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A Neural-Network Approach to the Modeling of the Impact of Market Volatility on Investment

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ABSTRACT

In recent years, authors have focused on modeling and forecasting volatility in financial series it is crucial for the characterization of markets, portfolio optimization and asset valuation. One of the most used methods to forecast market volatility is the linear regression. Nonetheless, the errors in prediction using this approach are often quite high. Hence, continued research is conducted to improve forecasting models employing a variety of techniques. In this paper, we extend the field of expert systems, forecasting, and model by applying an Artificial Neural Network. ANN model is applied to forecast market volatility. The results show an overall improvement in forecasting using the neural network as compared to linear regression method.

1 Introduction

Financial volatility refers to the intensity of the fluctuations in the expect return on investment or pricing of a financial asset due to market uncertainties. Volatility modeling and forecasting is imperative to financial market investors. Financial volatility forecasts allow the prudent investors to adjust or hedge their investment portfolios to mitigate investment risk and to customize their trading strategies in anticipation of forthcoming financial market movements [24]. There are a variety of investment instruments in the financial market, and each is characterized by return expectation and a different risk. Risk measurement in investment instruments may be captured through the variability of their price volatility [14]. The importance of understanding and reliably modeling financial risk has-again-become evident during the market turbulences in recent years. Accurate volatility predictions for asset prices are crucial when projecting risk measures, such as Value-at-Risk, that are commonly used in risk assessment, the design of risk-mitigation strategies, and for regulatory purposes. Although there has been a long tradition in attempting to predict asset prices, the intense interest in volatility modeling began only after the seminal works of Engle and Bollersley, and has since become an extensively researched area in the field of financial econometrics [15].

Traditional techniques reveal that the stock market earnings are predicted from previous stock returns and other financial variables and macroeconomics. The prediction of stock market revenues directed the investors towards examining the causes of predictability. The forecasting of stock trends

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is a difficult process as it is influenced by several aspects, which involve trader's expectations, financial circumstances, administrative events, and certain aspects related to the market trends. Moreover, the list of stock prices is usually dynamic, complicated, noisy, nonparametric, and nonlinear by nature [4]. The forecasting of financial time series becomes an issue due to certain complex features, like volatility, irregularities, noise, and changing trends [1]. During the financial crisis of 2007-2008, unexpected falls in stock prices resulted in significant losses for individual investors and financial institutions. Since then, new regulations have entered in force in order to ensure the correctness of the market risk assessment provided by financial institutions and to allow individual market participants to be aware of the risk linked to financial products. As volatility is an indicator of the uncertainty associated with the asset profitability, this variable tends to play a key role within the risk models. In fact, event like the bankruptcy of LTCM in 1998, the dotcom crash in 2001, or, more recently the aforementioned financial crisis of 2007-2008 were not foreseen by most of the risk models due to inaccurate estimates produced by the volatility forecasting models. It is worth mentioning that, as volatility is not directly observed, before estimating ny statistical model it is necessary to select a volatility proxy [18].

It has been well established that stock market volatility forecasting is important for investors, portfolio managers, asset valuation, hedging strategies, risk management purposes, as well as, policy makers [2, 5].For instance, investors and portfolio managers seek a prediction of their future uncertainty in order to estimate a specific upper limit of risk that are willing to accept, to reach optimal portfolio decisions and to form appropriate hedging strategies. Within the investment domain, the results presented here within may be used by different market agent to manage in a better way their investments in emerging markets. In other arenas, the results presented may be used to improve forecasting accuracy of volatility models for academic, legislators, consultants and governments to determine investment limits, restrictions, or policy. Given that investors seek to improve upon early forecasting models, techniques that are capable of reducing the amount of error in the forecast to be explored. Artificial Neural Network Model offer a potential improvement to earlier models since ANN models have ability to learn [14]. Flannery and Protopapadakis analyze the impact of real macroeconomic variables on aggregate equity return; and Engle and Rangle find that macroeconomic variables help predicting the low-frequency component of volatility. Paye and, especially, Christiansen et al. consider extended sets of macroeconomic factors and a broader range of asset classes. Both use conventional linear approaches to model log – transformed realized volatility and include lagged volatility as well as financial and macroeconomic factors as predictors [15].

This paper is organized as follows: the first section contains an introduction followed by a review of the literature to illustrate the state of art in this subject. Subsequently, the hypothesis is made and methodology used is defined. The comparison methodology for measuring the accuracy of the model is made and the results are analyzed. Finally, the most remarkable results are presented and conclusions will made.

2 Literature Review

Generally speaking, market volatility can be defined as disruptions in the normal function of the financial market [11]. In other words, market volatility is recognized as a situation resulting from uncertainty and change in expectations from the market language and financial firms with impacts on economic variables [6, 11, 17]. Cases of volatility can be found in various markets, including the banking system, the foreign exchange market, debt market, and stock market [11], raising risk (widening of the probability distribution of loss) and uncertainty (less certainty about the distribution of loss) when expected financial losses are exceeded. Market volatility is the product of shocks to a poorly-structured financial system. Financial fragility outlines weaknesses in financial conditions and the financial structure (Fig. 1). Shocks are more likely to disturb the market under poor financial conditions that is, in cases of rapid cuts in the cash flow, balance sheet leveraging, investors' risk aversion, poorly-structured financial systems, computer systems chocking with large amounts of accumulated data, and information asymmetry. The size of the shock and financial fragility determine the level of market volatility [11]. For example, a negative shock during poor financial conditions is likely to promote market volatility. Given the size and variety of financial systems, numerous potential culprits can be listed for volatility in the market. Accordingly, market volatility can appear anywhere in a financial system and remain unnoticed until it starts to expand and spread. Market volatility is a continuous variable and, in its extreme form, is known as a financial crisis [11, 6].

A financial crisis is an event that undermines the economic value and reliability of the financial system and is detrimental to the real economy [11]. Although market volatility cannot be observed directly, it is reflected in many market variables [20, 21].Market volatility can manifest itself in the financial system in various ways, spreading disruption from one market to another [11].

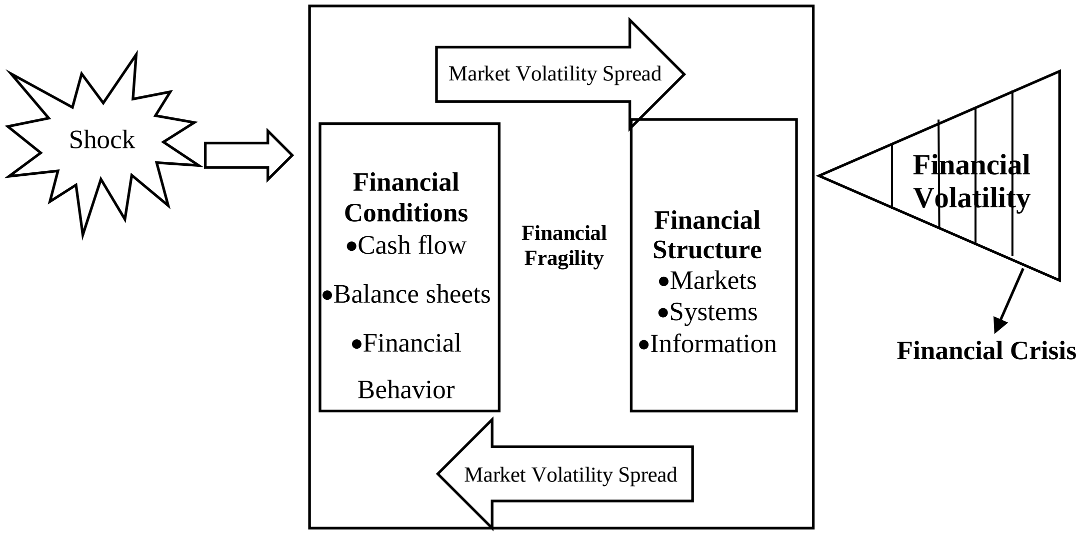

Fig. 1: Development of Volatility in the Market [11]

According to the literature, such attributes as uncertainty about the fundamental value of assets, disinterest in keeping risky assets, disinterest in non-liquidity assets and higher information asymmetry are recognized measures of market volatility [6, 10]. Study of volatility has been considered by the academics and decision makers during two last decades. First since the volatility has been a risk criterion it has been used by many decision makers and activists in capital market. Over the years it has been of more importance because of the effect of volatility on economy and capital markets stability for stocks, bonds, and foreign exchange markets [26]. Stock market forecast concepts can be classified into fundamental and technical analyses. Fundamental analysis is the scientific review of the fundamental contributors to the value of a stock. The fundamental analyzer reviews the assets, debts, sales, the debt structure, revenues, products, market share, business management evaluation, and its comparison with similar companies, and estimates the real value of the stock. This analysis relies on extensive macroeconomic data, such as basic monetary resources, interest rate, inflation rate, dividend, interest from cash flow, and the market value. The technical analysis of stocks involves a review of the stock value. This analysis relies only on price charts, trading volume, and calculated prices, and the information only includes prices and trading volume. A technical analysis never addresses the strengths or weaknesses of a company and aims solely on the behavior of investors and price trends. In other words, in technical analysis, the behavior of the market is studied using charts to forecast future price trends. The study of financial data is of much significance to the research and global trading community. Financial tools such as multiple-recursive methods and time-series analysis are excellent prediction techniques. However, the more complex the series gets, the more limited becomes their prediction capabilities [12, 13]. Recursive methods have long been adapted to model stock market developments. The multiple-recursive analysis is the process of finding the equation for the least-squares of prediction, testing the adequacy of the model, and experiments to estimate model parameters.

Table 1: The Model Variables Include

EVA	Market volatility, calculated using investment data and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method
TDPB	Exchange rate volatility, calculated using foreign exchange data and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method
GHD	The market price of one barrel of OPEC oil (U.S. dollars)
BHSS	Market price of one ounce of gold (U.S. dollar)
TED	Price index (*TEPIX*) volatility for the *Tehran Stock Exchange*
TEP	Price index and yield (*TEDPIX*) for the *Tehran Stock Exchange*
GDP	Real GDP
R	Long-term interest rate
BF	Money in circulation
INF	Inflation rate

Source: Research Results.

Table 2: ARIMA (1, 1, 1) Estimates

t-statistic	Coefficients	Symbol
3.3	24.2	(Constant)
-45.3	-89.5	TDPB
6.2	3.2	GHD
-34.2	-55.3	BHSS
91.2	3.1	TED
89.4	8.1	TEP
61.2	6.3	GDP
-76.3	-4.2	R
87.2	89.0	BF
7.2	76.1	INF
45.4	56.0	AR(1)
71.3	73.0	MA(1)

Source: Research Results.

Although these models are limited to predicting linear patterns, nonlinear patterns such as neural networks are excellent for modelling these changes. The power of neural networks lies in their capacity for modelling a nonlinear process without prior information about its intrinsic characteristics. Much effort has been made—Sharda and Patil [22], Tang and Fishwick [23] to compare neural networks with statistical tools. Neural networks have been successfully employed for evaluation, signature recognition, time-series prediction, among other difficult pattern recognition problems [19, 22, 23, 6]. According to Kalyani Dacha in the case of the recursion of the market, the inflation will be affected by the history of its behavior. Tang holds that it can be proved that neural networks capable of modelling these temporary developments in the capital market are the best predictors. Then, networks using the feedback mechanism for sequential learning can be trained better by changes in the stock exchange [13, 23]. Eduardo Ramos P´erez et al introduced a Stacked-ANN model based only on Machine Learning techniques with the aim to improve the accuracy of the volatility forecasts made by other hybrid models based on a combination of GARCH or EGARCH with ANNs. Its predictive power and performance has been tested in terms of RMSE, VaR and CVaR [18].
Stavros Degiannakis et al. compared parametric and non-parametric techniques in terms of their forecasting power for implied volatility indices. They extended their comparisons using combined and model-averaging models. More specifically, they generated 1-day and 10-days ahead forecasts based on the SSA, HW, ARFIMA and HAR models, as well as, combined models and model-averaged frameworks. In the study published by Davalu and Heydari on predicting the stock market index using the ANN and met heuristic models, it was demonstrated that hybrid neural network model based on the harmony search algorithm offers higher prediction accuracy than one based on the genetic algorithm [8]. Ghasemi and Nazari studied the relationship between economic growth and market volatility, concluding that high economic growth rate does not lead to volatility, but volatility in economic growth reduces the growth rate in the long-term by affecting productivity and demoting investment as a result of uncertainty [9]. Ghazi Fini and Panahian investigated the complete similarities or differences in the volatility of return in Iran's industries. They showed that the assumption of complete difference in the volatility of return in the industries did not hold. The results of their study for Iran's industries showed that there are similarities in terms of the y-intercept of conditional mean and variance equations PANEL-GARCH between the volatility of stock returns of 23 industries in the Tehran Stock Exchange as confirmed by LRT test [25]. Sarlak et al showed a direct linear relationship between the numbers of business deal with price volatility as a factor in companies listed on the Tehran Stock Exchange respectively. In addition, liquidity and credit risks and price fluctuations affect the relationship between business activities [27]. In a study of the spread of volatility in the Iranian capital market, NikooMaram et al. came to this conclusion that the capital market in Iran is susceptible to volatility in foreign exchange, gold, and petroleum markets. Further, they showed that the overall stock exchange index data are the best representative measures of the susceptibility of the Iranian capital market to the spread of volatility [16]. Instances of modelling the estimated market volatility that affects domestic and foreign investment are few in the above studies. The present study is unprecedented from this viewpoint.

3 Hypotheses and Methodology

The present research is practical from the standpoint of its objectives and a desk study as far as data collection is concerned. Further, it takes a descriptive and correlation approach. This study investigates and tests two hypotheses. The first hypothesis of the study is that the ANN and financial ratios are capable of predicting volatility in the capital market .The second hypothesis is that the presented model offers better performance, forecasting capital market volatility in comparison with linear regression. This study relies on two methods for modeling investment-affecting market volatility in the period from 2011 to 2017. The first method is estimation by *ARIMA (1,1,1)*, whereas the second involves a neural network. First, the equation below was estimated by *ARIMA (1,1,1)*, and the results were compared with a neural network. The required data for the 2011–2017 periods were collected from the *Tehran Stock Exchange*.

$$\boldsymbol{EVA_t = C + \beta_1 TDPB_t + \beta_2 GHD_t + \beta_3 BHSS_t + \beta_4 TED_t + \beta_5 TEP_t + \beta_6 GDP_t + \beta_7 R_t + \beta_8 BF_t + \beta_9 \, INF_t + \varepsilon_t} \quad (1)$$

4 Findings and Data Analysis

4.1 Prediction by *ARIMA (1,1,1)* Regression

The data are fitted by the *ARIMA (1,1, 1) method* after entering *Eviews*. Table 2 is the output. After estimating the regression, the data were used to predict and calculate the error, and the charts can be plotted using *MATLAB*, (Fig. 2). As evident, the regression error is higher in cases of increased diffraction.

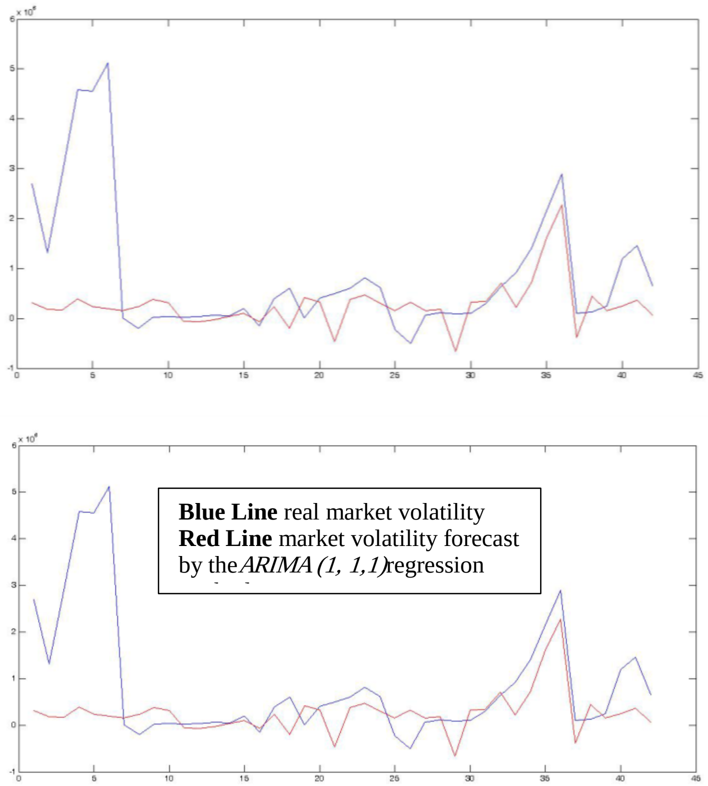

Fig. 2: ARIMA (1, 1,1) Regression Results in Comparison with Real Data.

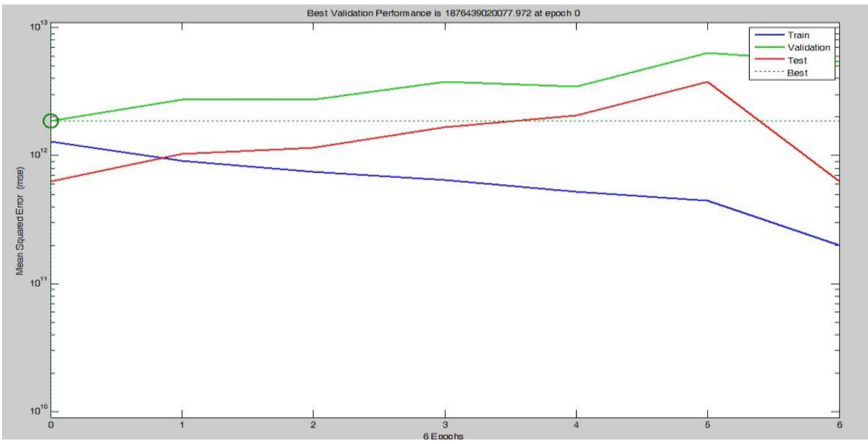

Fig. 3: The Levenberg–Marquardt Plot.

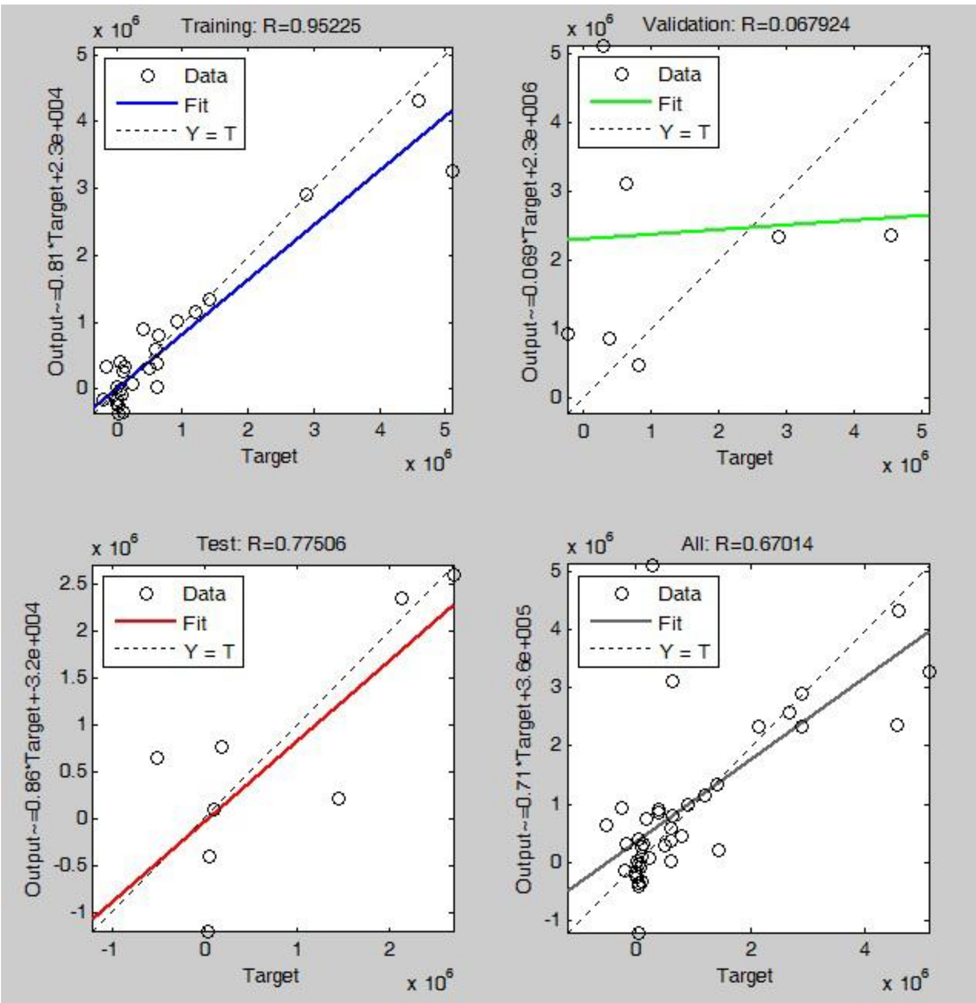

Fig. 4: Training the Neural Network.

Table 3: Weights of Various Variables.

TDPB	NBD	NPS	BHSS	BD	GD	BF	GMK	GHD	Quick	current	
-.659	-.9768	-1.082	.1283	-.5112	-.0396	-1.172	1.7479	.04225	.7973	.8331	Neuron 1
.06115	.38143	.08691	.7736	-6080	.58883	.2687	-.1104	.08010	-1.163	.6191	Neuron 2
.23146	-.2084	.98412	-.3043	.07395	-.2682	-.3818	.69292	.33068	-.8097	.8591	Neuron 3
.64893	.62149	-1.044	.37119	.43243	.6137	-.8187	.60572	-.8512	.02703	.7448	Neuron 4
.45455	-.5130	-.5428	1.0628	-.3251	-.3191	-.7735	-.1570	-.7725	.1911	-.2158	Neuron 5
.53333	.87685	.48803	.47058	-.2450	-.0550	-.9229	.54662	-.7237	.03688	.7311	Neuron 6
0.1194	.63901	-.5984	-.9089	.57508	-.8958	.66755	-.0539	-.2581	.5141	.5552	Neuron 7
.54083	1.0105	.76556	.38571	.49337	-.8973	-1.208	.26224	-.5956	-.0188	-.8969	Neuron 8
.59641	.89145	.64399	-.7204	-.2984	-.8961	.05737	-.6562	.75254	-.6853	-.5415	Neuron 9
-.2486	-.034	-.6146	.03014	.82588	-.2321	-.1755	.5179	-.8576	.5453	.6834	Neuron 10
-.4376	1.372	-1.070	-.8296	.16717	-.6487	-.9133	.14799	-.5103	-.0317	-.4202	Neuron 11
-.5985	-.4025	.36388	.05256	.35154	.98605	-.7296	.42086	-.3009	-1.349	.3932	Neuron 12
-.4923	-.3652	1.5773	.62241	.14162	.05501	-.9135	-.4530	.44005	.7381	.0920	Neuron 13
.99789	-.2093	.15859	.25275	.47895	.77235	.18042	1.0129	.6831	-.8496	1.029	Neuron 14
-.6908	.22643	.65831	-.6603	-.8347	-.1888	-.6796	.67354	.57493	.04451	.1019	Neuron 15

Source: Research Results.

The Fig. 5 represents the prediction of the network based on input data, as well as their comparison with real results. The red plot represents the neural network forecast, whereas the blue one shows the real data.

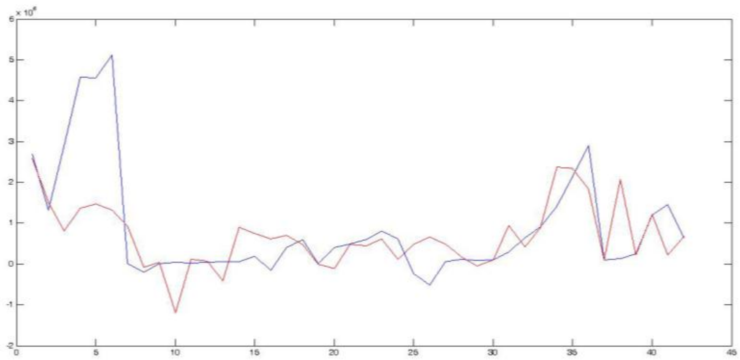

Fig. 5: The Prediction of the Network Based On Input Data in Comparison with Real Data.

4.3 Comparison of Neural Network and Regression Forecasts

A measure is needed for comparing the two approaches. The *Minimum Mean Square Error (MMSE)* was used for this purpose. Error in prediction is the deviation from the real result. *Table 4* presents the real and predicted results.

Table 4: The Real and Predicted Results.

Neural Network	Regression	Real	Neural Network	Regression	Real
2588412	444534	921006. 7	995160. 5	2693862	605353. 2
1510402	607192. 1	790774. 7	1080195	1316185	813606. 1
809912. 4	118993. 7	785794. 2	915303. 1	2893530	609033. 2
1370524	471081. 2	997552. 7	767070. 6	4582747	-232502
1469583	654372. 5	841832. 3	931651	4557681	-508884
1326516	487489. 9	808850. 7	763629. 7	5119305	60454. 79
932492. 7	179186. 7	771525. 4	789184. 8	5767. 49	109990. 9
-74614	-46918. 1	841383. 5	-52148	-203285	87685. 76
46234. 97	97591. 76	993677. 3	935611. 8	17997. 08	99732. 06
-1200640	946633. 7	930086. 6	945770. 3	37804. 39	303698. 9
111613. 2	422911. 5	554843. 9	1324634	24190. 29	643321. 9
75570. 87	906908. 8	544144. 7	838536. 3	36692. 1	920356. 1
-409399	2378703	583278. 4	1327153	59830. 15	1409183
906062. 5	2345335	654203	2210940	50620. 64	2139221
756334. 5	1839623	708267. 6	2885570	195163. 7	2896572
618245. 5	98014. 58	544857. 2	230093. 3	-154624	102848. 6
707163. 4	2069548	841716. 1	1059841	396683. 9	133547. 3
474278. 8	223201. 4	411050. 7	770359. 4	601644. 7	245267. 6
-1093. 38	1214243	1032403	859367. 7	9004. 92	1198961
-106553	220624. 2	937937. 7	984062. 3	406152	1458937
480200. 3	668135. 1	145504. 8	672318. 5	499669. 4	650079. 7

Source: Research Results.

After these calculations, the model was designated to predict prices. In the end, the resulting models were compared to obtain the optimal model. Here, the *Root-Mean-Square Error (RMSE)* was used as a measure of comparison. First, the errors of both methods were calculated; then, a conclusion was made based on the *RMSE* results. Generally speaking, the smaller the error, the better. The error in prediction is denoted by *e*. The error is the deviation of the estimate from the real value.
First, the value-added was estimated for each set of data by both models. Then, the discrepancy between the estimates and the real data were calculated by *Microsoft Excel 2010*.

$$RMSE = \sqrt{\frac{\sum \quad [Real - Estimate]}{Number}} \tag{2}$$

Table 5: Comparison of neural network and linear regression errors.

reg error		net error	
3143016716407	151949753000	11119730619	25862824533
276056427831	71069717445	37720077973	42606741128
4442551118802	93801269190	4341463309723	240138733828
12853620478817	999144353796	10318377405610	495028647361
13807529400374	2075139786710	9536349819146	1353164712505
18580018462753	494454917665	14385248933881	182358966380
586385242203	461304372541	858819574360	4788057553
1091332172277	19553492030	16556194001	18118189547
951951934835	698694962202	797378692	4580885
796167462933	412255769821	1533745023138	413365278432
281593242999	464186762739	7642772750	48580720123
257508147829	6694473825	1511558692	180830625
273998048787	6728897086	220176442822	939968400474
364311677218	5143613633	731780772492	42483155983
263275583838	121042703	314912715540	1117140965855
489273290328	16191231731	597326544393	23367421
198053661338	858019374365	96397566737	3748099142996
36326064628	275721372478	16222082457	486914730
1047344610194	115323293359	101975610	233566251
282796062145	225505975869	262866298537	1533418755323
125432590130	494562373	379043611	325998654
1268670. 483		1128588. 391	

Source: Research Results.

According to *Table 5*, the neural network and linear regression methods scored at *1128588* and *1268670*, respectively, which imply that the network error is less than that of linear regression. The neural network, then, offers higher prediction accuracy than the regression approach.

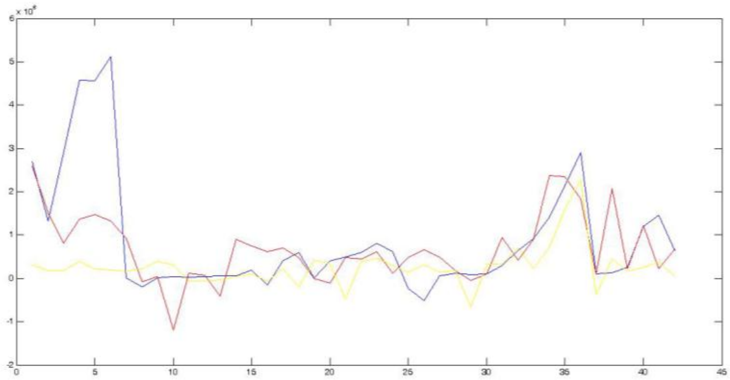

Fig. 6: Comparison of the two forecasts.

In Fig. 6, blue represents the real data, red the neural network predictions, and yellow the regression forecast. The results are suggestive of the potentials of the combination of *Artificial Neural Networks (ANN)* and financial ratios for predicting volatility in the capital market. Further, based on the *RMSE* results for the discussed approaches, the present model offers higher accuracy than linear regression in forecasting capital market volatility.

5 Conclusion

Forecasts are instrumental to successful management and integral to economic planning. Market volatility, as a significant macroeconomic variable influencing various internal and external sectors of the economy, plays a decisive role in economic policy-making, much alike balance of payments and international competitiveness. Changes in market volatility affect various sectors of a country. It is thus essential for developing economic and financial policies to model and predict its future variations. Given the significance of forecasting market volatility, the present study focused on designing a neural network for predicting market volatility in the Iranian economy. The results of this study were indicative of the smaller error in the neural network forecast than the linear regression forecast. Therefore, it is suggested to the government to use neural network methods as far as possible in the process of formulating the country's economic policies. It is also proposed to increase investment through the creation of a stable and secure macroeconomic environment that will be effective in creating and maintaining such an environment:

- Replace financial discipline instead of financial instability in the state budget
- Stability in the implementation of government policies
- Eliminate fluctuations in government-controlled economic variables

Since the present study uses a neural network for prediction, it can be used in future studies of other neural network tools and by combining other linear and nonlinear patterns such as Hopfield neural network, radial neural network, probabilistic neural network. And so on.

References

[1] AraúJo, R., Ferreira, T., *A morphological-rank-linear evolutionary method for stock market prediction*, Inform. Sci.2013, **237**, P.3–17.

[2] Barunik, J., Krehlik, T., Vacha, L., *Modeling and forecasting exchange rate volatility in time-frequency domain*, European Journal of Operational Research, 2016, **251**, P.329-340.

[3] Bishop, C.M., *Neural Networks for Pattern Recognition*, Oxford University press, 1996.

[4] Boyacioglu, M., Avci, D., *An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the Istanbul stock exchange*, Expert Syst. Appl, 2010, **37**, P.7908–7912.

[5] Charles, A., *The day-of-the-week effects on the volatility: The role of the asymmetry*, European Journal of Operational Research, 2010, **20**, P.143-152.

[6] Dargahi, H., Ansari, R., *Improvement of the modeling of neural networks in predicting exchange rate by applying turbulence indexes*, Quarterly Journal of Economic Research, 2008, **85**, P.144-117. (in Persian).

[7] Degiannakis, S., Filis, G., Hassani, H., *forecasting global stock market implied volatility indices*, Journal of Empirical Finance, march 2018, **46**, P.111-129, Doi: 10.1016\j.jempfin.2017.12.008

[8] Davalu, M., Heydari, T., *Projection of the stock index using artificial neural network and ultra-fast modeling of harmonic search and genetic algorithm, Journal of Financial Economics,* Islamic Azad University, Tehran University, Tehran, 2017, **11**(40), P.1-24. (in Persian).

[9] Ghasemi, A., Nazari, S., *investigating the role of financial deepening on macroeconomic turbulence*, Journal of Financial Economics, Islamic Azad University, Tehran Branch, 2016, **10**(35), P.27-44. (in Persian).

[10] Hakkio, CS., Keeton, WR., *Financial Stress: What Is It, How Can It Be Measured, and Why Does It Matter?* , 2009, Available: http://ideas.repec.org/a/fip/fedker/y2009iqiip5-50nv.94no.2.html.

[11] Illing, M., Liu, Y., *Measuring Financial Stress in a Developed Country: An Application to Canada*, Journal of Financial Stability, 2006, **2**(3), P.243-265.

[12] Izadikhah, M., *Improving the Banks Shareholder Long Term Values by Using Data Envelopment Analysis Model*, Advances in Mathematical Finance and Applications, 2018, **3**(2), P.27-41.
Doi: 10.22034/amfa.2018.540829

[13] Kalyani, D., *Causal Modeling of Stock Market Prices using Neural Networks and Multiple Regression: A Comparison Report*, Finance India, 2007, **21**(3), P.923-930.

[14] Kristjanpoller, W., Minutolo, C., *Expert system with applications: gold price volatility: A Fore casting approach using the artificial neural network-gharch model*, **42**(20),15 november 2015, P.7245-7251
Doi: 10.1016\j.eswa.2015.04.058

[15] Mittnik, S., robinzonov, N., Spindler, M., *stock market volatility: identifying major drivers and the nature of their impact* Journal of banking & Finance, 2015, **58**, P.1-14, Doi: 10.1016\j.jbankfin.2015.04.003

[16] NikooMaram, H., PourZamanni, Z., Dehghan, A., *Influence of turbulence in Iranian capital market, Quarterly Journal of Investment Knowledge*, 2014, **11**, P.179-199. (in Persian).

[17] Oet, M.V., Eiben, R., Bianco, T., Gramlich, D., Ong, S.J., *The Financial Stress Index: Identification of Systemic Risk Conditions,* Federal Reserve Bank of Cleveland, 2011, Working Paper 11-30.

[18] Perez. E., Alonso-Gonzalez, P., Nunez-velaquez J.Expert systems with applications: Forecasting volatility with a stacked model based on a hybridized artificial neural network, 1 september 2019, **129**, P.1-9.
Doi: 10.1016\j.eswa.2019.03.046

[19] Ripley, B.D., *Pattern Recognition and Neural Networks*, Cambridge University Press, 1996.

[20] Roye, BV. *Financial Stress and Economic Activity in Germany and the Euro Area*, 2011.

[21] Roye, BV. *Financial Stress and Economic Activity in Germany*, 2012.

[22] Sharda, R., Patil, R., *Neural Networks as forecasting experts: an empirical test*, Proceedings of the 1990 International Joint Conference on Neural Networks, 1960, **1**, P.491-494, Washington DC, USA.

[23] Tang, A., Fishwick, S., *Time series forecasting using neural networks vs. Box-Jenkins methodology*, November 1991, P.303- 310.

[24] Tung, W.L., Quek.C. *Expert system with applications: Financial volatility trading using a self-organising neural-fuzzy semantic network and option straddle-based approach*, 2011, **38**(5), P. 4668-4688.
Doi: 10.1016/j.eswa.2015.04.058

[25] Ghazi Fini, S.R., Panahian, H., *Modelling and Investigating the Differences and Similarities inthe Volatility of the Stocks Return in Tehran Stock Exchange Using the Hybrid Model PANEL-GARCH*, Advances in Mathematical Finance and Applications, 2018, **3**(2), P. 13-26. Doi: 10.22034/amfa.2018.540828

[26] Nasr, N., Farhadi Sartangi, M., Madahi, Z. *A Fuzzy Random Walk Technique to Forecasting Volatility of Iran Stock Exchange Index*, Advances in Mathematical Finance and Applications, 2019, **4**(1), P.15-30. Doi: 10.22034/amfa. 2019.583911.1172

[27] Sarlak, A., Mohamadtalebi, M., Mohammadtalebi, B., *The Effect of Liquidity and Credit Risk on the Relationship between Business Activities and Fluctuations in the Price of all Companies Listed on the Tehran Stock Exchange*, Advances in Mathematical Finance and Applications, 2017, **2**(1), P. 69-81. Doi: 10.22034/amfa. 2017.529062