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Novel Approaches on Sovereign Credit Ratings

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Abstract. In this study, sovereign credit rating methodologies of CRAs and studies in the relevant literature are examined in detail, and two dynamic methods are proposed. These models classify countries as investable or speculative in the short term. In the first model, we used stock market values and macroeconomic variables with the Normalized Least Mean Square (NLMS) algorithm. Ratings for 15 countries are determined according to the short-term domestic currency. The results that we obtained from this model are fully consistent with those of Fitch. When we compared the results with Standard and Poor's, we obtained different results for Turkey and Portugal. In the second model, we used only stock market closing data from 40 composite indexes with the Artificial Neural Networks (ANNs). Ratings are determined according to short-term foreign currency. The results that we acquired from this model are fully compliant with Standard and Poor's. However, when compared to the ratings of Fitch, the results differed in the case of Russia. It has been shown that contrary to standard approaches, high predictability is achievable for countries using short-term data. The suggested models are more objective and dynamic due to only short-term data being required.

2010 Mathematics Subject Classifications: 92B20, 62-07, 62F10

Key Words and Phrases: Artificial neural networks, Adaptive filters, Normalized least mean square algorithm, Sovereign credit ratings, Stock market prediction

1. Introduction

Sovereign credit rating is determined using quantitative and qualitative features developed by the CRAs, taking into account the economic and political risks of the countries. With the complexity of financial markets and the increase in asymmetric information, the importance of credit ratings has increased over time. The impact of internationalization and the widespread free market economy have removed obstacles for investors. With the increase of international financial and economic integration, country credit ratings have become one of the most important elements that direct the global capital flow. The impact of CRAs on global and national economies has increased. Over time, increased financial market complexity and borrowing diversity have gained confidence investors and regulators in the views of CRAs [12]. Credit ratings affect investor decisions, thus influencing

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fund inflow and borrowing costs. Due to these factors, credit ratings play a major role in the economic development and progress of countries. Factors of the CRAs affecting the economies of the countries and the methodologies of CRAs have begun to be examined from the 20th century [1, 7, 8, 11, 27, 34]. The implications of credit ratings and their role in financial markets have been examined [3, 4, 9, 12, 22, 28, 36]. However, CRAs had negative impacts on the 1997 Asia financial crises. Also, in 2008, CRAs were not able to predict the crisis which befell many countries and companies. Furthermore, the 2008 financial crisis occurred in many countries that had been highly rated by CRAs, and many of the high rated companies went bankrupt at that time. The realization that the illusion of high credit ratings led to crises made people lose trust in CRAs. Studies on the effects that CRAs have on crises, the duration of crisis and the later period have been carried out [2, 5, 10, 16, 32, 35]. The impact of sovereign credit ratings on developing countries, in particular, has been examined and discussed by analyzing the credit ratings of developed and developing countries after the crisis period [14, 23, 25, 26]. These studies were criticized for the fact that CRAs used non-public data and rated subjective evaluations in their methodologies. The statistical models used by the CRAs for credit rating have been examined and alternative models have been proposed [6, 15, 17, 29–31, 33]. In this study, we propose alternative models to sovereign credit rating methods that classify countries as investable or speculative. The first model assesses countries using macroeconomic variables and the stock market index monthly values with the NLMS algorithm. The stock market composite index values are estimated with six macroeconomic variables and historical stock market composite index values. Then, according to the estimation results, a model was developed that classifies countries according to their predictability. The results are compared with the short-term domestic currency credit ratings for the period. In the other model, we classified the countries using the values of daily closing stock market indices with ANNs. In the training process based on the sovereign credit ratings of the CRAs in terms of short-term foreign currency.

2. NLMS Algorithm

Normalized Least Mean Square (NLMS) algorithm is a type of the LMS algorithm. The difference between the LMS and NLMS algorithms is the speed of convergence. The convergence rate of the NLMS algorithm is faster than the LMS algorithm. In the NLMS algorithm, weight updating in time n+1 compute differently according to the LMS algorithm [19, 20]. The NLMS formulation is illustrated in the following: [19]

- The output value y^n is obtained by multiplying the input data by weights, as can be seen in (1).

$$y^n = \sum_{K=1}^{k} i_k^n w_k^n \tag{1}$$

- The error signal is calculated in (2) by the difference between the desired value and the output value.

$$e^n = d^n - y^n \tag{2}$$

- Minimization of error signal is made according to the Mean Square Error, as can be seen in (3).

$$J = \frac{1}{2}E[e^2] = \frac{1}{2}E[(d^n - i_k^n w_k^n)^2] \tag{3}$$

- Initial weights are zero. Weight updating is calculated in (4) by minimizing the error signal for each variable according to the following formula [13].

$$w_k{}^(n+1) = w^n + \frac{\mu e^n}{\|i_k^n i_k^n\|^2} i_k^n \tag{4}$$

The norm process is calculated according to the following equation (5).

$$\|i_k^n\| = \sqrt{\sum_{n=1}^{n} (i_k^n)^2} \tag{5}$$

where k is the number of variables, n is the time series vector dimension of variables, i_k^n is the input variable of k in time n, weight coefficient is w_k^n, the output of the system y^n is the estimation value for time n, the desired value is d^n, error value is e^n, and μ is the learning rate. Figure 1 shows the NLMS adaptive system.

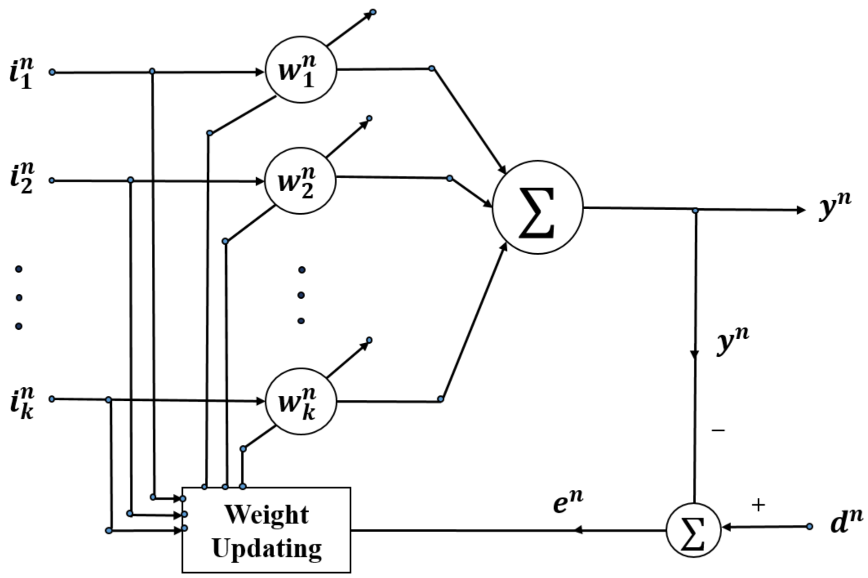

Figure 1: NLMS Adaptive System.

2.1. Proposed Model for NLMS

The proposed model consists of two phases. In the first step, stock market value is estimated by macroeconomic variables and stock market historical values using the NLMS algorithm. Macroeconomic variables were determined by considering the parameters used by the CRAs and the studies about CRAs. In the second stage, classification of countries is carried out according to the estimation results. In the NLMS model, the μ value is used as 0.12. Although convergence is faster when the selected μ value is big, convergence is slower but better if the μ value is smaller. For this reason, the μ value is determined by trial. The initial weights were determined as 0.1, which is the end result of the experiments. After the estimation, Mean Absolute Percentage Error (MAPE) values for the last 12 months of each country are calculated. The average of differentiation of the MAPE function is 1.18. Therefore, the threshold value was set at 11.8%. Countries with a value below the threshold value of MAPE can be invested, while those above are classified as speculative. MAPE is calculated by the equation (6) below.

$$MAPE = 1/n \sum_{i=1}^{n} \left| \frac{(v(n) - \tilde{v}(n))}{v(n)} \right| \times 100 \tag{6}$$

2.2. Dataset for NLMS

In this study stock composite indices, GDP per capita, U.S. foreign exchange rate, foreign trade, overnight interest rate, and consumer price index values are used. The dataset includes 15 countries monthly values between January, 2007-August, 2017. The countries in the dataset are Germany, USA, Brazil, France, Netherlands, UK, Spain, Italy, Canada, Mexico, Norway, Portugal, Russia, Turkey, and Greece. The value of the stock composite index for the end of the next month is estimated with this dataset. Therefore, the results are compared with stock composite index values between 02.2007-09.2017. Initially, the data are adjusted with the normalization equation (7). In normalization techniques, Min-Max Normalization is used for normalization of the data. Thus, the data are limited between 0.1 and 0.9. All data normalize in itself for it can be comparable.

$$\tilde{x} = 0.8 \times \frac{x_i - x_{min}}{x_{max} - x_{min}} + 0.1 \tag{7}$$

where x_i are the actual values of the series, the maximum value of the series is x_{max}, the minimum value of the series is x_{min}, and normalized values are $\tilde{x}$ in the series.

2.3. Results for NLMS

This study proposes a new model for sovereign credit ratings with the NLMS algorithm. Stock composite indices are estimated in the first stage. After the forecasting, MAPE values for the last 12 months are calculated for all countries. Figure 2 shows the calculated MAPE values of the countries. In Figure 2, MAPE values of countries are sorted from small to large. As seen in Figure 2, there is a first biggest break in values after Spain's

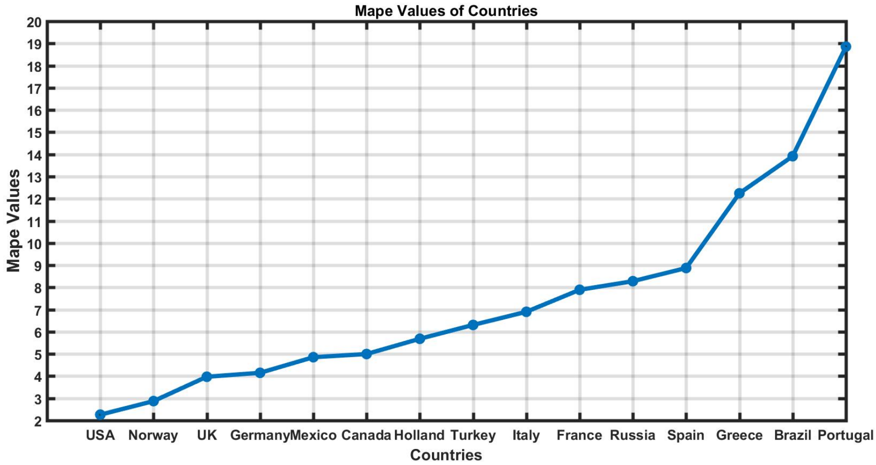

Figure 2: MAPE Values of Countries.

MAPE value. On the other hand, when we look at the derivation of MAPE function in Figure 3, in the first increase of the series, we see that there is a deviation after the eleventh point. Because the average of differentiation of MAPE function (T) is 1.18 to the equation (8), the threshold value is set at 11.8%.

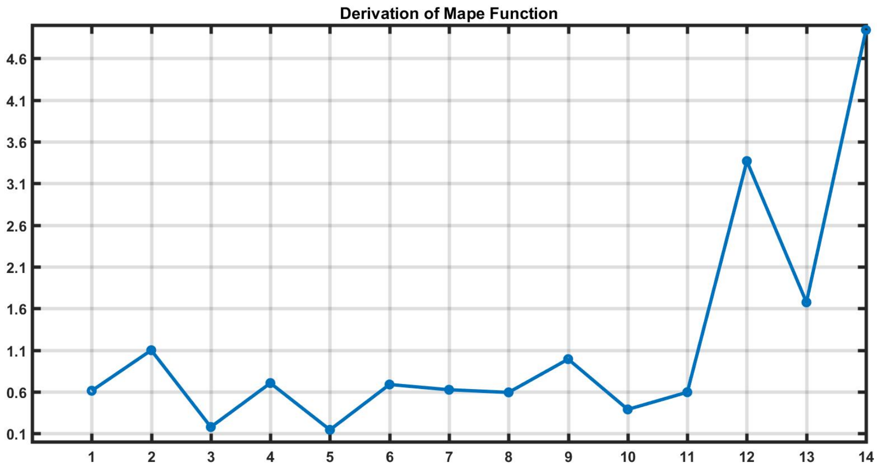

Figure 3: Derivation of MAPE Function.

$$T = \frac{1}{14} \sum_{n=1}^{14} \frac{\partial MAPE(n)}{\partial n} \tag{8}$$

Therefore, if the MAPE value of a country is less than 11.8%, it can be an investable country. If the MAPE value is greater than 11.8%, the country is classified as speculative.

Table 1 lists the stock code, MAPE values and investable and speculative classes of the countries as of October 2017. The classification for the NLMS method completely corresponds to the classification of Fitch. Additionally, compared with the Standard and Poor's

Table 1: Stock Codes, MAPE Values and Investable Classes of Countries for NLMS.

	Country	Stock Code	MAPE
Investable Countries	USA	DJI	2.261589
	Norway	OBX	2.873660
	UK	FTSE	3.972231
	Germany	GDAXI	4.149399
	Mexico	MXX	4.853806
	Canada	GTPSE	4.997015
	Holland	AEX	5.684330
	Turkey	XU030	6.308618
	Italy	FTMIB	6.901017
	France	FCHI	7.892553
	Russia	MCX	8.280763
	Spain	IBEX	8.875445
Speculative Countries	Greece	ATG	12.24368
	Brazil	BVSP	13.91732
	Portugal	PSI20	18.8586

classification, it was identical except for Turkey and Portugal. The application was made with the Matlab 2016 (b) program. Macroeconomic data in the dataset was obtained from the OECD database, stock index values and sovereign credit ratings from the Thomson Reuters Eikon program in Istanbul Technical University Finance Laboratory.

3. Artificial Neural Networks

ANNs are a system that has layers in parallel with each other and has enough neurons in each layer.

3.1. A Neuron Model

A neuron is called by Haykin (1994), an information processing unit that is fundamental to the operation of a neural network. The basic structure of a neuron as shown in Figure 4 is mathematically as follows;

- A signal i_j at the input of synapse j connected to neuron k is multiplied by synaptic weight w_{kj} in (9). The associated synapse is excitatory if the weight w_{kj} is positive, the synapse is inhibitory if it is negative.

$$u_k = \sum_{j=1}^{n} w_{kj} i_j \tag{9}$$

- Bias b_k is the positive or negative external parameter of a neuron k. It is added to the output of linear combiner u_k in (10).

$$v_k = u_k + b_k \tag{10}$$

- An activation function is called as a squashing function in the literature. The activation function determines limiting amplitude of the output of the neuron. Output shown by in equation (11);

$$y_k = \varphi(u_k + b_k) = \varphi(v_k) \tag{11}$$

where j=1,2, n, u_k is the output of linear combiner, v_k is the summing output, $\varphi(.)$ is the activation function, and y_k the output signal of the neuron [18, 21].

3.2. Multilayer Perceptron

Multilayer neural network is a feed forward network having at least one hidden layer between the input and output layers. The hidden layer is composed of hidden neurons directly related to the neurons of the input and output layers and it includes a non-linear activation function [21].

3.3. Application Model for ANN

In this study, multilayer feed-forward networks consisting of one hidden layer were used. In the hidden layer, the hyperbolic tangent function was used as a transfer function. A linear function was used in the output layer. The hidden layer contains three cells, and the output layer contains one cell.In Figure 4 represents that the application neural network architecture.

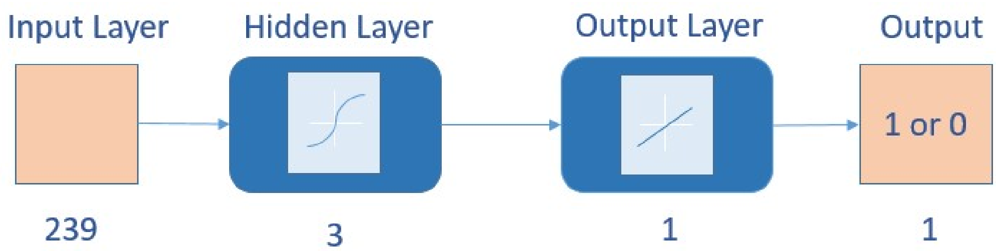

Figure 4: The Application Neural Network Architecture.

In the network training process, Mean Square Error was used as a cost function. Gradient descent with momentum and adaptive learning rate were used to update the weight values to equation (12).

$$\Delta w_{kj}(n) = -\mu \frac{\partial E(n)}{\partial w_{kj}} + \alpha \Delta w_{kj}(n-1) \tag{12}$$

where α is a momentum constant, w_{kj} is weight, and E is the mean square sum of differences between the values of target and output of the network [18]
. In the model, credit ratings are set as 1 for the investable grade and 0 for the speculative

grade. The stock price of the countries included in the training set have been trained according to the determined credit ratings (1 or 0). After the training, the rating classes of the countries in the test set were estimated. In the training and test results, '1' is assigned to the values that are greater than 0.6 for investable class. Values smaller than 0.4 are assigned to the speculative class by assigning a value of '0'. For the remaining values, it is planned to assign a value of '0.5'. However, when we look at training and test results as shown in Table 2, there is no class of '0.5' because none of the countries are between 0.4 and 0.6. If we had value in this range, we would use fuzzy logic methods to decide which one is investable or not [24].

3.4. Dataset for ANN

The model aims to classify the countries as investable or speculative with the Artificial Neural Networks method based on the sovereign credit ratings of the CRAs in terms of short term foreign currency. Changes in macroeconomic variables also affect and reflect the stock exchange market. Therefore, in this study, we only used stock exchange variables. A feed-forward network consisting of a single layer of three hidden neurons was used. For this model, 239 trading days daily closing data until 29.08.2017 from 40 stock exchange indices of 38 countries were used. Countries from various regions of the world were included. The dataset is divided into 70% training data and 30% test data because the best results obtained in that rates. Various rates of train, validation, and test have tried and see the results in the Table 2 below. Test data consist of the stock composite index of 12 countries in the America-Dow Jones Index, Argentina, Indonesia, Ghana, India, Hong Kong, Sweden, Malaysia, Mexico, Russia, Turkey, and Greece.

Table 2: The Rate of Train, Validation, and Test Data and Its Error.

Train Rate	Validation Rate	Test Rate	Number of Error
1/3	1/3	1/3	3
4/10	-	6/10	2
5/10	-	5/10	2
6/10	-	4/10	2
7/10	-	3/10	0(S&P) and 1(Fitch)

3.5. Results for ANN

The results were compared with the sovereign credit ratings of the CRAs in terms of short-term foreign currency. Table 3 indicates ANN results and class of the countries in the train and test set. The results that we acquired from this model are fully compliant with Standard and Poor's. However, when compared to the ratings of Fitch, the results differed in the case of Russia. In the Table 4 represent the accuracy rate of test result. Thus, this method can be used for determining the changes in the credit ratings of countries and predicting the credit ratings of countries. The application was made with the Matlab 2016 (b) program.

Table 3: Stock Codes, MAPE Values and Investable Classes of Countries for ANN.

	Country	Stock Index	Spot Code	Results	Class
Training Set	America	NASDAQ	NDX	1.002	1
	America	SP 500	SPX	0.98	1
	Australia	AXS 200	AXJO	0.99	1
	Belgium	BEL 20	BDX	1.00	1
	Britain	FTSE 100	FTSE	0.98	1
	Brazil	BOVESPA	BVSP	0.006	0
	Canada	SP/TSX	GSPTSE	1.006	1
	Chile	IPSA	IPSA	0.99	1
	China	CSI 300	CSI300	1.009	1
	Egypt	EGX 30	EGX 30	-0.0002	0
	France	CAC 40	FCHI	0.97	1
	Germany	XETRA DAX	GDAXI	1.01	1
	Israel	TEL AVIV	TA125	0.99	1
	Italy	FTMIB	FTMIB	1.002	1
	Netherlands	AEX	AEX	1.01	1
	New Zealand	NZX 50	NZ50	1.00	1
	Nigeria	NSE 30	NGSE30	-0.002	0
	Norway	OBX	OBX	0.99	1
	Pakistan	KSE 30	KSE	0.001	0
	Philippines	PSEI	PSI	0.99	1
	Portugal	PSI 20	PSI20	0.003	0
	Qatar	DOHA	QEAS	0.99	1
	South Korea	KOSPI 200	KS200	1.00	1
	Spain	IBEX35	IBEX	1.00	1
	Switzerland	OMXS30	OMXS030	0.99	1
	Taiwan	TSEC	TSE50	1.00	1
	Ukraine	UX	UAX	-0.005	0
	Vietnamese	HNX	HNXI	0.0002	0
Test Set	America DJI	DOW-JONES 30	DJI	1.05	1
	Argentina	MERVAL	MERV	-0.15	0
	Ghana	GSE	GSECI	0.04	0
	Greece	ATG	ATG	0.34	0
	Hong Kong	HANG SENG	HSI	0.61	1
	India	CNX NIFTY	NSEI	1.02	1
	Indonesia	JAKARTA	JKSE	0.85	1
	Malaysia	KLCI	KLSE	1.00	1
	Mexican	IPC	MXX	0.94	1
	Russia	MICEXFNL	MICEX	-0.02	0
	Sweden	SMI	SSMI	1.06	1
	Turkey	XU30	XU030	-0.05	0

Table 4: Accuracy Rate of Test Result in ANN model.

		STANDARD and POOR'S		FITCH	
	Results	Investable	Speculative	Investable	Speculative
ANN	Investable	7	0	7	1
	Speculative	0	5	0	4
	Accuracy Rate	100%		91.67%	

4. Conclusion

In this study, proposed two novel approaches about sovereign credit rating. The application results have been shown that contrary to standard approaches, high predictability can be made for countries using short-term data. In NLMS method, we have differentiated the data set of 15 countries using macroeconomic data. However, it is not possible to reach the data of every country, especially underdeveloped and developing countries. Due to this problem, we wanted to develop a more general model using ANNs that predicts sovereign credit ratings. It is important that the data set is sufficient for learning in ANNs. For this reason, we have included 40 countries from various regions of the world in our ANN data set. Because of the changes in macroeconomic variables also affect and reflect the stock exchange market, we only used stock exchange variables in the ANN data set.
Therefore, two novel approaches were obtained with two different data sets. The suggested models are more objective than CRAs ratings and offer more dynamic results because only short-term and public-data are required. Consequently, investors will be able to produce their own estimates with current values using the models recommended at intervals when the CRAs do not update.

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