Modeling the Inflation Rate in Algeria for the Period 1980–2023 Using Multiple Linear Regression: A Comparison Between Classical (OLS) and Bayesian (BA) Estimation

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Abstract:

In this study, we aimed to investigate the determinants of inflation in Algeria over 1980–2023 using multiple linear regression (MLR). The independent variables included the real exchange rate (Dinar/USD), changes in oil prices, the real interest rate, and the change in the export-to-GDP ratio. In contrast, the dependent variable was the change in the inflation rate.

The parameters of the specified model were estimated using the Ordinary Least Squares (OLS) method and the Bayesian estimation approach. The purpose was to examine whether the estimates obtained through both methods converge to similar values. The findings indicated a convergence of results between the two estimation techniques.

Keywords: econometric study; multiple regression; inflation; least squares; Bayesian estimation.

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I- Introduction

Inflation in Algeria is a matter of paramount importance, given the current economic challenges and the imperative for effective policy decisions. Inflation represents a rise in the general price level within the economy, profoundly affecting citizens' purchasing power on one hand, and macroeconomic stability on the other. For this reason, understanding this phenomenon is one of the most significant macroeconomic research topics at both the national and international levels. This understanding necessitates the use of statistical and econometric models to comprehend such economic phenomena, simplifying them and transforming them into mathematical equations that are easier to analyze and interpret. The following summarizes several previous studies addressing inflation in Algeria:

Mohammed K. S., Benyamina K., & Benhabib A. (2015) investigated determinants of inflation in Algeria from 1980 to 2012 using the Autoregressive Distributed Lag (ARDL) model. These determinants included import prices, oil prices, money supply, government expenditure, and the nominal effective exchange rate of the Algerian dinar. Their findings showed a long-term relationship between these variables and inflation, while in the short run, monetary and fiscal policies, represented by money supply and government expenditure, were not statistically significant factors.

Miloud Lacheheb & Abdalla Sirag (2016) analyzed the relationship between oil price changes and inflation from 1970 to 2014 using the Nonlinear Autoregressive Distributed Lag (NARDL) model. The findings indicated that increases in oil prices raise the inflation rate in both the short and long term.

Samer Mehibel & Yacine Belarbi (2017) studied inflation volatility in Algeria from 2002 to 2016 using a VAR model and Impulse Response Functions (IRF), focusing on government expenditure as a primary driver of aggregate demand and, consequently, inflation. Their results highlighted the significant role of government spending shocks—especially positive shocks in investment expenditure—in increasing inflation in the short run.

Mezhoud Warda & Achouche Mohamad (2021) examined the relationship between inflation rate and economic growth—represented by the average GDP growth rate—in Algeria from 1990 to 2019. They employed the Granger causality test followed by a Vector Autoregressive (VAR) model. The results revealed a unidirectional relationship from economic growth toward inflation: a 1% increase in economic growth led to a 1.56% decrease in the inflation rate.

Imène Laourari & Mustapha Abderrahim (2022) applied ARDL on monthly data from 2011 to 2022, analyzing inflation variations along with money supply, nominal effective exchange rate, import price index, and public expenditure. They concluded that money supply, import price index, and the nominal effective exchange rate are key long-term determinants of inflation volatility.

Despite the abundance of studies on inflation, most relied on traditional estimation methods—Ordinary Least Squares (OLS) or Maximum Likelihood Estimation (MLE)—applied to various econometric models. They did not utilize modern approaches like Bayesian estimation, which incorporate prior knowledg e of parameters with observed data to produce more precise and credible estimates.

Problem Statement:

Against this backdrop, the present study aims to estimate a multiple linear regression (MLR) model using annual time series data for Algeria from 1980 to 2023. The independent variables include changes in the real exchange rate (DA/USD), changes in oil prices, changes in the ratio of foreign investment to GDP, real interest rate, and changes in the export-to-GDP ratio. The dependent variable is the change in the inflation rate. Estimation will be carried out using two methods: OLS and the Bayesian approach **(Mayuri Pandya, 2011, p.2).**

Consequently, the study's main research question is: Do the estimated values obtained via OLS and Bayesian approaches converge?

Sub-questions:

Based on this main problem, the following sub-questions arise:

1-Do the independent variables have a statistically significant effect on inflation?

2-How is prior knowledge about parameters incorporated into the Bayesian estimation method?

3-How can the quality of the estimates resulting from each method be evaluated?

Hypotheses:

From these questions, the following testable hypotheses are formulated:

1-The study's variables have a statistically significant impact on the inflation rate.

2-Prior knowledge about parameters is incorporated in the Bayesian method through prior distributions, possibly derived from previous studies.

3-Several criteria can evaluate estimation accuracy, such as standard deviation and confidence intervals.

Importance and Objective:

This paper's importance lies in integrating applied mathematics into economics, thereby augmenting the role of mathematics in administrative and economic decision-making. The primary objective is to compare traditional and Bayesian approaches in estimating the determinants of inflation. The study proceeds by explaining the basic principles of Bayesian estimation, then introduces the multiple linear regression model, applies OLS followed by the Bayesian method, and concludes with a comparison of the results.

1. Methodology:

In this section, we will provide a brief overview of Bayesian statistics.

1.1. Foundations of Bayesian Statistics:

The foundation of Bayesian statistics lies in the theory introduced by the British mathematician Thomas Bayes (1763), which was published posthumously by Richard Price. This theory facilitates statistical inference about the parameters (estimators) of econometric models and is expressed as follows:

$$p(B/A) = \frac{p(A/B)p(B)}{p(A)} \dots\dots\dots..(1.1)$$

This equation represents the probability of event B occurring given that event A has occurred. It is the first of its kind to incorporate prior information about an experiment to calculate the probability of an event, contrasting with frequentist statistics, which evaluates probabilities based on the frequency of an event relative to the total possible occurrences in an experiment **(Al-Akari, 2022, p.5).**

Econometrics uses data to understand models of interest to researchers, which often depend on parameters. For instance, one of the most prominent examples is the linear regression model, where the focus is on estimating the regression parameters. By substituting y (a data matrix) for event A and θ (a vector of parameters under study) for event B in equation (1.1), the relationship becomes:

$$p(\theta/y) = \frac{p(y/\theta)p(\theta)}{p(y)} \dots \dots \dots . (1.2)$$

From equation (1.2), the question arises: Given the data y, what can we infer about the parameters θ? Bayesian statistics treats θ as a random variable, in contrast to frequentist statistics, which considers it a fixed value. **(Gary, 2003, p.16).**

Thomas Bayes extended the continuous formulation to give equation (1.2) the following form:

$$\pi(\theta/y) = \frac{f(y/\theta)\pi(\theta)}{f(y)} \dots \dots \dots . (1.3)$$

Where $f(y) = \int f(y/\theta)\,\pi(\theta)d\theta$ is constant and independent of θ, allowing the equation to be written as :

$$\pi(\theta/y) \propto f(y/\theta)\pi(\theta) \dots \dots . . (1.4)$$

This expression reads: "The posterior distribution is proportional to the likelihood function multiplied by the prior distribution. **(EDWARD, 2008, p.14).**

Thus, making effective statistical decisions using Bayesian inference relies on accurately determining three key components:

-The likelihood function $\pi(y/\theta)$.

-The prior distribution $\pi(\theta)$.

-The loss function $L(\theta,d)$.For further details, see **(Khawla, 2017, p.65).**

1.2. Quadratic Loss Function:

The quadratic loss function was proposed by Legendre (1805) and Gauss (1810). It is undoubtedly one of the most commonly used loss functions and is expressed as follows:

$$L(\theta,d) = (\theta - d)^2$$

It measures how far the expected value d of a variable deviates from its actual value θ, considering the posterior probability distribution of the variable. This function is widely used in Bayesian inference because it is simple and easy to calculate. Additionally, minimizing the quadratic loss reduces the root mean square error (RMSE), which is a common metric for assessing the accuracy of variables.

Consequently, the Bayesian estimator δ^{π} corresponding to the posterior distribution $\pi(\theta / y)$ and the quadratic loss function $L(\theta, d)$ is the mathematical expectation of the posterior distribution, given by the following relationship:

$$\theta_m = E(\theta / y) = \int_{\Theta} \theta \pi(\theta / y) d\theta$$

Proof: **See Appendix 01**

2. Results:

2.1. Model Presentation:

In this research paper, we will apply the following multiple linear regression model:

$$INFL_t = c + \beta_1 TCH_t + \beta_2 PP + \beta_3 INTER_t + \beta_4 EXPORT + \varepsilon_t$$

Where:

INFL represents the inflation rate (the dependent variable).

The independent variables are as follows:

TCH denotes the exchange rate (Dinar/USD), **INTER** refers to the interest rate, **EXPORT** represents exports, **PP** is the price of oil in USD, **c** is the constant term, and $\boldsymbol{\varepsilon}$ is the random error term.

Before estimating the model parameters, we will examine the stationarity of the time series used in the study.

2.2. Testing the Stationarity of Time Series: The Augmented Dickey-Fuller Test:

The Augmented Dickey-Fuller (ADF) test is used to determine whether a time series is stationary, meaning it does not exhibit significant and irregular fluctuations over time. For this study, we employed the ADF test using the Trend and Intercept model, which includes a constant and a general trend. The table (1) summarizes the results of the test:

Tab (1): Results of the ADF Test

Variables	**Series**	**Critical Value (5%)**	**t-Statistic**	**Probability (Prob)**	**Result**
TCH	Original	-3.51	-5.11	0.001	Stationary
PP	Original	-3.51	-2.55	0.3	Non-stationary
	First Diff	-3.51	-5.93	0.0001	Stationary
INTER	Original	-3.51	-4.95	0.0013	Stationary
EXPORT	Original	-3.51	-1.92	0.63	Non-stationary
	First Diff	-3.51	-5.28	0.0005	Stationary
INFL	Original	-3.51	-2.16	0.5	Non-stationary
	First Diff	-3.51	-5.85	0.0001	Stationary

Source: Prepared by the authors using the EViews 12 software.

A time series is considered stationary if the probability (Prob) is less than 0.05. Based on the table above, we observe the following:

-The time series TCH (exchange rate) and INTER (interest rate) are stationary at level, meaning they are integrated of order 0, denoted as **I(0).**

-The remaining series, EXPORT (exports), INFL (inflation rate), and PP (oil price), become stationary after the first difference, as their probability values drop below 0.05 after differencing. These series are integrated of order 1, denoted as **I (1).**

To ensure stationarity, we use the first differences of the non-stationary series, denoting them as DEXPORT, DINFL, and DPP. Consequently, the multiple linear regression model becomes:

$$DINFL_t = c + \beta_1 TCH_t + \beta_2 DPP + \beta_3 INTER_t + \beta_4 DEXPORT + \varepsilon_t$$

2.3. Estimation of the Multiple Linear Regression Model Using the Ordinary Least Squares (OLS) Method:

The OLS method is a statistical tool used to analyze the relationship between the dependent variable (DINFL) and the independent variables (TCH, DPP, DEXPORT, INTER). This analysis involves conducting the following tests:

-Student's t-test for the significance of individual coefficients.

-Fisher's F-test for overall model significance.

-Durbin-Watson (DW) test to check for autocorrelation in the residuals.

The results of the analysis are summarized as follows:

Dependent Variable: DINFL
Method: Least Squares
Date: 10/02/24 Time: 00:17
Sample (adjusted): 1981 2023
Included observations: 43 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.343749	1.542499	-2.816047	0.0077
TCH	0.064341	0.021906	2.937062	0.0056
DPP	-0.133738	0.059055	-2.264627	0.0293
INTER	-0.524863	0.119652	-4.386593	0.0001
DEXPORT	-0.389020	0.174865	-2.224684	0.0321

R-squared	0.337940	Mean dependent var	-0.005066
Adjusted R-squared	0.268249	S.D. dependent var	4.768006
S.E. of regression	4.078668	Akaike info criterion	5.758362
Sum squared resid	632.1504	Schwarz criterion	5.963153
Log likelihood	-118.8048	Hannan-Quinn criter.	5.833883
F-statistic	4.849147	Durbin-Watson stat	2.079451
Prob(F-statistic)	0.002934		

Source: Prepared by the authors using the EViews 12 software

. From the results of the table, we can see that:

-The variables **DPP**, **INTER**, **DEXPORT**, and the constant term ***c*** are significant at the 5% level and have negative coefficients, indicating they negatively affect **DINFL**.

-The variable **TCH** is significant at the 5% level and has a positive coefficient, indicating it positively affects **DINFL**.

-The coefficient of determination $R^2 = 0.34$ indicates that the independent variables explain 34% of the variation in the dependent variable.

-The Fisher test probability (prob-Fisher=0.003) is less than 0.05, suggesting the overall model is statistically significant.

-For the Breusch-Godfrey Serial Correlation LM Test, Prob. Chi-Square(2)=0.72 (greater than 0.05), indicating no serial correlation in the residuals.

-For the ARCH test, Prob. Chi-Square(1)=0.68 (greater than 0.05), indicating no heteroscedasticity in the model.

-The Jarque-Bera test for normality yields a probability of 0.13 (greater than 0.05), suggesting that the residuals follow a normal distribution.

-Regarding the economic interpretation of the model's parameters, the estimation results are consistent with economic theory. An increase in the foreign exchange rate is unfavorable for the national currency and thus contributes to a rise in the inflation rate. Conversely, an increase in oil prices enhances the state's revenues in foreign currency (dollars), thereby reducing price pressures. Meanwhile, a rise in interest rates signifies a tightening of monetary policy, which decreases the money supply within the national economy and consequently lowers inflation. Finally, an increase in export volume improves the trade balance and raises foreign currency reserves, which leads to a reduction in inflation.The Multiple Linear Regression Equation Obtained:

DINFL = -4.34374889279 + 0.0643405445498*TCH - 0.133737608643*DPP - 0.524863305145*INTER - 0.389019729047*DEXPORT

2.4. Estimation of the Multiple Linear Regression Model Using the Bayesian Approach:

-In the previous section, we determined the parameter values of the model under study. In this section, we will re-estimate the model parameters using the Gibbs sampling method (for more details, see **(LOTFI, 2007, p.26)**), which is one of the techniques of Markov Chain Monte Carlo (MCMC). This method is employed to generate a sequence of observations that approximate the multivariate posterior distribution when direct sampling is challenging **(Al-Akari, 2022, p.8)**. We will assess whether the parameter estimates obtained using both estimation methods converge to the same values.

- The model under study is defined as follows:

$$y_t = a_0 + a_1 X1_t + a_2 X2_t + a_3 X3_t + a_4 X4_t + \varepsilon_t$$

Where:

y_t represents the dependent variable **DINFL**, $X1_t$ represents the independent variable **TCH**, $X2_t$ represents the independent variable **DPP** , $X3_t$ represents the independent variable **INTER** , $X4_t$ represents the independent variable **DEXPORT**, ε_t denotes the error term, assumed to have a mean of 0 and variance σ^2 .

The parameters $a = (a_0, a_1, a_2, a_3, a_4)$ and σ^2 of the model are considered as random variables in the Bayesian estimation approach. **(Nadia & Oumelkheir, 2015, p.7)**

- We have a data vector of dimension n, denoted by y, and its corresponding random variable Y. The natural regression model can thus be summarized by the following relationship $Y / \sigma^2 \sim N(A, \sigma^2 I_n)$ **(Ioannis , 2008, p.33)**. The likelihood function mentioned in Equation (1.4) becomes:

$$f(y/\sigma^2) = \frac{1}{(\sqrt{2\pi})^N \sigma^N} \exp\{-\frac{1}{2\sigma^2}\sum_{t=1}^{N}(y_t - A)^2\}$$

With:

$A = E(y_i / A, \sigma^2) = a_0 + a_1 X1_t + a_2 X2_t + a_3 X3_t + a_4 X4_t$, $\mathrm{var}(y_i / A, \sigma^2) = \sigma^2$,and the parameter vector $a = (a_0, a_1, a_2, a_3, a_4)$ determined earlier using the ordinary least squares method.

Here, we adopt a conjugate multivariate inverse gamma prior distribution, which is specified as follows:

$$\sigma^2 \sim IG(v1, v2)$$

$$\pi(\sigma^2) = \frac{v1^{v2}}{\Gamma(v1)}(\frac{1}{\sigma^2})^{v1+1}\exp(\frac{-v2}{\sigma^2})$$

Leading to the posterior density expressed directly as:

$$\pi(\sigma^2 / a, y, X1, X2, X3, X4) = f(y/\sigma^2)\pi(\sigma^2) =$$

$$\frac{1}{\sigma^N}\exp(-\frac{1}{2\sigma^2}\sum_{t=1}^{N}\varepsilon_t{}^2) \times (\frac{1}{\sigma^2})^{v1+1}\exp(\frac{-v2}{\sigma^2}) =$$

$$\left(\frac{1}{\sigma^2}\right)^{\frac{N}{2}+v1+1} \exp\left(\frac{\frac{-(\sum_{t=1}^{N}\varepsilon_t{}^2 + 2v2)}{2}}{\sigma^2}\right)$$

Which follows an inverse gamma distribution as follows:

$$\sigma^2 / a, y, X1, X2, X3, X4 \sim IG(\frac{N}{2} + v1; \frac{\sum_{t=1}^{N}\varepsilon_t^2 + 2v2}{2})$$

-Finally, we integrated the Bayesian estimation program written in the WinBUGS programming language **(see Appendix 02)** with the data **(see Appendix 03)** using the R software **(see Appendix 04).** We performed 10,000 iterations with a burn-in period of 1,000. The Markov chains achieved convergence **(see Appendices 05 and 06)**, and the estimation results were as follows **(Plummer, Stukalov, & Denwood, 2024, p.2):**

```
Iterations = 1000:10000
Thinning interval = 1
Number of chains = 1
Sample size per chain = 9001

1. Empirical mean and standard deviation for each variable,
Plus standard error of the mean:

              Mean       SD     NaiveSE       Time-serie SE
R2B        0.304728 0.158144 1.667e-03      1.713e-03
a0        -4.299008 0.099207 1.046e-03      1.046e-03
a1         0.063623 0.008471 8.928e-05      9.584e-05
a2        -0.122537 0.044715 4.713e-04      6.246e-04
a3        -0.511667 0.061640 6.497e-04      8.273e-04
```

```
a4        -0.396492 0.081905 8.633e-04      1.020e-03
s2        15.806240 3.595225 3.789e-02      3.895e-02
sy2       22.733881 0.000000 0.000e+00      0.000e+00

HPDinterval(model.samples)
         lower       upper
R2B       -0.01421852  0.57418057
a0        -4.49638419 -4.10543100
a1         0.04732946  0.08094366
a2        -0.21058305 -0.03520069
a3        -0.63054105 -0.38868781
a4        -0.54666205 -0.22573940
s2         9.68052807 23.05712286
sy2       22.73388082 22.73388082
typical.y -1.07541581  1.02996004
attr(,"Probability("[1] 0.95)
```
Source: Prepared by the authors using the R software

From the obtained results, we observe that the Bayesian coefficient of determination **R2B =0.30** , indicating that 30% of the variance in the dependent variable is explained by the model. The variance of the error term $\hat{\sigma}^2 = 15.8$, and the sample variance **sy2=12.73**. Additionally, the credibility intervals provided a reasonable range for the potential values of the variables, taking into account their posterior distribution at a 95% confidence level. This highlights the importance of the Bayesian approach in assessing the significance of the model's variables. Notably, if the highest posterior density (**HPD**) interval does not include zero, the variable is deemed statistically significant.

Based on these findings, the model can be rewritten as follows:

$$y_t = -4.49 + 0.047X1_t - 0.21X2_t - 0.63X3_t - 0.56X4_t$$

2.5. Comparison between the results of the least squares method and the Bayesian method:

The following table presents a comparison of the estimated parameters of the multiple linear regression model using both the Ordinary Least Squares (OLS) and Bayesian estimation methods :

Parameters	**Ols method**	**BA method**
C	-4.343749	-4.299008
TCH	0.064341	0.063623
DPP	-0.133738	-0.122537
INTER	-0.524863	-0.511667
DEXPORT	-0.389020	-0.396492

Source: Prepared by the authors using the word software.

-From our observation of the previous table, it appears that the posterior means are approximately equal to the Ordinary Least Squares (OLS) estimates. This convergence is attributed to the use of non- informative priors, reflecting our lack of prior studies on similar datasets.

-The exclusion of zero from the Bayesian credible intervals supports the conclusion that these parameters are statistically significant, just as a p-value less than 0.05 does in the ordinary least squares (OLS) method.

-Despite the advantage of OLS in producing unbiased estimates under the Gauss–Markov assumptions—which include normality of errors, homoscedasticity, and absence of serial correlation—Bayesian estimation offers distinct benefits. Unlike OLS, the Bayesian approach provides a complete posterior distribution for each parameter, rather than a single point estimate.

-Additionally, Bayesian methods allow for the incorporation of prior knowledge into the estimation process, which can be especially valuable in contexts with theoretical or empirical insight. Finally, the posterior standard deviation (SD) serves as a direct measure of precision: The closer the standard deviation is to zero, the more accurate and reliable the parameter estimates become **(Pierre & Eric Matzner, 2011, p.12).**

Conclusion:

In this article, we demonstrated the convergence of results obtained using the ordinary least squares method and the Bayesian method on a sample of 44 observations for the variables $\boldsymbol{TCH}$, $\boldsymbol{EXPORT}$, **PP**and $\boldsymbol{INTER}$ to explain the dependent variable $INFL$. We observed the negative impact of most independent variables on the dependent variable.

-The Bayesian estimation method is an innovative and promising approach whose implementation on econometric models has become essential for every economist. It is a flexible methodology that leverages prior information external to the data, does not require the usual assumptions of classical statistics (e.g., normality, homoscedasticity, lack of serial correlation), and is capable of handling small sample sizes. Moreover, the success of Bayesian implementation owes much to Monte Carlo techniques, especially the Gibbs sampling algorithm, which is both easy to implement computationally and does not require informative priors.

-The primary goal of this paper was to elucidate how to apply the Bayesian framework to econometric models. Possible extensions include:

1. Applying Bayesian estimation to linear regression models that suffer from issues such as autocorrelated residuals, heteroskedasticity, and others.

2. Extending the Bayesian approach to dynamic models such as ARDL, ARCH–GARCH, and similar specifications.

3. Utilizing alternative loss functions—for example, absolute loss, 0–1 loss, and DeGroot's loss function.

Bibliography

- (n.d.). Retrieved from https://data.albankaldawli.org/country/algeria.
- Al-Akari, K. (2022). Measuring uncertainty in Syria's economic policy using a Bayesian random walk model. Journal of Development and Economic Policies, 24, 63-93.
- EDWARD , G. (2008). Introduction to Bayesian Econometrics. ENGLAND: Cambridge University Press.
- gary, k. (2003). Bayesian Econometrics. England.
- Ioannis , N. (2008). Bayesian Modeling Using WinBUGS. Athens, Greece: John Wiley & Sons, Inc., Hoboken, New Jersey.

- K. S, M., K, B., & A, B. (2015). The Main Determinants Of Inflation In Algeria: An ARDL Model. International Journal of Management, IT and Engineering, 71-82.
- Khawla, B. (2017). Etude de l’estimateur de Bayes sous différentes fonctions de perte. (Thesis submitted in fulfillment of the requirements for the Doctorate in Mathematics,Université Badji Mokhtar.Faculté des Sciences Département de Mathématiques,Annaba).
- Krishnam Bhatt, Paresh Andharia Mayuri Pandya .(2011) .Bayes Estimation of Two-Phase Linear Regression Model .International Journal of Quality, Statistics, and Reliability.357814 ,(1)2011 .
- Lacheheb, M., & Sirag, A. (2016). Oil price and inflation in Algeria: A nonlinear ARDL approach. The Quarterly Review of Economics and Finance, 45-60.
- LAOURARI, I., & ABDERRAHIM, M. (2022). INFLATION DYNAMICS AND DETERMINANTS IN ALGERIA: AN EMPIRICAL INVESTIGATION. World Bank Group. https://thedocs. worldbank. org/en/doc/91c4e0fe759e6410988a87804b744d04-0280032023/original/Inflation-Dynamics-And-Determinants-In-Algeria-An-Empirical-Investigation, 01-15.
- LOTFI, K. (2007). L'ÉCHANTILLONNAGE DE GIBBS POUR L'ESTIMATION. MONTRÉAL: UNIVERSITÉ DU QUÉBEC À MONTRÉAL-Service des bibliothèques.
- Mehibel, S., & Belarbi, Y. (2017). Inflation Dynamics in Algeria. Journal of Economics and Behavioral Studies, 174-187.
- Mezhoud , W., & Achouche , M. (2021). L’inflation et la croissance économique en Algérie. Revue de recherche en économie et gestion, 169-186.
- Nadia , L., & Oumelkheir, M. (2015). MODELISATION DE LA PARITE DOLLAR AMERICAIN /DINAR ALGERIEN: APPROCHE BAYESIENNE ET SERIES TEMPORELLES. Revue d’économie et de statistique appliquée, 486-496.
- Pierre, A., & Eric Matzner, L. (2011). Régression avec R. France: Springer-Verlag.
- Plummer, M., Stukalov, A., & Denwood, M. (2024). Package ‘rjags’. CRAN.

Appendixes

- **Appendix 01 :**

$$E[L(\theta,d)] = d^2 + E(\theta^2) - 2dE(\theta) = (d - E(\theta))^2 + \mathrm{var}(\theta)$$

$E[L(\theta,d)]$ It achieves a minimum threshold value when: $d = E(\theta)$

- **Appendix 02:** A Bayesian estimation program in winbugs:

```
model {

#likelihood
for (i in 1:n) {
        y[i] ~ dnorm(mu[i], tau)
        mu[i] <- a0 + a1 * x1[i] + a2* x2[i] +  a3* x3[i]+ a4*  x4[i]
        }
#priors
        tau ~ dgamma(1,1)
        a0~ dnorm(-4.3,100)
        a1~ dnorm(0.1,100)
        a2~ dnorm(-0.1,100)
        a3~ dnorm(-0.5,100)
        a4~ dnorm(-0.4,100)
#sigma
        s2<-1/tau
        s<-sqrt(s2)
#samplevar
        sy2<-pow(sd(y[]),2)


#bayes R2
        R2B<- 1 - s2/sy2
#expected y
typical.y<-a0+a1*mean(x1[])+a2*mean(x2[])+a3*mean(x3[])+a4*mean(x4[])

        }
```

- **Appendix 03:** The variables PP, INFL, TCH, EXPORT and INTER for the period 1980-2023:

years	INFL	TCH	PP	INT	EXPORT
1980	9,517824	3,83745	35,52	-18,164	34,33846
1981	14,65484	4,315808	34	-9,929	34,58725
1982	6,54251	4,592192	32,38	1,04	30,92486
1983	5,967164	4,7888	29,04	-3,562	27,94181
1984	8,116398	4,983375	28,2	-5,011	25,71002
1985	10,48229	5,0278	27,01	-1,879	23,58393
1986	12,37161	4,702317	13,53	0,825	12,85476
1987	7,441261	4,849742	17,73	-4,449	14,27247
1988	5,911545	5,914767	14,24	-4,64	15,50787
1989	9,304361	7,608558	17,31	-8,055	18,63926
1990	16,65253	8,957508	22,26	-17,089	23,44369
1991	25,88639	18,47288	18,62	-29,774	29,11782
1992	31,66966	21,83608	18,44	-11,422	25,31959
1993	20,54033	23,34541	16,33	-4,95	21,78388
1994	29,04766	35,0585	15,53	-13,747	22,53073
1995	29,77963	47,66273	16,86	-7,90217	26,19478
1996	18,67908	54,74893	20,29	-4,04921	29,76045

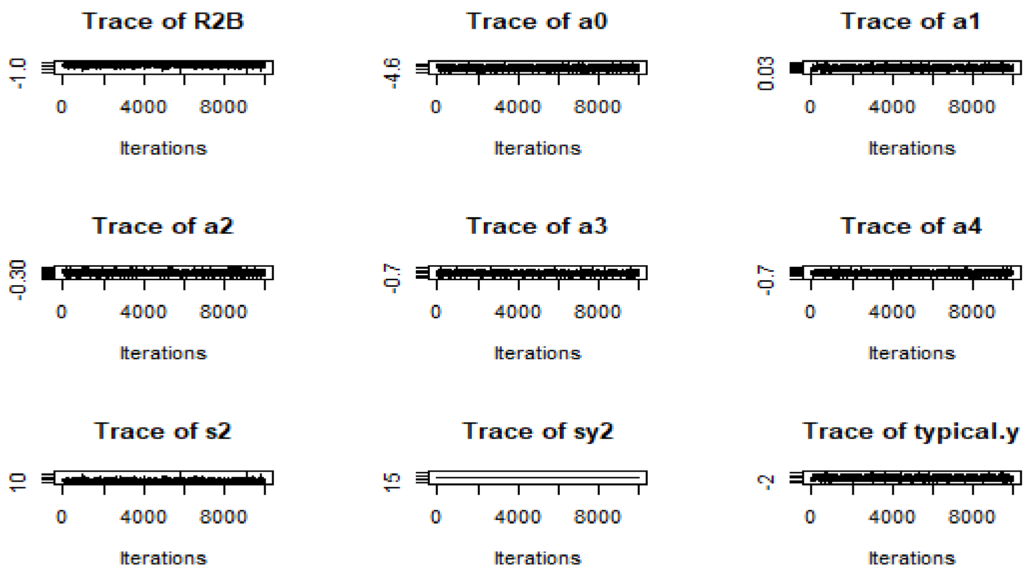
1997	5,733523	57,70735	18,86	8,136645	30,90631
1998	4,950162	58,73896	12,28	15,10401	22,57835
1999	2,645511	66,57388	17,44	-0,09592	28,15011
2000	0,339163	75,25979	27,6	-10,3344	42,06972
2001	4,225988	77,21502	23,12	10,02084	36,68931
2002	1,418302	79,6819	24,36	7,168254	35,50454
2003	4,268954	77,39498	28,1	-0,18991	38,24883
2004	3,9618	72,06065	36,05	-3,78416	40,05322
2005	1,382447	73,27631	50,59	-6,99705	47,2052
2006	2,311499	72,64662	61	-2,30374	48,81069
2007	3,678996	69,2924	69,04	1,508208	47,06816
2008	4,858591	64,5828	94,1	-6,3399	47,97334
2009	5,73706	72,64742	60,86	21,56907	35,37165
2010	3,911062	74,38598	77,38	-6,99275	38,44455
2011	4,524212	72,93788	107,46	-8,65109	38,78812
2012	8,891451	77,53597	109,45	0,504068	36,89055
2013	3,254239	79,3684	105,87	8,100863	33,2099
2014	2,916927	80,57902	96,29	8,325606	30,48766
2015	4,784447	100,6914	49,49	15,45326	23,17178
2016	6,397695	109,4431	40,76	6,352723	20,87249
2017	5,591116	110,973	52,51	1,512675	22,63223
2018	4,26999	116,5938	69,78	1,164003	25,86115
2019	1,951768	119,3536	64,04	8,512376	22,7144
2020	2,415131	126,7768	41,47	13,71518	17,46984
2021	7,226063	135,0641	69,89	-6,5479	26,73439
2022	9,265516	141,995	100,08	-9,78262	31,67691
2023	9,3	135,84	83	10,5	43,7

Source: From the World Bank website

- **Appendix 04:** A program that merges Appendix 02 with Appendix 03 and presents the output in R:

```
getwd()
require(rjags)
require(coda)
data <- read.table("regression.txt")
y <- data[,1]
x1 <- data[,2]
x2 <- data[,3]
x3 <- data[,4]
x4 <- data[,5]
n <- nrow(data)
model.inits <- list(tau=1, a0=0, a1=0, a2=0 , a3=0,a4=0 )
iterations <- 10000
burnin <- 1000
chains <- 1
file="Regression2JAGS.txt"
model.fit <- jags.model(file="Regression2JAGS.txt",
                        data=list(n=n, y=y, x1=x1, x2=x2 , x3=x3,x4=x4 ),
                        inits=model.inits, n.chains = chains)
model.samples <- coda.samples(model.fit, c("a0", "a1", "a2","a3","a4",
                              "R2B","s2","sy2","typical.y"), n.iter=iterations)
summary(window(model.samples, start = burnin))
plot(model.samples,trace =TRUE,density=FALSE)
HPDinterval(model.samples)
effectiveSize(model.samples)
```

- **Appendix 05:** Markov chain convergence results:



- **Appendix 06:** The number of iterations needed for each variable to obtain the convergence of Markov chains:

```
> effectiveSize(model.samples)
      R2B        a0        a1        a2        a3        a4        s2       sy2 
 9501.933 10000.000  8348.462  5641.565  5969.513  7103.277  9501.933     0.000 
typical.y 
 8573.148 
```