Emerging from the Storm: Forecasting Bank Loan Quality in the Aftermath of COVID-19

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Abstract

As part of the credit risk management process of financial institutions, the non-performing loans (NPLs) ratio remains one of the essential components that distinguishes the well-managed assets of a bank. In this paper, we aim to empirically forecast the level of non-performing loans (NPL) including afflicted periods like the COVID-19 pandemic using a seasonal ARIMA model. Our analysis is based on the NPLs level observed in the Albanian banking system between December 2015 and December 2022. The results indicate that the seasonal ARIMA (0,1,1)x(2,2,2)12 is the appropriate model that can be applied to predict the monthly level of NPLs. The results also reveal that the expected average monthly ratio of NPLs remains stable, with a slight decrease until the end of 2023. Efforts to be proactive rather than reacting post-factum involve using mechanisms and forecasting models to define non-performing loan ratios and better manage them. This paper considers significant implications in credit risk management in terms of developing actions to manage the magnitude of non-performing loans throughout the COVID-19 pandemic.

Keywords: COVID-19; forecasting; SARIMA; non-performing loans

JEL Classification: C53; E37; G21; C23

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1. Introduction

The imposition of strict lockdown measures during the ongoing COVID-19 pandemic has the potential to create a significant burden on the quality of the bank loan portfolio in any financial system. If left unaddressed, a sudden surge in the non-performing loans (NPL) ratio would increase the likelihood of severe economic instability (Gjeçi et al. 2023; Aiyar et al. 2015; Makri et al. 2014).

There are currently 12 banks operating in the Albanian market with combined ownership from local and international groups and an operating network of more than 400 branches all over the country. Based on the Bank of Albania report as of the end of 2021, the total assets amounted to 14.78 billion euro representing 93.84% of the GDP (Gross Domestic Product). The sector's

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total deposits were 11.94 billion euro divided into 80% retail deposits and 20% wholesale deposits, while the total loans reached 5.32 billion euro consisting of 34% retail loans and 63% business loans. The capital adequacy ratio amounted to 18.02%, while the liquidity ratio noted a level of 391% compared to the preset level from the regulator. Finally, the non-performing loans ratio has followed a declining trend and reached 5.65% at the end of 2021 (Kufo, 2022).

Following the pandemic, commercial banks have returned to their business-as-usual practices, where the management of NPLs has a crucial role and is one of the most important aspects of defining their loan portfolio quality. In this context, the Bank of Albania and the Council of Ministers approved a "loan moratoria" on 17 March 2020 with decision nr.13/2020, which defines the criteria for credit risk assessment and loan classification as well as the provisions for loan losses. With this decision the Bank of Albania allowed lenders to postpone their payments and entrusted banks with not reclassifying their loan portfolio according to their customer (non) repayment. Additionally, no extra provisions were required for the loan portfolio and no change in the loan classification was made. As such, it managed to keep a safe portfolio, with no extra losses and no deterioration of its quality accompanied by a stable NPL ratio (Kufo, 2022).

The NPLs level has triggered attention since the 2008 credit crisis and peaked as high as 24% in 2012 leading to restructuring efforts of loan portfolios by the Bank of Albania (BoA). Furthermore, a special interest has been attributed to the authorities and the commercial banks themselves to better control and monitor their level in an attempt to ensure a viable, stable, and sustainable financial system.

In this context, our study examines the influence of the COVID-19 pandemic shock on bank loan quality. Our investigation constitutes the first direct analysis of the quality of bank loan portfolios in the Albanian banking system during the COVID-19 pandemic. Furthermore, our paper provides two significant contributions to the literature. Firstly, we aim to expand the current body of research by focusing on the impact of NPLs on the financial system considering the ongoing COVID-19 outbreak. Secondly, we demonstrate that the overall findings refute any significant impact of the COVID-19 outbreak on the level of non-performing loans indicating that there is slight pandemic-induced variation during the examined period, leading to the stability of the banking and overall financial system.

The rest of the paper proceeds as follows. The second part presents the literature review, the third part outlines the data and methodology used in the study, the fourth part presents the results, and the final part concludes the study.

2. Literature Review

In a study of the Albanian banking system, Kola et al. (2019) have found that the performance of financial institutions is affected significantly by certain macroeconomic factors such as GDP growth, inflation, and the real effective exchange rate, by industry-specific factors such as market concentration, as well as by bank-specific factors like efficiency, capitalization and non-performing loans. The authors have emphasized that the NPL ratio as part of credit risk management is a major concern for the local banks, which have addressed it merely with restructuring and collateral execution, but in their opinion should be extended to more than that. Being aware that a slight increase in the NPLs ratio in the banking system represents increased credit risk, and will eventually affect the perseverance of the financial stability as such should be viewed and monitored with caution.

In a similar vein, Bayar's (2019) study on the effect of macroeconomic, institutional, and bank-specific factors behind non-performing loans in emerging market economies during the 2000-2013 period revealed interesting results. Running two models estimated by a system of GMM dynamic panel estimation method, the author showed that NPLs were affected positively by macroeconomic variables such as unemployment, public debt, and one lagged value of NPLs ratio, as well as by bank-specific factors including credit growth and cost to income ratio. NPLs ratio is also affected positively by the financial crises. On the other hand, NPLs are negatively affected on the macroeconomic level by economic growth, inflation, general government net lending/borrowing, and economic freedom (institutional development). On the bank-specific level, the regulatory capital to risk-weighted assets, the return on assets and equity, and the noninterest income to total income had a negative impact on the NPLs ratio. The conformity of these results with other previous studies on the same topic extends the understanding that NPLs are under the influence of general economic conditions, institutional development, and individual bank indicators, stressing the importance of careful and correct policies and procedures from the monitoring authorities, besides the institutional management at the bank's level. A pertinent strategy on all levels will guarantee the sustainability of the financial system.

Erdas & Ezanoglu (2022) have brought evidence from G-20 countries for the period 1998-2017 and the factors that affect the NPLs ratio, including macroeconomic and bank-specific factors. Their findings, using a two-step GMM model to deal with the endogeneity of the variables, suggest that the NPLs ratio is positively and significantly affected by the NPLs ratio of the previous period demonstrating their persistence and the effort to their management, profitability measured by ROE and capital adequacy are negatively and significantly affecting NPLs ratio. Additionally, they find the NPLs ratio to be positively affected by the operational expenses and the bank credit to bank deposits ratio, and finally, they find as the literature suggests that GDP growth has a negative relation with the NPLs ratio. Summarizing their findings, both macroeconomic and bank-specific factors affecting NPL ratio advocate the supposition that NPLs are not a simple individual banking matter, but should be considered a problem to be handled to a larger extent.

Kozarić & Delihodić (2020) in a study conducted regarding the Bosnia Herzegovina banking sector for the period 2006-2017, have shown that the NPLs ratio and the financial stability of the sector are significantly affected by macroeconomic conditions measured by GDP growth, inflation, and unemployment. Additionally, testing the correlation of variables proves a strong correlation between all variables, with the NPLs being negatively correlated with financial stability and GDP growth and positively correlated with inflation and unemployment rate. As a result, if emphasis is given to creating new jobs in the real sector, that will again create more income, which will result in better payment of debt, lower NPLs, and higher financial stability. That indicates that the NPLs ratio is not a simple bank issue but is related to larger economic, political, and social conditions including the well-being of individuals and companies in a country.

In continuance to the above study, Zunić et al. (2021) have tested the determinants and the impact of COVID-19 on the NPLs ratio during the period 2012-2020 using quarterly data for the Bosnia Herzegovina banking sector. Their results have shown that the NPLs ratio is negatively affected by GDP growth, positively affected by loan loss provisions, and negatively affected by COVID-19. The authors argue that better macroeconomic conditions would mean lower NPLs which is compliant with previous studies, higher loan loss provisions as part of compensating increased credit risk will also increase NPLs, and finally, moratoria posed during COVID-19 would have a negative effect on NPLs. All three hypotheses have been accepted and proved by the model, suggesting that the results of COVID-19 on financial stability were probably not yet observed in this market and that we need more time to see any results on the NPLs ratio.

In a recent study, Kozińska (2022) investigates the CEE EU Central Banks' policy during the first wave of COVID-19. Banks' actions included mostly the monetary policy to ensure liquidity in the financial markets and micro-prudential supervision, while the macroprudential policies were rarely affected. Most of their monetary policies included quantitative easing programs, intensifying market operations, decreasing the reserve requirements, and lowering the interest rates. While on the micro-prudential measures taken to maintain liquidity and strengthen the capital base, the main ones used were payout ban, moratoria, no automatic reclassification of NPLs, and waiver for fulfillment of the bank's binding requirements. The paper suggests that the strength of Central Banks has increased during the crises and the usage of tools of the monetary policy has assured their role as monitoring authorities, but the lack of any innovative approach has simply placed them as followers of other Central Banks and not independent ones. On the micro-prudential policies, their interference was not at the level of imposing a real effect on the economy, which makes us wonder whether the effect of COVID-19 is just postponed in time and not managed properly.

In light of the above literature review presented there is an evident interrelation between NPLs ratio, macroeconomic conditions, and financial stability which constitutes a spark on further efforts to identify proper models that may forecast the NPLs ratio.

3. Methodology

3.1 Data

We obtained data consisting of the ratio of non-performing loans (NPL) from the Bank of Albania database[2] for the period December 2015 – December 2022. The NPL ratio refers to loans more than 90 days past due. ***Table 1*** presents a summary of statistical indicators on the level of NPLs in the Albanian banking system. The average level of NPLs is 11.53% for the entire study period.

Table 1. Descriptive statistics

Variables	NPL
Mean	11.53 %
Median	11.19 %
Standard deviation	4.95 %
Minimum	5.00 %
Maximum	21.44 %

Source: Our own calculation.

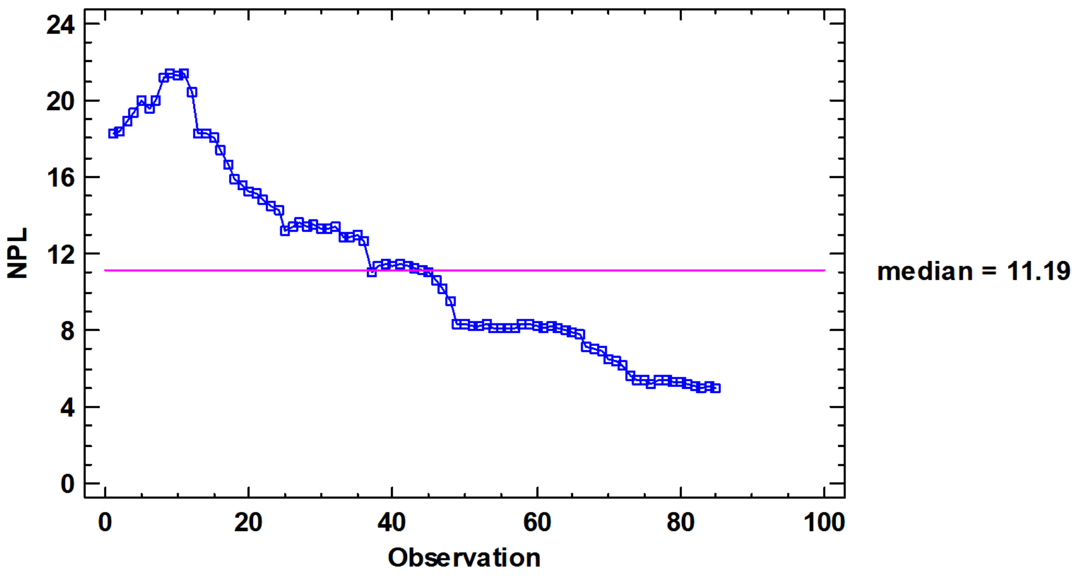
[2] We use monthly data. The data are available at: https://www.bankofalbania.org/Statistikat/Seri_Kohore/?evb=agregate&evn=agregate_detaje&cregtab_id=759&periudha_id=1

Figure 1 shows an overview of the monthly level of the NPL ratio for the Albanian banking system. From the observations, the median value of NPL for the period is 11.19%, the lowest value of the NPL ratio was 5% in October and December 2022, respectively, and the highest value of the NPL ratio reached 21.44% in August 2016. The decreasing tendency of non-performing loans starting from 2016 was attributed to the following interventions:

i) the regulation of the BoA forcing banks to write off the balance sheets of the loans classified as "loss-making" for more than three years,

ii) the administrative measures for managing the pandemic situation, such as deferring payments or restructuring loans, without worsening the borrower's status. In continuance, the rapid recovery of the economy during 2021 has played an important role in maintaining the quality of the loan portfolio.

Figure 1. Non-performing loans during the period December 2015 to 2022



Source: Bank of Albania and our calculation.

3.2 Model Specification

Several articles find that the ARIMA model is the most suitable technique for estimating and forecasting univariate time series economic variables. Mohamed (2022) using data of Somalia's GDP growth rates for the period between 1960 to 2022, found ARIMA (5,1,2) to be the appropriate model to approximate and forecast Somali economic growth. In the same vein, Prasad and Choubey (2018) set up the ARIMA model to forecast the total exports of India. They used data from the World Bank National Accounts over the period from 1960 to 2016 and found that ARIMA (0,1,3) was chosen as the best model for forecasting.

In this paper, the ARIMA model is used to forecast the impact of COVID-19 on the bank loan portfolio. ARIMA(p,d,q)x(P, D, Q)s is a specific seasonal ARIMA model that can be used to model time series data with a yearly seasonal pattern. Additionally, the notation ARIMA(p,d,q)x(P, D, Q)s refers to the model's parameters, where: (p) is the order of the autoregressive (AR) component, (d) is the degree of difference used to make the time series stationary, (q) is the order of the moving average (MA) component, (P) is the seasonal order of the AR component, (D) is the seasonal order of differencing, (Q) is the seasonal order of the MA component, (s) is the number of periods in a season. Our dependent variable is the NPL ratio. We use the NPL ratio as a proxy for banks' loan quality (Tarchouna, Jarraya, and Bouri, 2017; Vithessonthi, 2016; Ghosh, 2015). We apply the Box and Jenkins method which is widely used in many fields to find the appropriate model (Box and Jenkins, 1970; Dritsakis and Klazoglou, 2018). Moreover, SARIMA models could forecast the future values of a time series solely based on its past observations.

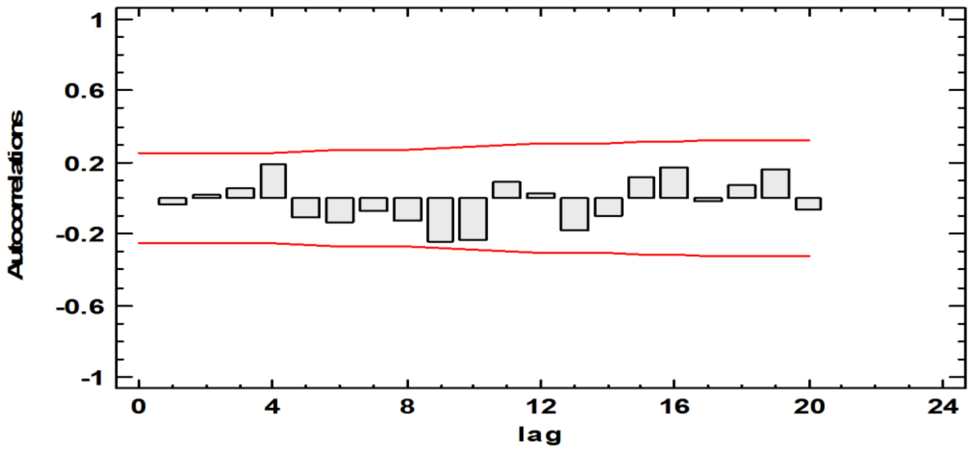
4. Empirical results

4.1 Model identification

We conducted the Augmented Dickey-Fuller (ADF) test to examine whether a unit root is present in our time series (Dickey and Fuller, 1979; Brockwell and Davis, 2016). The results of the ADF unit root test, indicate that non-performing loans exhibit a non-stationary nature at the 1% significance level. Furthermore, we conducted a first difference transformation of our time series and observed that the NPL ratio achieved stationarity at the first difference. This suggests that a first-order difference is sufficient to attain stationarity, eliminating the need for additional data processing. With the time series transformed to stationary at d=1, we proceeded to estimate the remaining SARIMA model parameters (p and q). We estimated several models with varying orders and compared them against one another. To determine the most suitable forecasting model, we used the Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC) (see Mensah, 2015). The model with the lowest AIC and BIC scores was deemed to have the best fit (refer to ***Appendix Table A.1***).

Additionally, our sample data has been seasonally adjusted, which allows for comparisons of non-performing loans with the previous months. Following our analysis, the seasonal ARIMA(0,1,1)x(2,2,2)12 model was determined to be the appropriate fit for the non-performing loans series, with a minimum AIC and BIC of (-2.9007) and (-2.75702), respectively. To ensure the accuracy of the model for forecasting purposes, a diagnostic check was conducted through residual autocorrelation (as shown in ***Figure 2***). Our results indicate that the chosen model has passed all the diagnostic tests, and hence, is considered the most suitable model for predicting the monthly NPL levels of the Albanian banking system.

Figure 2. The figure presents the residual autocorrelations for adjusted NPL



Source: Our own calculation.

4.2 Model estimation and forecasting

Table 2 shows the forecasted model selected and ***Table 3*** presents the forecasted NPL values, along with the predicted values generated by the fitted model and the residuals (i.e., the variation between the forecast and the actual data) for the duration in which actual data is accessible. The time frame spanning from has been allocated for conducting comparisons between forecasts.

Table 2. Forecast Model Selected: ARIMA(0,1,1)x(2,2,2)12

Parameter	Estimate	Stnd. Error	t	P-value
MA(1)	-0.367101	0.125844	-2.9171	0.005107
SAR(1)	-1.02985	0.0627264	-16.4182	0.000000
SAR(2)	-0.554915	0.0765735	-7.24683	0.000000
SMA(1)	1.27033	0.0841405	15.0978	0.000000
SMA(2)	-0.49345	0.0616683	-8.00167	0.000000

Estimated white noise variance = 0.0604706 with 55 degrees of freedom. Estimated white noise standard deviation = 0.245908. Number of iterations: 10. *Source:* Our own calculation.

The seasonal ARIMA (SARIMA) model includes both non-seasonal and seasonal components. Additionally, each term in the model means ARIMA (0,1,1)x(2,2,2)12: This is the non-seasonal component of the model. In our case, (0,1,1), it means there are no autoregressive (AR) terms, one non-seasonal differencing (I) term, and one moving average (MA) term for the non-seasonal part of the model. Furthermore, the seasonal components are denoted by the second set of numbers in parentheses, (2,2,2). This means that the model includes two seasonal autoregressive (SAR) terms, two seasonal differencing (SI) terms, and two seasonal moving average (SMA) terms. The number 12 specifies the seasonal period of the data, which in our case is 12 months. Taken together, this model suggests that the current value of the time series is a function of the first lagged value and the first difference of the series, as well as the two lagged seasonal values and the two lagged seasonal errors. This model can capture both non-seasonal and seasonal patterns in the data and is useful for forecasting time series data with a seasonal component.

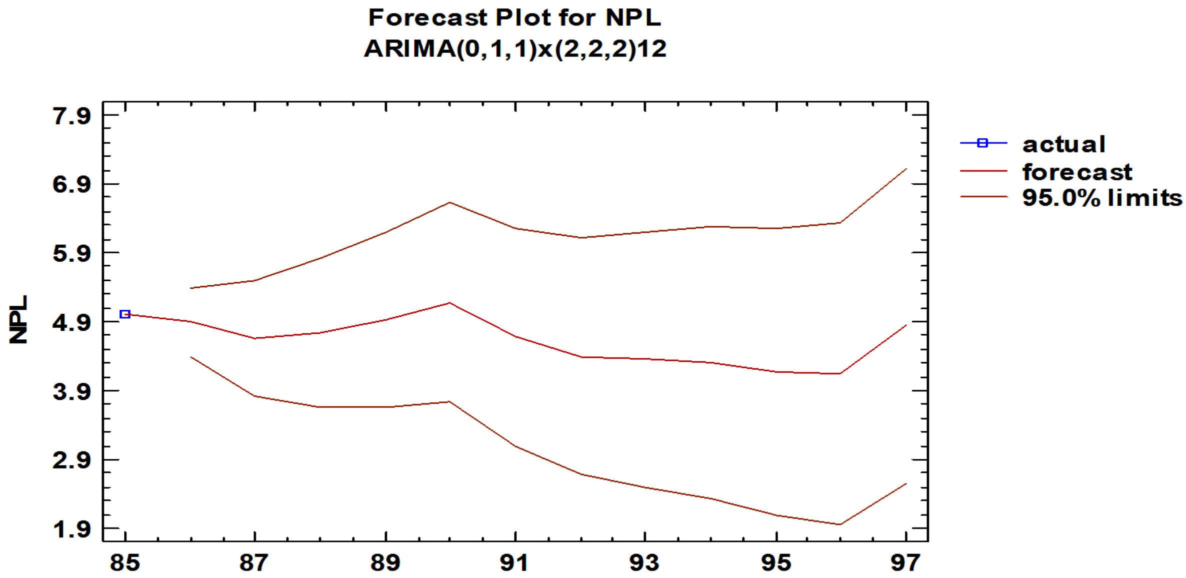
Table 3. Forecast Table for Non-performing Loans (%)

Period	Forecast (%)	Lower 95.0% Limit	Upper 95.0% Limit
January 2023	4.88688	4.39407	5.3797
February 2023	4.65286	3.81814	5.48759
March 2023	4.73858	3.66589	5.81127
April 2023	4.92581	3.6591	6.19253
May 2023	5.18127	3.74653	6.61601
June 2023	4.67732	3.09228	6.26237
July 2023	4.39797	2.67568	6.12026
August 2023	4.34651	2.49713	6.19588

September 2023	4.31268	2.34441	6.28094
October 2023	4.16604	2.08566	6.24642
November 2023	4.15701	1.97026	6.34376
December 2023	4.83446	2.54628	7.12265

Source: Our own calculation.

Figure 3. Time series plot for actual and forecasted NPL (%)



Source: Our own calculation.

5. Conclusion

The purpose of this paper is to elaborate an empirical forecast of non-performing loans (NPL) using the seasonal ARIMA model. To assess the quality of the model fit standardized residuals and the partial autocorrelation function of residuals were employed as test criteria. The different models' performances are compared using the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). We find that the seasonal ARIMA (0,1,1)x(2,2,2)12 model is recognized as the best-suited model to prognosticate NPL levels, even in distressed periods like the COVID-19 pandemic. We believe that the accuracy of this model, especially during the pandemic, is attributed to the prudent intervention of the supervisory authorities. In conclusion, this research suggests that the seasonal ARIMA (0,1,1)x(2,2,2)12 model is an appropriate forecasting approach to be considered by regulators, policymakers, and supervisory bodies.

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APPENDIX A

(A) Random walk
(B) Random walk with drift = -0.166566
(C) Constant mean = 11.5437
(D) Linear trend = 19.9806 + -0.196208 t
(E) Quadratic trend = 21.6722 + -0.312873 t + 0.00135657 t^2
(F) Exponential trend = exp(3.1199 + -0.0178814 t)
(G) S-curve trend = exp(2.25735 + 1.584 /t)
(H) Simple moving average of 2 terms
(I) Simple exponential smoothing with alpha = 0.9999
(J) Brown's linear exp. smoothing with alpha = 0.7003
(K) Holt's linear exp. smoothing with alpha = 0.9999 and beta = 0.0174
(L) Brown's quadratic exp. smoothing with alpha = 0.4804
(M) Winters' exp. smoothing with alpha = 0.9999, beta = 0.0878, gamma = 0.9999
(N) ARIMA(0,1,1)x(2,2,2)12
(O) ARIMA(2,2,2)x(2,0,2)12
(P) ARIMA(1,1,0)x(2,2,2)12
(Q) ARIMA(0,1,0)x(2,2,2)12
(R) ARIMA(0,1,1)x(2,2,2)12 with constant

Table A.1. Estimation Period (December 2015 to December 2022)

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	BIC
(A)	0.369628	0.256863	2.34514	-0.166534	-1.58348	-1.73169	-1.60454	-1.41558
(B)	0.325816	0.21247	1.89532	0.0000322082	0.176766	-1.96049	-1.82178	-1.61565
(C)	5.32291	4.18796	44.7194	-0.00946855	-21.261	3.62639	3.7651	3.97124
(D)	1.1839	0.900099	8.67981	0.00131309	0.406866	0.643518	0.793783	1.0171
(E)	0.876738	0.588529	4.90066	0.00256648	-0.35463	0.0663179	0.228142	0.468637
(F)	0.916	0.618082	5.20325	0.0112999	-0.190909	0.130405	0.28067	0.503987
(G)	5.60688	3.91428	36.6338	0.745366	-8.33619	3.75387	3.90414	4.12745
(H)	0.507023	0.357667	3.29791	-0.252468	-2.45611	-1.07605	-0.93734	-0.731201
(I)	0.36965	0.253855	2.31768	-0.164591	-1.56502	-1.70805	-1.56934	-1.3632
(J)	0.30242	0.20758	1.89157	0.00450315	0.17454	-2.10953	-1.97082	-1.76468
(K)	0.334306	0.2139	1.87871	-0.047623	-0.205393	-1.88551	-1.73525	-1.51193
(L)	0.328015	0.234146	2.13417	0.00350217	0.141255	-1.94704	-1.80833	-1.60219
(M)	0.342837	0.226837	2.32723	-0.00825089	0.0995705	-2.07041	-2.03574	-1.9842
(N)	**0.221092**	**0.179856**	**2.3254**	**0.00878134**	**0.101884**	**-2.9007**	**-2.84291**	**-2.75702**
(O)	0.215194	0.159293	1.58689	0.000576925	0.0841761	-2.88419	-2.79172	-2.65429
(P)	0.223389	0.182921	2.37012	0.00680844	0.0783411	-2.88004	-2.82224	-2.73635
(Q)	0.22772	0.185903	2.34675	0.0155063	0.209624	-2.86516	-2.81892	-2.75021
(R)	0.222931	0.181377	2.34495	0.0146471	0.23367	-2.86061	-2.79125	-2.68818

Table A.2. Validity Test Results Table

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	0.369628	OK	**	***	OK	***
(B)	0.325816	OK	**	***	OK	***
(C)	5.32291	***	***	***	***	***
(D)	1.1839	***	***	***	OK	*
(E)	0.876738	***	***	***	OK	***
(F)	0.916	***	***	***	OK	***
(G)	5.60688	***	***	***	***	***
(H)	0.507023	***	***	***	OK	***
(I)	0.36965	OK	**	***	OK	***
(J)	0.30242	*	OK	**	OK	***
(K)	0.334306	OK	**	***	OK	***
(L)	0.328015	**	OK	**	OK	***
(M)	0.342837	OK	OK	OK	OK	OK
(N)	**0.221092**	**OK**	**OK**	**OK**	**OK**	**OK**
(O)	0.215194	OK	OK	**	OK	OK
(P)	0.223389	OK	OK	OK	OK	OK
(Q)	0.22772	OK	OK	**	OK	OK
(R)	0.222931	OK	OK	OK	OK	OK

RMSE = Root Mean Squared Error
RUNS = Test for excessive runs up and down
RUNM = Test for excessive runs above and below median
AUTO = Box-Pierce test for excessive autocorrelation
MEAN = Test for difference in mean 1st half to 2nd half
VAR = Test for difference in variance 1st half to 2nd half
OK = not significant (p >= 0.05)
* = marginally significant (0.01 < p <= 0.05)
** = significant (0.001 < p <= 0.01)
*** = highly significant (p <= 0.001)

Table A.3. Estimated Autocorrelations for residuals

Lag	Autocorrelation	Stnd. Error	***Lower 95.0% Prob. Limit***	***Upper 95.0% Prob. Limit***
1	-0.0362033	0.129099	-0.253031	0.253031
2	0.0144252	0.129269	-0.253362	0.253362
3	0.0546725	0.129295	-0.253415	0.253415
4	0.189209	0.12968	-0.254169	0.254169
5	-0.105287	0.134202	-0.263032	0.263032
6	-0.139189	0.135572	-0.265717	0.265717
7	-0.076354	0.137933	-0.270344	0.270344
8	-0.129636	0.138636	-0.271722	0.271722
9	-0.245379	0.140642	-0.275653	0.275653
10	-0.229696	0.147605	-0.2893	0.2893
11	0.0896763	0.153446	-0.30075	0.30075
12	0.027528	0.154317	-0.302457	0.302457
13	-0.176594	0.154399	-0.302617	0.302617
14	-0.103236	0.15773	-0.309145	0.309145
15	0.113998	0.158852	-0.311344	0.311344
16	0.174337	0.160209	-0.314005	0.314005
17	-0.0224043	0.163341	-0.320142	0.320142
18	0.0715527	0.163392	-0.320243	0.320243
19	0.157536	0.163913	-0.321265	0.321265
20	-0.0672222	0.166418	-0.326173	0.326173