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Designing a Financial Market Analysis Training Model for Institutional Investors Based on Market Forecasting and Data-Driven Learning

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ABSTRACT

This research aims to design a financial market analysis training model to improve the quality of institutional investors' investment decisions. By examining the stock trends, gold, foreign exchange, and housing markets, this research has evaluated the future status of these markets as a basis for investment decision-making training. The results show that the stock market has experienced significant growth in different periods, including 2004, 2011, 2014, 2016, and 2019, and the peak of this trend in 2019 was accompanied by the recording of historical records of the Tehran Stock Exchange; However, after that, this market entered a period of stagnation and did not experience significant growth. The foreign exchange market also experienced relative growth in the first half of 2026, but then faced a downward trend. On the other hand, the housing and stock markets are still in a recession in 2026. Accordingly, the proposed model for teaching financial market analysis by emphasizing trend analysis, market forecasting and risk assessment can improve the decision-making ability of institutional investors and provide the basis for optimizing investment portfolios. Based on the forecasting results, a financial market analysis training model was proposed consisting of four main learning modules: market trend analysis, forecasting interpretation, risk assessment and portfolio diversification, and investment decision-making. The model integrates real market data, forecasting techniques, and case-based learning approaches to enhance institutional investors' analytical competencies. ©**authors**

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Introduction

In recent decades, financial markets have become a dynamic, complex and uncertain environment under the influence of economic globalization, the development of financial technologies, the spread of artificial intelligence, big data and the increase in the speed of information dissemination. In such circumstances, making effective investment decisions for institutional investors requires specialized knowledge, analytical skills and the ability to correctly interpret market information. Institutional investors include banks, investment companies, pension funds, insurance companies and investment funds, which play a decisive role in the efficiency, liquidity and stability of financial markets due to the large volume of financial resources under management (Ashrafzadeh et al., 2023). Therefore, the quality of decisions of these institutions affects not only their financial performance, but also the dynamics of the entire capital market. Despite the development of analytical tools and widespread access to financial data, investment decision-making is still one of the most complex management processes. Rapid changes in economic variables, fluctuations in financial markets, political developments, international crises, and the emergence of new technologies have made traditional methods of training in market analysis no longer meet the needs of institutional investors. As a result, designing new educational models that can strengthen the skills of analyzing market trends, assessing risk, predicting asset behavior, and selecting appropriate investment strategies has become a necessity for the financial system.

Training in financial market analysis goes beyond the transfer of theoretical concepts and is a systematic process for developing professional competencies in analyzing information, evaluating investment opportunities, and managing uncertainty. By combining fundamental analysis, technical analysis, macroeconomic analysis, risk management, investor behavioral analysis, and quantitative methods, this training provides a basis for more informed decision-making for investment managers. In addition, effective training increases the ability of institutional investors to identify investment opportunities, manage market fluctuations, and allocate financial resources optimally.

Different financial markets, including stocks, bonds, gold, currencies, housing, and other capital assets, each have different characteristics, opportunities, and risks. Understanding the behavior of these markets requires learning the specific analysis methods of each market and understanding the interrelationships between them. To achieve optimal performance, institutional investors must be able to analyze the state of each market and also consider the impact of macroeconomic variables such as inflation rates, interest rates, monetary and fiscal policies, exchange rates, and geopolitical developments in the decision-making process (Vega et al., 2023). Therefore, learning about inter-market analysis and understanding the relationship between different markets is considered one of the essential components of improving the quality of investment decisions. Technological developments have also added new dimensions to the training of financial market analysis. Today, tools based on artificial intelligence, machine learning, big data analysis, decision support systems, and predictive algorithms have transformed the process of analyzing financial information. In addition to increasing the accuracy of analyses, the use of these technologies allows for the identification of hidden market patterns and the prediction of future trends. As a result, the training of institutional investors should include, in addition to the classic concepts of market analysis, the skills of using modern analytical technologies and digital tools (Master et al., 2023).

On the other hand, recent research shows that the quality of investment decisions is not solely dependent on financial information, but factors such as behavioral biases, information processing methods, data analysis ability, continuous learning and updating of specialized knowledge also play an important role in the success of institutional investors. For this reason, modern educational approaches emphasize the development of analytical thinking, scenario-based learning, financial market simulation, real-world data analysis and strengthening decision-making skills under uncertainty (Ramos et al., 2023).

Despite the increasing importance of financial market analysis training, many existing training programs still lack a comprehensive and systematic framework that can cover the various dimensions of market analysis, risk management, financial technologies, data analysis, and investment decision-making in an integrated manner. This gap causes institutional investors to face challenges in converting data into applied knowledge and effective decisions, despite having access to a vast amount of information. Therefore, designing a comprehensive training model that can improve the quality of investment decisions while enhancing analytical capabilities is an undeniable necessity for financial institutions.

Accordingly, the present study was conducted with the aim of designing a financial market analysis training model to improve the investment decisions of institutional investors. This study attempts to provide a scientific and practical framework for improving the knowledge, skills, and decision-making ability of institutional investors by identifying the dimensions, components, and requirements of financial market analysis training; A framework that can improve the quality of investment decisions and provide the basis for increasing the efficiency and effectiveness of investment institutions' activities through systematic training, detailed market analysis, risk management, and the use of new technologies (Liu et al., 2023). This training model is specifically designed for institutional investors, including portfolio managers, investment analysts, and financial professionals who are responsible for evaluating investment opportunities and making asset allocation decisions. Unlike general financial literacy programs, the proposed framework focuses on developing advanced analytical capabilities required for professional investment decision-making under uncertain market conditions.

Literature Review

Institutional investors, as one of the main pillars of financial markets, play a decisive role in allocating resources, increasing market efficiency, and shaping investment trends. This group includes pension funds, insurance companies, investment banks, sovereign wealth funds, and other financial institutions that manage significant volumes of capital. Therefore, the quality of investment decisions of these institutions depends largely on their knowledge, skills, and ability to analyze financial markets (Guarino et al., 2023). One of the most important challenges in this area is the uncertainty in financial markets and the difficulty of predicting the reaction of markets to unexpected news, economic shocks, and unforeseen events; a topic that makes the need for systematic training in financial market analysis more and more evident.

Training in financial market analysis should enable institutional investors to recognize the characteristics of different markets and evaluate the variables affecting them. For example, in the bond market, analyzing interest rate trends, inflation, economic growth, and central bank policies are among the most important skills that should be considered in the training process. Even small changes in interest rates can significantly affect the value of debt securities and investment decisions; therefore, training in yield curve analysis models and monetary policy forecasting methods is an essential component of training programs (Giao et al., 2023).

In the commodity market, especially gold and oil, effective decision-making requires understanding the factors affecting supply and demand, geopolitical developments, climate change, and global economic conditions. Therefore, training in fundamental analysis, scenario models, and commodity price forecasting methods can increase the ability of institutional investors to manage the fluctuations of these markets. In such circumstances, training in risk management principles is also an integral part of the commodity market analysis process.

The foreign exchange market also requires advanced analytical skills due to its influence on macroeconomic variables, monetary policies, international relations, and expectations of economic actors. Training in analyzing economic data, examining countries' foreign exchange policies, and analyzing market sentiment can improve the accuracy of exchange rate forecasts and the quality of investment decisions (Qiu et al., 2023). In addition, familiarity with legal risks, financial regulations, and changes in tax policies are also important educational topics, because changes in laws and regulations can directly affect the investment structure of financial institutions and challenge investment decisions (Chan et al., 2023). Another important topic in teaching financial market analysis is understanding the interrelationships between different markets. In many financial crises, the correlation between assets changes contrary to usual patterns, reducing the effectiveness of traditional diversification strategies. Therefore, training in mid-market analysis, scenario analysis, active asset management, and hedging tools are essential to improving the quality of institutional investors’ decision-making.

Technological developments have also transformed the landscape of financial market analysis training. Today, the use of big data, artificial intelligence, machine learning, and predictive models has made it possible to analyze a large volume of information in a short time. Training on how to use these technologies, while increasing the speed and accuracy of analysis, can improve institutional investors’ ability to identify investment opportunities. Of course, along with these opportunities, issues such as cybersecurity, data quality, and overreliance on smart algorithms should also be addressed in training programs so that investment decisions are more sustainable and reliable.

In recent years, the expansion of the responsible investment approach has also made environmental, social, and corporate governance criteria more important in financial market analysis. Therefore, market analysis training should include, in addition to financial indicators, the assessment of sustainability and social responsibility criteria so that institutional investors can make more comprehensive decisions that are in line with new market developments.

On the other hand, predicting future trends in financial markets is always accompanied by uncertainty, and relying on historical data alone cannot guarantee correct decisions. Structural changes in the global economy, technological developments, and the occurrence of unexpected crises may change past patterns. Therefore, the simultaneous use of traditional analytical methods and new technologies, along with continuous education and improvement of investors' analytical skills, is an inevitable necessity (Spoke et al., 1403).

Also, changes in central bank monetary policies, economic developments in major economies of the world, especially China and the United States, and the development of technologies such as artificial intelligence, blockchain, and the Internet of Things, have a significant impact on financial market trends and asset values. Therefore, training in the analysis of these variables can improve the quality of market forecasting and investment decisions (Azami et al., 1403). In addition, analyzing the debt securities market, digital currencies, gold, oil, and other commodities requires a detailed understanding of economic, technological, and policy variables, and training in these areas can provide a basis for more informed decision-making for institutional investors (Darakhshan et al., 1403; Soltanipour et al., 1403).

Finally, given the increasing volatility of financial markets and the increasing complexity of the investment environment, the success of institutional investors depends more than ever on the quality of education, data analysis capabilities, the use of new analytical tools, and decision-making based on reliable information. Therefore, designing a comprehensive model for financial market analysis education can, while improving the professional competencies of institutional investors, provide the basis for making more accurate investment decisions, effective risk management, and increased investment efficiency (Mohaghegh et al., 1403).

Review of Studies

In their study, Kuei et al. (2024) examined multi-period portfolio optimization using a deep reinforcement learning meta-heuristic approach. In this study, they compared their proposed method with advanced trading strategies as well as the traditional deep reinforcement learning (DRL) method and achieved significant performance gains. The data used in this study includes five stock indices from 2012 to 2022. The results of this study show that their proposed approach performs better than traditional methods in portfolio optimization and investment strategy selection. These results can have important policy implications in formulating investment strategies and establishing effective regulatory frameworks for financial markets. In addition, their study can provide new solutions for creating intelligent investment systems that are capable of analyzing complex data and predicting market trends in real time. As a result, this study not only helps to improve portfolio optimization methods, but also introduces new tools for investment decision-making that can be applied in different market conditions. The deep reinforcement learning approach in this study is considered as an efficient tool, especially in volatile and nonlinear conditions of financial markets.

In their study, Brouga et al. (2023) investigated portfolio optimization using the Minimum Spanning Tree (MST) model in the Moroccan stock market. In this study, various criteria such as centrality, diversification, and backtesting were used to evaluate the performance of the models. The results of the analysis of the indicators in question show that the MST-Portfolio and MST-Portfolio 2 models have outstanding performance and form the strongest investment portfolios. One of the notable features of these models is that during the study period, even during the economic crisis caused by COVID-19, they were able to perform well and ensure a high level of diversification in the investment portfolio. These results are especially important for investors and portfolio managers, as they show that the proposed methods can help optimize portfolios and perform well even in critical situations.

The findings of this research can provide important evidence for improving investment strategies and help investors create optimal portfolios. As a result, these methods can be effective in the financial decision-making process, especially in markets with specific characteristics such as the Moroccan stock market.

Liu et al. (2023) investigated portfolio optimization in a multi-period model with dynamic risk preference and minimal number of transactions. This research focuses on the optimization objective problem that focuses on reducing the number of transactions in uncertain dynamic trading environments. One of the important aspects of this research is to consider the changes in investor risk preference over the investment horizon, which provides more flexibility in portfolio management. In this model, an average value-at-risk (VaR) framework is used to maximize wealth generation. As an important measure in risk assessment, VaR helps investors make more informed decisions about their portfolio and limit the amount of risk in their investments. To solve the optimization problem, genetic algorithms have been applied, which have effectively been able to provide optimal solutions for asset combinations considering the minimum possible transactions and investor risk preferences. This research can help portfolio managers and investors to implement more optimal strategies in managing their assets, especially in trading environments with high volatility and uncertainty. Overall, this model provides a useful tool for improving portfolio performance in financial markets by using advanced algorithms and considering dynamic risk preferences.

In her research, Kristina Brzezowska (2023) examined the challenges of institutional investors in private equity (PE) funds in Europe. Achieving high exposure to private equity investments is one of the key challenges facing institutional investors, especially given the significant allocations to this alternative investment vehicle in recent years. Successful acquisition, management and exit of PE investments requires expertise and strong incentives, which many institutional investors often lack. In particular, in private equity funds, investment decisions, capital raising and development of portfolio companies are carried out by limited partnerships. This organizational structure is usually designed in a limited manner with specific investment responsibilities. The results of Brzezowska's research show that many institutional investors in Europe still face serious challenges in various areas, including the appropriate allocation of capital to private equity funds, risk management and strategic decision-making. This research specifically emphasizes the need to create appropriate incentives and attract expertise to help these investors make sound and optimal decisions in complex PE markets. Overall, this research emphasizes the importance of a thorough understanding of private equity fund strategies, management structures, and the need for expertise in investment processes, and recommends that investors and fund managers use specific advisors and expertise to optimally exploit these types of investments.

Recent educational research emphasizes that professional financial training should move beyond theoretical knowledge toward experiential and data-driven learning. Case-based analysis of real financial markets enables learners to develop practical competencies, including market interpretation, risk evaluation, and strategic decision-making. Therefore, integrating forecasting tools into educational frameworks can enhance the effectiveness of professional investment training.

Method

This research is applied in terms of purpose and quantitative in nature, and was conducted with a time series analysis approach. In order to examine and predict the returns of financial markets and explain its application in improving institutional investors' decision-making, the autoregressive integrated moving average (ARIMA) model was used. Based on the content of the article, the analyses were conducted on data related to four financial markets and the foreign exchange market (REX) was specifically reported in the model estimation section.

In the first stage, in order to verify the usability of time series models, the stationarity of the variables under study was measured using the unit root test. The results showed that the rates of return of all four markets are stationary at a significance level of 1 percent; therefore, the necessary conditions for estimating the ARIMA model were met.

Table1. Transformation of Forecasting Results into Training Components

ARIMA Analysis Output	Educational Application	Developed Competency
Market trend patterns	Teaching market cycle identification	Trend analysis capability
Forecast values and uncertainty	Teaching prediction interpretation	Forecasting literacy
Market fluctuations	Teaching risk evaluation	Risk management skill
Comparison among markets	Teaching diversification strategies	Portfolio allocation capability

In the next step, to determine the appropriate components of the autoregressive (AR) and moving average (MA), autocorrelation (ACF) and partial autocorrelation (PACF) diagrams were used in the form of Correlogram. In this way, by examining the lags whose values exceeded the conventional limits, the initial orders of the model were determined. According to the article, in the foreign exchange market, the lags AR (1), MA (1) and MA (5) were identified as significant lags.

Then, in order to select the optimal model, the Akaike Information Index (AIC) and Schwartz Information Index (SC) were used, and the model with the lowest value of these two indices was selected as the final model. Accordingly, the Ls REX C AR (1) model was introduced as the most appropriate estimation model.

To assess the adequacy of the model, the residuals of the selected model were tested. The results of the studies showed that the residuals had white noise behavior and the values of the ACF and PACF diagrams did not exceed the significant limits. Also, the probability level for the examined values was reported to be more than 5 percent, which indicates the suitability of the model fit.

Finally, after confirming the model fit, the forecasting process was carried out in two modes: static and dynamic, and short-term and long-term forecasts were considered. In dynamic forecasting, the future values of the variables were calculated based on the observed data up to time t and using the estimated values of previous periods.

This model is based on the assumption that effective education in the field of financial markets is not simply the transfer of theoretical knowledge, but should enhance the analytical and decision-making abilities of investors through a combination of real market data, quantitative forecasting tools and application-oriented educational methods.

In the first stage, the inputs of the model include financial market data and the results of forecasting models. Market data includes historical information on asset prices, financial indicators, trading volumes and other variables related to market behavior, and the forecasting results include the output of time series models such as ARIMA, which are used to identify future market trends. This stage plays the role of the information base of the model and provides the necessary raw materials for the learning process.

In the second stage, there are Learning Modules, which constitute the main elements of the training program. This section includes five key components: analyzing market trends, interpreting ARIMA forecasting results, assessing risk, diversifying portfolios, and making investment decisions. In this phase, learners learn how to analyze financial data, interpret the results of forecasting models, assess the level of investment risk, and determine the optimal mix of assets based on analytical information.

The third phase, Pedagogical Methods, specifies how knowledge is transferred and practical skills are developed. This model uses three educational approaches: case study-based learning, simulation, and data-based exercises. Case studies allow learners to analyze real market situations; simulations create decision-making conditions close to the real investment environment; and data-based exercises strengthen practical ability to use data and analytical tools.

Finally, the learning outcomes of the model represent the expected outcomes of the implementation of this training program. These outcomes include increasing investors' analytical capabilities, improving the quality of investment decisions, and optimizing asset allocation. Therefore, the proposed model provides an integrated framework for developing the analytical competencies of institutional investors by establishing a connection between financial data, the learning process, and decision-making outcomes.

The model shows that the use of quantitative forecasts such as ARIMA is most effective when it is embedded in a structured educational system and transformed into investors' decision-making skills through active learning methods.

Findings

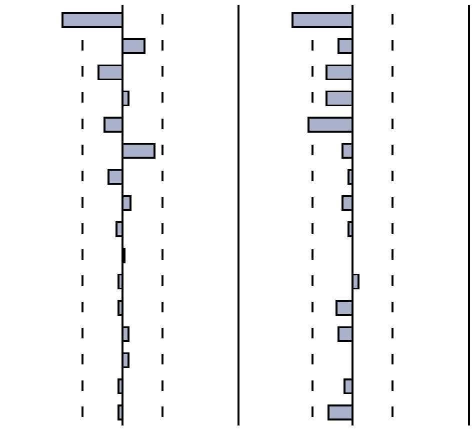
Results of ARIMA model estimation

In this study, to use the ARIMA model, the stationary state and collective degree of the variables must be carefully examined by using unit root tests, and the results of the reliability tests show that the return rates of all four markets are stationary at a significance level of 1 percent. Then, by observing the correlogram and looking at the status of Partial correlation (AR) and AutoCorrelation (MA) and the points protruding from the boundary; we obtain the value of AR and MA outside the mean, which is used in building the ARIMA model. Considering the values of AR and MA and also by examining the Akaike and Schwartz (AIC and SC) values (the valuation criterion is based on the smallness of these values), we can determine the appropriate ARIMA for the study.

Looking at the Partial correlation (AR) and Autocorrelation (MA) for the foreign exchange market (REX), we can see that AR(1), MA(1), and MA(5) are out of the specified average range. Also, in the table above, we use AC to determine the interval q (Moving Average (MA)), which is actually where q starts from where AC starts to decrease (autocorrelation).

***Table 1**. Observing correlogram values to obtain appropriate AR and MA*

Date: 03/26/25 Time: 23:08
Sample: 1371 1406
Included observations: 32



Autocorrelation / Partial Correlation	AC	PAC	Q-Stat	Prob
1	-0.542	-0.542	10.307	0.001
2	0.198	-0.135	11.731	0.003
3	-0.212	-0.236	13.420	0.004
4	0.057	-0.233	13.546	0.009
5	-0.170	-0.409	14.713	0.012
6	0.293	-0.087	18.301	0.006
7	-0.135	-0.046	19.089	0.008
8	0.076	-0.088	19.353	0.013
9	-0.055	-0.039	19.499	0.021
10	0.012	0.004	19.506	0.034
11	-0.043	0.046	19.604	0.051
12	-0.031	-0.143	19.658	0.074
13	0.046	-0.115	19.779	0.101
14	0.043	0.004	19.888	0.134
15	-0.039	-0.068	19.985	0.173
16	-0.038	-0.223	20.085	0.216

Source: Researchers' calculations

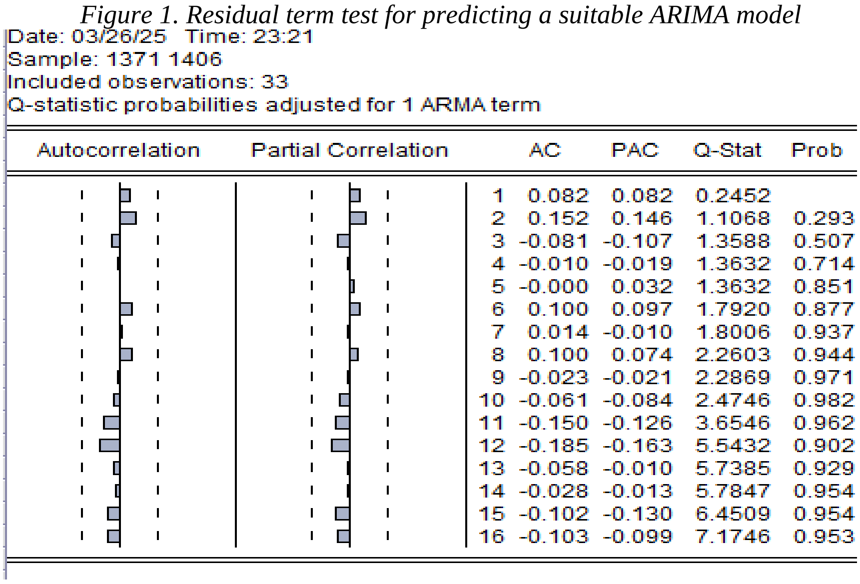
We use PAC to determine the interval P (Auto regressive (AR)), which is actually where p starts from where PAC starts to decrease (partial autocorrelation). Now, we build the necessary equation according to the intervals of AR and MA, and the best equation based on the lowest AIC and SC values is the equation Ls REX C AR(1).

***Table 2.** The appropriate equation based on AR and MA for forecasting the ARIMA model*

Ls REX C AR(1)				
Variable	**Coefficient**	**Standard deviation**	**t-statistic**	Prob
C	0.0719	1.865670	12.88669	24.04230
AR(1)	0.0672	1.899024	0.151453	0.287612
SIGMASQ	0.0006	3.810233	270.0901	1029.106
Akaike information criterion: 0.74				
Adjusted R-squared: -3.3944				
F-statistic:7.66 Schwarz criterion: -3.1699				
Prob(F-statistic):0				

The equation in Table 2 has the lowest Akaike and Schwarz (AIC and SC) values according to the types of AR and MA intervals. Therefore, after obtaining the best case, the residual term should be examined for being White noise, and if Partial correlation and AutoCorrelation do not protrude, it can be concluded that the ARIMA model does not have a residual problem.

Figure 1. Residual term test for predicting a suitable ARIMA model



Date: 03/26/25 Time: 23:21
Sample: 1371 1406
Included observations: 33
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.082	0.082	0.2452	
		2	0.152	0.146	1.1068	0.293
		3	-0.081	-0.107	1.3588	0.507
		4	-0.010	-0.019	1.3632	0.714
		5	-0.000	0.032	1.3632	0.851
		6	0.100	0.097	1.7920	0.877
		7	0.014	-0.010	1.8006	0.937
		8	0.100	0.074	2.2603	0.944
		9	-0.023	-0.021	2.2869	0.971
		10	-0.061	-0.084	2.4746	0.982
		11	-0.150	-0.126	3.6546	0.962
		12	-0.185	-0.163	5.5432	0.902
		13	-0.058	-0.010	5.7385	0.929
		14	-0.028	-0.013	5.7847	0.954
		15	-0.102	-0.130	6.4509	0.954
		16	-0.103	-0.099	7.1746	0.953

According to the results of the above graph, it can be seen that the Partial correlation and AutoCorrelation values do not deviate from the mean at any point, and the probability level for all values is above 5%, which indicates that the results are acceptable. After obtaining the appropriate ARIMA, we can continue to use the results of the above table for forecasting in the ARIMA model. Forecasting is done in two ways: static and dynamic, and short-term and long-term forecasting, respectively. To explain the difference between the two, consider the model $AR(1)$ $(Y_t = \mu + \phi Y_{t-1} + u_t)$. With this model, we want to forecast the years $t+1$. Dynamic forecasting is done with the assumption that $t+3$ ،$t+2$ ، we are in year t and we make a forecast for each of the future years. Therefore, the only information we have available is the data set of year t, which we represent with I_t.

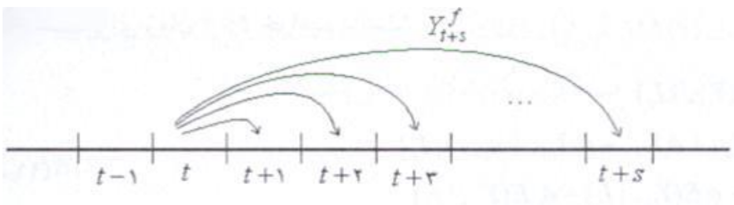
Dynamic forecast for the year $t+1$: $Y^f_{t+1} = E(Y_{t+1} | I_t) = \mu + \phi Y_t$

Dynamic forecast for the year $t+2$ $Y^f_{t+2} = E(Y_{t+2} | I_t) = \mu + \phi Y^f_{t+1}$

Dynamic forecast for the year $t+3$ $Y^f_{t+3} = E(Y_{t+2} | I_t) = \mu + \phi Y^f_{t+2}$

The above results show that our data set only contains Y_t and we do not have the values of Y_{t+1} and Y_{t+2}, so we use their predicted values. In fact, we are standing at a point (at time t) and making predictions for any future interval. Obviously, such predictions have larger errors for the further future.

Figure 2. *Dynamic forecasting trend*



Static forecasting is a type of step-by-step forecasting. This means that when we make a forecast for year t in year $t+1$, our data set in year (I_t) contains Y_t. Now we make a forecast for year $t+2$ when we get to year $t+1$. In this year, our data set I_{t+1} contains Y_{t+1}, because we have now observed the value of Y_{t+1}. So, in general, the forecast for year $t+s$ is a function of the observed value of Y in year $t+s-1$:

Dynamic forecast for the year $t+s$: $Y_{t+s}^{f}=E(Y_{t+s}|I_{t+s-1})=\mu+\phi Y_{t+s-1}$

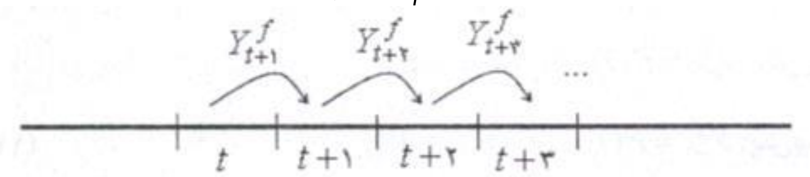
In year $t+s$ we have the value of Y_{t+s-1} and the pleasure is part of our information. Therefore, the prediction for years $t+1$, $t+2$, and $t+3$ is:

Dynamic forecast for the year $t+1$: $Y_{t+1}^{f}=E(Y_{t+1}|I_{t})=\mu+\phi Y_{t}$

Dynamic forecast for the year $t+2$: $Y_{t+2}^{f}=E(Y_{t+2}|I_{t+1})=\mu+\phi Y_{t+1}$

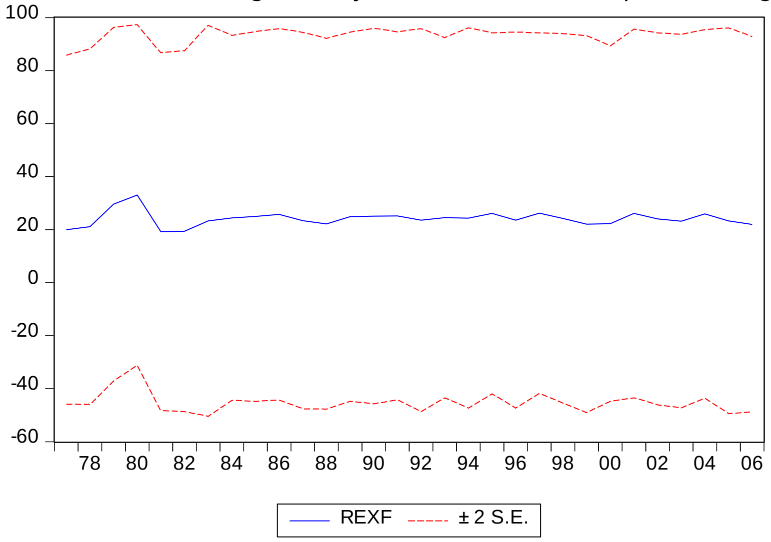
Dynamic forecast for the year $t+3$: $Y_{t+3}^{f}=E(Y_{t+3}|I_{t+2})=\mu+\phi Y_{t+2}$

Chart 3. Static forecast trend



The results of both dynamic and static forecasts for the years 1992 to 2027 are presented below for all four markets.

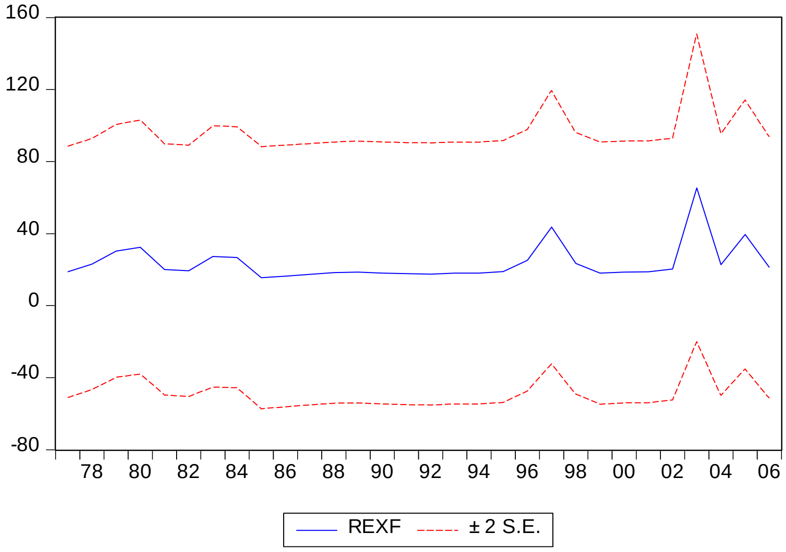
Figure 4. *Dynamic Forecast Results for the Foreign Exchange Market*



Forecast: REXF	
Actual: REX	
Forecast sample: 1371 1406	
Adjusted sample: 1377 1406	
Included observations: 30	
Root Mean Squared Error	36.44679
Mean Absolute Error	24.23849
Mean Abs. Percent Error	441.7458
Theil Inequality Coefficient	0.540868
Bias Proportion	0.000568
Variance Proportion	0.843509
Covariance Proportion	0.155923
Theil U2 Coefficient	2.117130
Symmetric MAPE	106.8125

According to the explanations given above, dynamic forecast results have larger errors for the distant future because we are standing at one point (in time). However, static forecast results are more reliable because they are step-by-step.

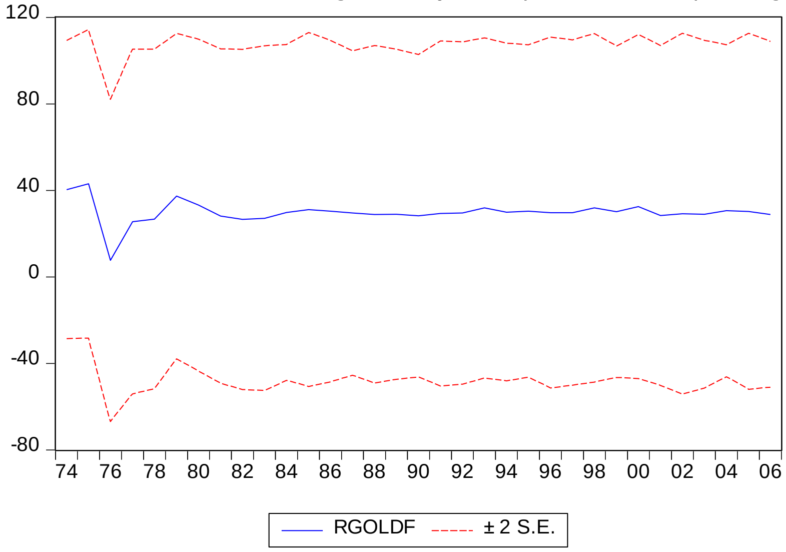
Figure 5. *Static forecast results for the foreign exchange market*



Forecast: REXF	
Actual: REX	
Forecast sample: 1371 1406	
Adjusted sample: 1377 1406	
Included observations: 30	
Root Mean Squared Error	34.42149
Mean Absolute Error	23.24566
Mean Abs. Percent Error	379.9112
Theil Inequality Coefficient	0.502895
Bias Proportion	0.000004
Variance Proportion	0.573187
Covariance Proportion	0.426809
Theil U2 Coefficient	1.824663
Symmetric MAPE	105.3299

According to the results of the static forecast for the foreign exchange market, it can be seen that in the years 2018-2019, 2025-2024, the foreign exchange market shows a price increase shock, which is more severe for the years 2025-2024, but since the end of 2025, the foreign exchange market shows a price decrease, and again in the years 2026-2027, the foreign exchange market witnesses a price increase and decrease fluctuation, which is not as severe as in the years 2025-2024.

Figure 6. *Dynamic forecast results for the gold market*

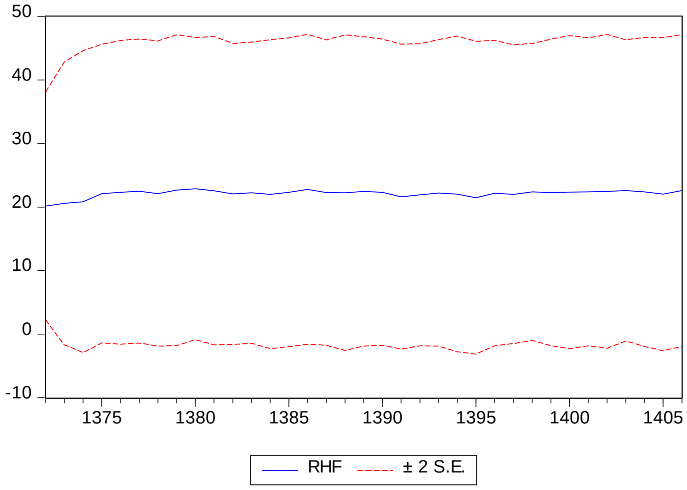


Forecast: RGOLDF	
Actual: RGOLD	
Forecast sample: 1371 1406	
Adjusted sample: 1374 1406	
Included observations: 33	
Root Mean Squared Error	37.10103
Mean Absolute Error	25.09433
Mean Abs. Percent Error	421.1105
Theil Inequality Coefficient	0.478177
Bias Proportion	0.000001
Variance Proportion	0.708801
Covariance Proportion	0.291198
Theil U2 Coefficient	1.002229
Symmetric MAPE	86.95082

Chart 7. *Static forecast results for the gold market*

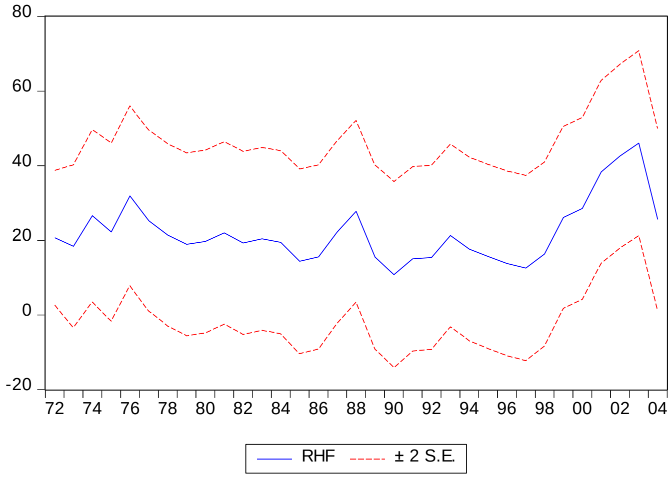
According to the results of the static forecast for the gold market, it can also be seen that in most years we see price fluctuations in this market. However, according to the results of the forecast for the gold market, we see an increase in the price of gold from 2024 onwards, and this price increase will continue with a gentle slope for other years until 2026, which is predictable given the increase in the global gold ounce and global events and crises.

Figure 8. *Dynamic forecast results for the housing market*



Forecast: RHF	
Actual: RH	
Forecast sample: 1371 1406	
Adjusted sample: 1372 1406	
Included observations: 35	
Root Mean Squared Error	11.91206
Mean Absolute Error	9.004248
Mean Abs. Percent Error	53.22965
Theil Inequality Coefficient	0.252481
Bias Proportion	0.000047
Variance Proportion	0.914457
Covariance Proportion	0.085496
Theil U2 Coefficient	1.461094
Symmetric MAPE	40.77157

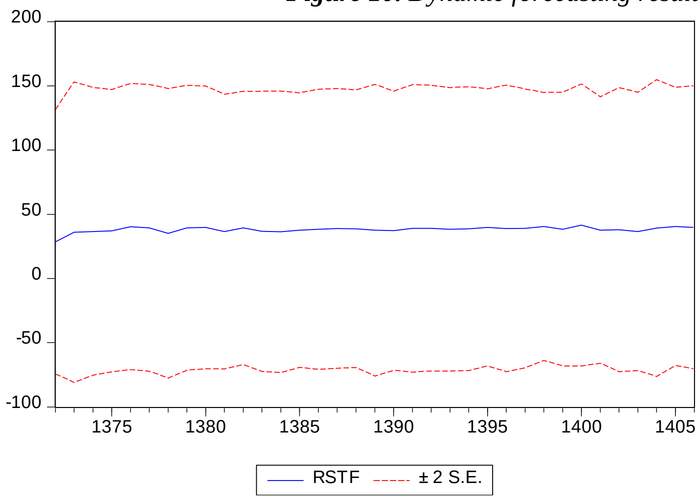
Figure 9. *Static forecast results for the housing market*



Forecast: RHF	
Actual: RH	
Forecast sample: 1371 1406	
Adjusted sample: 1372 1404	
Included observations: 33	
Root Mean Squared Error	8.520657
Mean Absolute Error	6.852158
Mean Abs. Percent Error	36.57113
Theil Inequality Coefficient	0.175833
Bias Proportion	0.000176
Variance Proportion	0.197676
Covariance Proportion	0.802148
Theil U2 Coefficient	0.845282
Symmetric MAPE	31.18157

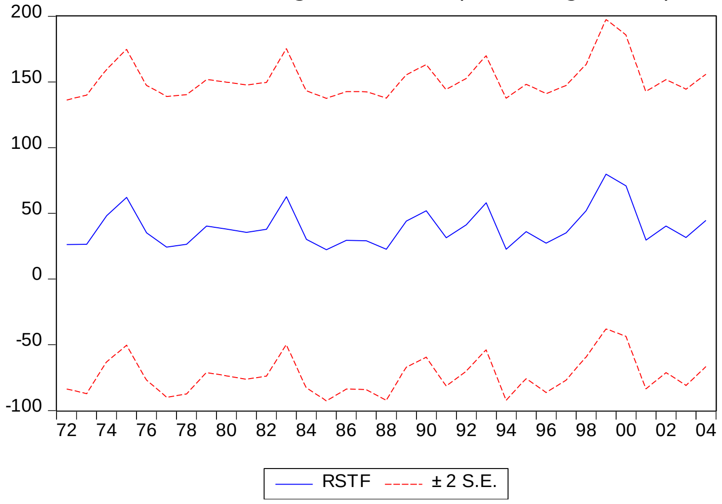
According to the results of the static forecast for the housing market, it can also be seen that we witness price fluctuations in this market every four years. However, according to the results of the forecast for the housing market in 2025, we will witness stagnation in this market and a decrease in prices, which is predictable given the events in the region and the existence of vacant houses and supply exceeding demand.

Figure 10. *Dynamic forecasting results for the stock market*



Forecast: RSTF	
Actual: RST	
Forecast sample: 1371 1406	
Adjusted sample: 1372 1406	
Included observations: 35	
Root Mean Squared Error	52.12549
Mean Absolute Error	40.66356
Mean Abs. Percent Error	260.6075
Theil Inequality Coefficient	0.499114
Bias Proportion	0.003267
Variance Proportion	0.923511
Covariance Proportion	0.073222
Theil U2 Coefficient	1.267104
Symmetric MAPE	104.3188

Figure 11. *Static forecasting results for the stock market*



Forecast: RSTF	
Actual: RST	
Forecast sample: 1371 1406	
Adjusted sample: 1372 1404	
Included observations: 33	
Root Mean Squared Error	50.26814
Mean Absolute Error	41.28321
Mean Abs. Percent Error	266.8109
Theil Inequality Coefficient	0.465050
Bias Proportion	0.001386
Variance Proportion	0.565246
Covariance Proportion	0.433368
Theil U2 Coefficient	1.091690
Symmetric MAPE	107.1826

According to the results of the static forecast for the stock market, it can also be seen that in 2004, 2011, 2014, 2015, and 2019, we witnessed an increase in the stock market price. After 2019, when the Tehran Stock Exchange was able to break its historical records in more than half a century of activity, we witnessed a recession in this market and the stock market failed to experience much increase. In general, and observing the price forecast trend for the four markets, it can be said that the highest and most stable return is related to the gold market, after which the foreign exchange market shows a relative increase for the first six months of 2015 and then follows a downward trend, while the housing and stock markets continue their recessionary trend in 2015.

From an educational perspective, the observed stability of the gold market provides a practical case for teaching defensive investment strategies, risk reduction principles, and diversification mechanisms. Therefore, this finding is incorporated into the risk management module of the proposed training model.

Discussion

The main objective of this study was to design and explain a financial market analysis training model to improve the quality of institutional investors' investment decisions. The findings of the study showed that training based on market trend analysis, prediction of financial asset behavior, and risk assessment can play an effective role in improving the investment decision-making process. The results also indicated that financial markets do not behave the same and each market is affected by different economic, monetary, and behavioral factors; therefore, financial market analysis training should be designed based on understanding the specific characteristics of each market and the interrelationship between them. One of the important findings of the present study was the significant growth of the stock market in different periods, especially in 2019 and the subsequent recession. This finding is consistent with the results of Lo (2004), which showed that financial markets have different cycles of boom and bust and that trend analysis is one of the most important decision-making tools for investors. The present results can also be explained by Fama (1970) research, because according to the efficient market hypothesis, new information is quickly reflected in asset prices and in different periods, changing economic conditions will change the market trend.

Therefore, the training of institutional investors should focus on interpreting new economic conditions in addition to analyzing historical information. Another finding of the research showed that the gold market has been more stable and has a more appropriate return compared to the stock, currency, and housing markets. This result is consistent with the research of Baur and Lucey (2010). They showed that gold has acted as a safe haven in many financial crises and has a favorable performance compared to other assets in periods of increased economic uncertainty. The results of the study of Baur and McDermott (2010) also show that gold can play an effective role in hedging risk and diversifying investors' portfolios. Therefore, the emphasis of the educational model of this study on risk management education through gold market analysis has appropriate theoretical and empirical support.

The results related to the foreign exchange market also indicated relative growth in the first half of 1404 and then entering a downward trend. This finding shows that the foreign exchange market is more affected by monetary policies, inflation expectations, and macroeconomic variables than other markets. This result is consistent with the research of Engel, Mark, and West (2007), who stated that forecasting the exchange rate is not possible without simultaneous analysis of macroeconomic variables and monetary policies. Therefore, one of the fundamental pillars of foreign exchange market analysis education is to strengthen the ability to analyze macroeconomic indicators and various economic scenarios.

The research findings also showed that the stock and housing markets are still in a recession in the horizon under study. This result is consistent with the studies of Case and Shiller (2003) who state that the housing market has long-term cycles and its behavior is strongly influenced by interest rates, household income, inflation and investor expectations. Therefore, housing market analysis training should be based on the analysis of macroeconomic variables and real sector indicators and not be limited to price analysis alone.

One of the most important achievements of the present study was the presentation of an educational model based on market trend analysis, asset behavior prediction, and risk assessment. This finding is consistent with the results of Grinblatt and Keloharju (2001), who showed that the quality of investment decisions depends more on analytical knowledge and the way investors process information than on any other factor. Barber and Odean (2001) also showed that weakness in information analysis and emotional decision-making reduces investment returns; therefore, the development of specialized training can reduce the likelihood of behavioral errors and improve the quality of investment decisions.

From the perspective of financial education, the findings of this study are also consistent with the studies of Lusardi and Mitchell (2014). These researchers showed that increasing financial literacy and training in market analysis skills have a direct impact on the quality of investment decisions, risk management, and optimal asset allocation. In fact, the educational model presented in this study is also designed on this basis and attempts to improve the decision-making ability of institutional investors by teaching market trend analysis, risk assessment, and asset behavior prediction. In summary, comparing the findings of this study with previous studies shows that the success of institutional investors does not only depend on access to financial information, but also the quality of education, the ability to analyze market trends, forecasting skills, risk management, and understanding the relationship between financial markets are considered to be the most important factors affecting investment decisions. Therefore, the financial market analysis education model presented in this study can be used as a practical framework to improve the analytical competencies of investment managers, improve the decision-making process, and increase investment efficiency in financial institutions.

Conclusion

The present study was conducted with the aim of designing a financial market analysis training model to improve investment decision-making of organized financial institutions. The increasing complexity, behavioral dynamics, and uncertainties prevailing in modern financial markets double the need to review traditional investor education models. The empirical findings from the estimation of autoregressive cumulative moving average (ARIMA) models on market rates of return indicate the existence of stationarity characteristics at high confidence levels and the ability to represent the time structure of data through autocorrelation (AR) and moving average (MA) models.

The methodological approach of this study confirms that equipping institutional investment analysts and portfolio managers with quantitative analysis and mathematical modeling tools plays an effective role in reducing information asymmetry, managing systematic and unsystematic risks, and predicting market dynamics. In this regard, the educational model developed in this study, by integrating basic market analysis concepts (such as inflation rates, interest rates, and monetary policies) and advanced portfolio management tools (such as algorithmic optimization and value-at-risk measures), provides a systematic platform for improving the quality of strategic decision-making.

Finally, the implementation of this educational framework not only helps improve the efficiency of decision-making at the level of institutional investment firms, but also enhances the sustainability and efficiency of resource allocation in the capital market by increasing the analytical wisdom of key actors. It is suggested that future research should evaluate the effectiveness of this educational model in the face of sudden structural market shocks and its combination with machine learning algorithms.

The proposed framework provides a structured educational approach for improving institutional investors' analytical capabilities by integrating financial forecasting with professional learning methods.

However, the proposed model represents a conceptual training framework, and future research can validate its effectiveness through experimental studies involving professional investors and financial analysts.

Declaration of Competing Interest

The author declares that he has no competing financial interests or known personal relationships that would influence the report presented in this article.

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