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# Forecasting the Liquidity in the Bank of Agriculture and Rural Development – BADR Tlemcen Agency-

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**Abstract:** Liquidity is a fundamental element to ensure a bank's ability to meet its financial obligations and maintain financial stability. This study aims to assess the effectiveness of Box-Jenkins forecasting method in enhancing bank liquidity in the Bank of Agriculture and Rural Development (BADR) during the January 2022 to December 2025. The Box-Jenkins model was used to predict the level of liquidity and the optimal model is moving average with one lag (MA(1)). The findings reveal that quantitative models offer greater accuracy in prediction compared to traditional approaches, with the Box-Jenkins model proving to be the most suitable for short-term liquidity forecasting. The results of this forecast are an effective tool that helps bank management improve financial planning and estimate the expected demand for liquidity from customers. This contributes to enhancing the quality of service provided and ensuring the bank's readiness to meet financial needs, thus maintaining customer satisfaction and confidence.
**Keywords**: Liquidity; Banks; BADR Tlemcen Agency; Box-Jenkins forecasting method

**JEL Classification**: C22 ; E52 ; G21

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## 1. Introduction:

A bank is a financial institution that collects deposits, accepts them, and then lends them in order to employ money and provide economic projects with sources of financing. Meanwhile, the banking system is of paramount importance within the economic system, as it is one of the fundamental pillars upon which financing and investment operations are based. Banks are considered the main source of financing for various economic sectors, making them a pivotal element in achieving stability and economic growth. Banks also represent an integral part of the daily lives of individuals and institutions, due to the multiple financial services they provide, and their effective role in creating job opportunities and stimulating economic activity. This importance increases in particular when banks improve their liquidity management, as sufficient liquidity enables them to fulfil their financial obligations and meet emergency requirements, which enhances customer confidence and ensures the continuity of their work in this context. Thus, the banking system becomes more capable of supporting economic development, as it ensures the provision of adequate financing for investments, and contributes to improving the efficiency of financial markets, which enhances the sustainability of economic growth in the long term.

Quantitative methods are emerging as effective tools for analysing liquidity conditions and accurately estimating future needs. Relying on mathematical and statistical models allows banking institutions to make decisions based on objective data, which helps improve liquidity management and predict potential market fluctuations, thus maintaining a balance between profitability and financial stability.

Therefore, achieving balance in liquidity management is one of the biggest challenges facing financial institutions, and this requires advanced methodologies that allow accurate forecasting of financial needs and efficient management of cash flows. Here, the importance of quantitative methods emerges, which allow banks to analyse financial data, assess risks, and develop effective liquidity management strategies. By using statistical and economic models, banks can improve their decisions regarding resource allocation, contributing to financial stability and enhancing the economy's ability to cope with crises.

The significance of liquidity forecasting in agricultural banking is paramount. Agricultural banks must address seasonal fluctuations in deposit inflows and loan distributions, reconcile timing discrepancies between agricultural output cycles and financial commitments, and sustain enough liquidity reserves to fulfil both anticipated and unforeseen cash requirements (**Shams et al., 2013**). In contrast to commercial banks that largely cater to urban and industrial clients, agricultural banks have significant seasonality in their liquidity, with peak demands typically aligning with planting and harvesting seasons when farmers necessitate considerable credit for inputs and operations (**Cowley et al., 2025**).

The Algerian banking sector has experienced substantial transformation since the economic reforms of the 1990s, shifting from a centrally controlled system to a more market-oriented structure. Nonetheless, agricultural banks such as BADR persist in

encountering difficulties concerning liquidity management, risk evaluation, and operational efficacy (**Bendob, 2015**). Research has established that liquidity risk affects bank performance in Algeria, indicating that proficient liquidity management substantially impacts profitability and financial stability (**Slimane et al., 2013**). The issues are exacerbated by the unique attributes of agricultural financing, such as elevated default risks, extended loan maturities, and the susceptibility of agricultural revenue to climatic conditions, market fluctuations, and policy alterations.

Recent advancements in forecasting algorithms provide interesting possibilities for enhancing liquidity management in agricultural banks. Time series models, including ARIMA, GARCH, and VAR, have been effectively utilized for forecasting bank liquidity, accurately capturing temporal patterns and volatility dynamics (**Wang, et al., 2013; Xu et al., 2024**). The integration of these advanced analytical methods with domain-specific knowledge of agricultural banking presents an opportunity to develop robust, context-appropriate forecasting systems for institutions like BADR.

This research paper seeks to deliver an exhaustive analysis of liquidity Box and Jenkins forecasting methodologies pertinent to the BADR Tlemcen Agency, integrating theoretical principles, empirical data, and actionable recommendations. The document examines multiple critical research inquiries: What are the most efficacious forecasting approaches for farm bank liquidity? In what ways do the distinctive features of agricultural banking affect the choice and execution of models? What particular obstacles does the BADR Tlemcen Agency have in liquidity management? What evidence-based recommendations can inform the creation and execution of a comprehensive liquidity forecasting system?

In the light of these statement, three hypotheses are defined as follow:

[1] Quantitative methods effectively contribute to improving liquidity management within banks;

[2] Quantitative methods help predict risk and reduce the likelihood of a liquidity deficit;

[3] The use of quantitative methods enhances the stability of the banking system and improves its financial efficiency.

This study enhances the sparse yet expanding body of literature on liquidity management inside agricultural banks, especially in the setting of developing economies. This study synthesizes international best practices while specifically addressing the Algerian agricultural banking context, offering theoretical insights and practical recommendations for financial institutions servicing agricultural and rural communities.

## 2. Literature review

Agricultural banks encounter unique obstacles that set them apart from commercial banks that largely cater to urban and industrial clientele. These issues arise from the intrinsic attributes of agricultural production, rural economic dynamics, and the particular risk profiles associated with agricultural lending. **Cowley et al. (2025)** performed a regional examination of agricultural bank liquidity, pinpointing numerous critical elements that affect liquidity management in this industry. Agricultural banks have significant seasonal

fluctuations in deposits and lending, influenced by agricultural production cycles. Planting seasons generally experience elevated loan demand as farmers seek financing for seeds, fertilizers, and equipment, whereas harvest seasons yield loan repayments and heightened deposits. This seasonality induces predictable yet substantial variations in liquidity positions that require meticulous management. The financial performance of rural banks has been analyzed in several circumstances. **Awo et al. (2019)** using the Generalized Method of Moments (GMM) to examine the financial performance of rural banks in Ghana, revealing that liquidity management has a substantial effect on profitability and sustainability. Their research indicated that rural banks encounter distinct challenges, such as restricted access to interbank markets, elevated transaction costs, and increased vulnerability to localized economic shocks. The findings have significant implications for agricultural banks such as BADR, indicating that successful liquidity forecasting must consider restricted liquidity buffers and limited access to external funding sources.

Time series models constitute the basis of quantitative liquidity forecasting, providing established statistical frameworks for identifying temporal patterns, trends, and volatility in financial data. The utilization of these models in bank liquidity has a substantial history, characterized by ongoing refinement and adaption to banking-specific settings. **Shams et al. (2013)** performed a significant study on liquidity risk forecasting in agricultural banks, presenting the liquidity at risk framework, which is analogous to the commonly utilized value at risk concept. Their research utilized four models: GARCH (Generalized Autoregressive Conditional Heteroskedasticity), ARCH (Autoregressive Conditional Heteroskedasticity), Moving Average (MA), and Exponentially Weighted Moving Average (EWMA) to predict liquidity risk. The research indicated that predicting liquidity and liquidity risk is achievable from historical bank liquidity data, with the GARCH model being especially proficient in handling significant volatility shocks in liquidity time series. At a 95% confidence level, these models demonstrated suitable performance in forecasting liquidity at risk, affirming the efficacy of econometric methods for predicting liquidity risk in agricultural banking settings. **Wang et al. (2013)** formulated an EGARCH-VaR (Exponential GARCH - Value at Risk) model for assessing bank liquidity risk, illustrating that this methodology yields superior accuracy and efficiency in risk measurement relative to conventional GARCH models. The EGARCH model facilitates asymmetric reactions to both positive and negative shocks, a characteristic especially pertinent in liquidity management, where liquidity deficits may yield more detrimental effects than liquidity excesses. **Xu et al. (2024)** utilized ARIMA models in conjunction with VAR to predict liquidity in Chinese small and medium-sized banks, establishing a thorough analytical framework that incorporates Granger causality tests and cointegration analysis. Their research indicated that ARIMA models can proficiently include both short-term dynamics and long-term trends in bank liquidity, yielding dependable forecasts for strategic planning and operational management.

The Algerian banking sector has garnered little yet increasing interest in the literature. **Slimane et al. (2013)** investigated the influence of liquidity risk on the performance of

Algerian banks, revealing substantial correlations between liquidity management and bank profitability. Their research underscored the difficulties encountered by Algerian banks in liquidity management amidst economic fluctuations and regulatory alterations. **Khaled et al. (2023)** examined the relationship between liquidity risk and bank solvency in Algeria through a simultaneous equation's framework, illustrating the essential interdependencies among several aspects of bank risk. **Bendob (2015)** examined the profitability of public and private commercial banks in Algeria utilizing panel data from 1997 to 2012, offering significant insights into the development of the Algerian banking sector. This study recorded the shift from a state-controlled banking system to a more varied framework, while emphasizing ongoing issues in efficiency, risk management, and financial performance. **Arifianto et al. (2022)** explored how Indonesian banks reacted to liquidity shocks, by analyzing liquidity management dynamics between 2003 and 2019. The researchers used the Dynamic Common Effects Estimator (DCCE) model in conjunction with the Error Correction Model (ECM) to analyze the liquidity behavior of 84 Indonesian banks across longitudinal data covering 17 years. The study framework is based on a combination of quantitative econometric analysis and banking theory Focusing on the speed of adaptation to liquidity shocks and the extent of banks' flexibility in rebalancing their financial positions after being exposed to a liquidity imbalance, the results showed that the average period that Indonesian banks need to recover from a liquidity shock ranges between 2.5 and 3.5 months. There is also a strong tendency for banks to seek financing through collective sources as a means of responding to liquidity shocks. **Harb et al. (2023)** examined the relationship between liquidity management and the financial performance of banks operating in 25 commercial and investment banks in the United Kingdom during the period from 2012 to 2021, by focusing on key liquidity indicators such as liquidity coverage ratio (Liquidity Coverage Ratio – LCR) and loan-to-deposit ratio (Loan-to-Deposit Ratio – LDR), The extent to which these ratios affect the return on assets (Return on Assets – ROA) and the return on equity (Return on Equity – ROE). The researchers concluded that there is a positive nonlinear relationship between LCR and ROA, with increasing LCR up to a certain level (about 120%) improving return on assets, and that higher LDR correlates positively with ROE, suggesting that banks that efficiently employ their deposits in lending achieve higher returns for shareholders. The study also found that optimal liquidity management is not in holding the highest possible percentage of liquid assets, but rather in achieving a dynamic balance between profitability and operating liquidity. **Sinha and Sharma (2019)** applied the methodology of the General Real-Time Dictionaries Method (GMM) to analyze liquidity management dynamics in 37 public banks in India over a period from 2008 to 2017. Researchers focused on identifying internal factors (such as capital adequacy, bank size, asset quality, return on equity, loan-to-deposit ratio) and external factors (such as economic growth and interest rates) that influence liquidity levels. The results showed that capital adequacy makes the bank better able to cope with fluctuations in liquidity demand, while a high percentage of stable deposits increases the bank's ability to meet short-term obligations, while a high percentage of non-performing loans reduces the bank's ability to generate liquidity from assets. Moderate economic growth then had a slight

impact on improving liquidity. **Ahmed (2024)** focused on the impact of brokerage efficiency on liquidity risks in Egyptian banks, by adopting a two-stage non-parametric approach (Non-parametric approach) based on the data envelopment analysis (Data Envelopment Analysis - DEA) method in the first stage, and regression analysis in the second stage. The analysis covers data on 25 banks operating in the Egyptian market during the period from 2010 to 2022. The researcher focused on the concept of banking intermediation efficiency in the study on the bank's ability to convert resources (such as deposits) into productive uses (such as loans), with minimal waste. Liquidity risk represents the possibility of a bank failing to meet its short-term obligations due to the unavailability of assets that can be quickly converted into cash. The results showed that banks with high operational efficiency face lower liquidity risks. While major banks have demonstrated relatively higher efficiency and, consequently, a greater ability to anticipate liquidity crises by diversifying financing products and managing the financing structure flexibly. Private banks have shown greater efficiency in banking intermediation than state-owned banks, due to more flexible operating systems and faster decision-making. While banks with strong governance structures and clear risk management policies performed better in terms of liquidity. **Hakimi and Zaghdoudi (2017)** employed the data methodology to 10 Tunisian commercial banks over the period from 1990 to 2013 to study the relationship between liquidity risk and bank performance in the Tunisian context. The researchers relied on the hypothesis that increased liquidity risk reduces a bank's operating efficiency and limits its ability to achieve stable profits, due to the need to hold a high percentage of low-yield liquid assets or the high costs of obtaining short-term financing. The results showed that higher loan-to-deposit ratios (as an indicator of liquidity shortages) lead to a significant decline in financial performance indicators. It was also shown that higher inflation rates and interest rates intensify the negative relationship between liquidity risk and performance, meaning that economic crises double the impact of liquidity risk. The researchers then noted that Tunisian banks lack the use of advanced liquidity management tools such as simulation models or liability asset management strategies, which further weakens their ability to react proactively to liquidity changes. **Noor & Jaddah (2021)** studied how to analyze the determinants of liquidity in Iraqi banks, focusing on both internal (bank-specific) and external (economic and macro) factors, over a period extending from 2006 to 2020. The researchers relied on annual financial data for 11 Iraqi commercial banks representing a wide segment of the Iraqi banking sector, both government and private banks. The researchers concluded that there was an inverse relationship between economic growth and financial stability in Iraq, where macroeconomic conditions were not favorable for enhancing bank liquidity. Whereas the more a bank is able to meet its obligations through its capital, the more resilient it is in the face of liquidity shortages. While high inflation erodes the real value of liquid assets and increases pressure on the bank's liabilities. The results confirmed that the Central Bank of Iraq's prudential policies during that period were insufficient to protect banks from the liquidity challenges they faced, especially during times of financial crises or security tensions.

## 3. Data and methodology

### 3.1 Overview of BADR in Algeria:

The Bank of Agriculture and Rural Development (Banque de l'Agriculture et du Développement Rural - BADR) holds a distinctive and vital role in Algeria's financial system as the principal entity focused on funding the agricultural sector and promoting rural development. BADR, being a specialized state bank, has a purpose that transcends traditional commercial banking, incorporating developmental aims that match with Algeria's agricultural policy and food security objectives.

BADR functions via a network of regional agencies strategically located throughout Algeria's varied agricultural zones, each customized to address the unique agricultural attributes and finance requirements of its respective region. The bank offers an extensive array of financial services, encompassing short-term production loans for seasonal agricultural inputs, medium-term loans for equipment and livestock, long-term loans for land development and infrastructure, as well as deposit services for farmers, agricultural cooperatives, and rural enterprises.

The bank's function in Algeria's agricultural development strategy is complex. In addition to financial intermediation, BADR functions as a channel for governmental agricultural support initiatives, manages subsidized loan programs, and offers technical help to agricultural borrowers. This developmental purpose presents distinct issues for liquidity management, as the bank must reconcile commercial viability with policy objectives that may include below-market interest rates or lending to higher-risk sectors.

### 3.2 Data:

The study is limited to analysing liquidity at the Bank of Agriculture and Rural Development (BADR) during the period from January 2022 to December 2025, where we will forecast liquidity values for the year of 2026 using the Box and Jenkins time series forecasting method.

In the following table, we show the amount of liquidity in the Bank of Agriculture and Rural Development during the study period:

**Table 1. The amount of bank liquidity in Algerian dinar (DZD) units for B the Bank of Agriculture and Rural Development (BADR) of Tlemcen Agency No. 013 for the period January 2022 to December 2025**

| | 2022 | 2023 | 2024 | 2025 |
|---|---|---|---|---|
| January | 534232790 | 797145839 | 1040529843 | 1240837849 |
| February | 651237881 | 828287484 | 1032512183 | 1212203714 |
| March | 738949982 | 873646253 | 1064300612 | 1202966693 |
| April | 513755132 | 832711455 | 1003755172 | 1190103871 |
| May | 618752429 | 856196769 | 1019542939 | 1184059956 |
| June | 672529194 | 863374277 | 1068121415 | 1192608666 |
| July | 528433166 | 835124467 | 936219036,4 | 1218131981 |
| August | 569121028 | 836976665 | 973300354,2 | 1256888189 |
| September | 683147159 | 860003942 | 1084191992 | 1300486255 |
| October | 689422514 | 851206486 | 1083626258 | 1338990160 |
| November | 735412893 | 889584843 | 1144198564 | 1364506731 |

| | | | | |
|---|---|---|---|---|
| December | 672700019 | 916087023 | 1112456146 | 1373963083 |

**Source:** Done by the author based on data available at the level of the Bank of Agriculture and Rural Development (BADR) of Tlemcen Agency No. 013

**3.3 Methodology:**

Time series models constitute the foundation of quantitative liquidity forecasting, providing established statistical frameworks for identifying temporal patterns in financial data. These models are especially beneficial for agricultural banks, as historical trends offer critical insights into future liquidity requirements.

Autoregressive Integrated Moving Average (ARIMA) models constitute a versatile category of time series models capable of encapsulating diverse patterns such as trends, seasonality, and autocorrelation. An ARIMA(p,d,q) model comprises p autoregressive components, d differences for stationarity, and q moving average components. SARIMA models enhance the fundamental foundation for agricultural bank liquidity by explicitly incorporating seasonal patterns.

The implementation of ARIMA for forecasting bank liquidity encompasses several stages:

In 1976, Box and Jenkins were interested in collecting the techniques used in time series to help determine the degree of the model and estimate its proposed features after methods to ensure the suitability of the model to take its final form. This is because estimated linear dynamic models and the theoretical analyses attached to them do not only give us the form of a model, but we also obtain it. On its estimated features for the purpose of forecasting and monitoring in the short term.

This methodology is broad and has great resonance in time series analysis, as it reflects the behaviour of the time series, whether seasonal or non-seasonal, and the Box and Jenkins methodology includes several stages, which are:

1- The identification stage is the most difficult stage of the methodology, as the stability of the time series is judged and the model to which the series can be subject is determined. This step is known also for assessing stationarity and executing necessary transformations;
2- Determining the order of autoregressive and moving average components via the analysis of autocorrelation and partial autocorrelation functions and estimate the linear models specified in the previous stage and then the preferred ones between them;
3- Testing stage: After defining and estimating a model, we summarize at this stage the extent of the model's acceptance statistically in order to use it to predict future values. If the model is rejected, we must return to the first stage;
4- The forecasting stage is the last stage of this methodology, through which we seek to find future values for the time series, and this is done by using the appropriate model obtained according to the previous stages. The optimal prediction is one in which the resulting error is very small and its variance is as small as possible.

## 4. Empirical result

In this section, several statistics, tests and models are conducting as follow:

### 4.1 Descriptive statistics and identification stage:

The following table shows the descriptive statistical data for the time series of bank liquidity:

**Table 2. The descriptive statistics of the amount of bank liquidity**

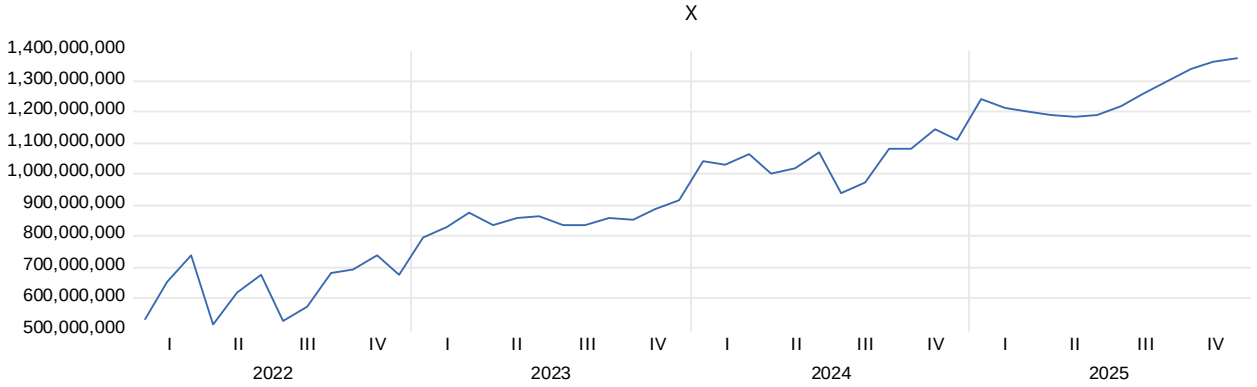
| Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | Probability |
|---|---|---|---|---|---|---|---|
| 948000000 | 1373963083 | 513,755,132 | 241000000 | -0,035 | 1,999 | 2,012 | 0,365 |

**Source:** Author calculation on EViews

Table 2 shows the arithmetic mean is estimated at 948,000,000 DZD, the minimum value is estimated at 513,755,132, and the maximum value is 1373963083, and the standard deviation is estimated at 241000000 DZD. As for the skewness and kurtosis coefficients, they have values close to 0 and 3, which shows that the data for this series follow a normal distribution. This can be confirmed by the Jarque-Bera test, and its probability value exceeds 5%. Therefore, we accept the null hypothesis, which states that the bank liquidity data follow a normal distribution

The next step is to draw the graph to display whether there is a principal component of time series such as trend, seasonality, variation stochastic or cyclical.

**Figure 1. The amount of bank liquidity**

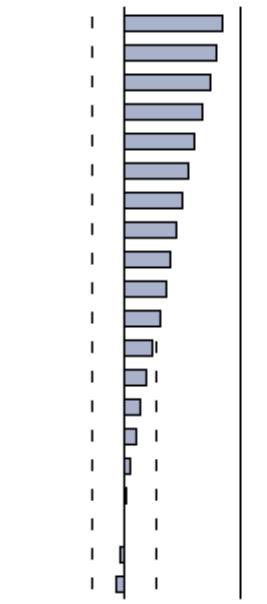



**Source:** Done by the author on EViews

The figure illustrates that the series depicting bank liquidity from January 2022 to December 2025 has a distinct pattern (linear trend), necessitating verification using a correlogram and unit root test.

**Figure 2. The correlogram of the amount of bank liquidity**

Included observations: 48



| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.892 | 0.892 | 40.644 | 0.000 |
| | | 2 | 0.823 | 0.135 | 76.019 | 0.000 |
| | | 3 | 0.785 | 0.145 | 108.87 | 0.000 |
| | | 4 | 0.697 | -0.211 | 135.39 | 0.000 |
| | | 5 | 0.628 | -0.007 | 157.41 | 0.000 |
| | | 6 | 0.579 | 0.023 | 176.58 | 0.000 |
| | | 7 | 0.523 | 0.019 | 192.60 | 0.000 |
| | | 8 | 0.472 | -0.009 | 205.98 | 0.000 |
| | | 9 | 0.419 | -0.065 | 216.79 | 0.000 |
| | | 10 | 0.370 | -0.013 | 225.45 | 0.000 |
| | | 11 | 0.317 | -0.059 | 231.95 | 0.000 |
| | | 12 | 0.247 | -0.112 | 236.03 | 0.000 |
| | | 13 | 0.189 | -0.034 | 238.49 | 0.000 |
| | | 14 | 0.136 | -0.020 | 239.80 | 0.000 |
| | | 15 | 0.100 | 0.092 | 240.53 | 0.000 |
| | | 16 | 0.053 | -0.078 | 240.74 | 0.000 |
| | | 17 | 0.023 | 0.038 | 240.78 | 0.000 |
| | | 18 | 0.004 | 0.001 | 240.78 | 0.000 |
| | | 19 | -0.034 | -0.058 | 240.88 | 0.000 |
| | | 20 | -0.071 | -0.065 | 241.31 | 0.000 |

**Source:** Done by the author on EViews

The correlogram indicates a significant reduction in autocorrelation, gradually decreasing from 0.892 to 0. Consequently, there is evidence of a linear trend in the time series principal component.

Moreover, the prob of Ljung-Box test is lower than 5%, indicating that the alternative hypothesis is accepted, therefore the series is not stationary.

**4.2 Unit root test or stationary test:**

The following table show the unit root test of augmented Dickey-Fuller:

**Table 3. Unit root test of augmented Dickey-Fuller on original series**

| | | | t-Statistic | Prob. |
|---|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | | **-5.970*** ** | **0.0001** |
| Test critical values: | 1% level | | -4.192 | |
| | 5% level | | -3.521 | |
| | 10% level | | -3.191 | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| X(-1) | -1.631 | 0.273 | -5.969 | 0.0000 |
| D(X(-1)) | 0.751 | 0.216 | 3.479 | 0.0014 |
| D(X(-2)) | 0.742 | 0.198 | 3.738 | 0.0007 |
| D(X(-3)) | 0.816 | 0.177 | 4.610 | 0.0001 |
| D(X(-4)) | 0.639 | 0.156 | 4.093 | 0.0002 |
| D(X(-5)) | 0.375 | 0.127 | 2.944 | 0.0058 |
| C | 8.29E+08 | 1.36E+08 | 6.081 | 0.0000 |
| **@TREND("2022M01")** | **27472716** | **4590892.** | **5.984*** ** | **0.0000** |

**Source:** Done by the author on EViews

*** indicate that the alternative hypothesis is accepted at the significance level of 1%

Through Dickey-Fuller test, the author notices that the time series is not stationary and therefore the series is affected by the general trend component.

In this case, we will remove the general trend compound effect from the raw series, after estimating the model in which the bank liquidity series is a dependent variable and is

affected by the general trend variable as an independent and constant variable, as shown in the following table:

**Table 4. Estimation of the model with linear trend and intercept**

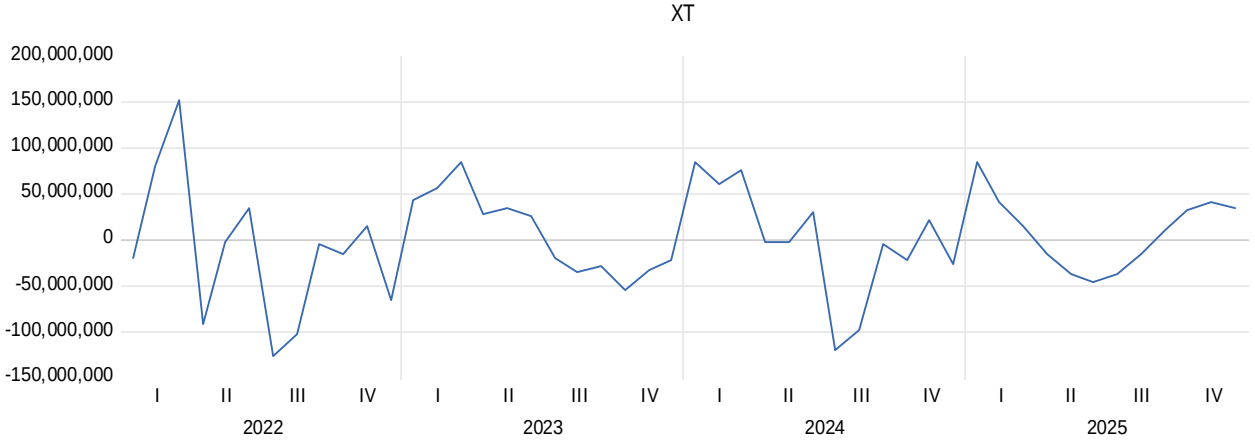
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.55E+08 | 16441067 | 33.77401 | 0.0000 |
| @TREND | 16695978*** | 602691.2 | 27.70237 | 0.0000 |

**Source:** Done by the author on EViews

*** indicate that the alternative hypothesis is accepted at the significance level of 1%

So, after estimating the model in which the general and constant trend is, and then deleting them from the raw series, the new time series without the influence of the vehicle becomes the general trend and takes the form of the following curve:

**Figure 3. Detrend (new series) of the amount of bank liquidity**




**Source:** Done by the author on EViews

From the previous curve, it is clear that the new series appears to be stable and there are not many changes or the effect of the compound on the general trend, so we will confirm through testing the unitary roots.

**Table 5. Unit root test of augmented Dickey-Fuller on detrend series**

| | | | t-Statistic | Prob. |
|---|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | | **-5.970*** ** | **0.0001** |
| Test critical values: | 1% level | | -4.192 | |
| | 5% level | | -3.521 | |
| | 10% level | | -3.191 | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| XT(-1) | -1.631 | 0.273 | -5.970 | 0.0000 |
| D(XT(-1)) | 0.751 | 0.216 | 3.479 | 0.0014 |
| D(XT(-2)) | 0.742 | 0.198 | 3.738 | 0.0007 |
| D(XT(-3)) | 0.816 | 0.177 | 4.610 | 0.0001 |
| D(XT(-4)) | 0.639 | 0.156 | 4.093 | 0.0002 |
| D(XT(-5)) | 0.375 | 0.127 | 2.944 | 0.0058 |
| C | -10897905 | 15432579 | -0.706 | 0.4849 |
| @TREND("2022M01") | 245762.1 | 527570.8 | **0.466** | **0.6443** |

**Source:** Done by the author on EViews

*** indicate that the alternative hypothesis is accepted at the significance level of 1%

From table 5, it is clear that there is no trend in this series so let move to other model

**Table 6. Unit root test of augmented Dickey-Fuller on detrend series for model 3, 2 and 1**

| Models | Augmented Dickey-Fuller test statistic | Decision |
|---|---|---|
| Model 3 with trend and intercept | -5.970*** | Stationary |
| Model 2 with intercept only | -6.038*** | Stationary |
| Model 1 without trend and intercept | -6.045*** | Stationary |

**Source:** Done by the author on EViews

*** indicate that the alternative hypothesis is accepted at the significance level of 1%

From table 6, the Augmented Dickey-Fuller test statistic show that three model has a significant coefficient and they indicate that this new series (detrend series) is stationary.

**4.3 Estimation of the optimal model and residual tests:**

After confirming that the series is stationary, the next step is to seek the optimal ARMA model.

**Table 7. Estimation of the optimal ARMA model**

| Statistics | AR (1) | MA (1) | ARMA |
|---|---|---|---|
| Coefficient | 0.284* (0.051) | 0.3383** (0.0174) | Not significant |
| Akaike | 38.5189 | 38.4866 | |
| Schwarz | 38.5583 | 38.5256 | |
| Hannan-Quinn | 38.5337 | 38.5014 | |
| $R^2$ | 0.080 | 0.092 | |
| Log likelihood | -904.1953 | -922.6799 | |

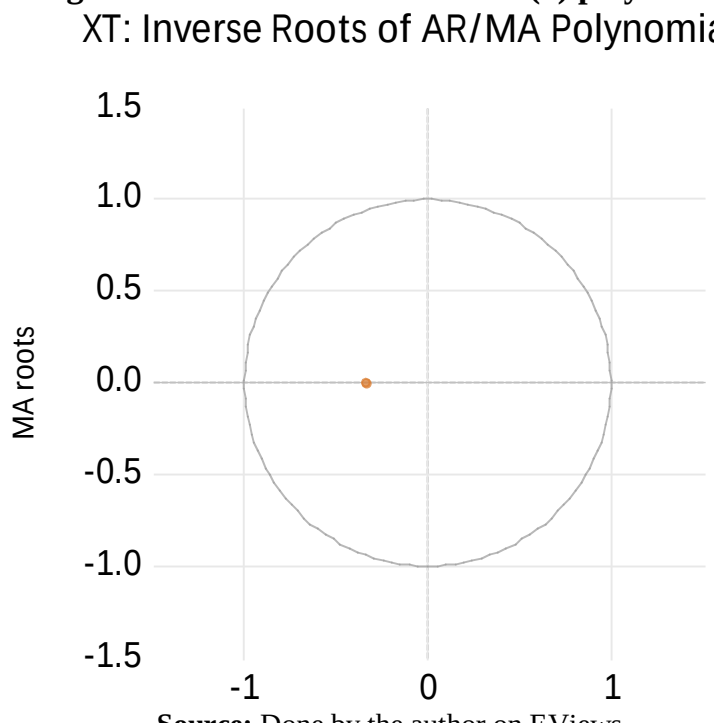
**Source:** Done by the author on EViews

*** indicate that the alternative hypothesis is accepted at the significance level of 1%

From table 7, the outcomes show that the optimal model is MA (1) due to its lowest value of Akaike Schwarz and Hannan-Quinn and also it has a higher coefficient of determination ($R^2$).

The next step is to examine the residual of the MA (1) model (residual diagnostic).

**Figure 4. The inverse root of MA (1) polynomial**

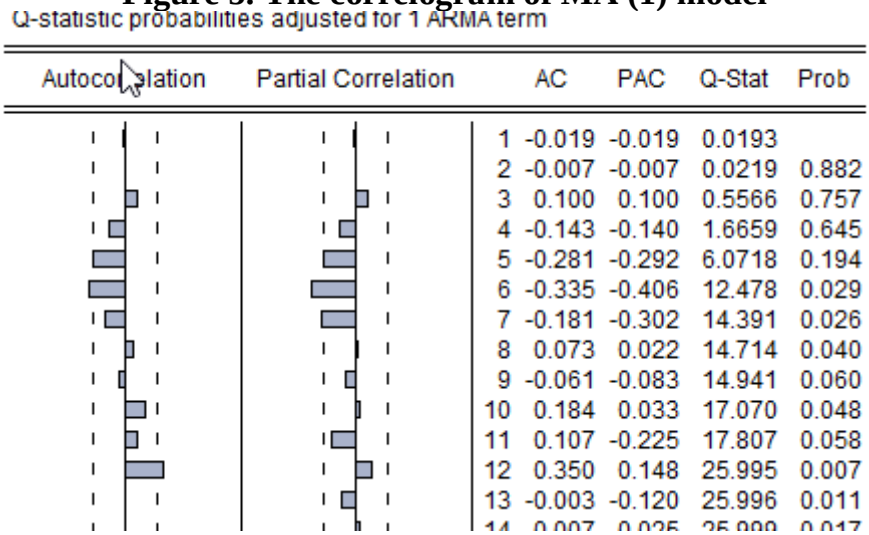



**Source:** Done by the author on EViews

The figure 4 shows that there are no inverse roots because the point of MA (1) is within the circle of stability between -1 and +1.

The next figure displays the whether the series is stationary or not.

**Figure 5. The correlogram of MA (1) model**

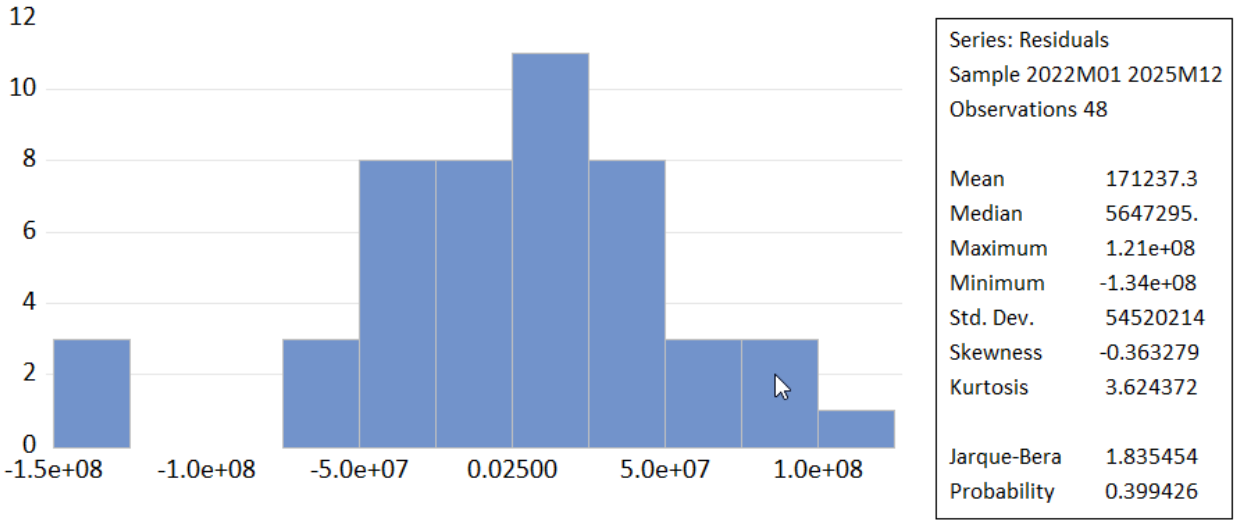



**Source:** Done by the author on EViews

The probability of Ljung-Box is greater than 5%, indicating that there is an evidence the residuals are stationary and are white noise.

The next figure is on normality test. Therefore, from figure 6, the prob of Jarque-Bera is greater than 5%, showing that the residuals are following a normal distribution.

**Figure 6. The histogram of MA (1) model**




**Source:** Done by the author on EViews

The next one is on testing whether there is an ARCH effect or not.

**Figure 7. The ARCH test of MA (1) model**

Heteroskedasticity Test: ARCH

| | | | |
|---|---|---|---|
| F-statistic | 1.576765 | Prob. F(1,45) | 0.2157 |
| Obs*R-squared | 1.591092 | Prob. Chi-Square(1) | 0.2072 |

**Source:** Done by the author on EViews

The outcome shows that there is no ARCH effect, showing that the ARMA structure is the best for this study.

**4.4 Box-Jenkins forecasting result and discussion:**

After doing all preliminary tests and estimating the optimal model, the last step is to forecast new data for the year of 2026.

**Table 8. Box-Jenkins forecasting result**

| | Detrend series | Original series |
|---|---|---|
| January 2026 | 7858697,43 | 1381242416 |
| February 2026 | 2658799,27 | 1392738495 |
| March 2026 | 899540,112 | 1407675214 |
| April 2026 | 304337,534 | 1423775990 |
| May 2026 | 102965,208 | 1440270595 |
| June 2026 | 34835,7755 | 1456898444 |
| July 2026 | 11785,838 | 1473571372 |
| August 2026 | 3987,45182 | 1490259552 |
| September 2026 | 1349,05741 | 1506952891 |
| October 2026 | 456,420786 | 1523647977 |
| November 2026 | 154,41888 | 1540343653 |
| December 2026 | 52,2438749 | 1557039529 |

**Source:** Author own calculation

The Box-Jenkins model was used to predict the level of liquidity within the Agricultural and Rural Development Bank – Tlemcen Agency 013 for the year of 2026. The choice of this model came due to its high ability to deal with time data that includes random fluctuations that are difficult to predict using other traditional models, which allowed us to reach accurate estimates about the size of expected liquidity. This model can also be adopted in the future to predict later periods, after verifying the validity of previous predictions. The results of this forecast are an effective tool that helps bank management improve financial planning and estimate the expected demand for liquidity from customers. This contributes to enhancing the quality of service provided and ensuring the bank's readiness to meet financial needs, thus maintaining customer satisfaction and confidence.

Seasonal liquidity fluctuations constitute the primary problem in agricultural bank liquidity management, stemming from the cyclical characteristics of agricultural production and the ensuing trends in loan demand and deposit flows. For the BADR Tlemcen Agency, comprehending and predicting these periodic trends is essential for proficient liquidity management. **Cowley et al. (2025)** performed a regional investigation of agricultural bank liquidity, revealing significant cyclical trends influenced by agricultural production cycles. During planting seasons, farmers utilize credit lines to acquire seeds, fertilizers, fuel, and other inputs, resulting in significant liquidity withdrawals from the bank. In harvest seasons, agricultural sales produce revenue that contributes to loan repayments and deposits, resulting in liquidity inflows. The timing and extent of these seasonal variations differ by crop variety and regional agricultural methods. In the Tlemcen region, cereal production adheres to an October planting and late spring harvest cycle, viticulture exhibits distinct seasonal patterns, and livestock operations operate on a different rhythm. The variety of agricultural practices generates an intricate seasonal pattern composed of numerous overlapping cycles. Efficient management of seasonal liquidity necessitates precise forecasting of the timing and extent of seasonal peaks and troughs. SARIMA models, which

explicitly integrate seasonal components, are very beneficial for this objective (**Xu et al., 2024**). Historical data over several years facilitates the recognition of consistent seasonal patterns, whereas recent data reflects any alterations in timing or intensity. Nonetheless, seasonal trends exhibit irregularity. Weather variations, commodity price swings, and policy alterations might affect the timing or volume of seasonal liquidity flows. Drought may postpone planting or diminish harvest yields, impacting both the schedule and quantity of loan repayments. Price declines may diminish farmers' income and their capacity to repay loans, even if output levels remain average.

BADR must sustain liquidity reserves adequate to satisfy peak seasonal demands while reducing the opportunity cost associated with retaining surplus liquidity during off-peak intervals. Liquidity at Risk models, which integrate seasonal forecasts with volatility assessments, can inform buffer sizing. Access to seasonal loan lines from the central bank or interbank markets might enhance internal liquidity management, however such access may be restricted for specialized agricultural banks. **Slimane et al. (2013)** concluded that regulatory mandates affect bank conduct and efficacy as well as adherence to liquidity laws necessitates strong forecasting systems, sufficient data infrastructure, and suitable management practices.

## 5. Conclusion:

Liquidity is a fundamental element in the stability of the banking system, playing a pivotal role in ensuring banks' ability to meet their financial obligations on time, fulfil withdrawal and transfer requests, and finance various economic activities. From this standpoint, this study came to highlight the role of quantitative methods in managing liquidity in the bank, due to the accuracy and objectivity that these tools provide in estimation, analysis and forecasting. Quantitative methods have been shown to enable the construction of a scientific understanding of an organization's future financial position, by predicting financial needs and potential liquidity fluctuations. A group of previous studies were then reviewed, which addressed the issue of liquidity or the use of quantitative methods in financial management, both locally and internationally. These studies have generally emphasized the effectiveness of quantitative models in improving financial decision-making within banking institutions, and the importance of integrating these models into financial control and analysis systems to ensure stable cash flow and an accurate balance between available liquidity and existing liabilities.

In this study, we project the above concepts onto the reality of the Bank of Agriculture and Rural Development – Tlemcen Agency 013, by studying and analysing liquidity data during the period from January 2022 to December 2025, and adopting the Box-Jenkins model to predict liquidity levels for the year 2026 using the statistical program EViews 13. The results demonstrated the model's ability to provide accurate and realistic forecasts, reflecting its potential use as a practical tool to assist banks in financial planning. It can also be emphasized that quantitative methods are not merely analytical tools; rather, they represent a strategic pillar for managing bank liquidity, enabling effective handling of sudden market changes, contributing to raising the efficiency of financial performance, and avoiding crises resulting from liquidity imbalances. It also enhances customers' confidence in the banking institution and establishes the principle of proactiveness in financial decision-making.

The literature about the Algerian banking industry, particularly BADR, is scarce, limiting the capacity to offer highly context-specific recommendations. Comprehensive information regarding

BADR's operations, data accessibility, technical proficiencies, and regulatory framework would facilitate more customized guidance.

The guidelines presuppose specific levels of data availability, technological proficiency, and organizational preparedness that may not accurately represent BADR's existing circumstances. The practicality of implementation is contingent upon aspects such as data quality, information technology infrastructure, personnel competence, and management support, which remain inadequately understood.

The regulatory framework in Algeria and its particular application to BADR may impose limits or stipulations not entirely encompassed in this analysis. Effective execution necessitates meticulous collaboration with Algerian banking authorities.

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