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A Study of the Effective Factors on Error of Forecasting Technical Analysis Indicators in Iran Stock Exchange (NNARX Approach)

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ABSTRACT

It is well documented that using linear models to forecast plenty of financial observations due to their nonlinearity is not satisfactory. Therefore, in this paper, the technical analysis indicators are forecasted using Neural Network Auto-Regressive model with exogenous inputs (NNARX). Then the effect of different factors (economic, systematic risk, company's properties and corporate governance) on their forecasting error (eRSI, eMA1, eMA2 and eMACD) was investigated. For this purpose, required data were collected using the removal sampling method for 323 companies listed on the Tehran Stock Exchange from 2014-2020. In addition, the mean absolute percentage error (MAPE) was applied to measure the error of forecasting technical analysis indicators. NNARX and dynamic panel data models (GMM) were used to study the effective factors on the error of forecasting technical analysis indicators. Results indicated that the error of forecasting technical analysis indicators is less than 0.1 and has sound accuracy. Also, the company's size and corporate governance indicators didn't significantly affect the error of forecasting technical analysis indicators. In addition, financial leverage doesn't significantly affect eRSI and eMACD but has a significant inverse effect on eMA1 and eMA2. On the other hand, return on assets has a significant inverse effect on eRSI, eMA1, eMA2 and eMACD. Also, economic recession and prosperity, inflation fluctuations, exchange rate fluctuations and systemic risk have a significant positive effect on eRSI, eMA1, eMA2 and eMACD.

1 Introduction

The capital market is one of the most important pillars of the country's economy, where people's deposits are directed toward production and large-scale economic projects. This market is a safe place for corporate financing and a place for savings holders to invest in their deceased accounts. Investors who invest in the capital market need sufficient information on how to manage their capital in order to achieve their desired return. In general, there are two types of price predicting analysis for capital management in the stock market, namely fundamental analysis, and technical analysis. Fundamental analysis focuses on the intrinsic stock value. Technical analysis, however, anticipates the stock price in tight of past trends in stock prices. The basic principle of technical analysis (TA) is that patterns related to past prices of instruments traded in the asset markets can be used to predict the direction of future prices. The background of TA goes from rice traders in Japan in the 1600s [1-4]. Usually, TA is defined

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an as "instrument of predicting asset price movements by previous prices" [5]. TA is vastly applied in speculative markets by practitioners, financial analysts, and fund managers [6]. Nevertheless, the opposite of practitioners, academics do not acquire TA for two main causes. First, TA contravenes the weakest shape of the efficient market hypothesis. Second, TA absence a theoretical groundwork. Therefore there is a wide blank between academic theories and TA. This debate is possibly one of the bygonese in finance subjects, with the first empirical testimony found by Cowles in 1933. Predicting financial market indexes has become an essential function for investors' decisions to maximize the return of their investments [7]. Technical analysis is a technique or a method that enables investors, or in other words traders in financial markets, to determine the appropriate time and price to buy or sell stocks and other tradable assets [8]. Technical analysis represents a challenge to the efficient market hypothesis (EMH), especially in its weak form [9]. In fact, this type of analysis tries to estimate the power of buyers and sellers in the financial markets by analyzing the three dimensions of price, trading volume, and time [10]. In general, technical analysis is based on the following three approaches and principles [11]: 1) Everything is included in the prices, 2) Prices move based on trends and 3) History repeats in markets. It is based on these principles that if the market is at a strong performance level [12] and the random walk theory is held the performance of this type of analysis is weakened [13].
According to the principles of technical analysis and the theory of performance of different financial markets at different time intervals, the strength of this analysis tool is changing [14]. Technical analysis is divided into two parts: patterns and indicators [14-16]. Patterns are usually presented on the basis of the form of prices, while indicators and oscillators are calculated based on price-based calculations and historical volumes of the asset in question [17]. Generally, profit forecasting, which may be done technically or fundamentally, will be applicable when being highly accurate. On the other hand, today it is well documented that using linear models in order to forecast plenty of financial observations due to their nonlinearity is not satisfactory. Therefore, in this paper firstly the technical analysis indicators forecasted using Neural Network Auto-Regressive model with exogenous inputs (NNARX) and then the effect of different factors (economic, systematic risk, company's properties, and corporate governance) on their forecasting error (eRSI, eMA1, eMA2, and eMACD) was investigated. The rest of the paper is organized as follows. Section 2 reviews the previous related studies, section 3 describes the research methodology, section 4 provides the results and discussions and finally section 5 represents the conclusions and recommendations.

2 Literature Review

Yu et al. [30] investigated the forecast power and profitability of elementary technical trading rules over January 1991 to December 2008. The findings indicated that the trading rules have robust forecasting ability in Malaysia emerging stock markets, Thailand, Indonesia, and the Philippines than in the more developed stock market of Singapore, consistent with previous literatures. Tehrani et al. [29] investigated the usefulness of applying the technical analysis to the world gold market by using daily world gold price data per ounce in the US Dollar during the last 37 years and the Relative Strength Index. Results indicated that the use of buy and sell signals derived from this method using the Relative Strength Index Junction 50 on the world gold market over the last 37 years has been significantly beneficial. Ko [17] stated that the use of technical analysis on the value of investing in technical analysis by professional investors and the buy and hold method on the Taiwan stock exchange is more appropriate than that of the buy and hold method. Chong et al. [6] revisited the performance of the two trading rules (MACD and RSI) of technical analysis in the stock markets of five OECD countries.
They conclude that the MACD (12,26,0) and RSI (21,50) rules coherently make significant irregular returns in the Milan Comit General and the S&P/TSX Composite Index. Furthermore, the RSI (14,30/70) rule is gainful in the Dow Jones Industrials Index. The findings indicated some light on investors' conviction in these two technical indexes in various developed markets. Fathi and

Parvizi [10] investigated the possible profits from TA by joining oscillators and moving averages in terms of 6 analytical plans. For this aim, in terms of 6 buy and sell plans, the shares of 10 stock petrochemical companies accepted in TSE are studied. Findings showed that the majority of all plans recomended buying signs had made a return over the risk-free return. Bader et al. [3] evaluated the difference of the returns of 22 technical analysis-based strategies for the China, Hong Kong, Indonesia, Japan, Malaysia, Philippines, Singapore, Taiwan and Thailand stock exchange indices with the return of buy and hold strategies in the time interval of 1995-2015. The result shows a significant and increased return on technical analysis compared to the buy and holds strategy in the financial markets of countries with poor performance. Nti et al. [27] compared the performances of the three oscillators of stochastic, stochastic relative strength index (RSI) and commodity channel index (CCI) on the Japan stock market index. This study showed that the commodity channel index oscillator performed better than the other two oscillators. Ling et al. [19] studied the effectiveness of 10 technical plans (simple moving average, moving average envelopes, Bollinger Bands, momentum, commodity channel index, relative strength index, stochastic, Williams percentage range, moving average convergence divergence oscillator and shooting star) in Malaysian Sharīʿah vs conventional stock.

The findings of Jensen’s alpha indicate 8 out of 10 plans are efficient in making uncommon returns in Sharīʿah-compliant samples while just 3 out of 10 plans are ifficient in conservative samples. The apparent usefulness of technical trading plans in Sharīʿah-compliant stocks shows transpicuous feeble in that stock market section instead of conventional stocks. Metghalchi et al. [21] used Simple Moving Averages and four other famous indexes to study the advantage of the TA viewpoint to Johannesburg stock exchange (JSE) in South Africa. Technical indixes are used to two JSE indexes depicting large-cap and small-cap companies from 1/2/2002 to 12/31/18. The excellent trading rules for both the Small-Cap and All Share indexes imply two simple moving averages. For the Small Cap Index, the excellent two trading rules and a low-risk plan have positive annual net excess return over the Buy and Hold (B&H) plan for the whole duration and each sub-period; therefore, trading rules can knock the B&H plan.

3 Methodology

In this study, firstly, the technical analysis indicators will be forecast using Neural Network Auto-Regressive model with eXogenous inputs (NNARX), then the error of forecasting technical analysis indicators will measure with mean absolute percentage error (MAPE), and finally, the effect of different factors (economic, systematic risk, company's properties and corporate governance) on the error of forecasting technical indicators include of: error of relative strength index (eRSI), error of moving average (eMA1), error of moving average crossover (eMA2) and error of moving average convergence/divergence (eMACD), will investigate.

3.1 Neural Network Auto-Regressive model with eXogenous inputs (NNARX)

Neural networks devided into dynamic (e.g. NNARX) and static (e.g. ANN) groups. Static networks have no feedback component and enclose no lags; the output is estimated directly from the input bt feed-forward links. In dynamic networks output depends not just to the present input to the network yet also on the present or past inputs, outputs, or states. Dynamic networks are basically more strong than static networks for this reason that dynamic networks have memory, they can be trained to learn consecutive or time-varying algorithms [27]. This model has a parametric part plus a nonlinear segment, where the nonlinear section is estimated by a single hidden layer feed-forward ANN. The neural network autoregressive with exogenous inputs (NNARX) is a dynamic network, with feedback links include of some network layers. The NNARX is based on the linear ARX model that widely applied in time-series designing. In addition, NNARX has utilization in various aspects such as a forecasting in financial markets, channel equalization in communication systems [23], phase discovery in power systems, sorting (Jayadeva and Rahman, 2004), fault discovery, speech identification and even forecasting protein construction in genetics [25]. The equation for NNARX pattern is as follow:

$$y(t) = f\,(y(t-1), y(t-2),...y(t-n_y), u(t-1), u(t-2),..., u(t-n_u)) \qquad (1)$$

The post quantities of dependent output signal y(t) is regressed on pre quantities of the output signal and pre quantities of an independent (exogenous) input signal. The output is fed back to the input of the feed-forward neural network as section of the norm NNARX structure, as presented in the left side of figure 1. For this reason that the true output is feasible within the network training, a series-parallel structure can be made [27], in which the true output is applied in place of feeding back the computed output, as presented in the right side of figure 1. NNARX has two advantages: 1) the input to the feed-forward network is more precise and 2) the concluded network has a virtuously feed-forward strucutre, and static backpropagation could apply for training.

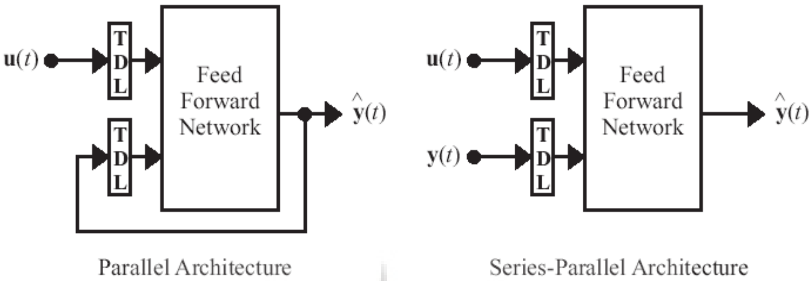

Fig1. Parallel and Series-Parallel Structurres

Dynamic networks are trained in identical gradient-based patterns which were applied in “Backpropagation.” Although they can be trained by the identical gradient-based patterns applied for static networks, the performance of the patterns on dynamic networks can be absolutely separate, and the gradient must be estimated in a more complicated method [29]. A schema of the concluded network is presented in fig 2, where a two-layer feed-forward network is applied for the estimation.

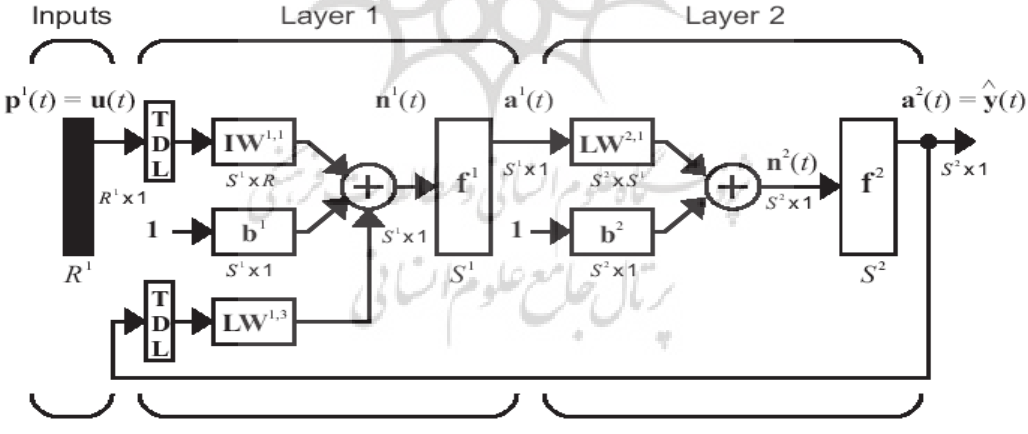

Fig2. Schema of neural network auto-regressive with exogenous inputs (NNARX)

This example of the network's weight has two various impacts on the network output: 1) the straight impact due to a change in the weight causes a quick change in the output at the existent time step. 2) an inverse impact due to some inputs to the layer, such as a(t,1), are also function of the weights. To account for this inverse impact, dynamic backpropagation must apply to estimate the gradients, which are more intensive [30]. Expect dynamic backpropagation to take more time to train, in part for this reason. Also, the error levels of dynamic networks could more complicate than those of static networks. Training is more probable to be trick in regional minima. This provides that it may need to train the network several times to obtain an optimum finding [31].

Table 1: Research variables and measurement

Variable	Type	Symbol	Definition/ Measurement
Relative strength index	Dependent	RSI	$RSI=100 - \frac{100}{1+RS}$ $RS= \frac{\text{average gain}}{\text{average loss}}$
Moving average	Dependent	MA1	$MA_t(n) = n^{-1}(\sum_{i=0}^{n-1} P_{t-i})$ n: Average period P: Closed price
Moving average crossover	Dependent	MA2	A crossover occurs when a faster-moving average (i.e., a shorter period moving average) crosses a slower moving average (i.e. a longer period moving average)
Moving average convergence/divergence	Dependent	MACD	MACD index is a set of three-time series estimated from historical price data, usually the closing price. These three series are the MACD series proper, the "signal" or "average" series, and the "divergence" series, which is the difference between the two.
Company's size	Endogenous independent	SIZE	Logarithmic form of the market value of stocks
Leverage	Endogenous independent	LEV	$\frac{\text{Total debts}}{\text{Total assets}}$
Return on asset	Endogenous independent	ROA	$\frac{\text{Net profit}}{\text{Total assets}}$
Cooperative governance indexes	Endogenous independent		- BI (board independence): percentage of independent non-executive directors to the total number of directors on board - GOWN (government ownership): percentage of ordinary shares belong to government investors - ACF (audit committee financial expert): dummy variable which if audit committee has at least one financial expert (=1) otherwise (=0).
Economic cycles	Exogenous independent	CYCLE	Dummy variable which if the gross domestic product (GDP) by more than its long-run 15 years average (=1 or prosperity) otherwise (=0 or recession).
Inflation rate fluctuations	Exogenous independent	INF	$\Delta INF = \frac{INF_2 - INF_1}{INF_1}$ INF1 is the inflation rate at the first financial year, and INF2 is the inflation rate at the end of the financial year.
Exchange rate fluctuations	Exogenous independent	EXR	$\Delta EXR = \frac{EXR_2 - EXR_1}{EXR_1}$ EXR_1 is the inflation rate at the first financial year, and EXR2 is the inflation rate at the end of the financial year.
Systematic risk	Exogenous independent	SRSK	$SRSK = \frac{COV(R_m, R_i)}{Var(R_m)}$ R_m is the market return, and R_I is the stock return.

3.2 Generalized method of moments (GMM) model

The GMM estimators are invariable, asymptotically normal, and proficient in the category of all estimators that do not apply any further information except that enclosed at the moment situations. Lars Peter Hansen advised GMM in 1982 as a popularization of moments, introduced by Karl Pearson in 1894. However, these estimators are mathematically the same as those based on "orthogonality conditions" or "unbiased estimating equations". The stability of GMM estimators depends on the specification test. Arellano and Bond [2] recommended testing the instrument's whole validity with

Sargan's over-identification test, which is based on the whole validity of the instruments by examining the sample match of the moment situations applied in the calculation procedure. The hypothesis tested by Sargan test is that the instrumental variable is related to several collections of residuals, and thus they are satisfactory, sound instruments, or "the instruments as a category are exogenous". If the null hypothesis is approved statistically, the instrument passes the test. Thus, the better calculation represents the higher the p-value of Sargan test. The result of test statistics is not misleading of the model [28].

3.3 Research variables

The research variables and measurements represented in Table 1.

3.4 Research Sample

In this research, sampling was performed purposefully so that the population was screened and companies were analyzed as sample companies selected by systematic elimination method. The statistical population included all companies listed in the Tehran stock exchange before 2014, which were active until 2020. Therefore, the below criteria were determined, and only companies were selected that had all of them:

- Companies have to list in Tehran stock exchange before 2014 and be active until end of 2020;
- The financial year of the firm needs to be ended on the last day of the year, and it is not supposed to have financial year change or be active;
- Companies have no trading interval more than three months during the financial year;
- Financial information of companies needs to be accessible.

Table 2: Descriptive statistics of research variables

Variable	Observations	Average	Max.	Min.	S.D.	kurtosis	Skewness
eRSI	2289	0.06	4.73	-9.621	0.33	372.49	-12.24
eMA1	2289	0.05	0.62	-1.346	0.06	142.23	-4.08
eMA2	2289	0.05	0.63	-1.492	0.06	279.61	-8.18
eMACD	2289	0.07	106.17	-73.268	3.37	597.29	13.07
SIZE	2289	13.13	15.88	10.97	0.76	1.18	0.56
LEV	2289	0.63	2.94	0.01	0.29	10.85	1.17
ROA	2289	69.96	1607.79	-884.97	134.89	8.30	2.86
BI	2289	0.53	1.00	0.00	0.32	-1.14	-0.60
GOWN	2289	5.42	34.08	0.00	5.48	1.24	1.94
ACF	2289	0.55	1.00	0.00	0.53	-2.01	-0.06
CYCLE	2289	0.75	1.00	0.00	0.48	-1.20	-1.01
INF	2289	0.26	2.38	-0.58	0.91	1.43	1.72
EXR	2289	0.34	1.73	-0.12	0.58	1.90	1.94
SRSK	2289	0.84	7.74	-10.06	1.13	8.34	-0.36

Source: Research findings

Taking all the above information into account, 323 companies remained as screened companies selected as a sample of the study.

In addition, in this study, to measure the error of forecasting technical analysis indicators, 3 scenarios were applied. The data relating to 4 years period was used as the training period, and related data for each of the considered indicators in the 5th year was used as the test period. Finally, the forecasted values of the NNARX model in the 5th year were compared with the real data using MAPE as the following formula:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{2}$$

Also, the required data were gathered from audited companies' financial statements, Rahavard Novin software and the Tehran stock exchange website. In addition, for data analysis, the Matlab and STATA softwares was applied.

4 Results and Discussions

4.1 Data Description

The statistical description of research variables includes average, maximum, minimum, standard deviation, kurtosis and skewness, represented in Table 2.

4.2 Measuring Error of Forecasting Technical Analysis Indicators Using NNARX

Results of measuring error of forecasting technical analysis indicators using NNARX model have been presented in table 3:

Table 3: Measuring error of forecasting technical analysis indicators using NNARX model

Indicators	Scenario	Training period	Testing period	Forecasted	Actual	MAPE
RSI	1	2014-2017	2018	42.813	46.46	0.066
	2	2015-2018	2019	42.666	46.312	0.048
	3	2016-2019	2020	42.684	46.331	0.053
MA1	1	2014-2017	2018	6917.302	7055.204	0.051
	2	2015-2018	2019	7866.488	8004.39	0.045
	3	2016-2019	2020	8471.76	8609.663	0.039
MA2	1	2014-2017	2018	6962.843	7083.746	0.044
	2	2015-2018	2019	7916.658	8037.561	0.039
	3	2016-2019	2020	8612.347	8733.25	0.034
MACD	1	2014-2017	2018	69.066	69.957	0.038
	2	2015-2018	2019	82.816	83.707	0.083
	3	2016-2019	2020	93.011	93.902	0.055

Source: Research findings

4.3 Stationarity Test

To prevent spurious regression, testing the stationarity of variables is essential. In this research, the Levin–Lin–Chu (LLC) test was applied that its assumption is the existence of common factors between companies and the auto correlation coefficient is equal for all companies. Table 4 represents the results of the stationarity test for research variables:

Table 4: Results of Stationarity of Research Variables Base on LLC Test

Variable	eRSI	eMA1	eMA2	eMACD	SIZE	LEV	ROA
t statistic	3.41	3.19	2.77	3.81	2.68	3.18	3.27
P-Value	0.00	0.00	0.01	0.00	0.01	0.00	0.00
Result	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Variable	BI	GOWN	ACF	CYCLE	INF	EXR	SRSK
t statistic	2.71	3.44	3.73	2.87	3.29	2.71	3.16
P-Value	0.01	0.00	0.00	0.00	0.00	0.01	0.00
Result	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

Source: Research findings

Results of Table 4 indicate that according to the P-value (< 0.05) of the LLC test, the whole research variable is station without differentiation (I(0)). To determine the model structure in panel data methods, the Breusch-Pagan and Hausman tests were applied which their results are represented in Table 5.

Tale 5: Results of the Brush- Pagan and Hausman tests

Test type	Test statistic	Test statistic value				P-Value			
		Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Mode 4
Poolability	F-Leamer	591.99	597.54	599.42	603.48	0.01	0.00	0.00	0.00
Breusch and Pagan	LM with χ2 distribution	391.23	398.50	404.49	409.43	0.00	0.00	0.00	0.00
Hausman	LM with χ2 distribution	76.50	80.76	82.66	88.45	0.01	0.00	0.00	0.00

Source: Research findings

Results of Table 4 indicate that according to P-value (< 0.05), Breusch-Pagan and Hausman tests, the OLS model is not efficient, and the panel data method must be used for specification of all studied models, there are random effects in studied models and fixed effects model is more efficient than random effects. Therefore, for the specification of all 4 studied models, the fixed effect panel data model based on the GMM approach was applied in this research. Table 6 represents the results of the fixed effect panel data model based on the GMM approach for all 4 studied models:

Table 6: Results of fixed effect panel data model specification based on GMM approach

Variable	Model 1: dependent variable eRSI		Model 2: dependent variable eMA1		Model 3: dependent variable eMA2		Model 4: dependent variable eMACD	
	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
eRSI(-1)	0.372	2.607***			---	---	---	---
eMA1(-1)	---	---	0.381	2.721***	---	---	---	---
eMA2(-1)	---	---	---	---	0.385	2.670***	---	---
eMACD(-1)	---	---	---	---	---	---	0.394	2.582***
SIZE	-0.296	-1.569 NS	-0.415	-1.629 NS	-0.338	-1.618 NS	-0.315	-1.603 NS
LEV	0.023	0.810 NS	1.030	2.733***	1.100	2.835***	0.376	1.628 NS
ROA	-7.956	-5.809***	-18.450	-9.023***	-17.948	-8.909***	-10.152	-5.518***
BI	0.058	1.177 NS	-0.363	-1.569 NS	-0.492	-1.721*	-0.308	-1.468 NS
GOWN	-0.716	-1.405 NS	1.153	1.623 NS	1.222	1.784*	1.059	1.582 NS
ACF	0.170	1.278 NS	-0.396	-1.595 NS	-0.600	-1.759*	-0.389	-1.506 NS
CYCLE	1.205	3.607***	2.334	3.809***	2.317	3.746***	0.057	0.962 NS
INF	2.299	3.556***	1.026	3.202***	1.134	3.632***	1.041	3.531***
EXR	1.854	3.126***	2.537	4.075***	2.545	4.125***	0.907	3.467***
SRSK	1.920	3.101***	2.515	4.632***	2.450	4.442***	1.067	3.164***
Intercept	6.473	4.404***	5.190	4.125***	7.742	4.012***	6.858	4.290***
Wald	2505.512	0.000	2504.857	0.000	2506.158	0.000	2510.783	0.000
Sargan	0.613	0.996	0.599	0.991	0.644	0.997	0.667	0.998
Arellano & Bond AR(1) test: Prob>z	0.023		0.027		0.020		0.014	

Source: Research findings

*** Significant in 99% significance level - ** Significant in 95% significance level - * Significant in 90% significance level – NS not significant.

Results of model specification are valid when classic regression assumptions are confirmed. The results of table 6 represent that according to P-values of the Wald test, in all 4 specified models, we can reject the null hypothesis that the coefficients are equal to zero. Therefore, the validation of coefficients for all 4 specified models was confirmed. Also, according to the P-value of Sargan and Arellano and Bond test, the overall validity of the instrument is confirmed, and the instrumental variable is related to several categories of residuals, and thus they are credible, sound instruments or “the instruments as a categoru are exogenous”. According to the results of table 6, the coefficient of the "Size" variable is not significant at 95% significance level. Therefore, the company's size doesn't significantly affect studied indicators of technical analysis efficiency (eRSI, eMA1, eMA2 and eMACD). This finding isn't associated with the results of [22,25], which found that bigger companies have more professional staffs - are more accurate and efficient in analysis and predictions and have high stock returns.

The coefficient of the "LEV" variable isn't significant in models 1 and 4 and is significant in models 2 and 3 at a 95% significance level. Therefore, leverage doesn't significantly affect eRSI and eMACD and has a significant inverse effect on eMA1 and eMA2. This finding is associated with Ahmadi et al. [1] results, which found that companies with more leverage have less stock return and, therefore, provide more invalid analysis and predictions. The coefficient of the "ROA" variable is negative and significant in all models at a 99% significance level. Therefore, return on assets has a significant inverse effect on eRSI, eMA1, eMA2 and eMACD. This finding is associated with [14-18], which found that the company's return of assets has a significant effect on the efficiency of their analysis predictions related to the stock exchange market. The coefficient of "BI", "GOWN" and "ACD" variables aren't significant at 95% significance level. Therefore, considered cooperative governance indexes don't significantly affect studied indicators of technical analysis efficiency (eRSI, eMA1, eMA2 and eMACD). This finding isn't associated with the results of [12], which found a significant relationship between the cooperative governance structure of companies and their efficiency of analysis and predictions related to the stock exchange market.

The coefficient of the "CYCLE" variable isn't significant for models 4 at 95% significance level and is positive and significant in models 1, 2, 3 at 99% significance level. Therefore, economic cycles don't have a significant effect on eMACD and directly affect eMA1, eMA2 and eRSI. This finding is associated with the results of [23-28], which found that unsuitable economic conditions reduce the efficiency and accuracy of a company's analysis and predictions related to the stock exchange market.

The coefficient of the "INF" variable is positive and significant for all models at a 99% significance level. Therefore, inflation rate fluctuations have a significant direct effect on eRSI, eMA1, eMA2 and eMACD. This finding is associated with the results of Khanifar et al. [16], which found a significant relationship between inflation rate fluctuations and the efficiency and accuracy of the company's analysis and predictions related to the stock exchange market. The coefficient of the "EXR" variable is positive and significant for all models at a 99% significance level. Therefore, exchange rate fluctuations have a significant direct effect on eRSI, eMA1, eMA2 and eMACD. This finding is associated with [16-19], which found a significant relationship between exchange rate fluctuations and the efficiency and accuracy of the company's analysis predictions related to the stock exchange market. The coefficient of the "SRSK" variable is positive and significant for all models at a 99% significance level. Therefore, systematic risk has a significant direct effect on eRSI, eMA1, eMA2 and MACD. This finding is associated with the results of Ebrahimi et al. [8], which found a significant relation between systematic risks and the efficiency and accuracy of the company's analysis and predictions related to the stock exchange market.

5 Conclusions and Recommendations

It is well documented that using linear models to forecast plenty of financial observations due to their nonlinearity is not satisfactory. Therefore, in this paper, firstly, the technical analysis indicators forecasted using Neural Network Auto-Regressive model with exogenous inputs (NNARX), and then the effect of different factors (economic, systematic risk, company's properties and corporate

governance) on their forecasting error (eRSI, eMA1, eMA2 and eMACD) was investigated. For this purpose, required data were collected using the removal sampling method for 323 companies listed on the Tehran Stock Exchange from 2014-2020. In addition, the mean absolute percentage error (MAPE) was applied to measure the error of forecasting technical analysis indicators. Results indicated that the error of forecasting technical analysis indicators is less than 0.1 and has sound accuracy. Also, the company's size and corporate governance indicators didn't significantly affect the error of forecasting technical analysis indicators. In addition, financial leverage doesn't significantly affect eRSI and eMACD but has a significant inverse effect on eMA1 and eMA2. On the other hand, return on assets has a significant inverse effect on eRSI, eMA1, eMA2 and eMACD. Also, economic recession and prosperity, inflation fluctuations, exchange rate fluctuations and systemic risk have a significant positive effect on eRSI, eMA1, eMA2 and eMACD. Finally, according to the research findings, which indicated that some endogenous independent variables have a significant effect on an error of forecasting considered indicators of technical analysis, it is suggested to technical analyzers and investors that have more attention to companies' properties, especially leverage and return on assets, because these factors can have a significant effect on profitability and risk of investments.
Finally, according to the research findings, which indicated that some exogenous independent variables have a significant effect on an error of forecasting considered indicators of technical analysis, it is suggested to technical analyzers and investors that have more attention to a macroeconomic variable such as economic cycles, inflation rate fluctuations, exchange rate fluctuations and systematic risk while selecting the securities.

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