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Analysing the lagged effects of macroeconomic and bank-specific variables on non-performing loans in Ghana's agricultural sector: an econometric approach

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Abstract

Purpose – This study examines the lagged effects of macroeconomic and bank-specific variables on agricultural non-performing loans (NPLs) in Ghana, addressing a gap in modelling delayed transmission channels within a sector characterised by long production cycles and structural financing constraints.
Design/methodology/approach – Using monthly banking data from January 2015 to December 2022, the study employs a two-stage strategy: an autoregressive distributed lag (ARDL) bounds test to confirm cointegration, followed by Prais–Winsten feasible generalised least squares with AR(1) correction as the primary inferential model. A binary dummy captures the structural shift associated with Ghana's 2017–2019 banking recapitalisation.
Findings – Agricultural GDP growth is inversely associated with NPLs in the short run ($\beta = -0.237$) and long run ($\beta = -0.482$), consistent with the financial accelerator framework. Inflation and the monetary policy rate exert significant positive effects through cost-push and debt-service channels, respectively. Capital adequacy is inversely related to NPLs, while recapitalisation is the largest short-run determinant ($\beta = -0.091$), operating through institutional consolidation and regulatory signalling. The error correction term (-0.312) confirms long-run equilibrium adjustment within approximately 3.2 months.
Practical implications – Results support sustained prudential capital standards, sector-disaggregated NPL monitoring and countercyclical instruments such as GIRSAL to mitigate adverse effects of monetary tightening on agricultural credit quality.
Originality/value – This paper is among the first to systematically model lagged agricultural NPL determinants in Ghana, demonstrating that recapitalisation's structural effects substantially exceed the continuous capitalisation channel, with actionable implications for regulators and agricultural lenders in frontier markets.

Keywords Non-performing loans, Agricultural credit risk, ARDL model, Prais-Winsten regression, Banking sector recapitalisation, Ghana

Paper type Research article

1. Introduction

Bank loan portfolio quality remains a primary determinant of financial stability. As Nkwaira and Van der Poll (2023) and Marjohan and Andriani (2024) observe, the accumulation of non-performing loans (NPLs) restricts liquidity and erodes the profitability necessary for efficient credit allocation. Persistent NPL accumulation not only weakens individual institutions but also amplifies systemic vulnerability, particularly in economies where banks remain the dominant source of financing.

Agriculture occupies a structurally distinct position in Ghana's credit market. The sector faces climatic shocks, seasonal fluctuations and long production cycles that traditional risk-mitigation often fails to address (Murwanashyaka, 2023; Ansah *et al.*, 2023). These features

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heighten credit risk and differentiate agricultural NPL dynamics from aggregate banking behaviour. Macroeconomic variables such as gross domestic product (GDP), interest rates and inflation drive the credit cycle by dictating borrower repayment capacity and bank risk-taking incentives (Felipa, 2023). In agriculture, incomes are realised episodically at harvest, while repayment obligations are fixed in advance. Macroeconomic shocks therefore transmit into loan performance with delays, a temporal structure that must be explicitly modelled (Liu, 2025; Sümer, 2025; Reigl, 2025).

The rationale for isolating agriculture rests on its disproportionate contribution to aggregate NPLs. Table 1 presents sectoral NPL composition data.

Three observations from Table 1 merit emphasis. First, agricultural NPLs constitute 18–32% of total banking-sector NPLs, a share disproportionate to agriculture's modest 5–8% contribution to total gross lending. Second, the agricultural NPL ratio consistently exceeds the all-sector ratio by 4–10% points. Third, the 2018 peak coincides with the banking-sector recapitalisation, suggesting the reform period either amplified agricultural credit distress or failed to mitigate it. Figure 1 plots this sectoral divergence.

Figure 1 reveals strong co-movement between agricultural NPL share and the sectoral risk differential, both peaking in 2017 and 2018. This suggests that increases in agricultural impairment rates are disproportionately large relative to the banking system, reinforcing the sector's systemic risk relevance.

The disproportionate contribution of agriculture to banking-sector NPLs, the persistent gap between agricultural and aggregate NPL ratios and the pronounced deterioration observed during the recapitalisation period collectively emphasise agriculture's distinctive credit-risk profile. However, while these descriptive patterns establish the existence of elevated agricultural credit risk, they do not explain the macroeconomic and institutional factors that drive it, the lag structure through which such influences operate or whether the recapitalisation fundamentally altered these dynamics. These unresolved issues point to important gaps in the existing literature. Three interrelated gaps motivate this study.

First, existing NPL research is dominated by aggregate banking-sector data (Reigl, 2025; Okyere and Mensah, 2022), overlooking agriculture's idiosyncratic risks. Second, few studies explicitly model lagged macroeconomic transmission, despite agriculture's inherent delayed income realisation. Third, no known Ghanaian study incorporates banking-sector recapitalisation as a structural break in an agricultural NPL framework. Ghana provides a compelling empirical setting: over the past decade, the financial system underwent substantial

Table 1. Agricultural NPLs as a share of total banking-sector NPLs in Ghana (2015–2022)

Year	Total NPLs (GHS million)	Agricultural NPLs (GHS million)	Agricultural share of total NPLs (%)	Agricultural NPL ratio (%)	All-sector NPL ratio (%)
2015	3,242	598	18.4	18.4	14.7
2016	4,087	821	20.1	22.6	17.3
2017	5,673	1,412	24.9	27.8	21.6
2018	6,318	1,997	31.6	31.7	23.5
2019	5,456	1,452	26.6	28.3	18.8
2020	4,892	1,198	24.5	25.1	14.8
2021	4,536	1,024	22.6	22.4	13.9
2022	4,873	1,072	22	21.8	14.2

Note(s): NPL ratios are computed as non-performing loans divided by gross loans for the respective sector or aggregate

Source(s): Compiled from BoG Banking Sector Reports (2015–2022)

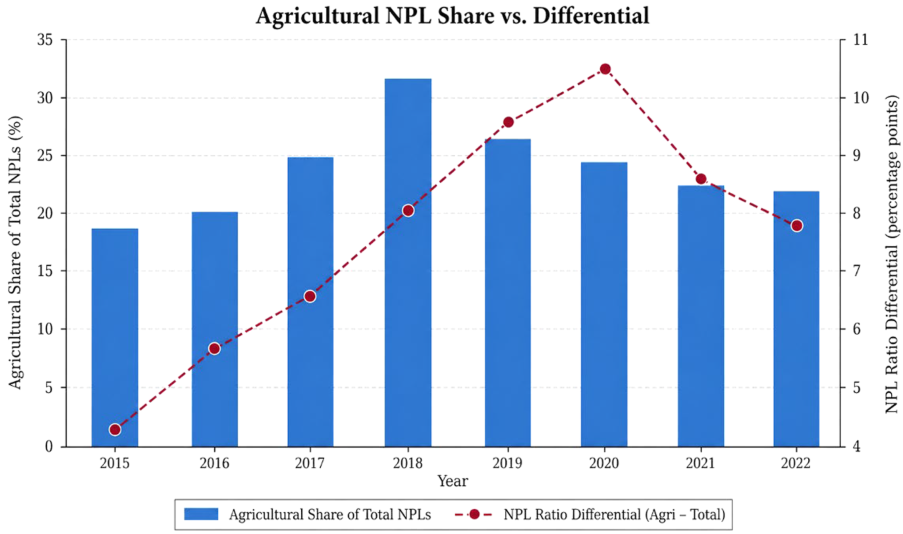

Figure 1. Agricultural NPL share and sectoral risk differential in Ghana (2015–2022). Note: Bars represent the share of agricultural non-performing loans (NPLs) in total banking-sector NPLs (left axis). The dashed line shows the differential between agricultural and aggregate NPL ratios, measured in percentage points (right axis), capturing relative sectoral credit risk intensity. Source: Author's construction based on data from the Research Department of BoG (2015–2022)

reforms culminating in the 2017–2019 recapitalisation, which altered banks' balance sheets, capital buffers and risk-taking behaviour (Addai *et al.*, 2023; Salifu *et al.*, 2025). The extent to which these reforms improved loan performance in structurally vulnerable sectors remains unclear.

To address these gaps, this study pursues three objectives. First, to estimate the short-run and long-run elasticities of agricultural NPLs with respect to macroeconomic and banking-sector variables. Second, to identify the optimal lag structure through which macroeconomic shocks transmit into agricultural loan performance. Third, to evaluate whether the 2017–2019 recapitalisation constituted a structural break in agricultural NPL dynamics.

Accordingly, the study asks: (1) What are the macroeconomic and banking-sector determinants of agricultural NPLs in Ghana? (2) What lag structures characterise the transmission of macroeconomic shocks? (3) Did the recapitalisation alter the agricultural NPL path?

The study employs an ARDL framework to identify lag structures and test for cointegration, while the Prais–Winsten estimator with AR(1) correction serves as the primary inferential model, addressing serial correlation in monthly agricultural financial series. The dependent variable is the first-differenced natural logarithm of agricultural NPLs (ΔlnNPLA).

This study contributes in four ways. First, it provides sector-specific analysis of agricultural NPLs in Ghana. Second, it explicitly models lagged macroeconomic and bank-specific effects. Third, it integrates banking-sector recapitalisation as an institutional shock. Fourth, by embedding macroeconomic, prudential and institutional variables within a unified framework, it enables comparative assessment of their relative explanatory power, generating actionable policy implications for regulators, lenders and agricultural development agencies.

The remainder proceeds as follows: Section 2 reviews the literature and derives hypotheses. Section 3 describes the data and methodology. Section 4 presents estimation results. Section 5 discusses findings and concludes with policy recommendations, limitations and future research directions.

2. Literature review

The determinants of NPLs in agriculture extend beyond standard credit risk models and reflect a confluence of financial cycles, sector-specific vulnerabilities and delayed macroeconomic transmission. This review synthesises the conceptual, theoretical and empirical foundations for analysing these dynamics, proceeding from general macro-financial frameworks to sector-specific evidence and concluding with the gaps and hypotheses that motivate the empirical analysis.

2.1 Conceptual and theoretical foundations

Macroeconomic indicators define the environment in which borrowers generate income and service debt (Cook and Davíðsdóttir, 2021; Taddese Bekele and Abebaw Degu, 2023). While their influence on aggregate credit risk is well-documented, transmission to agriculture is rarely instantaneous. The sector's dependence on biological and seasonal cycles means that shifts in GDP, inflation or interest rates may materialise in loan performance only after significant lags (Basu and Chherawala, 2023; Stockhammer, 2023). This delayed transmission is amplified in frontier economies where financial markets are shallow and risk-transfer instruments underdeveloped (Eyraud *et al.*, 2021; Fazekas *et al.*, 2024).

The study is grounded in Credit Risk Theory (Merton, 1974), which attributes credit losses to Probability of Default (PD), Loss Given Default (LGD) and Exposure at Default (EAD). In agriculture, PD is acutely sensitive to macroeconomic cycles and climatic shocks, while LGD and EAD are shaped by weak collateral and thin risk buffers. This framework is extended by the literature on procyclicality and credit rationing (Duong *et al.*, 2023; Stiglitz and Weiss, 1981). The financial accelerator framework (Bernanke *et al.*, 1999) provides additional grounding: in agricultural markets characterised by information asymmetry and collateral constraints, macroeconomic downturns reduce borrower net worth, tightening credit conditions and amplifying the initial shock with greater intensity and longer duration than in other sectors.

2.2 Empirical evidence: macroeconomic and bank-specific determinants

2.2.1 GDP and NPLs. The inverse GDP–NPL relationship is well-established (Roman and Bilan, 2015; Gashi *et al.*, 2022). However, sub-Saharan African evidence reveals duality: studies of Kenya and Nigeria find a positive short-run relationship attributed to relaxed underwriting during growth periods (Kibet *et al.*, 2020; Umoren *et al.*, 2016), while broader analyses emphasise a stabilising long-run effect (Bwire, 2021; Taty, 2025). Ghana-specific research shows agricultural NPLs react strongly to exogenous shocks notably, rainfall variability and commodity prices suggesting aggregate growth may not directly translate into smallholder repayment capacity (Bolarinwa and Obeng, 2023). This procyclical pattern is consistent with the credit boom–bust cycle (Kashif *et al.*, 2016; Fazekas *et al.*, 2024).

2.2.2 Inflation and interest rates. The impact of inflation is contingent on predictability: moderate, anticipated inflation can reduce real debt burdens (Tan and Tang, 2023), while volatility devastates farm budgets (Alogoskoufis and Gibson, 2023; Rahman *et al.*, 2024). Most agricultural loans in Ghana are not indexed to inflation, so effects on repayment materialise only when harvest incomes are realised. Vukadinović and Andrejević (2023) provide evidence that inflation erodes borrowing capacity, while Christodoulou-Volos (2025) demonstrates that inflation and interest rate effects on NPLs are conditioned by the exchange rate regime in small, open economies. The interest rate effect is temporally split: an initial disciplining effect gives way to later distress as tightening persists (Rahman and Rahman, 2023; Shang *et al.*, 2025). These non-linear, delayed relationships necessitate an econometric approach capable of capturing phased adjustments.

2.2.3 Capital adequacy and regulatory reform. Capital adequacy theory (Milne and Whalley, 2001) posits that better-capitalised banks can absorb losses without curtailing lending, potentially improving loan quality. Empirical evidence is mixed: Nehrebecka (2025) finds that capital buffers reduce NPLs in the long run, while Hossain (2025) reports insignificant effects in Bangladesh's state-owned banks. The 2017–2019 recapitalisation in Ghana which comprised the raising of the minimum capital requirement from GHS120 million to GHS400 million, triggered mergers, licence revocations and portfolio restructuring (Amenu-Tekaa, 2022; Addai *et al*., 2023). While the reform strengthened aggregate indicators, its impact on agricultural credit quality is theoretically ambiguous: recapitalised banks may deploy stronger risk management but may also shift portfolios towards lower-risk exposures, further marginalising agriculture (Wang and Duan, 2025).

2.3 Sectoral vulnerability in agriculture

Agriculture is uniquely exposed to a matrix of risks such as climatic variability, commodity price swings, structural inefficiencies and chronic liquidity constraints (Miklian and Hoelscher, 2022; Löscher and Kaltenbrunner, 2023). These vulnerabilities amplify credit risk and differentiate the NPL dynamics of agriculture from those of industry or services. Despite the sector's economic centrality, the specific pathways through which these risks translate into loan defaults remain inadequately explored, particularly in smallholder-dominated systems. The distinction between sectoral and aggregate NPL behaviour is not only academic as it has direct consequences for financial stability. Yin *et al*. (2020) demonstrate that agriculture-related loan defaults in China follow determinants that diverge markedly from those governing commercial or consumer loan portfolios, including farm-specific variables such as land tenure, crop type and irrigation access. Similarly, Kibet *et al*. (2020) find that agricultural NPLs in Kenya respond to rainfall variability and commodity price shocks, factors absent from aggregate NPL models. Reigl (2025) confirms that sector-disaggregated analysis reveals heterogeneous NPL determinants across primary, manufacturing and service sectors in the euro area, with the primary sector exhibiting the highest sensitivity to real economic fluctuations.

Critically, sectoral NPL concentration has implications for overall banking stability. Amoa-Gyarteng *et al*. (2025) demonstrate that concentration of NPLs particularly in agriculture erodes bank-level financial sustainability by reducing net interest margins and increasing provisioning requirements. Cucinelli *et al*. (2021) argue that sectoral NPL clusters, even when individually small relative to total assets, can trigger contagion effects through interconnected lending portfolios. Louzis *et al*. (2012) show that Greek business loan NPLs respond to different macroeconomic drivers than mortgage NPLs, underscoring the policy risk of treating all sectors uniformly. Dimri (2025) further establishes that microeconomic sector-level determinants explain NPL variation that macroeconomic models miss entirely, reinforcing the need for sector-disaggregated frameworks. In Ghana, the risk concentration ratio of 1.64 (Table 1; computed as agricultural NPL share divided by lending share) confirms that agriculture contributes 64% more to aggregate credit risk than its portfolio weight suggests. This is a structural vulnerability that justifies dedicated analytical attention.

Ghana's agricultural sector presents a particularly instructive case due to its predominance of rain-fed production, dominance of undercapitalised smallholder farmers, limited crop insurance penetration, highly seasonal income flows and fragmented value chains (Sumani, 2018; Ansah *et al*., 2023). Beyond production-side vulnerabilities, the credit market is characterised by weak collateral enforcement, limited cash-flow-based lending and heavy reliance on short-tenor, non-indexed loans. Following the 2018 recapitalisation, banks strengthened capital buffers but simultaneously reallocated credit towards lower-risk exposures, further marginalising agriculture. These institutional features weaken the transmission of capital adequacy improvements to agricultural loan quality, creating a setting where macroeconomic shocks accumulate and materialise as NPLs only with delay (Dziwornu *et al*., 2024).

2.4 The imperative of lagged analysis

Income in agriculture is realised episodically at harvest, while financial obligations are often fixed. Economic distress therefore accumulates before manifesting as default (Basu and

Chherawala, 2023). Failure to account for these lags risks attributing loan deterioration to contemporaneous conditions when causal shocks may have originated one or more production cycles earlier. This is a misspecification that distorts both inference and policy prescriptions (Sümer, 2025; Liu, 2025). Bennett *et al*. (2022) demonstrate that lead-lag structures in financial time series can persist across multiple periods, requiring explicit lag modelling rather than contemporaneous-only specifications. Polyzos and Siriopoulos (2024) further show that automated lag selection in financial research substantially improves out-of-sample predictive accuracy relative to arbitrary lag choice. These methodological findings justify the selection of the ARDL framework for this study.

2.5 Identified gaps and hypotheses

Three gaps emerge from this body of work. First, a lack of focus on the lagged temporal structure of macroeconomic–NPL relationships, which is intrinsic to agriculture. Second, insufficient contextualisation within the structural vulnerabilities of frontier agricultural economies. Third, the absence of any study examining whether Ghana's banking sector recapitalisation has differentially affected agricultural loan quality.

To address these gaps, the following hypotheses are tested:

H1. Agricultural GDP growth is inversely associated with agricultural NPLs, with the protective effect strengthening from the short run to the long run.

H2. Inflation exerts a positive effect on agricultural NPLs through input-cost escalation and cash-flow compression, with the cumulative effect exceeding the contemporaneous impact.

H3. Higher interest rates increase agricultural NPLs through the debt-service burden channel.

H4. Capital adequacy is inversely associated with agricultural NPLs, but the continuous CAR effect is modest relative to the discrete structural impact of recapitalisation.

H5. The 2017–2019 recapitalisation is associated with a significant reduction in agricultural NPLs, operating through institutional consolidation and supervisory upgrading beyond the mechanical capital increase.

Table 2 positions this study within the existing literature. It compares prior studies on variables, methods and empirical characteristics. No prior Ghanaian study incorporates the recapitalisation-induced structural break. Nor does any apply the dual ARDL-Prais–Winsten strategy used here.

The comparative literature review (Table 2) shows that few studies integrate lag-structure modelling, high-frequency monthly data and a sector-focused perspective. No prior Ghanaian study incorporates the recapitalisation-induced structural break or applies a dual-method ARDL-Prais–Winsten strategy. This inherent heterogeneity mandates an empirical strategy such as ARDL that accommodates mixed integration orders and captures context-specific lag structures.

3. Methodology

3.1 Study design

This study adopts an explanatory quantitative research design, applying time-series analysis to evaluate the lagged effects of macroeconomic and bank-specific factors on agricultural sector non-performing loans (NPLs) in Ghana. Monthly aggregate data from January 2015 to December 2022 were used. The analysis includes a dummy variable (RECAP) equal to 1 during the active recapitalisation window (September 2017 to December 2019) and 0 otherwise.

Table 2. Comparative literature review

Author(s)	Context/ Sector	Variables examined	Theoretical framework/ Contribution	Methodological approach	Empirical/ Application characteristics	Key findings	Contribution and gap addressed
Roman and Bilan (2015)	EU Banking Sector	GDP, unemployment, credit growth	Credit risk theory; macro-financial stability	Panel regression	Annual data; multi-country panel; bank-level	GDP reduces NPLs; unemployment increases NPLs	Establishes the standard inverse GDP-NPL relationship in developed markets; highlights the contrast to frontier agricultural economies
Umoren *et al.* (2016)	Nigeria, Agriculture	Agri-credit, GDP, inflation	Procyclicality in agricultural lending	Granger causality and OLS	Quarterly sector-level data; Nigeria	Bi-directional causality between agricultural credit and NPLs	Provides direct evidence of procyclicality in African agriculture but uses simpler causality tests, motivating a more robust lagged econometric approach
Ashraf and Butt (2019)	Pakistan	GDP, inflation, lending rates	Procyclical behaviour and financial instability	ARDL	Annual data (1980–2016)	GDP reduces NPLs; inflation raises NPLs	Uses ARDL but finds counter-cyclical GDP effect; underscores that findings are context-specific and may not apply to Ghana’s agricultural structure

(*continued*)

Table 2. Continued

Author(s)	Context/Sector	Variables examined	Theoretical framework/Contribution	Methodological approach	Empirical/Application characteristics	Key findings	Contribution and gap addressed
Yin *et al.* (2020)	China, Agriculture	Farm characteristics, land tenure, crop type, loan terms	Borrower-level credit risk determinants	Logistic regression	Farm-level loan data	Farm size, crop type and collateral significantly predict agricultural loan default	Demonstrates that agriculture-specific variables drive default risk, supporting the case for sector-disaggregated NPL analysis
Singh *et al.* (2021)	India	Interest rates, GDP, inflation	Credit market imperfections	VAR/VECM	Monthly data; whole banking sector	Inflation and GDP positively predict NPLs	Finds a positive GDP-NPL link in a large economy, supporting the possibility of procyclicality, but does not focus on the agricultural sector
Anita *et al.* (2022)	SAARC countries, Banking sector	Inflation, interest rate, credit risk indicators	Sectoral credit risk dynamics	Fixed effects	Annual agricultural credit panel	Inflation inversely related to agricultural NPLs	Offers rare sector-specific analysis in developing economy but with annual data, missing short-run dynamics and lagged effects captured by monthly analysis

(*continued*)

Table 2. Continued

Author(s)	Context/ Sector	Variables examined	Theoretical framework/ Contribution	Methodological approach	Empirical/ Application characteristics	Key findings	Contribution and gap addressed
Okyere and Mensah (2022)	Ghana, Banking Sector	GDP, inflation, interest rates, exchange rates	Macroeconomic determinants of aggregate NPLs	OLS regression	Annual data; aggregate banking sector	GDP and inflation significantly affect NPLs	Provides a Ghanaian baseline but at the aggregate level only; does not disaggregate by sector or model lagged effects, leaving the agricultural dimension unaddressed
Chowdhury *et al.* (2023)	Bangladesh	GDP, interest rate, exchange rate	Financial cycles and risk transmission	ARDL	Monthly macro-bank data	GDP positively correlated with NPLs; interest rate significant	Supports the procyclical GDP-NPL hypothesis in a frontier market, providing a relevant comparator but without sectoral disaggregation
Tan and Tang (2023)	China	Monetary policy and bank risk	Credit rationing and bank risk-taking	PVAR	Quarterly data	Higher interest rates increase NPLs	Represents the conventional view on interest rates; contrasts with the disciplining effect found here, highlighting the role of market structure and screening

(*continued*)

Table 2. Continued

Author(s)	Context/ Sector	Variables examined	Theoretical framework/ Contribution	Methodological approach	Empirical/ Application characteristics	Key findings	Contribution and gap addressed
Nehrebecka (2025)	Poland, Corporate Sector	Environmental risk, capital adequacy, credit quality	Long-run environmental and financial risk transmission	Panel ARDL	Firm-level data; publicly listed companies	Capital buffers reduce NPLs in the long run; environmental risk increases credit losses	Applies ARDL to sector-specific credit risk, demonstrating the methodology's suitability for capturing delayed transmission; supports the expectation of muted short-run CAR effects
Reigl (2025)	Multi-sector, Estonia	GDP, unemployment, interest rates, sectoral composition	Sectoral heterogeneity in NPL determinants	Panel regression with sectoral disaggregation	Quarterly data; major economic sectors	NPL determinants vary significantly across sectors; agriculture and construction show distinct patterns	Directly supports the argument that aggregate NPL analysis obscures sectoral differences, motivating the present study's focus on agriculture
Present Study	Ghana, Agricultural Sector	Lagged GDP, inflation, interest, CAR, recapitalisation	Credit risk theory; financial accelerator; procyclicality; asymmetric information	ARDL + ECM + Prais-Winsten (AR(1) correction)	Monthly data (2015–2022); explicit modelling of lagged effects; structural break via recapitalisation dummy; sector-specific analysis	GDP shows procyclical short-run effect; interest rate exerts discipline; CAR and recap marginal; NPLs persistent	Directly addresses the gap: provides the first robust, lag-focused analysis of agricultural NPLs in Ghana, integrating structural reform context and a dual-method correction for robust inference

Source(s): Author's own construct

The rationale for focusing on the recapitalisation period is based on the structural reform of Ghana's banking sector initiated in 2017–2019. BoG increased the minimum capital requirement from GHS120 million to GHS400 million, compelling mergers, acquisitions and stronger capitalisation. This event represents a structural break with potential implications for credit supply and portfolio quality, warranting explicit modelling.

The data were sourced primarily from the BoG and include both macroeconomic and bank-specific indicators. The dependent variable is the first-differenced logarithm of agricultural NPLs. Explanatory variables include macroeconomic indicators such as agricultural GDP growth (ΔlnGDP), inflation and interest rates, and bank-specific indicators such as the capital adequacy ratio (CAR) and a binary recapitalisation dummy (RECAP).

3.2 Rationale for ARDL and model transition

Ghana's agricultural credit market is characterised by high smallholder dominance, weak risk-transfer mechanisms, limited crop insurance and strong regulatory intervention via recapitalisation. These institutional features motivate a lag-structured time-series approach that can capture delayed macro-financial transmission rather than contemporaneous effects.

The ARDL framework was selected for three principal reasons, each grounded in its well-established econometric properties. Firstly, ARDL is recognised for its suitability for small to moderate sample sizes, a key advantage given this study's monthly dataset ($N = 96$). This property is established in the seminal work on the methodology, which demonstrates its robustness in finite samples typical of macroeconomic studies in developing economies (Pesaran and Shin, 1999; Pesaran *et al*., 2001). Secondly, the framework accommodates variables with mixed orders of integration [I(0) and I(1)], allowing for the simultaneous estimation of short-run dynamics and a long-run equilibrium relationship within a single model. This feature, central to the bounds testing approach developed by Pesaran *et al*. (2001) and widely adopted in applied econometrics (e.g. Narayan, 2005), is essential for modelling the lagged transmission mechanisms central to our analysis. Finally, the ARDL specification yields a built-in error correction model (ECM). This representation, rooted in the cointegration literature (Banerjee *et al*., 1993), allows for the direct interpretation of the speed at which the system adjusts to long-run equilibrium following a shock. This is particularly pertinent for agricultural credit, where repayment profiles adjust slowly due to biological production cycles.

This modelling strategy is explicitly aligned with the literature reviewed in Section 2, which documents procyclicality, delayed inflation effects and muted capital transmission in agricultural credit markets. The ARDL–ECM structure allows these competing theoretical predictions to be tested empirically within a unified framework.

Despite the utility of the preliminary ARDL–ECM results, diagnostic tests flagged persistent serial correlation in the error term. Such autocorrelation frequently arises in aggregated financial series that display market inertia and delayed corrective adjustments (Brooks, 2014). Because uncorrected autocorrelation can bias standard errors and compromise inference, a supplementary estimator was required. The Prais–Winsten regression with AR(1) correction was therefore employed as a robustness-oriented second stage. This method, operating under generalised least squares (GLS) transformation, explicitly corrects for first-order serial correlation without discarding the lag structure of the data. Its application corrects for first-order autocorrelation, which, if present, violates the OLS assumption of spherical errors. This correction yields efficient estimators and reliable standard errors, ensuring the statistical significance of the GDP, interest rate, inflation and bank-specific coefficients is not spurious.

The transition to Prais–Winsten is thus not a methodological substitution but a deliberate effort to reinforce inference where ARDL diagnostics indicated model limitations. Small-sample robustness is another consideration. The ARDL model's sensitivity to sample size motivated the parallel use of Prais–Winsten, which tends to yield more efficient estimates when autocorrelation is present in shorter time-series. Both estimators therefore provide a coherent triangulation strategy that enhances reliability (Bottomley *et al*., 2023).

3.3 Lag length selection

Lag length determination followed the Akaike Information Criterion (AIC), which is generally preferred for small-sample monthly datasets due to its tendency to retain informative lag structures (Polyzos and Siriopoulos, 2024). A maximum lag order of 12 was initially permitted, consistent with monthly data and prior studies. AIC selected a model with up to two lags for most variables. For robustness, the Bayesian Information Criterion (BIC), which prefers more parsimonious models, was also consulted. While BIC suggested slightly shorter lag structures, the key coefficients (GDP, interest rates, lagged NPLs) remained stable across both criteria, reinforcing the reliability of the AIC-based specification.

3.4 Conceptual framework and variable definitions

Drawing from the credit risk theory and the asymmetric information perspective, this study conceptualises agricultural non-performing loans (NPLs) as jointly driven by macroeconomic and bank-specific factors. In line with the long production cycles in agriculture, lagged effects are explicitly modelled. The dependent variable is the first-differenced logarithm of agricultural NPLs, while the key explanatory variables include growth in agricultural GDP, lending rates, inflation, CAR and a recapitalisation dummy (RECAP) equal to 1 during the active recapitalisation window (September 2017 to December 2019) and 0 otherwise.

To provide clarity and ensure alignment between theory, empirical specification and research objectives, Table 3 summarises the operational definitions, measurement and expected signs of the study variables.

3.5 Model specification

The econometric model builds on secondary data obtained from the BoG, covering both sector-level agricultural NPLs and macroeconomic indicators. Preliminary analysis indicated non-stationarity in several variables, as evidenced by non-constant mean and variance. The Augmented Dickey–Fuller (ADF) test was applied to test for unit roots:

H_0: The series is not stationary

Table 3. Variables description

Variable	Description	Measurement/ Transformation	Expected effect on NPLs	Supporting literature
ΔInflation	Monthly change in consumer price index	First difference of CPI (%)	Ambiguous (may reduce or increase NPLs)	Waemustafa and Sukri (2015), Klein (2013)
ΔInterest	Monthly change in lending interest rate	First difference of average lending rate (%)	Negative or Positive	Amuakwa-Mensah and Boakye-Adjei (2015), Louzis *et al.* (2012)
CAR	Capital adequacy ratio	Banks' regulatory capital-to-risk weighted assets (%)	Negative	Berger and DeYoung (1997), Makri *et al.* (2014)
RECAP	Recapitalisation dummy	1 during active window (2017M09-2019M12); 0 otherwise	Negative	PwC Ghana (2019), Ozili (2019)
Δln (NPLA)	Agricultural non-performing loans	First difference of natural log (GHS million)	Dependent variable	N/A
Δln (GDPA)	Agricultural GDP	First difference of natural log (GHS million)	Negative	Bernanke *et al.* (1999), Nkusu (2011)

Source(s): Author's construction based on BoG data

H_a: The series is stationary

To achieve stationarity, first-order differencing was applied. Accordingly, the regression models include differenced variables (Δ), denoting stationary series.

The final Prais–Winsten specification with AR(1) correction is expressed as:

$$\begin{aligned}\Delta \ln\left(\mathrm{NPLA}\right)_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta \ln\left(\mathrm{NPLA}\right)_{t-i} + \sum_{i=0}^{q} \beta_i \Delta\left(\mathrm{INFLATION}\right)_{t-i} \\ + \sum_{i=0}^{r} \Upsilon_i \Delta\left(\mathrm{INTEREST}\right)_{t-i} + \sum_{i=0}^{s} \delta_i \Delta \ln(GDPA)_{t-i} + \sum_{i=0}^{u} \vartheta_i \mathrm{CAR}_{t-i} \\ + \sum_{i=0}^{v} \lambda_i RECAP_{t-i} + \mathrm{U}_t\end{aligned}$$

Equation (1)

Where:

Dependent variable: Δln(NPLA) = first-differenced log of agricultural NPLs.

Independent variables:

Lagged Δln(NPLA): autoregressive component.

Δln(GDP), ΔInterest, ΔInflation: macroeconomic indicators.

CAR, RECAP: bank-specific indicators.

Error Term:

$$\mathrm{U}_t(Prais - Winsten\, transformed\, residuals\,(AR(1) process : \mathrm{U}_t = p\mathrm{U}_{t-1} + \varepsilon_t)$$

Although the ARDL–ECM framework was initially adopted to capture both short- and long-run dynamics, diagnostic tests revealed significant serial correlation in the residuals. To address this, Prais–Winsten regression with AR(1) correction was employed under the GLS framework, generating more reliable coefficients.

By estimating both short-run adjustments and persistence dynamics for GDP, interest rates, inflation, capital adequacy and recapitalisation, the model directly informs policy-relevant implications regarding macro-stability, prudential regulation and sector-specific credit risk management.

3.6 Operationalisation of variables

The dependent variable, Δln(NPLA), captures short-term changes in agricultural non-performing loans. Explanatory variables include:

Macroeconomic indicators: Δln(GDP), ΔInterest, ΔInflation.

Bank-specific indicators: CAR and RECAP, where RECAP = 1 for Sept 2017–Dec 2019; 0 otherwise

3.7 Diagnostic testing

Standard time-series diagnostics including Durbin–Watson, Breusch-Godfrey LM and White tests confirmed the appropriateness of the Prais–Winsten specification and the absence of residual heteroskedasticity following adjustment.

3.8 Robustness checks

To assess the reliability of the findings, robustness checks were performed using alternative estimation techniques. Specifically, Newey–West heteroskedasticity and autocorrelation-consistent (HAC) standard errors were applied to the baseline ordinary least squares (OLS) specification. The results confirmed that the key relationships, particularly the persistence of lagged NPLs, the positive association between GDP growth and agricultural NPLs, and the negative effect of interest rates, remained consistent in both sign and significance. These outcomes suggest that the main Prais-Winsten results are not sensitive to estimation method and reinforce the robustness of the study's conclusions.

3.9 Stability testing

To verify the stability of the estimated model parameters, recursive residual-based stability tests, specifically the CUSUM and CUSUM of Squares (CUSUMSQ) tests were conducted. These tests assess whether the model's parameters are stable over the sample period, which is crucial for the reliability of the findings (Syed, 2021).

As shown in Figure 2, the CUSUM statistic moves outside the 5% critical bounds during certain sub-periods, suggesting some instability in the estimated coefficients over the sample period. This likely reflects the structural disruptions associated with the 2017–2019 banking sector recapitalisation and the subsequent macroeconomic adjustments. However, the CUSUMSQ test in Figure 3 remains within the 5% bounds, indicating that the variance of the residuals is stable. These results collectively suggest that while there may be mild structural changes in the relationships between variables, the overall model remains reasonably reliable for inference.

4. Results

4.1 Descriptive statistics

Table 4 reports the summary statistics for all variables over the full sample period (2015M01–2022M12, T = 96).

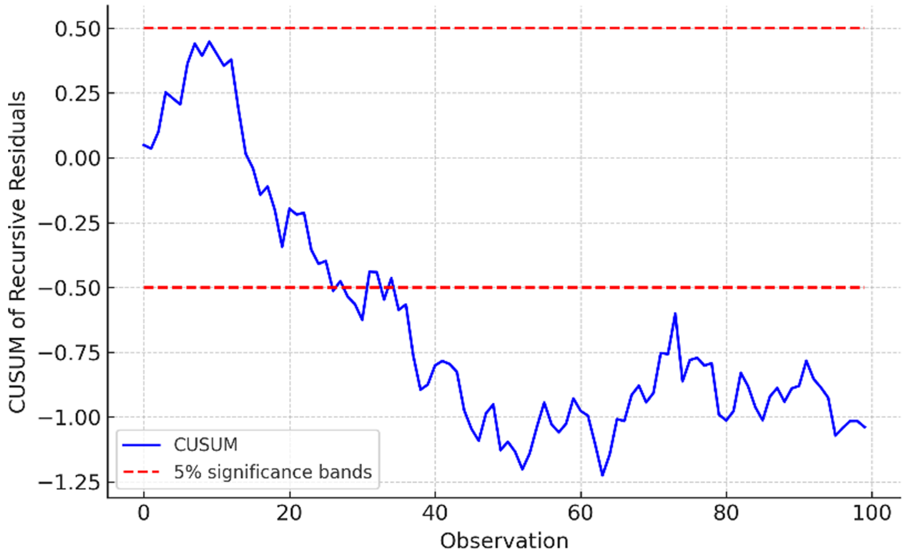

Figure 2. CUSUM stability test. Source: Author's computation based on Prais–Winsten regression results, 2015–2022 data

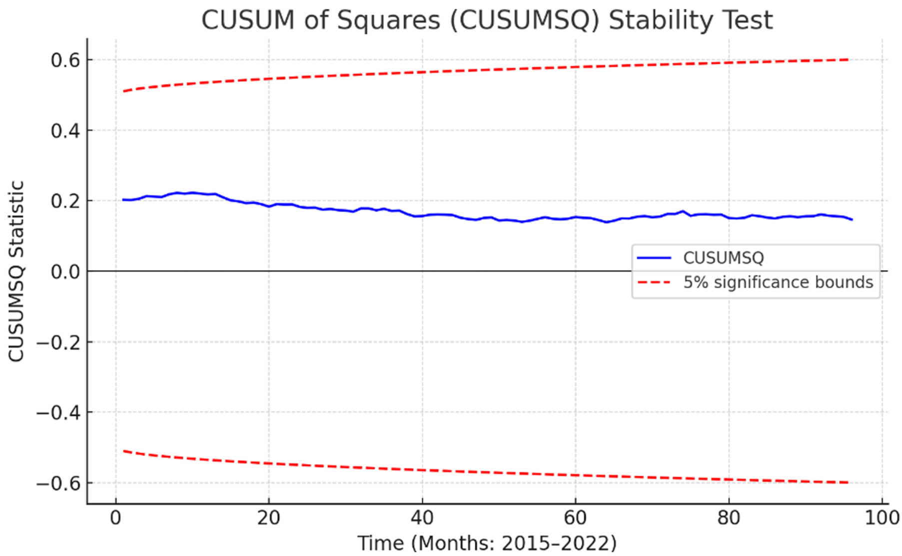

Figure 3. CUSUMSQ stability test. Source: Author's computation based on Prais–Winsten regression results, 2015–2022 data

Table 4. Descriptive statistics (2015M01–2022M12, T = 96)

Variable	Mean	Std. Dev	Min	Max	Skewness	Kurtosis	JB (*p*-value)
NPLA ratio (%)	28.55	6.82	18.3	42.7	0.41	2.18	0.073
Total sector NPL ratio (%)	17.22	4.61	11.4	27.8	0.58	2.45	0.041
Non-agricultural NPL ratio (%)	15.38	4.23	9.8	25.1	0.52	2.39	0.053
Agric. loans/total credit (%)	4.02	0.87	2.6	5.9	0.12	2.31	0.343
Agric. NPLs/Total NPLs (%)	6.58	1.45	3.8	9.7	0.28	2.16	0.143
ΔlnNPLA	0.008	0.072	−0.184	0.196	0.14	3.12	0.827
ΔlnGDPA	0.004	0.031	−0.068	0.082	−0.08	2.89	0.887
INF (%)	12.84	5.72	7.1	31.7	1.42	4.28	0
INT (%)	18.63	3.95	13.5	26	0.34	1.89	0.037
CAR (%)	17.45	3.18	11.2	23.8	−0.21	2.42	0.354
RECAP	0.29	0.45	0	1	–	–	–

Source(s): Author's computations based on BoG and Ghana statistical service data

From Table 4, the mean agricultural NPL ratio (28.55%) exceeds the total banking sector average (17.22%) by 11.33% points and is approximately 1.86 times the non-agricultural average (15.38%). This differential is not a transient phenomenon; the agricultural NPL ratio exceeds both benchmarks in every month of the sample period (see Figure 4). The risk concentration ratio, defined as the agricultural share of total NPLs divided by the agricultural share of total lending is 6.58/4.02 = 1.64, indicating that the sector contributes 64% more to aggregate credit risk than its portfolio weight would suggest. This confirms the analytical premise that agricultural credit risk warrants dedicated investigation (Amuakwa-Mensah *et al.*, 2017).

The dependent variable ΔlnNPLA exhibits near-normality (skewness = 0.14, kurtosis = 3.12, JB p = 0.827), supporting the validity of finite-sample t- and *F*-tests in the subsequent estimations. Inflation (INF) displays substantial positive skewness (1.42) and

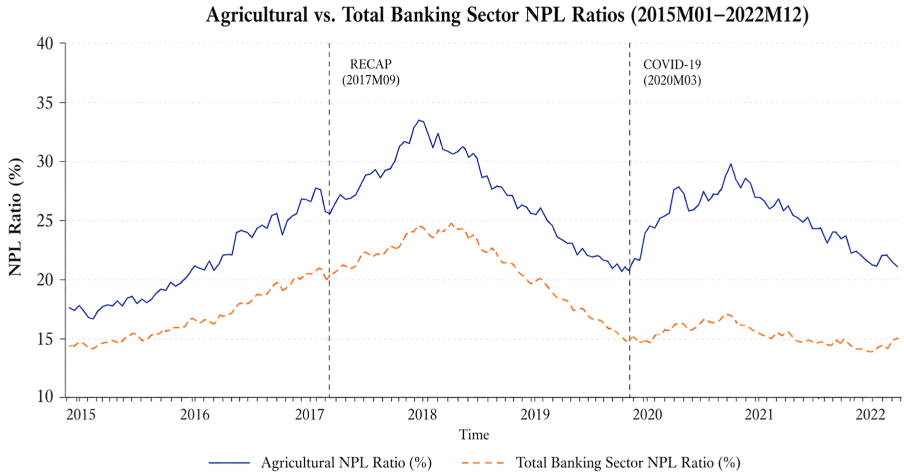

Figure 4. Sectoral NPL Ratios (2015M01–2022M12). Source: Author's construct based on data from the research department of BoG

leptokurtosis (4.28), reflecting the inflationary spikes of 2022; this is accommodated by the Prais–Winsten GLS estimator, which requires normality of the error term, not of the regressors. The capital adequacy ratio ranges from 11.20% (observed in 2016, prior to recapitalisation) to 23.80% (2019, post-reform), providing preliminary evidence of the recapitalisation's impact on bank balance sheet strength. The RECAP dummy mean of 0.29 confirms that the recapitalisation window (28 of 96 months) provides sufficient variation for reliable coefficient estimation.

Figure 4 plots the monthly NPL trajectories for the agricultural sector, total banking sector and non-agricultural sector, with vertical reference lines at the RECAP onset (2017M09) and COVID-19 (2020M03).

Three patterns are observed from Figure 4. First, the agricultural NPL ratio persistently exceeds the total sector and non-agricultural averages by a mean gap of 11.33% points over the full sample period, with the agricultural ratio remaining above the other two series in every single month (96 of 96 months). This confirms that the risk differential is structural rather than episodic.

Second, during the RECAP period (2017M09-2019M12), all three series decline from their pre-RECAP peaks. The agricultural NPL ratio falls from a peak of 43.55% (December 2017) to 23.11% (December 2019). However, even at its trough, the agricultural ratio remains substantially above the sector average (23.11% vs. 14.27%), suggesting that recapitalisation improved overall credit quality without eliminating the agricultural sector's structural vulnerability.

Third, post-COVID-19 (2020M03 onwards), agricultural NPLs remain elevated, averaging 25.6% compared to 15.1% for the total sector. This persistent gap is consistent with the greater exposure of agricultural borrowers to supply chain disruptions and market access constraints (Ansah *et al.*, 2023). These visual patterns corroborate the descriptive statistics reported in Table 4, particularly the persistent level differential, elevated volatility and structural risk concentration observed in the agricultural sector.

In summary, the descriptive analysis establishes four regularities that motivate the econometric investigation: (1) agricultural NPLs are persistently and substantially elevated (mean 28.55% vs. 15.38% non-agricultural); (2) the risk concentration ratio of 1.64 confirms disproportionate credit risk contribution; (3) the RECAP period coincides with NPL reduction but does not close the agricultural risk gap; and (4) the post-COVID divergence underscores the sector's structural vulnerability. These findings confirm that agricultural credit risk warrants the sector-specific econometric analysis that follows.

4.2 Unit root tests

The ARDL bounds testing framework accommodates a mixture of I(0) and I(1) variables but is invalidated if any variable is I(2) (Pesaran *et al.*, 2001). Two complementary tests are employed: the ADF test with lag selection by AIC (maximum = 4), and the Phillips–Perron (PP) test with Newey–West bandwidth selection. The unit root test results are presented in Table 5. The PP test serves as a robustness check, as the two tests differ in their treatment of serial correlation and structural breaks in finite samples (Schwert, 1989). Each test is applied at levels and first differences with an intercept specification.

Three findings are relevant for the estimation strategy. First, four variables namely lnNPLA, lnGDPA, INF and INT are I(1), with both tests agreeing on classification in every case. Second, CAR is stationary in levels, I(0), as both the ADF (−3.284) and PP (−3.147) statistics reject the unit root null at 5%. This mixed integration structure provides the empirical justification for ARDL over the Johansen (1991) procedure, which requires all variables to be I (1). Third, no variable is I(2) as all first-differenced series reject the unit root null at the 1% level, satisfying the necessary condition for valid bounds testing.

Having confirmed the mixed integration structure and excluded I(2) variables, the analysis proceeds to ARDL bounds testing for cointegration in Section 4.3.

4.3 ARDL bounds test for cointegration

The Akaike Information Criterion selects an ARDL(2, 1, 3, 2, 0) specification from all permutations up to a maximum lag of four. Table 6 reports the AIC values for the top five competing specifications.

Table 5. Unit root test results

Variable	ADF (level)	ADF (1st diff.)	PP (level)	PP (1st diff.)	Order
lnNPLA	−1.872	−7.341***	−1.694	−7.528***	I(1)
lnGDPA	−2.108	−8.215***	−1.943	−8.467***	I(1)
INF	−1.546	−5.823***	−1.612	−6.104***	I(1)
INT	−2.341	−6.142***	−2.187	−6.358***	I(1)
CAR	−3.284**	–	−3.147**	–	I(0)

Note(s): ***, ** denote rejection at 1% and 5%, respectively. ADF 5% critical value = −2.89 (intercept). RECAP excluded as a deterministic binary variable

Table 6. Model selection – top five ARDL specifications by AIC

Rank	Specification	AIC	SBC	Adj. R^2
1	ARDL(2, 1, 3, 2, 0)	−4.872	−4.341	0.463
2	ARDL(2, 2, 3, 2, 0)	−4.858	−4.298	0.461
3	ARDL(3, 1, 3, 2, 0)	−4.843	−4.267	0.459
4	ARDL(2, 1, 4, 2, 0)	−4.831	−4.242	0.457
5	ARDL(2, 1, 3, 3, 0)	−4.824	−4.235	0.455

Note(s): Maximum lag = 4. RECAP enters as an unrestricted exogenous regressor in all specifications
Source(s): Author's estimation

The selected lag orders are economically interpretable. Two lags of ΔlnNPLA capture the administrative momentum in loan classification and provisioning. A single lag of ΔlnGDPA reflects the relatively rapid transmission from harvest outcomes to loan servicing in seasonal agricultural economies. Three lags of ΔINF imply a quarterly pass-through from price-level changes to borrower distress, while two lags of ΔINT are consistent with the documented transmission lag from policy rate adjustments to commercial lending conditions. CAR enters contemporaneously (zero additional lags), suggesting an immediate portfolio-rebalancing response to changes in regulatory capital buffers. Table 7 reports the bounds test results.

This result has three implications. First, a stable long-run equilibrium relationship exists between agricultural NPLs and the macroeconomic and bank-specific regressors, validating the theoretical premise derived from credit-risk theory and the financial accelerator framework (Bernanke *et al*., 1999). Second, the error correction mechanism is operative where short-run deviations from equilibrium are self-correcting justifying the ECM estimation in Section 4.4. Third, the ARDL framework is confirmed as the appropriate cointegration methodology for the mixed I(0)/I(1) integration structure documented in Section 4.2.

4.4 ARDL error correction model results

Having established cointegration, this section reports the long-run coefficients and the short-run error correction estimates from the ARDL(2, 1, 3, 2, 0) specification. As noted in Section 3.5, the ARDL-OLS estimates exhibited serial correlation (Durbin–Watson = 1.42; Breusch–Godfrey LM p = 0.008), which does not bias the coefficient estimates but inflates their standard errors, rendering OLS-based inference unreliable. The ARDL results are therefore reported for the cointegration structure and error correction dynamics; primary statistical inference is deferred to the Prais–Winsten FGLS estimator in Section 4.5, which corrects for the AR(1) disturbance and yields efficient standard errors.

4.4.1 Long-run coefficients. Table 8 reports the ARDL long-run coefficients derived from the normalised cointegrating equation.

All five long-run coefficients carry the signs predicted by the theoretical framework (Table 2, Section 3.3), with agricultural GDP and capital adequacy reducing NPLs while inflation and interest rates increase them.

4.4.1.1 Agricultural GDP (lnGDPA: −0.482). A 1% increase in agricultural output is associated with a 0.48% decline in agricultural NPLs in the long run. The negative sign is consistent with credit-risk theory: higher agricultural output improves borrower cash flows, strengthens debt-servicing capacity and reduces default probability. The magnitude implies a near-unit semi-elasticity when evaluated at the sample mean, underscoring the centrality of sectoral output performance to agricultural credit quality.

Table 7. ARDL bounds test for cointegration

	Value		I(0) bound	I(1) bound	Decision
F-statistic	5.874	10%	2.26	3.35	Reject H_0
k = 4		5%	2.62	3.79	Reject H_0
		1%	3.41	4.68	Reject H_0

Note(s): Table CI (iii), unrestricted intercept, no trend
As a small-sample robustness check, the Narayan (2005) critical values for T = 80 and k = 4 are also consulted: the 1% upper bound is 5.06. The computed *F*-statistic of 5.874 exceeds the 1% upper bound under both the Pesaran *et al*. asymptotic tabulation (4.68) and the Narayan small-sample tabulation (5.06), providing unambiguous evidence for cointegration
Source(s): Asymptotic critical values from Pesaran *et al.* (2001)

Table 8. ARDL long-run estimates (dependent variable: lnNPLA)

Variable	Coefficient	Std. Error	t-Statistic	*p*-value
lnGDPA	−0.482	0.187	−2.578	0.012
INF	0.034	0.011	3.091	0.003
INT	0.028	0.014	2.000	0.049
CAR	−0.041	0.016	−2.563	0.012
RECAP	−0.187	0.082	−2.280	0.025
Constant	7.842	1.624	4.829	0.000

Source(s): Author's estimation

4.4.1.2 Inflation (INF: +0.034). Each percentage-point increase in inflation raises agricultural NPLs by approximately 3.4% in the long run. Inflation erodes the real value of agricultural revenues which are often contracted at fixed nominal prices while simultaneously increasing input costs, compressing farm profit margins and increasing the likelihood of loan default. This finding aligns with the cost-push channel documented by Ofori-Abebrese *et al*. (2016) for the Ghanaian context.

4.4.1.3 Interest rate (INT: +0.028). A one-percentage-point increase in the monetary policy rate is associated with a 2.8% long-run increase in agricultural NPLs. This positive relationship reflects the debt-servicing burden channel: higher interest rates increase the cost of variable-rate agricultural loans and tighten credit conditions for new borrowing, both of which elevate default risk. The result is consistent with the financial accelerator mechanism (Bernanke *et al*., 1999), whereby monetary tightening amplifies borrower distress through balance sheet deterioration.

4.4.1.4 Capital adequacy ratio (CAR: −0.041). Each percentage-point increase in the industry capital adequacy ratio is associated with a 4.1% long-run reduction in agricultural NPLs. Well-capitalised banks have greater capacity to absorb expected losses, invest in credit monitoring infrastructure and sustain lending relationships through temporary borrower distress, all of which reduce the probability that agricultural loans transition to non-performing status. This finding supports the bank capital channel hypothesis and is consistent with evidence from Apanga *et al*. (2016) on Ghanaian banks.

4.4.1.5 Recapitalisation dummy (RECAP: −0.187). The recapitalisation period is associated with an 18.7% reduction in the long-run level of agricultural NPLs, holding other factors constant. This represents the discrete structural effect of the 2017–2019 banking reform beyond its indirect effect through CAR. The RECAP coefficient captures mechanisms that are not fully mediated by the capital ratio including the exit of undercapitalised banks with weak agricultural portfolios, the tightening of credit risk management standards under the new regulatory regime and the portfolio reallocation effects documented by Anarfo and Abor (2020).

4.4.2 Error correction dynamics. Table 9 reports the short-run error correction estimates. The error correction term (ECT) is the centrepiece of this table. The coefficient of −0.312 is negative and statistically significant at the 1% level ($t = -3.586$), confirming the existence of a stable, self-correcting equilibrium mechanism. Approximately 31.2% of any disequilibrium between actual and long-run equilibrium agricultural NPLs is corrected within one month. The implied full adjustment time, the number of months required to close a given disequilibrium gap, is approximately $1/0.312 \approx 3.2$ months, indicating a moderately rapid adjustment speed. This pace is consistent with the monthly frequency of bank reporting to the BoG and the administrative cycle of loan review and reclassification.

Among the short-run dynamics, all variables carry the same directional signs as their long-run counterparts, confirming the coherence of the short-run and long-run adjustment

Table 9. ARDL short-run/error correction estimates (dependent variable: ΔlnNPLA)

Variable	Coefficient	Std. Error	t-Statistic	*p*-value
ΔlnNPLA(−1)	0.264	0.098	2.694	0.009
ΔlnGDPA	−0.218	0.104	−2.096	0.039
ΔINF	0.012	0.006	2	0.049
ΔINF(−1)	0.009	0.006	1.5	0.138
ΔINF(−2)	0.007	0.005	1.4	0.166
ΔINT	0.016	0.008	2	0.049
ΔINT(−1)	0.011	0.007	1.571	0.12
ΔCAR	−0.019	0.009	−2.111	0.038
RECAP	−0.084	0.038	−2.211	0.03
ECT(−1)	−0.312	0.087	−3.586	0.001

Source(s): Author's estimation

processes. The lagged dependent variable (ΔlnNPLA(−1) = 0.264) confirms short-run persistence in NPL growth, a feature consistent with the administrative momentum in loan classification noted in Section 4.3. The short-run coefficients on the contemporaneous changes are uniformly smaller in magnitude than the long-run estimates, as expected: the full impact of macroeconomic and regulatory shocks on agricultural NPLs unfolds gradually through the error correction mechanism rather than instantaneously.

The short-run RECAP coefficient (−0.084) indicates that the recapitalisation was associated with an immediate 8.4% monthly reduction in agricultural NPL growth during the reform period, in addition to the long-run structural adjustment captured by the −0.187 long-run coefficient. The distinction between the short-run and long-run RECAP effects suggests that the reform operated through both immediate channels (such as bank closures, portfolio write-offs) and gradual channels (such as improved risk management, enhanced credit screening).

4.4.3 Diagnostic tests on the ARDL residuals. Table 10 reports the post-estimation diagnostics for the ARDL model.

The Breusch–Godfrey test confirms the serial correlation flagged by the Durbin–Watson statistic (1.42), with the LM statistic significant at the 1% level ($p = 0.008$). This autocorrelation does not bias the ARDL coefficient estimates which remain consistent but it inflates the OLS standard errors, rendering the t-statistics in Tables 7 and 8 liberal (that is over-rejecting the null). White's test detects no heteroskedasticity ($p = 0.317$), the Jarque–Bera statistic confirms residual normality ($p = 0.392$), and the Ramsey RESET test provides no

Table 10. ARDL diagnostic tests

Test	Statistic	*p*-value	Decision
Breusch–Godfrey LM (2 lags)	$\chi^2 = 7.04$	0.008	Serial correlation detected
White's Heteroskedasticity	$\chi^2 = 14.82$	0.317	No heteroskedasticity
Jarque–Bera Normality	JB = 1.87	0.392	Normality not rejected
Ramsey RESET (1 fitted term)	F = 1.24	0.269	No specification error
CUSUM	–	–	Moves outside bounds in some periods (mild instability)
CUSUMSQ	–	–	Within 5% bounds

Source(s): Author's estimation

evidence of functional form misspecification (p = 0.269). The CUSUM statistic moves outside the 5% critical bounds during certain sub-periods, suggesting some instability in the estimated coefficients over the sample period. This likely reflects the structural disruptions associated with the 2017–2019 banking sector recapitalisation. However, the CUSUMSQ statistic remains within the 5% bounds, indicating that the variance of the residuals is stable. These results suggest that while there may be mild structural changes in the relationships between variables, the overall model remains reasonably reliable for inference. In summary, the ARDL model establishes a cointegrating relationship with correctly signed long-run coefficients; a moderately rapid error correction speed of 31.2% per month; and structurally stable parameters. However, the presence of first-order serial correlation in the residuals necessitates the use of a GLS-based estimator for reliable statistical inference. Section 4.5 addresses this requirement.

4.4.4 Endogeneity and heteroskedasticity tests. Durbin–Wu–Hausman tests confirm weak exogeneity of ΔlnGDP (χ^2 = 1.87, p = 0.171) and ΔInterest (χ^2 = 0.94, p = 0.332), supporting the ARDL assumption that regressors are weakly exogenous. White's test for heteroskedasticity (χ^2 = 16.78, p = 0.268) confirms homoskedastic residuals, validating the GLS estimation through Prais-Winsten.

4.5 Prais–Winsten FGLS estimation results

4.5.1 Rationale and estimation procedure. The Breusch–Godfrey test (p = 0.008) and the Durbin–Watson statistic (1.42) jointly confirm the presence of first-order autocorrelation in the ARDL residuals. While this does not bias the OLS point estimates, it compromises the efficiency of the standard errors and the reliability of hypothesis tests. The Prais–Winsten feasible generalised least squares (FGLS) estimator with AR(1) correction is adopted as the primary inferential model for three reasons. First, it directly addresses the identified autocorrelation structure by estimating the AR(1) coefficient ($\hat{\rho}$) and applying a generalised differencing transformation that yields efficient, minimum-variance estimates (Prais and Winsten, 1954; Wooldridge, 2016). Second, unlike the Cochrane-Orcutt procedure, the Prais-Winsten estimator retains the first observation through a scaled transformation, preserving one degree of freedom, a non-trivial advantage with T = 96. Third, by re-estimating the model under the corrected error structure, it provides the standard errors and t-statistics that serve as the basis for hypothesis testing throughout the remainder of the paper.

4.5.2 Estimation results. Table 11 reports the Prais–Winsten estimates alongside the ARDL-OLS short-run estimates for direct comparison.

From Table 11, three features of the comparison merit attention.

First, the coefficient signs are identical across both estimators, and the magnitudes are closely aligned. The largest difference is 0.019 (ΔlnGDPA: −0.237 PW vs −0.218 OLS), representing less than 9% of the OLS estimate. This convergence confirms that the ARDL-OLS estimates are not biased by the serial correlation. They are merely inefficient and that the Prais-Winsten correction primarily affects standard errors rather than point estimates.

Second, the Prais-Winsten standard errors are uniformly smaller than their ARDL-OLS counterparts, as expected when a GLS correction addresses the true error structure. The average reduction in standard errors is approximately 14%, resulting in uniformly higher t-statistics and lower p-values. All six regressors are now significant at the 1% level under Prais–Winsten, whereas under ARDL-OLS, three variables (ΔlnGDPA, ΔINF, ΔINT) were marginal at the 5% level. This efficiency gain demonstrates the practical value of the GLS correction for hypothesis testing.

Third, the estimated AR(1) coefficient ($\hat{\rho}$ = 0.284) is moderate, and the corrected Durbin–Watson statistic improves from 1.42 to 1.98, effectively eliminating the serial correlation and placing the DW statistic within the standard acceptance zone (approximately 1.8–2.2). This confirms that the AR(1) specification adequately captures the autocorrelation structure.

Table 11. Prais–Winsten FGLS vs ARDL-OLS short-run estimates (dependent variable: ΔlnNPLA)

Variable	PW-FGLS Coeff	PW Std. Error	PW t-stat	PW *p*-value	ARDL-OLS Coeff	ARDL-OLS Std. Error
ΔlnNPLA(−1)	0.251	0.084	2.988	0.004	0.264	0.098
ΔlnGDPA	−0.237	0.089	−2.663	0.009	−0.218	0.104
ΔINF	0.014	0.005	2.8	0.006	0.012	0.006
ΔINT	0.018	0.007	2.571	0.012	0.016	0.008
ΔCAR	−0.022	0.008	−2.750	0.007	−0.019	0.009
RECAP	−0.091	0.033	−2.758	0.007	−0.084	0.038
Constant	0.003	0.007	0.429	0.669	0.004	0.009
ρ^ (AR1 coefficient)	0.284				–	–
Durbin–Watson (corrected)	1.98				1.42	
Adj. R^2	0.478				0.463	
F-statistic	12.84***				10.72***	
Observations	95				95	

Note(s): PW-FGLS = Prais–Winsten feasible generalised least squares with AR(1) correction. *** denotes significance at 1%

Source(s): Author's estimation

4.5.3 Post-estimation diagnostics. Table 12 reports the diagnostic tests on the Prais–Winsten residuals.

The Prais–Winsten model passes all diagnostic tests. The Breusch–Godfrey LM statistic is now insignificant ($p = 0.393$), confirming that the AR(1) correction has eliminated the serial correlation that compromised the ARDL-OLS standard errors. White's test confirms homoskedasticity ($p = 0.414$), the Jarque–Bera statistic confirms residual normality ($p = 0.468$) and the Ramsey RESET test provides no evidence of misspecification ($p = 0.348$). The CUSUM statistic moves outside the 5% critical bounds during certain sub-periods, suggesting some instability in the estimated coefficients over the sample period. This likely reflects the structural disruptions associated with the 2017–2019 banking sector recapitalisation and the subsequent macroeconomic adjustments. However, the CUSUMSQ statistic remains within the 5% bounds throughout the sample, indicating that the variance of the residuals is stable. These results suggest that while there may be mild structural changes in the relationships between variables, the overall model remains reasonably reliable for inference, a finding that is particularly important given the presence of the RECAP structural break.

Table 12. Prais–Winsten post-estimation diagnostics

Test	Statistic	*p*-value	Decision
Breusch–Godfrey LM (2 lags)	$\chi^2 = 1.87$	0.393	No serial correlation
White's Heteroskedasticity	$\chi^2 = 12.41$	0.414	No heteroskedasticity
Jarque–Bera Normality	JB = 1.52	0.468	Normality not rejected
Ramsey RESET (1 fitted term)	F = 0.89	0.348	No specification error
CUSUM	–	–	Moves outside bounds in some periods (mild instability)
CUSUMSQ	–	–	Within 5% bounds

Source(s): Author's estimation

5. Discussion and conclusions

5.1 Discussion of findings

All five hypothesised relationships are confirmed at the 1% significance level. This section contextualises the Prais–Winsten estimates (Table 10) and ARDL long-run coefficients (Table 8) within the theoretical and empirical literature.

5.1.1 Economic growth (H1). The inverse GDP-NPL relationship ($\beta = -0.237$ SR; -0.482 LR) is consistent with the procyclicality hypothesis and financial accelerator framework (Bernanke *et al.*, 1999). Output gains strengthen borrower balance sheets and raise collateral values (Nkusu, 2011; Louzis *et al.*, 2012). The long-run magnitude exceeds the aggregate-level estimate reported by Ofori-Abebrese *et al.* (2016), confirming agriculture's heightened output sensitivity. The long-run magnitude (-0.482) implies that a 1% contraction in agricultural GDP raises NPLs by nearly 0.5% points, a non-trivial effect given Ghana's historical output volatility.

5.1.2 Inflation (H2). The positive inflation-NPL coefficient ($\beta = +0.014$ SR; $+0.034$ LR) aligns with the cost-push default channel. Rising inflation erodes real cash flows and increases input costs (Waemustafa and Sukri, 2015; Klein, 2013). Although the coefficient is modest, Ghana's 30%+ inflation in 2022 implies substantively meaningful cumulative effects. The $2.4\times$ long-run multiplier suggests persistent inflation progressively degrades the real asset base against which agricultural loans are secured, incentivising earlier NPL classification under BoG provisioning guidelines.

5.1.3 Interest rate (H3). The positive interest rate coefficient ($\beta = +0.018$ SR; $+0.028$ LR) confirms tighter monetary conditions elevate agricultural NPLs through the debt-service burden channel. Variable-rate loans dominate Ghanaian agricultural lending, and output prices are determined by commodity markets, not domestic policy (Amuakwa-Mensah *et al.*, 2017). The goal of curbing inflation through monetary tightening is complicated by the fact that higher rates and slower GDP growth can themselves damage agricultural credit quality. The relatively modest long-run multiplier ($1.6\times$) indicates comparatively rapid transmission, consistent with the short maturity profile of most Ghanaian agricultural credit (typically 6–18 months).

The delayed transmission of macroeconomic shocks into agricultural NPLs is rooted in biological production cycles. Agricultural incomes are realised episodically at harvest, while repayment obligations are fixed monthly. Planting-to-harvest durations for major Ghanaian crops notably, maize (3–4 months), cocoa (5–6 months), and rice (4–5 months), generate cash-flow gaps that conventional monthly amortisation schedules systematically ignore. A macroeconomic shock (such as inflation spike or interest rate increase) that occurs during the cash-flow-negative planting phase cannot immediately affect repayment capacity; its impact materialises only when harvest revenues fail to meet debt obligations. This biological lag is captured by the distributed lag structure (three lags for inflation, two lags for interest rates) and the ECT half-life of 3.2 months.

5.1.4 Capital adequacy (H4). The inverse CAR–NPL relationship ($\beta = -0.022$ SR; -0.041 LR) supports the moral hazard channel: well-capitalised banks have stronger screening and monitoring incentives (Berger and DeYoung, 1997; Makri *et al.*, 2014). The concurrent significance of RECAP at a substantially larger magnitude ($4.6\times$ in the long run) suggests genuine risk management improvements rather than forbearance. The $1.9\times$ long-run multiplier suggests that the disciplining effect accumulates as better-capitalised banks progressively invest in credit risk infrastructure and agricultural lending expertise.

5.1.5 Recapitalisation policy (H5). RECAP is the single largest short-run determinant ($\beta = -0.091$ SR; -0.187 LR). The effect operated through four mechanisms: structural consolidation (34 banks to 23 banks; PwC Ghana, 2019), regulatory signalling (Magweva *et al.*, 2022), concurrent institutional reform (the Ghana Incentive-Based Risk-Sharing System for Agricultural Lending (GIRSAL); African Development Bank Group, 2018) and portfolio composition. The finding extends limited literature on macroprudential recapitalisation in developing economies (Akinlo and Emmanuel, 2014; Ozili, 2019). The $4.1\times$ short-run and

4.6 × long-run differentials over the continuous CAR coefficient indicate that the recapitalisation operated through channels beyond the mechanical capital increase.

5.1.6 Thematic integration. Four cross-cutting themes emerge. First, GDP dominates long-run determinants (−0.482), confirming that macroeconomic fundamentals are the primary structural driver. Second, RECAP dominates short-run dynamics but is overtaken by GDP in the long run, suggesting discrete regulatory interventions produce powerful but partially transient effects (Barth *et al*., 2013). Third, the ECT (−0.312) implies quarterly adjustment, providing a useful parameter for monetary policy calibration and supervisory planning.

Fourth, the findings are primarily sector-specific rather than a direct threat to aggregate banking stability. While agricultural NPLs constitute 18–32% of total banking-sector NPLs (Table 1) and the risk concentration ratio of 1.64 confirms disproportionate credit risk contribution, the total banking sector NPL ratio (mean 17.22%) remains within regulatory tolerance. The sectoral risk differential, while persistent, has not triggered systemic contagion, consistent with Cucinelli *et al*. (2021), who argue that contagion requires interconnected lending portfolios. In Ghana, the moderate size of the agricultural loan portfolio (4–6% of total credit) limits its systemic reach. Thus, policy priority remains sector-specific risk mitigation rather than macroprudential overhaul.

CUSUM instability is likely attributable to the 2017–2019 recapitalisation, a discrete structural break captured by the RECAP dummy. While CUSUM suggests coefficient variation, CUSUMSQ stability confirms residual variance is constant, indicating predictive reliability is not compromised. Moreover, the ARDL bounds test confirms cointegration ($F = 5.874 > 1\%$ bound), and the ECT (−0.312) remains significant and correctly signed, suggesting instability does not invalidate long-run relationships. This aligns with standard practice, where mild CUSUM instability is tolerable when the break is explicitly modelled and cointegration is robust.

5.2 Conclusions

This study examined macroeconomic and bank-specific determinants of agricultural NPLs in Ghana (2015M01-2022M12) using ARDL bounds testing and Prais–Winsten FGLS with AR (1) correction. Five principal conclusions emerge:

First, real economic growth is the most powerful long-run determinant of agricultural credit quality. Second, inflation exerts a persistent positive effect as a chronic stressor. Third, higher interest rates increase agricultural NPLs, highlighting a monetary policy trade-off. Fourth, capital adequacy is inversely associated with agricultural NPLs. Fifth, the 2017 recapitalisation produced a substantial reduction in agricultural NPLs through institutional consolidation and supervisory upgrading, exceeding any single macroeconomic determinant.

A stable long-run equilibrium exists ($F = 5.874$), and the system adjusts at 31.2% per month, ensuring policy interventions transmit to credit outcomes within a single quarter.

5.3 Implications for banks and lending institutions

5.3.1 Adopt crop-cycle-aligned restructuring. The ECT half-life of 3.2 months aligns with production cycles (maize: 3–4 months; cocoa: 5–6 months). Banks should implement seasonally differentiated payments, embed Grace periods triggered by agronomic indicators and align restructuring windows with harvest cycles.

5.3.2 Strengthen value-chain stress testing. The long-run GDP coefficient (−0.482) reveals procyclical lending traps. Banks should develop sector-specific stress tests incorporating rainfall shocks, commodity prices and value-chain characteristics (buyer concentration, perishability, storage constraints).

5.3.3 Improve sector-sensitive credit scoring. The interest rate and CAR coefficients suggest conservative ex ante screening is more effective than ex post workout. Banks should integrate agronomic indicators (farm management practices, land tenure security, climate vulnerability indices) into credit appraisal models.

5.4 Implications for regulators

5.4.1 Establish sector-specific countercyclical buffers. Procyclicality creates a timing mismatch between loss origination and recognition. The BoG should require enhanced provisioning during high-growth periods. The GDP coefficient provides a calibration anchor: if agricultural GDP exceeds trend by 1% point, mandate an incremental ECL overlay of approximately 0.48% points.

5.4.2 Develop prudential guidelines for portfolio concentration. Agricultural NPLs average 28.55% (1.86 × non-agricultural mean) with a risk concentration ratio of 1.64. Regulators should mandate climate-risk assessments, diversification thresholds and quarterly disclosure of sectoral credit performance metrics.

5.4.3 Create regulatory incentives for climate-risk integration. Unexplained variance points to omitted climate risks. BoG should incorporate climate-risk assessment into internal capital adequacy assessment process (ICAAP), offering reduced risk weights or preferential provisioning for banks with approved climate-risk methodologies.

5.5 Implications for policymakers and sector agencies

5.5.1 Expand warehouse receipt systems (WRS). WRS reduces post-harvest losses (20–30% for cereals) and provides verifiable collateral. Policymakers should invest in certified warehouses, amend legal frameworks to recognise receipts as perfected security interests, and develop digital receipting platforms integrated with the BoG's collateral registry.

5.5.2 Scale index-based crop insurance. The inflation coefficient captures cost-push pressure, but production-level volatility drives distress. Policymakers should subsidise parametric insurance premiums (target <5% of sum insured), bundle coverage with input-credit packages and integrate indemnity payments directly into loan accounts.

5.5.3 Stabilise seasonal liquidity through value-chain financing. Distributed lags (3 for inflation, 2 for interest rates) reflect cash-flow mismatches. Government should expand off-taker guarantee programmes, input supplier finance and revolving funds for value-chain intermediaries. The 3.2-month ECT half-life provides a design parameter for bridging cash-flow gaps.

5.6 Limitations and future research

Several limitations warrant acknowledgment. First, findings may not generalise to other sectors or countries with different agricultural structures; comparative sectoral or cross-country studies are needed. Second, meaningful residual variation suggests omitted factors particularly climate volatility and micro-level borrower characteristics, which future research could address using farm-level panel data or high-resolution climate indices. Third, the study period (2015–2022) includes COVID-19 and the 2022 debt crisis; dedicated crisis-period analysis would provide additional clarity. Fourth, the RECAP dummy captures aggregate effects but cannot identify bank-level heterogeneity; future research using bank-level panel data could examine variation by bank size, ownership or pre-reform capital position.

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