

Trends and Forecasting of Total Credit to the Economy in Albania: A Time Series Modelling Approach

Odeona Veizaj*

Assistant Lecturer, University “Ismail Qemali” of Vlora, Vlora, Albania

*Corresponding Author

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ABSTRACT

Bank lending channels funds from surplus to deficit economic units and supports economic activity, making aggregate credit a relevant indicator for financial monitoring and medium-term planning. This study models and forecasts the monthly evolution of total credit to the economy in Albania using 192 observations covering January 2010 to December 2025. Following the Box–Jenkins framework, non-seasonal ARIMA and seasonal SARIMA specifications were evaluated using stationarity diagnostics, information criteria, forecast-error measures, residual tests, and chronological out-of-sample validation. The logarithmically transformed series required two non-seasonal differences ($d = 2$) and no seasonal differencing ($D = 0$), indicating strong trend persistence but no stable annual seasonal pattern. During the training-stage analysis, ARIMA(5,2,0) was retained as a parsimonious baseline because its residuals were consistent with white noise; a subsequent full-sample log-scale grid search provided an ex post robustness check and ranked ARIMA(5,2,0) first by AICc. A 2024–2025 holdout evaluation of the training-sample ARIMA(5,2,0) order on the original credit scale produced a MAPE of 4.11%, while an expanding-window robustness exercise across five 12-month forecast origins yielded an average MAPE of 1.61%. Formal structural-break tests also identified instability around the COVID-19 period, which qualifies the interpretation of long-horizon projections. After validation, ARIMA(5,2,0) was re-estimated on the full logarithmically transformed sample to generate ex-ante forecasts for 2026–2028. Back-transformed forecasts imply year-on-year credit growth of approximately 13.8% in 2026, 14.6% in 2027, and 14.6% in 2028. The results provide a statistically supported reference path for aggregate credit monitoring, but the projections remain conditional on the continuation of historical dynamics and should not be interpreted as causal forecasts. The analysis therefore contributes an empirical forecasting benchmark that can support, but not replace, broader macroeconomic and financial-stability assessment.

Keywords: Albania, credit forecasting, ARIMA, SARIMA, time series analysis.

INTRODUCTION

Lending is one of the core activities of the banking sector, channelling funds from economic agents with a surplus of resources to those seeking financing, with financial institutions acting as intermediaries. The relevance of credit is not confined to household or business balance sheets: aggregate credit dynamics are closely intertwined with the pace and stability of a country's national economy.

Following the transition of the 1990s from a centrally planned to a market-based economy, the role of total credit in Albania's economic development expanded steadily. More recently, the Bank of Albania has implemented a series of macroprudential and monetary policy measures designed to preserve financial stability, enhance policy transmission, and support sustainable credit expansion across the banking sector.

Notwithstanding the critical policy relevance of overall credit growth for macroeconomic stability, dedicated empirical forecasting of the aggregate volume of credit to the economy in Albania remains limited. The existing literature has concentrated primarily on the macroeconomic determinants of credit demand and supply or on the

long-run co-integration between credit and economic growth, rather than on developing and validating a statistically robust time-series forecasting benchmark. This paper addresses that empirical gap.

Specifically, this study analyzes the aggregate volume of credit to the economy in Albania using monthly data over the period 2010–2025, pursuing two main objectives: first, to characterize the statistical properties of the series—its structural trend, variance behavior, and potential seasonality—through formal time-series diagnostics; and second, to identify, estimate, and out-of-sample validate an optimal univariate forecasting model (ARIMA versus SARIMA) to project aggregate credit trajectories over the 2026–2028 medium-term horizon.

Secondary data published by the Bank of Albania were processed in the RStudio environment using the R programming language. To evaluate genuine forecasting ability rather than in-sample fit alone, the dataset was partitioned into a training set (January 2010–December 2023; $n_1 = 168$ observations) and a test set (January 2024–December 2025; $n_2 = 24$ observations) for predictive validation. The selected ARIMA(5,2,0) specification was evaluated using the independent 2024–2025 test period, with out-of-sample accuracy metrics detailed in the out-of-sample validation section. The remainder of the paper is organized as follows. The Literature Review examines the theoretical and empirical literature on bank credit dynamics in Albania and the Central and Eastern European (CEE) region, alongside time-series forecasting methodologies. The Data and Methodology section describes the empirical dataset and the Box–Jenkins econometric framework. The Empirical Results section presents descriptive statistics, stationarity testing, model selection, out-of-sample validation, and medium-term forecasts. The Discussion section considers the findings, their implications, and limitations. The paper concludes with policy recommendations.

LITERATURE REVIEW

The existing literature on bank lending has focused on credit dynamics, banking-sector development, and time-series forecasting methods. Adedoyin and Sobodun [1] argue that lending is central to banking activity and requires careful judgement because of the trade-off between profitability and prudent risk management. Égert, Backé, and Zumer [12] show that Central and Eastern European banking sectors underwent comprehensive transformation through regulatory reform, consolidation, and foreign privatization, developments relevant to Albania's liberalization path. Regarding the credit–growth relationship, empirical evidence points to a positive interaction, with credit-to-GDP ratios tending to rise with income and financial deepening [3], [21], [25].

In the early 2000s, Albanian lending stood at very low levels: tight credit ceilings and rising non-performing loans limited banks' ability to meet demand until the Bank of Albania abandoned direct credit controls at the end of 2000 [22]. Growth accelerated after 2004, coinciding with the privatization of the country's largest bank, foreign entry, and sector consolidation. Shijaku and Kalluci [23] identify both demand-side factors (economic activity and financing needs) and supply-side factors (funding costs, capitalization, and risk perception) as determinants of bank credit in Albania. Albanian private-sector credit subsequently grew relative to economic activity, although the credit-to-GDP ratio remained comparatively low; Kalluci [18] concludes that lending remained below its long-run potential. Using a vector error-correction framework, Matuka [20] finds a stable long-run relationship between bank credit and its macroeconomic determinants, reinforcing the case for monitoring credit as a variable with both short-run fluctuations and a long-run trend.

The finance–growth literature reports mixed results: many studies associate higher private-sector credit and deeper financial systems with faster growth, while this relationship may weaken in bank-based developing economies such as those in Central and Eastern Europe [4]. Rapid credit growth may also coincide with macroeconomic imbalances and deteriorating credit quality, underscoring the value of a dedicated and validated forecasting model for Albania.

Time-series forecasting is widely used for monitoring economic variables. Seasonality was traditionally treated as noise to be filtered out [7], [24], whereas later work treats it as an integral and potentially informative part of the data-generating process [2], [6], [9], [10], [13], [15]. Box and Jenkins [5] formalized the identification–estimation–diagnostic-checking cycle underlying ARIMA and SARIMA modelling. Because many economic series are non-stationary, the literature commonly combines the Augmented Dickey–Fuller test [11] with the

complementary KPSS test [19] to reduce reliance on a single stationarity diagnostic. Hyndman and Khandakar [17] describe automated order-selection methods for univariate forecasting, building on earlier order-selection procedures such as Hannan and Rissanen [14]; the grid-search exercise in this study follows that tradition while retaining manual residual diagnostics.

Taken together, the literature on Albanian lending has concentrated mainly on macroeconomic determinants, credit demand and supply, and the credit–GDP relationship [18], [20], [23], while dedicated out-of-sample-validated forecasting of aggregate credit volume remains scarce. Building on this gap, the present study analyzes total credit to the economy in Albania over 2010–2025, estimates and compares candidate ARIMA and SARIMA models, validates the preferred specification out of sample, and projects aggregate credit developments over 2026–2028.

DATA AND METHODOLOGY

Data source and variable definition

The database on total credit to the economy was obtained from the data registry of the Bank of Albania and contains 192 monthly observations, expressed in millions ALL, covering January 2010 to December 2025. total credit to the economy is defined, following the Bank of Albania's methodology, as the sum of all claims of deposit-taking corporations (second-tier banks, savings and loan associations, and the Central Bank) on other financial corporations, local government, non-financial public corporations, other non-financial corporations, and other resident sectors.

The data were processed using the R programming language in RStudio. The raw monthly series was converted into a regular ts object and checked for coding errors or gaps by specifying the appropriate frequency (12) and starting period. First, the training dataset (January 2010–December 2023) was used for stationarity analysis with the Augmented Dickey-Fuller (ADF) and KPSS tests, establishing the required order of integration ($d = 2$). Second, candidate non-seasonal ARIMA and seasonal SARIMA specifications were evaluated on the training set using information criteria (AIC, AICc, BIC), in-sample error measures, and residual diagnostics. Third, the selected ARIMA(5,2,0) specification was estimated on the original-scale training series and evaluated against the independent test dataset (January 2024–December 2025) to assess out-of-sample predictive accuracy. Fourth, after validation, the selected specification was re-estimated on the complete logarithmically transformed 2010–2025 series for the final 2026–2028 ex-ante forecasts.

The chronological train–test procedure separates the historical observations into a training period (January 2010–December 2023; $n_1 = 168$ observations) and a testing period (January 2024–December 2025; $n_2 = 24$ observations). The ARIMA(5,2,0) model estimated on the training period is evaluated against the testing observations to assess out-of-sample forecasting performance. This training–testing exercise is a methodological validation stage. After validation, the same ARIMA(5,2,0) specification is re-estimated using the complete January 2010–December 2025 dataset and is then used to produce the final ex-ante forecasts for January 2026–December 2028.

Clarification on the two ARIMA(5,2,0) estimations

The ARIMA(5,2,0) order is estimated at two distinct stages. First, it is estimated using only the training sample (January 2010–December 2023), while the January 2024–December 2025 observations are reserved for chronological out-of-sample evaluation. This validation-stage model is estimated on the original credit scale and is used to assess the predictive adequacy of the retained ARIMA(5,2,0) order. After this evaluation, the same order is re-estimated using the complete January 2010–December 2025 sample on the logarithmically transformed series so that all available information is used for the final 2026–2028 ex-ante forecasts. Accordingly, the two sets of coefficients are not expected to be identical because they refer to different samples and transformations. The holdout statistics therefore provide evidence on the predictive adequacy of the ARIMA(5,2,0) order, but they should not be interpreted as a direct validation of the exact full-sample log-scale forecasting pipeline. Coefficients, likelihood values, information criteria, variance estimates, and error measures from the two stages are not directly comparable.

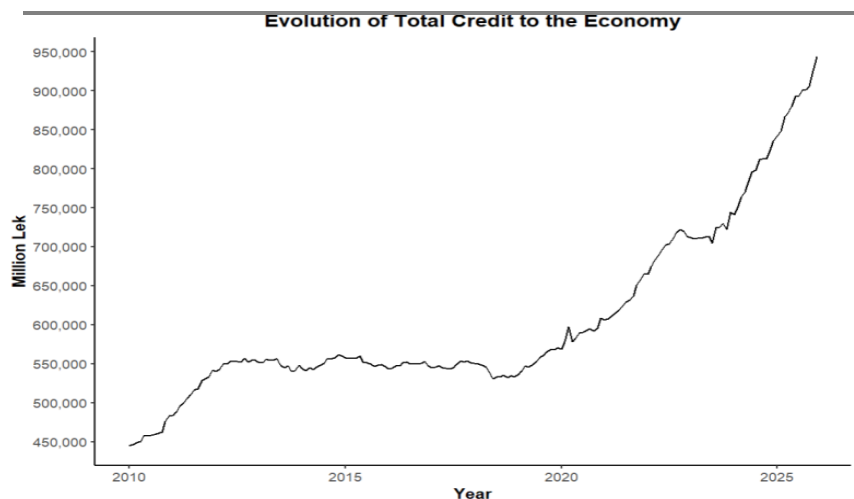


Figure 1: Evolution of total credit to the economy in Albania, 2010–2025 (million ALL)

As shown in Figure 1, total credit increased steadily from 2010 to 2013, while 2015–2019 was characterized by moderate fluctuations around a broadly flat trend. From 2020 onward the series shows a marked, sustained increase, consistent with intensified use of credit as a financing source for firms and households during and after the pandemic period.

Methodological framework

To structurally formalize the time series forecasting process, the empirical model is specified over a partitioned dataset comprising a training set (January 2010 – December 2023, $n_1 = 168$) for parameter estimation and model calibration, and an independent test set (January 2024 – December 2025, $n_2 = 24$) reserved for out-of-sample forecast validation.

Furthermore, this study relies on univariate time series analysis, following the classical Box–Jenkins [5] identification–estimation–diagnostic-checking cycle. Given the monthly frequency and the potential influence of monetary and financial policy cycles, a seasonal periodicity of $s = 12$ was considered plausible a priori, motivating the joint estimation of ARIMA and SARIMA specifications. The general SARIMA(p, d, q)(P, D, Q) s model is expressed as:

$$\Phi P(B^s) \phi_p(B) (1 - B)^d (1 - B^s)^D Y_t = \Theta Q(B^s) \theta_q(B) \varepsilon_t \quad (1)$$

where B is the backshift operator ($BY_t = Y_{t-1}$); $\phi_p(B)$ and $\theta_q(B)$ are the non-seasonal AR and MA polynomials; $\Phi P(B^s)$ and $\Theta Q(B^s)$ are their seasonal counterparts; and d and D denote the orders of non-seasonal and seasonal differencing required to induce stationarity in the mean.

Because total credit exhibits an increasing trend with fluctuations that widen over time, the logarithmic transformation was used for model identification and model-selection exercises. The transformed series is defined as $L_t = \ln(C_t)$, where C_t denotes total credit to the economy in million ALL. Stationarity in the mean was subsequently evaluated using the differencing operator $\nabla^d \nabla_s^D L_t = (1 - B)^d (1 - B^s)^D L_t$, where ∇^d denotes non-seasonal differencing applied d times and ∇_s^D denotes seasonal differencing applied D times with seasonal period $s = 12$. Formal confirmation of stationarity at each stage was obtained jointly from the Augmented Dickey-Fuller (ADF) test — H_0 : unit root present — and the KPSS test — H_0 : trend/level stationarity, thereby mitigating the risk of spurious conclusions driven by either test's limited statistical power in isolation. The required integration orders were cross-checked using the `ndiffs()` and `nsdiffs()` algorithms from the R forecast package [17], while sample autocorrelation (ACF) and partial autocorrelation (PACF) correlograms of the training set were systematically examined to identify candidate autoregressive (p, P) and moving-average (q, Q) orders. For the subsequent chronological holdout validation, the selected ARIMA(5,2,0) order was estimated on the original-scale training series so that forecasts could be evaluated directly against observed credit values in million ALL. After validation, the selected specification was re-estimated on the logarithmically transformed complete 2010–2025 series for the final ex-ante forecasting exercise. Thus, the validation-stage coefficients and

error measures and the final full-sample coefficients are not directly comparable across scales, and information criteria should only be compared among models estimated on the same scale.

Model estimation and selection criteria

Candidate ARIMA and SARIMA specifications were estimated by maximum likelihood during the training-stage model-selection exercise, using the training series. Models were ranked using AIC, its finite-sample-corrected version (AICc), and BIC, with lower values indicating a preferable fit–parsimony trade-off. In-sample accuracy was further evaluated using RMSE, MAE, and MAPE. Residual adequacy was assessed through the Ljung–Box portmanteau test, under H_0 that residuals are serially uncorrelated (“white noise”); a model was retained as adequate only if H_0 could not be rejected at the 5% level, together with visual inspection of the residual ACF and distribution. After completion of the chronological 2024–2025 holdout validation, an exhaustive ARIMA/SARIMA grid search was conducted on the complete logarithmically transformed 2010–2025 series solely as an ex post robustness verification. Because this full-sample exercise includes the former holdout observations, it did not influence the 2024–2025 test evaluation. The retained ARIMA(5,2,0) order was then re-estimated on the full log series for the final 2026–2028 forecast.

EMPIRICAL RESULTS

Research question and working hypothesis

RQ1: Which univariate time series specification—non-seasonal ARIMA or seasonal SARIMA—provides the most accurate and stable forecast of total credit to the economy in Albania over an out-of-sample holdout period (2024–2025)?

RQ2: What is the projected baseline trajectory and annual growth rate of total credit to the Albanian economy over the 2026–2028 medium-term horizon based on the full-sample re-estimated model?

Motivated by the monthly frequency of the Bank of Albania dataset and the a priori plausibility of seasonal dynamics driven by holiday demand and fiscal cycles, we hypothesize that a SARIMA specification would outperform a purely non-seasonal ARIMA model. To test this hypothesis, candidate models were evaluated across model-selection criteria (AIC, AICc, BIC) during in-sample fitting, alongside out-of-sample predictive error metrics (RMSE, MAE, MAPE) on the 2024–2025 holdout evaluation sample ($n_2 = 24$). The optimal specification identified through this validation process is subsequently selected to generate medium-term projections for the 2026–2028 period.

Descriptive statistics and stationarity analysis

Since credit typically displays an increasing trend with widening fluctuations, the log-transformed series (Figure 2) was examined first.

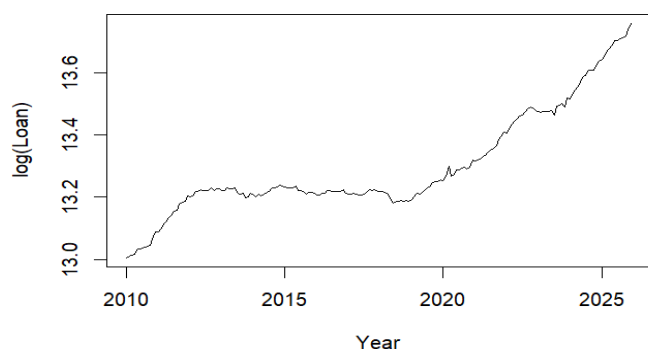


Figure 2: Natural logarithm of credit to the economy in Albania, 2010–2025

Although the log transformation stabilizes variance, Figure 2 shows the series still exhibits a pronounced upward trend and is not yet stationary. Formal testing proceeds through first differencing, the ADF and KPSS tests, and ACF/PACF inspection.

For the first difference of $\log(\text{credit})$: Dickey-Fuller = -2.6479 , lag order = 5, $p = 0.3051$, so the unit-root null cannot be rejected. For the log-transformed series, KPSS = 3.096 ($p = 0.01$); for the first-differenced log series, KPSS = 0.791 ($p = 0.01$) — in both cases rejecting the stationarity null. The ADF and KPSS tests therefore agree that both the log-level and once-differenced series remain non-stationary (Table 1), requiring further transformation.

Table 1: Comparison of ADF and KPSS test results (first-differenced log series)

Test	p-value	Decision	Conclusion
ADF	$0.3051 > 0.05$	H_0 not rejected	Non-stationary
KPSS	$0.01 < 0.05$	H_0 rejected	Non-stationary

Source: Author's calculation

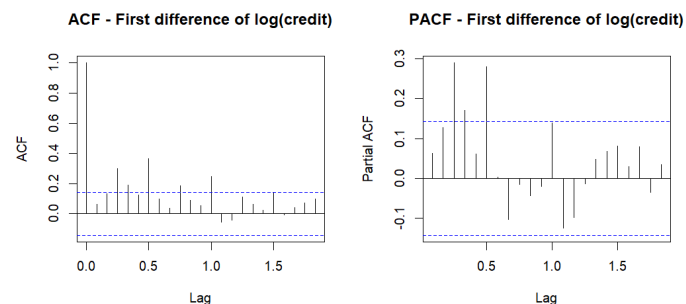


Figure 3: Sample ACF and PACF plots for the first difference of $\log(\text{credit})$

In Figure 3, several ACF bars cross the confidence bounds without decaying quickly toward zero, indicating non-stationarity; the PACF exhibits a similar pattern, so model orders cannot yet be reliably identified.

Given the objective of testing SARIMA as a candidate, seasonal and non-seasonal stationarity were assessed jointly using `ndiffs()` and `nsdiffs()`: `nsdiffs(log_credit) = 0` (no seasonal differencing required, $D = 0$); `ndiffs(log_credit) = 2` (two non-seasonal differences required, $d = 2$) — indicating a strong deterministic trend rather than a stable annual pattern. After second differencing, the ADF test rejects the unit-root null (Dickey-Fuller = -9.1596 , lag order = 5, $p = 0.01$), while the KPSS test fails to reject stationarity (KPSS = 0.02986, $p = 0.10$). Both tests jointly confirm the twice-differenced log series is stationary.

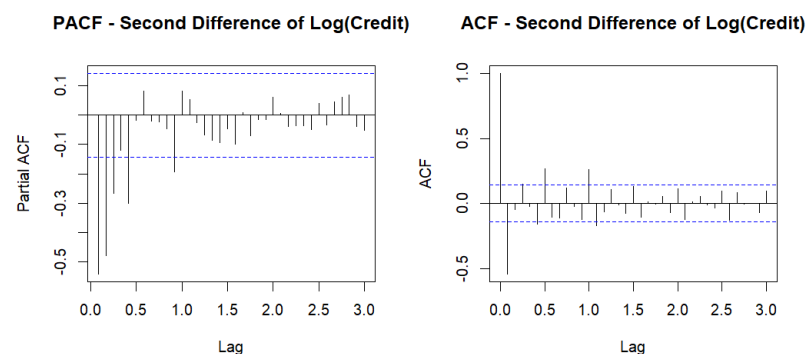


Figure 4: Sample ACF and PACF plots for the twice-differenced series

In Figure 4's ACF, a strong negative spike at lag 1 lies outside the confidence bounds, followed by smaller, rapidly declining fluctuations — consistent with a low-order MA component. The PACF shows the first two to three lags markedly negative before decaying, consistent with a low-order AR component. Together these correlograms suggested ARIMA(3,2,3) as an initial candidate, evaluated formally in the algorithmic grid-search verification subsection.

Descriptive statistics (training set: 2010–2023)

To evaluate genuine forecasting ability rather than in-sample fit alone, the dataset was partitioned chronologically into a training set (Jan 2010–Dec 2023; $n_1 = 168$ observations) and an out-of-sample test set (Jan 2024–Dec 2025; $n_2 = 24$ observations). Candidate specifications were fitted strictly to the training data to generate 24-month-ahead dynamic point forecasts. These forecasts were subsequently evaluated against the actual, previously unobserved test-period values using RMSE, MAE, MAPE, and Theil's U2 inequality coefficient. This standard pseudo-real-time forecasting procedure [16] helps assess out-of-sample generalization and reduces reliance on in-sample fit alone, while providing a realistic accuracy estimate before generating ex-ante medium-term projections for 2026–2028. Table 2 presents descriptive statistics for credit to the economy in Albania over the Jan 2010–Dec 2023 training period, expressed in levels (million ALL).

Table 2: Descriptive statistics for credit to the economy, Jan 2010– Dec 2023

Statistical indicator	Level value
Minimum	444,827
First quartile (Q1)	544,222
Median	551,527
Mean	571,748
Third quartile (Q3)	591,074
Maximum	744,163
Standard deviation	67,620.83
Skewness	0.8976947
Kurtosis	3.430709

Source: Author's calculation

The series ranges from ALL 444,827 million to ALL 744,163 million, with a mean of ALL 571,748 million, a median of ALL 551,527 million, and a standard deviation of ALL 67,620.83 million. Positive skewness (+0.898) and a mean exceeding the median indicate a longer right tail, consistent with the gradual increase in credit over the sample period. A kurtosis of 3.430709 (above the normal-distribution benchmark of 3) indicates mild leptokurtosis, consistent with episodes of unusually large movements in credit.

In time-series analysis, stationarity is a key requirement for reliable ARIMA modelling. A series is stationary when its statistical properties, including its mean, variance, and autocorrelation structure, remain stable over time. Stationarity was assessed using the Augmented Dickey-Fuller (ADF) and KPSS tests. The ADF test evaluates the null hypothesis that the series contains a unit root, whereas the KPSS test evaluates the null hypothesis of stationarity; using both tests therefore provides complementary evidence.

For the training series at level ($d = 0$), the ADF test yields $p = 0.9568 > 0.05$, so the unit-root null is not rejected. The KPSS test yields $p = 0.01 < 0.05$, rejecting the stationarity null. Taken together, the two tests indicate that the credit series is non-stationary in levels.

Augmented Dickey-Fuller Test

data: train_ts

Dickey-Fuller = -0.83315, Lag order = 5, p-value = 0.9568

alternative hypothesis: stationary

KPSS Test for Level Stationarity

data: train_ts

KPSS Level = 2.429, Truncation lag parameter = 4, p-value = 0.01

First difference Level($d = 1$)

Augmented Dickey-Fuller Test

data: train_diff1

Dickey-Fuller = -2.4041, Lag order = 5, p-value = 0.4076

alternative hypothesis: stationary

KPSS Test for Level Stationarity

data: train_diff1

KPSS Level = 0.46893, Truncation lag parameter = 4, p-value = 0.04866

After first differencing ($d = 1$), the series remains non-stationary. The ADF test yields $p = 0.4076 > 0.05$, while the KPSS test yields $p = 0.04866 < 0.05$. Therefore, a second non-seasonal difference ($d = 2$) is required.

Stationarity tests on the second-differenced series ($d = 2$)

The time series remains non-stationary after the first difference, so a second difference is required to achieve stationarity. The second-differencing transformation ($d = 2$) indicates that the time series of total credit to the economy in Albania is stationary, based on the ADF and KPSS tests.

Augmented Dickey-Fuller Test

data: train_diff2

Dickey-Fuller = -8.4138, Lag order = 5, p-value = 0.01

alternative hypothesis: stationary

KPSS Test for Level Stationarity

data: train_diff2

KPSS Level = 0.091238, Truncation lag parameter = 4, p-value = 0.1

Table 3: Comparison of ADF and KPSS test results

Difference Level	Test	p-value	Decision	Conclusion
Level (d=0)	ADF	$0.9568 > 0.05$	H_0 not rejected	Non-stationary
	KPSS	$0.01 < 0.05$	H_0 rejected	Non-stationary
Level (d=1)	ADF	$0.4076 > 0.05$	H_0 not rejected	Non-stationary
	KPSS	$0.04866 < 0.05$	H_0 rejected	Non-stationary
Level (d=2)	ADF	$0.01 < 0.05$	H_0 rejected	Stationary
	KPSS	$0.1 > 0.05$	H_0 not rejected	Stationary

Source: Author's calculation

Model identification, estimation, and selection

Autocorrelation analysis and model identification on the training set (ACF and PACF)

The sample Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were examined using the Jan 2010–Dec 2023 training data to identify plausible candidate model orders.

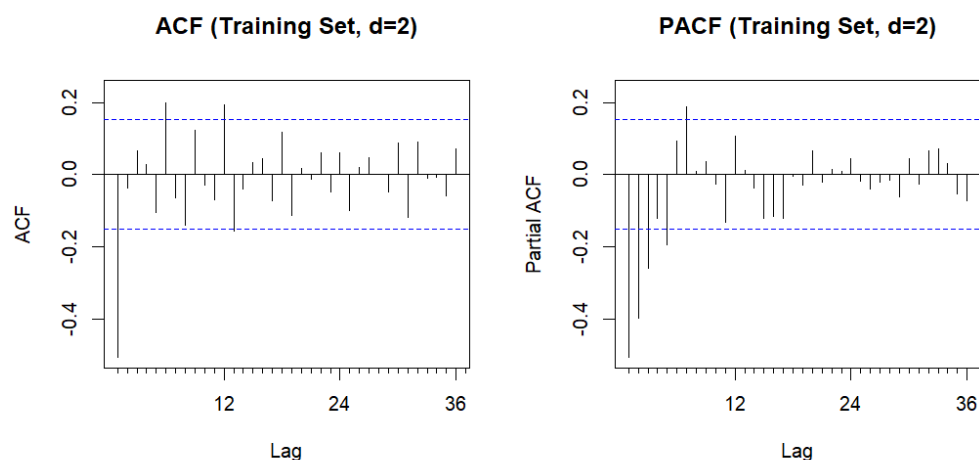


Figure 5: Sample ACF and PACF plots for the second difference level($d = 2$)

Figure 5 shows a strong negative ACF spike at lag 1, while most subsequent autocorrelations remain within the 95% confidence bounds. The PACF displays notable spikes at several early lags, including lags 1, 2, 3, and 5. Because ACF/PACF patterns after second differencing do not uniquely determine the final AR and MA orders, these correlograms were used to define plausible candidate structures rather than to justify $q = 0$ directly. The final order was therefore selected using information criteria and residual diagnostics across the candidate model set.

In-Sample Candidate Model Selection (Training Set: Jan 2010–Dec 2023)

Although monthly financial time series frequently exhibit seasonal patterns, following the evaluation of candidate forecasting models, a non-seasonal ARIMA specification was selected over a seasonal SARIMA (p, d, q) $\times$ (P, D, Q)₁₂ model.

```

> evaluate_models <- function(ts_data, max_p = 5, max_q = 3) {
+   results <- data.frame(Model = character(), AIC = numeric(), BIC = numeric(),
+   RMSE = numeric(), stringsAsFactors = FALSE)
+   for (p in 0:max_p) {
+     for (q in 0:max_q) {
+       if (p == 0 && q == 0) next
+       tryCatch({
+         fit <- Arima(ts_data, order = c(p, 2, q))
+         results[nrow(results) + 1, ] <- list(
+         paste0("ARIMA(", p, ", 2, ", q, ")"),
+         AIC(fit),
+         BIC(fit),
+         accuracy(fit)[1, "RMSE"]
+       ), error = function(e) NULL)
+     }
+   }
+   results <- results[order(results$AIC), ]
+   return(results)
+ }
> top_models <- evaluate_models(train_ts_mem, max_p = 5, max_q = 3)
> print(head(top_models, 5))

```

Figure 6: Evaluation of the training dataset for forecasting model selection

The second-order differencing transformation ($d = 2$), required to achieve stationarity, removed the persistent trend component, while the formal seasonal-differencing test indicated that no seasonal differencing was required. The training-sample information criteria in Table 4 do not uniquely favor ARIMA(5,2,0): ARIMA(5,2,2) has the lowest AIC (3290.401), whereas ARIMA(2,2,3) has the lowest BIC (3309.174). ARIMA(5,2,0) remains a comparatively parsimonious candidate and its residuals pass the Ljung–Box diagnostic ($p = 0.5335$), but model selection should therefore be interpreted jointly with residual adequacy and forecast validation rather than from Table 4 alone.

Table 4: Model Selection and Information Criteria Comparison

Information Criteria	ARIMA(5,2,2)	ARIMA(2,2,3)	ARIMA(5,2,3)	ARIMA(5,2,0)	ARIMA(5,2,1)
AIC	3,290.401	3,290.502	3,290.988	3,291.253	3,293.239
BIC	3,315.297	3,309.174	3,318.996	3,309.925	3,315.023
MA(Moving average)	2	3	3	0	1

Source: Author's calculation.

Table 4 reports the information criteria for candidate models estimated over the training period (January 2010–December 2023). The differences are small, but the ranking varies by criterion: ARIMA(5,2,2) has the lowest AIC, while ARIMA(2,2,3) has the lowest BIC. ARIMA(5,2,0) is therefore retained as a parsimonious baseline candidate rather than being identified as the unique information-criterion winner at this stage.

Applying the principle of parsimony [8], ARIMA(5,2,0) was retained for further diagnostic and predictive evaluation because it contains no moving-average terms and its residuals are consistent with white noise. This choice is not based on a claim that ARIMA(5,2,0) has the lowest AIC or BIC in Table 4; rather, the training-sample information criteria and residual diagnostics are considered jointly.

Setting the moving-average order to zero ($q = 0$) means that the ARIMA(5,2,0) specification contains no explicit moving-average terms in lagged forecast errors. This reduces the number of estimated parameters and avoids moving-average invertibility constraints, although model adequacy must still be established through residual diagnostics and forecast validation.

Algorithmic grid-search verification (ARIMA vs. SARIMA)

Step 1: ARIMA(3,2,3) — automated non-seasonal specification

Automated selection (auto.arima, seasonal = FALSE) identified ARIMA(3,2,3), consistent with the ACF/PACF diagnostics. Estimated coefficients: $ar1 = -1.2279$, $ar2 = -1.145$, $ar3 = -0.2147$, $ma1 = 0.2134$, $ma2 = 0.0070$, $ma3 = -0.6575$ (standard errors 0.2355, 0.139, 0.1595, 0.2220, 0.1717, 0.1141). $\sigma^2 = 6.588 \times 10^{-5}$, log-likelihood

= 649.8, AIC = -1285.6, AICc = -1284.99, BIC = -1262.87; in-sample RMSE = 0.007946, MAE = 0.005709, MAPE = 0.0429, ACF1 = -0.0102.

A Ljung–Box test on the residuals ($Q^* = 30.836$, $df = 18$, $p = 0.0301$) rejects the white-noise null, indicating remaining serial correlation.

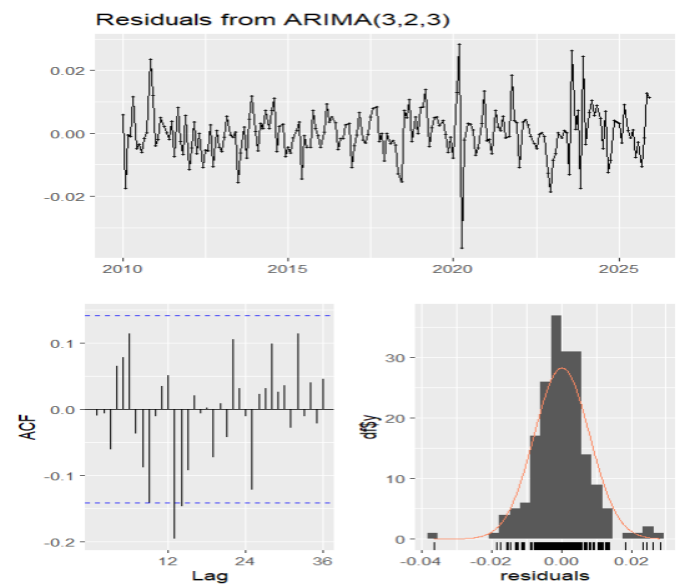


Figure 7: Diagnostic plots for the ARIMA(3,2,3) model

The residual plot fluctuates around zero but shows a marked negative deviation in 2020, coinciding with the onset of COVID-19: credit demand froze in the first half of that year, while the Bank of Albania intervened with monetary-policy measures in the second half. The residual ACF shows lag 13 (one year) approaching -0.2 and crossing the confidence bound, with lags 9, 10 and 14 also tending toward the boundary — suggesting an unmodelled seasonal or structural component and motivating a SARIMA alternative.

Step 2: SARIMA(2,2,1)(1,0,0)12 — automated seasonal specification

Enabling the seasonal search selects SARIMA(2,2,1)(1,0,0)[12], with $ar1 = -0.3212$, $ar2 = -0.2137$, $ma1 = -0.6871$, $sar1 = 0.1492$ (standard errors 0.1035, 0.0933, 0.0902, 0.0793); $\sigma^2 = 6.746 \times 10^{-5}$, log-likelihood = 646.58, AIC = -1283.16, AICc = -1282.83, BIC = -1266.92; RMSE = 0.008084, MAE = 0.005837, MAPE = 0.04386, ACF1 = -0.01246.

Table 5: Comparison of the ARIMA(3,2,3) and SARIMA(2,2,1)(1,0,0)12 specifications

Indicator	ARIMA(3,2,3)	SARIMA(2,2,1)(1,0,0)12
AIC	-1285.60	-1283.16
AICc	-1284.99	-1282.83
BIC	-1262.87	-1266.92
RMSE	0.007946	0.008084
MAE	0.005709	0.005837
MAPE	0.04289	0.04386
ACF1	-0.01022	-0.01246

Source: Author's calculation

Table 5 shows ARIMA(3,2,3) attains lower AIC, AICc and error metrics than SARIMA(2,2,1)(1,0,0)₁₂; only BIC, which penalizes additional parameters more heavily, favours the seasonal model. Although sar1 (0.1492) is estimated precisely, its inclusion does not materially improve accuracy, and the ARIMA(3,2,3) residuals already fail Ljung–Box. Neither candidate is fully adequate, motivating a broader search.

Step 3: Full-sample grid-search robustness verification of ARIMA(5,2,0)

After the chronological validation stage, a full-sample grid search across 22 ARIMA and SARIMA specifications was conducted as an ex post robustness check on the logarithmically transformed 2010–2025 series. The full results are reported in Appendix Table A1 and the five lowest-AICc specifications are summarized in Table 6. This exercise is not used to construct the 2024–2025 holdout result; rather, it assesses whether the retained ARIMA(5,2,0) order remains competitive when all observations are subsequently available.

Table 6: Top five candidate models by AICc (full-sample log-scale ex post grid search; 22 specifications in Appendix Table A1)

Candidate model	AICc
ARIMA(5,2,0)	−1,287.83 (best model)
ARIMA(2,2,3)	−1,284.13
ARIMA(2,2,1)(1,0,0) ₁₂	−1,282.83
ARIMA(0,2,3)(1,0,0) ₁₂	−1,282.19
ARIMA(1,2,4)	−1,282.15

Source: Author's calculation

As an ex post robustness exercise, an exhaustive grid search was conducted across candidate ARIMA and SARIMA specifications using the complete logarithmically transformed series. Models were compared using the Corrected Akaike Information Criterion (AICc). Because this exercise uses the full 2010–2025 sample, including the former holdout observations, its information criteria are interpreted as full-sample model-comparison evidence and not as part of the earlier out-of-sample validation procedure.

As presented in Table 6, the full-sample comparison ranks the non-seasonal ARIMA(5,2,0) specification first among the 22 evaluated structures, with the lowest AICc (−1,287.83). It outperforms alternative non-seasonal structures such as ARIMA(2,2,3) (AICc = −1,284.13) and the leading seasonal alternative SARIMA(2,2,1)(1,0,0)₁₂ (AICc = −1,282.83; Δ AICc = 5.00 relative to ARIMA(5,2,0)).

These full-sample results provide additional robustness support for the retained ARIMA(5,2,0) order and indicate that adding seasonal autoregressive or moving-average terms does not improve AICc within the evaluated model set. They are reported as ex post confirmation rather than as the basis for the chronological 2024–2025 holdout evaluation.

Step 4: Full-sample re-estimation of ARIMA(5,2,0) and final model diagnostics

Following completion of the chronological train–test validation stage and the subsequent ex post full-sample robustness check, the retained ARIMA(5,2,0) specification was re-estimated on the complete monthly sample from January 2010 to December 2025 (192 observations), using the logarithmically transformed credit series. The final full-sample model produced coefficients $ar_1 = -1.0221$, $ar_2 = -0.9456$, $ar_3 = -0.6813$, $ar_4 = -0.4630$, and $ar_5 = -0.3303$ (standard errors 0.0691, 0.0976, 0.1095, 0.0976, and 0.0694, respectively); $\sigma^2 = 6.534331 \times 10^{-5}$, log-likelihood = 650.1438, AIC = −1288.288, AICc = −1287.829, and BIC = −1268.806. The corresponding in-sample log-scale RMSE, MAE, and MAPE are 0.007935, 0.005644, and 0.04240, respectively,

with $ACF1 = -0.02345$. The Ljung–Box test ($Q^* = 18.684$, $df = 19$, $p = 0.4773$) fails to reject the white-noise null, indicating no statistically significant residual autocorrelation. These estimates constitute the final full-sample model used for the 2026–2028 ex-ante forecasts. The information criteria reported here are therefore specific to the logarithmically transformed series and should not be compared numerically with the information criteria from the original-scale training-sample estimation reported in the training-sample estimation subsection.

Table 7: Comparison of the ARIMA(3,2,3), SARIMA(2,2,1)(1,0,0)₁₂ and ARIMA(5,2,0) specifications

Indicator	ARIMA(3,2,3)	SARIMA(2,2,1)(1,0,0) ₁₂	ARIMA(5,2,0)
AIC	-1,285.60	-1,283.16	-1,288.29
AICc	-1,284.99	-1,282.83	-1,287.83
BIC	-1,262.87	-1,266.92	-1,268.81
RMSE	0.007946	0.008084	0.007935
MAE	0.005709	0.005837	0.005644
MAPE	0.04289	0.04386	0.04240
ACF1	-0.01022	-0.01246	-0.02345

Source: Author's calculation¹

Within the full-sample log-scale comparison in Table 7, ARIMA(5,2,0) has the lowest AIC, AICc, and in-sample error measures among the three displayed candidates, and its residuals satisfy the Ljung–Box white-noise diagnostic. Together with the training-stage evidence, these results do not support the working hypothesis that a seasonal SARIMA specification would outperform the non-seasonal alternative. The observed series is therefore more consistently represented by a strongly trending, non-seasonal specification within the model class considered.

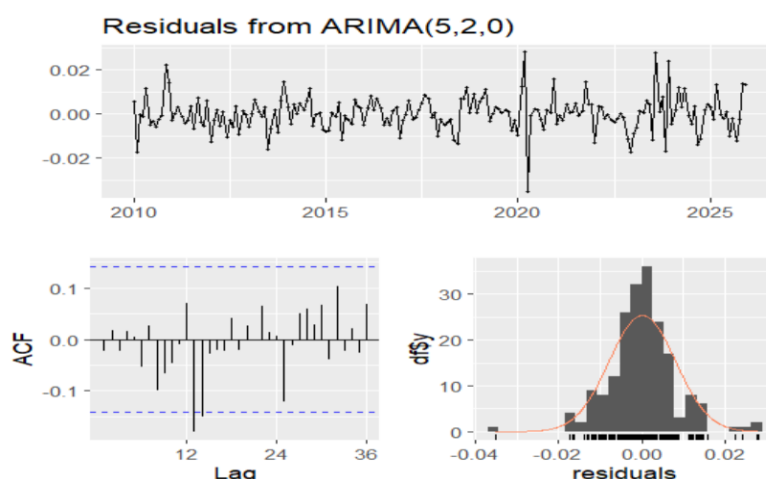


Figure 8: Diagnostic plots for the selected ARIMA(5,2,0) model

Comparing Figures 7 and 8, the lag-13 spike that crossed the confidence bound under ARIMA(3,2,3) lies well within bounds for ARIMA(5,2,0), and the residual distribution is closer to normal. In the final full-sample estimation, all coefficients $ar1$ – $ar5$ are statistically significant at the 1% level; for example, $|ar1/s.e.| = 14.79$.

¹ Note: The information criteria and in-sample error measures in this table are calculated for models estimated on the logarithmically transformed series.

The uniformly negative signs indicate persistent autoregressive adjustment in the differenced process, although these coefficients should be interpreted as statistical dynamics rather than causal effects.

Estimation and diagnostic checking of baseline ARIMA(5,2,0) on the training sample

For the chronological out-of-sample validation, the selected ARIMA(5,2,0) order was estimated using the original-scale training series covering January 2010–December 2023 (168 observations). This validation-stage estimation is distinct from the final full-sample estimation reported in Step 4: the training model is on the original credit scale, whereas the final model is estimated on the logarithmic scale using all 192 observations. The distinction explains the different coefficient values and information criteria reported for the two estimation stages.

Table 8: ARIMA(5,2,0) coefficient estimates on the original-scale training sample (January 2010–December 2023)

Parameter	Coefficient	S.e.	t-statistic
Ar1	-1.0901	0.0755	-14.44
Ar2	-1.0074	0.1056	-9.54
Ar3	-0.8008	0.1189	-6.735
Ar4	-0.4841	0.1075	-4.503
Ar5	-0.3581	0.0817	-4.383

Source: Author's calculation.

The statistical significance of the autoregressive coefficients in the training-sample ARIMA(5,2,0) model was assessed using coefficient-to-standard-error ratios. The estimated coefficients are $ar1 = -1.0901$, $ar2 = -1.0074$, $ar3 = -0.8008$, $ar4 = -0.4841$, and $ar5 = -0.3581$, with corresponding t-statistics of -14.44 , -9.54 , -6.74 , -4.50 , and -4.38 . All five autoregressive coefficients are statistically significant at the 1% level. Model adequacy is assessed separately through residual diagnostics and out-of-sample forecast evaluation.

For the original-scale training estimation, the model achieved a log-likelihood of -1639.63 , an AIC of $3,291.25$, an AICc of $3,291.78$, and a BIC of $3,309.93$, with $\sigma^2 = 22,633,340$. The in-sample mean absolute percentage error (MAPE) was 0.55% , with an RMSE of ALL $4,657.28$ million and MAE of ALL $3,204.11$ million. The first-lag residual autocorrelation ($ACF1 = -0.0101$) is close to zero. These statistics describe the original-scale training model used in the validation stage and should not be interpreted as the final full-sample model statistics reported in Step 4.

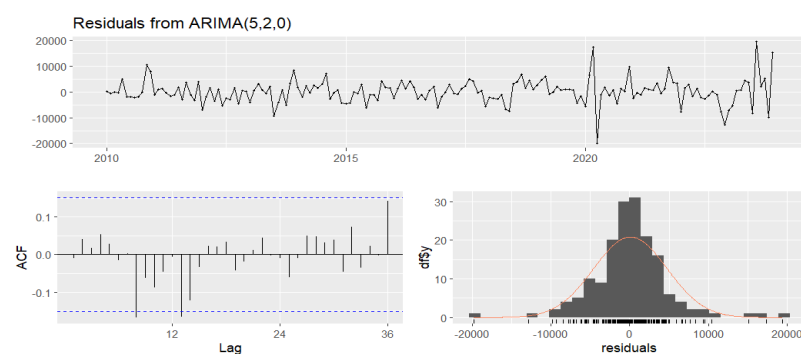


Figure 9: Residuals diagnostic plot

Figure 9 shows residuals fluctuating around zero, with a pronounced volatility episode around 2020 and a more moderate fluctuation in 2023. These episodes coincide with periods of substantial macroeconomic change and

should not, by themselves, be interpreted as causal effects. The residual ACF is largely contained within the 95% confidence bounds, and the Ljung–Box test yields $p = 0.5335$ ($p > 0.05$), so the null hypothesis of no residual serial correlation is not rejected. The histogram and density curve appear approximately symmetric around zero; however, visual inspection alone is not treated as a formal test of normality or homoscedasticity.

Out-of-sample validation and accuracy metrics (2024–2025 test set)

Table 9: Test dataset forecast

Period	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2024	742132.1	736035.2	748229.1	732807.7	751456.6
Feb 2024	751334.5	743091.4	759577.6	738727.8	763941.2
Mar 2024	753195.0	742939.6	763450.4	737510.7	768879.2
Apr 2024	761107.6	748539.4	773675.8	741886.2	780329.0
May 2024	761671.8	746199.5	777144.1	738008.9	785334.7
Jun 2024	773168.8	754923.2	791414.5	745264.5	801073.1
Jul 2024	774835.1	752837.7	796832.5	741193.0	808477.2
Aug 2024	781788.6	756383.2	807194.0	742934.4	820642.8
Sep 2024	785516.4	756545.6	814487.3	741209.4	829823.5
Oct 2024	792646.3	759914.7	825378.0	742587.6	842705.1
Nov 2024	795926.4	759115.3	832737.5	739628.7	852224.1
Dec 2024	803520.5	762652.5	844388.4	741018.3	866022.6
Jan 2025	807233.6	761973.9	852493.4	738014.8	876452.5
Feb 2025	813422.8	763768.7	863077.0	737483.3	889362.3
Mar 2025	818013.0	763795.1	872230.9	735093.9	900932.1
Apr 2025	824250.3	765339.4	883161.2	734153.9	914346.7
May 2025	828653.7	764863.4	892444.0	731094.9	926212.5
Jun 2025	834868.8	766144.0	903593.5	729763.3	939974.2
Jul 2025	839524.6	765682.7	913366.6	726593.1	952456.2
Aug 2025	845299.1	766260.1	924338.0	724419.4	966178.7
Sep 2025	850271.9	765899.1	934644.7	721234.9	979309.0
Oct 2025	856020.2	766208.0	945832.3	718664.3	993376.0
Nov 2025	860940.8	765555.5	956326.2	715061.6	1006820.1
Dec 2025	866641.4	765599.1	967683.7	712110.5	1021172.2

Source: Author's calculation.

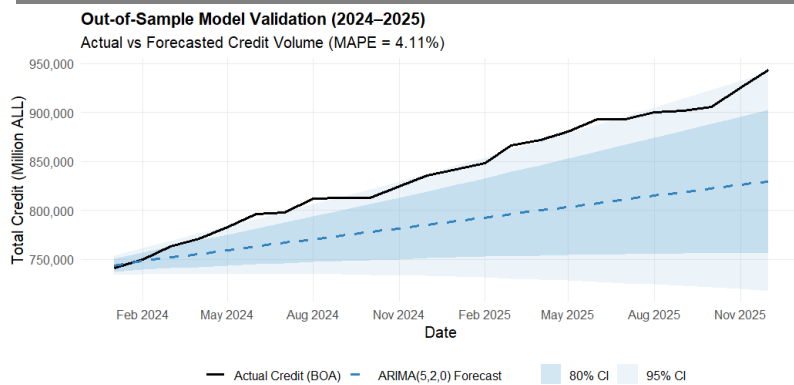


Figure 10: Out-of-Sample Forecast Evaluation-Actual vs. Forecasted Total Credit (2024–2025)

Figure 10 shows that the trend of credit to the economy for the forecast period Jan 2024–Dec 2025 is positive, indicating continued growth in aggregate credit over the evaluation period. The smoothed trajectory reflects the effect of second differencing in removing the persistent trend component while retaining the underlying dynamics of the series. Furthermore, the 80% and 95% confidence intervals exhibit a standard fan-out dispersion over the 24-month forecast horizon. The widening prediction intervals appropriately reflect increasing forecast uncertainty as the horizon extends and therefore provide useful information about the uncertainty surrounding the point forecasts.

To evaluate the predictive performance of the retained ARIMA(5,2,0) order under chronological out-of-sample conditions, the model estimated on the original-scale training dataset was used to generate dynamic forecasts over the holdout period (January 2024–December 2025, $n_2 = 24$). Assessing forecasting ability on observations excluded from that training estimation provides evidence on out-of-sample generalization rather than relying solely on in-sample fit [16]. The generated 24-month forecasts were evaluated directly against actual credit statistics published by the Bank of Albania using the metrics reported in Table 10. Table A4 in the Appendix reports the monthly actual values, point forecasts, forecast errors, absolute errors, and absolute percentage errors for all 24 observations in the test period. Because the final 2026–2028 model is subsequently re-estimated on the logarithmic scale, these holdout metrics should be interpreted as validation of the retained model order on the original scale rather than as a direct accuracy estimate for the final log-scale specification.

Table 10: Forecast accuracy metrics

Data	Sample period	ME	RMSE	MAE	MPE (%)	MAPE (%)	MASE	Theil's U2
Training set	Jan 2010–Dec 2023	83.86819	4,657.283	3,204.112	0.01431165	0.5507457	0.1282696	NA
Test set	Jan 2024–Dec 2025	35,489.77432	40,807.692	35,702.164	4.08102112	4.11	1.4292575	0.365

Source: Author's calculation.

The model achieved a MAPE of 4.11% over the 2024–2025 holdout period, indicating relatively low average percentage forecast error. The MAPE indicates that the model generated relatively small average percentage errors in the test sample and captured the broad upward movement in credit during 2024–2025. However, MAPE alone cannot establish the absence of overfitting or prove that the model will retain the same accuracy outside the evaluation window. The positive values of ME (35,489.77) and MPE (4.08%) suggest that actual market credit expanded slightly faster than predicted by the model, reflecting the acceleration of lending activity in the Albanian economy during the Jan 2024–Dec 2025 period. The increase in RMSE from 4,657 to 40,807 should be interpreted in the context of the 24-month forecast horizon and the scale of the credit series; relative measures such as MAPE and Theil's U2 provide complementary evidence on predictive accuracy. The MAPE result

should therefore be interpreted as evidence of relatively good predictive accuracy, rather than as proof that the model did not suffer from overfitting. Additionally, evaluation of Theil's U2 inequality coefficient against a multi-step naïve benchmark that holds the last training observation constant across the holdout horizon yielded a score of 0.3650. Because $U2 < 1$, the empirical results confirm that the ARIMA(5,2,0) specification substantially outperforms the baseline naïve process, reducing the out-of-sample forecast error by over 63.5% ($100\% - 36.5\%$).

Robustness check: expanding-window forecast evaluation

To assess whether the predictive performance of the selected ARIMA(5,2,0) specification depends critically on a single train-test split, an additional expanding-window forecast evaluation was conducted. The same ARIMA(5,2,0) specification was re-estimated at five successive forecast origins, using an expanding training sample and a 12-month-ahead forecast horizon. The evaluation covers forecasts for 2021, 2022, 2023, 2024, and 2025, thereby providing multiple out-of-sample forecast windows across the sample period.

The results indicate relatively stable predictive performance across the different forecast origins. The MAPE ranged from 0.78% in 2021 to 2.37% in 2024, while the average MAPE across the five forecast windows was 1.61%. The corresponding average RMSE and MAE were 14,804.38 and 12,317.78 million ALL, respectively. Although forecast accuracy varies across individual windows, the relatively low MAPE values across all five periods provide additional evidence that the predictive performance of the ARIMA(5,2,0) specification is not confined to the single 2024–2025 holdout evaluation. These results should be interpreted as evidence of robustness in out-of-sample predictive performance rather than as definitive proof that the model is free from overfitting. The detailed results are reported in Table A5 in the Appendix.

Structural-break analysis and the COVID-19 period

To examine whether the credit series experienced structural instability during the COVID-19 period, formal structural-break tests were conducted on the full monthly series covering January 2010–December 2025. A manual Chow-type test was first performed at March 2020, allowing both the intercept and the trend to differ before and after the specified break. The test strongly rejected the null hypothesis of parameter stability, with an F-statistic of 498.88 ($F(2,188)$, $p < 0.001$). This provides strong statistical evidence of a structural change around the beginning of the COVID-19 period.

To avoid imposing the break date a priori, a supremum F test was also conducted. The test produced a statistic of 1025.1 with $p < 2.2 \times 10^{-16}$, providing further evidence against parameter stability over the sample period. In addition, the multiple-breakpoint analysis identified four break dates under the specification preferred by the Bayesian Information Criterion (BIC): April 2012, May 2018, September 2020, and March 2023. Among these dates, the September 2020 breakpoint is temporally consistent with the COVID-19 period.

These findings suggest that the dynamics of total credit to the economy were not fully stable throughout the sample period and that the pandemic period coincided with a statistically significant structural change. However, the structural-break results should not be interpreted as establishing a direct causal effect of COVID-19 on credit. Rather, they indicate that the statistical properties of the credit series changed around this period. The evidence therefore provides an important qualification for interpreting the ARIMA forecasts, particularly because standard ARIMA models assume that the underlying data-generating process remains sufficiently stable over the forecasting horizon.

Table 11: Structural break tests for total credit to the economy

Test / Method	Result	p-value	Interpretation
Chow-type test at March 2020	$F(2,188) = 498.88$	< 0.001	Rejects parameter stability at the specified break
Supremum F test	sup.F = 1025.1	$< 2.2 \times 10^{-16}$	Strong evidence of parameter instability
Bai–Perron-type breakpoint procedure	4 breaks preferred by BIC	—	Endogenous multiple-break specification preferred by BIC
Break 1	April 2012	—	Estimated structural change
Break 2	May 2018	—	Estimated structural change
Break 3	September 2020	—	Temporally consistent with the COVID-19 period
Break 4	March 2023	—	Estimated structural change

Source: Author’s calculation.

Medium-term forecasting

Following the chronological evaluation of the ARIMA(5,2,0) order, a final estimation was conducted using the complete dataset covering January 2010–December 2025. This re-estimation incorporates all available observations, including the previously held-out 2024–2025 period, and uses the logarithmically transformed credit series. The resulting full-sample log-scale model provides the basis for the final ex-ante forecasts for January 2026–December 2028. The earlier holdout statistics refer to the original-scale validation-stage estimation and therefore support the order choice without constituting a direct validation of this exact final transformation-and-estimation pipeline.

For concise reporting, Table 12 summarizes the December forecasts from the final ARIMA(5,2,0) model re-estimated on the complete 2010–2025 logarithmic series. The full set of monthly point forecasts is reported in Appendix Table A2, while Appendix Table A3 reports the corresponding logarithmic forecasts and prediction intervals.

Table 12: Final full-sample ARIMA(5,2,0) December forecasts, 2026–2028 (million ALL)

Horizon	Point Forecast	Lo 80%	Hi 80%	Lo 95%	Hi 95%
Dec 2026	1,074,007.3	997,672.2	1,156,177.7	959,483.1	1,202,195.5
Dec 2027	1,230,378.4	1,024,873.8	1,477,083.4	930,372.2	1,627,116.5
Dec 2028	1,410,103.0	1,023,460.4	1,942,817.9	863,759.8	2,302,025.6

Source: Author’s calculation.

The final forecasting results are obtained from the ARIMA(5,2,0) model re-estimated over the complete 2010–2025 dataset on the logarithmic scale. The final model has $ar1 = -1.0221$, $ar2 = -0.9456$, $ar3 = -0.6813$, $ar4 = -0.4630$, and $ar5 = -0.3303$, with $\log\text{-likelihood} = 650.1438$, $\sigma^2 = 6.534331 \times 10^{-5}$, $AIC = -1288.288$, $AICc = -1287.829$, and $BIC = -1268.806$. Forecasts are first generated on the logarithmic scale and then directly back-transformed to the original credit scale using the exponential function. No additional bias adjustment is applied;

consequently, the reported values are direct exponential back-transformations rather than bias-adjusted conditional-mean forecasts. The resulting monthly forecasts in million ALL are reported in Appendix Table A2, while the corresponding logarithmic forecasts and 80% and 95% prediction intervals are reported in Appendix Table A3. For example, the January 2026 logarithmic point forecast is 13.76145, which back-transforms to approximately ALL 947,374.7 million and corresponds to the value reported in Appendix Table A2. The December point forecasts are ALL 1,074,007.3 million for 2026, ALL 1,230,378.4 million for 2027, and ALL 1,410,103.0 million for 2028. Relative to the December 2025 observed value, these imply year-on-year growth rates of approximately 13.8%, 14.6%, and 14.6%, respectively.

The final full-sample forecast therefore indicates a continued upward trajectory in aggregate credit to the economy over the 2026–2028 horizon. These estimates should be interpreted as a statistical forecast path conditional on the historical dynamics captured by the ARIMA(5,2,0) model, rather than as structural or causal projections of future credit developments.

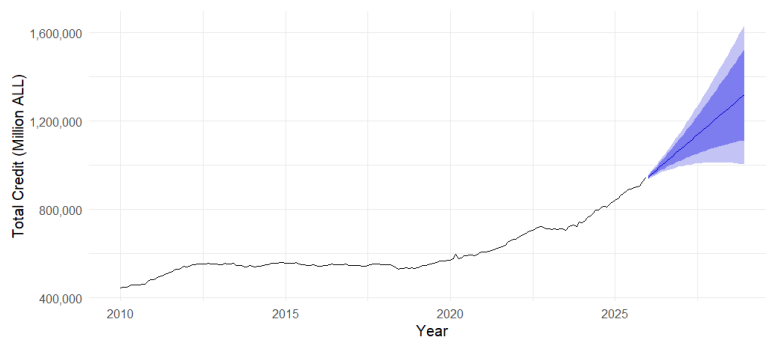


Figure 11: Total credit forecast in Albania generated from the final full-sample ARIMA(5,2,0) model, 2026–2028.

DISCUSSION

The central finding — that total credit to the economy in Albania is best characterized by a strongly trending, non-seasonal ARIMA(5,2,0) process rather than a seasonal SARIMA specification — answers RQ1. The results indicate that, over 2010–2025, the aggregate credit series is dominated by persistent trend-like dynamics rather than recurring intra-year seasonal patterns. This statistical finding is consistent with the literature on Albanian credit, including Kalluci [18], who describes private-sector credit as following a structural convergence path, and Shijaku and Kalluci [23], who identify demand- and supply-side factors associated with credit growth. However, because the present analysis is univariate, these factors are used only as contextual interpretations and are not estimated as causal determinants in the model.

The finding that no seasonal differencing was required, together with the selection of a non-seasonal specification, is broadly consistent with the long-run credit relationships documented by Matuka [20]. The present univariate forecasting results are therefore complementary to the multivariate determinants literature: while those studies examine factors associated with credit dynamics, ARIMA(5,2,0) provides a statistically validated benchmark for the continuation of the historical credit trajectory, conditional on the persistence of the estimated process and absent major new structural changes.

The projected annual credit expansion over the 2026–2028 medium-term forecast horizon—approximately 13.8% in 2026, 14.6% in 2027, and 14.6% in 2028—indicates continued growth under the model’s baseline dynamics. These figures are conditional statistical projections and are not interpreted as causal forecasts. More broadly, this projected trajectory is consistent with the established empirical literature linking financial deepening and credit expansion with income development [3], [21], [25], although the present univariate model does not estimate or identify these underlying relationships.

However, the mixed empirical evidence regarding the finance–growth nexus in bank-based CEE economies [4] cautions against viewing rapid credit expansion as unambiguously growth-enhancing. Unchecked aggregate credit expansion can be associated with macroeconomic imbalances and potential credit-quality deterioration.

Consequently, a statistically validated forecasting benchmark such as ARIMA(5,2,0) may provide macroprudential authorities and monetary policymakers with supplementary information for monitoring aggregate credit developments and assessing whether observed outcomes warrant further investigation alongside broader financial-stability indicators.

Theoretical and practical implications

Methodologically, the analysis illustrates the value of testing, rather than assuming, seasonality in economic time series: the a priori plausibility of SARIMA was not confirmed once formal stationarity tests, information criteria, and residual diagnostics were applied jointly. Relying on economic intuition or information criteria alone — which here favoured ARIMA(3,2,3) on some metrics despite its residuals failing the white-noise requirement — could have led to an inferior model being adopted for policy use, underscoring the importance of the full Box–Jenkins cycle, and specifically of the Ljung–Box test.

From a policy standpoint, the ARIMA(5,2,0)-based forecast provides the Bank of Albania, commercial banks, and fiscal authorities with a statistically grounded medium-term reference path that may be used:

- as a monitoring benchmark, with material deviations from the projected path prompting closer examination of underlying credit-demand, credit-supply, liquidity, and macroeconomic conditions;
- as supplementary information for medium-term liquidity and funding planning by banks, subject to internal risk assessment and prevailing financial conditions;
- as a complementary macroprudential monitoring indicator, rather than as a standalone basis for calibrating monetary-policy instruments.

For businesses and households, the projected upward trend represents a continuation of the historical pattern captured by the model and should not be interpreted as a guarantee of future financing availability, which may depend on broader economic, financial, regulatory, and borrower-specific conditions.

Limitations

The analysis has five main limitations. First, it is univariate and does not incorporate explanatory macroeconomic variables (GDP, interest rates, exchange rate), so the forecast captures statistical continuation of past patterns rather than a structural, causal model. Second, the ex-ante projections for 2026–2028 assume that the historical data-generating process estimated over the 2010–2025 baseline period remains sufficiently persistent over the forecast horizon. Consequently, the projections do not explicitly incorporate counterfactual policy scenarios, major regulatory changes, or severe external shocks. This limitation is particularly relevant given the evidence of structural instability around the COVID-19 period documented in the structural-break analysis subsection. Third, although the study includes chronological holdout validation and an expanding-window robustness exercise, forecast performance remains dependent on the selected evaluation windows and may change under alternative forecast horizons or during periods of unusually high volatility. Fourth, the analysis is confined to linear ARIMA/SARIMA-type specifications; non-linear or regime-switching alternatives were not tested and could capture asymmetries between expansion and contraction periods that a linear model may not represent. Fifth, the chronological holdout model is estimated on the original credit scale, whereas the final ex-ante model is re-estimated on the logarithmic scale. The holdout exercise therefore supports the predictive adequacy of the retained ARIMA(5,2,0) order but is not a direct validation of the exact final log-scale forecasting pipeline; future work should replicate the holdout exercise using the identical transformation and estimation procedure used for the final forecasts.

Directions for future research

Future research could address these limitations in several directions. First, macroeconomic covariates such as GDP, policy rates, inflation, and the exchange rate could be incorporated within ARIMAX, ARDL, VAR, or vector error-correction frameworks to distinguish statistical persistence from structurally interpretable

relationships. Second, credit could be disaggregated by currency, maturity, borrower sector, or loan category to assess whether the aggregate trending pattern is uniform across portfolio segments. Third, regime-switching, threshold, or other non-linear models could be tested to capture possible asymmetries between expansion and contraction phases and to model structural changes such as those identified around the COVID-19 period. Finally, future studies could employ longer recursive or rolling-origin evaluation schemes and alternative forecast horizons to assess whether predictive accuracy remains stable across different economic regimes.

CONCLUSION AND RECOMMENDATIONS

This study set out to characterize the empirical properties of total credit to the economy in Albania over the 2010–2025 period and to identify the time-series specification providing the most accurate and reliable forecast over the 2026–2028 horizon. The series required two non-seasonal differences ($d = 2$) but no seasonal differencing ($D = 0$), indicating persistent trend-like behavior rather than a stable annual periodicity. This empirical result did not support the initial expectation that a seasonal SARIMA specification would outperform the non-seasonal ARIMA model.

Among the specifications considered during the training stage, ARIMA(5,2,0) was retained as a parsimonious baseline after joint consideration of information criteria, residual adequacy, and forecast validation. The chronological 2024–2025 holdout evaluation of the original-scale training model yielded a MAPE of 4.11%, supporting the out-of-sample predictive adequacy of the retained order, while the expanding-window exercise provided additional robustness evidence. After the holdout stage, a full-sample log-scale grid search was conducted as an ex post robustness check; within that comparison ARIMA(5,2,0) ranked first by AICc ($-1,287.83$) and its residuals satisfied the Ljung–Box white-noise diagnostic. Because the final 2026–2028 model is re-estimated on the logarithmic scale, the holdout metrics should be interpreted as evidence supporting the model order rather than as a direct validation of the exact final forecasting pipeline.

The formal structural-break analysis identified significant instability in the deterministic intercept-and-trend representation of the credit series, including strong evidence of a break at March 2020 and an endogenous breakpoint in September 2020. These findings indicate that the historical credit process was not fully stable over the sample period; they do not establish a causal COVID-19 effect or imply that every ARIMA parameter changed at those dates. The results reinforce the need to interpret the 2026–2028 forecasts as conditional statistical projections rather than unconditional predictions.

The resulting ex-ante forecast, obtained after re-estimating the selected ARIMA(5,2,0) model over the complete 2010–2025 dataset, indicates a projected expansion in total credit to the economy over 2026–2028, reaching approximately ALL 1.07 trillion in December 2026, ALL 1.23 trillion in December 2027, and ALL 1.41 trillion in December 2028, corresponding to year-on-year growth of approximately 13.8%, 14.6%, and 14.6%, respectively. These projections should be interpreted as a statistical baseline scenario conditional on the persistence of the historical dynamics captured by the model, rather than as causal predictions of future economic or policy outcomes. The projected upward trajectory may be useful as a reference path for monitoring credit developments, while the associated forecast intervals highlight the uncertainty surrounding the point forecasts.

Recommendations

- The Bank of Albania and the banking supervisory authority could use the ARIMA(5,2,0) forecast interval as a statistical monitoring benchmark, with material deviations of actual credit from the projected path prompting closer examination of underlying credit-demand, credit-supply, liquidity, and macroeconomic conditions.
- For commercial banks, the projected credit path may provide supplementary information for medium-term liquidity and funding planning, subject to prevailing regulatory conditions, internal risk assessments, and broader financial conditions.
- Aggregate credit developments should be interpreted together with indicators of credit quality, leverage, liquidity, and financial stability. The ARIMA forecast does not identify the structural causes of changes in aggregate credit and therefore should not be used alone for macroprudential or monetary-policy calibration.

- Because this univariate forecast represents a statistical extrapolation rather than a causal macroeconomic model, policymakers should complement it with macroeconomic scenario analysis incorporating GDP, interest-rate, exchange-rate, and other relevant developments before making specific policy decisions.
- Future research should extend this univariate benchmark by incorporating explanatory macroeconomic covariates into dynamic multivariate models (e.g., ARDL or VAR/VEC frameworks).

Data Availability

The monthly credit data used in this study are publicly available from the Bank of Albania statistical time-series database (Credit to economy, monthly series).

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APPENDIX

Table A1: Full-sample log-scale ARIMA/SARIMA grid-search results used for ex post robustness verification (AICc criterion)

Candidate model	AICc
ARIMA(0,2,0)	-1143.322
ARIMA(0,2,0)(0,0,1)[12]	-1153.658
ARIMA(0,2,0)(1,0,0)[12]	-1155.438
ARIMA(0,2,1)	-1275.945
ARIMA(0,2,1)(1,0,0)[12]	-1279.83
ARIMA(0,2,2)	-1280.125
ARIMA(0,2,2)(1,0,0)[12]	-1281.988
ARIMA(0,2,3)(1,0,0)[12]	-1282.191
ARIMA(1,2,0)	-1207.032
ARIMA(1,2,1)	-1278.333
ARIMA(1,2,1)(1,0,0)[12]	-1280.644
ARIMA(1,2,2)(1,0,0)[12]	-1280.897
ARIMA(1,2,4)	-1282.154
ARIMA(2,2,0)	-1254.491
ARIMA(2,2,1)	-1281.493
ARIMA(2,2,1)(1,0,0)[12]	-1282.833
ARIMA(2,2,3)	-1284.125

ARIMA(3,2,0)	-1267.506
ARIMA(3,2,1)	-1279.438
ARIMA(3,2,2)	-1279.93
ARIMA(4,2,0)	-1268.706
ARIMA(4,2,1)	-1278.17
ARIMA(5,2,0)	-1287.829 (best model)

Source: Author's calculation

Table A2: Full monthly forecast of credit to the economy, 2026–2028 (million ALL; exponential back-transformation of logarithmic point forecasts)

Month	2026 (million ALL)	2027 (million ALL)	2028 (million ALL)
January	947,374.6	1,085,367.2	1,244,350.6
February	957,777.0	1,098,081.2	1,258,625.3
March	968,299.2	1,110,860.0	1,273,034.3
April	978,308.9	1,123,318.7	1,287,537.7
May	991,970.3	1,136,306.4	1,302,271.3
June	1,004,765.1	1,149,376.9	1,317,169.1
July	1,013,441.4	1,162,230.3	1,332,192.7
August	1,025,427.1	1,175,654.5	1,347,436.8
September	1,037,584.6	1,189,170.3	1,362,844.0
October	1,049,004.8	1,202,649.4	1,378,402.4
November	1,061,589.2	1,216,441.7	1,394,163.7
December	1,074,007.3	1,230,378.4	1,410,103.0

Source: Author's calculation

Table A3: Full monthly ARIMA(5,2,0) forecast with 80% and 95% confidence intervals, 2026–2028 (logarithmic scale; before exponential back-transformation)

Month	Point (log)	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2026	13.76145	13.75109	13.77181	13.74561	13.77729
Feb 2026	13.77237	13.75788	13.78686	13.75021	13.79453
Mar 2026	13.78330	13.76515	13.80145	13.75554	13.81105

Apr 2026	13.79358	13.77088	13.81628	13.75887	13.82829
May 2026	13.80745	13.77977	13.83512	13.76512	13.84977
Jun 2026	13.82026	13.78751	13.85302	13.77017	13.87036
Jul 2026	13.82886	13.78944	13.86829	13.76857	13.88916
Aug 2026	13.84062	13.79489	13.88635	13.77068	13.91056
Sep 2026	13.85241	13.80027	13.90454	13.77267	13.93214
Oct 2026	13.86335	13.80427	13.92244	13.77299	13.95372
Nov 2026	13.87528	13.80895	13.94160	13.77384	13.97671
Dec 2026	13.88691	13.81318	13.96063	13.77415	13.99966
Jan 2027	13.89743	13.81578	13.97908	13.77256	14.02230
Feb 2027	13.90907	13.81941	13.99874	13.77194	14.04621
Mar 2027	13.92065	13.82276	14.01853	13.77094	14.07035
Apr 2027	13.93180	13.82535	14.03824	13.76901	14.09459
May 2027	13.94329	13.82807	14.05852	13.76707	14.11951
Jun 2027	13.95473	13.83054	14.07893	13.76479	14.14467
Jul 2027	13.96585	13.83240	14.09930	13.76175	14.16995
Aug 2027	13.97734	13.83445	14.12022	13.75881	14.19587
Sep 2027	13.98877	13.83624	14.14130	13.75549	14.22204
Oct 2027	14.00004	13.83763	14.16245	13.75166	14.24842
Nov 2027	14.01144	13.83896	14.18392	13.74765	14.27523
Dec 2027	14.02283	13.84008	14.20558	13.74334	14.30232
Jan 2028	14.03412	13.84090	14.22735	13.73861	14.32964
Feb 2028	14.04553	13.84164	14.24942	13.73371	14.35735
Mar 2028	14.05691	13.84218	14.27165	13.72850	14.38533
Apr 2028	14.06824	13.84246	14.29402	13.72294	14.41355
May 2028	14.07962	13.84261	14.31663	13.71715	14.44209
Jun 2028	14.09100	13.84259	14.33940	13.71109	14.47090
Jul 2028	14.10234	13.84234	14.36233	13.70471	14.49996

Aug 2028	14.11371	13.84197	14.38546	13.69811	14.52932
Sep 2028	14.12508	13.84141	14.40876	13.69124	14.55893
Oct 2028	14.13644	13.84066	14.43221	13.68408	14.58879
Nov 2028	14.14781	13.83976	14.45585	13.67669	14.61892
Dec 2028	14.15917	13.83870	14.47965	13.66905	14.64930

Source: Author's calculation

Table A4: Actual versus point forecasts for the 2024–2025 test period

Period	Actual	Point Forecast	Error	Absolute Error	APE (%)
Jan 2024	740,971	742,132.1	-1,161.1	1,161.1	0.16
Feb 2024	749,947	751,334.5	-1,387.5	1,387.5	0.19
Mar 2024	763,589	753,195.0	10,394.0	10,394.0	1.36
Apr 2024	770,971	761,107.6	9,863.4	9,863.4	1.28
May 2024	782,965	761,671.8	21,293.2	21,293.2	2.72
Jun 2024	795,984	773,168.8	22,815.2	22,815.2	2.87
Jul 2024	798,301	774,835.1	23,465.9	23,465.9	2.94
Aug 2024	812,279	781,788.6	30,490.4	30,490.4	3.75
Sep 2024	812,921	785,516.4	27,404.6	27,404.6	3.37
Oct 2024	812,574	792,646.3	19,927.7	19,927.7	2.45
Nov 2024	824,369	795,926.4	28,442.6	28,442.6	3.45
Dec 2024	835,817	803,520.5	32,296.5	32,296.5	3.86
Jan 2025	841,955	807,233.6	34,721.4	34,721.4	4.12
Feb 2025	848,596	813,422.8	35,173.2	35,173.2	4.14
Mar 2025	866,431	818,013.0	48,418.0	48,418.0	5.59
Apr 2025	871,963	824,250.3	47,712.7	47,712.7	5.47
May 2025	880,592	828,653.7	51,938.3	51,938.3	5.90
Jun 2025	893,034	834,868.8	58,165.2	58,165.2	6.51
Jul 2025	893,110	839,524.6	53,585.4	53,585.4	6.00
Aug 2025	900,582	845,299.1	55,282.9	55,282.9	6.14

Sep 2025	901,771	850,271.9	51,499.1	51,499.1	5.71
Oct 2025	906,069	856,020.2	50,048.8	50,048.8	5.52
Nov 2025	925,202	860,940.8	64,261.2	64,261.2	6.95
Dec 2025	943,745	866,641.4	77,103.6	77,103.6	8.17

Source: Author's calculation

Table A5: Expanding-window robustness check for ARIMA(5,2,0)²

Forecast Window	Training Observations	ME	RMSE	MAE	MPE (%)	MAPE (%)
2021	132	2,339.92	7,739.52	5,054.43	0.34	0.78
2022	144	-15,564.83	19,346.06	15,564.83	-2.20	2.20
2023	156	-8,042.94	11,413.36	10,002.25	-1.14	1.40
2024	168	18,653.74	21,723.67	19,078.51	2.31	2.37
2025	180	11,888.87	13,799.27	11,888.87	1.32	1.32
Mean	—		14,804.38	12,317.78		1.61

Source: Author's calculation.

² Note: Forecasts use an expanding training window, a fixed ARIMA(5,2,0) specification, and a 12-month forecast horizon. Forecast accuracy is evaluated against the corresponding actual observations on the original scale in million ALL.