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Forecasting Non-Performing Loans in Bangladesh: Evidence from ARIMA and Markov-Switching Autoregressive Models

Abstract

This study investigates the dynamics of non-performing loans (NPLs) across Bangladesh's banking sector using quarterly data from 2007 to 2024. Employing Autoregressive Integrated Moving Average (ARIMA) and Markov-Switching Autoregressive (MSAR) models, we analyze NPL behavior across state-owned commercial banks, specialized banks, private commercial banks, foreign commercial banks, and industry totals. Structural break analysis using the PELT (L2) algorithm identifies critical shifts aligned with major economic shocks and policy changes, including the global financial crisis, regulatory reforms, COVID-19 moratorium, and recent classification threshold adjustments. Results reveal state-owned commercial banks and specialized banks contribute predominantly to rising aggregate NPLs, exhibiting persistent high-NPL regimes. While the MSAR models are effective at capturing the regime-switching NPL dynamics, the Auto-ARIMA specifications provide the best out-of-sample validation for forecasting. Eight-quarter forecasts (2025-2026) using the optimized ARIMA model offer reliable and stable predictive accuracy compared to multi-regime alternatives. These findings provide critical insights for regulators and policymakers to enhance macro-prudential oversight and implement proactive credit risk monitoring strategies.

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1. Introduction

The persistent challenge of non-performing loans (NPLs) has long been recognized as a central impediment to financial stability in emerging economies. Elevated NPL ratios weaken banks' profitability, erode capital adequacy, and constrain the capacity to extend credit, thereby obstructing economic growth and undermining financial intermediation (Louzis, Vouldis, & Metaxas, 2012; Klein, 2013; Nkusu, 2011). The experience of countries across Asia and Europe suggests that poorly managed NPL portfolios amplify systemic risk and delay post-crisis recoveries (Aiyar, Calomiris, & Wieladek, 2015; Beck, Jakubik, & Piloiu, 2015). Bangladesh presents an especially urgent case where state-owned commercial banks and specialized banks have persistently recorded disproportionately high NPL ratios compared to their private and foreign counterparts, raising questions about governance quality, regulatory oversight, and credit culture (Amin et al., 2019). Understanding the dynamics of

NPLs within this context is not merely a matter of academic inquiry but also a pressing policy priority to safeguard the resilience of the financial system.

Forecasting NPLs with accuracy has become an essential tool for policymakers, regulators, and bank managers as they prepare for potential credit shocks. Traditional econometric models, particularly linear time-series approaches, often fall short in capturing the nonlinear and regime-dependent behavior inherent in credit markets (Clements & Krolzig, 2008; Hamilton, 1989). While ARIMA models remain widely applied due to their simplicity and interpretability (Box, Jenkins, & Reinsel, 2015), they fail to incorporate structural breaks or account for abrupt changes caused by regulatory reforms, global crises, or political instability (Altınbaş & Hanişoğlu, 2023; Foglia, 2022). In contrast, non-linear approaches such as Markov-Switching Autoregressive (MSAR) models offer more flexibility in modeling dynamic shifts between stable and volatile states to enhance forecasting reliability (Filardo & Gordon, 1998; Kim & Nelson, 1999; Grosvenor & Guy, 2013; Petropoulos et al., 2018; Wakumelo & Phiri, 2023). Against this background, we examine the behavior of NPLs in Bangladesh using ARIMA, structural break analysis, and MSAR frameworks while positioning our work within the growing literature on advanced credit risk modeling (Kufo, Gjeci, & Tori, 2024; Ashiagbor et al., 2024).

This study investigates quarterly NPL data from 2007 to 2024, encompassing state-owned commercial banks, specialized banks, private commercial banks, foreign commercial banks, and the total banking sector. The gross NPL ratio is used as the primary metric, which represents the total value of classified loans relative to the total outstanding loan portfolio. These 72 quarterly data were collected from the quarterly publications of the Bangladesh Bank (Banking Regulation and Policy Department). Though this 72 quarterly data points possess limitations for the time series analysis, it aligns with recent emerging market literature. For instance, Dinh (2020) utilized 22 annual observations to model credit growth in Vietnam and China. Likewise, Wanigasooriya and Jayatilake (2019) used 41 quarterly data points to forecast NPLs in the banking sector of Sri Lanka. Additionally, this study reflects the modern regulatory environment of Bangladesh by explicitly focusing on post-2007 era.

Initial descriptive statistics reveal notable heterogeneity across categories, with state-owned banks recording average NPL ratios exceeding 24 percent and specialized banks following closely, while private and foreign banks maintain significantly lower levels at 5.6 and 4.8 percent, respectively. These patterns reflect structural inefficiencies and governance weaknesses within public banks, which are further compounded by regulatory forbearance and political lending practices (Laeven & Valencia, 2013; Reinhart & Rogoff, 2011; Demirgüç-Kunt & Detragiache, 2002). The persistence of such high ratios among public institutions suggests that aggregate financial stability remains highly vulnerable to shocks emanating from these segments, a finding that echoes similar experiences in other emerging markets (Beck et al., 2015; Aiyar et al., 2015; Klein, 2013).

The results reveal noteworthy differences in how credit shocks are processed across different bank categories in Bangladesh. ARIMA models for the private and total

industry proved to be the most robust, with all significant autoregressive and moving average terms. In contrast, the state-owned banks' NPL possess the most complex and volatile lag structure. Furthermore, all ARIMA models failed the Jarque-Bera normality test and demonstrate that the market is disrupted by sudden non-linear shocks. This highlights the limitations of linear models in contexts characterized by frequent shocks and regime shifts (Clements & Krolzig, 2008; Box et al., 2015; Chauhan, Roy, & Singhal, 2024).

We therefore extend our analysis by conducting structural break tests using the PELT algorithm, which identifies critical breaks corresponding to the global financial crisis of 2008–2009, regulatory tightening in 2012–2016, the COVID-19 moratorium period, and a major regulatory reform in 2024 when loan classification thresholds were reduced. These results reinforce the argument that Bangladesh's NPL dynamics cannot be explained through stationary linear processes alone (Allaro, Kassa, & Hundie, 2018; Altınbaş & Hanişoğlu, 2023; Foglia, 2022).

Recognizing the inadequacy of linear frameworks, we estimate Markov-Switching Autoregressive (MSAR) models with two regimes, representing stable and volatile phases. Results indicate that state-owned and specialized banks are particularly prone to prolonged stress regimes, with high persistence of elevated NPLs once they emerge. In contrast, private and foreign banks demonstrate relatively stable regimes, with volatility episodes being short-lived. The aggregate NPL series similarly reveals greater persistence in the stable regime. These findings echo prior work that highlights the importance of regime-switching models in identifying credit market vulnerabilities that are masked in linear frameworks (Hamilton, 1989; Filardo & Gordon, 1998; Kim & Nelson, 1999; Lim, 2025). By uncovering the cyclical and nonlinear behavior of NPLs, we provide deeper insights into how institutional weaknesses and regulatory shocks shape the risk environment in emerging economies (Kufo et al., 2024; Ashiagbor et al., 2024; Foglia, 2022).

The result suggests that in Bangladesh market, the linear ARIMA models offer more reliable predictive stability. These findings contradict broader empirical evidence that regime-switching models outperform linear specifications in periods of heightened uncertainty (Clements & Krolzig, 2008; Hamilton, 1989; Kim & Nelson, 1999; Petropoulos et al., 2018; Wakumelo & Phiri, 2023; Altınbaş & Hanişoğlu, 2023).

We contribute to the literature on credit risk forecasting in three distinct ways. First, we bring together linear and non-linear time-series methodologies to examine the dynamics of NPLs in a volatile emerging economy. While prior studies have applied either ARIMA or regime-switching models in isolation, few have undertaken a systematic comparison across multiple bank categories with explicit attention to structural breaks (Clements & Krolzig, 2008; Altınbaş & Hanişoğlu, 2023; Ashiagbor et al., 2024). Second, our bank-level evidence highlights the heterogeneous risk profiles of state-owned, specialized, private, and foreign banks, showing that institutional ownership and governance structures strongly shape credit quality. By documenting that state-owned and specialized banks experience prolonged stress regimes, our results reinforce arguments about the governance failures and political interference underlying

persistent NPLs (Islam & Nishiyama, 2016; Beck, Jakubik, & Piloiu, 2015; Laeven & Valencia, 2013). Third, we advance methodological practice by applying structural break analysis in tandem with MSAR forecasting, thereby identifying both discrete shocks and gradual regime transitions. This dual approach responds to calls for more robust, forward-looking risk modeling frameworks in the post-crisis literature (Hamilton, 1989; Kim & Nelson, 1999; Kufo, Gjeci, & Tori, 2024). Collectively, these contributions strengthen the empirical foundations for understanding credit risk dynamics in emerging economies and provide a richer toolkit for policymakers and scholars alike.

From a policy perspective, our findings have important implications. The evidence that state-owned banks remain trapped in persistent high-NPL regimes suggests that regulatory forbearance and recapitalization measures may only provide temporary relief without structural reforms. Regulators must strengthen supervisory capacity, enforce stricter loan classification standards, and prioritize governance reforms in public banks to mitigate systemic risks. Furthermore, despite the fact that ARIMA models provide superior point forecasts, policymakers should monitor MSAR signals for transitions to volatile regimes. Such proactive macro prudential measures can help prevent the intensification of credit cycles. Moreover, the relative stability of private and foreign banks suggests that broader financial stability can be enhanced by promoting greater competition and diversification within the banking system. These implications resonate with global experiences where effective management of NPLs has proven essential for sustained growth and crisis resilience (Aiyar et al., 2015; Reinhart & Rogoff, 2011; Louzis et al., 2012).

We structure this paper as follows: Section 2 reviews the literature; Section 3 describes the data and empirical methodology; Section 4 presents results; Section 5 discusses the findings; and Section 6 concludes.

2. Literature Review

We frame nonperforming loans as a focal point where macro shocks, bank incentives, and regulatory choices interact to shape banking-sector fragility and economic outcomes. The financial accelerator and related macrofinance frameworks explain how small shocks to borrowers' net worth or collateral can propagate into large real effects by tightening borrowing terms and raising default probabilities (Bernanke, Gertler, & Gilchrist, 1999; Schularick & Taylor, 2012). Complementary work on procyclical leverage shows that intermediaries' balance-sheet adjustments amplify cycles in credit supply and asset prices, thereby affecting loan quality (Adrian & Shin, 2010; He & Krishnamurthy, 2013). Empirical cross-country studies document robust links between credit booms and later banking distress, but they also reveal that institutional differences modulate that channel (Schularick & Taylor, 2012; Laeven & Valencia, 2013; Beck, Jakubik, & Piloiu, 2015). We therefore position NPL dynamics as the product of interacting macro and micro mechanisms rather than the consequence of a single dominant force (Bernanke et al., 1999; Adrian & Shin, 2010; Schularick & Taylor, 2012; Laeven & Valencia, 2013; Beck et al., 2015).

We draw on five theoretical lenses

to organize the determinants of loan performance. First, the financial accelerator emphasizes endogenous amplification through net worth and collateral channels (Bernanke et al., 1999; Schularick & Taylor, 2012). Second, liquidity and leverage theories explain why intermediary funding structures generate procyclicality in lending and risk-taking (Adrian & Shin, 2010; Brunnermeier & Pedersen, 2009). Third, agency theory and corporate-governance models link ownership and incentive misalignment to lax monitoring and risk shifting, with implications for loan screening and recovery (Jensen & Meckling, 1976; Berger & DeYoung, 1997). Fourth, political-economy accounts emphasize directed or politically connected lending by state-controlled institutions as a persistent source of poor loan quality (Sapienza, 2004; Khwaja & Mian, 2005; Micco, Panizza, & Yañez, 2007). Fifth, classic bank-fragility and maturity-transformation frameworks show how deposit funding and information asymmetries can amplify losses once asset-quality problems become visible (Diamond & Dybvig, 1983; Diamond & Rajan, 2005). These perspectives are complementary: governance failures and political lending can intensify accelerator effects and interact with procyclical leverage to produce prolonged NPL episodes (Jensen & Meckling, 1976; Sapienza, 2004; Adrian & Shin, 2010).

Empirical studies suggest the complex mix of macro and bank-level drivers of NPLs, but they also highlight methodological limits. Louzis, Vouldis, and Metaxas (2012) show that macro variables, loan composition, and bank characteristics jointly explain NPL movements in Greece, yet linear panel models abstract from regime dependence that matters in crises. Beck, Jakubik, and Piloiu (2015) use wide cross-country panels to identify GDP growth, asset prices, and interest rates as key covariates of NPLs, but their aggregation can obscure heterogeneity across ownership types and local supervisory regimes. Schularick and Taylor (2012) convincingly link credit booms to subsequent crises across long historical samples, but their macro focus leaves open how bank governance channels produce differential persistence in loan quality.

A parallel strand examines ownership, political connections, and governance as determinants of loan quality. Sapienza (2004) documents that government ownership alters pricing and allocation of credit in ways that favor political or regional objectives, while Khwaja and Mian (2005) find that politically connected firms obtain larger and cheaper loans and subsequently default at higher rates. Micco, Panizza, and Yañez (2007) provide cross-country evidence that state ownership often correlates with weaker performance, including asset-quality deterioration. Agency-based explanations tie these patterns to incentive misalignment and weak monitoring: managers and politically appointed boards may have softer budget constraints and lower incentives to enforce discipline, generating persistent NPLs (Jensen & Meckling, 1976; Berger & DeYoung, 1997).

Recent evidence from South Asia gives the literature stronger regional grounding and speaks more directly to the institutional environment of Bangladesh. Rehman et al. (2024) show that weaker control of corruption is associated with higher NPLs in Pakistan, India, and Bangladesh, which reinforces the view that governance

quality shapes loan outcomes beyond standard macro controls. Bhowmik & Sarker (2024) likewise find that NPLs are closely related to bank non-performance in South Asian banks, again pointing to the role of institutional weakness in the region. For Bangladesh specifically, Chowdhury et al. (2023) report that bank-specific and macroeconomic factors both matter in the Islamic banking segment, while Khan et al. (2023) show that bank-specific and macroeconomic determinants differ across conventional and Islamic banks in an emerging-market setting that includes Bangladesh. Karim et al. (2023) also document a negative relation between NPLs and profitability in Bangladeshi banks, underscoring the balance-sheet and income effects of persistent credit problems. These studies strengthen the case that Bangladesh should not be treated as a generic emerging market, because ownership structure, governance frictions, and regulatory practice appear to shape credit quality in distinctive ways.

Turning to policy-relevant evidence on forecasting and supervision, several studies demonstrate that accounting and regulatory choices materially affect reported NPLs. Temporary forbearance, classification thresholds, and provisioning rules can delay recognition and then create backloaded jumps when relief ends, complicating early-warning systems (Nkusu, 2011; Laeven & Valencia, 2013). Studies of the global financial crisis and subsequent policy responses reveal that supervisory regime changes and recapitalizations often change the measurement of asset quality as much as the underlying risk, producing identification challenges for empirical models (Reinhart & Rogoff, 2009; Laeven & Valencia, 2013).

Critically appraising the literature on model performance, we note a tension between parsimony and realism. Panel regressions and ARIMA-style baselines remain valuable for their interpretability and often give reasonable short-run forecasts in tranquil times (Box et al., 2015; Louzis et al., 2012). Regime-switching specifications deliver improved performance in volatile episodes but require careful validation, including out-of-sample tests and rigorous residual diagnostics, because spurious regimes can arise from overfitting or mis-differencing (Hamilton, 1989; Kim & Nelson, 1999; Clements & Krolzig, 2003). Machine-learning approaches offer accuracy gains in some contexts, but their opaqueness reduces policy traction where supervisors need interpretable triggers.

We identify three immediate gaps that the existing literature has yet to close. First, many cross-country and panel studies lack the institutional granularity needed to separate state, specialized, private, and foreign banking segments; failure to disaggregate masks the fact that institutional ownership correlates strongly with both level and persistence of loan distress as governance and political incentives differ across types (Sapienza, 2004; Micco et al., 2007; Beck et al., 2015; Louzis et al., 2012). Second, literature seldom operationalizes a data-driven route from breakpoint detection to regime estimation; relying on ex ante regime timing or ignoring discrete policy-induced classification changes risks misspecifying persistence and transition probabilities (Filardo & Gordon, 1998; Clements & Krolzig, 2003; Hamilton, 1989). Third, applied forecasting work often omits a full suite of diagnostics and comparative benchmarks that supervisors require to

trust model outputs; practitioners need transparent comparisons of baseline linear models and regime-aware specifications using RMSE, information criteria, and residual tests so they can evaluate tradeoffs between accuracy and interpretability (Box et al., 2015; Kim & Nelson, 1999; Louzis et al., 2012). Addressing these gaps calls for studies that combine institutional disaggregation, breakpoint-informed regime modeling, and a comprehensive diagnostics protocol so that forecasts map reliably to policy levers and governance reforms (Laeven & Valencia, 2013; Nkusu, 2011; Beck et al., 2015).

3. Methodology

We apply time-series econometric techniques to examine the dynamics of Non-Performing Loans (NPL) across five banking segments: State-Owned Commercial Banks (SOCBs), Specialized Banks (SBs), Private Commercial Banks (PCBs), Foreign Commercial Banks (FCBs), and the aggregate banking sector. We use the best available quarterly NPL data from the first quarter of 2007 to the fourth quarter of 2024, taken from the quarterly publications of Bangladesh Bank. We acknowledge that these official NPL figures are subject to reporting lags and classification shifts. Accordingly, accounting filters can introduce noise to the data and potentially lead to an underestimation of the actual credit risk. To comprehend the behavior and drivers of NPL with NPL forecasting, our empirical toolkit comprises three complementary elements: Auto-ARIMA, Structural Break Analysis, and Markov-Switching Autoregressive (MSAR) models. Below, we present the steps of our methodology in sequence and explain the rationale that guides each choice.

3.1 Data Preprocessing

To ensure stationarity of data prior to model estimation, this paper evaluated the unit root properties of the NPL series by using the Philips-Perron (PP) test. The raw levels for all five NPL categories exhibited unit roots. After first differencing, the PP test confirms stationarity of all NPL series by demonstrating a p-value less than 0.05. We treat this preprocessing as essential to avoid spurious inferences and to improve the reliability of subsequent break detection and time-series estimation.

3.2 Autoregressive Integrated Moving Average (ARIMA) Modeling

As a baseline, we estimate non-seasonal ARIMA (p,d,q) models. The ARIMA framework decomposes a series into three components - autoregressive (AR), differencing (d), and moving average (MA) - to analyze and forecast time series data. The ARIMA model used for this paper is specified as:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad \text{.....(i)}$$

Where,

y_t= Stationary form of the NPL series. For categories where d=1, $y_t = \Delta NPL_t$. For categories where d=0,

$y_t = NPL_t$

ϕ : The Autoregressive (AR) coefficient, representing the persistence of NPL dynamics

ϕ : The Moving Average (MA) coefficient, representing the impact of past shocks

ε_t: Error term

This study used the "Auto-ARIMA" procedure for selecting the optimal models. This algorithm selects the optimal lag structure among various combinations of autoregressive and moving average components based on the minimum Akaike Information Criterion (AIC). Thus, the data-driven selection process helps to balance between model parsimony and goodness-of-fit.

Residual Diagnostic:

To ensure the adequacy of the selected Auto ARIMA models, three diagnostic tests were performed on the residuals. First, the Ljung-Box test was applied to examine the null hypothesis of no serial autocorrelation. A p-value greater than 0.05 ensures the model has captured all available linear information in the NPL series. Second, the Jarque-Bera test was conducted to verify the assumption of normality. JB test result ($p>0.05$) states the residuals are normally distributed. Finally, the Engle's ARCH test was applied to detect the presence of Autoregressive Conditional Heteroscedasticity. The ARCH test results ($p>0.05$) ensure that the residuals possess constant variance. These diagnostic tests are conducted to confirm that the residuals behave as white noise, which validates the robustness of the model parameters.

3.3 Structural Break Analysis

The ARIMA model is suitable for modeling and forecasting the temporal dynamics of NPLs because it assumes a stable trend without unexpected changes. However, the economic and regulatory environments affecting NPLs are often prone to structural shifts and policy changes. The motivation behind conducting this step emerges from the existence of potential non-linearity as evident in the JB test results and regime shifts in the data, mostly from an emerging country like Bangladesh.

To consider these potential changes on NPL trends, we conduct structural breakpoint analysis using the Pruned Exact Linear Time (PELT) algorithm (Killick et. al., 2012) via the Python ruptures library. The PELT algorithm effectively identifies multiple breakpoints by providing a solution to the minimization of the penalized cost function. This study used the Least Squares (L2) cost function within the Python Rapture framework, which is mathematically optimized for detecting shifts in the piecewise constant mean (Killick et. al., 2012). The motivation behind this step is to distinguish between stable trends and sudden shifts related to policy changes, regulatory shocks, credit shocks, or macroeconomic volatility.

This study adopted a two-stage validation process to ensure the robustness of the findings and satisfy the requirement of model parsimony.

Penalty Value and Minimum Segment Length: First, a penalty value of 15 is adopted after experimenting with a range of penalty values (1, 5, 10, and 15). This higher penalty threshold enables us to focus on the major shifts in the NPL series by filtering out the stochastic noise. Additionally, a minimum segment length of eight quarters ($h=8$) was imposed to address the limitation of limited data points. Adding this constraint helps to detect regimes with enough data points to be statistically meaningful.

Cross-validation: The cross-validation of the identified shift is done by using Welch's T-test. By comparing the means of adjacent regimes without assuming equal variance, we confirm

that the detected break represents a mathematically significant shift ($p < 0.05$). These validated breakpoints serve as the empirical foundation for the subsequent Markov Switching Autoregressive (MSAR) estimation.

3.4 Markov Switching Autoregressive Model

Based on the evidence of structural changes and policy shifts identified through PELT (L2) breakpoint analysis, we further explore the existence of potential regime shifts in NPL dynamics using a non-linear MSAR model. We apply this model to each of the four bank categories along with the aggregate one. For data preprocessing, based on PP test results, this study opts for the first differencing (d=1) for all five categories to avoid convergence issues and to ensure interpretability. We specify the MSAR model with two specific regimes, specifically the stable NPL regime and the volatile NPL regime. Further, an autoregressive order of 1 is opted to make the model parsimonious and to avoid model complexity. Due to the small sample size, this study assumes the error term (to be constant across regimes in order to keep the model parsimonious. Finally, we evaluate the model performance with the help of out-of-sample validation by using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) in comparison with Auto-ARIMA models. Table 2 presents the particulars of the MSAR model selection specifications.

Table 2: MSAR Model Selection for NPL Categories

Category	Model Order (p)	Differencing Order (d)	Regime (k)	MSAR Model
State NPL	1	1	2	MS(2)-AR (1)
Specialized NPL	1	1	2	MS(2)-AR (1)
Private NPL	1	1	2	MS(2)-AR (1)
Foreign NPL	1	1	2	MS(2)-AR (1)
Total NPL	1	1	2	MS(2)-AR (1)

Model Specification: Given the small sample size of 72 observations, this study employed an MSAR model with two states (k=2) along with an autoregressive order of one (p=1). Therefore, the model allows the mean to switch between two latent states (stable vs stress) and assumes the current value depending on one lag of itself.

Regime 0: Low Growth (Stable) State

Regime 1: High Growth (Stress) State

Transition Matrix:

The switching between stable and stress states are governed by a first-order Markov chain. The transition probabilities are defined by P:

$$P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}$$

Where,

$p_{0|0} = P(s_t = 0|s_{t-1} = 0)$: Probability of remaining in a stable state.

$p_{0|1} = P(s_t = 0|s_{t-1} = 1)$: Probability of switching from stable to stress.

$p_{1|1} = P(s_t = 1|s_{t-1} = 1)$: Probability of remaining in a stress state.

$p_{1|0} = P(s_t = 1|s_{t-1} = 0)$: Probability of switching from stress to stable.

Constraints: $p_{0|0} + p_{0|1} = 1$ and $p_{1|1} + p_{1|0} = 1$

Mathematical Structure: The MS(2)-AR(1) model for the differenced NPL series (y_t) is defined as:

$$\Delta y_t = \mu s_t + \phi s_t \Delta y_{t-1} + \varepsilon_t; \quad \varepsilon_t \sim N(0, \sigma^2)$$

Where:

$s_t \in \{0,1\}$ = Latent state at time t $(0 = stable, 1 = stress)$

μs_t = Regime-dependent intercept (Mean growth for state); $\mu s_t \in \{\mu_0, \mu_1\}$

ϕs_t = Regime dependent autoregressive coefficient; $\phi s_t \in \{\phi_0, \phi_1\}$

ε_t = Error term

Estimation: The MS(2)-AR(1) model parameters are estimated by using the Maximum Likelihood Estimation (MLE) in the Python 'statsmodels'. Additionally, the Hamilton filter is used to iteratively calculate the probabilities of being in the stable and stress regimes at any given time.

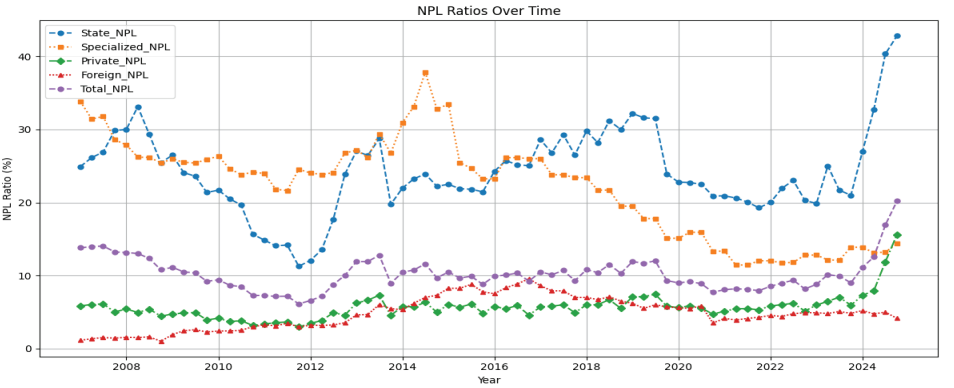
3.5 Model Validation and Selection

To determine the optimal forecasting method, an out-of-sample predictive validation approach was employed with a 64-8 sample split. The dataset was divided into a training period (2007Q1- 2022Q4, T=64) and a test period (2023Q1-2024Q4, T=8). The linear ARIMA models from Auto-ARIMA were compared with the parsimonious non-linear MSAR model by using comparative metrics. The comparison is based on two loss functions, namely RMSE and MAPE. Finally, for forecasting synthesis, only the model with the lowest RMSE and MAPE in the test period is selected as the 2025–2026 baseline projections.

4. Results

This section presents the empirical findings of the study of the non-performing loans across different categories of banks in Bangladesh. We begin with the visual presentation of NPLs by bank and total category, as shown in Figure 1, along with a brief descriptive overview in Table 3. We present ARIMA and MSAR models with structural breakpoint identifications. Finally, we forecast with both models, followed by robustness checks for further model validity and goodness-of-fit test.

Figure 1: NPL Trends



Source: Authors' own calculation

4.1 Descriptive Statistics

The analysis of non-performing loans across different bank categories and the overall banking sector shows notable variation in their trends, as illustrated in Figure 1. Additionally, Table 3 presents the descriptive overview of different categories of NPLs over 72 quarters from 2007 to 2024.

On average, the industry records an NPL ratio of 10.21% over 72 observed quarters. State-owned commercial banks show the highest average NPL of 24.12%, with a maximum value of 42.83%. In addition, Figure A1 in the Appendix also shows that the State-owned commercial banks contribute the most to the total non-performing assets of the banking industry over the study period. Specialized banks record a mean NPL of 22.11% and a maximum value reaching 37.84%.

In contrast, private commercial banks and foreign commercial banks experience relatively lower average NPL ratios, 5.65% and 4.81%, respectively. The overall descriptive statistics emphasize the persistent challenges in managing credit risk in the Bangladesh banking sector, mostly within state-owned and specialized banks category.

Table 3: Descriptive Analysis

	State NPL	Specialized NPL	Private NPL	Foreign NPL	Total NPL
Mean	24.122	22.114	5.651	4.814	10.210
St. Dev	5.776	6.731	1.772	2.215	2.323
Min	11.270	11.440	2.950	1.000	6.120
25%	20.908	15.100	4.865	3.155	8.798
50%	23.735	23.830	5.635	4.785	9.980
75%	26.990	26.150	6.030	6.275	11.215
Max	42.830	37.840	15.600	9.560	20.200
Count	72	72	72	72	72

Source: Authors' own calculation

4.2 Unit Root Test

Table 4 demonstrates the unit root results across the five NPL series. PP test results show that NPL across all five bank categories exhibit non-stationarity at their levels, as their p-values are significantly higher than the 0.05 threshold. After first differencing, the test results confirm that all series become stationary at the 1% significance level. Consequently, this statistical evidence justifies the use of an integrated framework for our subsequent ARIMA and MSAR models to ensure the reliability of regression outputs.

Table 4: Phillips-Perron Unit Root Test

Category	P-value (Level)	P-value (1st Diff)
State NPL	0.553	0.000
Specialized NPL	0.476	0.000
Private NPL	0.995	0.000
Foreign NPL	0.377	0.000
Total NPL	0.527	0.000

Source: Authors' own calculation

4.3 Baseline Linear Dynamics: ARIMA

This study adopts the Auto-ARIMA framework to capture the linear memory of the non-performing loans in Bangladesh. As outlined in the Auto-ARIMA summary (Table 5), the optimal ARIMA models reveal distinct behaviors across five different categories. For example, state-owned and total industry NPL categories exhibit complex lag structures, such as ARIMA (3,0,0) and ARIMA (3,0,1). ARIMA models in the state and total series suggest that the credit shocks in these sectors spread over several quarters. In contrast, NPL for foreign banks follows a simpler ARIMA (0,1,0) or random walk, which indicates its distress level is less tied to long-term historical persistence and gets resolved immediately.

Table 5: Auto-ARIMA Model Selection

Category	Order	Log-Likelihood	AIC	BIC	Ljung-Box (p)	Jarque-Bera (p)	ARCH (p)
State NPL	(3,0,0)	-173.72	357.44	368.82	0.858	0.163	0.724
Specialized	(3,1,0)	-139.91	287.82	296.87	1.000	0.000	0.009
Private NPL	(1,1,2)	-87.57	183.13	192.18	0.786	0.000	0.011
Foreign NPL	(0,1,0)	-60.24	122.49	124.75	0.026	0.000	0.998
Total NPL	(3,0,1)	-104.54	221.09	234.75	0.214	0.001	0.778

Source: Authors' own calculationThe ARIMA (1,1,2) structure for NPL in the private sector reflects a traditional business-cycle sensitivity (Table A2 in the Appendix).

This model shows that private NPL holds a moderate memory of past NPL levels and quickly becomes responsive to management actions (evident in significant AR and MA coefficients). In Bangladesh, private banks usually fall under strict credit monitoring, and the model structure reflects that swifter recovery pattern. Conversely, Specialized banks' NPLs also follow a complex ARIMA (3,1,0) specification. The significance of the second-lag autoregressive term indicates that the bad loans in this sector are heavily influenced by their own historical values from two prior periods (Table A2 in the Appendix). In Bangladesh, this two-period lag is persistent with the cyclical nature of the agricultural and sectoral risks. In this sector, the impact of a shock such as crop failure or political interference takes time to be categorized as distress loans.

In addition, the variance in the model estimates presents a noteworthy gap in asset quality stability. Table A2 in the Appendix depicts that the state NPL series shows the highest volatility (), while the foreign NPL category holds the lowest (). Notably, the volatility of private NPLs () is roughly ten times lower than that of the state-owned category. These findings reveal that while private and foreign banks maintain relatively stable asset quality, state-owned banks are highly volatile. These results align with the practical reality in Bangladesh, where poor governance, directed lending, a lack of monitoring, political interference, and a culture of willful defaults dominate the state-owned sector. Conversely, private and foreign banks are subject to stricter monitoring and far less external control, leading to a more organized credit environment.

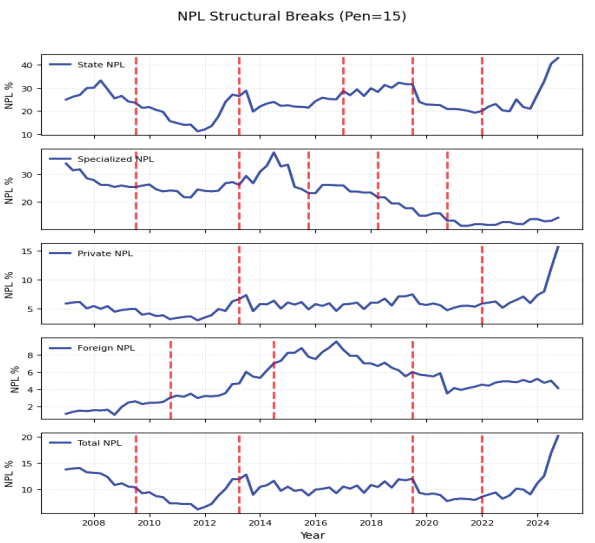
The residual diagnostics of ARIMA models present an interesting distinction between the model's structural accuracy and data volatility. All five NPL categories passed the Ljung-Box test with p-values exceeding 0.05 thresholds. Thus, ARIMA specifications are adequate to capture predictable historical patterns in the Bangladesh market. However, the Jarque-Bera test results (p-values approx. 0.000) reject the null hypothesis of data normality. It demonstrates that the NPL residuals do not follow a bell-shaped pattern, but possess outliers. Thus, the JB test confirms that the Bangladesh market NPL data is susceptible to sudden, volatile shocks that linear models cannot predict. Further, the ARCH test results indicate that specialized and private NPLs data possess heteroscedasticity. Whereas, state, foreign, and total NPL categories show no evidence of volatility clustering (p-value>0.05).

The results of Auto-ARIMA provide a baseline for NPL projections, but the rejection of normality suggests the presence of structural breaks. To explore the possible disruptions in the trends, we conduct a structural break analysis using the PELT (L2) algorithm. Thus, ARIMA and structural-break analysis help us trace NPL trends and pinpoint when major shifts occur, linking those breaks to major external factors.

4.4 Structural Break Analysis

The application of the PELT algorithm with a trimming parameter of eight (h=8) and penalty value of fifteen (c=15) reveals that NPL trajectories in Bangladesh are not merely volatile, but are defined by five distinct, policy-driven regimes. The breakpoint analysis indicates that NPL behavior in the Bangladesh banking industry is not random noise, but rather follows a specific pattern. Thus, the market remains stable until a major policy or economic event forces it into a new phase.

Figure 01: Structural Break Analysis



Source: Authors' own calculation

The Post Global Financial Crisis and Stock Market Crash (2009-2010): The initial breakpoints identified in the foreign (2010 Q4) and specialized (2009 Q3) sectors reflect the delayed spillover effects of the Global Financial Crisis (GFC) tied with the 2010 major domestic stock market crash in Bangladesh. The significant downward shift in the total NPL mean (dropping to 8.37% from 12%) represents a credit contraction period. During this time, banks curtailed aggressive lending to preserve liquidity, which establishes a lower baseline for NPLs over the following decade.

The Transparency Shock (2012-2013): This period experienced a major shift in data across all categories except the foreign sector. During this era, NPL for state-owned banks jumped to 23.61% from 18.07% (as shown in Table 6). This major shift in NPL is not a random spike. The break was caused by a new rule that tightened existing accounting standards to an international level. Due to major policy changes, hidden bad loans from lax reporting and financial scams were unmasked. Thus, PELT captures the moment when the banking industry was forced to stop hiding the bad loans.

Table 6: Structural Break Analysis (Mean Shift Significance)

Sector	Regime Period	Obs (n)	Mean (%)	Std. Dev	T-Stat	P-Value	Status
State	2007-Q1 to 2009-Q2	10	27.63	2.69	-	-	Baseline
	2009-Q3 to 2013-Q1	15	18.07	4.67	6.2177	0.000003	*Significant*
	2013-Q2 to 2016-Q4	15	23.61	2.25	-3.9997	0.000696	*Significant*
	2017-Q1 to 2019-Q2	10	29.42	1.84	-6.7748	0.000001	*Significant*
	2019-Q3 to 2021-Q4	10	22.52	3.29	5.4984	0.000076	*Significant*
	2022-Q1 to 2024-Q4	12	26.31	7.70	-1.4775	0.159562	Insignificant
Special-ized	2007-Q1 to 2009-Q2	10	28.28	2.89	-	-	Baseline
	2009-Q3 to 2013-Q1	15	24.54	1.54	3.5770	0.003654	*Significant*
	2013-Q2 to 2015-Q3	10	30.07	4.07	-3.8941	0.002649	*Significant*
	2015-Q4 to 2018-Q1	10	24.52	1.28	3.8970	0.002588	*Significant*
	2018-Q2 to 2020-Q3	10	18.00	2.40	7.1865	0.000005	*Significant*
	2020-Q4 to 2024-Q4	17	12.67	0.88	6.4353	0.000063	*Significant*
Private	2007-Q1 to 2013-Q1	25	4.52	0.95	-	-	Baseline
	2013-Q2 to 2021-Q4	35	5.79	0.72	-5.5138	0.000002	Significant
	2022-Q1 to 2024-Q4	12	7.61	2.93	-2.0323	0.066015	Insignificant
Foreign	2007-Q1 to 2010-Q3	15	1.84	0.53	-	-	Baseline
	2010-Q4 to 2014-Q2	15	4.08	1.14	-6.6944	0.000002	Significant
	2014-Q3 to 2019-Q2	20	7.60	0.98	-9.3277	0.000000	Significant
	2019-Q3 to 2024-Q4	22	4.81	0.64	10.516	0.000000	Significant
Total	2007-Q1 to 2009-Q2	10	12.6	1.27	-	-	Baseline
	2009-Q3 to 2013-Q1	15	8.37	1.56	7.1179	0.000000	Significant
	2013-Q2 to 2019-Q2	25	10.47	0.98	-4.5522	0.000182	Significant
	2019-Q3 to 2021-Q4	10	8.83	1.18	3.6950	0.002437	Significant
	2022-Q1 to 2024-Q4	12	11.14	3.58	-2.0043	0.065024	Insignificant

Source: Authors' own calculation

Political Instability and the Rescheduling Buffer (2014–2017): The breaks identified by PELT in the mid-2010s reflect a banking sector trying to absorb the shocks from the political unrest of 2013 and 2014. At that time, the Bangladesh bank allowed a widespread rescheduling, which created an artificial declassification of loans. The model captures a significant shift in mean total NPLs, where actual credit risk was masked by the regulatory safety net.

The Forbearance Reorientation and Covid-19 (2019-2021): During this period, NPLs exhibited a negative trend. But this was driven by major policy shifts rather than improved credit management. According to Table 6, the aggregate NPL for the Bangladesh banking industry dropped to 8.83%. This reduction was initially triggered by the central bank's policy to clean up loans with a 2% down payment. This was followed by a pandemic era where the central bank directed banks to stop labeling any new loan as bad. Therefore, the break identified by PELT was an artificial stability caused by changing the loan policy.

The Post-Pandemic Correction (2022–2024): The most recent period (2022–2024) shows a surge in mean NPLs across major categories. Though insignificant, this stage economically reflects a volatile transition due to the withdrawal of forbearance policies, high inflation, and the global dollar crisis.

These five PELT regimes are merged into two latent stages for the MSAR model. Where the stable state shows low mean driven by policy, and the stress state is driven by market corrections.

4.5 Markov Switching Autoregressive Model

The MSAR diagnostic results (Table 7) reveal a significant deviation in the structural persistence of credit risk across the Bangladesh banking sector. Even though the model provides a unique lens into the "stickiness" of non-performing loans (NPLs), it also exposes the inherent limitations of non-linear estimation in a dataset of this scale (T=72).

Table 7: Markov Switching Parameters

Category	AIC	BIC	LLF	RMSE	P_{00} (Stay Stable)	P_{11} (Stay Stress)	Duration (Stable)	Duration (Stress)	Diagnostics
State	348.69	364.43	-167.34	2.21	0.96	0.76	29.85	4.1	Reliable
Specialized	285.46	301.20	-135.73	1.49	0.97	0.55	38.34	2.24	Reliable
Private	178.24	193.98	-82.12	0.72	0.89	0.99	9.63	76.91	Overfitted
Foreign	124.40	140.14	-55.20	0.40	0.90	0.42	10.24	1.73	Reliable
Total	221.38	237.12	-103.69	0.89	0.96	0.80	30.47	5.12	Reliable

Source: Authors' own calculation; Note: Duration Calculation: $1/(1-p_{ii})$

The MSAR model indicates that state-owned banks and the aggregate sector exhibit realistic stress durations of 4.10 and 5.12 quarters, respectively. This suggests that systemic shocks in the public sector are not temporary spikes but sticky crises requiring over a year of corrective policy to subside. On the other hand, foreign banks demonstrate the most efficient recovery, with stress periods lasting only 1.73 quarters. This quick recovery in foreign banks reflects more

aggressive asset cleaning and superior risk management frameworks. However, a critical diagnostic failure is observed in the Private Banking sector. The model estimates an expected stress duration of 76.91 quarters (). Since this duration exceeds the entire 72-quarter sample period, it indicates regime entrapment or overfitting. In this instance, the MSAR model fails to differentiate between a high-NPL regime and a long-term linear trend, rendering its non-linear coefficients mathematically valid but economically implausible for that specific category. Our results imply that the Central Bank cannot use a 'one-size-fits-all' policy. State-owned banks need immediate liquidity support during their 4-quarter stress windows, while the long-term stability of private banks justifies lower regulatory intervention unless a rare structural shift is identified.

Given these MSAR inconsistencies, specifically the risk of over-parameterization in low-volatility sectors, the ARIMA model is selected as the primary forecasting engine for the 2025–2026 projections. ARIMA's lower Information Criteria (AIC) and its ability to handle the "levels" of NPLs without the bias of regime-switching entrapment make it a more robust tool for point-forecasting. By utilizing the MSAR results for structural diagnostics and ARIMA for predictive execution, this study ensures that the final forecasts are both contextually aware and statistically stable.

4.6 Comparative Forecasting: ARIMA vs. MSAR

The MSAR model provides a significant insight into the stickiness of the distress states as outlined in Table 7. However, the MSAR models lack predictive power, as evident in RMSE and MAPE values. The higher error rates in MSAR suggest that it is over-parameterized and chasing for shocks rather than projecting a stable future trend. Additionally, limited data (72 points) can statistically lower the predictive power for a complex Markov model. Besides, Bangladesh's banking sector NPLs get smoothen by restructuring and forbearance, which masks the actual data.

Table 8: Out-of-Sample Validation

	RMSE		MAPE	
Category	**ARIMA**	**MSAR**	**ARIMA**	**MSAR**
Foreign	0.310986	1.001303	0.046465	0.176766
Private	4.563388	5.168215	0.306569	0.355551
Specialized	0.75948	1.065938	0.045758	0.066377
State	10.55906	12.68627	0.209045	0.266327
Total	4.929842	6.760035	0.227662	0.351609

Source: Authors' own calculation

Table 8 shows that the consistent lower RMSE and MAPE in Auto-ARIMA models across all 5 NPL categories. Accordingly, ARIMA is best suited for NPL projection in the Bangladesh context. Consequently, for 2025–2026 forecast, the ARIMA model is selected for its superior out-of-sample predictive stability.

4.7 NPL Forecasting

Recursive multi-stage ARIMA models trained on the full 72 data points were used to forecast the NPL through 2026. This method allows for capturing the long-term momentum and incorporating the post-pandemic recovery trend in the Bangladesh banking sector.

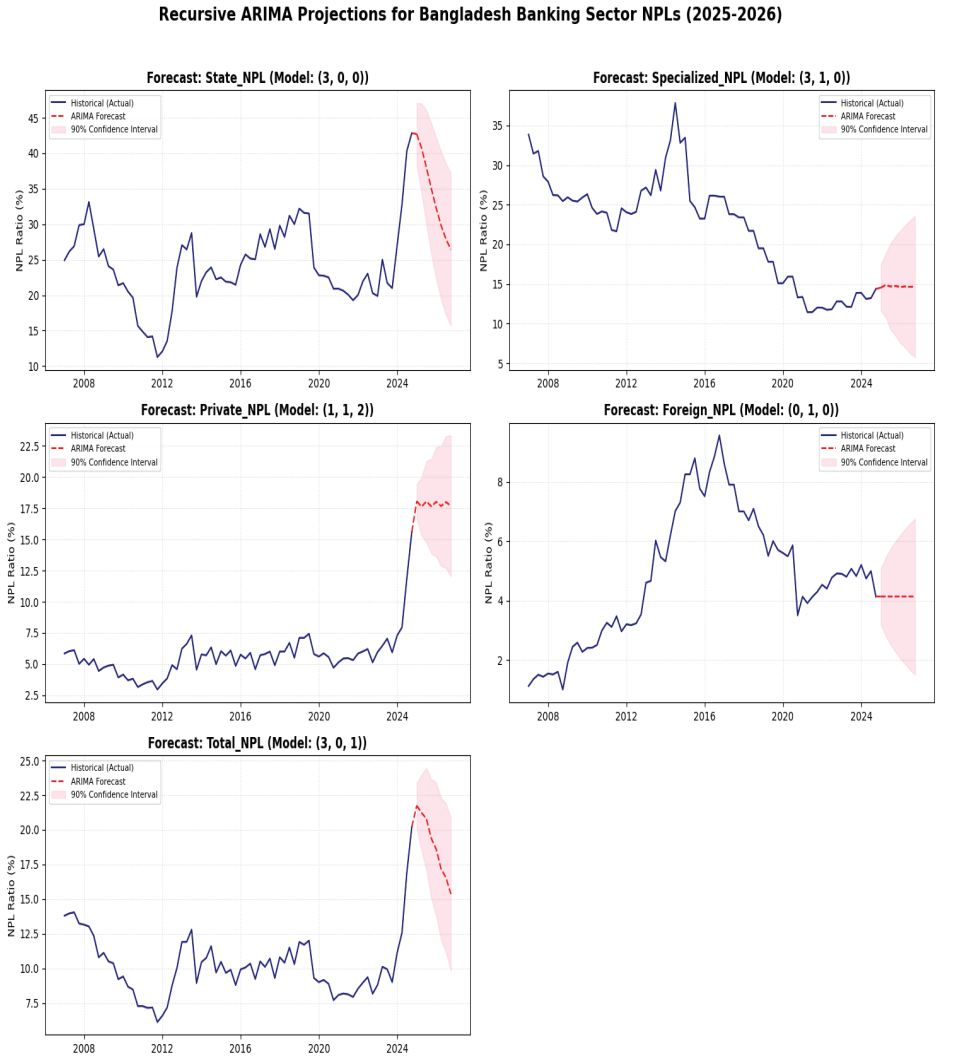
Table 9: Forecasting with ARIMA

	State (3,0,0)	Specialized (3,1,0)	Private (1,1,2)	Foreign (0,1,0)	Total (3,0,1)
2025 Q1	42.71175	14.53397	18.068	4.13	21.74832
2025 Q2	40.73249	14.86165	17.62955	4.13	21.23061
2025 Q3	37.99401	14.68141	18.04214	4.13	20.79168
2025 Q4	35.01278	14.75068	17.65388	4.13	19.3647
2026 Q1	32.22275	14.63185	18.01924	4.13	18.59073
2026 Q2	29.81662	14.68931	17.67543	4.13	17.17163
2026 Q3	27.89181	14.6393	17.99896	4.13	16.54601
2026 Q4	26.44737	14.68035	17.69452	4.13	15.36497

Source: Authors' own calculation

The projected NPL in Table 9 suggests a stable trend for private and foreign banks in the NPL categories. However, the state-owned banks' NPLs are projected to undergo a significant downward correction. Consequently, the downward pressure in state NPL put the aggregate NPL ratio to drop from 21.7% to 15.4% by the end of 2026. This forecast signals a leaner and resilient financial future for the Bangladesh banking industry.

Figure 02: NPL Forecasting



Source: Authors' own calculation

5. Discussion

We begin by highlighting the main patterns that emerge from our analysis. Non-performing loan ratios vary significantly across bank groups. State-owned and specialized institutions consistently carry higher levels of distressed credit, and their weak loan quality persists over extended periods. MSAR model (Table 7) identified a stress duration of 4.1 quarters for the public sector. In contrast, private and foreign banks exhibit lower average ratios and revert to healthier positions more quickly. ARIMA Forecasts in Table 8 recognize these differences and provide a more accurate assessment of

future credit stress than those that treat the banking system as homogenous. This heterogeneity is central to understanding where vulnerabilities lie and how they evolve during financial cycles.

We interpret these differences as the result of incentives, governance structures, and market discipline. Institutions with weaker internal controls, politically influenced lending, and softer budget constraints are slower to resolve problem exposures, which prolongs distress. The ARIMA (3,0,1) lag structure in state-owned banks also suggests that shocks have a long memory. Private and foreign banks, operating under stronger commercial incentives and closer scrutiny from markets, tighten credit standards more quickly and pursue loan recovery more aggressively. These contrasts explain why shocks of similar magnitude, such as PELT-identified shock in 2012-2013, produce prolonged deterioration in some institutions but only short-lived stress in others.

The systemic implications are clear. When a significant share of lending is concentrated in banks that remain in distress for extended periods, the entire financial system becomes more vulnerable to shocks. Persistent NPLs limit lending capacity, increase funding costs, and heighten the risk of credit contractions that amplify economic downturns. For instance, PELT findings regarding the 2019-2020 forbearance pivot show how an aggregate indicator can be misleading. During this period, the drop of mean NPLs to 8.83% was a result of policy interventions and loan reclassifications rather than actual asset recovery. In this setting, aggregate indicators can be misleading, as they understate systemic risk by masking the persistence of fragility within certain institutions. Supervisors who rely solely on aggregate data may therefore fail to identify early signs of long-lived weaknesses.

Our findings call for differentiated policy responses. While recapitalization or temporary regulatory relief can provide immediate stability, these measures do little to address structural weaknesses in banks that habitually accumulate problem loans. More durable solutions require reforms that strengthen governance, improve accountability, and limit politically directed or related-party lending. In addition, when regulatory changes affect the recognition or classification of distressed loans (as shown in 2022-2024 volatility), authorities should phase in implementation and communicate expected impacts clearly. Such steps reduce the risk that abrupt jumps in reported non-performing loans trigger overreactions in credit supply.

For bank managers and boards, the results underline the importance of forward-looking provisioning and active resolution of distressed exposures. Institutions with a history of prolonged credit weakness must adopt more conservative provisioning strategies to offset the high variance and accelerate recovery processes to reduce the duration of stress. Meanwhile, private and foreign banks, which tend to recover more quickly, can play a stabilizing role during downturns but must remain vigilant to systemic spillovers. These differentiated strategies enhance resilience at both the institutional and system-wide levels.

6. Conclusion

We examine the dynamics and persistence of non-performing loans in a banking system characterized by institutional diversity and recurrent policy shocks.

Our motivation lies in the observation that aggregate indicators often obscure concentrated weaknesses, and that conventional models fail to capture the abrupt shifts and extended stress episodes common in emerging-market credit cycles. By disaggregating bank groups and adopting approaches that account for persistence and structural changes, we provide a sharper understanding of credit risk and its implications for policy.

The results show that the burden of non-performing loans falls disproportionately on state-owned and specialized banks, where distress not only reaches higher levels but also endures longer. Private and foreign banks exhibit greater resilience and recover more swiftly. Forecasts that incorporate these ownership differences deliver more credible predictions than aggregate models, particularly during periods of volatility. The recursive ARIMA forecasts for 2025-2026 project a total industry NPL correction to 15.36%. These findings reinforce the view that governance, incentives, and market discipline are decisive in shaping credit quality.

Our contribution is threefold. First, we demonstrate how institutional heterogeneity in ownership translates into divergent trajectories of credit distress. Results show that state-owned NPL has high variance (5.12) compared to private sector NPLs (0.38). Second, we illustrate the value of combining structural break analysis with forecasting tools that capture persistent regimes, thereby improving accuracy and interpretability. Third, we provide a framework that aligns empirical modeling with supervisory needs by emphasizing transparent comparisons across ARIMA and MSAR methods. Together, these contributions enrich the literature on credit risk and offer actionable insights for regulators and practitioners in Bangladesh.

While this study provides robust projections for Bangladesh's banking sector, it has certain limitations. The 72-quarterly dataset, though covering multiple cycles, limits our ability to use high-parameter specifications to design complex MSAR models with additional regimes. Further, we kept the variance constant in MSAR models to maintain model stability and comparability, which may not consider the time-varying volatility during extreme market shifts. Finally, limited data points restrict the complexity of feasible specifications and the inclusion of granular bank-level governance measures. Causal channels linking ownership and persistence cannot be fully disentangled with time series alone. While our ARIMA models enhance predictive accuracy as shown by the superior RMSE and MAPE scores, further refinements with higher-frequency supervisory indicators, governance data, or ensemble approaches would improve robustness.

Future research should extend our analysis through three dimensions. First, integrating detailed governance and board characteristics into forecasting frameworks will clarify how institutional incentives shape persistence. Second, combining quarterly financials with higher-frequency supervisory data can sharpen early-warning capacity. Third, comparative studies across other emerging economies will help establish whether the persistence we document reflects country-specific dynamics or a broader institutional pattern.

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Benazir Imam Majumder: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Validation; Visualization; Writing – original draft; Writing – review & editing

Md Jahir Uddin Palas: Conceptualization; Investigation; Project administration; Supervision; Validation; Writing – original draft; Writing – review & editing

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Forecasting Non-Performing Loans in Bangladesh: Evidence from ARIMA and Markov-Switching Autoregressive Models

Appendix

Figure A1: Proportional Contribution to Total NPL over Time

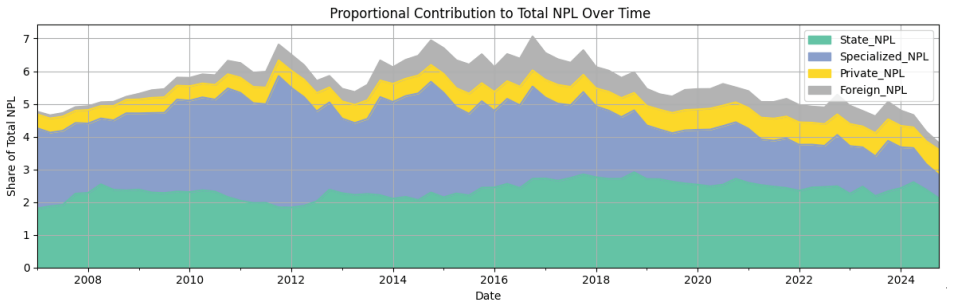

Table A2: Auto-ARIMA Outputs

Category	ARIMA Model	Term	Coef	P-Value	AIC	LB-p (Autocorrelation)	ARCH-p (Volatility)	JB-p (Normality)
State	ARIMA(3, 0, 0)	intercept	3.7296	0.0430	357.4400	0.8580	0.7780	0.1630
State	ARIMA(3, 0, 0)	ar.L1	1.0321	0.0000	357.4400	0.8580	0.7780	0.1630
State	ARIMA(3, 0, 0)	ar.L2	0.0947	0.5920	357.4400	0.8580	0.7780	0.1630
State	ARIMA(3, 0, 0)	ar.L3	-0.2760	0.0250	357.4400	0.8580	0.7780	0.1630
State	ARIMA(3, 0, 0)	sigma2	7.0973	0.0000	357.4400	0.8580	0.7780	0.1630
Specialized	ARIMA(3, 1, 0)	ar.L1	-0.0135	0.9070	287.8200	1.0000	0.7780	0.0000
Specialized	ARIMA(3, 1, 0)	ar.L2	0.3011	0.0010	287.8200	1.0000	0.7780	0.0000
Specialized	ARIMA(3, 1, 0)	ar.L3	-0.1941	0.1240	287.8200	1.0000	0.7780	0.0000
Specialized	ARIMA(3, 1, 0)	sigma2	2.9998	0.0000	287.8200	1.0000	0.7780	0.0000
Private	ARIMA(1, 1, 2)	ar.L1	-0.9410	0.0000	183.1300	0.7860	0.7780	0.0000
Private	ARIMA(1, 1, 2)	ma.L1	1.3757	0.0000	183.1300	0.7860	0.7780	0.0000
Private	ARIMA(1, 1, 2)	ma.L2	0.6284	0.0000	183.1300	0.7860	0.7780	0.0000
Private	ARIMA(1, 1, 2)	sigma2	0.6731	0.0000	183.1300	0.7860	0.7780	0.0000
Foreign	ARIMA(0, 1, 0)	sigma2	0.3195	0.0000	122.4900	0.0260	0.7780	0.0000
Total	ARIMA(3, 0, 1)	intercept	1.6510	0.2800	221.0900	0.2140	0.7780	0.0010
Total	ARIMA(3, 0, 1)	ar.L1	0.4426	0.0000	221.0900	0.2140	0.7780	0.0010
Total	ARIMA(3, 0, 1)	ar.L2	0.9061	0.0000	221.0900	0.2140	0.7780	0.0010
Total	ARIMA(3, 0, 1)	ar.L3	-0.4932	0.0000	221.0900	0.2140	0.7780	0.0010
Total	ARIMA(3, 0, 1)	ma.L1	0.8674	0.0000	221.0900	0.2140	0.7780	0.0010
Total	ARIMA(3, 0, 1)	sigma2	1.0134	0.0000	221.0900	0.2140	0.7780	0.0010

Table A3: Markov Switching Model Summary for State Owned Commercial Banks NPL

Dep. Variable:	State_NPL	No. Observations:	70
Model:	MarkovAutoregression	Log Likelihood	-167.346
Date:	Mon, 11 Aug 2025	AIC	348.692
Time:	04:51:09	BIC	364.431
Sample:	04-01-2007	HQIC	354.943
		- 10-01-2024	
	Covariance Type:	approx	

Regime 0 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.2913	0.240	-1.216	0.224	-0.761	0.178
ar.L1	-0.2223	0.120	-1.846	0.065	-0.458	0.014

Regime 1 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	5.5425	0.626	8.860	0.000	4.316	6.768
ar.L1	-0.9571	1.035	-0.925	0.355	-2.986	1.071

Non-switching parameters

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	5.1814	0.912	5.679	0.000	3.393	6.970

Regime transition parameters

	coef	std err	z	P>|z|	[0.025	0.975]
p[0->0]	0.9665	0.024	39.988	0.000	0.919	1.014
p[1->0]	0.2438	0.197	1.239	0.215	-0.142	0.629

Table A4: Markov Switching Model Summary for Specialized Banks NPL

Dep. Variable:	Specialized_NPL	No. Observations:	70
Model:	MarkovAutoregression	Log Likelihood	-135.733
Date:	Mon, 11 Aug 2025	AIC	285.465
Time:	04:51:09	BIC	301.205
Sample:	04-01-2007	HQIC	291.717
		- 10-01-2024	
	Covariance Type:	approx	

Regime 0 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0154	0.205	-0.075	0.940	-0.416	0.386
ar.L1	0.0158	0.130	0.121	0.904	-0.239	0.271

Regime 1 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.6265	0.774	-3.393	0.001	-4.144	-1.109
ar.L1	-0.9018	0.333	-2.706	0.007	-1.555	-0.249

Non-switching parameters

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	2.3418	0.414	5.652	0.000	1.530	3.154

Regime transition parameters

	coef	std err	z	P>|z|	[0.025	0.975]
p[0->0]	0.9739	0.032	30.183	0.000	0.911	1.037
p[1->0]	0.4456	0.334	1.334	0.182	-0.209	1.101

Table A5: Markov Switching Model Summary for Private Commercial Banks NPL

Dep. Variable:	Private_NPL	No. Observations:	70
Model:	MarkovAutoregression	Log Likelihood	-82.121
Date:	Mon, 11 Aug 2025	AIC	178.242
Time:	04:51:09	BIC	193.981
Sample:	04-01-2007	HQIC	184.494
	- 10-01-2024		
Covariance Type:	approx		

Regime 0 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	3.5094	1.804	1.945	0.052	-0.027	7.046
ar.L1	0.6269	2.489	0.252	0.801	-4.252	5.506

Regime 1 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.0256	0.061	0.423	0.672	-0.093	0.144
ar.L1	-0.4491	0.107	-4.180	0.000	-0.660	-0.239

Non-switching parameters

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	0.5236	0.089	5.911	0.000	0.350	0.697

Regime transition parameters

	coef	std err	z	P>|z|	[0.025	0.975]
p[0->0]	0.8961	0.227	3.941	0.000	0.450	1.342
p[1->0]	0.0130	0.013	0.971	0.332	-0.013	0.039

Table A6: Markov Switching Model Summary for Foreign Commercial Banks NPL

Dep. Variable:	Foreign_NPL	No. Observations:	70
Model:	MarkovAutoregression	Log Likelihood	-55.204
Date:	Mon, 11 Aug 2025	AIC	124.408
Time:	04:51:10	BIC	140.147
Sample:	04-01-2007	HQIC	130.659
	- 10-01-2024		
Covariance Type:	approx		

Regime 0 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.1596	0.088	1.815	0.070	-0.013	0.332
ar.L1	-0.1149	0.138	-0.835	0.404	-0.385	0.155

Regime 1 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.5956	0.192	-3.105	0.002	-0.971	-0.220
ar.L1	-1.0000	0.423	-2.367	0.018	-1.828	-0.172

Non-switching parameters

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	0.2029	0.057	3.573	0.000	0.092	0.314

Regime transition parameters

	coef	std err	z	P>|z|	[0.025	0.975]
p[0->0]	0.9024	0.083	10.909	0.000	0.740	1.065
p[1->0]	0.5785	0.356	1.625	0.104	-0.119	1.276

Table A7: Markov Switching Model Summary for Total Banking Sector NPL

Dep. Variable:	Total_NPL	No. Observations:	70
Model:	MarkovAutoregression	Log Likelihood	-103.692
Date:	Mon, 11 Aug 2025	AIC	221.384
Time:	04:51:10	BIC	237.123
Sample:	04-01-2007	HQIC	227.636
	- 10-01-2024		
	Covariance Type:		approx

Regime 0 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.1548	0.087	-1.777	0.076	-0.326	0.016
ar.L1	-0.4182	0.124	-3.382	0.001	-0.661	-0.176

Regime 1 parameters

	coef	std err	z	P>|z|	[0.025	0.975]
const	2.0651	0.539	3.833	0.000	1.009	3.121
ar.L1	0.2670	0.443	0.603	0.546	-0.601	1.135

Non-switching parameters

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	0.8695	0.156	5.583	0.000	0.564	1.175

Regime transition parameters

	coef	std err	z	P>|z|	[0.025	0.975]
p[0->0]	0.9672	0.024	40.587	0.000	0.920	1.014
p[1->0]	0.1954	0.162	1.203	0.229	-0.123	0.514

Table A8: ARIMA Forecast with 95% Confidence Interval

	State NPLs			Specialized NPLs			Private NPLs			Foreign NPLs			Total NPLs		
	Forecast	L_95	U_95	Forecast	L_95	U_95	Forecast	L_95	U_95	Forecast	L_95	U_95	Forecast	L_95	U_95
2025 Q1	42.71	37.49	47.93	14.53	11.14	17.93	18.07	16.46	19.68	4.13	3.02	5.24	21.75	19.78	23.72
2025 Q2	40.73	33.23	48.24	14.86	10.09	19.63	17.63	14.82	20.44	4.13	2.56	5.7	21.23	17.98	24.48
2025 Q3	37.99	28.35	47.64	14.68	8.21	21.15	18.04	14.17	21.91	4.13	2.21	6.05	20.79	16.41	25.17
2025 Q4	35.01	24.00	46.03	14.75	7.31	22.20	17.65	13.14	22.17	4.13	1.91	6.35	19.36	14.24	24.49
2026 Q1	32.22	20.30	44.15	14.63	6.17	23.09	18.02	12.79	23.25	4.13	1.65	6.61	18.59	12.86	24.32
2026 Q2	29.82	17.37	42.26	14.69	5.50	23.88	17.68	11.94	23.41	4.13	1.42	6.84	17.17	11.07	23.28
2026 Q3	27.89	15.17	40.61	14.64	4.68	24.60	18.00	11.69	24.30	4.13	1.20	7.06	16.55	10.14	22.95
2026 Q4	26.45	13.60	39.30	14.68	4.07	25.29	17.69	10.96	24.43	4.13	1.00	7.26	15.36	8.79	21.94