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Comparative analysis of private sector financing forecasting in Algeria: Empirical approaches using exponential smoothing and ARIMA models

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Abstract

This article conducts a forecasting analysis of private-sector financing in Algeria based on two distinct methods. The time series studied is the share (% of GDP) of credit allocated to the private sector, covering the annual period from 1964 to 2023. The two forecasting methods employed are exponential smoothing and ARIMA modelling. The results show that the forecasting method by exponential smoothing provides stable forecasts in the short and/or medium term by underestimating major economic shocks. In contrast, the ARIMA approach generates more dynamic forecasts, effectively capturing unpredictable variations. Theoretically, the financial analysis is guided by the works of Box and Jenkins on ARIMA modelling, highlighting the adaptability and precision of this method for adjusting economic policies. In conclusion, combining the two approaches would allow for a more robust evaluation of private-sector financing in Algeria while emphasising the importance of accurate data for reliable economic forecasting.

Keywords: Algeria; private-sector financing; exponential smoothing; ARIMA modelling.
JEL Classification: G21 ; C22; C53

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Introduction

Private sector financing plays a crucial role in economic development by stimulating investment, innovation, and growth. Accurately forecasting financing needs is essential for strategic planning and decision-making by financial institutions and monetary authorities. This topic's significance has been underscored by several researchers and economists, such as (Levine & al, 2005), who have highlighted the significant impact of private financing on economic performance and business development. They argue that effective financial systems, incorporating robust forecasting and resource distribution mechanisms, are essential for sustaining long-term economic growth.

In Algeria, as in many developing countries, anticipating private sector financing needs is fundamental for economic stability and growth. In this context, monetary authorities, particularly the Bank of Algeria, and local financial institutions must employ reliable forecasting methods to anticipate financing needs and adjust policies accordingly. Two commonly used short-term and medium-term forecasting techniques include the classical exponential smoothing method and autoregressive integrated moving average (ARIMA) modelling. Exponential smoothing is often favoured for its simplicity and ability to react quickly to changes in data, while ARIMA modelling, specified through the Box-Jenkins technique, is valued for its capability to model complex time series with trends and seasonal variations. This study aims to address the question: which forecasting method, between classical exponential smoothing and ARIMA modelling, offers the most precise and reliable results for anticipating private sector financing needs in Algeria? To answer this question, we formulated three hypotheses: *i*) Exponential smoothing provides more accurate short-term and mid-term forecasts due to its design based on all observations of the series; *ii*) the Box Jenkins method offers more robust short-term and mid-term forecasts due to its ability to model trends and seasonal variations; *iii*) the relative performance of both methods may vary depending on the economic specificities and characteristics of private sector data in Algeria. This article aims to empirically compare these two methods using real data on private-sector financing. In assessing the accuracy and reliability of their forecasts, this study aims to offer practical policy recommendations for economic decision-makers and financial institutions .

This article is structured as follows: Section 1, presents a literature review of classical forecasting methods, focusing on exponential smoothing and Box Jenkins, with particular emphasis on their application in the financing sector. Section 2, describes the methodology used and presents the results. Section 3, discusses the results in light of economic theory. Finally, we offer conclusions based on the study's findings.

Literature review

Exponential smoothing is a simple and effective forecasting technique that has been applied to various economic time series. In contrast, ARIMA models, introduced by (Box & Jenkins, 1976), are among the most robust methods for modelling economic time series. Their systematic approach to identifying, estimating, and verifying ARIMA models makes them particularly useful for non-stationary economic data.

In the literature, (Brown, 1963) significantly contributed to the popularisation of exponential smoothing forecasting techniques, highlighting their usefulness for economic and commercial applications. He demonstrated that these methods could quickly respond to recent changes in time series, which is essential for economic forecasting.

(Friedman & Schwartz, 1982) examined fluctuations in the demand for money in the United States using exponential smoothing and ARIMA models. They concluded that these methods improved understanding of economic cycles and enhanced the stability of monetary policies.

(Gardner, 1985) explored extensions of exponential smoothing to include trend and seasonality components, making this method even more applicable to complex economic data. He showed that exponential smoothing models with trends and seasonality were particularly useful for medium-term demand forecasts .

(Hafer & Jansen, 1991) used ARIMA models to analyse money demand in OECD countries. Their research demonstrated that these models could capture the long-term effects of monetary policies and economic shocks, providing valuable tools for economic forecasting and policy management.

(Mehra, 1993) applied ARIMA models to forecast money demand in the United States, finding that these models effectively captured structural changes and long-term trends in monetary data. His study's results showed that ARIMA models offered accurate forecasts, aiding in the formulation of more effective monetary policies .

(Box & al, 1994) provided a comprehensive methodology for applying ARIMA models, including techniques for handling seasonal data and structural shocks. Their work enabled economists to better understand and forecast money demand by integrating autoregressive and moving average components.

(Sriram, 2001) studied the aggregate financing of the economy in developing countries using ARIMA and exponential smoothing techniques. His results showed that, despite challenges related to limited data and frequent economic shocks, these methods provided useful forecasts for policymakers.

(Gujarati, 2003) used ARIMA models to analyse monetary financing variations in India, demonstrating the effectiveness of these models in capturing the complex dynamics of monetary time series. He showed that ARIMA-based forecasts were robust even in the presence of significant economic fluctuations .

(Mishkin, 2007) highlighted the importance of accurate forecasts for formulating monetary policies. He showed that reliable forecasting models could help central banks stabilise the economy by proactively adjusting interest rates and managing the money supply .

(Hamilton, 2011) examined the stability of money demand functions using ARIMA models adjusted for recent economic shocks and found that the Box-Jenkins technique was highly robust .

(Ardizzi & al, 2014) used exponential smoothing techniques and aggregate money demand to forecast private sector financing in a European context, highlighting the importance of these methods for policymakers.

(Bredin & al, 2018) explored the implications of monetary policies on private-sector financing using ARIMA models adapted to recent economic data.

(Zhang & al, 2020) used ARIMA models to analyse factors influencing money demand in China, highlighting the implications of monetary policy on the economy.

(Makridakis & Hibon, 2021) applied the Box-Jenkins methodology in the M4 competition and their results showed that ARIMA modelling is robust and interpretable for stationary time series with linear relationships. However, it is very limited in capturing nonlinear relationships and requires complex data preparation.

(Nair & Vittala, 2024) exploited Box-Jenkins ARIMA modelling on infrastructure sector credit in India and found that the method is very robust for predicting measures that encourage infrastructure development in India.

In summary, the results of these studies clearly show that exponential smoothing methods and ARIMA models offer powerful tools for forecasting money demand, which measures the share of private sector financing. By capturing trends and the complex dynamics of monetary time series, these methods allow policymakers to better anticipate changes in money demand and adjust monetary policies accordingly.

1- Methodological approach and results

The financing of the private sector is typically measured by the percentage share of GDP of the credits allocated to the private sector, denoted as CSP (Beck & Levine, 2004) The monetary aggregate (% GDP) is sourced from the World Bank database.
The short- and/or medium-term forecasting of this variable will be carried out using the following methods:

2-1- ARIMA Modelling

The forecasting method using ARIMA modelling, specified by the Box-Jenkins technique, employs the autoregressive integrated moving average (ARIMA) models and consists of primarily five (5) steps (Box & Jenkins, 1976):

- Stationarity: This phase begins with a preliminary analysis of the time series to identify its components, followed by assessing the presence of a unit root primarily using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests.
- Identification: This stage involves examining the autocorrelation functions simple (ACF) and partial (PACF) of the stationary series to select statistically significant models.
- Estimation: After selecting the model based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), parameters are estimated to form a model.
- Validation: This phase verifies that the model residuals behave like white noise, meaning they exhibit a normal distribution (Jarque-Bera test) and no autocorrelation (Q-Ljung test and Durbun Watson test).
- Forecasting: Based on the validated model, this stage generates future forecasts.

2-1-1- Statistical description of the private sector financing variable

Descriptive statistics of the private sector financing (CSP; Table 1) reveal several important characteristics of the time series.

The average private sector financing is 28.5, with a significantly lower median at 17.4.

This suggests an asymmetric data distribution skewed towards lower values, as indicated by a positive Skewness (S) coefficient of 0.82.

The maximum observed value for private sector financing is 69.9, while the minimum value is 3.9, showing a considerable range in the data. The standard deviation of 22.6 indicates a relatively wide dispersion of values around the mean.

The high Kurtosis (K) of 2.16 indicates a leptokurtic distribution, meaning the data have thicker tails and higher concentrations around the mean compared to a normal distribution.

The Jarque-Bera (JB) test yields a statistic of 6.28 with an associated probability of 0.04, indicating that the data distribution deviates from a perfectly normal distribution.

Table (1): Summary statistics of CSP

Mean	**Median**	**Max**	**Min**	**Std. Dev.**	**S**	**K**	**JB**	**Prob**	**Sum**
28.5	17.4	69.9	3.9	22.6	0.82	2.16	6.28	0.04	1211.

Source: Authors' compilation. Notes: (S) Skewness; (K) Kurtosis

The analysis of the time series about the share of credits allocated to the private sector in Algeria from 1964 to 2023 (Figure 1) reveals several significant trends and fluctuations. Initially, the series demonstrated sustained growth until the 1980s, averaging over 37%.

This growth phase could be associated with economic reforms aimed at promoting private initiatives and attracting domestic and foreign investments.

These reforms potentially stimulated private sector expansion during the decade, although it remained relatively small compared to the public sector.

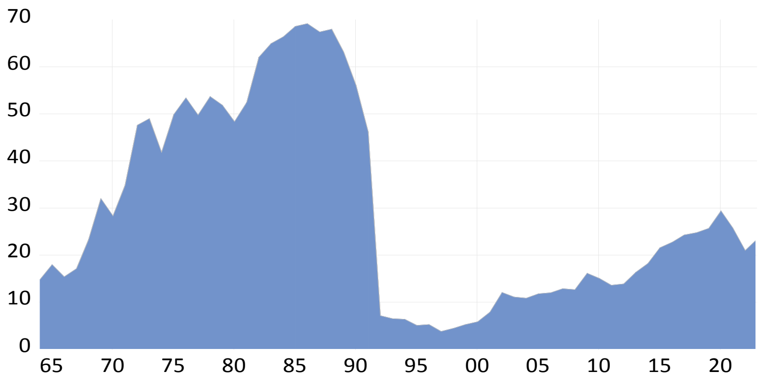
From the 1980s onwards, the series shows a notable and steady increase in private sector financing, reaching substantial levels in the 1990s (over 67% of GDP). This peak can be attributed to a series of economic reforms aimed at liberalising and stimulating the national economy, coupled with a period of relative macroeconomic stability. However, starting in the 2000s, the time series exhibits a marked decline in private sector financing in Algeria (nearly 6%). This period coincides with internal economic and political changes, including monetary and fiscal reforms, which may have impacted investor confidence and financial sector dynamics.

Additionally, external economic shocks such as commodity price volatility contributed to this decline by affecting national income and foreign reserves (Boudjema, 2011).

Subsequent years show some volatility, characterised by periods of recovery followed by slight declines or stabilisation.

This variability can be explained by the private sector's sensitivity to global economic fluctuations and the impact of national economic policies on the business environment.

Figure (1): Share (%) of private sector credit in GDP (1964–2023)



Source: Authors' Own Work

In summary, the results indicate that private sector financing in Algeria exhibits significant variations over time, with a notable trend towards lower values. The data distribution is asymmetric, concentrated around the mean, and has thicker tails than expected in a normal distribution, which may reflect economic fluctuations and policies influencing this specific sector.

2-1-2- Stationarity

The results obtained from the stationarity tests (unit root) are presented in Table 2.

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests applied to the logarithmic time series (ln(CSP)) indicate that the series becomes stationary after first differencing I(1). The results show that all unit roots are eliminated once the series is integrated into order 1. Additionally, the tests reveal the absence of a significant trend or constant in the series, confirming that there are no significant linear components affecting the time series. These findings are crucial for the appropriate modelling of the series, allowing for the consideration of econometric models that account for stationarity and the absence of significant trends or intercepts in the analysis of private-sector financing in Algeria.

Table 2: Unit test roots of *ln*(CSP)

ADF : Model [6]		PP : Model [6]		ADF : Model [5]		PP : Model [5]	
I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
[-1.011] (0.937)	[-5.426]** (0.000)	[-1.253] (0.886)	[-5.418]** (0.000)	[-1.329] (0.6070)	[-5.296]** (0.000)	[-1.543] (0.5021)	[-5.348]** (0.000)
The trend is not significant (P-value 0.41 > 0.05), the series becomes stationary after first differencing.				The intercept is not significant (P-value 0.23 > 0.05), and the series becomes stationary after first differencing.			

Source: Authors' compilation. Notes: [ ] t-stat; ( ) Prob; ** The null hypothesis of the presence of a unit root is rejected at the 5% level.

2-1-3- Identification

According to the autocorrelation function (ACF: Table 3) and partial autocorrelation function (PACF) of the stationary series (Table 3), the identified models are AR(1); AR(3); MA(1); MA(3); ARIMA(1, 1, 1); ARIMA(1, 1, 3); ARIMA(3, 1, 1), and ARIMA(3, 1, 3).

However, only four models with coefficients significant at the 5% level are selected using the Akaike (AIC) and Schwarz Bayesian (BIC) Information Criteria (Table 4).

The value minimising the AIC and BIC information criteria is associated with the autoregressive model of order 3: AR(3).

Table (3): (ACF) and (PACF) of the CPS

Sample (adjusted): 1965 2023
Included observations: 59 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |** |	. |** |	1	0.249	0.249	3.8493	0.032
. |*. |	. | . |	2	0.075	0.014	4.2027	0.122
. |** |	. |**. |	3	0.221	0.212	7.3428	0.048
. |*. |	. | . |	4	0.091	-0.014	7.8900	0.096
. | . |	. | . |	5	-0.019	-0.051	7.9132	0.161
. | . |	. | . |	6	0.013	-0.017	7.9239	0.244
. | . |	. | . |	7	-0.003	-0.021	7.9246	0.339
.*| . |	.*| . |	8	-0.111	-0.101	8.7992	0.360
.*| . |	.*| . |	9	-0.129	-0.085	10.004	0.350
.*| . |	.*| . |	10	-0.145	-0.104	11.542	0.317
. | . |	. |*. |	11	-0.027	0.082	11.598	0.395
. | . |	. |*. |	12	0.034	0.087	11.688	0.471
. | . |	. |*. |	13	0.064	0.106	12.005	0.527
. | . |	.*| . |	14	-0.027	-0.078	12.064	0.601
. | . |	. | . |	15	0.019	0.006	12.095	0.672
. | . |	.*| . |	16	-0.058	-0.133	12.377	0.718
.*| . |	.*| . |	17	-0.150	-0.140	14.294	0.646
. |*. |	. |*. |	18	0.075	0.122	14.788	0.676
. | . |	.*| . |	19	-0.059	-0.107	15.101	0.716
*| . |	.*| . |	20	-0.228	-0.148	19.910	0.464
.*| . |	.*| . |	21	-0.154	-0.077	22.144	0.391
. | . |	. | . |	22	-0.053	0.049	22.416	0.435
*| . |	.*| . |	23	-0.223	-0.133	27.371	0.241
.*| . |	. | . |	24	-0.134	-0.033	29.223	0.212

Source: Authors' compilation .

Table (4): Selection of the most significant model

	AR(1)	AR(3)	MA(1)	ARIMA (1, 1, 1)
AIC	-1.054769	-1.172779	-0.982924	-1.116690
BIC	-0.972853	-0.973772	-0.901008	-0.993815

Source: Authors' compilation .

2-1-4- Estimation

The three terms of the Autoregressive model are statistically significant (P-value < 0.05), indicating that each of the three lags in the model contributes significantly to explaining the variation in the time series of private sector financing (Table 5).

The Durbin-Watson statistic (DW) is 1.97, close to the critical value of 2, suggesting no significant autocorrelation of errors.

The Fisher probability associated with the model (P-value: 0.009 < 0.05) indicates that the model as a whole is statistically significant at the 5% level.

These initial results are promising, but further validation of the AR(3) model is necessary to ensure its robustness and its ability to effectively capture the underlying dynamics of private sector financing in Algeria.

Table (5): AR(3) model estimation

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.082819	0.083682	0.989682	0.3286
AR(1)	0.305434	0.135135	2.260214	0.0296**
AR(2)	-0.031342	0.065919	-2.103234	0.0183**
AR(3)	0.338697	0.941862	2.780842	0.0029**
SIGMASQ	0.014107	0.002857	4.937041	0.0000**

Source: Authors' compilation; ** significant at the α=5% level.

2-1-5- Validation

The residuals of the AR(3) model follow a normal distribution according to the Jarque-Bera test results : JB = 1.139 and P-value (JB)= 0.567.

Table (6): Normality tests of residuals

	Jarque Bera	Kurtosis	Skewness
t-statistic	1.139**	3.523	0.3187
Prob	0.567	-	-

Source : Authors' compilation; ** The null hypothesis of residual normality is accepted at the α=5% level.

In terms of residual autocorrelation, the Box-Ljung statistic: Q = 19.79 is lower than the Chi-square value $\chi^2_{(20)}$ = 31.41 at the 5% critical level. This indicates that there is no significant autocorrelation of errors in the AR(3) model (Table 7). The residuals of the AR(3) model thus exhibit white noise.

Table (7): (ACF) and (PACF) of the residuals AR(3) model

Sample (adjusted): 1965 2023
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.004	-0.004	0.0008	
. | . |	. | . |	2	0.024	0.024	0.0382	0.845
. |*. |	. |*. |	3	0.200	0.201	2.6212	0.270
. | . |	. | . |	4	0.051	0.055	2.7938	0.425
. | . |	. | . |	5	-0.035	-0.045	2.8758	0.579
. | . |	. | . |	6	0.017	-0.028	2.8959	0.716
. | . |	. | . |	7	0.017	-0.003	2.9153	0.819
.*| . |	.*| . |	8	-0.097	-0.087	3.5789	0.827
.*| . |	.*| . |	9	-0.072	-0.074	3.9556	0.861
.*| . |	.*| . |	10	-0.126	-0.135	5.1238	0.823
. | . |	. | . |	11	0.001	0.036	5.1238	0.883
. | . |	. | . |	12	0.017	0.070	5.1449	0.924
. | . |	. |*. |	13	0.073	0.141	5.5578	0.937
. | . |	. | . |	14	-0.055	-0.052	5.8022	0.953
. | . |	. | . |	15	0.041	0.009	5.9366	0.968
. | . |	.*| . |	16	-0.025	-0.080	5.9874	0.980
.*| . |	.*| . |	17	-0.175	-0.198	8.6074	0.929
. |*. |	. |*. |	18	0.129	0.096	10.072	0.901
. | . |	. | . |	19	-0.044	-0.038	10.243	0.924
.*| . |	.*| . |	20	-0.189	-0.142	13.529	0.810
.*| . |	.*| . |	21	-0.114	-0.130	14.762	0.790
. | . |	. | . |	22	0.030	0.059	14.848	0.830
**| . |	.*| . |	23	-0.213	-0.112	19.364	0.623
. | . |	. | . |	24	-0.065	-0.032	19.798	0.654

Source: Authors' compilation.

2-1-6- Forecasting

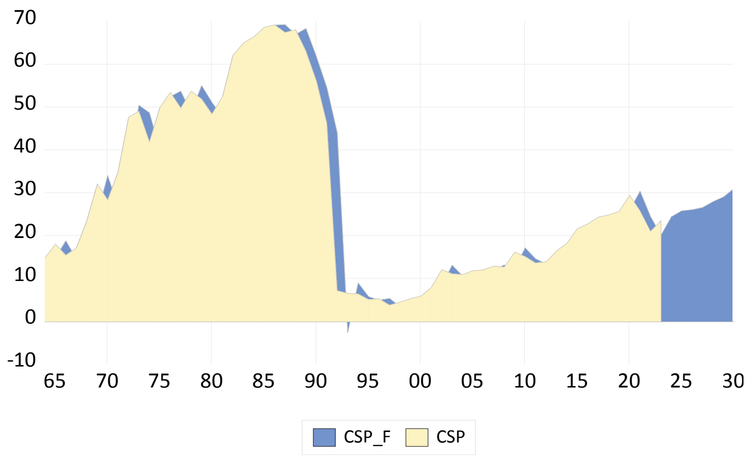
We have tested a medium-term forecast on the horizon of h = 7 (Table 8). The root mean squared error: RMSE=6.23 of the ARIMA modelling forecast is significantly lower than the mean: 28.5, indicating that the model accurately captures data variations with good precision.

Table (8) : CSP series forecasting using ARIMA modelling

Horizon (h)	1	2	3	4	5	6	7
CSP_F (%GDP)	24.49	25.86	26.13	26.64	28.03	29.11	31.14

Source: Authors' compilation.

Figure (2): Observed, Estimated, and Forecasted CSP



Source: Authors' Own Work. CSP _F is the series estimated and predicted by the ARIMA modelling; CSP is the observed series.

2-2- Exponential smoothing

Referring to the results obtained from the ARIMA model forecast, the CSP series does not exhibit a trend. Furthermore, for a series with an annual frequency, seasonality defined by intra-annual cycles (monthly, quarterly, or semi-annual) cannot be identified.

The CSP series forecasting, characterised by the absence of trend and seasonality, corresponds to the simple exponential smoothing method:

$$CSP_t = a + \varepsilon_t$$

The forecast of the series CSP_t at the horizon h, $\widehat{CSP}_T$ (h), provided by the simple exponential smoothing method, is given by the model below, which smooths the series once and then predicts it:

$$\widetilde{CSP}_t = \alpha\, CSP_t + (1-\alpha)\widetilde{CSP}_{t-1}$$

$$\widetilde{CSP}_{T+1} = \alpha\, CSP_t + (1-\alpha)\widetilde{CSP}_t$$
$$CSP_1 = \widetilde{CSP}_1$$

$\widetilde{CSP}_t$: The smoothed series

$\widetilde{CSP}_{T+\square}$: The predicted series

$0 \leq \alpha \leq 1$: Smoothing coefficient

In practice:
If a flexible forecast is desired, one would choose $\alpha \in [0.7; 0.99]$.
If a rigid forecast is desired, one would choose $\alpha \in [0.01; 0.3]$. Alternatively, another data-driven solution is to select α that minimises the sum of squared forecast errors at times 1,.., T at h (Hyndman & Athanasopoulos, 2018).
The time series of private sector financing requires a more flexible rather than rigid forecast because it provides the essential flexibility to respond to economic uncertainties, policy changes, and unforeseen events (Friedman, 1960).
This improves forecast accuracy and ensures more efficient and responsive economic management (Taylor, 1993).
The forecast at the horizon h=7, using simple exponential smoothing, yields the results presented in Tables 9 and 10.

Table (9): Showing exponential smoothing forecasting of CSP

Sample: 1964 2023
Included observations: 60
Method: Single Exponential
Original Series: CSP
Forecast Series: CSPSM

Parameters:	Alpha	0.9990
Sum of Squared Residuals		3343.312
Root Mean Squared Error		7.464708
End of Period Levels:	Mean	23.58714

Source: Authors' compilation.

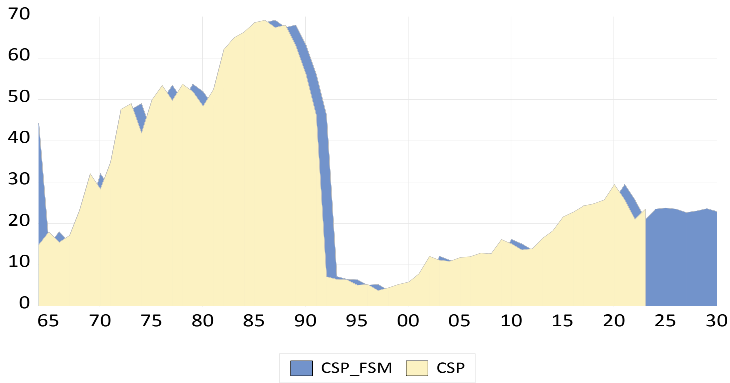
Table (10): CSP forecasting using exponential smoothing

Horizon (h)	1	2	3	4	5	6	7
CSP_FSM (%GDP)	23.58	23.89	23.58	22.79	23.16	23.69	23.11

Source : Authors's compilation .

The root mean squared error: RMSE=7.46 of the forecast obtained using the simple exponential smoothing method is lower than the mean: 28.5, indicating that the forecast is reasonable and exhibits effective precision quality.

Figure (3): Observed, Estimated, and Forecasted CSP



Source: Authors' Own Work. CSP_FSM: the series estimated and predicted by the exponential smoothing method; CSP: the observed series.

3- Discussion

First, the forecasts obtained through the simple exponential smoothing method show relatively stable values over the seven-year horizon (2024–2030). This suggests that this method has failed to capture significant economic fluctuations or specific shocks that often affect the Algerian economy. According to (Brown, 1963), simple exponential smoothing is better suited to relatively smooth time series that are less subject to sudden changes.

In contrast, the forecasts from ARIMA modelling, specifically using the Box-Jenkins method, exhibit more dynamic and responsive trends. This method is renowned for its ability to model complex time series with seasonal structures and non-linear trends (Harvey, 2020). It therefore appears better suited to capturing significant variations in the Algerian economy, including the effects of economic policies, fluctuations in commodity prices, and other external and internal factors.

Statistically, comparing the RMSE between the two methods is also instructive. The lower RMSE for the ARIMA method suggests better forecasting accuracy relative to the observed values in the tested data sample. This observation aligns with (Chatfield, 1993) findings, which highlight the effectiveness of ARIMA models in reducing forecasting errors compared to smoothing approaches.

Economically, choosing the best forecasting method depends on specific objectives and the nature of the data. The financing of the private sector in Algeria is characterised by highly significant and unpredictable economic shocks due to several factors:

- Dependence on Natural Resources: The economy's heavy reliance on natural resources means that fluctuations in oil prices on international markets directly impact public finances and the country's balance of payments (Mehlum & al, 2006 ; Jensen, 2015)
- Volatility of Public Revenues and Expenditures: The volatility of oil revenues leads to fiscal and budgetary policies that are often influenced by these revenue fluctuations.
- Exchange Rate Fluctuations: Changes in exchange rates can affect the competitiveness of non-oil exports and domestic inflation. These variations impact import costs and the country's ability to maintain a sustainable external economic balance.

Given these circumstances, where the financing of the Algerian private sector operates, the ARIMA method is superior in terms of adaptability and responsiveness to economic changes (Brockwell & Davis, 2016 and Moataz, 2023) However, the use of simple exponential smoothing can be justified in contexts where the time series is more stable and changes are less volatile ((Makridakis & Hibon, 2021).

Conclusion

This study empirically examined the forecasting of private sector financing in Algeria using two methods: exponential smoothing and ARIMA modelling. The results obtained from an annual time series measuring private sector financing, covering the period from 1964 to 2023, highlighted significant differences in medium-term forecasts, with important implications for the country's economic policy.

Simple exponential smoothing, while offering relatively stable forecasts over the seven-year horizon (2024–2030), appears less sensitive to major economic shocks such as oil price fluctuations and rapid budgetary adjustments that characterise the Algerian economy. In contrast, ARIMA modelling, particularly the Box-Jenkins method, demonstrated superior capability in capturing these unpredictable variations, providing more dynamic and fluctuating forecasts.

Economically, these results underscore the importance of choosing forecasting methods suited to the country's economic volatility. ARIMA modelling has proven effective in accurately anticipating fluctuations in private sector financing, thus providing economic policymakers with robust tools to adjust economic policies in response to changing conditions.

However, it is essential to acknowledge the intrinsic limitations of both approaches. Simple exponential smoothing may lack the flexibility to model abrupt changes and non-linear trends, while ARIMA modelling requires comprehensive historical data and may be sensitive to the initial model specification.

In conclusion, this study enriches the literature on forecasting private sector financing in Algeria by highlighting the strengths and limitations of exponential smoothing and ARIMA modelling methods. For effective and prudent economic policy management, it is recommended to integrate the results from both approaches for a more robust assessment of private sector financing. Additionally, continuous efforts to improve data collection and adapt models to Algeria's specific economic realities are crucial for more accurate and reliable forecasting.

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