

ЭКОНОМИКА

Banking stability multifactor modelling in Armenia using Machine Learning

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Հայաստանի բանկային կայունության մոդելավորումը նեյրոնային ցանցերի կիրառությամբ

Մինասյան Դավիթ Գ.

*Տնտեսաանալիտիկական մեթոդների ամբիոն, Բնֆորմատիկայի ու Վիճակագրության Ֆակուլտետ,
Հայաստանի պետական տնտեսագիտական համալսարանի ասպիրանտ,
ՀՊՏՀ ԱՄԲԵՐԴ ՀԿ «Ինովացիոն և ինստիտուցիոնալ հետազոտություններ» լաբորատորիայի
գիտաշխատող (Երևան, ՀՀ)*

Անփոփագիր. Սույն հոդվածում ներկայացվում է բանկային կայունության մոդելավորման մեթոդաբանությունը նեյրոնային ցանցերով և random forest մոդելների միջոցով: Որպես բանկային կայունության ցուցիչ ընտրվել է բանկային Z-score, որը ցույց է տալիս բանկերային համակարգի անվճարունակության ռիսկը: Փոփոխականների հավաքածուն ընտրված է տնտեսության տարբեր ոլորտներից՝ հիմնվելով միջազգային գրականության և ամսական տվյալների առկայության վրա: Ընտրված փոփոխականների օգնությամբ բանկային կայունությունը կանխատեսելու համար ներկայացվել է 2 մոդել՝ նեյրոնային ցանցեր և random forest ռեգրեսիոն մոդել: Երկու մոդելներն էլ ցույց են տալիս փոքր քանակությամբ ստանդարտ սխալներ և լավ կանխատեսման հզորություն՝ չափված կանխատեսումների և թեստի տվյալների համեմատության վրա: Ըստ մոդելավորման արդյունքների, կարելի է փաստել, որ մեքենայական ուսուցման մոդելները, հատկապես random forest մոդելները համապատասխանում են Հայաստանի ֆինանսական և տնտեսական տվյալներին՝ բանկային կայունությունը կանխատեսելու համար և կարող են կիրառվել որպես Հայաստանի Կենտրոնական բանկի համար ֆինանսական ճգնաժամերի նախազգուշացնող գործիք:

Հանգուցաբառեր: Նեյրոնային ցանցեր, random forest, բանկային կայունության մոդելավորում, Z-score

Многофакторное моделирование банковской стабильности в Армении с использованием машинного обучения

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Аннотация. В этой статье представлен методологию оценки моделей банковской стабильности с помощью нейронных сетей и методологии random forest. В качестве индикатора банковской стабильности мы выберем банковский Z-score: меру риска неплатежеспособности банков. Набор переменных выбран из разных секторов экономики на основе международной литературы и наличия ежемесячных данных. В статье представлены две модели для прогнозирования банковской стабильности с помощью выбранных переменных: нейронные сети и random forest регрессии. Обе модели демонстрируют небольшое количество стандартных ошибок и хорошую прогностическую способность на основе сравнения прогнозов и тестовыми данными. Кроме этого указано, что модели машинного обучения, особенно модели случайного леса, хорошо подходят для моделирования финансовых и экономических данных Армении для прогнозирования банковской стабильности и могут быть реализованы в качестве методологии раннего предупреждения кризисов для Центрального банка Армении.

Ключевые слова: Нейронные сети, random forest, моделирование банковской стабильности, Z-score

Introduction

Banking stability is a sensitive topic in economic literature and a lot of economists are trying to suggest better and better solutions, to foresee banking crises, and respond in a timely manner.

Recent advancements in machine learning models as well as the increase in their usability, makes it inevitable their application in banking stability literature, especially when the policy makers are interested in early warning strategy and want to mitigate cumulative or systematic risks. The main concern about using ML models in banking stability tends to be the “Black box” side of neural network models, but this is compensated with their incredible predictive power, if used in a reasonable manner, taking into account best practices in a field. Apart from that, ML is not just limited to NN-s, Random forest approach suggests a way to understand which factors are more useful in the result of prediction.

Methodology

Early warning models were developed to predict banking stability forecasting methodology based on Armenian banking data. Data is chosen from 2013 till 2022 in monthly granularity. It is stationarised, scaled and fed for model. Majority of data is coming from CBA statistical data.

For evaluating models, Python programming language is used: sklearn (for random forest) and Tensorflow (for neural networks) libraries. For feature engineering, some factors are combined based on multicollinearity. Apart from current values of variables, their lagged values are also used: first 2 lags, which is selected with the help of VAR model evaluation, and choosing optimal lags based on Akaike information criterion. As the test split, the 10 % of the entire dataset is chosen. After first evaluation of the models, hyperparameters are adjusted to get a more valid model.

Decision trees

Using ML approaches in banking and financial stability modelling is becoming quite common, due to the flexibility of this kind of models to the data and strong predictive power.

Banking stability modelling using such an approach is implemented on the Indonesian data, and is mentioned in the paper “Predicting Banking Stability Using Machine Learning Technique of Random Forest” (Agus Afiantara, et.al, 2019) [1]. In paper, is taken the data from 2004 -2007, and was implemented random forest approach, using python scikit-learn library. The model evaluation showed that such an approach was able to correctly predict 2008/9 global financial crises. In the model, chosen

principal components explain 97% of the total variance and show 89% accuracy.

Another early indication of application of Random Forest approach in banking stability is “Random forests-based early warning system for bank failures” (Katsuyuki Tanaka, et.al., 2016). In the article it is shown that early warning models can predict crises for individual banks as well, showing higher predictive power then conventional models [7].

In (Sri Hartini, et.al., 2021) “Estimating probability of banking crises using random forest” random forest is applied from its other use-case: classification possibility. The authors took the financial crises data for 79 countries, and fed to the model both: labelled data for crises samples and non crisis samples. Then, 90 % of the data was taken as a training set, and predicted the rest 10%. Model showed 98% accuracy, overperforming state-of-the-art methods used on the same dataset [12].

Another implementation of classification capability of Random Forest model is mentioned in “Financial Credit Risk Control Strategy Based on Weighted Random Forest Algorithm” by Guo Yangyudongnanxin. The author applies a weighted random forest algorithm for classifying financial credit risk. The method suggested in the paper proved its advantage and predictive power against 2 other methods, by scoring higher classification accuracy on credit dataset [6].

Neural networks

Neural networks (NN-s) are more common in banking stability than decision trees. There is a large amount of literature related to the application of NN-s in banking/financial stability modelling.

The methodology is applied both in micro and macro level analyses. For example, in the “Neural Networks for Financial Stability of Economic System” paper (Viktoriia Tyschenkoi, et.al., 2023) the authors construct a neural network-driven model for assessing the financial stability of economic systems. The study investigated financial and economic activity data from 12,573 enterprises. For the model development where applied both forward feeding and recurrent neural nets [16].

Related to macro level analyses, in 2020 was published “Predicting systemic financial crises with recurrent neural networks” by Eero Tölö, where the author describes 5 years out of sample prediction of systematic financial crises using neural networks. The dataset includes the data for 17 countries, from 1870 till 2016. In the research paper, authors proved that neural networks like Long-Short Term Memory (RNN-LSTM) and the Gated Recurrent Unit (RNN-GRU) can significantly improve

existing methodologies designed with neural nets [6].

There are controversial studies as well, that warn about shortcomings and hidden long term effects of deep learning models that can cause low financial stability and trigger risks. Such an example is the paper by Gary Gensler and Lily Bailey, “Deep Learning and Financial Stability”, where alongside are presented application of NN-s and deep learning methodologies in the financial sector, as well as risks related to broad adoption of such models. The author states that existing financial sector regulatory regimes are mainly relying on state-of-the-art data analytics technology which often fall short in addressing the systemic risks that arise due to broad application of deep learning [4].

For tackling systematic risks, in the paper “Predicting systemic risk in financial systems using Deep Graph Learning” authors describe the application of a set of ML tools to deal with complex relations. They proposes Graph Neural Networks (GNNs) for systemic risk analysis. It is also stated that GNN models are better suited for systemic risk prediction on financial networks and should be preferred over traditional Machine Learning [14].

Methodology

Our goal is to model banking/financial stability in the Republic of Armenia, by maximally using the available data provided by the Central Bank of Armenia (CBA).

For that reason, Z-score was taken as the indicator for financial stability, which is calculated based on return on assets, and their standard deviation, as well as equity/assets ratio. The higher the indicator, the less likely the financial system to collapse. In other words, it compares the buffer of a country's banking system with the volatility of those returns.

For designing the model, a set of variables are considered to predict Z-score, financial and economic variables: altogether 46 are included in the model. Apart from traditional economic and banking indicators, cryptocurrency prices and house market prices were also included in the model. All the factors are stationarised before feeding to the model. To also include lagged relationships, we have combined values from previews to months for each observation. This makes the model more flexible, and puts better logic, according to the behaviour of the economic data. The variables are also scaled, using min-max scaler methodology.

To build and evaluate the model, CNN was used with 3 layers, and Relu is chosen as an activation function. Model includes 2

hyperparameters: epochs and batch size. Those parameters were adjusted on training data to get the minimal possible prediction error and better fit of the model. The main data source is CBA statistics [18] for financial indicators, and coinmarketcap [19] for monthly crypto prices.

Main

Understanding the current situation in the banking sector

Having information about upcoming crises, being more prepared is an important feature of the financial system for every country. For that reason, central banks use a variety of techniques to have good early warning models in hand. As mentioned in literature review, machine learning models allow us to do so. But despite having a good tool in hand it is as much important to have a good indicator, reflecting the health or vulnerable state of the banking system. Indeed there is evidence for such an indicator in the work of Bilal Hafeez, Xiping Li “Measuring bank risk: Forward-looking z-score”. In this paper, banking Z-score is chosen as a signal of whether the entire banking system is solvent, or there is a risk for insolvency. As mentioned in the paper, the basic principle of the z-score is to relate a bank's capital level to variability in its returns to 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 [2]. There is also criticism to the Z-score calling it “backward looking” as it is reliant on accounting data. The other way is proved in the paper “How Accurately Can Z-score Predict Bank Failure?” (Chiaramonte, Liu, Poli, & Zhou, 2016) where authors state that the Z-score is capable of identifying 76% of bank failure. They also found that the prediction power of Z-score to predict bank default remains stable within the three-year forward window [8]. Z-score is stated to be a good measure for banking and financial stability also in the works of Hannan and Gerald, 1988 “Bank Insolvency Risk and the Market for Large Certificates of Deposit”. Z-score is applied in a lot of papers in modelling banking stability. Such example is usage of Z-score in measuring the Indian financial stability, in the work by Santanu Mallick, Ahana Sen, “Emerging Issues in Banking, Insurance and Financial Services”. Z-score is also an accepted measure for New Zealand and Australian banks to measure insolvency and risk level [17].

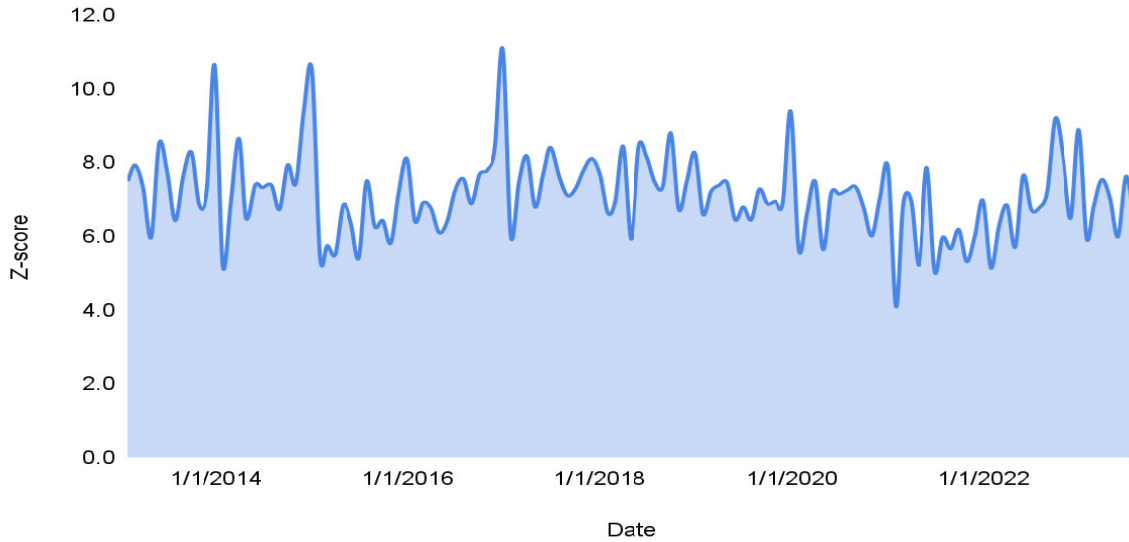
In the “Predicting Financial Stability of Banks in Nigeria Using the Altman Z Score Model” paper, the author applied Z-score for 10 Nigerian banks and predicted future stability. The author also states that the Z-score model is an effective tool for predicting distress in financial institutions [5].

As this Article is designed for the financial stability modelling for the RA, lets dive deeper on how was the financial stability based on the Z-score, which risks does the CBA mentions in his recent

report (2022), and what are the existing mechanisms for tackling those risks.

The observed period is chosen to be from 2013.01.01 till 2023.07.01. Let's explore the time variation of Z-score using graphical representation:

Chart 1: Monthly Z-score dynamics



We can see the highest risk during Jan. 2014, Jan.-July 2015, Jan. 2017, April 2018, Jan, April 2020, and the lowest Z-score in the observed period was registered in Jan. 2021. After that, Z-score started to have an upper trend till December 2022, which means CBA makes some policies to control the situation. After that, Z-score goes down again in Jan., May 2023.

The main risk is associated with overheating in the mortgage and real estate market.

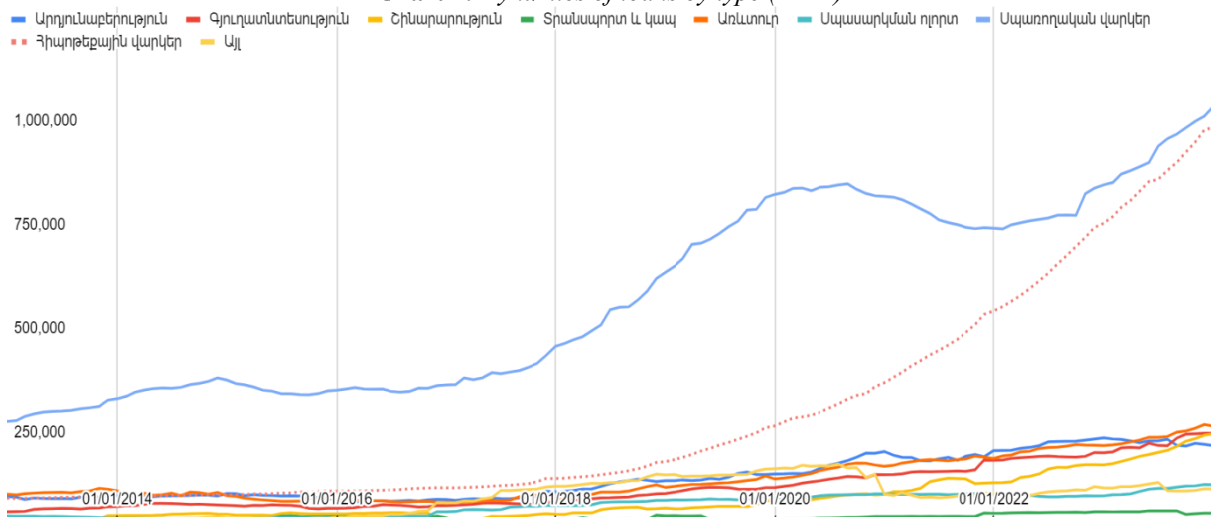
The recent years' dramatic increase in mortgage loans and real estate prices have been mutually reinforcing in their nature, arising potential risks of overheating in the real estate market. As of the end of 2022, the Central Bank estimates that the real estate price overvaluation represents a deviation of about 16-22% from their fundamental levels [21].

According to the latest available release of CBA financial stability report (2022), Armenian banking stability ratios, such as Liquidity Coverage Ratio, Total Liquidity, Capital Adequacy are

Leloans explore loan amount dynamics for different types of loans in recent years, and see how it changes over time.

In an acceptable range, and more than meeting stability requirements.

Chart 2: Dynamics of loans by type (AMD)



From the chart above, we can see the sharp increase of mortgage loans in recent 4 years, and we can see that in 2024 the mortgage loans are almost becoming equal to consumer loans. For comparison, compared to Jan. 2020, in Jan. 2024 Mortgage loans have increased more than 4 times. Interesting fact is that this dynamic is only relevant for Mortgage loans in AMD. Mortgage loans in USD have been stable during the observed period (See Chart 3).

In the real estate sector, the risk is associated not only with the amount of the loans getting bigger and bigger, but also with the increase of house prices, due to the high demand.

Let's explore financial stability indicators with the latest available data to understand which aspects of the banking system are more vulnerable and assess financial stability arising risks.

Chart 3: Dynamics of loan amount by loan type(USD)

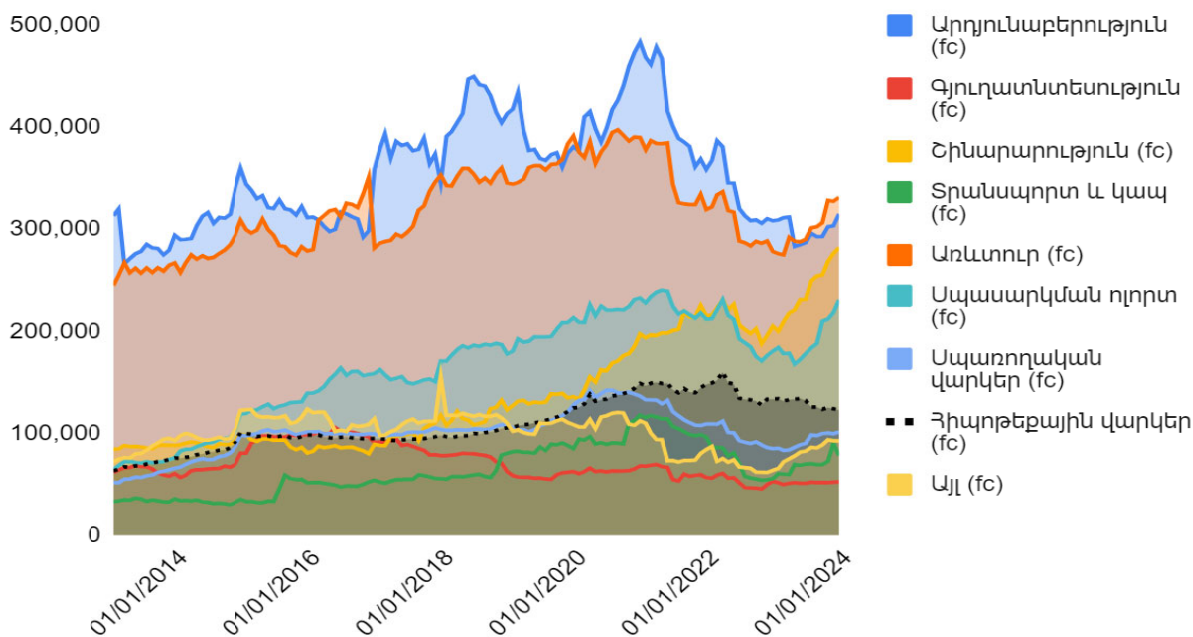
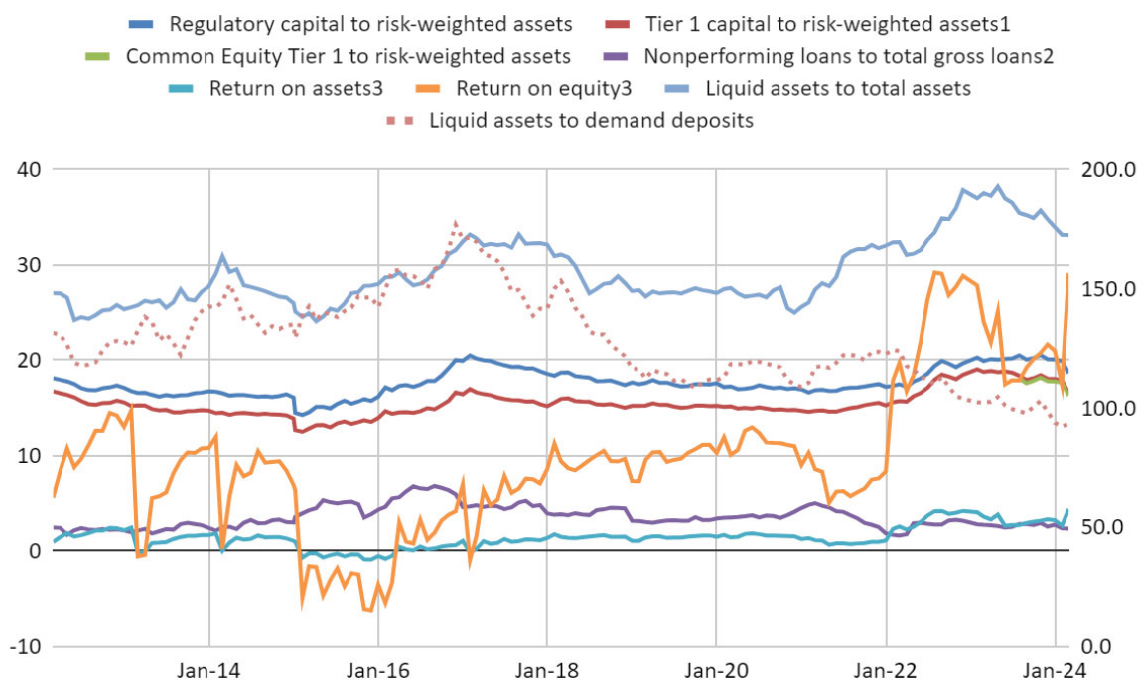


Chart 4. Financial stability indicators of the CBA (01/2013-01/2024)



Data: CBA.am [20]

In the graph below (Chart4) are presented core 7 indicators that are monitored by CBA. Visually we can see decline in 2 main indicators: Liquid assets to demand deposits and Liquid assets to total assets. First indicator started its decline from December 2016 and the second one from

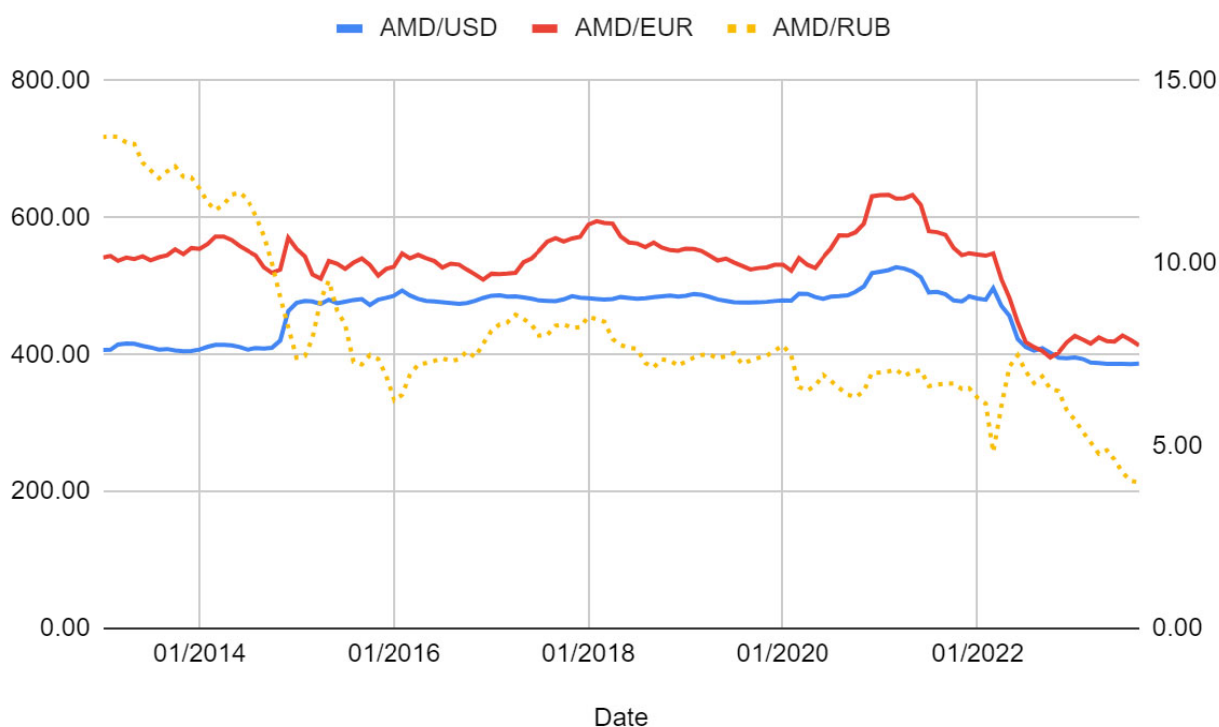
April 2023. We can see that both of those indicators are related to liquidity of assets.

Liquid assets to demand deposits ratio reflects a bank's ability to meet its short-term obligations. Liquid assets, such as cash reserves and government securities, are readily convertible to cash. A higher ratio indicates that banks have enough liquid assets to cover sudden withdrawals by depositors,

enhancing financial stability. This means that there is an increasing risk for banks to unexpected cash outflows.

Another risk area is related to the fluctuations of foreign currencies, as Armenia is highly dependent on foreign economies. The Armenian economy is especially sensitive to USD price fluctuations, as 60 % of government foreign debt is in USD. In the graph above, we can see recent fluctuations of the 3 core foreign exchange rates. In 03/2022 there was a sharp decline in all 3 currencies and the reduced rates are presented until the end of the observed period: 09/2023.

Chart 5. Armenian exchange rates from 01/2013-09/2023



Apart from that, the inflation rate was high, and inflationary expectations were also increasing. During these circumstances, the increase of interest rates for existing and new loans were small.

While observing the Macroprudential dashboard, it was registered accumulation of risks in the market risks sub-group. This is related to the increase of real estate prices and yields of government bonds. Apart from that, sub-indicators like interest rate and currency risks have played their part in that.

NN-s and random forest models

Knowing all of these issues, choosing a good model for forecasting the Z-score ratio will help policy makers and financial institutions to make better decisions and react timely to the crises. For

this reason we propose 2 models: neural network based prediction and random forest models.

NN-s are unique for their ability to be applied for the wide range of data, ignoring a lot of constraints that other statistical models have. Apart from that, they can have really good predictive power, prone to improve through each iteration of training.

All of those are accompanied with some drawbacks as well. While using NN-s one should be careful from overfitting: data is predicting good on test data, but for new observations it will perform poorly [11]. Another downside of this kind of model is the difficulty to explain the results, which is, we can't tell which factors specifically had effect on the dependent variable. For this characteristics, those models are usually called black-box models [15].

The same is partially true for random forest models as well. Those models don't give exact coefficients like regression models do, but on the other hand, random forest models output feature importance, showing which factors mainly took part in the prediction [22].

For comparison each of this model has its own credit in modelling process.

Random forest models are less prone to overfitting than NN-s does, also Random Forest models allow to interpret results as mentioned above. On the contrary, NN-s are better at identifying complex nonlinear relationships and are able to give more accurate predictions.

Based on those assumptions, we will train those models separately and compare the results [9].

Choosing variables

Let's go through the chosen variables and see their importance in our study.

As mentioned in the methodology section, 47 initial variables are chosen for evaluating models, according to their 2 levels of lagged values. Lagged values are chosen due to the nature of economic variables: the impact is not always happening immediately and directly. Some economic variables may be affected after a certain period of time when a shock happens.

As mentioned previously, exchange rates of the most common foreign currencies: USD, EUR and RUB have been declining sharply after 2022, and this could not have any impact on the Armenian financial sector. It affects balance of trade, expenses of Government debt, as well as can lead to the capital flight and Investor confidence decline. Considering all of this, we have included AMD/USD, AMD/EUR and AMD/RUB exchange rates as independent variables. Apart from those, export, import amount based on the commercial and noncommercial status, also, government reserves in USD are included.

Government bond profitability is also included in the list of factors, as it indicates how liquid banks are, the quality of their assets, also can be good indicators for interest rate risks.

How can banking stability be modelled without considering bank assets? They are a good indicator for banking system profitability, liquidity, and overall financial health. In the list of variables are included government assets, bank assets and other assets with net amounts.

For measuring the inflation, CPI for both consumer goods and non consumer goods and services is considered. Economic activity index is also taken as a factor for banking stability modelling, as it provides valuable insights into the level of economic activity, trends, and potential risks. Apart from that, for evaluating level of investments, we

have included buy-sell transactions, and REPO transactions.

Banking stability indicators monitored by the CBA are also included, which are listed in Chart4. Those factors show profitability of assets, equity, the liquidity of bank assets, as well as share of nonperforming loans. Another factor is cash in circulation, as an indicator of liquidity of the financial system and economic activity level. On Demand deposit amount also is a good indicator for liquidity and it reflects the saving behaviour of economic actors. We have also included time deposits and foreign currency deposits as separate indicators to better capture saving behaviour. Deposit level overall is determining the interest rates and investment sentiments. All 5 dollarisation components are included in the model, as they reflect the currency risk, Interest rate risk, financial deepening. The last group of factors include total liabilities, total capital, accumulated profit, repo contracts. All of them are important financial indicators reflecting the current state of financial health and profitability of the banking sector.

Modelling banking stability

Modelling with random forests.

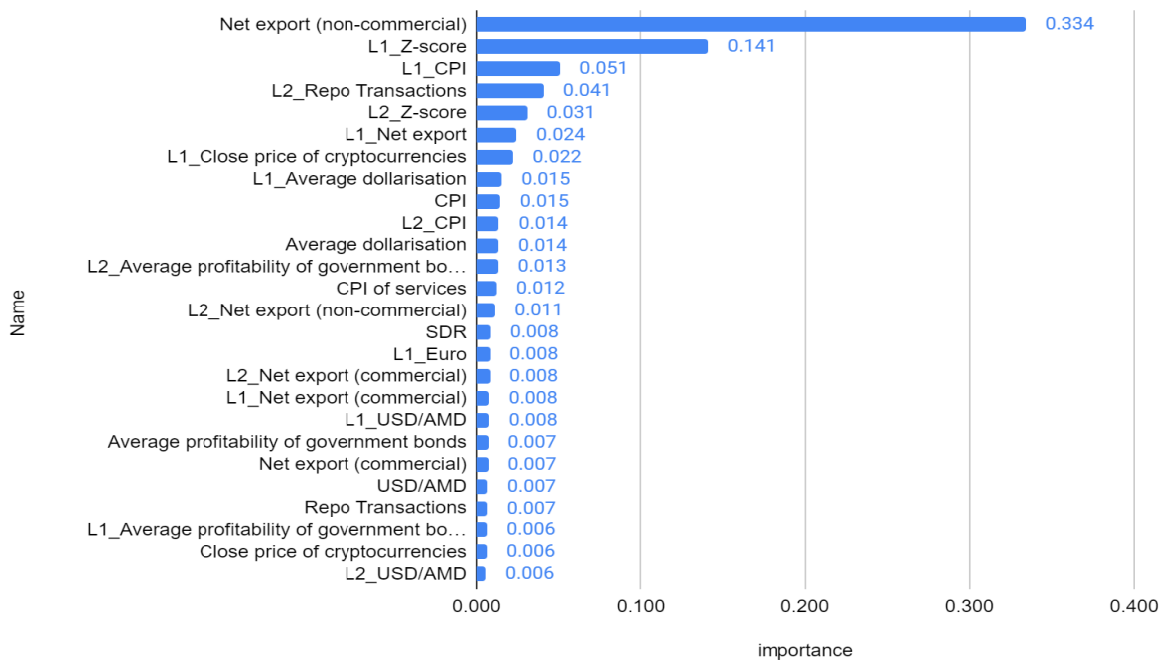
Random forest models use decision tree logic for solving regression problems. They create a model, which is a combination of a certain amount of trees, for better fitting and prediction.

Compared to a single tree model, random forest models reduce overfitting and improve model accuracy. Random forests are less sensitive to variations in the training data compared to single decision trees. The model evaluation starts with splitting the data to train and test split, and choosing 5% as test data. As mentioned before, our factors include all factors and corresponding 1st and 2nd lags for each of them. The random forest model is estimated with the help of Python scikit-learn library. For specifying random forest models, generally some parameters needed to be chosen. Those are N of trees in a random forest model, depth of trees and the best split to train the model. For that reason, a grid search technique was applied, which is basically iterating through different parameter values, and choosing the ones which give the model the smallest value of Mean Squared Error (MSE)[10]. Based on this methodology, we have chosen a random forest model with the following properties: max_depth-20 and n_estimators -150. It means that tree depth is 20, which is that each tree in a random forest can have a maximum 20 different splits. Also, for training we will use 20 different trees. In the result, our model will have a mean squared error equal to 1,66 for the 10 % test data. As we mentioned in the methodology section,

random forest models also output the importance of the variables in the prediction.

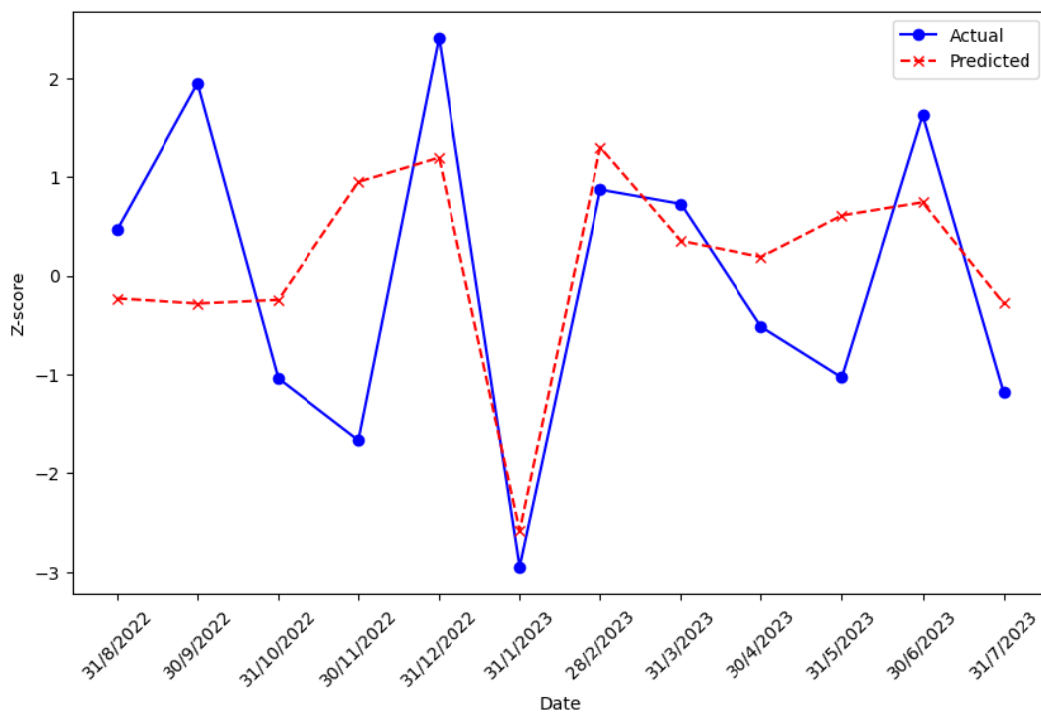
The bar chart below shows the list of predictors from the most important to the least important.

Chart 6: The importance of variables for modelling banking Z-score



Below, we can also see predictive power of decision tree algorithm on the test data:

Chart 7. Actual VS predicted values of Z-score for Random Forest model



Let's specify the NN regression model for comparing predictive power.

Neural networks are specific in a way that they improve every time you iterate the network struc-

ture, and the parameters are recalculated to lower the error. In this case, it's important to choose the proper number of transformation layers, and epochs (N of time data is passing through the networks and

back) in order to have a model that captures the specifics of the data and is not overfitting.

For that reason, we have partitioned data to validation split as well, and compared validation loss with training loss, and chose an epoch size, till validation loss was improving along with training loss. Our network consists of 3 layers with RELU as an activation function, ADAM as optimization algorithm and mean squared error as a loss function. The model is evaluated using the tensorflow library in Python. We have chosen 90 epochs to train our model, as it gives stable results around loss 1.8. In the chart below, we can see the prediction of the model with NN-s, as well as validation and test loss for the chosen NN model. Validation loss is worsening after iterating data mode in the network, that's why the training is stopped on the 90th epoch [13].

Chart 8. Training VS Validation loss

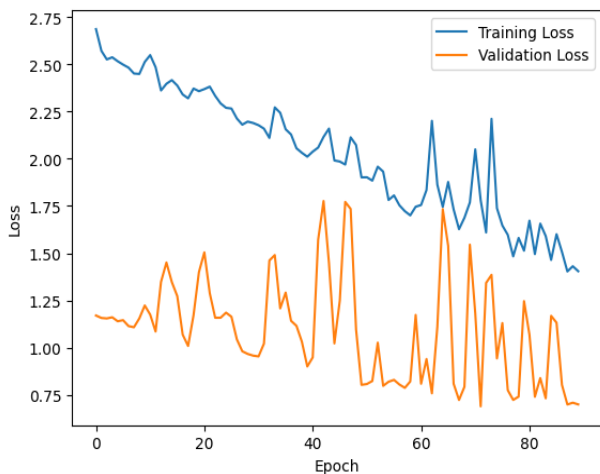
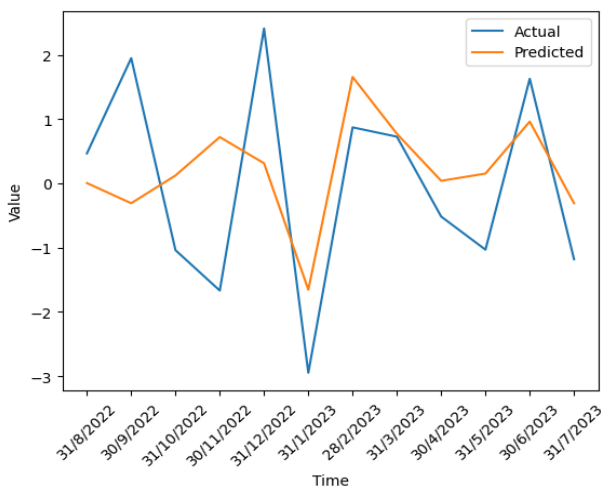


Chart 9. Actual VS predicted values of Z-score for Neural Network based model



Conclusion:

As a result, we can see that Neural networks and random forest models are capable of predicting

banking stability with the help of Z-score as an indicator of banking stability.

Comparing model performance, random forests are better, as they give lower MSE value, as well as they give some sort of explainability for understanding which factors mainly played a role in prediction output. Based on random forest model importance values, we can assume that for banking stability are mainly responsible factors like Net export, previews month's stability Z-score, CPI, Dollarisation rate, profitability of government loans, exchange rates of different currencies, as well as SDR.

The article results are a solid proof that ML models like Random forests and NN based models can serve as a good tool, early warning systems for upcoming shocks and weaknesses of the banking/financial system. CBA can use those models alongside with traditional time series modelling tools to have more precise predictions of financial situation, and if necessary dive deeper into the problem with the help of traditional models with coefficients, to get exact reason with the help of a model that gives coefficients for the independent variables.

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