

# Ranking the Determinants of the Tunisian Central Bank's Efficiency: Evidence from Var, Impulse Response Functions and Variance Decomposition

Faiza Bouhouch\*

*Faculty of Management and Economics of Nabeul, University of Carthage, Tunisia*

**Abstract:** While the determinants of banking efficiency have been extensively debated, there is a notable lack of analysis regarding the efficiency of central banks. This study aims to identify and prioritize the macroeconomic and institutional factors that have the greatest impact on the efficiency of the Central Bank of Tunisia between 2000 and 2020. To accomplish this, we employed a dynamic approach using a Vector Autoregression model, Impulse Response Functions, and Variance Decomposition methods to assess the effects of each variable on the efficiency score. Our analysis shows that the most significant factors affecting the Central Bank of Tunisia's efficiency include GDP, internal conflicts, fiscal deficits, government stability, and inflation. Moreover, the findings suggest that the degree of central bank independence has a relatively limited impact on its efficiency.

**Keywords:** Central banking, Efficiency, VAR model, Impulse response function, Variance decomposition.

**JEL Codes:** C51, D610, C32, E52, E58.

## 1. INTRODUCTION

As financial globalization continues to grow and the global banking industry expands, evaluating the performance of banking institutions has become increasingly important. The evaluation process has evolved by adapting Farrell's (1957) concept of efficiency, initially applied to firms, to the banking sector. Berger and Mester (1997) suggest that a thorough assessment of banking efficiency should go beyond just the technical aspects of production technology. Instead, it should include economic optimization, considering market prices and competition.

The performance and efficiency of banks have been extensively studied from theoretical and empirical perspectives. However, a review of the literature reveals a clear gap in research focused on central banks, where studies remain relatively limited (Gomez Gallego, 2020; Faroq Dar and al., 2021a-b; Veyrune and Zerbo, 2023).

The assessment of the efficiency of central banks is a complex undertaking, due to the distinctive nature of their operations and the multiplicity of objectives they pursue (Mester, 2003; Veyrune and Zerbo, 2023). In contrast to commercial enterprises or banks, profitability does not apply to central banks because they are non-profit public institutions. Consequently, it is essential to comprehend the notion of central bank efficiency in terms of how the central bank generates its output with the inputs employed (Blix and al., 2003; Mester, 2003).

The research undertaken by Gomez Gallego (2020), Faroq Dar and al. (2021a, 2021b), and Veyrune and Zerbo (2023) suggest that the efficiency scores of central banks are

influenced by a multitude of economic (GDP, export, import...) and non-economic variables (corruption, central bank independence...). In the same vein, the primary goal of this research is to identify and prioritize the macroeconomic and institutional elements that have the greatest impact on the Central Bank of Tunisia (CBT) efficiency and assess the relative significance of each factor.

The selection of an appropriate methodology is crucial. By drawing upon existing literature (2), we can identify the best way to specify our models (3), which will then allow us to discuss the results of the decomposition of the CBT efficiency scores (4).

## 2. LITTERATURE REVIEW

According to Zaefarian and al. (2022), variance decomposition technique play a crucial role in understanding the relative contribution of different factors to outcomes in various disciplines like strategic management, international business, and economics. They allow researchers to dissect the total variability of a phenomenon into distinct components, revealing the specific impact of each factor. Conducting variance decomposition (VD) and the related impulse response functions (IRF) requires the implementation of a suitable vector modeling protocol.

### 2.1. Vector Modeling Protocols

Vector Autoregressive Model (VAR) and Vector Error Correction Model (VECM) are the main techniques for differentiating the effects and sensitivities of variables using the decomposition method. According to Sims (1980), a VAR ( $p$ ) model with a general formulation of  $N$  variables and  $p$  lags takes the following form where each of the  $Y_{it}$  variables is related to its past values:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + \varepsilon_t \quad (1)$$

\*Address correspondence to this author at the Faculty of Management and Economics of Nabeul, University of Carthage, Tunisia;  
E-mail: b\_faiza@yahoo.com

Where:  $Y_{it}$ : variables,  $i$ : 1, ...,  $n$ ;  $t$ : 1, ...,  $T$ ,  $N$  number of variables  $p$ : number of lags,  $\Phi_{ij}$ : coefficients of the model variables of the polynomial matrix  $\Phi(p)$  in the delay operator,  $\varepsilon_t$ : white noise.

Before estimating a VAR model, it's essential to test for unit roots to ensure the variables are stationary. The Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) is commonly used for this purpose. It evaluates the null hypothesis that a unit root is present in the time series, indicating non-stationarity. The formal definition of the ADF test involves estimating the following regression:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \sum_{i=1}^p \gamma_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

Where:  $y_t$ : the variable of interest,  $\varepsilon_t$ : white noise error term,  $\alpha$ ,  $\beta$ ,  $\gamma$ : parameters to be estimated.

If the estimated  $\gamma$  is significantly less than zero, it suggests that the series is stationary.

In second step, the optimal lag is specified according to the Akaike Criteria (AIC) (Akaike, 1973) whose respective values are calculated by:

$$AIC(p) = \log|\hat{\Sigma}| + \frac{2}{T} n^2 p \quad (3)$$

Where:  $\hat{\Sigma}$ : variance-covariance matrix,  $T$ : the number of observations,  $p$ : optimal lag,  $n$ : number of regressors.

Once the appropriate number of lags is determined, the Johansen (1988) test is employed to identify the number of cointegration relationships ( $r$ ). This test is based on maximizing the following log-likelihood function:

$$\log L(\alpha, \beta, B_1, \dots, B_{p-1}, \Sigma) = -\frac{NT}{2} \log(2\pi) - \frac{T}{2} \log[\det(\Sigma)] - \frac{1}{2} \sum_{t=1}^T \varepsilon_t \Sigma^{-1} \varepsilon_t \quad (4)$$

Where:  $T$ : the number of observations,  $N$ : the number of variables in  $X$ ,  $\det(\Sigma)$ : the determinant of the variance-covariance matrix.

The maximum likelihood estimator of  $\beta$  is obtained by solving equation (5):

$$\text{Det} [\lambda S_{pp} - S_{p0} S_{00}^{-1} S_{0p}] = 0 \quad (5)$$

Where:  $S_{ij} = \frac{1}{T} \sum_{t=1}^T e_{it} e_{jt}'$  where  $i, j=0$ .

The Trace test is used to determine the number of cointegrating relationships ( $r$ ). It tests the null hypothesis  $H_0$  that there are at most ( $r$ ) cointegrating relationships:

$$H_0: \lambda_i = 0, \quad i = r + 1, \dots, N$$

The TR statistic for the Trace test is:

$$TR = -T \sum_{i=r+1}^N \log(1 - \bar{\lambda}_i) \quad (6)$$

The Trace test compares the TR statistic to critical values to determine the number of cointegrating vectors. Two possible scenarios can be considered:

1. The null hypothesis is rejected ( $r = 0$ ): there is no cointegration relationship among the variables. In this case, it is recommended to estimate either: a VAR model in levels if the variables are stationary

I(0) or a VAR model in first differences if the variables are non-stationary I(1).

2. The null hypothesis is accepted ( $r \neq 0$ ): there is, at least, one cointegrating relationship among the variables. Vector Error Correction Model (VECM) can be estimated.

The VECM approach, proposed by Engel and Granger (1987), VECM accounts for both the short-term dynamics and the long-term equilibrium relationships between the variables. In light of the following VAR( $p$ ) representation of a vector  $X_t$  comprising  $N$  variables:

$$X_t = A_1 X_{t-1} + A_p X_{t-p} + \varepsilon_t \text{ avec } \varepsilon_t \sim N(0, \Sigma) \quad (7)$$

$$(N, 1) \quad (N, N) \quad (N, 1) \quad (N, N) \quad (N, 1) \quad (N, 1)$$

The VECM model can be written as follows:

$$\Delta X_t = B_1 \Delta X_{t-1} + B_{p-1} \Delta X_{t-p+1} + \Pi X_{t-1} + \varepsilon_t \quad (8)$$

Where:  $B_i = \sum_{j=i+1}^p -A_j$ ,  $i = 1, \dots, k-1$ ;  $\Pi = A_1 + \dots + A_k - I = \alpha\beta'$ .  $\beta'$ : matrice ( $r, N$ ) comprenant les  $r$  relations de cointégration.  $\alpha$ : matrice ( $N, r$ ) contenant les vitesses d'ajustement pour chacun des vecteurs de cointégration.

## 2.2. Vector Model Extensions

To better understand the dynamic relationships between variables, forecast error variance decomposition and impulse response functions are commonly employed. Both (VAR) and (VECM) can be utilized to analyze dynamic effects through the simulation of random shocks (Swanson and Granger, 1997; Lütkepohl, 2010). By introducing artificial shocks (or innovations), it is possible to examine the impact of disturbances in one variable on others, while assuming that all other factors remain constant.

Impulse response functions (IRFs) represent a methodology employed to quantify the influence exerted by a discrete shock upon a system of variables within a given model. The impulse is equivalent to an isolated shock with a value equal to the standard deviation of the variable in question. The first step in analyzing IRF is to rewrite the VAR process in Vector Moving Average (VMA) (Bourbonnais, 2018) where the  $M$  matrix is referred to as the "impact multiplier," signifying that each shock ( $v_t$ ) influences the other variables through this matrix.

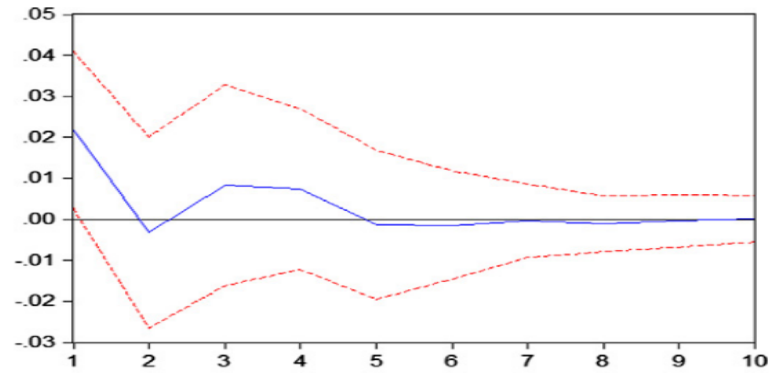
$$Y_t = \mu + v_t + M_1 v_{t-1} + \dots = \mu + \sum_{i=0}^{\infty} M_i v_{t-i} \quad (9)$$

Where:  $\mu = (I - A_1 - A_2 - \dots - A_p)^{-1} * A_0$ ,

$$M_i = \sum_{j=1}^{\min(p, i)} A_j M_{i-j}, i = 1, 2, \dots \text{ et } M_0 = I$$

The impact of an innovative concept can be assessed with its deviation from established norms, with this effect diminishing over time. Fig. (1) illustrates how the variables in the model respond to a 1% standard deviation shock to another variable. The horizontal axis represents the number of periods (10 years), while the vertical axis indicates the magnitude of the shock's effect.

The analysis of IRF is frequently enhanced by examining the variance decomposition of forecast errors (VDFE). This methodology provides valuable insights into the degree to



**Fig. (1).** Impulse Response Function.

**Table 1.** Definition of variables.

Variable	Definition	Source
GDP	Annual growth rate of GDP	(WDI)
INF	Annual inflation rate as measured by CPI	(WDI)
BD	Budget deficit as % of GDP	(WDI)
UN	Unemployment rate as % of labor force	(WDI)
IC	Internal Conflicts: Evaluation of political violence in the country	(ICRG)
SGOV	Government stability: Assessment of the government's ability to implement the program(s) it has declared and its ability to remain in power	(ICRG)
PS	Political stability and absence of violence measure perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism	(WGI)
STA	A binary variable of status: 0 for CBT dependency and 1 for independent CBT	Author
EFF	CBT efficiency scores calculated by SFA	Author

which forecast errors can be attributed to the initial shock as opposed to other underlying factors. By quantifying the relative contributions of each innovation, variance decomposition offers a nuanced understanding of the dynamics at play, elucidating both the direction and magnitude of a system's evolution in response to a shock.

Consider a VAR (1) with two variables  $Y_{1t}$  and  $Y_{2t}$ . The variance of the forecast error for  $Y_{1t}$  at horizon  $h$  is written as:

$$\sigma_{y_1}^2 = \sigma_{v_1}^2 [m_{11}^2(0) + m_{11}^2(1) + \dots + m_{11}^2(h-1)] + \sigma_{v_2}^2 [m_{21}^2(0) + m_{21}^2(1) + \dots + m_{21}^2(h-1)] \quad (10)$$

The variance decomposition, in percent, of  $Y_{1t}$  on  $Y_{2t}$  is given by:

$$\frac{\sigma_{v_2}^2 [m_{21}^2(0) + m_{21}^2(1) + \dots + m_{21}^2(h-1)]}{\sigma_{y_1}^2(h)} \quad (11)$$

In the presence of a shock ( $v_t$ ) to  $Y_{1t}$  which does not impact the variance of the forecast error for  $Y_{2t}$ , it can be concluded that  $Y_{2t}$  evolves independently and can be regarded as exogenous. Conversely, if the shock ( $v_t$ ) affects the variance of the forecast error, then  $Y_{2t}$  is considered endogenous.

### 3. DATA AND METHODOLOGY

#### 3.1. Data

The study focuses on the Central Bank of Tunisia case over the 2000-2020 period. Macroeconomic and institutional variables are employed as explanatory variables (Table 1). The CBT efficiency scores were subsequently calculated by Ati, Bouhouch, and Daly (2023).

#### 3.2. Methodology

The requisite unit root tests were conducted before the selection of a VAR or VECM model (Table 2). Akiak information tests are employed to determine the optimal lags. It is defined as two lags for macroeconomic and institutional variables (Appendix 1). These lags are unlikely to weaken the model's explanatory power.

The VAR (2) estimated for the group of macroeconomic variables is written as:

$$\Delta EFF = \beta_0 + \sum_{i=1}^2 \beta_{1i} \Delta EFF_{t-1} + \sum_{i=1}^2 \beta_{2i} \Delta GDP_{t-1} +$$

Table 2. ADF stationary tests.

Variable	At level t-Statistic (Prob.)	In difference 1 <sup>st</sup> t-statistic (Prob.)	Results
EFF	-2.39* (0.15)	-5.76 (0.00)	Stationary in level I (1)
GDP	-2.56 (0.29)	-4.43* (0.00)	Stationary in first difference I (1)
BD	0.14 (0.71)	-4.04* (0.00)	Stationary in first difference I (1)
INF	-5.89* (0.00)	-5.96 (0.00)	Stationary first difference I (1)
UN	-1.85 (0.34)	-4.21* (0.00)	Stationary in first difference I (1)
PS	-2.35 (0.16)	-2.92* (0.00)	Stationary in first difference I (1)
IC	-2.21 (0.45)	-5.41* (0.00)	Stationary in first difference I (1)
SGOV	-1.18 (0.20)	-3.83* (0.00)	Stationary in first difference I (1)

Source: Authors' estimates on Eviews

\*Values are significant at the 5% threshold.

Table 3. Robustness tests of the macroeconomic and institutional variables.

Macroeconomic Variables			Institutional Variables		
Tests	F-stat (Proba)	Decision	Tests	F-stat (Proba)	Decision
Normality (Jarque-Berra)	1.38 (0.50)	Normal Distribution	Normality (Jarque-Berra)	1.41 (0.54)	Normal Distribution
Breusch-Godfrey Test	0.19 (0.82)	No Autocorrelation	Breusch-Godfrey Test	1.46 (0.05)	No Autocorrelation
Breusch-Pagan-Godfrey Test	0.72 (0.52)	Heteroscedasticity	Breusch-Pagan-Godfrey Test	0.85 (0.44)	Heteroscedasticity

Source: Authors' estimates on Eviews.

$$\sum_{i=1}^2 \beta_{3i} \Delta INF_{t-1} + \sum_{i=1}^2 \beta_{4i} \Delta BD_{t-1} + \sum_{i=1}^2 \beta_{5i} \Delta UN_{t-i} + u_t \quad (12)$$

Where:  $\Delta$ : first difference operator.  $\beta_{ij}$ : variables coefficients.  $u_t$ : white noise.

The VAR (2) estimated for the group of institutional variables is written as:

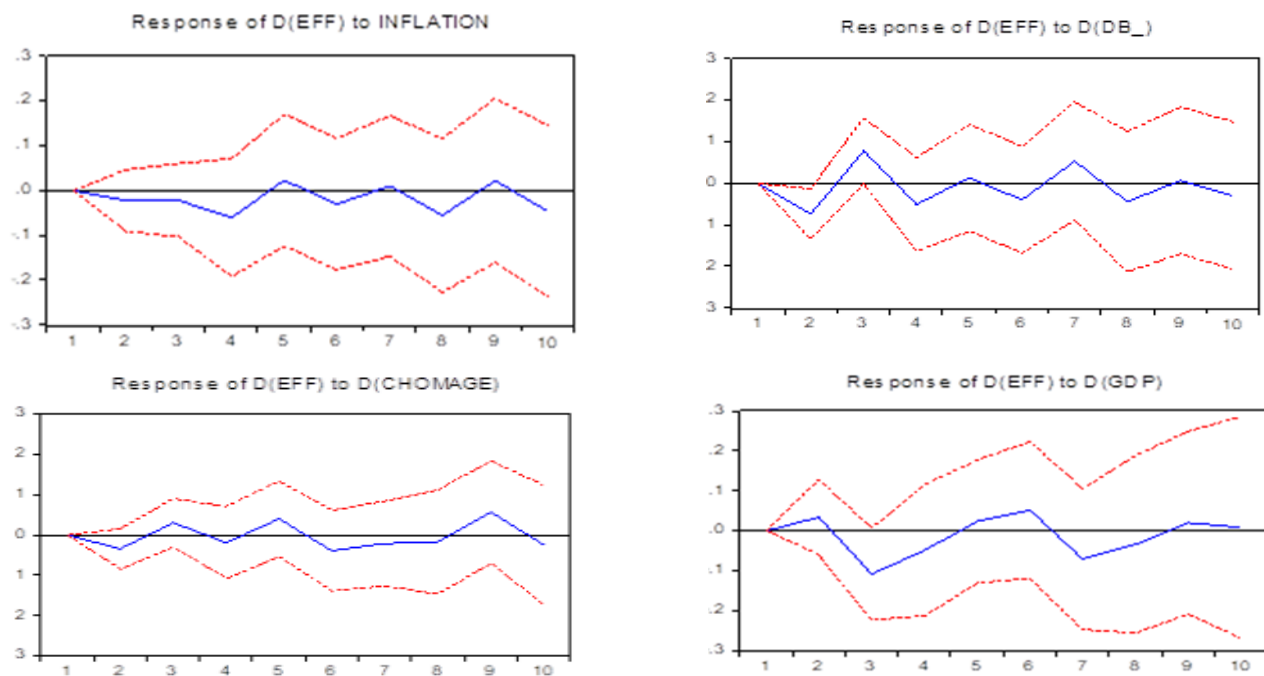
$$EFF = \beta_0 + \sum_{i=1}^2 \beta_{1i} EFF_{t-1} + \sum_{i=1}^2 \beta_{2i} IC_{t-1} +$$

$$\sum_{i=1}^2 \beta_{3i} SGOV_{t-1} + \sum_{i=1}^2 \beta_{4i} PS_{t-1} + \sum_{i=1}^2 \beta_{5i} STA_{t-i} + u_t \quad (13)$$

Where:  $\Delta$ : first difference operator.  $\beta_{ij}$ : variables coefficients.  $u_t$ : white noise.

The results of the VAR model are reported in Appendix 2 (macroeconomic model) and 3 (institutional model).

The robustness tests are presented in Table 3. These tests demonstrate the absence of error autocorrelation the absence of heteroscedasticity and normality. Consequently, it can therefore be concluded that the model is well-specified.



**Fig. (2).** IRF of macroeconomic shocks on CBT's efficiency.

Source: Authors' estimates on Eviews.

## 4. FINDINGS AND DISCUSSION

The objective of this section is to examine the impact of external shocks on macroeconomic and institutional variables on the efficiency score of the CBT, using the technique of impulse response functions. This analysis will be complemented by a decomposition of the variance of the residuals for each category of variables mentioned previously.

### 4.1. Macroeconomic Factors

An impulse response function analysis was conducted to ascertain the impact of a one-standard-deviation shock of each macroeconomic variable on the CBT's efficiency scores (Fig. 2).

The findings show that the efficiency score of the CBT decreases in response to an inflation shock starting from the second period. This impact is even more pronounced in the fourth period, with a 1% increase in inflation leading to a 0.06% decrease in the efficiency rating. This result indicates that despite multiple increases in policy rates, the CBT's attempts to control inflation have not been effective due to the significant impact of imported inflation. Our findings align with Belhedi and al. (2015), demonstrating that reducing one standard deviation in imported inflation positively affects GDP for approximately nine quarters. Controlled inflation in periods 5, 7, and 9 leads to enhanced savings, surplus supply, increased exports, GDP growth, and improved the efficiency of the CBT.

An investigation into the CBT's efficiency in response to a fiscal shock manifested as a 1% increase in public spending, reveals fluctuating effects. The CBT's efficiency score initially exhibits a negative reaction in the second period, with a decline of -0.07%. This is followed by a slight in-

crease of 0.07% in period 3, and these oscillations persist until the end of the period. These results indicate that the anticipated growth in GDP resulting from a fiscal spending shock is only slightly positive and does not accelerate growth or employment in the near term. This is because more and more public funds are being directed towards managing expenses and paying salaries, while less money is being invested in development and public projects.

Based on Fig. (2), a 1% increase in unemployment caused minor changes in the CBT's efficiency score starting from the second period. We believe that this outcome is caused by the high unemployment rate in Tunisia, which lowers wage earnings, hampers savings formation, and diminishes deposits in commercial banks, forcing them to borrow from the CBT to provide loans. This source boosts the CBT's revenue and consequently improves its performance.

The findings indicate that the CBT's efficiency score exhibits oscillatory behavior in response to a shock to GDP. The impact of the GDP shock is first observed in the second period, where the efficiency score shows a small positive increase (0.033%) with a 1% rise in GDP. However, this effect becomes significantly negative in the third period, with a 0.10% decline in efficiency. There is a slight increase in the influence of the GDP shock on efficiency from the fifth to the sixth periods. This is followed by a 0.07% decrease in the seventh period, but then the trend reverses, leading to no change by the end of the period.

Typically, we can expect that the supply shock initially had a beneficial impact on local demand and inflation, which was then positively transmitted to the central bank. The diminishing positive impact could be due to the lack of a direct relationship between GDP and the efficiency of the CBT, as demonstrated by the Granger test. A disturbance in GDP

**Table 4. Variance decomposition (macroeconomic variables).**

Période	S.E.	D(EFF)	D(GDP)	D(INF)	D(DB)	D(UN)
1	0.100282	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.135674	55.29028	6.268231	2.688131	29.41281	6.340540
3	0.196847	29.10931	33.41695	2.485556	29.58769	5.400498
4	0.228460	30.14923	29.40040	8.886534	26.88274	4.681082
5	0.235172	28.88882	28.70407	9.338817	25.69210	7.376200
6	0.251745	27.43982	29.25399	9.572708	24.92558	8.807894
7	0.280973	31.01663	29.90119	7.818996	23.63209	7.631097
8	0.294782	29.83183	28.50098	10.66227	23.71500	7.289920
9	0.304773	29.81105	27.09002	10.51575	22.23479	10.34839
10	0.311197	28.89379	26.05365	12.31698	22.20505	10.53054

Source: Authors' estimates on Eviews.

indirectly affects efficiency through its impact on the budget deficit and unemployment.

The findings from the impulse response analysis are combined with the results of the variance decomposition (Table 4). This demonstrates that during the initial period, the efficiency score is entirely attributable to these inherent innovations. The influence of the other variables becomes apparent in the second period, particularly the importance of the budget deficit in explaining the efficiency score (at 29.41%). The decomposition of the variance over 10 periods shows that the efficiency score of the CBT is first explained by its innovations (28.89%), then by GDP (26.05%), and subsequently by the budget deficit (22.20%). Inflation and unemployment account for 12.31% and 10.53% of the CBT scores, respectively.

#### 4.2. Institutional Factors

As depicted in Fig. (3), the CBT's efficiency is significantly impacted by internal conflicts. The onset of an unexpected internal disruption, such as the Arab Spring, adversely affects economic and social stability leading to declines in tourist numbers, investment, and GDP and resulting in a significant loss of currency value. Consequently, the CBT's efficiency score has shown a decline starting from the third period. However, this negative impact gradually dissipates after the fifth period.

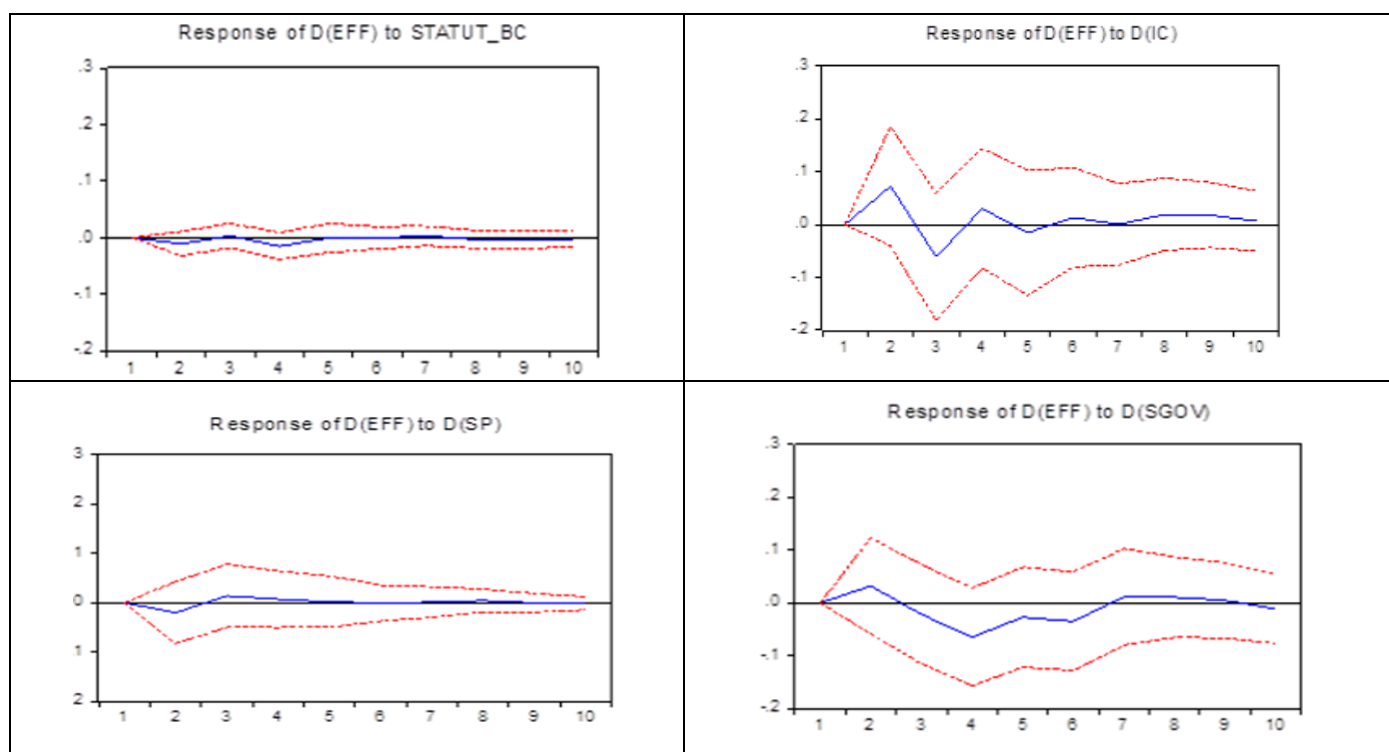
This finding aligns with the work of Lanouar and Goaid (2019), who concluded that a terrorist shock negatively affects tourist flows for 1 year and 2 months. The increase in the CBT's efficiency during the first period, immediately after the Arab Spring, can be attributed to the broad sympathy of Tunisia by major economic powers. This sympathy was reflected in the financial and economic assistance provided by international financial institutions, particularly the IMF and the World Bank, as well as aid from the European Union.

Theoretically, political stability and governance improvements should positively impact GDP growth and, consequently the efficiency of the CBT score. However, our findings indicate that the CBT score exhibited only a slight and insignificant positive reaction from the second period onwards in response to a 1% increase in government stability. This effect turned negative in the third period and ultimately dissipated by the end of the seventh period. These results can be reasonably attributed to the uncertainty and risk aversion inherent in the Tunisian business climate, which impedes economic growth. In Tunisia, factors such as the outflow of funds by several multinational companies, the low resilience of the stock market, and pervasive corruption compel investors to exercise caution.

The analysis of the impact of institutional shocks on efficiency indicates that a one-percentage-point change in the CBT's status has a minimal effect on its efficiency. These conclusions contradict the findings of Anwar and Suhenra (2023), who conducted a VAR panel analysis on 25 developing economies, including Tunisia (1990- 2021). They demonstrated that a shock, represented by a 1% increase in the central bank independence level, positively impacts market capitalization, consumption, and investment, as this increase is perceived as a commitment to combating inflation.

The variance decomposition of the CBT's efficiency score reveals that in the initial period, the score is entirely driven by its innovations. Institutional variables began to influence efficiency only in the second period, with internal conflicts and government stability contributing weights of 17.78% and 3.44%, respectively. After ten periods, over 50% of the variance in the CBT's efficiency score can be attributed to its innovations, while 23.87% is linked to internal conflicts and 17.47% to government stability. In contrast, the status and political stability of the CBT are assigned very low weights of 0.85% and 1.45%, respectively.





**Fig. (3).** IRF of institutional shocks on CBT's efficiency.

Source: Authors' estimates on Eviews.

**Table 5.** Variance decomposition (institutional variables).

Période	S.E.	D(EFF)	D(IC)	D(SGOV)	D(PS)	STA
1	0.148993	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.171788	76.97711	17.78427	3.440083	1.398627	0.399905
3	0.184389	66.94678	26.48613	4.417544	1.769758	0.379782
4	0.200855	58.75437	24.59082	14.16841	1.606202	0.880193
5	0.203647	57.49902	24.51576	15.55728	1.570105	0.857828
6	0.211639	57.48601	23.08253	17.18109	1.455628	0.794744
7	0.212019	57.32634	23.00008	17.40767	1.452714	0.813205
8	0.213353	56.76261	23.50314	17.43912	1.471166	0.823960
9	0.214178	56.33004	24.00341	17.34861	1.460173	0.857767
10	0.215175	56.33885	23.87121	17.47946	1.450655	0.859823

Source: Authors' estimates on Eviews.

## 5. CONCLUSION

This study aimed to highlight the most influential factors affecting the efficiency of CBT between 2000 and 2020. To achieve this, models for macroeconomic and institutional variables were developed using VAR impulse response functions and variance decomposition techniques. The analysis of how efficiency responds to shocks from various macroeconomic and institutional variables revealed that shocks from inflation, unemployment, budget deficits, and government stability significantly impact efficiency scores, with these

effects lasting for up to ten periods. Furthermore, the variance decomposition showed that the most significant contributors to CBT efficiency are GDP, internal conflicts, budget deficits, government stability, and inflation rates. Additionally, the insignificant effect of CBT's status on its efficiency points to a need for further investigation in future research.

## FUNDING

This study received no specific financial support.

DATA AVAILABILITY STATEMENT

The corresponding author may provide study data upon reasonable request.

The author declares that they have no competing interests.

AUTHORS' CONTRIBUTIONS

The author contributed to the conception and submission of the study.

COMPETING INTERESTS

APPENDIX 1: AKIAK INFORMATION TESTS

1. Macroeconomic variables model

VAR Lag Order Selection Criteria						
Endogenous variables: D(EFF) D(GDP) INFLATION D(DB_) D(CHOMAGE)						
Exogenous variables: C						
Date: 03/09/23 Time: 13:12						
Sample: 2000 2020						
Included observations: 18						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-132.4476	NA	2.953934	15.27195	15.51928	15.30605
1	-92.14063	53.74257*	0.615204	13.57118	15.05513	13.77580
2	-53.60893	29.96910	0.324358*	12.06766*	14.78824*	12.44279*
* indicates lag order selected by the criterion				-	-	-
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error			-	-	-	-
AIC: Akaike information criterion			-	-	-	-
SC: Schwarz information criterion			-	-	-	-
HQ: Hannan-Quinn information criterion			-	-	-	-

2. Institutional variables model

VAR Lag Order Selection Criteria						
Endogenous variables: D(EFF) D(IC) D(SGOV) D(SP) STATUT_BC						
Exogenous variables: C						
Date: 03/09/23 Time: 13:20						
Sample: 2000 2020						
Included observations: 18						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-25.37846	NA	2.01e-05	3.375385	3.622710	3.409488
1	5.315549	40.92535	1.22e-05	2.742717	4.226670	2.947334
2	66.89541	47.89545*	4.97e-07*	-1.321712*	1.398868*	-0.946581*
* indicates lag order selected by the criterion				-	-	-
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error			-	-	-	-
AIC: Akaike information criterion			-	-	-	-



SC: Schwarz information criterion	-	-	-	-
HQ: Hannan-Quinn information criterion	-			

**APPENDIX 2: VAR MODEL (MACROECONOMIC VARIABLES)**

Vector Autoregression Estimates					
Date: 06/30/23 Time: 11:05					
Sample (adjusted): 2003 2020					
Included observations: 18 after adjustments					
Standard errors in ( ) & t-statistics in [ ]					
-	D(EFF)	D(GDP)	INFLATION	D(DB_)	D(CHOMAGE)
D(EFF(-1))	0.389185	7.568715	-0.696278	-0.982097	-2.764464
	(0.27390)	(5.99853)	(3.23876)	(4.93175)	(3.64882)
	[ 1.42088]	[ 1.26176]	[-0.21498]	[-0.19914]	[-0.75763]
D(EFF(-2))	-0.376782	-0.537702	-3.755540	1.356296	-2.578565
	(0.24027)	(5.26187)	(2.84102)	(4.32610)	(3.20072)
	[-1.56819]	[-0.10219]	[-1.32190]	[ 0.31351]	[-0.80562]
D(GDP(-1))	-0.018139	-0.583543	0.210133	-0.378891	-0.061640
	(0.02106)	(0.46115)	(0.24899)	(0.37914)	(0.28051)
	[-0.86145]	[-1.26542]	[ 0.84396]	[-0.99935]	[-0.21974]
D(GDP(-2))	-0.020963	-0.440985	0.033869	-0.064270	-0.092622
	(0.01522)	(0.33333)	(0.17997)	(0.27405)	(0.20276)
	[-1.37730]	[-1.32297]	[ 0.18819]	[-0.23452]	[-0.45681]
INFLATION(-1)	-0.027897	0.297268	0.427611	-0.104192	-0.577597
	(0.03381)	(0.74044)	(0.39978)	(0.60876)	(0.45040)
	[-0.82511]	[ 0.40147]	[ 1.06960]	[-0.17115]	[-1.28240]
INFLATION(-2)	-0.021154	-1.396320	0.418732	0.368826	0.669760
	(0.03740)	(0.81905)	(0.44223)	(0.67339)	(0.49822)
	[-0.56561]	[-1.70480]	[ 0.94687]	[ 0.54771]	[ 1.34431]
D(DB_(-1))	-0.064992	1.046641	0.073807	-0.844163	-0.737336
	(0.02649)	(0.58007)	(0.31320)	(0.47691)	(0.35285)
	[-2.45370]	[ 1.80432]	[ 0.23566]	[-1.77005]	[-2.08965]
D(DB_(-2))	0.034957	0.605590	0.102088	-0.475421	0.200193
	(0.02716)	(0.59485)	(0.32118)	(0.48907)	(0.36184)
	[ 1.28697]	[ 1.01805]	[ 0.31786]	[-0.97210]	[ 0.55326]
D(CHOMAGE(-1))	-0.036387	0.245814	0.135306	0.092009	0.088910
	(0.02595)	(0.56842)	(0.30690)	(0.46733)	(0.34576)
	[-1.40193]	[ 0.43246]	[ 0.44088]	[ 0.19688]	[ 0.25714]
D(CHOMAGE(-2))	0.064012	-0.522266	0.051427	0.998046	0.050741
	(0.02751)	(0.60258)	(0.32535)	(0.49542)	(0.36654)

	[ 2.32644]	[-0.86672]	[ 0.15807]	[ 2.01457]	[ 0.13843]
C	0.193488	3.262517	0.979705	-0.644972	-0.030646
	(0.09096)	(1.99208)	(1.07557)	(1.63781)	(1.21175)
	[ 2.12713]	[ 1.63775]	[ 0.91087]	[-0.39380]	[-0.02529]
R-squared	0.813647	0.835550	0.701191	0.658702	0.696986
Adj. R-squared	0.547427	0.600621	0.274320	0.171134	0.264108
Sum sq. resids	0.070395	33.76259	9.842446	22.82175	12.49256
S.E. equation	0.100282	2.196185	1.185776	1.805616	1.335908
F-statistic	3.056302	3.556612	1.642630	1.350995	1.610122
Log likelihood	24.35514	-31.20173	-20.10789	-27.67697	-22.25375
Akaike AIC	-1.483905	4.689081	3.456432	4.297441	3.694861
Schwarz SC	-0.939789	5.233197	4.000548	4.841558	4.238977
Mean dependent	0.008943	-0.558752	4.263048	0.383420	0.136111
S.D. dependent	0.149066	3.475173	1.391970	1.983276	1.557291
Determinant resid covariance (dof adj.)		0.029881	-	-	-
Determinant resid covariance		0.000266	-	-	-
Log likelihood		-53.60893	-	-	-
Akaike information criterion		12.06766	-	-	-
Schwarz criterion		14.78824	-	-	-

**APPENDIX 3: VAR MODEL (INSTITUTIONAL VARAIBLES)**

Vector Autoregression Estimates					
Date: 06/30/23 Time: 11:06					
Sample (adjusted): 2003 2020					
Included observations: 18 after adjustments					
Standard errors in ( ) & t-statistics in [ ]					
	D(EFF)	D(IC)	D(SGOV)	D(SP)	STATUT_BC
D(EFF(-1))	0.064996	1.695887	5.428315	0.169168	0.316192
	(0.30461)	(0.91484)	(2.05757)	(0.30977)	(0.57840)
	[ 0.21337]	[ 1.85376]	[ 2.63822]	[ 0.54611]	[ 0.54666]
D(EFF(-2))	-0.662995	-0.119568	-1.077205	-0.368239	-0.369143
	(0.33273)	(0.99928)	(2.24750)	(0.33836)	(0.63179)
	[-1.99259]	[-0.11965]	[-0.47929]	[-1.08830]	[-0.58428]
D(IC(-1))	0.015248	-0.113125	0.189520	-0.023960	0.106303
	(0.08173)	(0.24544)	(0.55203)	(0.08311)	(0.15518)
	[ 0.18658]	[-0.46090]	[ 0.34331]	[-0.28830]	[ 0.68502]
D(IC(-2))	-0.095881	-0.354278	-0.307794	-0.006021	-0.246676
	(0.08383)	(0.25175)	(0.56622)	(0.08524)	(0.15917)
	[-1.14382]	[-1.40725]	[-0.54360]	[-0.07063]	[-1.54977]

D(SGOV(-1))	0.114865	-0.173144	0.202364	0.163153	0.017282
	(0.06320)	(0.18981)	(0.42691)	(0.06427)	(0.12001)
	[ 1.81742]	[-0.91218]	[ 0.47402]	[ 2.53849]	[ 0.14401]
D(SGOV(-2))	-0.042459	0.232652	-0.098855	0.027916	0.191824
	(0.06631)	(0.19914)	(0.44788)	(0.06743)	(0.12590)
	[-0.64035]	[ 1.16830]	[-0.22072]	[ 0.41401]	[ 1.52358]
D(SP(-1))	-0.256476	0.432075	-1.095051	-0.520273	-0.718194
	(0.40413)	(1.21372)	(2.72979)	(0.41097)	(0.76737)
	[-0.63463]	[ 0.35599]	[-0.40115]	[-1.26596]	[-0.93592]
D(SP(-2))	0.055901	1.724577	1.362540	-0.037375	0.107390
	(0.30037)	(0.90209)	(2.02890)	(0.30545)	(0.57034)
	[ 0.18611]	[ 1.91176]	[ 0.67157]	[-0.12236]	[ 0.18829]
STATUT_BC(-1)	-0.172077	1.466665	1.130961	0.053896	1.003696
	(0.16828)	(0.50540)	(1.13670)	(0.17113)	(0.31954)
	[-1.02255]	[ 2.90201]	[ 0.99495]	[ 0.31494]	[ 3.14111]
STATUT_BC(-2)	0.098239	-1.506780	-0.534229	0.196252	-0.021847
	(0.20330)	(0.61056)	(1.37323)	(0.20674)	(0.38603)
	[ 0.48322]	[-2.46785]	[-0.38903]	[ 0.94927]	[-0.05659]
C	0.023562	-0.247125	-0.450086	-0.087460	0.032625
	(0.06104)	(0.18333)	(0.41233)	(0.06208)	(0.11591)
	[ 0.38599]	[-1.34799]	[-1.09157]	[-1.40891]	[ 0.28147]
R-squared	0.588637	0.767854	0.533385	0.671803	0.844850
Adj. R-squared	0.000975	0.436216	-0.133209	0.202951	0.623206
Sum sq. resids	0.155393	1.401587	7.089961	0.160697	0.560265
S.E. equation	0.148993	0.447467	1.006405	0.151515	0.282910
F-statistic	1.001659	2.315341	0.800165	1.432868	3.811750
Log likelihood	17.22866	-2.565996	-17.15567	16.92656	5.686553
Akaike AIC	-0.692073	1.507333	3.128407	-0.658507	0.590383
Schwarz SC	-0.147957	2.051449	3.672524	-0.114391	1.134499
Mean dependent	0.008943	-0.196759	-0.222222	-0.043634	0.277778
S.D. dependent	0.149066	0.595943	0.945405	0.169712	0.460889
Determinant resid covariance (dof adj.)		4.58E-08			
Determinant resid covariance		4.07E-10			
Log likelihood		66.89541			
Akaike information criterion		-1.321712			
Schwarz criterion		1.398868			

## REFERENCES

- Abdelatif, I., Bouhouch, F., & Daly, L. (2023). The Determinants of Central Bank Efficiency Scores: The Case of Tunisia. *Business and Economic Research*, 13 (3), 40-55. <https://doi.org/10.5296/ber.v13i3.20749>.
- Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. *Second International Symposium on Information Theory*, 267-281. [https://doi.org/10.1007/978-1-4612-0919-5\\_37](https://doi.org/10.1007/978-1-4612-0919-5_37).
- Anwar, C.J., Suhendra, I. (2023). Measuring Response of Stock Market to Central Bank Independence Shock. *SAGE Open*, 13(1), 1-12. <https://doi.org/10.1177/21582440231152>.
- Belhedi, M., Slama, I., & Lahiani, A. (2015). Transmission of international shocks to an emerging small open-economy: Evidence from Tunisia. *Région et Développement*, 42, 231-258.
- Berger, A.N. & Mester, L.I. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking and Finance*, 21(7), 895-947. [https://doi.org/10.1016/S0378-4266\(97\)00010-1](https://doi.org/10.1016/S0378-4266(97)00010-1).
- Blix, M., Daltung, S., & Heikensten, S. (2003). On central bank efficiency. *Sveriges Riksbank*, 3, 81-93. [https://archive.riksbank.se/Upload/Dokument\\_riksbank/Kat\\_publicerat/Artiklar\\_PV/PV03\\_3\\_artikel1.pdf](https://archive.riksbank.se/Upload/Dokument_riksbank/Kat_publicerat/Artiklar_PV/PV03_3_artikel1.pdf).
- Bourbonnais, R. (2018). *Chapitre 10. La modélisation VAR*. R. Bourbonnais, *Économétrie* (pp. 297-320). Paris: Dunod.
- Dar, Q.F., Ahn, Y.H., & Dar, G. F. (2021, a). Evaluation and investigation: the determinants of central banking efficiency. *RAIRO Operations Research*, 55(2), 481-493. <https://doi.org/10.1051/ro/2021017>.
- Dar, Q.F., Ahn, Y.H., & Dar, G. F. (2021, b). Impact of international trade on Central Bank efficiency: An application of DEA and Tobit regression analysis. *Statistics, Optimization and Information Computing*, 9 (1), 223-240. <https://doi.org/10.19139/soic-2310-5070-1077>.
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association*, 74(366), 427-431. <https://doi.org/10.2307/2286348>.
- Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, 55(2), 251-276. <https://doi.org/10.2307/1913236>.
- Farrell, M.J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society, Series A (General)*, 120(3), 253-290. <https://doi.org/10.2307/2343100>.
- Gómez Gallego, J.C. (2020). Efficiency in European Central Banks: The Role of Economic Freedom. *Strategies in Accounting and Management*, 2(1), 1-9. <http://dx.doi.org/10.31031/SIAM.2020.02.000529>.
- International Country Risk Guide (ICRG), <https://www.prsgroup.com/explore-our-products/icrg/>.
- Johansen, S. (1988), Statistical analysis of cointegration vectors, *Journal of Economic Dynamics and Control*, 12 (2-3), 231-254, [https://doi.org/10.1016/0165-1889\(88\)90041-3](https://doi.org/10.1016/0165-1889(88)90041-3).
- Lanouar, C., Goaiad, M. (2019). Tourism, terrorism and political violence in Tunisia: Evidence from Markov-switching models. *Tourism Management*, 70, 404-418. <http://dx.doi.org/10.1016/j.tourman.2018.09.002>.
- Lütkepohl, H. (2010). Impulse response function. In: *Macroeconometrics and Time Series Analysis*. The New Palgrave Economics Collection, London. [https://doi.org/10.1057/9780230280830\\_16](https://doi.org/10.1057/9780230280830_16).
- Mester, L.J. (2003). Applying efficiency measurement techniques to central banks. *FRB of Philadelphia Working Paper*, 13(3), 1-40 (P 16). <https://www.philadelphiafed.org/-/media/frbp/assets/working-papers/2003/wp03-13.pdf>.
- Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48(1), 1-48. <https://doi.org/10.2307/191201>.
- Swanson, N. R., & Granger, C. W. J. (1997). Impulse Response Functions Based on a Causal Approach to Residual Orthogonalization in Vector Autoregressions. *Journal of the American Statistical Association*, 92(437), 357-367. <https://doi.org/10.1080/01621459.1997.10473634>.
- Veyrune, R., & Zerbo, S. (2023). *Estimation and determinants of cost efficiency: Evidence from Central Bank operational expenses*. International Monetary Fund WP/23/195, WPIEA2023195.
- World Development Indicators (WDI) Database. <https://databank.worldbank.org/source/world-development-indicators>.
- Worldwide Governance Indicators (WGI) Database. <https://databank.worldbank.org/source/worldwide-governance-indicators>.
- Zaefarian, G., Iurkov, V., & Koval, M. (2022). Variance decomposition analysis: What is it and how to perform it – A complete guide for B2B researchers, *Industrial Marketing Management*, 107, 315-322. <https://doi.org/10.1016/j.indmarman.2022.10.020>.

Received: July 15, 2024

Revised: July 20, 2024

Accepted: July 25, 2024

Copyright © 2024– All Rights Reserved

This is an open-access article.