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A Predictive Analysis of Non-Performing Assets Using ARIMA Method- A Case of Government-owned Indian Bank

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Abstract

Non-performing assets are a constant economic issue affecting its integrity and stability. In this paper, the researcher aims to analyze the trends and the factors influencing the NPAs in banking sector by using the ARIMA method. By doing an extensive and empirical review of the literature, the study identifies the key factors promoting the rise or increase of NPAs and provides a prediction for better risk management. In this paper, we have used time series data of NPAs in Indian banks. We used publicly available data from RBI from the year 2000 to 2023 from its annual reports. The researcher estimated a time series model like ARIMA on it. In this research study, the findings of the paper are expected to aid policymakers and bankers in reducing and mitigating the risk associated with the impact of NPAs.

Keywords: Arima Model, Non-Performing Assets, Banks.

Introduction

The banking sector serves as a cornerstone of every financial system. Non-performing assets represent the loans and advances that are in default when interest or principal amount remain overdue for some time. Recent research has labeled NPAs as an important “financial threat” (Mishra et al., 2019). According to the Reserve Bank of India (RBI), “an asset is classified as NPA if, interest and/or installment of principal remain overdue for more than 90 days” (RBI Annual Report, 2021). Non-performing assets arise when a borrower defaults in making the payment on time. “Any asset that cease to generate profit for its investors for a specified period of time is known as a Non-Performing Asset (NPA)” (Kapoor, B & Kumar, R. 2020). The rise in NPAs affects the profitability and efficiency of the banks that leads to the deterioration in asset quality (Ali et al., 2020).

The Narasimhan Committee Report (1991) proposed that any advances in savings, cash credits, or overdrafts where the interest remain unpaid for a period of 80 days should be classified as Non-performing Assets (NPAs). Additionally, if the interest payments or installments of the principal remain overdue for more than 180 days, any previously credited amount should also be classified as an NPA. However, the report acknowledges that a lenient requirement of ‘90 days’ has been adopted in line with international standards, ensuring greater transparency and adherence to global norms.

1.1 Literature Review

Trends & Determinants of NPAs

Over the past 25 years, studies on non-performing assets (NPAs) and credit recovery in India have revealed various factors that contribute to different outcomes. Weak legal provisions, lengthy legal battles, loan waiver schemes, and priority sector lending were identified as factors hindering credit recovery (Samir, 2013). Loans extended under government schemes and debt waiver programs were major reasons for low recovery, along with wilful debt default (Tripathi, Parashar & Mishra, 2014). Negligence and ineffectiveness of recovery tribunals also led to high non-recovery by banks (Gupta, 2012). However, contradictory views exist, with some studies highlighting satisfactory credit recovery policies by the State Bank of India (Murthy & Pathi, 2013). A lack of trained manpower in recovery departments was identified as an issue affecting loan recovery (Saha, Zaman &

Basumati, 2021).

Credit appraisal processes were found to contribute to the NPA problem, as banks granted loans to borrowers unable to repay (Gupta, 2012). Poorly defined policies and inconsistent practices further exacerbated the issue (Siraj and Pillai, 2013; Joseph, 2014). The rise of wilful defaulters also added to the NPA problem, facilitated by target-based jobs in banks and personal financial difficulties (Gupta, 2012; Joseph, 2014; Hawaldar, Spulbar & Rebegea, 2020). Government policies, including poverty alleviation programs, debt waivers, and loan moratoriums during the COVID-19 pandemic, have shaped the banking systems and affected the NPA problem (Singh, 2013; Gupta, 2012; Hawaldar, Spulbar & Rebegea, 2020). The lending policies of banks have been a concern, with inadequate redefinition despite increasing NPAs (Debbarma, Kuma & Laskar, 2005). Management involvement in addressing NPAs has seen positive changes through the hiring of specialized employees, although training inadequacies persist (Singh, 2013; Mittal & Suneja, 2017).

Asset quality in Indian banks has fluctuated, with periods of improvement and deterioration (Sirisha, 2011; Saha, 2018). The banking sector has faced challenges due to the economic slowdown, increased NPAs, and the COVID-19 pandemic's impact on businesses, leading to loan defaults and a decrease in recovery (Saha, 2018).

Public and private banks operate differently, with private banks emphasizing proper borrower selection and trained staff, while public banks prioritize lending to specific sectors but face challenges such as ineffective recovery mechanisms and political interference (Singh, 2013; Gupta, 2012; Mittal & Suneja, 2017; Joseph, 2014; Samir, 2007). The pandemic has increased digital payments and frauds, impacted asset quality, and posed challenges for the banking sector due to supply chain disruptions and unemployment (Panchal, 2021).

1.2 Objectives

1. To analyze the trend of non-performing assets (NPAs) in the government banks.
2. To analyze the key determinants that contribute to NPAs.
3. To apply the ARIMA model to predict future NPAs.

1.3

1.4 ARIMA Method

While doing time series forecasting ARIMA method is widely used because of its accuracy and flexibility. In domains like finance, it can be successfully applied to predict future trends and patterns (Bon & Jenkins, 1976; Hyndman & Athanasopoulous, 2018). To predict the future NPA trend, the ARIMA model can provide best-fit insight. Chaurasia and Singh (2017)used the ARIMA model for forecasting NPAs in Indian banks and found that this model provides reliable predictions for NPAs prediction. Similarly, Ghosh (2010) investigated the influence of macroeconomic factors on NPAs using ARIMA and concluded the economic influence on NPA level.

Methodology

2. Data Collection

The study uses secondary data on the NPAs of Indian banks obtained from the Reserve Bank of India (RBI) and other financial databases. The data spans from 2000 to 2023, offering a thorough perspective of NPA trends over the years.

3. ARIMA Model

The ARIMA model is used to gather data to predict future non-performing assets. The model comprises of three important components:

1. **Autoregressive (AR) Component**: This component is used to seize the relationship
between an observation and the previous value
2. **Integrated (I) Component**: This involves adjustment of data by subtracting the previous value to construct the time series stable.
3. **Moving Average (MA) Component**: This means how an observation can relate to left error from moving average based on past values.

The ARIMA model is represented as ARIMA (a, b, c), where:

- **a**: Number of previous observations used in the model (AR part).
- **b**: Number of times the original observations are in difference (I part).
- **c**: Size of the moving average period (MA part).

4. Model Implementation

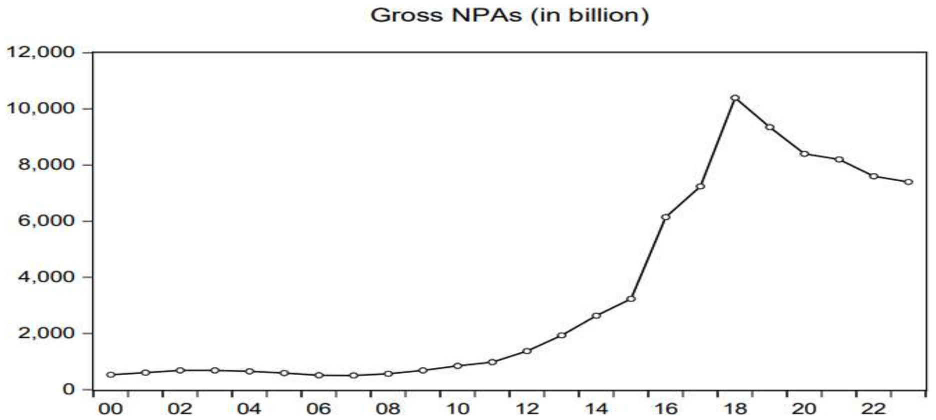
The ARIMA model is implemented using the following steps:

1. **Data Preprocessing**: Cleaning and transforming the data to ensure stationarity.
2. **Model Identification**: Using plots and statistical tests to understand the values of a, b, and c.
3. **Parameter Estimation**: Interpreting the ARIMA model parameters using maximum likelihood estimation.

4. **Model Validation**: Checking the model's accuracy using diagnostic tests.
5. **Forecasting**: Using the validated model to forecast future NPAs.

4.1 DATA ANALYSIS

The Graphical presentation of the Gross NPAs in Indian banks from 2000 to 2023 is shown in Graph 1.



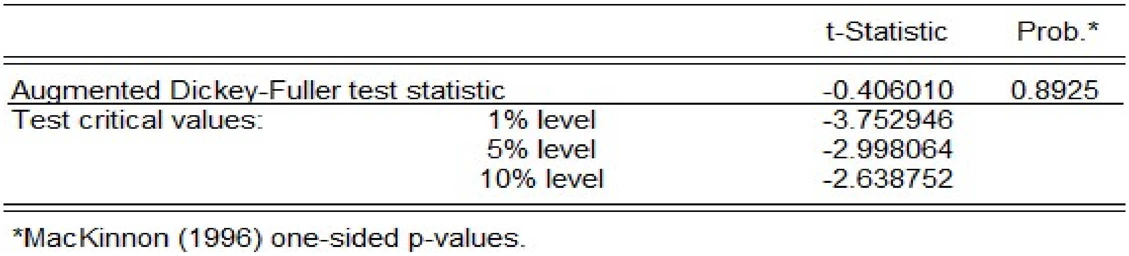
4.2 Graph 1: Time series graph of Gross Non-performing assets (NPAs).

*Source: RBI annual report from 2000 to 2023.*In Graph 1, we can see that gross NPA fluctuates from the period 2000 to 2023 without any seasonal pattern, even though there is an overall upward trend.

Ho: Data is not stationary. H1: Data is stationary.

However, the correlogram shows a slow decay, up to two lags and shows statically significant where data indicate non-stationery of data. Further, the Augmented Dickey-Fuller (ADF) test implements the unit root test process as follows:

4.3 Table 1: Unit Root Test

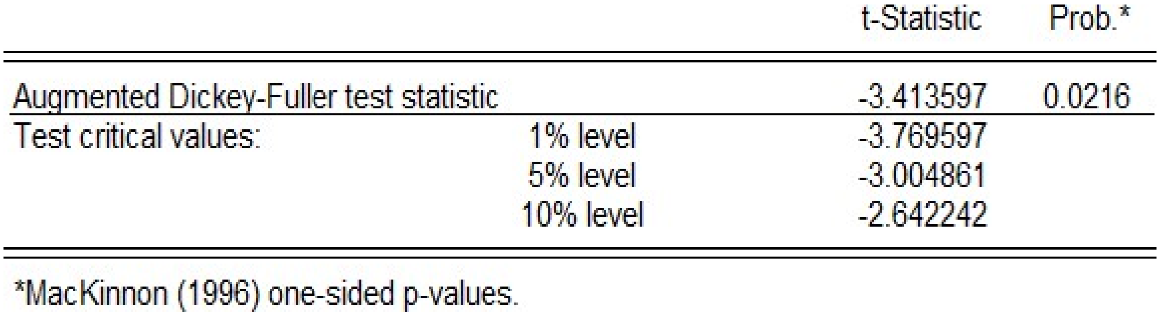


		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.406010	0.8925
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

*MacKinnon (1996) one-sided p-values.

As per Table 1, the p-value is 0.8925 which is higher than the 5% level of significance. This indicates data is not stationary. Hence, we accept the null hypothesis suggesting that data is not stationary. Since data is not stationary, we use differencing to achieve stationarity. We again perform the ADF test to assess the stationery of data and the results are:

Table 2: Unit Root Test

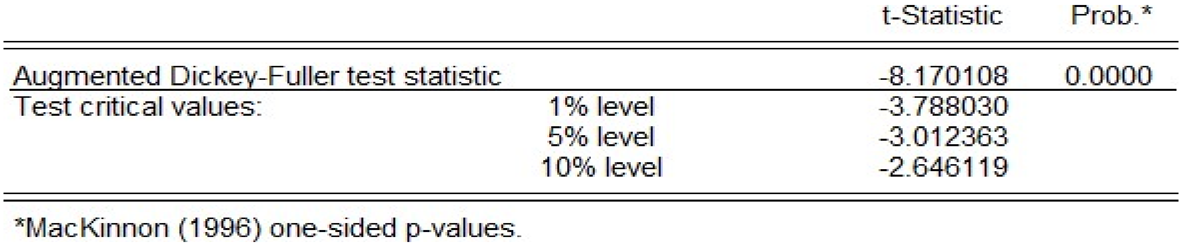


		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.413597	0.0216
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

*MacKinnon (1996) one-sided p-values.

In Table 2, the P value is 0.0216 which indicates that p value is $0.0216 < 0.05$. Thus, H1 is accepted at a 5% level of significance and indicates that the data is stationary. The ADF test shows that the data is stationary of series. However, the theoretical representation of ACF, PACF, and the unit root ADF test confirm the stationarity of second differenced series both graphically and numerically.

4.4 Table 3: Unit Root Test at Second Difference.



		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.170108	0.0000
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

4.5 *MacKinnon (1996) one-sided p-values.

4.6

4.7 In this Table 3, the P value is 0.0000 which indicates that p value is 0.0000<0.05. Thus, null hypothesis is accepted at a 5% level of significance indicating that data is stationary. As the data becomes stationary, to find the best-fit model we have to evaluate all the possible models and identify which one is fit and has the lowest AIC and SBC value.

4.8

4.9 ARIMA Model:

Fitting of ARIMA Model:

Since, data is stationary, we can apply different ARIMA models to the data to determine the best fit based on AIC and SBC values. The table is as follows:

4.10 **Table 4: Model Adequacy of Parsimonious Models**

MODEL	**Akaike Information Criterion (AIC)**	**Schwartz Bayesian Criterion (SBC)**
ARIMA (1,1,1)	16.78	16.93
ARIMA (1,1,0)	16.77	16.92
ARIMA (0,1,1)	16.80	16.95

Based on the values provided in AIC and SBC from the various ARIMA models we can interpret the best fit of these models. From the various models, ARIMA (1,1,0) is the optimal model as it has the lowest AIC and SBC score. The next best-fit modal is ARIMA (1,1,0) with AIC (16.73) and SBC (16.88).
Other models are higher with AIC and SBC values which makes them less preferable.

4.11 Interpretation:

Model Equation:

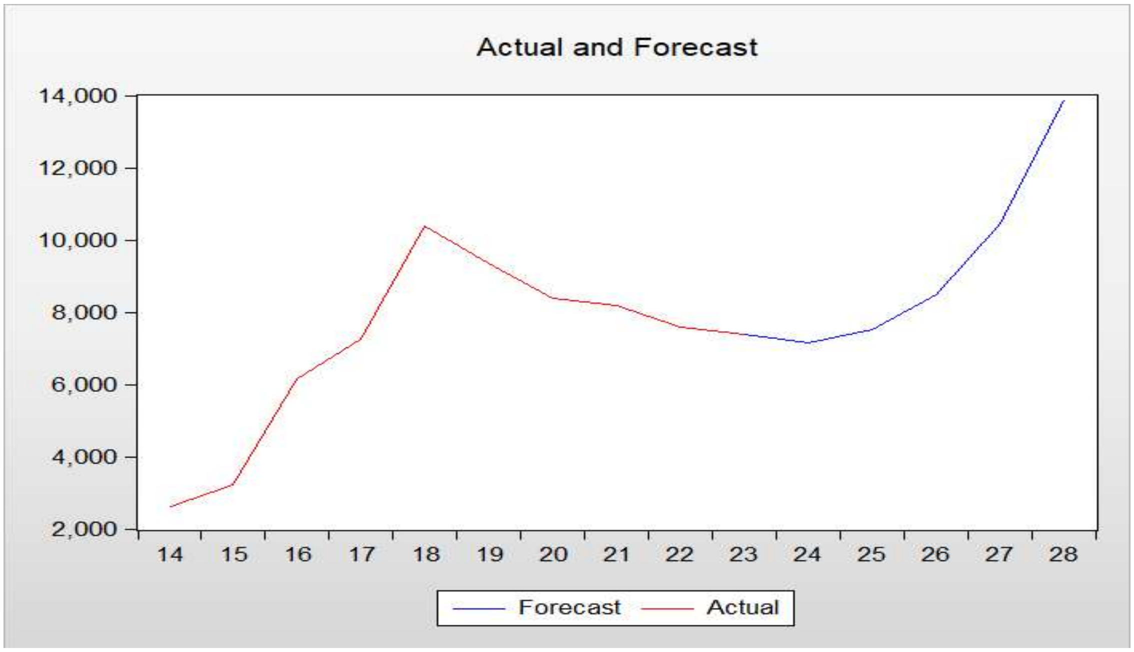
Gross NPAst = μ + θ1εt – 1 + θ2εt−2 Where:

- M is constant term.
- θ1 and θ2 represent the coefficients for the moving average.
- εt−1 and εt−2 are the error terms from one and two periods ago.

This modal interprets that the current value of Gross NPAs is influenced by the past error (moving averages) of the previous two periods. It shows that from the previous two years, there is historical shock effects are significant in predicting current Gross NPAs. The moving average predicts that past unexpected changes in NPAs due to economic events or policy changes play a very crucial role in predicting the current NPAs.

4.12 Forecasting

In the final stage of forecasting, we have identified the optimum-fitted model that can be used to predict the future forecast for future periods for the banking sector.



4.13 Graph 2: Gross NPAs Forecast of ARIMA Model.

4.14

4.15 The above graph indicates the actual value from 2014 to 2023 (red line) and forecasted values from 2024 to 2028 (blue line) of Gross NPAs.

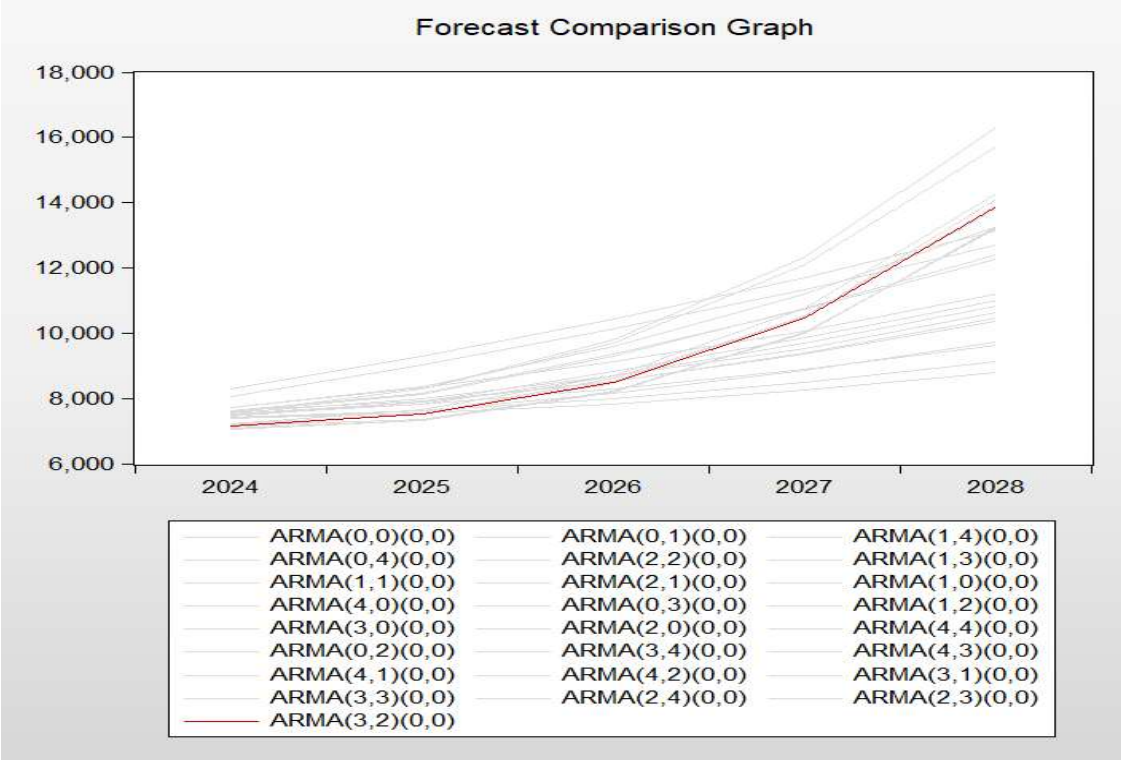
4.16 KEY OBSERVATIONS:

1. Historical Data (2014-2023):

- In 2014-2017, a sharp increase can be seen that peaks out in 2018. This can be due to various factors, such as economic downturns, high bad debts, and policy changes.
- After peaking in 2018, there is a decline from 2018-2021 that indicates some recovery and improvement in asset quality. The banking sector improved its recovery processes or restructured bad loans.
- In 2021-2023, Gross NPAs continue to decline but at a slower pace.

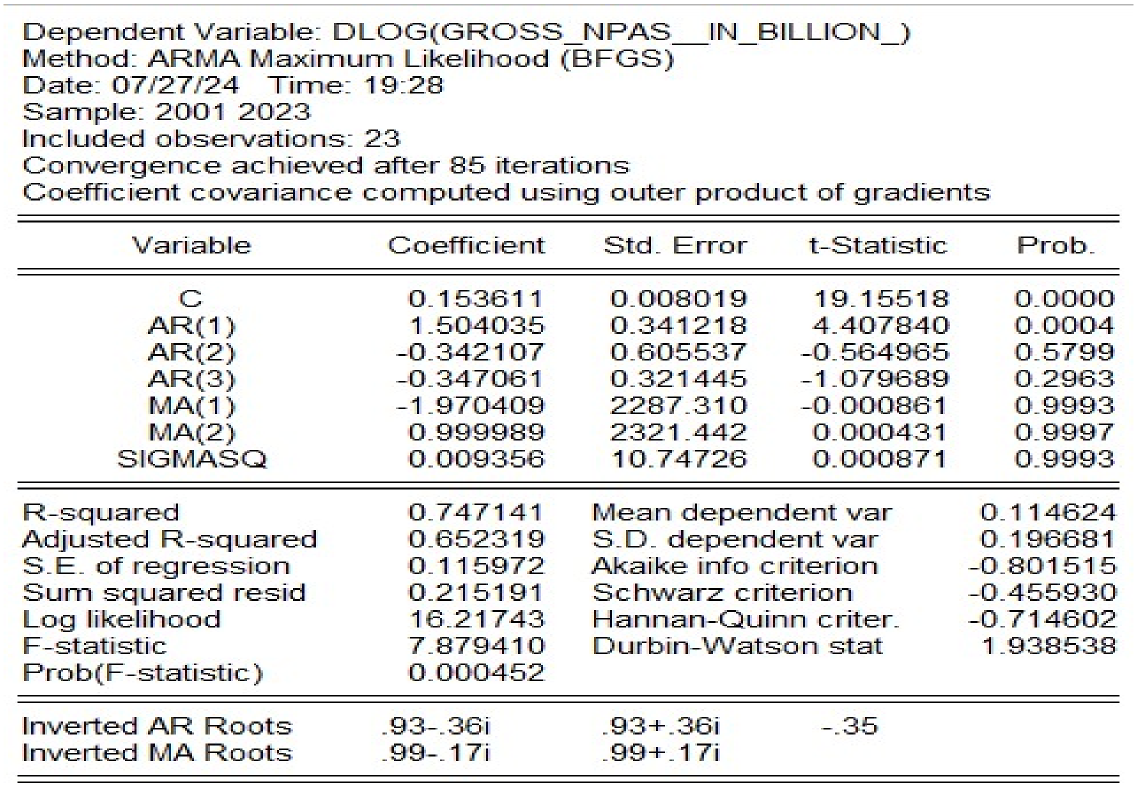
2. Forecasted Data (2024-2028):

- From 2024 to 2026, the forecast shows a relatively stable trend as Gross NPAs remain steady and the steps taken by the banks to manage NPAs will be effective in the short run.
- In 2027-2028, there is a significant increase in Gross NPAs that indicates certain upcoming challenges in asset quality which can be an upcoming economic downturn, policy change, and loans based on bias.



Graph 3: Forecast Comparison Graph of NPAs from 2024 - 2028.

The above graph forecasts various models of ARMA from 2024 to 2028 on Gross NPAs. Every line in the graph represents different ARMA models, and the red line represents the ARMA models (3,2)(0,0). It can also be noted that all the models predict an upward trend of Gross NPAs from 2024 to 2028. The red line represents the ARMA(3,2)(0,0) model that is chosen for comparison and predicts an increase in Gross NPAs, reaching 14,000 by 2028.

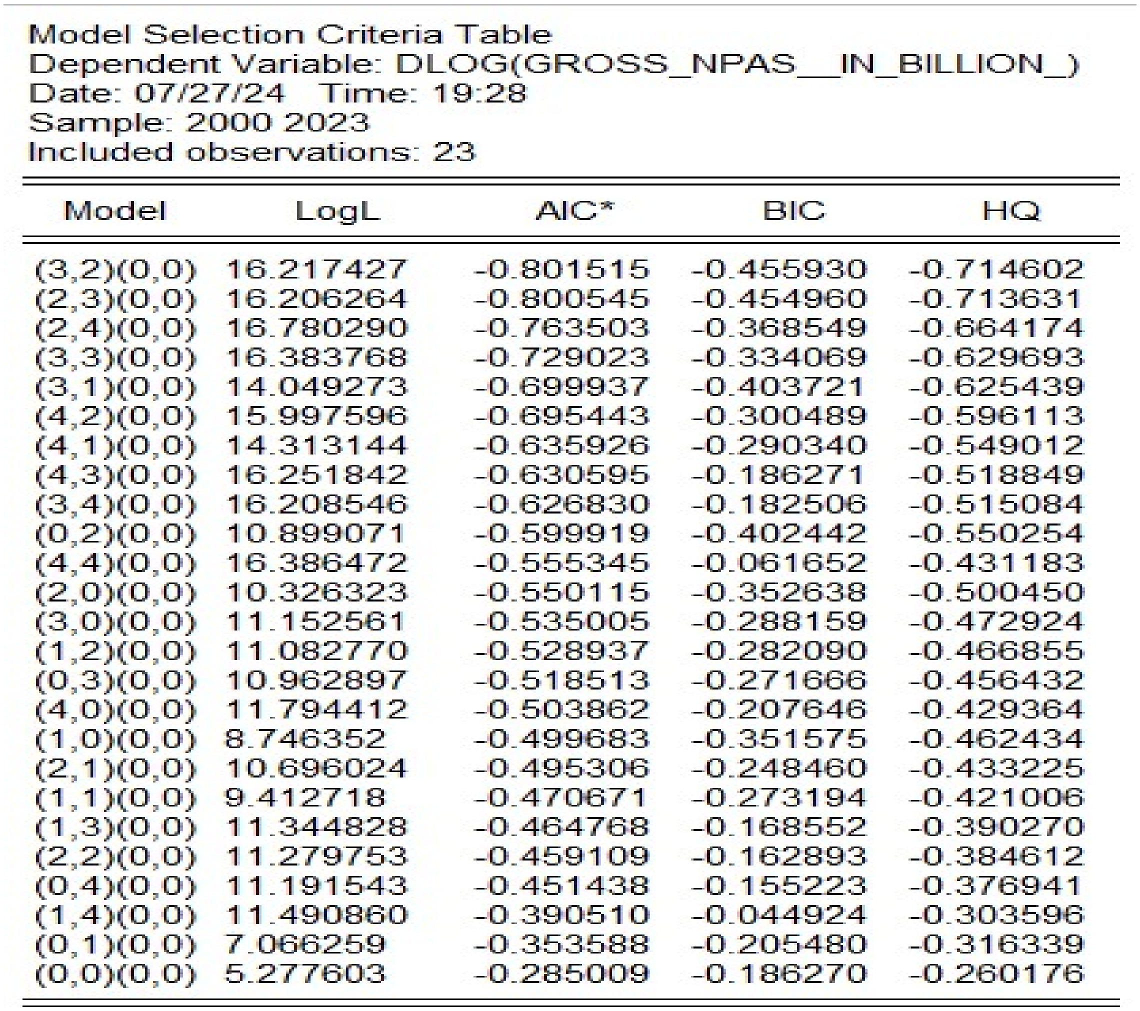


```
Dependent Variable: DLOG(GROSS_NPAS__IN_BILLION_)
Method: ARMA Maximum Likelihood (BFGS)
Date: 07/27/24   Time: 19:28
Sample: 2001 2023
Included observations: 23
Convergence achieved after 85 iterations
Coefficient covariance computed using outer product of gradients

        Variable        Coefficient    Std. Error    t-Statistic     Prob.

           C             0.153611      0.008019      19.15518       0.0000
         AR(1)           1.504035      0.341218      4.407840       0.0004
         AR(2)          -0.342107      0.605537     -0.564965       0.5799
         AR(3)          -0.347061      0.321445     -1.079689       0.2963
         MA(1)          -1.970409      2287.310     -0.000861       0.9993
         MA(2)           0.999989      2321.442      0.000431       0.9997
        SIGMASQ          0.009356      10.74726      0.000871       0.9993

R-squared                0.747141    Mean dependent var       0.114624
Adjusted R-squared       0.652319    S.D. dependent var       0.196681
S.E. of regression       0.115972    Akaike info criterion   -0.801515
Sum squared resid        0.215191    Schwarz criterion       -0.455930
Log likelihood           16.21743    Hannan-Quinn criter.    -0.714602
F-statistic              7.879410    Durbin-Watson stat       1.938538
Prob(F-statistic)        0.000452

Inverted AR Roots      .93-.36i      .93+.36i        -.35
Inverted MA Roots      .99-.17i      .99+.17i
```

4.17 Table 5: Estimated Result of ARMA Model.

The table interprets:

ARMA Model (3,2)(0,0) is the statistically significant model that explains a substantial portion of the variance in the logged difference of Gross NPAs. AR and MA values are significant that indicate past values and errors influence current values. The model is a best fit with no sign of autocorrelation and satisfactory explanatory power. This model can be used to forecast future values for Gross NPAs



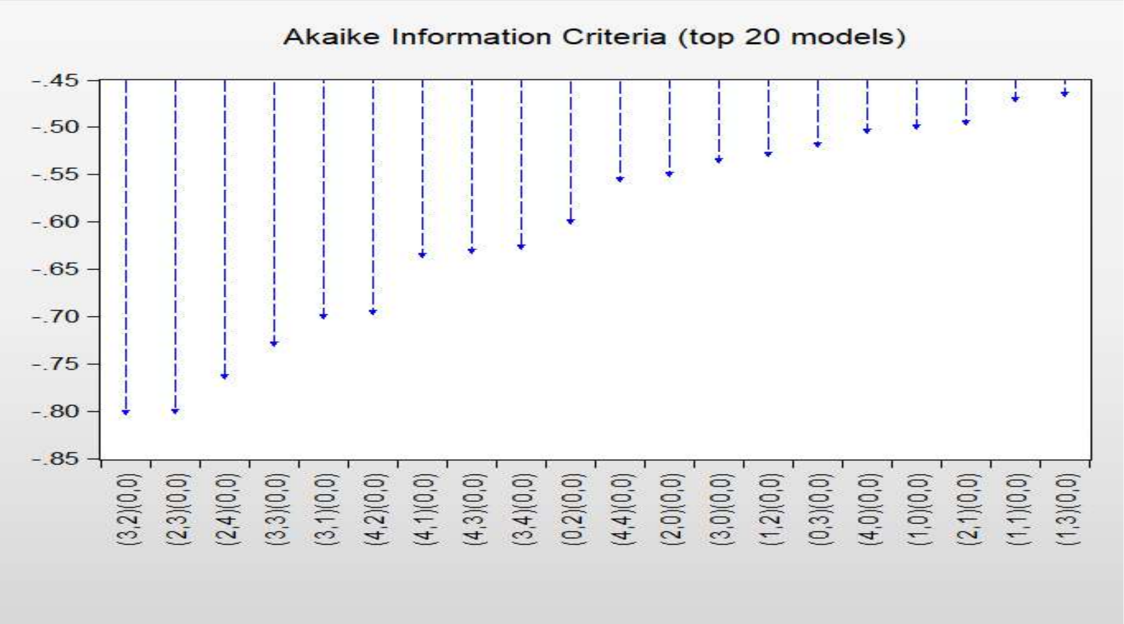
Model Selection Criteria Table
Dependent Variable: DLOG(GROSS_NPAS__IN_BILLION_)
Date: 07/27/24 Time: 19:28
Sample: 2000 2023
Included observations: 23

Model	LogL	AIC*	BIC	HQ
(3,2)(0,0)	16.217427	-0.801515	-0.455930	-0.714602
(2,3)(0,0)	16.206264	-0.800545	-0.454960	-0.713631
(2,4)(0,0)	16.780290	-0.763503	-0.368549	-0.664174
(3,3)(0,0)	16.383768	-0.729023	-0.334069	-0.629693
(3,1)(0,0)	14.049273	-0.699937	-0.403721	-0.625439
(4,2)(0,0)	15.997596	-0.695443	-0.300489	-0.596113
(4,1)(0,0)	14.313144	-0.635926	-0.290340	-0.549012
(4,3)(0,0)	16.251842	-0.630595	-0.186271	-0.518849
(3,4)(0,0)	16.208546	-0.626830	-0.182506	-0.515084
(0,2)(0,0)	10.899071	-0.599919	-0.402442	-0.550254
(4,4)(0,0)	16.386472	-0.555345	-0.061652	-0.431183
(2,0)(0,0)	10.326323	-0.550115	-0.352638	-0.500450
(3,0)(0,0)	11.152561	-0.535005	-0.288159	-0.472924
(1,2)(0,0)	11.082770	-0.528937	-0.282090	-0.466855
(0,3)(0,0)	10.962897	-0.518513	-0.271666	-0.456432
(4,0)(0,0)	11.794412	-0.503862	-0.207646	-0.429364
(1,0)(0,0)	8.746352	-0.499683	-0.351575	-0.462434
(2,1)(0,0)	10.696024	-0.495306	-0.248460	-0.433225
(1,1)(0,0)	9.412718	-0.470671	-0.273194	-0.421006
(1,3)(0,0)	11.344828	-0.464768	-0.168552	-0.390270
(2,2)(0,0)	11.279753	-0.459109	-0.162893	-0.384612
(0,4)(0,0)	11.191543	-0.451438	-0.155223	-0.376941
(1,4)(0,0)	11.490860	-0.390510	-0.044924	-0.303596
(0,1)(0,0)	7.066259	-0.353588	-0.205480	-0.316339
(0,0)(0,0)	5.277603	-0.285009	-0.186270	-0.260176

4.18 Table 6: Tabular representation of AIC, BIC and HQ.

4.19

This table predicts that the highest LogL and the lowest value of AIC, BIC, and HQ make it a best-fit model. The table for the best fit is (3,2)(0,0). Other model such as (2,3)(0,0) and (2,4)(0,0) are second and third best-fit.



4.20 Table 6: AIC

4.21

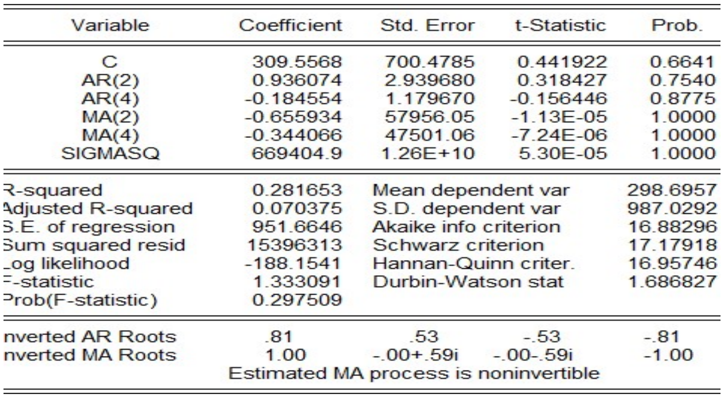
Suggestions:

- Policymakers and bank management need to be aware of the projected increase in NPAs as it indicates uncertainty. With proactive action, banks can handle the future increase in NPAs.
- Banking institutes should consider new strategies for risk management.
- Banks should keep checking on the quality of assets.
- Before granting loans banking institutes conduct credit appraisal mechanisms with no default, and documentation should be proper.
- The underlying causes of the increasing NPAs should be analysed and strategies must be developed to mitigate the risks.

4.22 Conclusion:

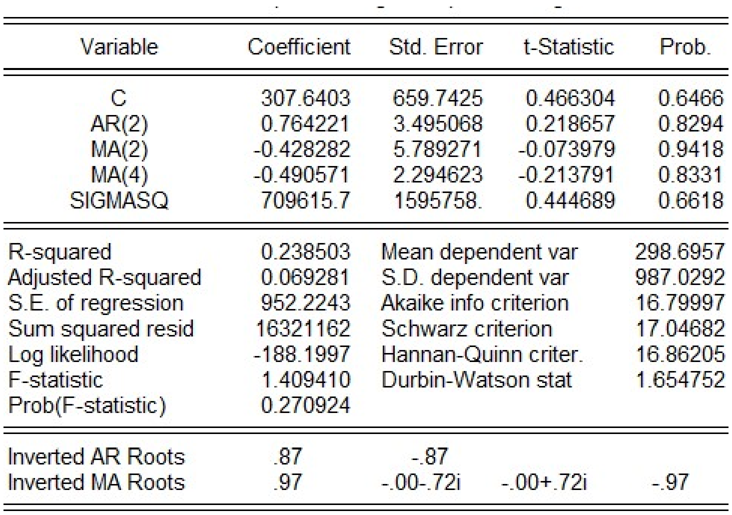
With the help of the ARIMA (0,2,2) model, it is forecasted that there will be a slight increase in Gross NPAs over the five years. With the increase in NPAs, there will be an increase in uncertainty also. While the central forecast provides a useful indication of future trends, the wide confidence intervals highlight the need for caution and further analysis to better understand and address the underlying factors contributing to this trend.

4.23 Appendix:

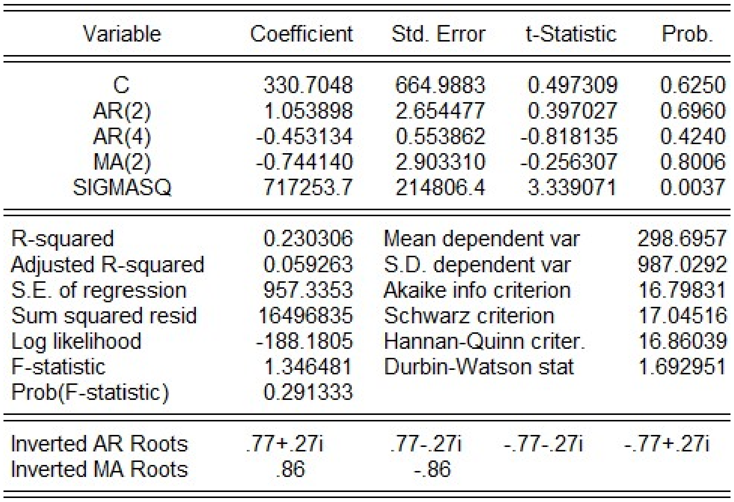


```
        Variable        Coefficient   Std. Error   t-Statistic   Prob.

           C             309.5568     700.4785      0.441922     0.6641
         AR(2)           0.936074     2.939680      0.318427     0.7540
         AR(4)          -0.184554     1.179670     -0.156446     0.8775
         MA(2)          -0.655934     57956.05     -1.13E-05     1.0000
         MA(4)          -0.344066     47501.06     -7.24E-06     1.0000
        SIGMASQ          669404.9     1.26E+10      5.30E-05     1.0000

R-squared                0.281653   Mean dependent var     298.6957
Adjusted R-squared       0.070375   S.D. dependent var     987.0292
S.E. of regression       951.6646   Akaike info criterion  16.88296
Sum squared resid        15396313   Schwarz criterion      17.17918
og likelihood           -188.1541   Hannan-Quinn criter.   16.95746
F-statistic              1.333091   Durbin-Watson stat     1.686827
Prob(F-statistic)        0.297509

nverted AR Roots          .81          .53         -.53        -.81
nverted MA Roots          1.00      -.00+.59i    -.00-.59i     -1.00
                      Estimated MA process is noninvertible
```

4.24



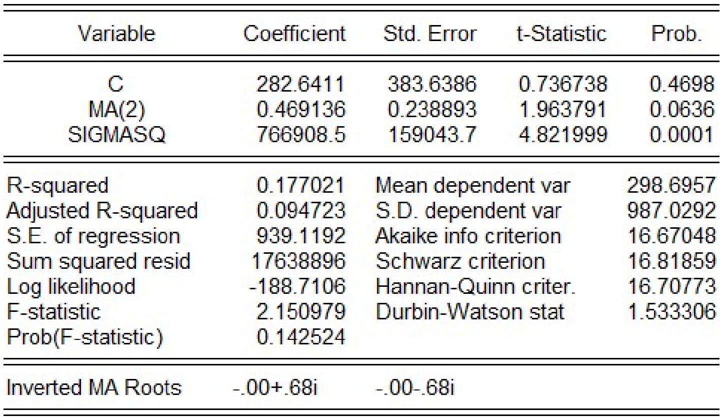
```
        Variable        Coefficient   Std. Error   t-Statistic   Prob.

           C             307.6403     659.7425      0.466304     0.6466
         AR(2)           0.764221     3.495068      0.218657     0.8294
         MA(2)          -0.428282     5.789271     -0.073979     0.9418
         MA(4)          -0.490571     2.294623     -0.213791     0.8331
        SIGMASQ          709615.7     1595758.      0.444689     0.6618

R-squared                0.238503   Mean dependent var     298.6957
Adjusted R-squared       0.069281   S.D. dependent var     987.0292
S.E. of regression       952.2243   Akaike info criterion  16.79997
Sum squared resid        16321162   Schwarz criterion      17.04682
Log likelihood          -188.1997   Hannan-Quinn criter.   16.86205
F-statistic              1.409410   Durbin-Watson stat     1.654752
Prob(F-statistic)        0.270924

Inverted AR Roots         .87          -.87
Inverted MA Roots         .97       -.00-.72i    -.00+.72i     -.97
```



Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	330.7048	664.9883	0.497309	0.6250
AR(2)	1.053898	2.654477	0.397027	0.6960
AR(4)	-0.453134	0.553862	-0.818135	0.4240
MA(2)	-0.744140	2.903310	-0.256307	0.8006
SIGMASQ	717253.7	214806.4	3.339071	0.0037

R-squared	0.230306	Mean dependent var	298.6957
Adjusted R-squared	0.059263	S.D. dependent var	987.0292
S.E. of regression	957.3353	Akaike info criterion	16.79831
Sum squared resid	16496835	Schwarz criterion	17.04516
Log likelihood	-188.1805	Hannan-Quinn criter.	16.86039
F-statistic	1.346481	Durbin-Watson stat	1.692951
Prob(F-statistic)	0.291333		

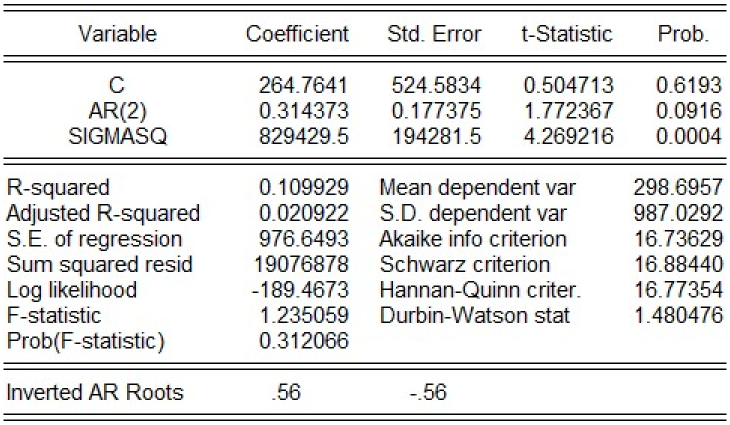
Inverted AR Roots	.77+.27i	.77-.27i	-.77-.27i	-.77+.27i
Inverted MA Roots	.86	-.86		



Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	282.6411	383.6386	0.736738	0.4698
MA(2)	0.469136	0.238893	1.963791	0.0636
SIGMASQ	766908.5	159043.7	4.821999	0.0001

R-squared	0.177021	Mean dependent var	298.6957
Adjusted R-squared	0.094723	S.D. dependent var	987.0292
S.E. of regression	939.1192	Akaike info criterion	16.67048
Sum squared resid	17638896	Schwarz criterion	16.81859
Log likelihood	-188.7106	Hannan-Quinn criter.	16.70773
F-statistic	2.150979	Durbin-Watson stat	1.533306
Prob(F-statistic)	0.142524		

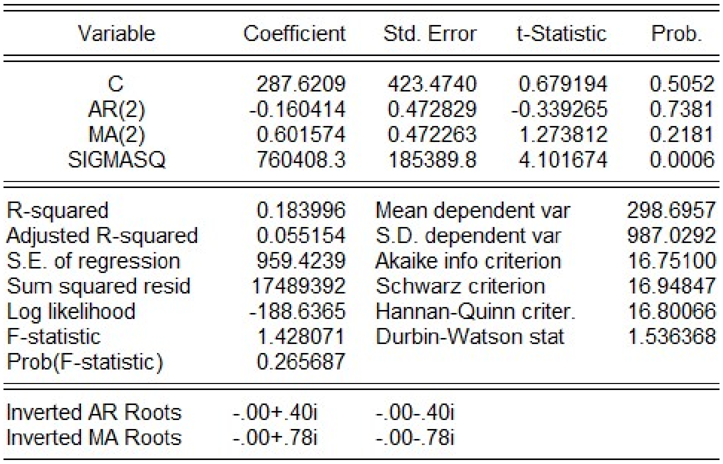
Inverted MA Roots	-.00+.68i	-.00-.68i



Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	264.7641	524.5834	0.504713	0.6193
AR(2)	0.314373	0.177375	1.772367	0.0916
SIGMASQ	829429.5	194281.5	4.269216	0.0004

R-squared	0.109929	Mean dependent var	298.6957
Adjusted R-squared	0.020922	S.D. dependent var	987.0292
S.E. of regression	976.6493	Akaike info criterion	16.73629
Sum squared resid	19076878	Schwarz criterion	16.88440
Log likelihood	-189.4673	Hannan-Quinn criter.	16.77354
F-statistic	1.235059	Durbin-Watson stat	1.480476
Prob(F-statistic)	0.312066		

Inverted AR Roots	.56	-.56



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      Variable         Coefficient    Std. Error    t-Statistic     Prob.

          C             287.6209      423.4740      0.679194      0.5052
        AR(2)          -0.160414      0.472829     -0.339265      0.7381
        MA(2)           0.601574      0.472263      1.273812      0.2181
      SIGMASQ           760408.3      185389.8      4.101674      0.0006

R-squared               0.183996    Mean dependent var       298.6957
Adjusted R-squared      0.055154    S.D. dependent var       987.0292
S.E. of regression      959.4239    Akaike info criterion    16.75100
Sum squared resid       17489392    Schwarz criterion        16.94847
Log likelihood         -188.6365    Hannan-Quinn criter.     16.80066
F-statistic             1.428071    Durbin-Watson stat       1.536368
Prob(F-statistic)       0.265687

Inverted AR Roots     -.00+.40i      -.00-.40i
Inverted MA Roots     -.00+.78i      -.00-.78i
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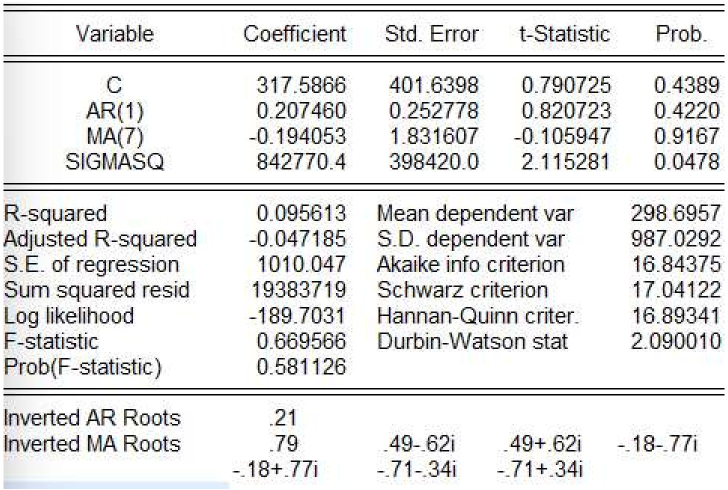

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      Variable         Coefficient    Std. Error    t-Statistic     Prob.

          C             317.5866      401.6398      0.790725      0.4389
        AR(1)           0.207460      0.252778      0.820723      0.4220
        MA(7)          -0.194053      1.831607     -0.105947      0.9167
      SIGMASQ           842770.4      398420.0      2.115281      0.0478

R-squared               0.095613    Mean dependent var       298.6957
Adjusted R-squared     -0.047185    S.D. dependent var       987.0292
S.E. of regression      1010.047    Akaike info criterion    16.84375
Sum squared resid       19383719    Schwarz criterion        17.04122
Log likelihood         -189.7031    Hannan-Quinn criter.     16.89341
F-statistic             0.669566    Durbin-Watson stat       2.090010
Prob(F-statistic)       0.581126

Inverted AR Roots        .21
Inverted MA Roots        .79        .49-.62i      .49+.62i     -.18-.77i
                     -.18+.77i     -.71-.34i     -.71+.34i
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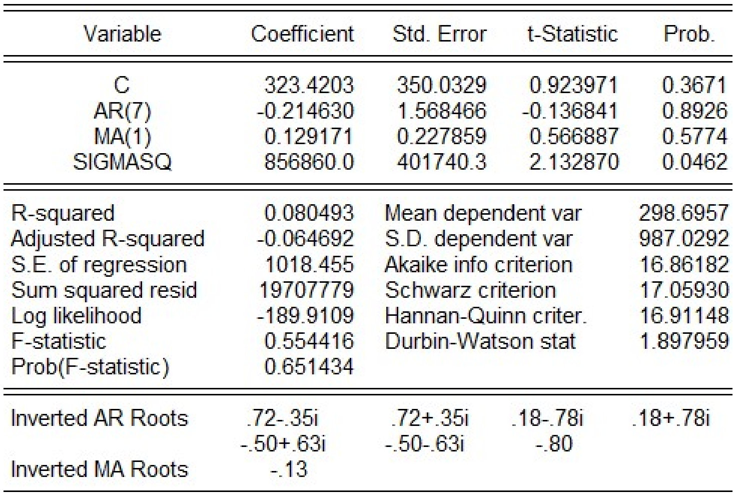

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      Variable         Coefficient    Std. Error    t-Statistic     Prob.

          C             323.4203      350.0329      0.923971      0.3671
        AR(7)          -0.214630      1.568466     -0.136841      0.8926
        MA(1)           0.129171      0.227859      0.566887      0.5774
      SIGMASQ           856860.0      401740.3      2.132870      0.0462

R-squared               0.080493    Mean dependent var       298.6957
Adjusted R-squared     -0.064692    S.D. dependent var       987.0292
S.E. of regression      1018.455    Akaike info criterion    16.86182
Sum squared resid       19707779    Schwarz criterion        17.05930
Log likelihood         -189.9109    Hannan-Quinn criter.     16.91148
F-statistic             0.554416    Durbin-Watson stat       1.897959
Prob(F-statistic)       0.651434

Inverted AR Roots      .72-.35i      .72+.35i      .18-.78i      .18+.78i
                     -.50+.63i     -.50-.63i       -.80
Inverted MA Roots       -.13
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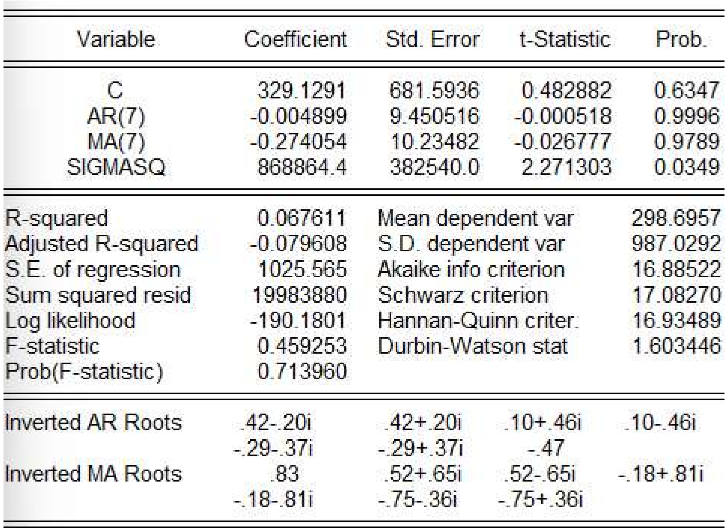

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        Variable        Coefficient   Std. Error   t-Statistic    Prob.

           C             329.1291     681.5936     0.482882     0.6347
         AR(7)          -0.004899     9.450516    -0.000518     0.9996
         MA(7)          -0.274054     10.23482    -0.026777     0.9789
        SIGMASQ          868864.4     382540.0     2.271303     0.0349

R-squared                0.067611    Mean dependent var        298.6957
Adjusted R-squared      -0.079608    S.D. dependent var        987.0292
S.E. of regression       1025.565    Akaike info criterion     16.88522
Sum squared resid        19983880    Schwarz criterion         17.08270
Log likelihood          -190.1801    Hannan-Quinn criter.      16.93489
F-statistic              0.459253    Durbin-Watson stat        1.603446
Prob(F-statistic)        0.713960

Inverted AR Roots       .42-.20i      .42+.20i     .10+.46i    .10-.46i
                       -.29-.37i     -.29+.37i      -.47
Inverted MA Roots          .83        .52+.65i     .52-.65i   -.18+.81i
                       -.18-.81i     -.75-.36i    -.75+.36i
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