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ARIMA-BASED FORECASTING OF NON-PERFORMING LOANS: EVIDENCE FROM ALBANIA

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Abstract

This study presents a straightforward approach to forecasting time series data related to Non-Performing Loans (NPLs) in the Albanian banking sector using the ARIMA model(2,1,0) specification. The analysis focuses on capturing the general trend and dynamics of the series, providing short-term predictions for the upcoming 12 months. The results indicate a gradual decline in forecasted values, reflecting an improvement in the quality of the loan portfolio, consistent with the historical developments of the Albania banking system. The forecasting results demonstrate that the ARIMA(2,1,0) model provides a reasonable approximation of the observed series and generates meaningful short-term predictions. These findings highlight the persistence of NPLs and emphasize the importance of proactive risk management strategies within the banking sector. While the model proves effective for short-term analysis, the study concludes that it should be complemented with broader regulatory and institutional measures to better address structural risks and external shocks. Overall, the approach shows that even a relatively simple model can deliver valuable insights, supporting decision-making processes where clarity, practicality, and interpretability are essential for policymakers and financial institutions.

Keywords: Time series forecasting, ARIMA model, Non-performing loans, Diagnostics, Albanian banking sector

INTRODUCTION

The stability of the banking sector is closely linked to the effective management of non-performing loans (NPLs), which represent a key indicator of financial health and credit risk. In emerging economies such as Albania, fluctuations in NPL levels can significantly affect financial stability, lending capacity, and overall economic growth. Consequently, understanding the behavior and evolution of NPLs has become a central concern for both financial institutions and policymakers.

One of the most widely used approaches for analyzing and forecasting economic and financial time series is the ARIMA model, introduced by (Box & Jenkins, 2015). This model combines autoregressive (AR) and moving average (MA) components with differencing techniques to capture both the deterministic and stochastic properties of a time series. Its flexibility and relatively simple structure make it particularly suitable for modeling financial indicators such as NPLs.

This study applies an ARIMA(2,1,0) model to analyze the behavior of NPLs in the Albanian banking sector. The analysis focuses on the period from 2016 to 2022, and forecasts are generated for the subsequent 12 months. The choice of model is based on the identification of autoregressive patterns, the need for first-order differencing to achieve stationarity, and diagnostic testing of residuals. The model is estimated using statistical software and evaluated through standard criteria such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and residual diagnostics.

The aim is to illustrate the capacity of the ARIMA model to provide interpretable and actionable predictions regarding the evolution of NPLs, while maintaining methodological simplicity suitable for a broader audience, including policymakers and financial analysts.

The study also emphasizes the importance of visualizing trends and understanding the temporal dynamics of the NPL series before applying forecasting models. This step is particularly relevant in the context of the Albanian banking sector, where monitoring credit risk and the behavior of non-performing loans is essential for assessing banking system resilience and supporting effective regulatory decision-making.

By combining quantitative modeling with sector-specific interpretation, this paper contributes to a better understanding of NPL dynamics and highlights the role of forecasting tools in supporting informed decision-making within the banking system.

Definition of Non-Performing Loans (NPLs)

According (IMF, 2019) non-performing loans generally refer to loans that, over a relatively extended period, fail to generate income and/or for which the principal or interest payments remain unpaid for at least 90 days. In general, (ECB, 2017) based on standard definitions, non-performing loans exhibit the following characteristics:

- They do not generate any income;
- Full repayment of principal and interest is no longer expected;
- The principal or interest is overdue by 90 days or more; or
- The maturity date has passed, and full payment has not been made.

These characteristics highlight the key indicators of credit risk in the banking sector and are widely used in both regulatory frameworks and financial analyses to identify loans that may negatively impact a bank's financial stability. Recognizing and monitoring non-performing loans is essential for effective risk management, as they reflect underlying weaknesses in borrowers' repayment capacity and can influence overall banking performance.

Non-Performing Loans as a Credit Risk Indicator

Studying the level of non-performing loans is crucial, as it reflects the quality of a bank's credit portfolio and, in aggregate terms, the quality of the banking sector's credit portfolio within a country. Understanding the factors that influence the level of non-performing loans is vital for effective risk management, both for banking institutions and for regulatory and supervisory authorities responsible for sector stability provides (Bank for International Settlements, 2017).

The evaluation and forecasting of the non-performing loans indicator (commonly denoted as NPL) is a key component of a country's economic development, given its significant impact on the volume of credit. Accordingly, studying non-performing loans and their determinants has been the focus of numerous researchers, supervisory authorities, and international institutions such as the World Bank and the IMF (World Bank, 2020).

Banks conduct "banking activities" defined as the acceptance of repayable deposits or other funds from the public and their use for lending, which inherently carries credit risk (European Central Bank, 2017). Not all loans are fully repaid on schedule; while most loans are serviced as agreed, some borrowers fail to meet repayment terms. Such loans, highlights (BIS, 2017) identified as non-performing, are the main focus of banking regulators, as many banks face challenges in removing these loans from their balance sheets.

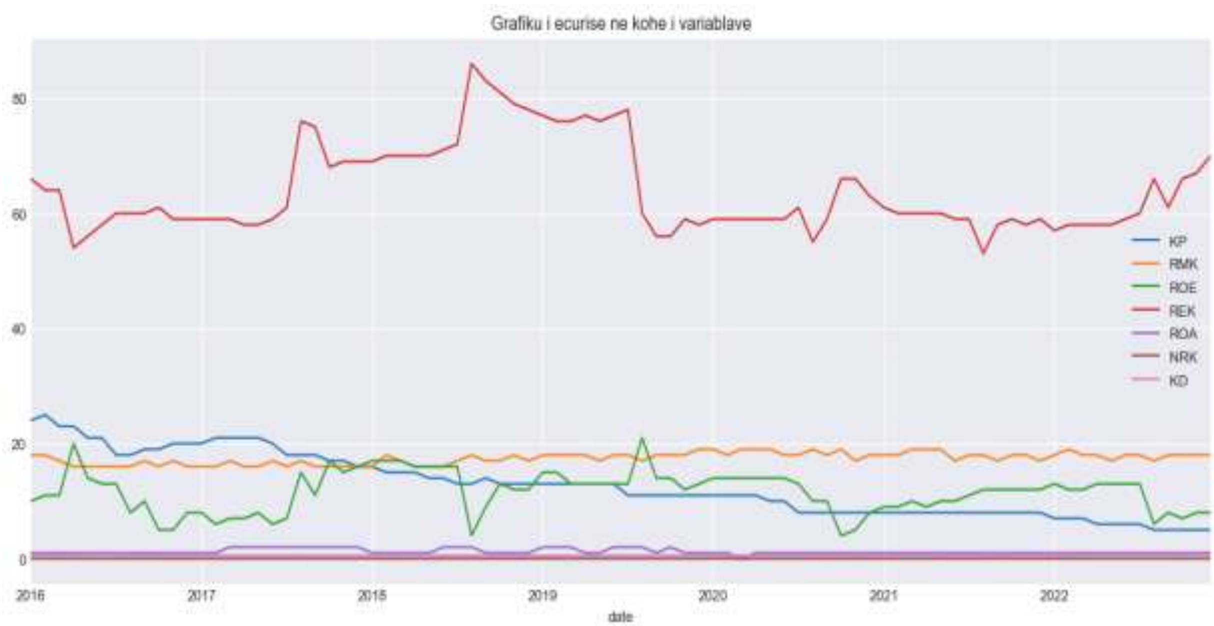
TIME SERIES MODELING

The nature of a time series is fundamental for selecting an appropriate analytical and forecasting approach. In this context, particular importance is given to the preliminary graphical analysis of the data, as it provides essential insights into the underlying structure of the series before any formal modeling is undertaken. Visual inspection allows for the identification of key features such as trends, volatility patterns, structural breaks, and potential irregular components, all of which are critical in determining the suitability and specification of models such as ARIMA. Without this initial step, there is a risk of model misspecification and unreliable forecasting results.

A central issue in time series analysis concerns the prediction of future values and the selection of the most appropriate forecasting model. Among the available methodologies, ARIMA-type models are widely applied; however, their proper implementation depends on a clear understanding of the data-generating process, which is often first revealed through graphical examination.

In this part, the selected indicators are based on (Sulejmani, 2026) study, where the key determinants influencing non-performing loans (NPL) are identified. Building on this framework, the figure below presents the time-series evolution of these variables over the analyzed period, offering a visual basis for assessing their behavior and guiding the subsequent modeling process.

Figure 1: Plot of values over time



The figure illustrates the time-series evolution of selected financial indicators over the period 2016–2022 (Sulejmani, 2026).

In particular, relatively high values are observed for the cost efficiency ratio (CER), which is graphically positioned above the other indicators. This suggests that the proportion of gross banking income used to cover non-interest expenses is considerable. The variable displays significant fluctuations, suggesting a high sensitivity to changing economic conditions.

In contrast, the credit growth rate (CGR) is observed at significantly lower levels relative to the other indicators. This reflects changes in credit conditions that led to a reduction in lending activity during the period, consequently contributing to the decline in the values of this indicator.

The capital adequacy ratio (CAR) appears more stable compared to the other indicators and does not fall into negative values, indicating that the Albanian banking sector remained well-capitalized throughout the analyzed period. Moreover, this indicator does not exhibit signs of undercapitalization at any point during the period. It remains relatively stable, with only minor deviations around its mean, indicating limited responsiveness to external shocks.

As for ROE, NPL, and CAR, these indicators remain relatively close to each other and fluctuate within similar ranges. NPL demonstrates a gradual downward trend throughout the period, indicating a consistent decline over time. Meanwhile, indicators such as ROA, LDR, and CGR remain clustered near lower values and fluctuate within narrow ranges, without exhibiting a clear long-term trend.

On the other hand, loan-to-deposit ratio reached their minimum values in 2020, reflecting the impact of the COVID-19 pandemic. This supports the presence of an irregular component affecting the behavior of the variable during the analyzed period.

Overall, the variables do not demonstrate consistent upward or downward trends but instead show a combination of cyclical movements, relative stability, and irregular components driven by external shocks.

ARIMA MODEL SPECIFICATION

(Box et al., 2015; Hyndman & Athanasopoulos, 2021) argue that to build a forecasting model that combines both AR(p) and MA(q) components while also accounting for the level of differencing required to make a time series stationary, we use the ARIMA model.

ARIMA belongs to a class of models that explains a given time series based on its own past values (lags) as well as past forecast errors. In this way, it captures both the internal structure of the series and the randomness present in it highlights (Brockwell & Davis, 2016).

Determining the appropriate values of (p, d, q) is a crucial step in building an ARIMA model:

- The parameter $p = 2$ is identified earlier, indicating that an AR(2) model best captures the autoregressive structure of the data.
- The parameter $q = 1$ is typically suggested by analyzing the autocorrelation function (ACF). To avoid misspecification, different values can be tested, especially when the MA component is not immediately clear. An important practical approach is that once a suitable AR(p) model is estimated, its residuals can be analyzed. If these residuals still

show patterns, they can guide the specification of the MA(q) component. In particular, one may estimate an MA model on the residuals, often starting with (p − 1) lags.

- The parameter *d = 1* is determined by the level of differencing needed to achieve stationarity. The correct value is the minimum number of differences required for the series to fluctuate around a constant mean, with the autocorrelation function decaying relatively quickly toward zero.

In summary, the ARIMA model integrates autoregression, differencing, and moving average components into a single framework, making it a powerful and flexible tool for time series forecasting.

ARIMA(2,1,0) Model

An ARIMA(2,1,0) model is estimated using the *statsmodels* library. The specification includes two autoregressive terms, first-order differencing, and no moving average component. This initial choice serves as a baseline model, allowing for the evaluation of the autoregressive structure before introducing additional complexity.

RESULTS

The estimated coefficients for both AR terms are statistically significant, as indicated by very low p-values. This confirms that past values of the series contribute meaningfully to explaining its current behavior. The negative signs of the coefficients suggest an inverse relationship between current and lagged observations.

Model fit (AIC/BIC)

Model selection criteria such as AIC and BIC provide measures of goodness-of-fit adjusted for model complexity. These values are useful for comparing alternative specifications, with lower values indicating a more suitable model.

Diagnostics

Diagnostic checks on the residuals indicate satisfactory performance in terms of autocorrelation. The Ljung–Box test yields a high p-value, suggesting that the residuals behave as white noise and that the model has adequately captured the dependence structure in the data.

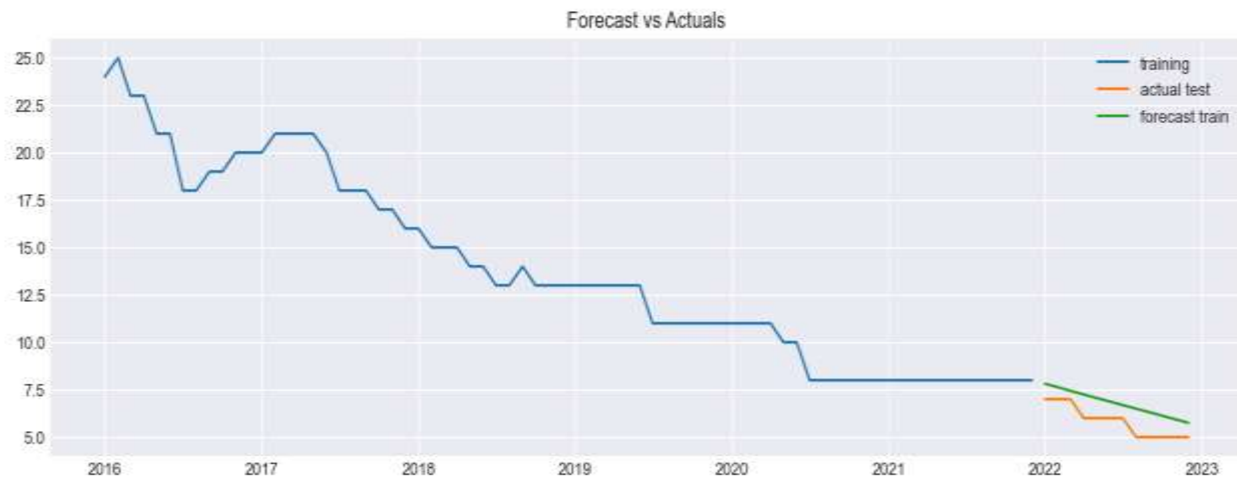
However, the Jarque–Bera test indicates a deviation from normality in the residuals, supported by the elevated kurtosis value. This suggests the presence of heavier tails than expected under a normal distribution, implying that some characteristics of the data may not be fully captured by the model.

Overall, the ARIMA(2,1,0) model provides a reasonable initial fit. Nonetheless, further refinement may be achieved by incorporating a moving average component and evaluating alternative specifications.

Forecast

The ARIMA model is used to generate predictions, which are visualized alongside the observed series. The results indicate that the model captures the general pattern and dynamics of the data, providing reasonable forecasts for the analyzed period.

Figure 2: Forecast vs Actuals



CONCLUSIONS ABOUT ARIMA MODEL

The results of the analysis indicate that the ARIMA(2,1,0) model adequately captures the underlying trends of the selected series and produces reliable short-term forecasts. The forecasted values for the 12-month period show a gradual decline, consistent with the historical behavior observed in the data. The simplicity of the model facilitates easy interpretation and practical application, making it suitable for decision-making contexts where clarity and usability are essential.

The forecasts provide meaningful insights into the expected dynamics of the series, highlighting underlying patterns in its future behavior. This approach demonstrates that even relatively simple time series models can yield valuable information for planning and strategic decision-making. Although the model remains intentionally simple, it produces clear and interpretable results, making it well-suited for applications that require straightforward and practical forecasting. Overall, this shows that basic ARIMA models can effectively capture key aspects of time series behavior and can also serve as a solid foundation for more advanced analyses in future research.

Future research may enhance this analysis by incorporating additional explanatory variables, testing alternative ARIMA or hybrid model specifications, and applying more rigorous validation techniques, including advanced error metrics and confidence intervals, thereby enhancing the predictive accuracy and applicability of the forecasts. Moreover, expanding the dataset across longer time horizons or different contexts could improve the robustness and generalizability of the findings.

Conclusions Linked to the Albanian Banking Sector

The results of the ARIMA(2,1,0) model have important implications for the Albanian banking sector, particularly in understanding and managing non-performing loans (NPLs).

The strong statistical significance of the autoregressive terms indicates that NPL levels in Albania are highly persistent. This means that increases in problematic loans are likely to continue over time if not addressed early. For banks, this highlights the importance of proactive risk management, as delays in intervention can lead to prolonged deterioration in asset quality.

The negative coefficients suggest a degree of correction or stabilization in the system. In the context of the Albanian banking sector, this may reflect the impact of regulatory measures and improved credit risk practices over time, which help gradually reduce elevated NPL levels.

The good diagnostic performance of the model, particularly the absence of autocorrelation in residuals, implies that the model captures the main dynamics of NPL behavior. As a result, it can serve as a useful tool for short-term forecasting and monitoring trends within the banking system.

However, the presence of non-normal residuals and high kurtosis indicates that extreme events or economic shocks are not fully captured. This is especially relevant for Albania, where the banking sector can be sensitive to macroeconomic fluctuations, changes in interest rates, or external crises. It suggests that relying solely on this model may underestimate risk during periods of economic stress.

From a practical perspective, the model can support decision-making by helping banks anticipate short-term changes in NPL levels, adjust provisioning policies, and refine lending strategies. At the same time, the central regulatory authority, such as Banka e Shqipërisë, can use such forecasts to monitor financial stability and implement timely macroprudential measures. Overall, while the ARIMA(2,1,0) model is useful for capturing historical patterns and providing short-term forecasts.

RECOMMENDATIONS

Building on the empirical findings of the ARIMA(2,1,0) model, this section focuses on practical recommendations for the active management of non-performing loans (NPLs), which are directly relevant for banking practice (International Monetary Fund, 2015; World Bank, 2019).

Active Management of Non-Performing Loans

The results of the ARIMA(2,1,0) model indicate a high degree of persistence in the NPL series, suggesting that current levels of non-performing loans are strongly influenced by past values. This implies that delays in addressing problematic loans may lead to prolonged deterioration in asset quality. Therefore, early identification and timely intervention are essential components of effective NPL management.

Problem Identification

Given the strong temporal dependence identified in the model, banks should ensure transparent and accurate assessment of asset quality. Proper classification of loans and adequate provisioning are critical, as early recognition of problem loans can prevent their accumulation over time and reduce long-term financial risks.

Provision of Guidance

The model also reveals a degree of mean-reverting behavior, indicating that NPL levels may stabilize over time under appropriate conditions. In this context, providing clear and credible guidance to market participants becomes essential in maintaining confidence and supporting the stabilization process.

Setting Deadlines

The persistence observed in the ARIMA model suggests that relying solely on voluntary actions by banks may be insufficient. Regulatory authorities may need to introduce specific deadlines and structured frameworks to ensure timely resolution of non-performing loans. Such measures can help break the cycle of persistence and accelerate balance sheet repair.

Establishing a Legal Framework

The presence of non-normal residuals and high kurtosis in the model indicates that NPL dynamics may be affected by unexpected shocks or extreme events. This highlights the importance of a strong legal and institutional framework that enables efficient restructuring and resolution of distressed assets, particularly during periods of economic stress.

Encouraging a Secondary Market

Since the model performs better in capturing regular patterns than extreme fluctuations, complementary mechanisms are needed to handle large volumes of distressed assets. Developing a secondary market for NPLs, including the potential use of asset management companies ("bad banks"), can facilitate faster resolution and reduce systemic risk (IMF, 2015).

Government Guarantees

In the presence of market imperfections and uncertainty, government guarantees may help bridge the gap between book values and market prices of NPLs. This becomes particularly relevant in scenarios where shocks, not fully captured by the model, lead to sudden increases in non-performing exposures.

Overall, the empirical findings of the ARIMA(2,1,0) model support the need for proactive and structured NPL management policies. While the model provides reliable short-term forecasts and captures the main dynamics of the series, its limitations in accounting for extreme events highlight the necessity of combining quantitative forecasting tools with institutional, regulatory, and policy-based measures to ensure financial stability.

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