How to cite this paper: Minasyan D. (2024). Banking Stability Multifactor Modelling Using VARMA Methodology in the Republic of Armenia. *Messenger of ASUE, 1*(76), 66-79.
DOI:10.52174/1829-0280_2024.1-66
Received: 26.03.2024. ***Revision:*** 01.04.2024. ***Accepted:*** 27.05.2024.

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BANKING STABILITY MULTIFACTOR MODELLING USING VARMA METHODOLOGY IN THE REPUBLIC OF ARMENIA

The banking stability modelling with VARMA model has been conducted in the given research where 48 factors, representing different sectors of economy, have been selected. After that, by using RIDGE and Lasso regressions, as well as correlation coefficients with the dependent variable, only the most significant factors have been chosen. As the determinant of the banking stability, the banking Z-score has been selected, which is calculated as a country level measure, and not for individual banks. Using these factors, the VARMA model has been estimated, and the best model is identified as the VARMA(2,1). It is proven, that factors like Regulatory capital to risk-weighted assets, dollarization rate, exchange rates, CPI, profitability of government bonds, nonperforming loans, ROA, ROC, liquid assets to demand deposits, and other factors selected in the result of model evaluation are good indicators for modelling the banking stability.

The model prediction power is tested by splitting data into train and test parts and comparing predicted values with test dataset. The model shows quite small mean squared error and proves to be useful for modelling Armenian banking stability with existing dataset.

Keyword: *banking stability, Z-score, VARMAX, stationarity, Ridge, Lasso, correlation*

JEL: C23, G21
DOI: 10.52174/1829-0280_2024.1-66

INTRODUCTION. During the volatility of the current economic and political situation, a lot of shocks are occurring all over the world. They include a huge number of migrations, currency is changing in a big magnitude and then coming back to equilibrium, cryptocurrency price is growing rapidly on a daily basis, and all these combined with other shocks are affecting a stable financial and banking system. Armenia is considered as a developing country with a volatile economy and should have a strong banking system in order to be able to withstand crises and effects from global shocks. As we all know, the financial system and in general, economics, is a complex multirelated system, where the impact of a certain factor may occur not directly, but after some period, which may have a lagged impact on observed economic variables. The same is true for financial stability: besides considering direct impact of the factors, determining stability, lagged or delayed impact examination may play a huge role in the prediction power of the model. For this reason, the VARMA model, which evaluates relationships between different lags for observed variables has been further used in the research. As an indicator of banking stability, banking Z-score has been considered, defined by the World bank group. Z score is composed mainly from RAO, equity/asset ratio and STD from RAO.

RESEARCH METHODOLOGY. Independent variables are included variables from different economic sectors, such as foreign sector, real sector, financial sector. In total, for the model evaluation, 47 variables have been considered. The majority of the data are collected from the public data of the "Statistics" section at the Central Bank of Armenia (CBA). All the variables have monthly granularity, and include the period from 2013/01-2023/07. Before starting the model evaluation, all the variables have been stationarised. For choosing the most significant variables, closely related to the financial stability, a multistep approach has been applied.

The first step performs lasso regression with different values of the alpha parameter. Based on that, variables, which have 0 lasso coefficient, have been removed from the model.

The second step conducts ridge regression, which shows independent variables' impact on the dependent variable. Only variables with high absolute value of ridge coefficient have been considered in the model. Apart from that, correlation analyses have been conducted and some variables have been combined to reduce multicollinearity. Also, only variables with high correlation coefficient with dependent variables have been included. The data was split into train and test parts, and after evaluation, the actual values were compared with predicted values to check the model prediction performance.

After the model evaluation, several tests have been conducted, to check the quality of the model: Ljung Box test for Autocorrelation check and Jarque Bera test for checking normality of residuals. The analyses were implied using Python statsmodels library.

Here is the formula representation of the VARMA model:

$$X_t = \sum_{i-1}^{p} \phi_i X_{t-i} + \epsilon_i - \sum_{j=1}^{p} \Theta_j \epsilon_{t-j}$$

$X_t = (x_{1t} . \cdots . x_{kt})'$ denotes an (k x1) vector of time series of variables .

$\Phi_i = (i = 1 . 2 . \dots . p)$ denotes an (k x k) matrix of autoregression parameters.

$\Theta_j = (j = 1 . 2 . \dots . q)$ denotes an (k x k) matrices of moving average parameters.

ϵ_t denotes an (k x1) vector of random error (A. H. Al-Nasser & L. T. Abdullah, 2021).

LITERATURE REVIEW. There is a vast amount of sources in literature referring to the existing modelling methodologies of banking stability with time series data: the most relevant of them to our study methodology is “Canadian Monetary Policy Analysis using a Structural VARMA Model (Raghavan, et al., 2014), where SVARMA model was implemented and uncovered the effects of the monetary policy on the inflation rate and the output level in the economy. Similar to that study, there is another paper: “VARMA models for Malaysian Monetary Policy Analysis" (Raghavan, et al., 2009), where the authors describe the application of VARMA in monetary policy analyses, advantages of the model compared to more popular modelling approaches like VAR and SVAR. In the evaluated model, both foreign and domestic variables were included , where oil price, federal funds rates represent foreign part, and the industrial production index, CPI, monetary aggregate M1, interbank rates and nominal effective exchange rates represent the domestic variables.

There is extensive research conducted for VARMAX and VARMA processes and modelling in economic research, by SAS Institute Inc.: “SAS/ETS® 14.2 User’s Guide The VARMAX Procedure” (SAS Institute Inc., 2015). In the article, there is a complete mathematical and statistical background and formula derivation for VARMAX procedures, their modelling, and combination with different modelling methodologies, including VARMA.The early indication about VAR and SVAR models was found in Sims’ work (Sims, 1980).

Sims’ approach was prevalent until Athanasopoulos and Vahid (2008) brought VARMA models in monetary policy analyses into the game. This methodology basically is the extension of the work of Tiao and Tsay (1989). In the literature related to the modelling of the monetary policy, there are indications about the advantage of the VARMA models above VAR-s. Among such papers Dufour and Pelletier ́s study is listed (2014). This is true also in case of the modelling of the macroeconomic variables, and papers written by Zellner and Palm (1974), Granger and Morris (1976), Wallis (1977), Maravall (1993) state the preference of VARMA over VAR-s while modelling macroeconomic variables. For codes and statsmodels library specification of VARMAX modelling, was referred to Statmodels.org documentation of VARMAX model (Statsmodels.org, 2024).

Based on the recent literature directly related to the modelling of banking stability and bank risk, in the article entitled "Measuring bank risk: Forward-looking z-score" (Bilal Hafeez, 2022), the author describes a methodology of modelling banking stability, using forward looking Z-score as an indicator for measuring banking system risk. The basic principle of the Z-score measure is to relate a bank's capital level to variability in its returns so that one can identify how much variability in returns can be absorbed by capital without the bank becoming insolvent. A higher value of the z-score means lower bank risk.

ANALYSIS. Financial and banking systems are day by day becoming more complex, based on the evolving technology, greater number of institutions and players, open banking regulations and different types of interactions. This makes it more challenging to identify the patterns of healthy banking systems, and implement different policies. Central banks, more than ever, need advanced modelling techniques and indicators to forecast financial stability and apply preventative measures from different types of shocks and strengthen systems. So, which is the best model to use in this case? This question has been in the centre of interest for a lot of researchers. Before answering this question, let us dive deeper into what banking stability is, and try to define it. There is no clear definition of banking stability, it is generally defined as the collective stability of individual banks, but in the scope of our research, we will target the stability of the entire system. In Armenia, the financial system is associated with the banking sector, as banks do comprise 85% of the whole financial system. Based on that, we can hereby refer to banking stability as financial stability. In IMF working paper (Mr. Garry J. Schinasi, 12 December, 2005) financial stability is defined as a situation in which the financial system is capable of performing its three key functions:

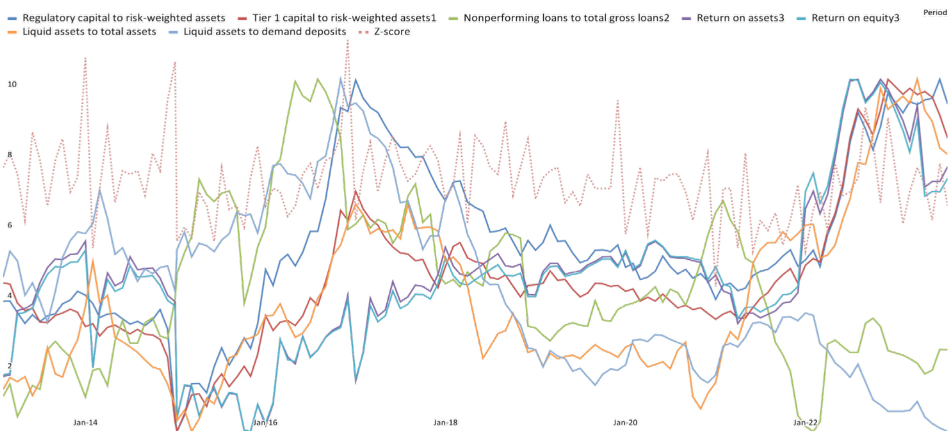
- financial system is efficiently allocating economic resources, as well as resources from savers to investors and
- forward-looking financial risks are being assessed and targeted and are being well managed,
- the financial system is in such a condition that it can smoothly absorb financial and real economic shocks.

Let us thoroughly consider the data and the model evaluation process. Economic and financial time series data are rarely used without some kind of transformation, which can include preprocessing like detrending, seasonal adjustments and different kinds of aggregations. This kind of time series usually assume moving average dynamics. That is an indication that the MA component will reveal extra insights for this kind of data involved in modelling. Moreover, Cooley and Dwyer (1998) claim that the basic real business cycle models follow VARMA processes. VARMA models, in comparison to simple VAR models, are far less spread and it is due to their more complex nature. All this states that VARMA models are good and useful predictors for the financial and banking systems. Given a multivariate time series, the VARMAX (VARMA) procedure estimates the model parameters and generates forecasts that are associated with vector autoregressive moving average processes with exogenous regressors (VARMAX) models. Often, economic or financial variables are not only contemporaneously correlated with each other, but also correlated with each other's past values. VARMAX procedures help to model these types of time relationships (SAS Institute Inc., 2016).

Compared to other time variable models, VARMA also captures short-term dynamics, based on MA component, while AR allows to explore long term relationships between variables. It is a good fit for banking stability modelling, as short-term shocks are quite common, and unexpected in the financial sector of the economy: such as market speculations, drop and increase of oil prices, political climate can have significant impact on financial markets, causing different kinds of fluctuations. Besides, the MA component helps filter out noise and fluctuations in data and enhance signal-to-noise ratio in the model, also helping in identifying structural breaks. It will help understand when the shocks took place, as well as how the variables of our interest react to those shocks and structural breaks. Literature suggests that high order VAR models are used to approximate true VARMA structure. In addition, VAR models are well documented in macroeconomic literature, but there are very few practical implementations of VARMA models. This is related to complexity of identifying and estimating the VARMA model, contrary to the simplicity of VARs (Poskitt, 2011).

Using all these claims, as well as research described in the literature review, a VARMA approach has been chosen for the modelling of the banking stability of the Republic of Armenia.

As the indicator to evaluate banking stability, banking Z-score is calculated for Armenian data. Z-score is calculated using this formula: Z-Score=**(ROA+ +(equity/assets))/sd(ROA)**. This methodology is mentioned in the World Bank Group glossary (World Bank Group, 2015). The essence of the score is that it compares the buffer of a country's commercial banking system (capitalization and returns) with the volatility of those returns. We have calculated Z-score in a monthly granularity, which provides sufficient data to make assumptions from the model. The information is gained from the publicly available data from the Central Bank of Armenia (CBA). Let us see how Z-score captures financial shocks compared to other indicators of banking stability in Armenia.



Data: CBA.am, Financial soundness indicators

Figure 1. ***Comparing Z-score with financial stability indicators tracked by CBA***

Based on the figure above, we can see that Z-score is relatively smooth compared to banking stability indicators, but in the time of drastic shifts in indicators, Z-score reacts quite effectively and registers sharp declines and rises. This states the hypothesis in the literature review, that Z-score can be a good indicator for modelling Armenian banking stability.

For the initial evaluation, we have selected the VARMA model, to find out how different lags of variables affect each other. The VARMA model is designed for multifactor analyses and it can capture lagged dependencies. The main advantage and the difference from the normal VAR model, VARMA has a moving average (MA) component, which allows it to capture the "memory" of past errors in the forecasting equation, offering a more detailed modelling of the time series data (Mala Raghavan,et. al. 2009).

Model specification

For identifying proper lags to include in the model, lagged values are also included in the analyses. For that reason, we have estimated the VAR model, and we can see that the optimal lag for the dependent variables is 2.

In VARMA, like in ARIMA we need to choose p, d, q but as we have stationarised our series before evaluating the main model, we won’t need to specify d parameter for our model. It is done because our variables are stationary in different lags. Based on VAR results, p is 0. Regarding q, we have estimated the VARMA model with 0 ,1 q parameters, and model performance is better while q is 1. Based on that insight, we will keep the q parameter as 1.

For a better model performance, we have combined some independent variables containing autocorrelation, and created new variables. It includes averaging of dollarization 4 components, subtracting non-commercial inflows and outflows to create net export (the same for commercial export), averaging income from long term and medium term government bonds. For identifying proper variables, more related to our model and giving better performance power, Lasso regression has been applied. Lasso is useful in the context of feature selection, as it gives 0 coefficient to low quality variables. It does this by adding a penalty term to the residual sum of squares (RSS), which is then multiplied by the regularisation parameter (lambda or λ). This regularisation parameter controls the amount of regularisation applied. Larger values of lambda increase the penalty, shrinking more of the coefficients towards zero, which subsequently reduces the importance of (or altogether eliminates) some of the features from the model, which results in automatic feature selection (Kavlakoglu, 2024).

Another technique applied for the feature selection is Ridge regression. It is a widely used technique in machine learning, and helps filter out variables with 0 effect on dependent variables. One of the most important things about ridge regression is that without wasting any information about predictions it tries to determine variables that have exactly zero effects. Ridge regression is popular because it uses regularisation for making predictions and regularisation is intended to resolve the problem of overfitting (Verma, 2022). Apart from that, the variables that have higher than 0.2 Pearson correlation coefficients to the Z-score have been chosen. In Figure 2, we can see that 14 factors have correlation coefficients higher than 0.2, which justifies the selection of a model based on linear assumptions.

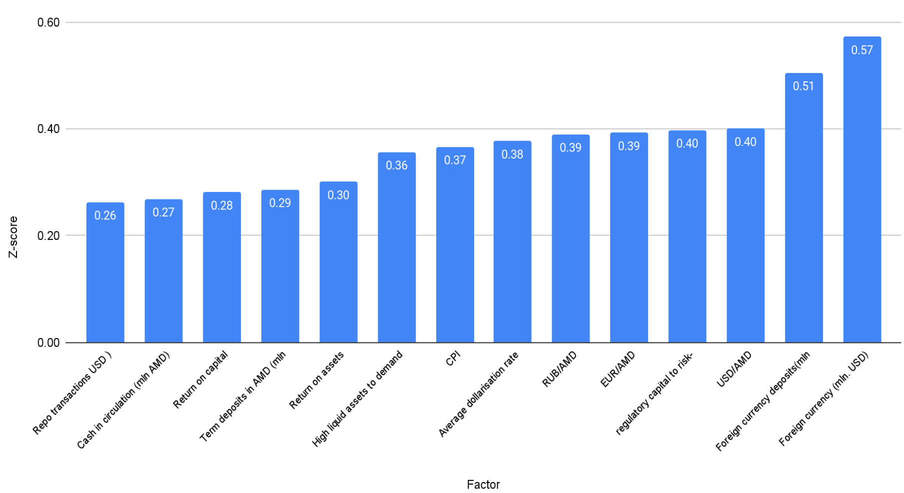


Figure 2. ***Factors with greater than 0.2 correlation coefficient with Z-score***

As a result of the three-step filtering process of the total pool of variables, the following factors are filtered:

RUB/AMD, EUR/AMD, USD/AMD exchange rates, return on capital, average profitability of government bonds, nonperforming loans to total gross loans, cpi, regulatory capital to risk-weighted assets, return on capital, return on assets, average dollarisation rate, liquid assets to demand deposits, medium term government bonds in foreign currency, repo transactions, cash in circulation, foreign currency deposits, term deposit.

After feature engineering, and identifying parameters the evaluation of VARMA follows. Using selected variables, a VARMA (2,1) model has been estimated.

Let us specify VARMA(2,1) model with the formula:

$$A_0Y_t = A_1Y_{t-1} + A_2Y_{t-2} + M_0u_t + M_1u_{t-1}$$

Here A_i is 16:16 matrix, which means each value of matrix shows the impact of the corresponding lag of a Y_t variable to the same lag of other variables.

For simplicity, let us show only the impact of other variables and their own lags on Z-score.

We will have the following results:

A_1=[-0.044, 0.549,0.004,0.034,-0.003,-0.018, -0.585,0.285,-0.774,-0.218, -0.302]
A_2=[0.030,-0.001,0.039, -0.002, -0.002, -0.002, 0.444,0.134, -0.456, -0.282, -0.029]
e_1=[-0.019, 0.058, -0.035, -0.015, 0.019, -0.034, 0.046, -0.090, -0.048, -0.318, -0.022]

The intercept : M_0u_t will be 0.2690 for the Z-score.

A1 is the impact of the first lag of endogenous variables to Z-score, A2 is the impact of the lag 2 of all endogenous variables to Z-score and e1 is the MA coefficient of Z-score.

All these vectors are listed in the following order of variables:

CPI, regulatory capital to risk-weighted assets, return on capital, liquid assets to demand deposits, USD/AMD, EUR/AMD, RUB/AMD, average dollarisation rate, Z-score, nonperforming loans to total gross loans, average profitability of government bonds.

The significant lags and factors are listed in below in Table 1 and Table 2, by descending orders of coefficients for positive, and ascending for negative coefficients:

Interpreting the coefficients:

As we can see, from Table1, the first lag of Regulatory capital to risk-weighted assets has the highest positive coefficient, but, at the same time, its second lag has a negative impact on banking stability. It can be interpreted as the penalty for keeping an increased amount of capital instead of assets, in the long run. For the Russian ruble/AMD exchange rate, its second lag has the second highest positive impact, while its first lag has the second highest negative impact. For the first lag being negative, we can say that when Armenian dram is becoming more stable, the financial sector is becoming unstable, as we rely on a lot of foreign transfers from Russia, but in the long run when Armenian dram is getting valuation, it is good for the economy. In case of the dollarisation rate, both the 1-st and 2-nd lags have a positive impact on Z-score. The positive impact of the dollarization rate may be explained by several factors:

- Reduced Exchange Rate Risk: Dollarization can mitigate exchange rate risk for both banks and borrowers, which can reduce the likelihood of bank failures due to sudden currency devaluations.
- Lower Inflation Risk: By using a stable foreign currency like the US dollar, countries with high levels of dollarization tend to have lower inflation rates.

As expected, return on capital has a positive impact on the economy, as it indicates the constant income for the banking system, profitability and earnings stability, as well as investor confidence. The negative impacts (see Table 2) are primarily related to the previous lags of Z-score. the It can be explained by the fact that a very stable banking system can lead to the decrease of stability in the upcoming periods, bringing back to equilibrium. The more profitable government bonds are, the less stable the economy is. Government bond profitability increase will lead the Z-score coefficient to go down by -0.46(L1) and -0.003(L2) points. This can be an indication of the increase of overall interest rates, and, presumably can result in lower stability of the financial system. Nonperforming loans, both the 1-st and 2nd lags, have significant negative influence on Z-score, which is rational, as nonperforming loans are one of the biggest red flags for a stable banking system. The increase in CPI also has a negative effect, which can be explained by the risk of inflation. We can see that the second lag of Regulatory capital to risk-weighted assets has a really small, but negative impact on Z-score. As we know from economic theory, this indicator is mainly positively correlated with banking stability, but it is not always like that. Negative impact may be connected with:

- Reduced Lending: Banks may reduce lending activity or increase lending costs which could harm credit availability and economic growth.
- Impact on Profitability: Higher capital requirements can impact banks' profitability
- Competitiveness: Banks operating with higher capital requirements may face competitive disadvantages

EUR/AMD and USD/AMD exchange rates all have negative effects, as the increase of these exchange rates means that local currency is being depreciated.

It can cause some unwanted effects for the country and banking system, such as a higher burden on borrowers: the countries/banks/individuals should pay a higher price for serving foreign currency loans or liabilities. Apart from that, it will cause an increase in the cost of imported goods and services, leading to higher inflation.The first lag of CPI has a negative impact, but the second lag has a small positive impact on the stability. Usually, increase in CPI means inflation, and it may harm the economy in different ways, causing uncertainty and volatility. This explains the negative effect of the first lag. Small positive effect of the second lag can be explained with enhancing some economic activity by increased loan demand, as well as can have a direct impact on the banking system by higher interest margins for a lot of bank products. This can lead to higher profitability and stronger balance sheets. For the Liquid assets it's the opposite: the first lag has a small negative impact on Z-score , while the second lag has a small negative impact. The positive impact indicates that the bank can meet its short-term obligations, reducing the risk. Apart from it, the higher the indicator is the greater the customer confidence, which means that the bank has sufficient liquid assets to meet withdrawal demands. While maintaining a high ratio of liquid assets to deposits can improve liquidity coverage, it may also lead to reduced profitability, as liquid assets are usually less profitable than other assets. Besides, liquid assets, particularly bonds and other securities, can be susceptible to interest rate changes: rising interest rates can reduce the market value of these assets.

Checking the model quality:

For our model, to check correlation among residuals, Ljung Box test is implemented, using statsmodels acorr_ljungbox function: While checking the amount of proper lags for errors (10 in our case), based on p value and Ljung-Box statistics, there is no autocorrelation in residuals for Z-score up to 10 lags (Zach, 2020).

Table 1

Positive Impact of variables on Banking Z-score

Variable name	*Coefficient*
L1.Regulatory capital to risk-weighted assets	0.5493320959
L2.RUB/AMD	0.4439157563
L1.Average dollarisation rate	0.2845419419
L2.Average dollarisation rate	0.1338347785
L2.Return on capital	0.03871434999
L1.Liquid assets to demand deposits	0.03364174939
L2.CPI	0.03041134407
L1.Return on capital	0.003536063991

Apart from that, a Jarque-Bera normality test has been conducted, to check the normality for the residuals (Misha Sv., 2021). The model has failed to meet the test, as the P-value is less than 0,05 and there is enough evidence to reject the null hypothesis that the residuals are normally distributed.

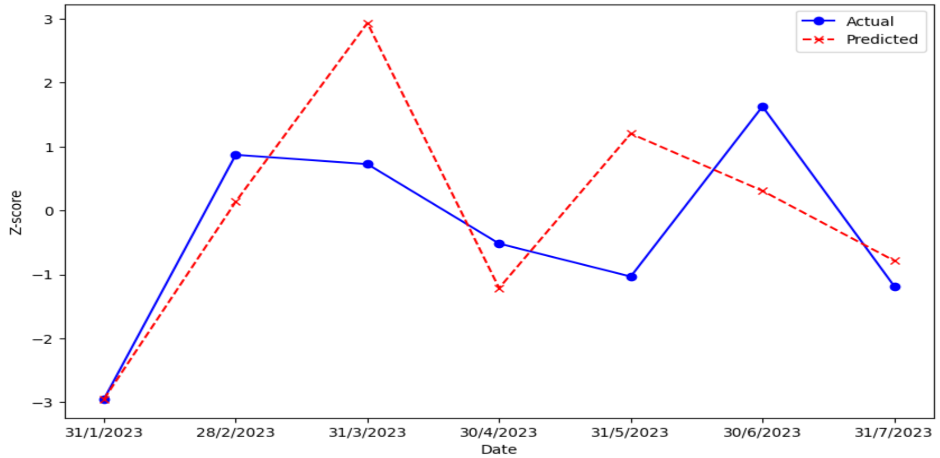
Table 2

Negative Impact of variables on Banking Z-score

Variable name	*Coefficient*
L1.Z-score	-0.774
L1.RUB/AMD	-0.585
L1.average profitability of government bonds	-0.456
L1.Nonperforming loans to total gross loans	-0.302
L1.CPI	-0.282
L1.EUR/AMD	-0.218
L1.USD/AMD	-0.044
L2.Z-score	-0.029
L2.Nonperforming loans to total gross loans	-0.018
L2.average profitability of government bonds	-0.003
L2.EUR/AMD	-0.002
L2.Liquid assets to demand deposits	-0.002
L2.USD/AMD	-0.002
L2.Regulatory capital to risk-weighted assets	-0.001

As mentioned in earlier sections, our data were split to train and test data, and we have included 120 observations in train data and 7 observations in test data.

In result of the model forecasting using test data, we have received a low standard error and predicted data follow the patterns of the test data. The graphical representation can be seen in Figure 3.



MAE: 1.084, RMSE: 1.35

Figure 3. ***Comparison of Actual and Predicted Values for VARMA(2,1)***

Although having some disadvantages (residuals are not normally distributed), the model has quite a good predicting power and is performing well on test data. We can use this model to make out a sample prediction as well and apply it as a decision-making mechanism for policymakers.

CONCLUSION. Based on the methodology described in the article, modelling banking stability with VARMA approach, we can conclude that the inclusion of the moving average component in the standard VAR model is a good practice to model the country level banking stability and gives valuable insights on identifying the factors which indicate the presence of risk of insolvency for the banking system.

Apart from that, the factor selection with the help of Ridge and Lasso regressions is giving penalty to the factors that worsen the model predictive power. According to that, by combining these 2 methodologies and removing low performing factors from our model, the selection of only those variables that are highly correlated with the dependent variable, will give the model a better performance and more significant results.

The banking Z-score is selected to be the indicator for banking stability and several reasons have led to that decision:

- There is enough data available to calculate Z-score on a monthly granularity.
- Z-score is interpretable, the higher the Z-score, the less likely that the banking system will collapse
- It represents both, states of assets and equity of the banks, as well as how the ROA is deviated from its mean, meaning it covers more dimensions than classic banking stability indicators the Central Bank of Armenia (CBA) is tracking.

As a result of the model evaluation, we can see that for Armenian banking system modelling, the major factors determining the stability of the system are as follows:

Regulatory capital to risk-weighted assets (first lag), dollarisation rate (both lags), RUB/AMD exchange rate (second lag) with positive influence, and lagged values of Z-score, nonperforming loans to total gross loans (both lags), CPI (first lag), average profitability of government bonds (both lags), RUB/AMD (first lag), EUR/AMD (both lags), USD/AMD (both lags) with negative impact.

References

1. Athanasopoulos, G. (2008). A complete VARMA modelling methodology based on scalar components. *Journal of Time Series Analysis*, vol. 29, no. 3. https://research.monash.edu/en/publications/a-complete-varma-modelling-methodology-based-on-scalar-components
2. Cooley, T. F., & Dwyer, M. (1998). Business cycle analysis without much theory A look at structural VARs. *Journal of econometrics*, *83*(1-2), 57-88.
3. Dufour, Jean-Marie. Pelletier, D. (2008, November). Practical methods for modelling weak VARMA processes: identification, estimation and specification with a macroeconomic application. *Journal of Business and Economic Statistics,* 40(4). https://www.researchgate.net/publication/228647110_Practical_Methods_for_Modeling_Weak_VARMA_Processes_Identification_Estimation_and_Specification_With_a_Macroeconomic_Application
4. Hafeez, B., et al. (2022). Measuring bank risk: Forward-looking z-score. *International Review of Financial Analysis*, vol. 80. https://www.sciencedirect.com/science/article/abs/pii/S1057521922000187
5. Kavlakoglu, E. (2024, March 6). Apply lasso regression to automate feature selection. *IBM developer.* https://developer.ibm.com/tutorials/awb-lasso-regression-automatic-feature-selection/
6. Misha, SV. (2021). Test for Normality Using Python: Complete Guide. *Towards AI.* https://pub.towardsai.net/test-for-normality-using-python-complete-guide-5ae98fb24c2a
7. Poskitt, D.S. (2011, March 22). Vector Autoregresive Moving Average Identification for Macroeconomic Modeling: A New Methodology. *Econometrics & Business Statistics.* https://www.eui.eu/Documents/DepartmentsCentres/Economics/Researchandteaching/Conferences/TSEConference-NewDevelopmentsinTimeSeries/Poskitt.pdf
8. Raghavan, M., et al.. (2009). VARMA models for Malaysian Monetary Policy Analysis. *Monash University.* https://www.researchgate.net/publication/228995968_VARMA_models_for_Malaysian_Monetary_Policy_Analysis
9. Raghavan, M., et al. (2014). Canadian Monetary Policy Analysis using a Structural VARMA Model. *Tasmanian School of Business and Economics*. https://www.utas.edu.au/data/assets/pdf_file/0004/537817/2014-06_Raghavan.pdf
10. SAS/ETS.(2015). The VARMAX Procedure. *SAS/ETS® 14.1 User's Guide*. https://support.sas.com/documentation/onlinedoc/ets/141/varmax.pdf
11. Schinasi, G.J. (2005, December 12). Defining Financial Stability. *IMF eLibrary.* https://www.elibrary.imf.org/display/book/9781589064409/ch005.xml
12. Sims, C. (1980). Macroeconomics and Reality. *Econometrica*, vol.48. https://www.jstor.org/stable/1912017

13. Statsmodels.org. (2024). VARMAX. https://www.statsmodels.org/dev/generated/statsmodels.tsa.statespace.varmax.VARMAX.html
14. Tiao, G. & Tsay, R. (1989). Model Specification in Multivariate Time Series. *Journal of the Royal Statistical Society*, vol. 51, no. 2. https://www.jstor.org/stable/2345602
15. The World Bank. (n.d.). Bank Z-score. *Glossary | DataBank*. https://databank.worldbank.org/metadataglossary/global-financial-development/series/GFDD.SI.01
16. Verma, Y. (2022). A hands-on guide to ridge regression for feature selection. *Analytics India Magazine*. https://analyticsindiamag.com/a-hands-on-guide-to-ridge-regression-for-feature-selection
17. Zach. (2020, October 15). How to Perform a Ljung-Box Test in Python. *Statology*. https://www.statology.org/ljung-box-test-python/