Modelling the Banking stability of Armenia using ARIMA model

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Git-Hub link: https://github.com/DavMLPath/banking_stability_arima/blob/main/ARIMA.py

ՀՀ Բանկային կայունության մոդելավորումը ARIMA մոդելի միջոցով

Մինասյան Դավիթ Գ.
Տնտեսագիտության Մագիստրոս, ՀՊՏՀ Ասպիրանտուրայի ուսանող (Երևան, ՀՀ)
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Ամփոփագիր. Մեր օրերում համաշխարհային բանկային համակարգը գտնվում է տարբեր տեսակի արտաքին ցնցումների և սթրեսների ազդեցության տակ, ինչպիսիք են՝ COVID-19-ը, Ռուս-Ուկրաինական պատերազմի հետ կապված ֆինանսական ճգնաժամը, միգրացիան և այլն:
Այդ գործոնները ստիպում են քաղաքականություն մշակողներին լինել ավելի ռեակտիվ, արագ որոշումներ կայացնել, փոփոխություններին ավելի լավ հարմարվելու և կանխարգելիչ միջոցառումներ իրականացնելու համար:
Նման որոշումների օրինակներ են՝ Հաշվի առնելով ՀՀ ԿԲ գների կայունության ռազմավարությունը և գնաճի ընթացիկ զարգացումները՝ ԿԲ խորհուրդը COVID-ի ժամանակ նվազեցրել է վերաֆինանսավորման տոկոսադրույքը 0.25 տոկոսային կետով: Բացի այդ, Հայաստանի կառավարությունը նախաձեռնել է 300 միլիոն դոլարի աննախադեպ սոցիալական փաթեթ՝ ստեղծված իրավիճակի ազդեցությունը մեղմելու համար:
Բանկային կայունությունը շատ կարևոր գործոն է երկրի ֆինանսական առողջության համար, որը ցույց է տալիս, թե արդյոք բանկային համակարգը ի վիճակի է նորմալ գործել և դիմակայել ցնցումներին, և նախանշում է թե արդյոք դրա որոշ ասպեկտներ պահանջում են փոփոխություններ և բարելավումներ:
Սույն հետազոտական աշխատանքում ներկայացվում է բանկային կայունության չափման եղանակ՝ հիմնվելով մակրոտնտեսական ցուցանիշների վրա, ինչպես նաև ժամանակային շարքերի մոդելների միջոցով կանխատեսելով կայունության միտումը ապագայում: Որպես բանկային կայունության ցուցիչ, օգտագործվում է Z-score-ը, որը նույնպես վերահսկվում է Համաշխարհային բանկի կողմից յուրաքանչյուր երկրի համար:
Հոդվածի նպատակն է ոչ ավանդական մոտեցումների կիրառմամբ Հայաստանի Հանրապետության բանկային կայունության մոդելավորման արդյունավետ ուղիներ գտնել: Հետազոտության նպատակն է ընտրել այնպիսի մոդել, որը հնարավորինս ճշգրիտ կլինի բանկային կայունությունը կանխատեսելու համար:
Կատարված էմպիրիկ հետազոտությունները ցույց են տալիս, որ հնարավոր է օգտագործել ARIMA մոդելը՝ կանխատեսելու բանկային կայունությունը Հայաստանի բանկային համակարգի առկա տվյալների հիման վրա, և կանխատեսման արդյունքները մոտ են առանձնացված թեստային տվյալների ցանկի իրական արժեքներին:
Հանգուցաբառեր՝ Բանկային կայունություն, Z-score, ARIMA, կանխատեսում, Հայաստան

Моделирование банковской стабильности Армении с помощью ARIMA

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Аннотация. В настоящее время мировая банковская система находится под влиянием разного рода внешних потрясений и стрессов, таких как COVID, финансовый кризис, связанный с войной, миграция и т.д.
Эти факторы заставили политиков действовать более оперативно, принимать быстрые решения, чтобы лучше приспосабливаться к изменениям, и проводить превентивные меры до того, как произойдет шок.
Примеры таких решений: Учитывая цель ЦБ Армении по стабильности цен и оценив текущую динамику инфляции, Совет ЦБ во время COVID снизил ставку рефинансирования на 0,25 процентных пункта. Кроме того, правительство Армении инициировало беспрецедентный экономический пакет в размере 300 миллионов долларов США, чтобы смягчить воздействие текущей ситуации.
Стабильность банковской системы является очень важным фактором для финансового здоровья страны, показывающим, способна ли банковская система нормально функционировать и противостоять потрясениям, или же некоторые ее аспекты требуют изменений и улучшений.

В этой исследовательской работе представлен способ измерения банковской стабильности путем выбора соответствующих показателей, а также прогнозирования будущей тенденции стабильности с использованием моделей временных рядов. В качестве показателя банковской стабильности используется Z-score, который также отслеживается Всемирным банком для каждой страны.
Целью статьи является поиск эффективных способов моделирования банковской стабильности Республики Армения с использованием нетрадиционных подходов эконометрики. Цель исследования – выбрать модель, которая будет максимально точной для прогнозирования банковской стабильности.
Проведенный эмпирический анализ показывает, что можно использовать модель ARIMA для прогнозирования банковской стабильности на банковских данных Армении, а результаты прогноза близки к реальным значениям тестового набора данных.
Ключевые слова: банковская стабильность, Z-score, ARIMA, прогнозирование, Армения

Methodology

As an indicator to measure banking stability, the banking Z-score is used, which measures the risk of default for an individual bank or for the entire financial system. After choosing a proper indicator, banking stability is forecasted with the ARIMA model which is based on past values of the time series of calculated Z-score. For choosing the main parameters(p, d, q values) for the ARIMA, 2 approaches are used: Python built-in pmdarima library, and PACF and ACF plots. All calculations are conducted with the help of Python statsmodels library. The observation period includes January. 2012 - March 2023 and data is taken in monthly granularity. All components of the Z-score are calculated based on macroeconomic country-level indicators, and the main source of the data is the official website of the Central Bank of Armenia (CBA.am).

Literature review

There are various well-adopted methods to measure banking stability in universal settings. The most well-known method is the Basel principles. Here is a more detailed explanation.

The Basel Committee on Banking Supervision (BCBS) proposes official assessment methods to deal with global systemically important banks (G-SIBs) (BCBS, 2013) and domestic systemically important banks (D-SIBs) (BCBS, 2012), using confidential accounting and regulatory data. According to the methods, indicators of systemic significance are quantified and transformed into systemic scores, which represent the contribution of each systemically important bank to the whole system. Alternatively, academic researchers also propose several approaches to measure systemic significance of individual banks, most of which rely on share market data.

Traditionally, bank risk is measured and regulated at an individual bank level. Basel Accords provide a set of bank regulations, in regard to capital for credit risk, market risk and operational risk. Value-at-Risk (VaR) and Expected Shortfall (ES) are two standard risk measures, and are recommended by Basel II and Basel III, respectively. Other market-based methods, such as the CAPM model, are also widely used to measure individual bank risks. It is common to measure risk using banks' share prices (return), which can link banks' risk with return, and are widely applicable to listed banks. As a complement or where banks are not listed, bank risk can also be estimated with accounting data. Examples of traditional accounting data-based risk measures include the ratio of nonperforming loans to total assets, and z-score. The recent financial crisis led to suggestions that these traditional measures failed to fully capture bank risks, especially downside risk (Haldane, 2009). The Z-score is considered to be a well-known indicator for banking stability modeling, and in literature you can find examples of when it is used for simple empirical calculations to advanced econometric models. It is worth mentioning that there are different methodologies for calculating Z-score. Referring to the definition of WBG, Z-score compares the buffer of a country's commercial banking system with the volatility of those returns. In other words, it captures the probability of default of a country's banking system. The Z-score is considered to be a good measure of a bank's financial health and stability, which is calculated based on a combination of a bank's capital, earnings, and asset quality. The first and the most well-known approach is Altman Z-score **[1]**. It uses multiple parameters to measure banking system stability.

The Altman Z-score formula is as follows: Altman Z-Score = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E, where

- A = working capital / total assets
- B = retained earnings / total assets
- C = earnings before interest and tax / total assets
- D = market value of equity / total liabilities
- E = sales / total assets

An Altman Z-score close to 0 suggests a company might be headed for bankruptcy, while a score closer to 3 suggests a company is in solid financial state.

Another well-known approach is the "Leave One Out" methodology of modelling banking stability, defined in Feng, Cheng, and Xu (2013).

This method suggests subtracting 1 bank Z-score from the total banking Z-score, to understand the impact of each individual bank on total stability of the system.In the majority of articles, modeling is done using different statistical and ML techniques, and it is also important to understand and to choose the right methodology alongside with a good indicator.

Summing up the information from all sources, we can conclude that the Z-score can be a useful tool for modeling banking stability and predicting bank failures. Policymakers and regulators may consider using this approach to monitor the health of their banking systems and identify banks that are at risk of failure.In this article, Z-score is used for indicating country banking system effectiveness, and is calculated using macro-level data. Initially, Altman presented Z-score as an indicator to measure insolvency risk for businesses, which later on started to be applied for banks and banking systems.

The Z-score that will be used in further calculations, is based on accounting data. That kind of measure is widely used in evaluating banking stability, and in some studies it is mentioned that the Z-score can predict 76% of bank failure **[3]** (Chiaramonte, Liu, Poli, & Zhou, 2016).

Analyses

After carefully analyzing existing modeling opportunities of banking stability, as well as going through different indicators, we have chosen the Z-score formula, which calculates banking stability based on country-level macroeconomic data. This model is chosen, as based on the data availability, it allows us to get a monthly dataset and have enough data points to perform statistical analyses.

For predicting banking stability, there are various ways, including NN-s and other ML methodologies, but for simplicity, we will start with the ARIMA model. ARIMA will help us derive information on how its past values affect the series.

When starting a time series analysis, it is a good practice to start with simple models that may satisfy the use case requirements. ARIMA models are simple and transparent and it is useful to derive rigorous statistical properties. They are performant on small datasets and are cheap to build and retrain.**[2]**

Apart from that, while choosing significant P, D and Q values for the ARIMA we can take into account the number of optimal lags(p), stationarity(d) and error in predictions from past values (q). We will compare predictive performance of 2 ARIMA models: 1 with orders found based on pmdarima library and another with the help of differencing, AIC and BIC criterion.

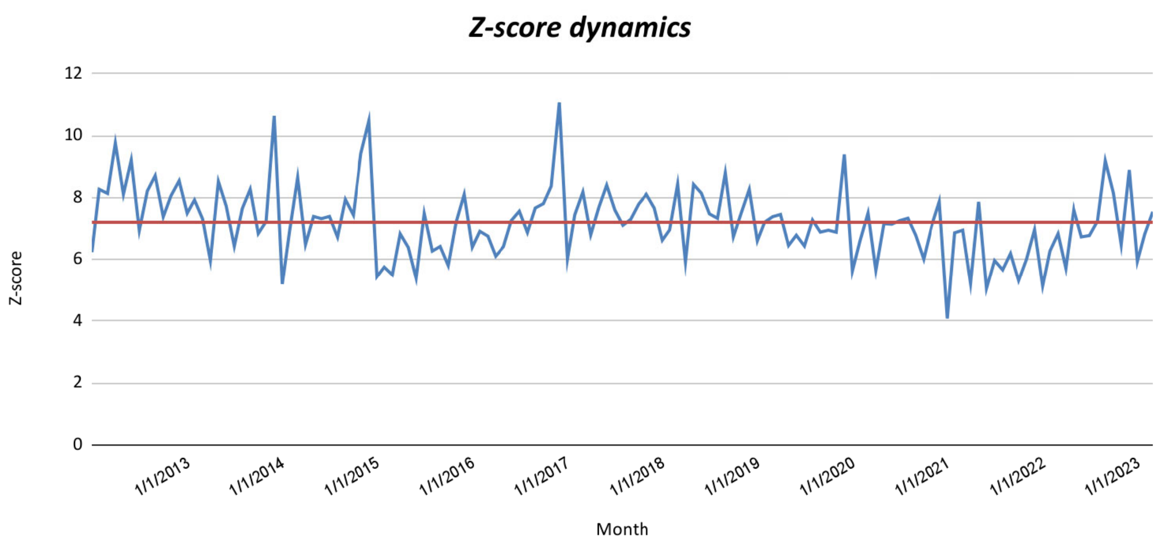
Diving into empirical studies, let's derive the proper calculation methodology of Z-score and see its trend over time.

To calculate Z-score, the following formula is used:

5 ↕ 55555 = 555+ (555555Δ55555) 5(555)

Using the above-mentioned formula, the Z-score will show the following trend in the observed time period:

Chart 1



Above is showcased (Chart 1), that at the end of 2022 and at the beginning of 2023, Z-score was moving up and down, and changing constantly. This fact of volatility in recent years increases the importance of good predictions.

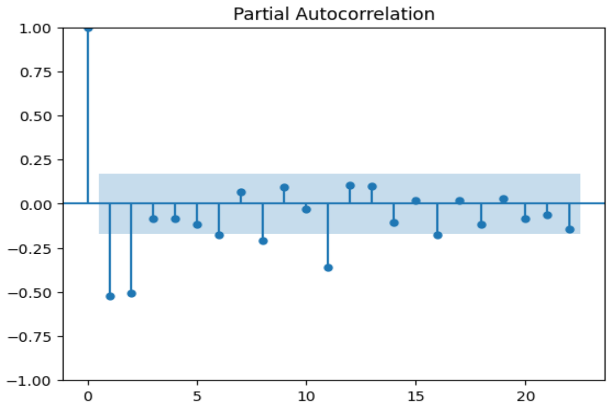
Let's deep dive into ARIMA analysis. Based on the econometric theory ARIMA consists of 3 main parameters, which are p, d, q. In literature there are 2 main methodologies to find those parameters: one is using ACF and PACF graphs for p, q and differencing for d **[12]**. Another method is Python built-in function from pmdarima library. Let's use both of those approaches and compare the results:

In order to get the parameter d, we need to differentiate our model and see after how many differences our time series will become stationary. For checking stationarity, it is accepted to use ADF test results **[8]**, and here is the test result for the original data and its 1st lag:

Original series:
ADF Statistic: -2.19
p-value: 0.20
1st difference value:
ADF Statistic: -5.17
p-value: 0.0000099

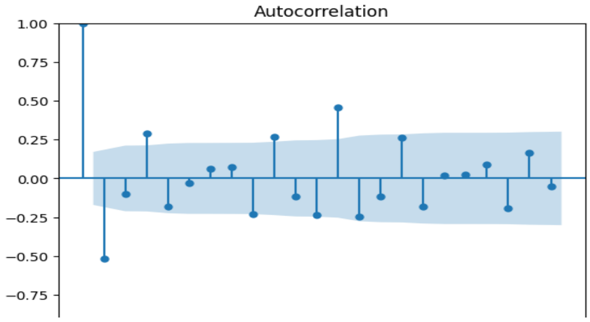
We can see that after differencing 1 time, our series is becoming stationary, and we can consider that d=1. Now let's find out the values for the p and q parameters respectively with ACF and PACF.

Chart 2 *Pacf Plot*



From the chart above (Chart 2), we can conclude that the value of the p parameter, according to n-1 low is 2. Let's do the same for ACF plot and find q **[10]**:

Chart 3 *Acf Plot*



According to the ACF plot, the value for the q is 2.

Concluding, we can say that the best model would be ARIMA (2,1,2).

Getting into the pmdarima library, we can get the same values, but here the logic is based on AIC (Akaike Information Criteria) error matrix. It shows that the best model is ARIMA (3,1,1). From now on we can evaluate the model and see what results we will get for each of p, d, q values.

The first model will be ARIMA (2,1,2). You can see the model summary in Table 1:

Table 1 *SARIMAX Results: ARIMA (2,1,1)*

Dep. Variable:	Z-score	No. Observations:	131
Model:	ARIMA(2, 1, 1)	Log Likelihood	-196.051
Date:	Sat, 08 Jul 2023	AIC	400.101
Time:	23:03:25	BIC	411.571
Sample:	0 - 131	HQIC	404.762
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.2896	0.097	-2.978	0.003	-0.480	-0.099
ar.L2	-0.2243	0.098	-2.300	0.021	-0.416	-0.033
ma.L1	-0.6797	0.088	-7.706	0.000	-0.853	-0.507
sigma2	1.1832	0.115	10.301	0.000	0.958	1.408

Ljung-Box (L1) (Q):	0.23	Jarque-Bera (JB):	15.69
Prob(Q):	0.63	Prob(JB):	0.00
Heteroskedasticity (H):	0.58	Skew:	0.41
Prob(H) (two-sided):	0.08	Kurtosis:	4.49

Arima (2,1,1) evaluation gives us insights on whether all lags are significant.

Apart from that, if we look at the results of the Ljung-Box test, we will see that there is no autocorrelation among errors in the model, as the P-value is higher than 0,05. With the same logic, there is no heteroscedasticity in the model , as the p=0.08>0.05.

Now let's evaluate ARIMA (3,1,1). You can see the interpretation of the results in Table 3. What we see here is that the first 2 lags are not statistically significant, and only the 3rd lag is significant. Now, when the model is evaluated on both p, d, q parameter cases, we can compare ARIMA (3,1,1) and ARIMA(2,1,1).

For doing that, we have 2 options: first we can compare Based on AIC, BIC and Log Likelihood, and the second is to test the model based on the test data.

AIC and BIC parameters and Log Likelihood show that for ARIMA(3,1,1) AIC and BIC are lower, at the same time Log Likelihood is higher, which indicates a better model, but BIC is lower for ARIMA (2,1,1). Apart from that ARIMA 2,1,1 has no autocorrelation, while ARIMA 3,1,1 has. This means that there is still room to argue on which model performs better so for choosing the best-performing model, we can rely on the test set, and minimal MSE on predictions. The test set is taken as the last 4 points of the data (Table 2).

Here are the predicted results from our model based on train data: 4 months ahead:

Table 2 *Predictions and MSE on test data*

Month	**2022-12-31**	**2023-01-31**	**2023-02-28**	**2023-03-31**	**MSE**
ARIMA(3,1,1)	8.893276	5.944494	6.816333	7.542902	0.847
ARIMA(2,1,1)	7.618272	7.663522	7.395409	7.4629	1.23

Table 3 *SARIMAX Results: ARIMA (3,1,1)*

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==============================================================================
Dep. Variable:                  y          No. Observations:          131
Model:              SARIMAX(3, 1, 1)        Log Likelihood           -193.597
Date:             Sat, 08 Jul 2023         AIC                        397.195
Time:                     23:03:25          BIC                        411.532
Sample:                          0         HQIC                       403.021
                             - 131
Covariance Type:                  opg
==============================================================================
                 coef    std err        z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0140      0.070      0.200      0.841      -0.123      0.151
ar.L2          0.0562      0.089      0.635      0.526      -0.117      0.230
ar.L3          0.3129      0.091      3.422      0.001       0.134      0.492
ma.L1         -0.9598      0.042    -22.981      0.000      -1.042     -0.878
sigma2         1.1331      0.113     10.024      0.000       0.912      1.355
==============================================================================
Ljung-Box (L1) (Q):             0.00   Jarque-Bera (JB):             15.77
Prob(Q):                        0.99   Prob(JB):                      0.00
Heteroskedasticity (H):         0.60   Skew:                          0.36
Prob(H) (two-sided):            0.10   Kurtosis:                      4.55
==============================================================================
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Based on the predictions table on test data (Table 3), we can see that ARIMA(3,1,1) shows better and more meaningful prediction results, and we can make further assumptions based on that.

Here is the visual representation of the predictions for the both models and actual test data:

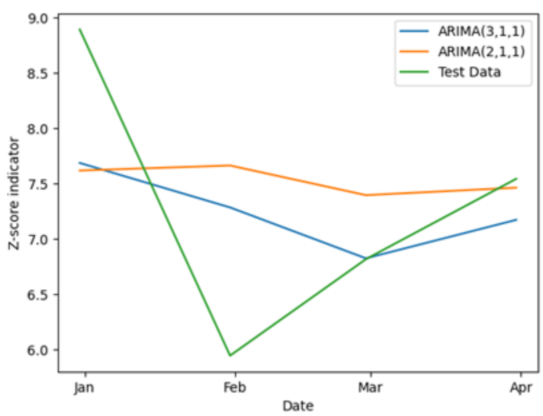


Chart 4 *Predictions VS test data*

Evaluating our test data against predictions, we can see that ARIMA(3,1,1) manages to catch all the ups and downs of the test dataset, as well as give us a small MSE.

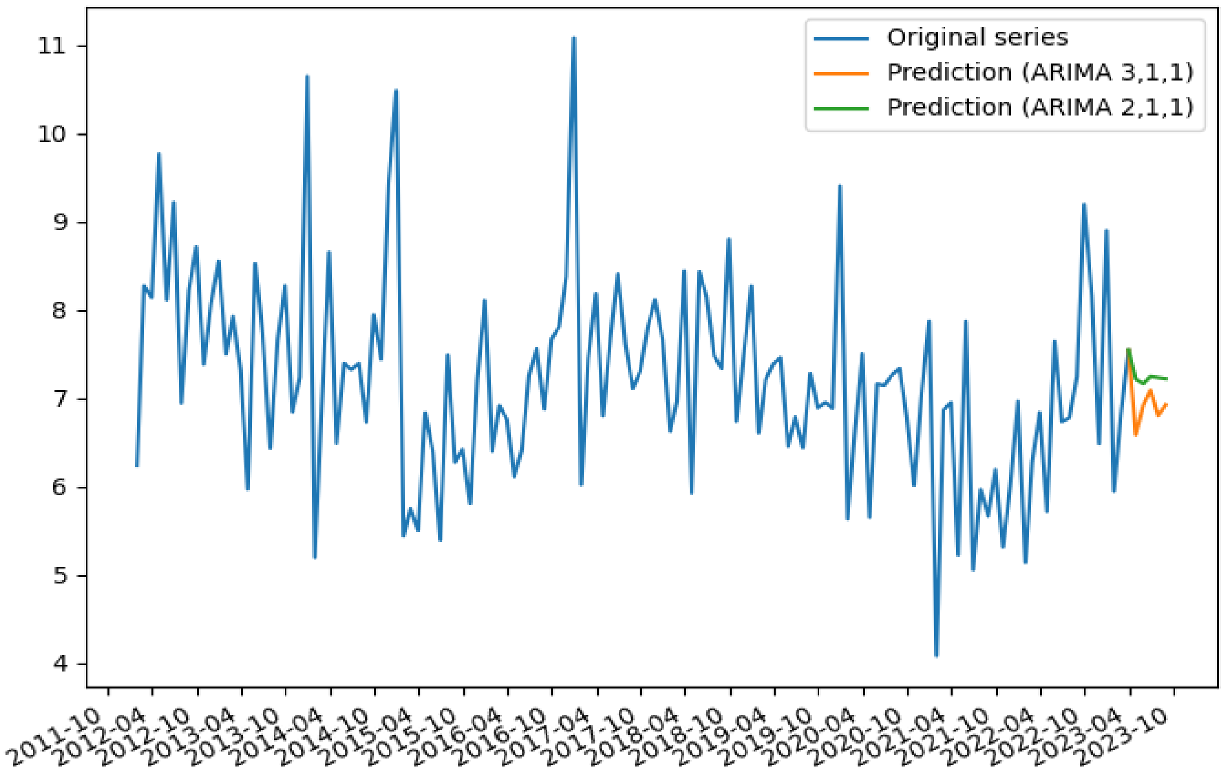
Relying on the ARIMA(3,1,1) we can use the full dataset to train our model and make predictions 5 months ahead on the full available dataset (Chart 5).

After evaluating our model, we will have the following prediction values for the upcoming 5 months. The ARIMA predictions would be as follows:

Table 4. *5 months ahead prediction results of the Z-score*

Date	2023-03-31	2023-04-30	2023-05-31	2023-06-30	2023-07-31	2023-08-31
Z-score	7.54	6.58	6.92	7.08	6.79	6.92

Chart 5. *Z-score predictions based on ARIMA (3,1,1)*



Conclusion

Based on the literature review and empirical analyses, we can conclude that the banking Z-score calculated based on the macroeconomic data is a valid indicator for measuring the financial stability of the country and financial system. The forecast of banking stability using the ARIMA model, shows that the best model is ARIMA (3,1,1), and in this model, the first and second lag of the Z-score series are not significant, but the 3rd lag is significant. It means that if there is an increase or decrease in financial stability, it will affect the future banking stability after 3 months. Apart from that, predictions based on the methodology described in the article can catch the trend of the test data and show realistic values for future data points.

Concluding, the ARIMA model is a good fit for the Armenian banking data and we can use previous data points to predict the Z-score with the help of the ARIMA model.

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