



Modeling Industrial Production of Pasteurized Milk in Algeria: Insights from the Box-Jenkins

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Abstract :

This study aims to estimate a model for forecasting the annual industrial production of pasteurized milk in Algeria using the Box-Jenkins methodology, applied to data from 1980 to 2022. The analysis concluded with the estimation of an Autoregressive Integrated Moving Average (ARIMA) model, specifically ARIMA (13, 1, 9), demonstrating reasonable accuracy with a MAPE of 21%. The model forecasts that the industrial production of pasteurized milk will increase to approximately 11,955,000 hectoliters by 2028.

Key Words: ARIMA, Box-Jenkins Methodology, Forecasting, Industrial Production, Pasteurized Milk.

JEL Classification : Q13, Q18, C22.

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Introduction

Milk is rich in nutrients, including carbohydrates, fats, proteins, and vitamins, making it a valuable source of nutrition at all stages of life. It is considered one of the solutions that can improve living standards and promote healthy nutrition. It provides income for families that raise livestock and, in doing so, creates jobs in activities such as milk collection, processing, and its use in the food industry. Consequently, milk is considered a significant contributor to wealth, population growth, and economic development.

The milk and dairy industry in Algeria is one of the most recognized and widely practiced economic and commercial activities due to the high demand for these food products. It encompasses the production of pasteurized milk, cheese, and butter. However, the current crisis in the milk market specifically affects pasteurized milk, which has recently experienced supply fluctuations and distribution problems. Additionally, the consumption culture among Algerians plays a role, some traders, particularly those owning cafes and hotels, exploit this product for commercial gain. This situation contradicts the state's support policy aimed directly at the end consumer to protect their purchasing power, which is appears in the regulated price of 25 Algerian dinars per liter. However, recent studies indicate that the average daily calcium intake is only 585.9 ± 282.3 mg,



which does not meet international recommendations (Bentaleb, Sersar, Bencharif, Boukef, & Nar, 2023, p. 14).

This is from the perspective of marketing and consumption, while from the production side; during the Algerian Milk Forum, Azeddine Tamni, President of the National Professional Council for the Milk Sector, stated that Algeria requires 40 million hectoliters of milk annually to achieve self-sufficiency without relying on imports. This necessitates providing two million dairy cows and cultivating over 200,000 hectares of irrigated land for fodder production (APS, 2022).

This study examines the production of pasteurized milk in Algeria, setting aside the complex and interconnected factors that influence this industry, such as the number of dairy cows, their breeds and health, nutrition, climate-related factors, and the use of technology. Researchers utilize time series analysis through the Box-Jenkins methodology to forecast future quantitative values of phenomena, relying on historical analyses of time series and studying the behavior of variables through moving averages regression.

Based on the above, the research question can be formulated as follows:

What are the future predictions for milk production in Algeria using the Box-Jenkins model?

To deepen the understanding of the identified problematic, the main question can be divided into the following sub-questions:

-What is the accuracy of forecasting industrial production of pasteurized milk in Algeria using the Box-Jenkins methodology?

-What are the future predictions for pasteurized milk production in Algeria in the near future?

In the context of this study, two main hypotheses will be presented as follows:

Hypothesis 1: In light of the government support directed towards the agricultural sector, the availability of reasonably priced and subsidized feed, along with the utilization of desert groundwater, these factors contribute to attracting investments in dairy cattle breeding technologies, which will lead to an increase in milk production in the near future.

Hypothesis 2: Considering that the historical data for pasteurized milk production has undergone economic cycles, with a growth period from 1980 to 1994, followed by a decline from 1995 to 2006, and then a general growth from 2007 to 2022, the forecasting accuracy can be reasonable and acceptable.

Objectives of the Study

- To grasp the phases of the Box-Jenkins methodology for forecasting and its application to relevant data.
- To estimate the annual industrial production of pasteurized milk for a period of six years.



I. Literature Review:

1. Background of the Study

Several studies have investigated forecasting methods for milk production. (Deshmukh & Paramasivam., 2016) sought to identify effective forecasting techniques, determining that the ARIMA (1, 1, 1) model was optimal, predicting milk production in India to reach 160 million tonnes by 2017. Similarly, (Sankar & Prabakaran, 2012) focused on Tamil Nadu (India), using data from 1978 to 2008 and finding that The ARIMA (1, 1, 0) model anticipated an increase in production, forecasting it to reach 7.15 million tons by 2015. (Mishra, Chellai, Niranjana, Tiwari, Devi, & Dubey, 2020) analyzed time series data from 2001-02 to 2015-16 in Chhattisgarh (India), identifying ARIMA (0, 2, 0) as the most suitable model, with predictions of 219.73 million metric tons (MMT) for India and 1.599 MMT for Chhattisgarh by 2022-23. (Mishra, Matuka, Abotaleb, Weerasinghe, Karakaya, & Das, 2021) examined annual data from 1961 to 2018 for South Asian countries, revealing that ARIMA models outperformed Holt's Linear approach, with India projected to have the highest production, followed by Pakistan and China, while the GARCH model was more effective for Bangladesh. The study of (Waiswa, 2023) identified suitable ARIMA models for Uganda's milk production using data from 1961 to 2020, finding the ARIMA (0, 1, 0) model best for milk. Forecasts indicated an annual average growth of 1.63% for milk production from 2021 to 2025, providing valuable insights for enhancing Uganda's livestock sectors.

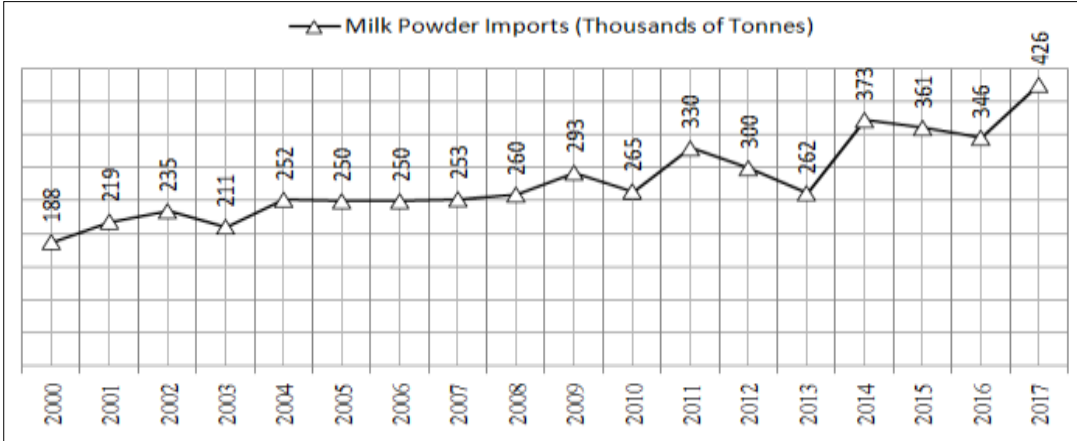
2. The Current State of Pasteurized Milk Production in Algeria:

Algeria has witnessed significant changes in pasteurized milk production over the years, with a gradual increase during the 1980s, rising from an average of about 4,200 thousand hectoliters to an average of 9,500 thousand hectoliters in the 1990s, peaking in the early 1990s. However, a notable decline in production occurred between 2001 and 2005, with an average of around 7,200 thousand hectoliters. This was followed by a gradual recovery until 2022, when production reached approximately 11,237.50 thousand hectoliters, indicating improvement in the sector but highlighting the ongoing need for development and sustainability (Table 1).

This recent growth is primarily attributed to the increase in the number of cattle in Algeria, which rose from 1,127,723 in 2010 to 1,732,964 in 2021 (ONS, 2020-2021, p. 11). This represents 4.73% of the total livestock population in Algeria. Despite the government's efforts, evident through policies supporting widely consumed goods and regulating activities, there remains a gap between production and consumption, as illustrated by the import bill (Zagaye, 2020, p. 26).



Fig.1: «Milk Powder Imports (Thousands of Tonnes)»



Source: (Sahali, Sahnoune, & Guendouzi, 2022, p. 87).

The fig.(01) indicates a consistent upward trend in milk powder imports in Algeria from 2000 to 2017, highlighting an increasing gap between production and consumption. Particularly notable is the significant surge in imports during 2016 and 2017, which peaked at 426 thousand tonnes, reflecting a growing reliance on imported dairy products.

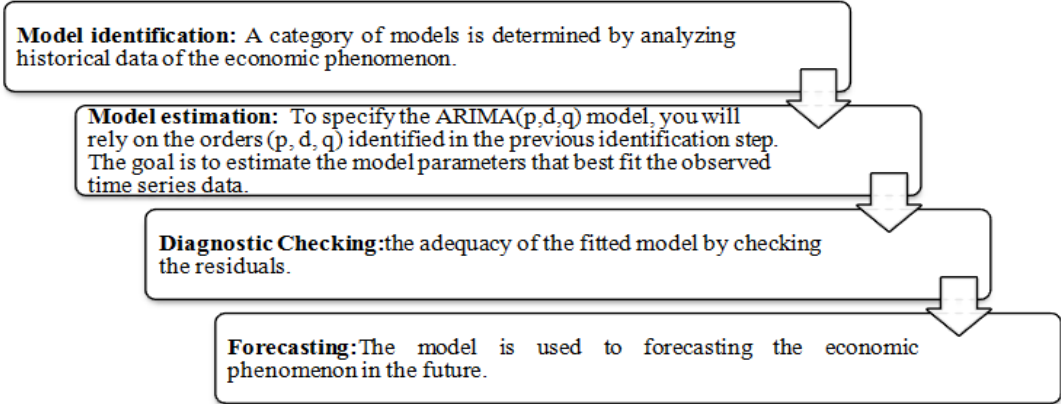
This study aims to identify trends in pasteurized milk production in Algeria and will analyze the behavior and direction of the time series in order to forecast the future of this industry, following a review of the relevant literature.

II. Research Methodology

1. The Box-Jenkins method

The Box-Jenkins method is a quantitative approach to forecasting that involves constructing a model to accurately represent the behavior of a time series (Adala, 2011, p. 136). This process follows a four-phase procedure, as illustrated in Figure 2.

Fig.2: «Box-Jenkins methodology steps»



Source: (Aldjandali, 2017, p. 59)



2. Data Collection:

The data for this study consists of the annual trends in industrial production of pasteurized milk in Algeria from 1980 to 2022 (measured in thousands of hectoliters). This data was sourced from the Algerian Office for National Statistics.

Table1: « Annual data on industrial production of pasteurized milk (period: 1980-2022) (unit: 10³HL)»

Years	1980	1981	1982	1983	1984	1985	1986	1987	1988
Pasteurized milk	3 242	3 590	4 066	4 297	4 593	4 633	5 444	6 549	7 453
Years	1989	1990	1991	1992	1993	1994	1995	1996	1997
Pasteurized milk	7 770.40	9 110	9 542.80	10 902.50	11 400	12 150.20	11 408.90	11 189.60	9 897.90
Years	1998	1999	2000	2001	2002	2003	2004	2005	2006
Pasteurized milk	9 375.10	8 442.10	8 590.90	7 827.50	7 154.60	5 780.00	5 106.00	4 754.00	4 382.80
Years	2007	2008	2009	2010	2011	2012	2013	2014	2015
Pasteurized milk	5 847.80	6 872.40	6 191.70	6 721.80	8 498.90	8 581.20	9 294.80	9 852.90	9 992.50
Years	2016	2017	2018	2019	2020	2021	2022		
Pasteurized milk	10 124.80	10 015.90	11 051.20	11 877.30	10 918.30	11 401.30	11 237.50		

Source: (ONS, 2020-2021, p. 11) & (ONS, 2020, pp. 226-229)

3. Application of method

3.1. Estimation of mixed ARMA

An autoregressive model, often referred to as an autoregressive process, is a statistical model where a variable y is influenced by its previous values. This is represented by the general form that includes p lagged values $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$. Such a model is known as an autoregressive model of order p (Hill, William, & Guay, 2018, p. 421), abbreviated as $AR(p)$.

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t$$

In the framework of a model, the coefficients $\phi_1, \phi_2, \dots, \phi_p$ reflect the intensity of the linear relationship between consecutive values. Meanwhile, c is a constant, ε_t represents white noise.

The process $\{y_t\}$ has a finite moving average representation of order q if it can be expressed in a specific form involving a white noise process ε_t with a mean of 0 and constant variance σ^2 , where $a_q \neq 0$. A white noise process is serially uncorrelated, and we can assume $a_0 = 1$ without loss of generality. This representation is known as a "one-sided moving average process," distinguishing it from the two-sided version (Pesaran, 2015, p. 269).

$$Y_t = a + \varepsilon_t + \omega_1 \varepsilon_{t-1} + \omega_2 \varepsilon_{t-2} + \dots + \omega_q \varepsilon_{t-q}$$

Where the $\omega_1, \dots, \omega_q$ are the parameters;

μ is the expectation of Y_t ($\mu = 0$);

$\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}$ are white noise error terms.



The ARMA (Autoregressive Moving Average) model is characterized by linear difference equations that have constant coefficients. The general form of the (Brockwell & Davis, 2016, p. 47), ARMA(p, q) model can be written as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t \mu + \varepsilon_t + \omega_1 \varepsilon_{t-1} + \omega_2 \varepsilon_{t-2} + \dots + \omega_q \varepsilon_{t-q}$$

The ARMA(p, q) model serves the purpose of modeling and forecasting in time series, as demonstrated by the statistician Wold in 1954. This model is characterized by its high flexibility and ability to generate a wide range of autocorrelation structures (Paolella, 2019, p. 31).

3.2. Autoregressive Integrated-Moving Average Models ARIMA (p,d,q)

ARIMA models ($ARIMA(p, d, q)$) are used for time series that are not stationary in the mean, where:

p is the number of autoregressive terms;

d is the degree of differencing;

q is the number of moving average terms.

A time series $\{X_t\}$ is considered an $ARIMA(p, d, q)$ process if the transformed series $Y_t = (1 - B)^d X_t$ is a causal ARMA(p, q) process (Brockwell & Davis, 2016, p. 158).

The $ARIMA(p, d, q)$ is written (Mouffok & Souar, 2018, p. 123):

$$\Delta^d Y_t = Y_t - Y_{t-1} - Y_{t-2} - \dots - Y_{t-d}$$

3.3. Stationary

A stochastic process X or $\{X_t\}$ is stationary if (Dor, 2009, p. 151):

▪ x_i is constant: $E(X_t) = \mu x \forall t$;

▪ The variance is: $VAR(X_t) = \sigma_x^2 \forall t$;

▪ The covariance between X_t and $X_{t-\theta}$ depends only on the time:

$$COV(X_t, X_{t-\theta}) = v(\theta) \forall t, \forall \theta.$$

III. Analysis, results and discussion

In this study, data entry was facilitated by the EViews 10 software, which was also utilized to generate the results, as reflected in the software outputs.

1. Identification

To assess the stationarity of a time series, several techniques may be employed:

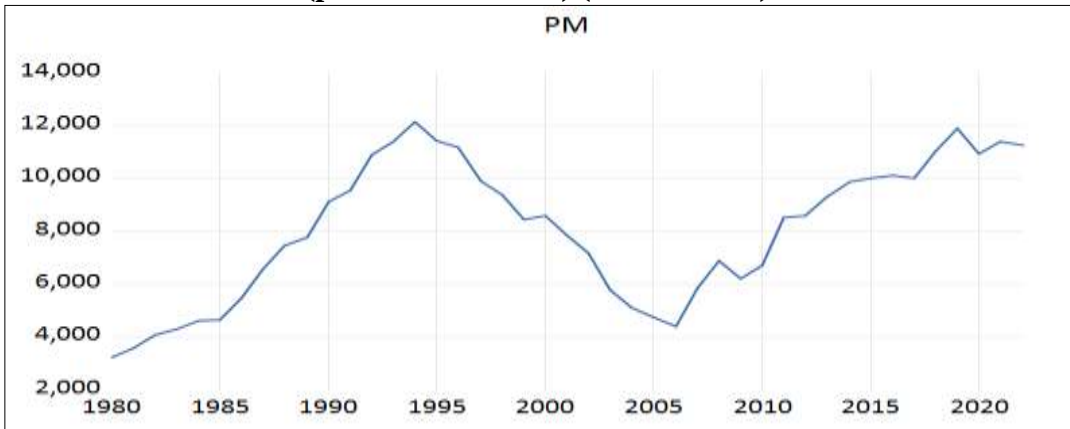
1.1. Visual Inspection

The time series representing the industrial production of pasteurized milk is abbreviated in this study as: $\{PM\}$

A plot of the time series data (Fig. 3) can reveal discernible trends or irregular patterns, which suggest non-stationarity.



Fig.3. «Annual data on industrial production of pasteurized milk (period: 1980-2022) (Unit: 10³HL)»



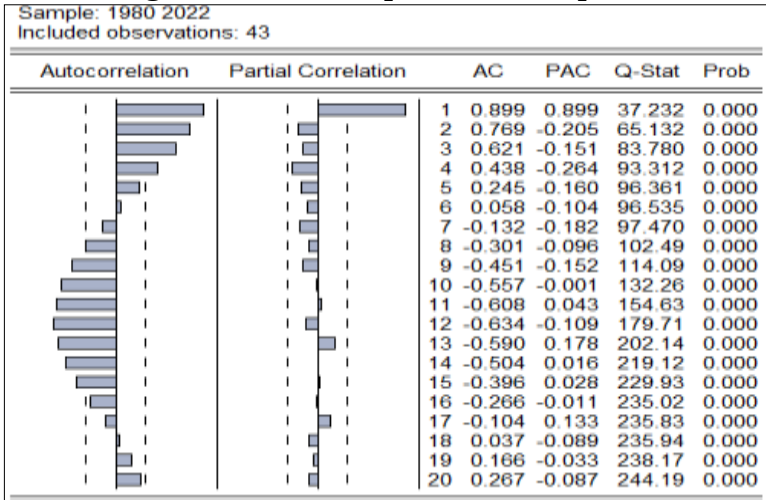
Source: Eviews 10 output.

1.2. Correlogram:

The correlogram, or sample autocorrelation function, is a graphical tool used to assess the significance of autocorrelations, showing correlations between observations at various lags. An autocorrelation r_s is deemed significant at a 5% level if $\sqrt{T}r_s$ exceeds ± 1.96 , or alternatively, if r_s exceeds $\pm \frac{1.96}{\sqrt{T}}$. The correlogram typically features bars representing autocorrelation magnitudes, with significance bounds at $\pm \frac{2}{\sqrt{T}}$, enabling quick identification of significant correlations (Hill, William, & Guay, 2018, p. 426).

The identification process necessitated the use of various tools, including the correlogram, the autocorrelation function (ACF), and the partial autocorrelation function (PACF). Each term derived from this analysis is considered significantly different from zero at the 5% significance level. (Bourbonnais, 2015, p. 253).

Fig.4. «Correlogram “industrial production of pasteurized milk data”»



Source: Eviews 10 output.



From the correlogram presented in Figure 4, the autocorrelation function (ACF) is observed to exceed the standard error bounds, ultimately declining to zero and -1 . The pattern observed in the PACF correlogram indicates that the time series demonstrates non-stationarity.

1.3. Augmented Dickey-Fuller:

The Augmented Dickey-Fuller (ADF) test is commonly employed to assess whether there is a unit root in time series data. The ADF test is grounded in the following regression equation: (Agung, 2009, pp. 446-447):

$$\Delta y_t = \mu + \delta y_{t-1} + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \dots + \beta_p \Delta y_{t-p} + \varepsilon_t$$

Where:

- Δy_t : represents the differenced series;
- t : is a linear trend term;
- $y_{(t-1)}$: represents the lagged level of the series;
- $\Delta y_{(t-1)}, \Delta y_{(t-2)}, \dots, \Delta y_{(t-p)}$: represent the differenced lagged terms;
- $\delta, \mu, \beta_1, \beta_2, \dots, \beta_p$: are coefficient parameters;
- ε_t : is the error term.

To perform an ADF test, the regression equation must be estimated. A hypothesis test is conducted to assess the null hypothesis that $\delta = 0$, signifying non-stationarity. The resulting test statistic is compared against critical values.

1.4. Phillips-Perron test:

(Phillips & Perron, 1988) proposed an alternative unit root test that addresses autocorrelation without adding extra lags, modifying test statistics to account for autocorrelation effects. This allows the use of standard Dickey-Fuller critical values under conditions of weak dependency (Terence, 2019, p. 81).

1.5. The KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test:

Kwiatkowski et al. (1992) proposed using a Lagrange Multiplier (LM) test based on the null hypothesis of stationarity. After estimating models Autoregressive model with constant or Autoregressive model with trend, the partial sum of the residuals is calculated as: $S_t = \sum_{i=1}^t \varepsilon_i$. The long-term variance is estimated as S_t^2 . (Bourbonnais, 2015, p. 250).

In the table 2, the (ADF) test for $\{PM\}$ with and without intercept, with and without trend (refer to Appendix 01).

Table2: « Augmented Dickey-Fuller (ADF) test result»

Hypothesis H0: {PM} has a unit root				
Lag Length: 3 (Automatic - based on SIC, maxlag=5)				
ADF test	t - statistic	critical values	Prob.	Hypothesis
without intercept and without trend	-2.5647	-2.9389	0.1088	H ₀ is accepted
with intercept and without trend	-1.3514	-3.5207	0.8606	H ₀ is accepted
with intercept and with trend	1.0511	-2.6211	0.9206	H ₀ is accepted

Source: Prepared by researchers based on Eviews10 output.



Based on the results obtained, it can be concluded that the time series contains unit roots and is non-stationary; thus, it is classified as a DS type series.

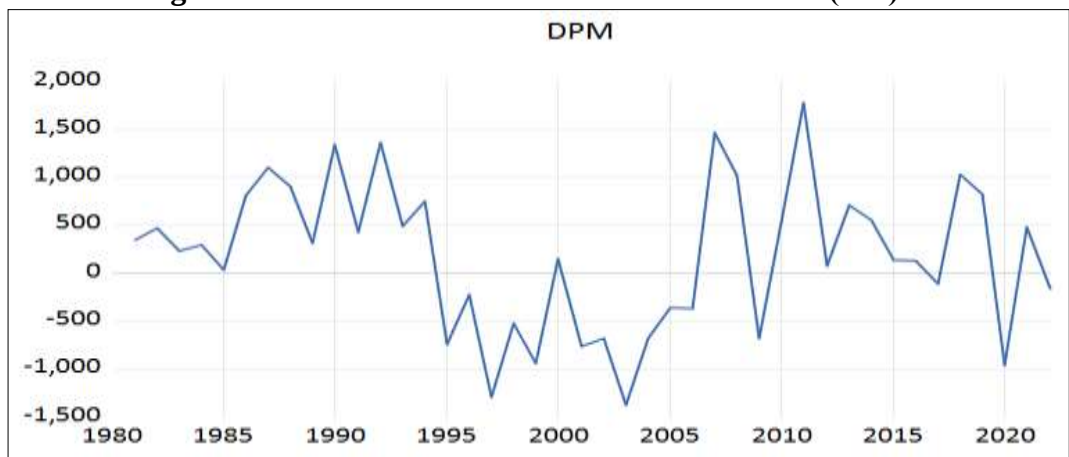
To tackle the instability, differences are applied to generate a new time series, the same tests—Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)—are utilized. Here, "D(PM)" represents the new time series. (refer to Appendix 02, 03, 04).

From Table 3, the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests indicate that $|t\text{-Statistic}| > |\text{critical values}|$ at the 5% significance level, with a probability lower than 5%. This leads to the rejection of H_0 and acceptance of H_1 , which states that "D(PM)" does not have a unit root, indicating that the time series is stationary at the first difference. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test further confirms this finding, as $LM - stat < asymptotic critical values$ at the 5% level.

Table3: « (ADF),(PP),(KPSS), tests for the new time series "D(PM)" »

Hypothesis H_0: D(PM) has a unit root				
Lag Length: 3 (Automatic - based on SIC, maxlag=5)				
ADF test	t - statistic	critical values in the level of significant 5%	Prob.	Hypothesis
without intercept and without trend	-4.3905	-2.9350	0.0011	H_1 is accepted
with intercept and without trend	-4.3905	-3.5236	0.0066	H_1 is accepted
with intercept and with trend	-4.2779	-1.9490	0.0001	H_1 is accepted
PP test	Adj t - statistic	critical values in the level of significant 5%	Prob.	Hypothesis
without intercept and without trend	-4.4861	-2.9350	0.0009	H_1 is accepted
with intercept and without trend	-4.4626	-3.5236	0.0050	H_1 is accepted
with intercept and with trend	-4.3524	-1.9490	0.0001	H_1 is accepted
KPSS test	LM-Stat.	Asymptotic critical values	***	Hypothesis
with intercept and without trend	0.1274	0.4630	***	H_0 is accepted
with intercept and with trend	0.1160	0.1460	***	H_0 is accepted

Source: Prepared by researchers based on Eviews10 output.

Fig.5. «The new time series in the 1st difference “D(PM)”»

Source: Eviews 10 output.

Figure 5 demonstrates that the new time series "D(PM)" is stationary. The series exhibits a tendency to revert upward toward its mean. This behavior suggests stability in the time series. The observed fluctuations indicate a lack of persistent trends. Overall, the evidence supports the conclusion of stationarity.

2. Estimation

By analyzing the intersections of the ACF and PACF plots, the parameters of the ARIMA(p, d, q) model can be determined (figure 6), There are many possibilities of ARIMA model: (0,1,1), (0,1,9) (1,1,0), (1,1,1) (1,1,9) (2,1,0), (2,1,1) (2,1,9) (9,1,0), (9,1,1) (9,1,9) (10,1,0), (10,1,1) (10,1,9) (12,1,0), (12,1,1) (12,1,9) (13,1,9) (13,1,9) (13,1,9)

Fig.6. «ACF&PACF of 1st Difference»

Sample: 1980 2022 Included observations: 42						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	0.334	0.334	5.0432	0.025
		2	0.316	0.230	9.6591	0.008
		3	0.273	0.136	13.187	0.004
		4	0.243	0.090	16.056	0.003
		5	0.014	-0.187	16.065	0.007
		6	0.131	0.076	16.941	0.010
		7	-0.042	-0.130	17.035	0.017
		8	-0.068	-0.071	17.289	0.027
		9	-0.426	-0.462	27.463	0.001
		10	-0.301	-0.157	32.680	0.000
		11	-0.222	0.127	35.626	0.000
		12	-0.325	-0.102	42.115	0.000
		13	-0.308	0.007	48.160	0.000
		14	-0.199	-0.089	50.778	0.000
		15	-0.241	0.039	54.755	0.000
		16	-0.215	-0.019	58.052	0.000
		17	-0.047	0.099	58.216	0.000
		18	0.009	-0.062	58.222	0.000
		19	0.058	-0.069	58.492	0.000
		20	0.046	0.015	58.669	0.000

Source: Eviews 10 output.



After comparing the results obtained without a constant using the Least Squares Method, the most suitable model identified is (13, 1, 9) among the alternatives. This model is preferred due to its lower values of the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Value (HQV). Additionally, the model features significant parameters (refer to Appendix 05), with probabilities for the autoregressive term ($\text{prob}_{AR(13)}=0.0195$), the moving average term ($\text{prob}_{MA(9)}=0.0406$), the constant term $\text{prob}_{(c)}=0.0599$, $\text{prob}_{(\text{SIGMA}^2)}=0.0006$, and The coefficient of determination is $R\text{-squared}=0.40$, as presented in Table 4.

Table4: «ARIMA (13, 1, 9)»

Dependent Variable: D(PM)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Date: 09/01/24 Time: 17:13				
Sample: 1981 2022				
Included observations: 42				
Convergence achieved after 15 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	108.9588	56.18528	1.939277	0.0599
AR(13)	-0.422878	0.173408	-2.438629	0.0195
MA(9)	-0.504584	0.238029	-2.119839	0.0406
SIGMASQ	347013.2	92629.88	3.746234	0.0006
R-squared	0.402384	Mean dependent var		190.3690
Adjusted R-squared	0.355204	S.D. dependent var		771.2488
S.E. of regression	619.3068	Akaike info criterion		15.90921
Sum squared resid	14574553	Schwarz criterion		16.07470
Log likelihood	-330.0933	Hannan-Quinn criter.		15.96986
F-statistic	8.528652	Durbin-Watson stat		1.795868
Prob(F-statistic)	0.000186			

Source: Eviews 10 output.

The model estimating is:

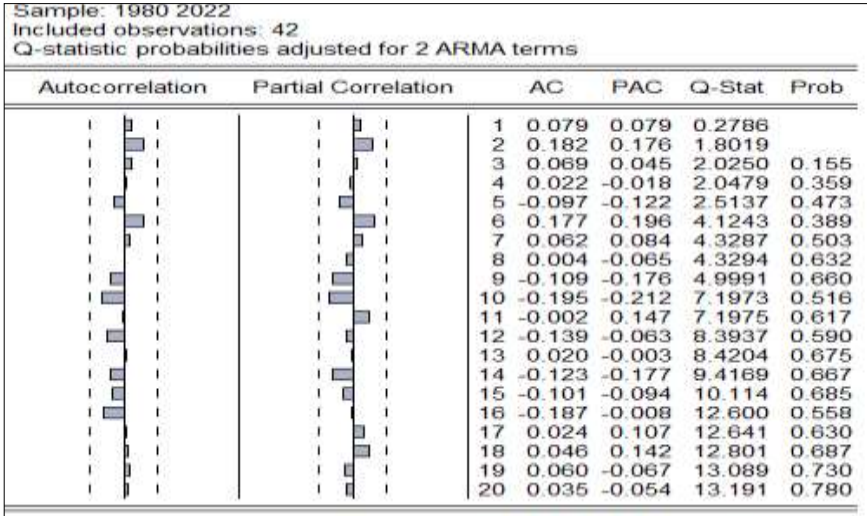
$$D(PM) = 108.95 + AR(13) * (-0.42) + MA(9) * (-0.50)$$

3. Diagnostic Checking

To verify the model, the Ljung-Box test is employed. The correlogram of residuals (Figure 7) indicates that there are no significant estimated autocorrelations in the ARIMA (13, 1, 9) model. All autocorrelation coefficients fall within the confidence intervals, suggesting that the residuals conform to a white noise distribution.



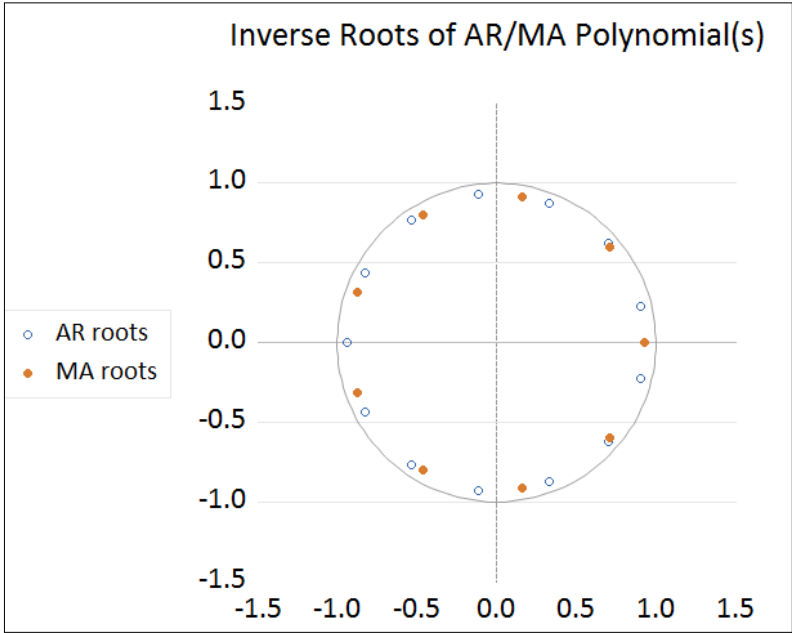
Fig.7. «Correlogram of residuals»



Source: Eviews 10 output.

From the correlogram of residuals (Figure 8), the following is observed:
Q-stat=13.191, lag=20, $\chi^2_{0.05,20} = 31.410$
 $\chi^2_{0.05,20} = 31.410 > Q\text{-stat} = 13.191$, it can be concluded that the residuals follow a white noise distribution.

Fig.8. «Inverse roots of ARIMA polynomial (s)»



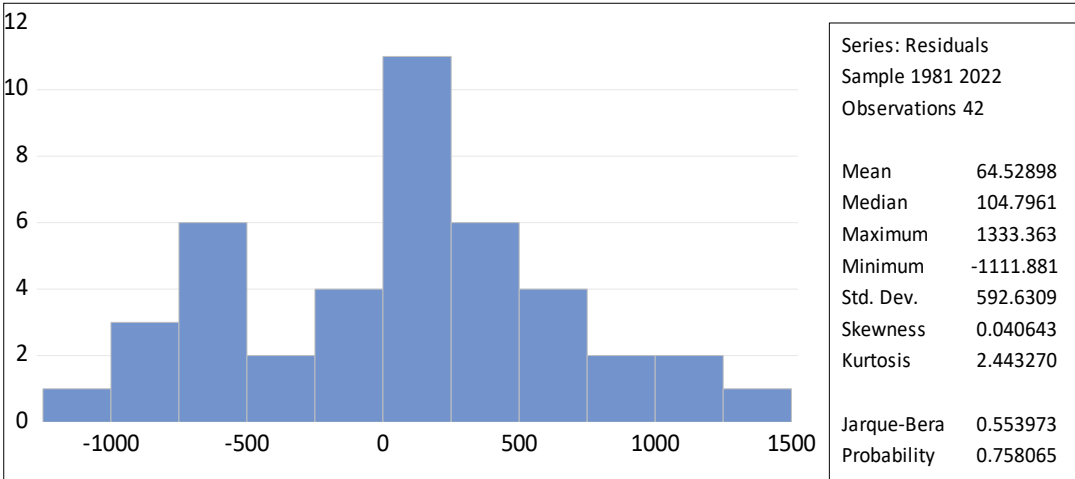
Source: Eviews 10 output.

The inverse roots of the ARIMA polynomial are presented in Figure 8. All roots lie inside the unit circle, confirming the stability of the model. This stability suggests that any shocks to the time series will dissipate over time, leading to



reliable forecasts. The absence of roots without the unit circle further reinforces the model's capacity to adequately capture the underlying data dynamics.

Fig.9. «Normality test of residues»



Source: Eviews 10 output.

By employing the Jarque-Bera test alongside the histogram shown in Figure 9 to evaluate the normality of the residuals, it was found that $JB = 0.5539$ with a corresponding probability of 0.7580. Since $JB < \text{probability}$, both the test results and the histogram suggest that the residuals adhere to a normal distribution.

4. Forecasting

After the identification, estimation, and verification phases, the final step is to utilize the ARIMA (13, 1, 9) model to forecast the industrial production of pasteurized milk in Algeria, measured in units of 10^3 hectoliters (HL).

Table 5: «the industrial production of pasteurized milk forecast results for Algeria (2022-2025)»

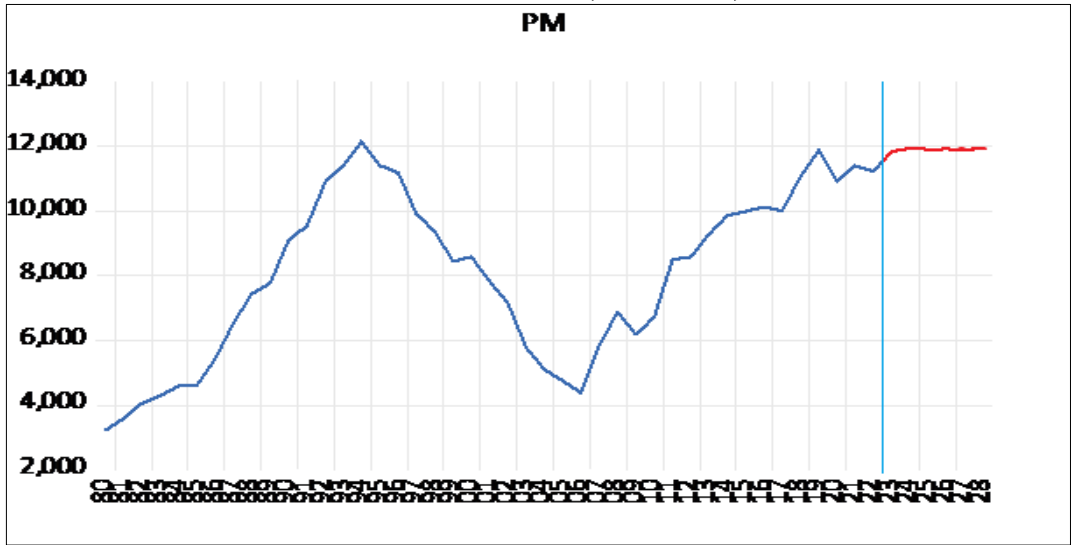
Years	(Unit: 10 ³ hectoliters)
2023	11840.9476
2024	11945.0884
2025	11910.65
2026	11922.9437
2027	11890.3902
2028	11955.4094

Source: Eviews 10 output.



Table 5 displays the projected industrial production of pasteurized milk in Algeria for the period from 2023 to 2028, based on the selected ARIMA(13, 1, 9) model. The forecasted results indicate an upward trend, with production expected to reach approximately $11,955 \times 10^3$ hectoliters by 2028. This trend is further illustrated by the curve in Figure 10, which clearly depicts the anticipated growth.

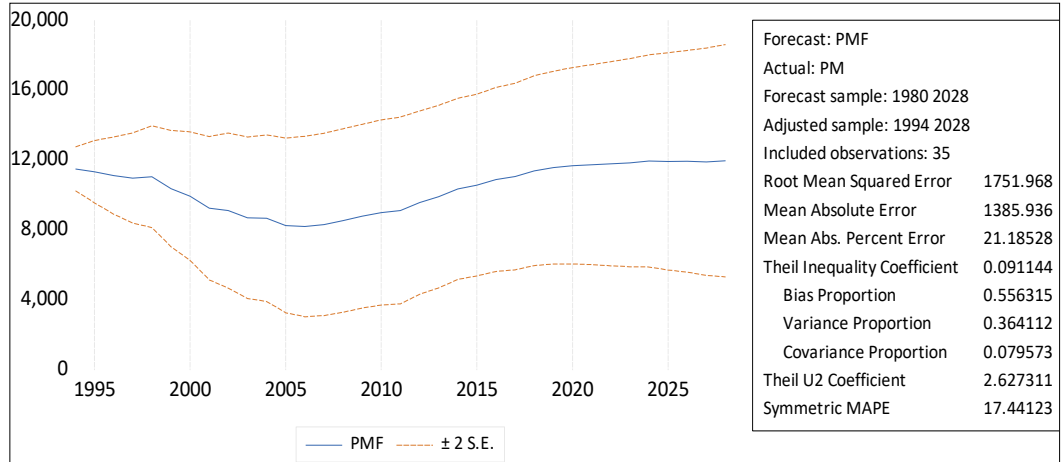
Fig.10. «the industrial production of pasteurized milk during period 1980-2022, forecast (2023-2028)»



Source: Eviews 10 output.

To evaluate the ARIMA (13, 1, 9) model, the following measures were employed: Mean Absolute Percentage Error (MAPE) and Theil Inequality Coefficient. These metrics provide insights into the model's accuracy and performance in forecasting the industrial production of pasteurized milk.

Fig.11. «tests for evaluation of ARIMA (13,1,9) model»



Source: Eviews 10 output.

According to Figure 11, the performance evaluation metrics for the ARIMA (13, 1, 9) model are as follows:



- The Mean Absolute Percentage Error (MAPE) is 21.18%, which is relatively high. This indicates that the model's predictions exhibit, on average, a 21.18% error compared to the actual values. Generally, a MAPE below 21% is considered indicative of a reasonable model fit (Lewis, 1982) from (H. Rangika Iroshani, 2016, p. 103) (refer to Appendix 06).

- Henri Theil introduced the Theil Inequality Coefficient as a measure of forecast accuracy. This coefficient ranges from 0 to 1, with values closer to 0 indicating a better model fit. A lower Theil Inequality Coefficient signifies that the model's predictions are more accurate relative to the actual observations. (Theil, Beerens, Tilanus, & De Leeuw, 1966). In this case, the Theil Inequality Coefficient of 0.091 serves as a normalized measure of overall model error. This relatively low value indicates that the model is performing reasonably well, even in light of the higher RMSE and MAE values.

Conclusion

This study analyzed the annual data on the industrial production of pasteurized milk in Algeria from 1980 to 2022, measured in units of 103 hectoliters. The results from the (ADF), (PP), (KPSS) tests indicated that the time series is stationary at the first difference.

The ACF and PACF correlograms helped determine the best parameters for the ARIMA model, with ARIMA (13, 1, 9) being the most suitable due to its lowest AIC, SC, and HQV values. The model's parameters were significant, with autoregressive and moving average terms showing probabilities of 0.0195 and 0.0406, respectively. The coefficient of determination was $R^2=0.40$, indicating a moderate fit.

The estimated model is expressed as:

$$D(PM) = 108.95 + AR(13) * (-0.42) + MA(9) * (-0.50)$$

The analysis and forecasting of the industrial production of pasteurized milk in Algeria using the ARIMA (13, 1, 9) model demonstrate a comprehensive approach to time series modeling. The Ljung-Box test indicated that the residuals show no significant autocorrelations, as evidenced by the Q-statistic of 13.191, which is less than the critical value of 31.410. This indicates that the residuals are consistent with a white noise distribution, reflecting a well-fitted model.

The back-root test confirmed the model's stability, indicating that shocks to the time series dissipate over time, which ensures reliable predictions. Additionally, the Jarque-Bera test verified the normality of the residuals, showing a JB statistic of 0.5539 and a probability of 0.7580, suggesting that the residuals follow a normal distribution.

Forecasting results for the industrial production of pasteurized milk from 2023 to 2028, as presented in Table 5, show an upward trend, with production expected to reach approximately $11,955 \times 10^3$ hectoliters by 2028, this serves as conclusive evidence supporting the validity of the first hypothesis of the study.

To assess the model's accuracy, performance evaluation measures, including the (MAPE) and the Theil Inequality Coefficient, were employed. The MAPE of



21.18% suggests a relatively high average error in predictions, while the Theil Inequality Coefficient of 0.091 indicates a reasonable model fit despite higher RMSE and MAE values. This indicates the validity of the second hypothesis of the study.

In summary, the ARIMA (13, 1, 9) model provides a robust framework for forecasting the industrial production of pasteurized milk, offering valuable insights for stakeholders in the dairy industry in Algeria.

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Appendices:

Appendix 01: Augmented Dickey-Fuller(ADF) test result

Null Hypothesis: PM has a unit root Exogenous: Constant Lag Length: 3 (Automatic - based on SIC, maxlag=8)		
	t-Statistic	Prob. *
Augmented Dickey-Fuller test statistic	-2.564743	0.1088
Test critical values:		
1% level	-3.610453	
5% level	-2.938967	
10% level	-2.607932	
Null Hypothesis: PM has a unit root Exogenous: Constant, Linear Trend Lag Length: 0 (Automatic - based on Modified AIC, maxlag=8)		
	t-Statistic	Prob. *
Augmented Dickey-Fuller test statistic	-1.351477	0.8806
Test critical values:		
1% level	-4.192337	
5% level	-3.520787	
10% level	-3.191277	
Null Hypothesis: PM has a unit root Exogenous: None Lag Length: 0 (Automatic - based on SIC, maxlag=8)		
	t-Statistic	Prob. *
Augmented Dickey-Fuller test statistic	1.051101	0.9208
Test critical values:		
1% level	-2.821185	
5% level	-1.948886	
10% level	-1.611932	
MacKinnon (1996) one-sided p-values		

Source: Eviews 10 output.

Appendix 03: (PP test for the new time series “D(PM)”.

Null Hypothesis: D(PM) has a unit root Exogenous: Constant Bandwidth: 3 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob. *
Phillips-Perron test statistic	-4.486167	0.0009
Test critical values:		
1% level	-3.600867	
5% level	-2.935001	
10% level	-2.605836	
Null Hypothesis: D(PM) has a unit root Exogenous: Constant, Linear Trend Bandwidth: 3 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob. *
Phillips-Perron test statistic	-4.462688	0.0050
Test critical values:		
1% level	-4.198503	
5% level	-3.523623	
10% level	-3.192902	
Null Hypothesis: D(PM) has a unit root Exogenous: None Bandwidth: 3 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob. *
Phillips-Perron test statistic	-4.352416	0.0001
Test critical values:		
1% level	-2.622585	
5% level	-1.949097	
10% level	-1.611824	

Source: Eviews 10 output.

Appendix 02: (ADF) test for the new time series “D(PM)”.

Null Hypothesis: D(PM) has a unit root Exogenous: Constant Lag Length: 0 (Automatic - based on SIC, maxlag=9)		
	t-Statistic	Prob. *
Augmented Dickey-Fuller test statistic	-4.390514	0.0011
Test critical values:		
1% level	-3.600867	
5% level	-2.938967	
10% level	-2.605836	
Null Hypothesis: D(PM) has a unit root Exogenous: Constant, Linear Trend Lag Length: 0 (Automatic - based on SIC, maxlag=9)		
	t-Statistic	Prob. *
Augmented Dickey-Fuller test statistic	-4.361296	0.0006
Test critical values:		
1% level	-4.198503	
5% level	-3.523623	
10% level	-3.192902	
Null Hypothesis: D(PM) has a unit root Exogenous: None Lag Length: 0 (Automatic - based on SIC, maxlag=9)		
	t-Statistic	Prob. *
Augmented Dickey-Fuller test statistic	-4.277908	0.0001
Test critical values:		
1% level	-2.622585	
5% level	-1.949097	
10% level	-1.611824	

Source: Eviews 10 output.

Appendix 04: (KPSS) test for the new time series “D(PM)”.

Null Hypothesis: D(PM) is stationary Exogenous: Constant Bandwidth: 4 (Newey-West automatic) using Bartlett kernel		
	LM-Stat.	
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.127417	
Asymptotic critical values:		
1% level	0.739000	
5% level	0.463000	
10% level	0.347000	
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		
Null Hypothesis: D(PM) is stationary Exogenous: Constant, Linear Trend Bandwidth: 4 (Newey-West automatic) using Bartlett kernel		
	LM-Stat.	
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.116008	
Asymptotic critical values:		
1% level	0.218000	
5% level	0.146000	
10% level	0.119000	
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		

Source: Eviews 10 output.



Appendix 05: Least Squares Method test of ARIMA (p,d,q)

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	188.1493	139.8250	1.348368	0.1902	C	164.2738	64.8939	2.360217	0.0228	C	188.1285	185.0200	1.00036	0.3212
MA(1)	0.234665	0.200349	1.171288	0.2490	MA(1)	0.627794	0.237259	2.644918	0.0113	AR(1)	0.528749	0.175148	3.017080	0.0060
SGMASQ	536651.0	138532.3	3.869349	0.0004	SGMASQ	422107.1	125986.1	3.340100	0.0011	SGMASQ	515322.1	126502.2	4.076471	0.0002
R-squared	0.077500	Mean dependent var	190.3090		R-squared	0.255822	Mean dependent var	190.3090		R-squared	0.112527	Mean dependent var	190.3090	
Adjusted R-squared	0.030192	S.D. dependent var	771.2488		Adjusted R-squared	0.217212	S.D. dependent var	771.2488		Adjusted R-squared	0.067616	S.D. dependent var	771.2488	
S.E. of regression	756.5108	Akaike info criterion	16.17334		S.E. of regression	680.2338	Akaike info criterion	16.02115		S.E. of regression	744.4576	Akaike info criterion	16.13003	
Sum squared resid	22497154	Schwarz criterion	16.29746		Sum squared resid	18152270	Schwarz criterion	16.14527		Sum squared resid	21645338	Schwarz criterion	16.29012	
Log likelihood	-336.6801	Hannan-Quinn criter.	16.21883		Log likelihood	-333.4441	Hannan-Quinn criter.	16.06664		Log likelihood	-335.8561	Hannan-Quinn criter.	16.10150	
F-statistic	1.678204	Durbin-Watson stat	1.882568		F-statistic	6.898483	Durbin-Watson stat	1.881041		F-statistic	3.472483	Durbin-Watson stat	2.123899	
Prob(F-statistic)	0.207418				Prob(F-statistic)	0.003157				Prob(F-statistic)	0.060166			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	189.9610	237.4027	0.800164	0.4286	C	158.4111	87.3348	1.813946	0.0776	C	184.2062	164.2129	1.129567	0.2641
AR(1)	0.788312	0.210250	3.746778	0.0011	AR(1)	0.281000	0.146675	1.910340	0.0619	AR(1)	0.305672	0.175148	1.745201	0.0878
MA(1)	-0.495234	0.205402	-1.970655	0.0512	MA(1)	-0.461864	0.188726	-2.447920	0.0161	SGMASQ	521997.5	127404.3	4.095246	0.0002
SGMASQ	484252.3	112898.9	4.285285	0.0003	SGMASQ	492972.5	107526.9	3.747694	0.0006					
R-squared	0.195909	Mean dependent var	190.3090		R-squared	0.306012	Mean dependent var	190.3090		R-squared	0.101031	Mean dependent var	190.3090	
Adjusted R-squared	0.155232	S.D. dependent var	771.2488		Adjusted R-squared	0.261224	S.D. dependent var	771.2488		Adjusted R-squared	0.054600	S.D. dependent var	771.2488	
S.E. of regression	731.5765	Akaike info criterion	16.12538		S.E. of regression	697.3758	Akaike info criterion	15.98031		S.E. of regression	749.7674	Akaike info criterion	16.15032	
Sum squared resid	20337759	Schwarz criterion	16.26508		Sum squared resid	16602485	Schwarz criterion	16.03300		Sum squared resid	21973803	Schwarz criterion	16.27494	
Log likelihood	-336.5985	Hannan-Quinn criter.	16.18444		Log likelihood	-331.7544	Hannan-Quinn criter.	16.04890		Log likelihood	-330.1673	Hannan-Quinn criter.	15.98022	
F-statistic	2.522435	Durbin-Watson stat	2.077306		F-statistic	5.685354	Durbin-Watson stat	2.107041		F-statistic	2.101608	Durbin-Watson stat	1.597939	
Prob(F-statistic)	0.073238				Prob(F-statistic)	0.000629				Prob(F-statistic)	0.125321			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	192.8715	186.5201	1.031759	0.3153	C	161.4363	88.1089	1.832068	0.0748	C	165.4981	76.0799	2.176161	0.0357
AR(1)	0.268807	0.142769	1.884651	0.0671	AR(1)	0.271229	0.153789	1.763079	0.0856	AR(1)	-0.427542	0.137791	-3.101225	0.0026
MA(1)	0.255123	0.187650	1.360196	0.1818	MA(1)	-0.456258	0.233130	-1.957102	0.0577	SGMASQ	453257.5	127667.0	3.526219	0.0006
SGMASQ	490005.9	120744.4	4.100112	0.0002	SGMASQ	404951.3	119430.4	3.390711	0.0015					
R-squared	0.147412	Mean dependent var	190.3090		R-squared	0.326505	Mean dependent var	190.3090		R-squared	0.218240	Mean dependent var	190.3090	
Adjusted R-squared	0.089152	S.D. dependent var	771.2488		Adjusted R-squared	0.247542	S.D. dependent var	771.2488		Adjusted R-squared	0.178201	S.D. dependent var	771.2488	
S.E. of regression	730.7148	Akaike info criterion	16.14514		S.E. of regression	695.0147	Akaike info criterion	15.99350		S.E. of regression	698.7357	Akaike info criterion	16.04852	
Sum squared resid	20792738	Schwarz criterion	16.31063		Sum squared resid	17068804	Schwarz criterion	16.15899		Sum squared resid	21973803	Schwarz criterion	16.27494	
Log likelihood	-335.9479	Hannan-Quinn criter.	16.20560		Log likelihood	-331.8634	Hannan-Quinn criter.	16.05416		Log likelihood	-334.2148	Hannan-Quinn criter.	16.08361	
F-statistic	2.149982	Durbin-Watson stat	2.038836		F-statistic	5.486528	Durbin-Watson stat	2.100009		F-statistic	6.475869	Durbin-Watson stat	1.401548	
Prob(F-statistic)	0.148584				Prob(F-statistic)	0.003009				Prob(F-statistic)	0.008018			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	187.7678	88.07083	2.133533	0.0373	C	152.0281	69.27833	2.203149	0.0307	C	159.7864	87.8842	1.824601	0.0741
AR(1)	-0.413512	0.136477	-3.022376	0.0041	AR(1)	-0.428107	0.162150	-2.633350	0.0099	AR(1)	-0.317456	0.132854	-2.015703	0.0446
MA(1)	0.238942	0.171005	1.395593	0.2316	MA(1)	-0.391315	0.177886	-2.197350	0.0319	SGMASQ	511907.5	148382.5	3.433991	0.0012
SGMASQ	426813.5	112529.2	3.783819	0.0005	SGMASQ	435980.1	129994.2	3.353967	0.0015					
R-squared	0.294781	Mean dependent var	190.3090		R-squared	0.254885	Mean dependent var	190.3090		R-squared	0.118820	Mean dependent var	190.3090	
Adjusted R-squared	0.236738	S.D. dependent var	771.2488		Adjusted R-squared	0.196000	S.D. dependent var	771.2488		Adjusted R-squared	0.073651	S.D. dependent var	771.2488	
S.E. of regression	686.9148	Akaike info criterion	16.03584		S.E. of regression	681.5254	Akaike info criterion	16.00374		S.E. of regression	742.3118	Akaike info criterion	16.15140	
Sum squared resid	17930371	Schwarz criterion	16.19943		Sum squared resid	16017175	Schwarz criterion	16.13134		Sum squared resid	21480054	Schwarz criterion	16.27588	
Log likelihood	-332.7127	Hannan-Quinn criter.	16.08405		Log likelihood	-331.3805	Hannan-Quinn criter.	16.03416		Log likelihood	-335.1807	Hannan-Quinn criter.	16.19998	
F-statistic	4.261771	Durbin-Watson stat	1.883787		F-statistic	4.320448	Durbin-Watson stat	1.613403		F-statistic	2.628415	Durbin-Watson stat	1.936579	
Prob(F-statistic)	0.007965				Prob(F-statistic)	0.010100				Prob(F-statistic)	0.084871			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	184.7864	108.8631	1.670191	0.1247	C	158.4203	55.71468	2.844455	0.0075	C	180.8368	82.40563	2.191765	0.0318
AR(1)	0.248665	0.171826	1.435487	0.1560	AR(1)	0.248800	0.166106	1.495338	0.1407	AR(1)	-0.412826	0.137711	-3.000500	0.0046
MA(1)	0.159417	0.223577	0.680341	0.4967	MA(1)	-0.406823	0.215200	-2.354452	0.0217	SGMASQ	475431.5	115865.3	3.962406	0.0002
SGMASQ	502910.7	140002.9	3.526654	0.0011	SGMASQ	404031.8	120202.6	3.358828	0.0018					
R-squared	0.132601	Mean dependent var	190.3090		R-squared	0.334188	Mean dependent var	190.3090		R-squared	0.118820	Mean dependent var	190.3090	
Adjusted R-squared	0.065225	S.D. dependent var	771.2488		Adjusted R-squared	0.249205	S.D. dependent var	771.2488		Adjusted R-squared	0.150239	S.D. dependent var	771.2488	
S.E. of regression	745.5525	Akaike info criterion	16.12333		S.E. of regression	688.2525	Akaike info criterion	16.00622		S.E. of regression	713.5432	Akaike info criterion	16.10030	
Sum squared resid	21122048	Schwarz criterion	16.33752		Sum squared resid	16999136	Schwarz criterion	16.13141		Sum squared resid	21480054	Schwarz criterion	16.27588	
Log likelihood	-335.6125	Hannan-Quinn criter.	16.23269		Log likelihood	-332.1390	Hannan-Quinn criter.	16.06688		Log likelihood	-335.2280	Hannan-Quinn criter.	16.15159	
F-statistic	1.964305	Durbin-Watson stat	1.912517		F-statistic	6.537496	Durbin-Watson stat	1.505700		F-statistic	4.316123	Durbin-Watson stat	1.898883	
Prob(F-statistic)	0.158678				Prob(F-statistic)	0.002986				Prob(F-statistic)	0.025262			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	124.6230	114.8609	1.171052	0.2482	C	120.6915	53.66872	2.248474	0.0310	C	123.3867	87.17418	1.415404	0.1649
AR(1)	-0.200261	0.141070	-1.350068	0.1793	AR(1)	-0.348067	0.146004	-2.379747	0.0236	AR(1)	-0.381885	0.179744	-2.181313	0.0345
MA(1)	0.100000	0.230264	0.432238	0.6681	MA(1)	-0.457047	0.216796	-2.083151	0.0440	SGMASQ	898008.2	138526.7	3.488878	0.0012
SGMASQ	467533.0	117833.3	3.967438	0.0003	SGMASQ	259377.1	101423.4	2.549183	0.0006					
R-squared	0.194829	Mean dependent var	190.3090		R-squared	0.349047	Mean dependent var	190.3090		R-squared	0.106455	Mean dependent var	190.3090	
Adjusted R-squared	0.137822	S.D. dependent var	771.2488		Adjusted R-squared	0.295007	S.D. dependent var	771.2488		Adjusted R-squared	0.123759	S.D. dependent var	771.2488	
S.E. of regression	716.9511	Akaike info criterion	16.12287		S.E. of regression	647.5427	Akaike info criterion	15.96233		S.E. of regression	721.8892	Akaike info criterion	16.12214	
Sum squared resid	20648805	Schwarz criterion	16.28623		Sum squared resid	15963940	Schwarz criterion	16.12789		Sum squared resid	20582843	Schwarz criterion	16.24626	
Log likelihood	-334.9110	Hannan-Quinn criter.	16.18503		Log likelihood	-331.2103	Hannan-Quinn criter.	16.02335		Log likelihood	-335.5858	Hannan-Quinn criter.	16.18764	
F-statistic	3.004801	Durbin-Watson stat	1.902521		F-statistic	6.720517	Durbin-Watson stat	1.688881		F-statistic	3.884053	Durbin-Watson stat	1.584212	
Prob(F-statistic)	0.039497				Prob(F-statistic)	0.000949				Prob(F-statistic)	0.027116			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	131.7560	160.5298	1.348557	0.2186	C	59.8568	56.18528	1.062777	0.2858	C	131.7560	160.5298	1.348557	0.2186
AR(1)	-0.200261	0.141070	-1.350068	0.1793	AR(1)	-0.422878	0.173458	-2.438029	0.0195	AR(1)	-0.200261	0.141070	-1.350068	0.1793
MA(1)	0.161296	0.232792	0.693069	0.4945	MA(1)	-0.504584	0.238529	-2.118838	0.0400	MA(1)	0.161296	0.232792	0.693069	0.4945
SGMASQ	479304.8	134000.4	3.552912	0.0010	SGMASQ	247013.2	92529.88	2.645254	0.0006	SGMASQ	479304.8	134000.4	3.552912	0.0010
R-squared	0.170721	Mean dependent var	190.3090		R-squared	0.402384	Mean dependent var	190.3090		R-squared	0.170721	Mean dependent var	190.3090	
Adjusted R-squared	0.114862	S.D. dependent var	771.2488		Adjusted R-squared	0.356204	S.D. dependent var	771.2488		Adjusted R-squared	0.114862	S.D. dependent var	771.2488	
S.E. of regression	725.5634	Akaike info criterion	16.19397		S.E. of regression	679.3066	Akaike info criterion	15.99021		S.E. of regression	725.5634	Akaike info criterion	16.19397	
Sum squared resid	20064805	Schwarz criterion	16.33497		Sum squared resid	14574553	Schwarz criterion	16.10740		Sum squared resid	20064805	Schwarz criterion	16.33497	
Log likelihood	-334.9110	Hannan-Quinn criter.	16.19923		Log likelihood	-333.0653	Hannan-Quinn criter.	16.06980		Log likelihood	-334.9110	Hannan-Quinn criter.	16.19923	
F-statistic	2.775239	Durbin-Watson stat	1.906027		F-statistic	6.626662	Durbin-Watson stat	1.719698		F-statistic	2.775			