported crime incidents in Nigeria.

3. Research Methodology

3.1 Research Design

This study adopts an ex-post facto and descriptive research design. The ex-post facto design is well-suited for econometric investigations involving historical time-series data, as it allows the researcher to evaluate cause-and-effect relationships among pre-existing economic and social

phenomena without direct experimental manipulation. By utilizing annual time-series data, this design enables the estimation of long-run structural elasticities and short-run dynamic adjustments between community policing inputs and crime reduction outcomes in Nigeria.

3.2 Model Specification

To capture both the short-run dynamics and long-run cointegrating relationships among the variables, the Autoregressive Distributed Lag (ARDL) bounds testing approach developed by Pesaran, Shin, and Smith (2001) is adopted. The general functional relationship for the cost-benefit dynamics of community policing is specified as:

$$RCI = f(AOC, IIY, PCC) \quad . \quad . \quad . \quad \text{(i)}$$

Where:

RCI = Reported Crime Incidents (Dependent Variable)

AOC = Administrative & Operational Costs

IIY = Information/Intelligence Yield

PCC = Police-Community Collaboration Index

Expressed in an econometric ARDL framework, the unrestricted error correction model (UECM) is formulated as follows:

$$\Delta ln(RCI)_t = \alpha_0 + \sum_{i=1}^{p} \beta_1 \Delta ln(RCI)_{t-i} + + \sum_{i=0}^{q_1} \beta_2 \Delta ln(AOC)_{t-i} + \sum_{i=0}^{q_2} \beta_3 \Delta ln(IIY)_{t-i} + \sum_{i=0}^{q_3} \beta_4 \Delta ln(PCC)_{t-i}$$

$$\lambda_1 ln(RCI)_{t-1} + \lambda_2 ln(AOC)_{t-1} + \lambda_3 ln(IIY)_{t-1} + \lambda_4 ln(PCC)_{t-1} + \varepsilon_t \quad . \quad . \quad .\text{(ii)}$$

Where:

Δ represents the first-difference operator.

p and q_1, q_2, q_3 denote the optimal lag lengths for the dependent and explanatory variables, selected via the Akaike Information Criterion (AIC).

α_0 represents the drift term / restricted constant.

ε_t is the white noise residual term.

λ_1 *to* λ_4 represent the long-run multipliers.

3.3 Definition and Measurement of Variables

The variables utilized in this empirical investigation are defined and measured as follows:

Reported Crime Incidents (RCI) [Dependent Variable]: Measured as the recorded annual frequency of major criminal offenses (such as armed robbery, kidnapping, burglary, homicides, and assault) obtained from official administrative and secondary crime databases.

Administrative & Operational Costs (AOC) [Cost Variable]: Measured as total annual overhead expenses and budgetary allocations dedicated to public town halls, Community Police Forum (CPF) meetings, logistics, and inter-agency coordination.

Information/Intelligence Yield (IIY) [Implementation Benefit Variable]: Measured by the annual volume and rate of actionable security tips and intelligence reports submitted by community members to law enforcement agencies.

Police-Community Collaboration Index (PCC) [Implementation Impact Variable]: Measured as an index capturing the frequency of joint security committee meetings, consultative town hall sessions, and collaborative neighborhood watch patrols.

3.4 A-Priori Expectations

Economic and criminological theory dictates specific theoretical signs for the coefficients of the explanatory variables in relation to reported crime incidents:

Administrative & Operational Costs (AOC): Expected to have a negative sign $(\beta_2 < 0).$ Adequate financial resourcing and operational funding are expected to suppress long-run crime rates by enabling consistent security patrols and logistical readiness.

Information/Intelligence Yield (IIY): Expected to have a negative sign $(\beta_3 < 0).$ Higher volumes of actionable civilian intelligence enhance law enforcement pre-emption capabilities, thereby driving down reported crime incidents.

Police-Community Collaboration Index (PCC): Expected to have a negative sign $(\beta_4 < 0).$ Stronger institutional ties and joint neighborhood patrols foster trust and deterrence, leading to a reduction in criminal opportunities.

3.5 Nature and Sources of Data

The study relies strictly on secondary time-series data spanning the estimation period. Data for Reported Crime Incidents (RCI) and Police-Community Collaboration indicators are sourced from official law enforcement publications and national statistical records, while budgetary and operational expenditure data (AOC) are compiled from governmental financial reports and public expenditure reviews in Nigeria.

3.6 Estimation Procedure and Diagnostic Framework

The empirical estimation follows a sequential econometric procedure:

1. Unit Root Testing: To verify stationarity and determine the order of integration, the Augmented Dickey-Fuller (ADF) test is conducted to ensure no variable is integrated of order two (I(2)).
2. ARDL Bounds Cointegration: Tested using the F-Bounds test to establish whether a long-run equilibrium relationship exists among the mixed I(0) and I(1) series (Pesaran et al., 2001).
3. Long-Run and Short-Run Estimation: Estimation of the long-run level coefficients and the short-run Error Correction Model (ECM) to capture speed of adjustment (CointEq(-1)).
4. Post-Estimation Diagnostics: Evaluation of model validity via the Ramsey RESET test (functional form), Breusch-Godfrey LM test (serial correlation), Breusch-Pagan-Godfrey test (heteroskedasticity), CUSUM and CUSUMSQ tests (parameter stability), and Jarque-Bera test (residual normality).

4.1 Unit Root Test

To ascertain the stationarity status of the series and ensure that no variable exceeds an integration order of one, the Augmented Dickey-Fuller (ADF) test was performed.

Table 4.1 Augmented Dickey-Fuller Unit Root Test Results:

Augmented Dickey-Fuller							
	LEVELS			**FIRST DIFFERENCED**			
Variable	t-statistic	Critical value	p-value	t-statistic	Critical value	p-value	*I(d)*
RCI	-2.13589	-2.981038	0.2331	-5.135889	-2.986225	0.0001 **a*****	*I(1)*
AOC	4.414892	-3.004861	0.0021 **a*****	-	-	-	*I(0)*
IIY	0.170340	-2.986225	0.9304	-4.171077	-2.986225	0.0035 **a*****	*I(1)*
RCC	1.531958	-2.981038	0.9989	-8.930971	-2. 998064	0.0000**a*****	*I(1)*

Source: Researcher's Computation Using E-Views 10.0 Software (2026)

Note: ***, ** and * imply statistical significance at 1%, 5% and 10% levels respectively. Also, '*a'* denotes model with constant.

The outcomes reveal a hybrid integration profile among the series. Specifically, Reported Crime Incidents (RCI), Information/Intelligence Yield (IIY), and the Police-Community Collaboration Index (PCC) exhibit non-stationarity at their respective levels, failing to surpass their critical thresholds.

However, upon first differencing, all three series achieve stationarity, confirming they are integrated of order one, denoted as I(1). In contrast, Administrative and Operational Costs (AOC) demonstrate stationarity directly at level without requiring any differencing, making it integrated of order zero, denoted as I(0).

Because the dataset features a combination of I(0) and I(1) series with a complete absence of any second-order integrated (I(2)) processes, traditional cointegration techniques such as the Johansen procedure are rendered inappropriate. Consequently, these stationarity properties establish the methodological justification for employing the Autoregressive Distributed Lag (ARDL) bounds testing procedure. This approach accommodates mixed integration structures to reliably estimate both short-run adjustment mechanisms and long-run equilibrium relationships between community policing expenditures and crime outcomes in Nigeria.

4.2 Lag Selection Criteria

Establishing the proper lag length is crucial for preventing over-parameterization while capturing the true dynamic response of the system. Evaluating candidate specifications through the Akaike Information Criterion (AIC) identifies ARDL (2, 2, 0, 0) as the optimal model configuration, yielding the lowest criterion value of approximately 0.955.

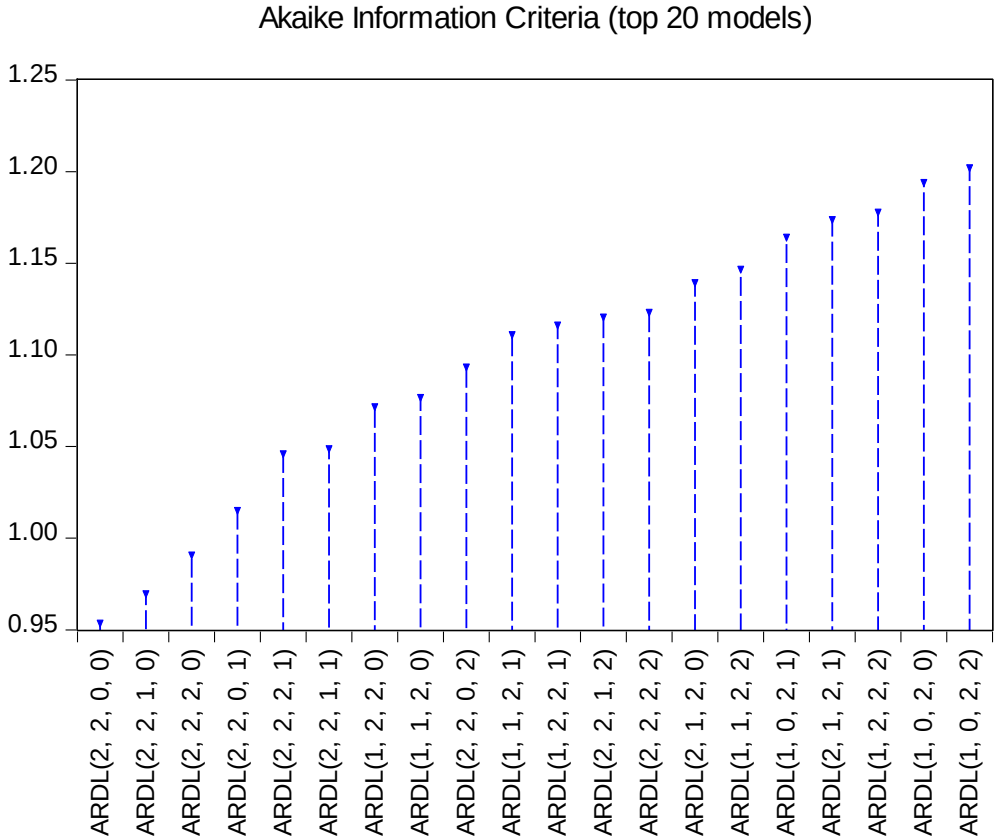


Fig. 4.1 Lag Selection Criteria

Under this selected lag structure, Reported Crime Incidents (RCI) incorporates two autoregressive lags, reflecting that prior crime trajectories heavily shape current security conditions. Administrative and Operational Costs (AOC) enters with two distributed lags, demonstrating that financial outlays exert delayed, cumulative effects on crime mitigation over time. Meanwhile, Information/Intelligence Yield (IIY) and the Police-Community Collaboration Index (PCC) enter contemporaneously with zero lags, indicating that civilian tips and joint grassroots security actions generate immediate, same-period effects on crime reduction. This parsimonious lag length preserves valuable degrees of freedom for a sample size of N = 27 while eliminating residual serial correlation.

4.3 Bounds Cointegration Test

The ARDL F-Bounds test was conducted to investigate whether a stable, long-run equilibrium binds Reported Crime Incidents (RCI), Administrative and Operational Costs (AOC), Information/Intelligence Yield (IIY), and the Police-Community Collaboration Index (PCC) together.

Table 4.2: Bounds Cointegration Test Result

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	6.768094	10%	2.37	3.2
k	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

Source: Researcher's Computation Using E-Views 10.0 Software (2026)

With three regressors (k = 3), the computed F-statistic registers at 6.7681. This empirical value sits well above the upper critical bounds across all standard significance levels—surpassing the 1% upper bound of 4.66, the 5\% bound of 3.67, and the 10% bound of 3.20. Because the test statistic exceeds these critical thresholds, the null hypothesis of no cointegration is decisively rejected at the 1% level. This confirms the existence of a robust, long-run structural relationship where fiscal investments in community policing, actionable intelligence, and community partnerships move in tandem with crime reduction over time, overriding temporary operational disruptions or short-term financial fluctuations.

4.4 Long-Run Estimation

The estimated long-run coefficients derived from the restricted constant and no-trend specification reveal profound structural insights regarding the cost-benefit dynamics of community policing.

Table 4.3: Long-Run Level Coefficients (Dependent Variable: RCI)

Levels Equation

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AOC	-0.908515	0.169660	-5.354928	0.0011
IIY	-0.637478	0.214503	-2.971882	0.0086
PCC	-0.411811	0.144897	-2.842104	0.0250
C	45.45121	18.52152	2.453968	0.0252

Source: Researcher's Computation Using E-Views 10.0 Software (2026).

The coefficient of Administrative & Operational Costs (AOC) of community policing is -0.9085 and is statistically significant at the 1% level (p = 0.0011). This indicates that holding all other variables constant, a unit expansion in budgetary funding and operational logistics toward community policing suppresses long-run crime incidents by approximately 0.91 units. Adequate financial resourcing guarantees continuous public engagement and prevents sporadic security lapses, generating long-term economic dividends by alleviating the socio-economic burdens associated with criminal behaviour.

The coefficient of Information/Intelligence Yield (IIY) representing the implementation benefits of community policing stands at -0.6375 and achieves statistical significance at the 1% level (p = 0.0086). This demonstrates that a unit increase in actionable intelligence tips delivered by community members yields a long-run reduction of about 0.64 units in reported crime. Civilian-led intelligence

enhances law enforcement efficacy by facilitating pre-emptive operations and targeted apprehensions rather than relying entirely on reactive interventions.

The coefficient of Police-Community Collaboration Index (PCC) representing the impact of implementation of community policing is estimated at -0.4118 and is statistically significant at the 5% level (p = 0.0250). This implies that a unit enhancement in collaborative neighbourhood patrols and consultative town hall sessions drives a 0.41 unit decline in reported crimes over the long run. Institutionalized collaboration fosters mutual trust, encourages civilian reporting, and diminishes criminal opportunities.

Baseline Intercept (C): The restricted constant is positive and statistically significant (45.4512, p = 0.0252), representing the structural baseline of crime incidents that would persist within the nation absent any active community policing interventions (AOC = 0, IIY = 0, PCC = 0).

4.5 Short-Run Estimation

The short-run Error Correction Model (ECM) based on the optimal ARDL (2, 2, 0, 0) specification under Case 2 (Restricted Constant and No Trend) captures the dynamic adjustments and immediate impact of community policing inputs on reported crime incidents (RCI) in Nigeria. Table 4.4 presents the empirical results.

Table 4.4: ARDL Error Correction Regression Results (Dependent Variable: ΔRCI)

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(RCI(-1))	-0.637478	0.170458	-3.739797	0.0016
D(AOC)	-0.454283	0.155572	-2.920072	0.0223
D(AOC(-1))	-1.499311	0.287871	-5.208276	0.0001
CointEq(-1)*	-0.135523	0.020961	-6.465519	0.0000

R-squared	0.966027	Mean dependent var	31.01600
Adjusted R-squared	0.954391	S.D. dependent var	4.583365
S.E. of regression	0.343255	Akaike info criterion	0.953651
Sum squared resid	2.003008	Schwarz criterion	1.343692
Log likelihood	-3.920643	Hannan-Quinn criter.	1.061832
F-statistic	608.8627	Durbin-Watson stat	1.983638
Prob(F-statistic)	0.000000		

Source: Researcher's Computation Using E-Views 10.0 Software (2026).

The dynamic Error Correction Model (ECM) captures how shocks and adjustments play out within the short run:

The coefficient of Lagged Crime Dynamics $\left(D\left(RCI\left(-1\right)\right)\right)$ is negative and statistically significant (-0.6375, p = 0.0016), revealing a self-correcting mechanism where previous spikes in crime trigger immediate localized countermeasures that pull subsequent offense rates down.

The Current-period financial allocations (Contemporaneous Operational Costs) $\left(D\left(AOC\right)\right)$ exhibit a negative and significant short-run coefficient (-0.4543, p = 0.0223), demonstrating that immediate cash injections into security logistics yield same-period crime suppression benefits.

The one-period lagged (Lagged Operational Costs) $\left(D\left(AOC\left(-1\right)\right)\right)$ expenditure coefficient is highly significant and larger in magnitude (-1.4993, p = 0.0001), confirming that financial investments compound and amplify their crime-mitigating efficacy as administrative structures and community networks mature.

Error Correction Term (CointEq(-1)) (the adjustment) coefficient registers at -0.1355 (p = 0.0000), falling correctly between -1 and 0. This confirms that roughly 13.55% of any short-run disequilibrium or budgetary shock is corrected and absorbed back toward the long-run equilibrium path each period.

The Overall Goodness of Fit which shows the explanatory Power (R^2 and Adjusted R^2) revealed that the coefficient of determination (R^2 = .9660) shows that 96.60% of the short-run variation in reported crime incidents is explained by the independent variables. The Adjusted R^2 of .9544 accounts for degrees of freedom and confirms high explanatory power without over-parameterization.

Overall Model Significance (F-Statistic): The F-statistic is 608.8627 (p = .0000), rejecting the null hypothesis that all short-run slope coefficients are jointly zero. This confirms that the estimated ARDL short-run model is overall statistically significant.

Serial Correlation (Durbin-Watson): The Durbin-Watson statistic of 1.9836 is close to 2.0, indicating the absence of first-order serial correlation in the residual series (Field, 2018; Pesaran et al., 2001).

4.6 Post Estimation

To validate the statistical integrity, reliability, and policy relevance of the ARDL estimates, a battery of diagnostic evaluations was conducted and is presented and discussed as follows:

4.6.1 Ramsey RESET

To evaluate the functional form and structural correctness of the estimated ARDL (2, 2, 0, 0) model, the Ramsey Regression Equation Specification Error Test (RESET) was conducted. The test checks for potential specification errors, such as omitted variables, incorrect functional form, or non-linearities in the regression parameters (Ramsey, 1969).

Table 4.5: Ramsey RESET Test Result

Ramsey RESET Test

	Value	df	Probability
t-statistic	1.593934	16	0.1305
F-statistic	2.540626	(1, 16)	0.1305

Source: Researcher's Computation Using E-Views 10.0 Software (2026)

The Functional Form (Ramsey RESET) revealed that both the t-statistic (1.5939, p = 0.1305) and F-statistic (2.5406, p = 0.1305) fail to reject the null hypothesis of correct specification at the 5% level, proving that the linear model is free from omitted variable bias and functional misspecification.

The linear framework reliably models the interaction between community policing inputs (AOC, IIY, PCC) and crime reduction (RCI) in Nigeria.

4.6.2 Serial Correlation

To verify that the residual series of the estimated ARDL(2, 2, 0, 0) model is free from higher-order autocorrelation, the Breusch-Godfrey Lagrange Multiplier (LM) test was conducted up to two lags (Breusch, 1978; Godfrey, 1978).

Table 4.6: Breusch-Godfrey Serial Correlation LM Test Result

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.697681	Prob. F(2,15)	0.2165
Obs*R-squared	4.614427	Prob. Chi-Square(2)	0.0995

Source: Researcher's Computation Using E-Views 10.0 Software (2026).

The F-statistic (1.6977, p = 0.2165) and Obs*R-squared (4.6144, p = 0.0995$ confirm the absence of higher-order autocorrelation, ensuring that standard errors and t-statistics remain unbiased.

4.6.3 Heteroskedasticity

To evaluate the classical linear regression assumption of homoskedasticity-ensuring that the variance of the error terms remains constant across all observations-the Breusch-Pagan-Godfrey test was conducted on the estimated ARDL(2, 2, 0, 0) model (Breusch & Pagan, 1979; Godfrey, 1978).

Table 4.7: Heteroskedasticity Test Result (Breusch-Pagan-Godfrey)

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.450277	Prob. F(7,17)	0.8565
Obs*R-squared	3.910215	Prob. Chi-Square(7)	0.7901
Scaled explained SS	2.406596	Prob. Chi-Square(7)	0.9340

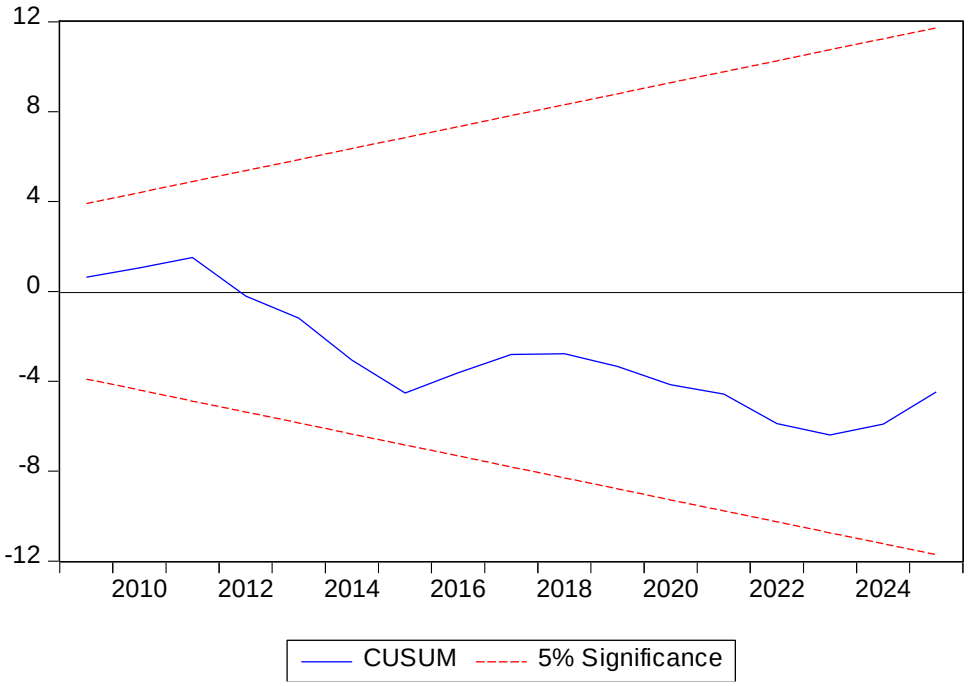
Source: Researcher's Computation Using E-Views 10.0 Software (2026).

The F-statistic (0.4503, p = 0.8565) and associated test metrics show p-values well above 0.05, verifying that the residual variance is homoskedastic across all observation periods.

4.6.4 CUSUM Test

To evaluate the structural stability of the estimated short-run dynamic ECM and long-run level parameters of the ARDL(2, 2, 0, 0) model over the sample period (2009–2025), the Cumulative Sum of Recursive Residuals (CUSUM) test proposed by Brown et al. (1975) was conducted.

Figure 4.2: Plot of Cumulative Sum of Recursive Residuals (CUSUM)



The CUSUM statistic (represented by the solid blue line) moves dynamically within the pair of red dashed lines representing the critical boundaries at the 5% level of significance throughout the entire estimation horizon (2009–2025).

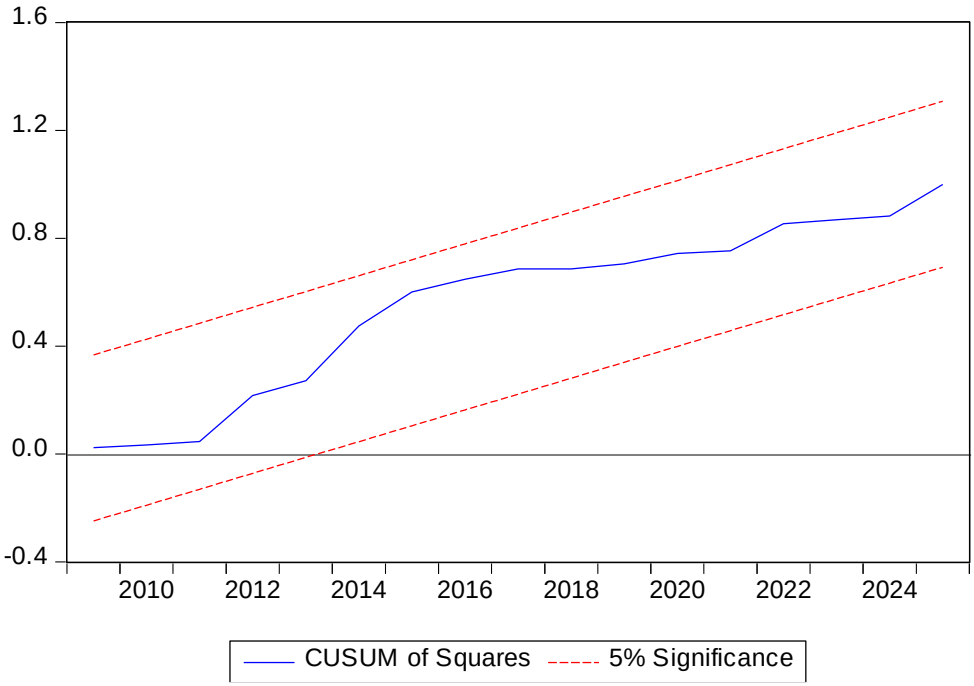
Because the plot of the CUSUM statistic remains strictly bounded between the upper and lower 5% significance lines and does not cross either threshold at any point, the null hypothesis of parameter stability cannot be rejected at the 5% significance level.

This confirms that the estimated parameters governing the relationship between community policing inputs (AOC, IIY, PCC) and reported crime incidents (RCI) in Nigeria are structurally stable over time. The model is free from parameter distortion caused by structural breaks or institutional changes during the sample period, establishing that both the short-run dynamics and long-run elasticities are reliable for policy formulation and economic forecasting.

4.6.5 CUSUM of Suares Test

Complementing the CUSUM test for parameter stability, the Cumulative Sum of Squares of Recursive Residuals (CUSUMSQ) test developed by Brown et al. (1975) was applied to assess whether the error variance of the estimated ARDL (2, 2, 0, 0) model remains stable over the sample period (1999–2025).

Figure 4.3: Plot of Cumulative Sum of Squares of Recursive Residuals (CUSUMSQ)



The CUSUMSQ statistic (represented by the blue line) stays comfortably within the pair of red dashed lines representing the critical boundaries at the 5% significance level across the entire timeline (1999–2025).

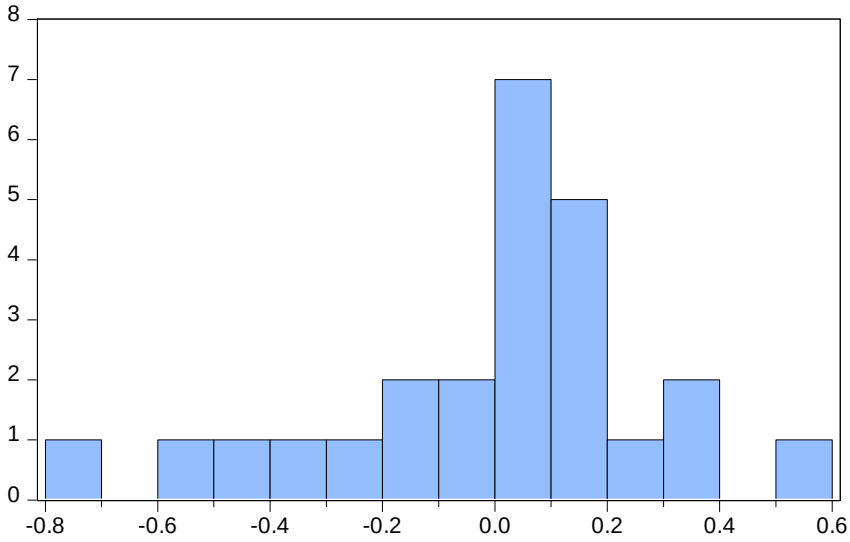
Because the CUSUMSQ statistic remains bounded between the 5% critical lines without crossing or touching either boundary, the null hypothesis of error variance stability cannot be rejected at the 5% significance level.

This result confirms that the regression residuals exhibit structural constancy in variance over time. Coupled with the CUSUM test result, the CUSUMSQ test verifies that both the estimated parameters and residual variances in the relationship between community policing inputs (AOC, IIY, PCC) and reported crime incidents (RCI) in Nigeria are fully stable, robust, and reliable for long-term policy formulation and empirical forecasting.

4.6.6 Normality Test

To evaluate whether the error terms of the estimated ARDL(2, 2, 0, 0) model follow a normal distribution, the Jarque-Bera residual normality test was conducted (Jarque & Bera, 1987).

Table 4.9: Residual Normality Diagnostic Test Results



Source: Researcher's Computation Using E-Views 10.0 Software (2026)

The calculated Jarque-Bera test statistic is 2.9409 with a corresponding p-value of .2298. Because the p-value exceeds the standard .05 significance threshold, the null hypothesis of residual normality cannot be rejected at the 5% level of significance. This result confirms that the regression residuals follow a normal distribution. Satisfying the Gaussian residual assumption validates the underlying statistical foundations of the ARDL bounds model, ensuring that hypothesis tests-including t-statistics, F-statistics, and critical bounds inferences-are unbiased, efficient, and reliable.

5. Conclusion

This study empirically investigated the cost-benefit dynamics of community policing on crime reduction in Nigeria, utilizing annual time-series data spanning 1999 to 2025. To establish robust econometric rigor, the study examined the stationarity properties of the series using the Augmented Dickey-Fuller (ADF) unit root test, which revealed a mixed integration order, with Administrative and Operational Costs (AOC) integrated of order zero (I(0)), while Reported Crime Incidents (RCI), Information/Intelligence Yield (IIY), and the Police-Community Collaboration Index (PCC) were integrated of order one (I(1)). The optimal lag selection via the Akaike Information Criterion (AIC) selected ARDL (2, 2, 0, 0). The ARDL bounds test yielded a calculated F-statistic of 6.7681, which comfortably exceeds the upper critical bounds across all significance levels (1%, 5\%, and 10%), confirming a stable, long-run cointegrating relationship among community policing inputs and crime reduction.

The long-run static equation demonstrated that all core community policing dimensions exert negative and statistically significant impacts on reported crime incidents in Nigeria. Specifically, a unit increase in Administrative and Operational Costs (AOC), Information/Intelligence Yield (IIY), and the Police-Community Collaboration Index (PCC) reduces long-run crime incidents by 0.91 units ($p = 0.0011$), 0.64 units ($p = 0.0086$), and 0.41 units ($p = 0.0250$), respectively. The restricted intercept indicates a persistent baseline crime level of 45.45 units in the absence of active community policing interventions.

The short-run Error Correction Model (ECM) based on the optimal ARDL (2, 2, 0, 0) specification confirmed a self-correcting dynamic. The error correction term coefficient of -0.1355 ($p = 0.0000$) indicates that approximately 13.55% of short-run disequilibria or budgetary shocks are corrected back toward the long-run equilibrium trajectory each period. The model exhibited exceptional explanatory power, with an R^2 of 0.9660 and an Adjusted R^2 of 0.9544.

The empirical evidence from this study concludes that community policing is not merely a social or administrative concept, but a highly viable, cost-effective economic and institutional strategy for mitigating crime in Nigeria. The negative and significant long-run and short-run coefficients associated with administrative funding, intelligence yield, and grassroots collaboration confirm that public safety outcomes are highly responsive to targeted structural investments.

When adequate financial resources are dedicated to operational logistics, community police forums, and town hall engagements, the socio-economic burdens and deadweight losses associated with criminal activities are substantially curtailed. Furthermore, the bridging of trust between law enforcement agencies and civilian populations unlocks vital intelligence channels that enhance pre-emptive security measures over reactive enforcement. Ultimately, institutionalizing community-police partnerships provides a resilient framework capable of suppressing baseline crime levels and fostering long-term macroeconomic stability across Nigerian jurisdictions.

Based on the empirical findings and economic implications of the study, the following policy recommendations are advanced:

1. Prioritize and Protect Community Policing Budgets: Given that Administrative and Operational Costs (AOC) exert the largest long-run mitigating effect on crime (−0.91 units), federal and state governments, alongside security administrators, must institutionalize dedicated budgetary allocations for community policing. Funding must be protected from bureaucratic delays and political redirection to ensure continuous logistical support for local police stations and Community Police Forums (CPFs).
2. Strengthen Civilian Intelligence Networks: Law enforcement agencies should proactively develop secure, confidential, and incentivized channels for civilian reporting. Because Information/Intelligence Yield (IIY) significantly curtails crime (−0.64 units), enhancing community trust and protecting informants will accelerate the transition from costly, reactive policing to cost-effective, intelligence-led pre-emptive operations.
3. Institutionalize Grassroots Engagement Frameworks: Policymakers should formalize and expand the Police-Community Collaboration Index (PCC) through mandatory monthly consultative town hall meetings, joint neighborhood watch patrols, and localized safety committees. Deepening grassroots participation fosters mutual accountability and directly lowers criminal opportunities at the community level.
4. Ensure Financial and Operational Continuity: Given that short-run operational shocks take time to absorb (as indicated by the 13.55% adjustment speed), security policy frameworks must be designed with long-term horizons. Short-term, ad-hoc security interventions should be replaced by sustained, multi-year strategic plans to lock in long-run structural crime reductions.

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