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Estimate stock returns using CAPM models and CAPM integration with neural networks (comparative study): An analytical study in the Iraq Stock Exchange

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Abstract:
The current research presents the idea of using deep learning tools and employing them in financial aspects due to their significant role and ability to explore unobservable aspects in light of financial models governed by a set of restrictions, conditions and linear relationships. On the other hand, the nature of financial data that tends to be non-linear and suffers from the missing of monthly closing prices, which imposes a state of data loss. All of this provides preference for deep learning models, including the neural network tool. The research aims to estimate financial returns in light of the capital asset pricing model CAPM as a financial model and neural networks as a deep learning tool in addition to the mask & padding tool to address the problem of missing data. The knowledge gap was determined by the inability of the capital asset pricing model to explore hidden and invisible aspects and overcome non-linear relationships. The research sample consisted of 42 organizations listed on the Iraq Stock Exchange for the period from 1/1/2021 to 31/12/2024 with 60 observations. The research concluded that the neural network tool is able to overcome the determinants in light of financial models and provide accurate estimates of returns are close to estimates under the capital asset pricing model.

Keywords: Capital asset pricing, neural networks.

Introduction:
Measuring the return on a security is a complex issue because these returns are subject to a set of explanatory variables with different effects, especially the market index variables and the systematic risk coefficient β (Fallahgoul et all. 2021:1). With the systematic risk coefficient β, the process of estimating returns becomes a comprehensive issue because it reflects the general economic situation that affects the financial asset. Accordingly, the process of estimating the financial asset is affected by the random discount factor (the theory of non-control of profits, which states that market factors affect the estimation process for all financial assets in varying proportions because the response of each asset differs according to the characteristics of each asset, and these characteristics represent a reflection of the characteristics of the entity issuing the security) (Huberman & Wang,2005:1; Chen wt all.,2019:1). According to the capital asset pricing model, the linear relationship between the model variables imposes a specific pattern of structural conditions for the model in a way that is unable to address the case of financial data that is characterized by non-linearity, abnormal distribution, randomness, and volatility (Alaminos et all.,2023:58).Accordingly, the role of neural networks emerged as one of the financial tools for their ability to process the state of vagueness and randomness of data or that which is characterized by a state of rapid volatility or anomaly, such as the case of the closeness of the time periods of monthly, weekly or daily closing prices that do not reflect the true picture of the reality of the information flowing from

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the company's business (Agrawal et all.,2016:20). Neural networks developed for the first time in 1959 by Rosenblatt. They are tools based on learning from current operations and generalizing the knowledge derived from processing operations in a way that provides more accurate results than operations under traditional models built on non-modifiable foundations (Shapiro,2003:2). What encouraged the expansion of the use of neural networks is their ability to provide accurate estimates and predictions of the risk premium. The process of exploring these elements is not clear to observe with the capital asset pricing model, as it goes beyond non-linear relationships (Fallahgoul et all.,2024:2), as the process of dealing non-linearly with financial data is a relatively recent issue, as it goes beyond many restrictions with financial statistical models that require a linear relationship. In general, non-linear methods have achieved the accuracy rate exceeded 93%. What is important is that neural networks simulate the decision-making process by investors, who tend to make decisions based on a large accumulation of knowledge arising from dealing with different situations that require making a quick decision without referring to quantitative mathematical financial models)Jan et all.,2024:266).

Research Methodology

1. Problem Statement

Due to the **inaccuracy of return estimates**, which is justified by the existence of estimation error in all statistical models, along with the **significant constraints of financial models** with a mathematical nature, there arises a challenge in financial data analysis. Additionally, **financial data** is characterized by **anomalies, randomness, and non-normal distribution patterns**, making it essential to adopt **technical tools** capable of handling such issues. Therefore, the **CAPM model** was proposed in conjunction with **neural networks** as one of the most prominent **artificial intelligence tools**.

2. Objectives

To address the research problem, the objective was defined as **employing neural networks** to improve the **estimation of monthly returns** for a set of assets listed in the **Iraq Stock Exchange**. The study focused on estimating the **β coefficient** using both the **CAPM model** and **neural networks**, aiming to achieve **higher estimation accuracy**.

3. Study Hypotheses

To guide the analytical direction of the research, two hypotheses were formulated:

1. The neural network tool has the ability to overcome the limitations of linear models when estimating returns.
2. The accuracy of the neural network tool increases after integrating it with a capital asset pricing model.

4. Conceptual Model

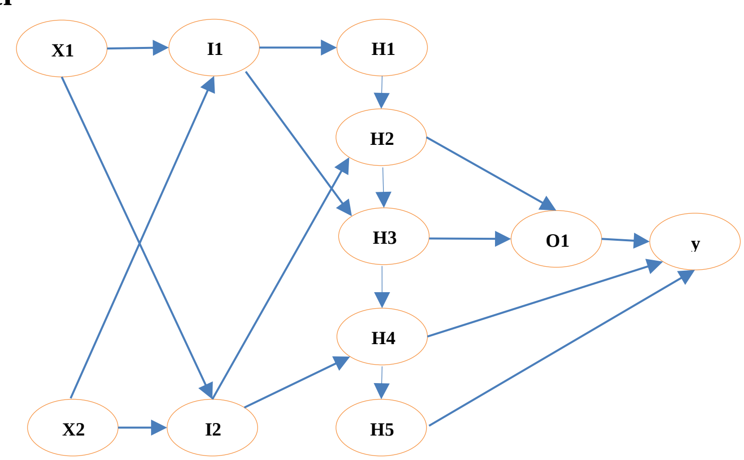

Figure (1): Procedural Diagram of the Study

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It is evident from **Figure (1)** that the inputs consist, for example, of two stocks **(1 and 2)**. These inputs are then transferred to the **two hidden layers (I and H)**, where data processing occurs through the application of the **CAPM model**. The results are then output in **two stages**: the first stage **(O)** and the final output **(Y)**, the neural network is fed with the initial data used to estimate the returns as is the case with CAPM, but with the neural network the process will not be subject to the restrictions imposed by linear relationships and the network is left with the task of determining the weights for each stage and repeating the process multiple times in a way that reduces the error.

5. Population and Sample

The study population consists of **companies listed on the Iraq Stock Exchange**. A **comprehensive sampling approach** was used, including all listed companies in the market, except for those that **did not meet the listing requirements**, leading to a **data loss exceeding 20%**. However, companies with **missing values below this threshold** were included in the study after appropriate data processing.

6. Quantity and programing tools

a. CAPM: capital asses pricing model implementation on closing price for estimation return of stock as in the equation (4):
b. $r_a = r_f + \beta_a(r_m - r_f)$….. (4)
c. Let: r_a (return of stock), r_f (risk free), β_a(beta coefficient) and r_m(market return) Neural Network.
d. Comparing model: MSE (Mean Squared Error), MBE (Mean Bias Error).
e. R program.
f. Mask & padding: In case of missing data, this tool is used to replace these values.

Theoretical Aspect

First: Literature reviews of study:

The current research examines the possibility of estimating stock returns using the Capital Asset Pricing Model (CAPM) while integrating it with artificial neural networks (ANNs) to achieve a highly accurate estimation. In this context, several studies in the literature have explored return estimation using neural networks. For instance, (Fallahgoul et all.,2014) aimed to employ neural networks to estimate stock returns, leveraging their ability to handle data complexity and randomness. Their findings demonstrated the superiority of neural networks in return estimation. Similarly, (Fang et all. 2019) investigated the ability of neural networks to estimate stock returns in the Shanghai Stock Market and found that these models outperformed traditional financial models in return estimation. Moreover, (Chen et all,.2019) tested the capacity of neural networks to operate under non-normal data distributions, which lead to nonlinear relationships, particularly in the presence of vast amounts of data in the U.S. market. Their results showed that neural networks excel in handling such cases. (Ayub et all. 2020) Introduced the concept of linear and nonlinear relationships, emphasizing that neural networks outperform traditional models in situations where CAPM fails to achieve precise estimation due to its foundational assumptions about linear model construction. Furthermore, (Adnan & Isma'eel, 2021) examined the limited adoption of neural networks in the Iraqi Stock Market, attributing this to the substantial fluctuations in stock returns, which weakened the estimation accuracy. Conversely, (Gu et all.,2021) demonstrated the ability of neural networks to identify nonlinear relationships in stock data, significantly enhancing return estimations. Similarly, (Alaminos et all.2023) analyzed estimation accuracy in relation to the nonlinear nature of financial stock data. Their study found that neural networks were key to addressing issues arising from non-normally distributed data, ultimately improving the estimation of the beta parameter and enhancing CAPM accuracy. In another study, (Drobetz et all.,2024) assessed the capacity of machine learning to capture nonlinear relationships, which cannot be effectively modeled using simple financial mathematical models that combine linear and nonlinear relations into a single framework. Additionally, (Liu et all.,2024) proposed a novel tool inspired by neural network outputs to interpret results, which contributed to the accurate estimation of the beta parameter within CAPM. This tool, referred to as **NeuralBeta**, significantly enhanced the precision of stock return predictions. Finally, (Bagnara,2024) discussed estimation accuracy in the presence of multiple factors influencing stock return estimations. The study highlighted the pivotal role of neural networks in addressing complex scenarios. Although several studies have demonstrated the potential of neural networks in handling financial data, they have also encountered challenges, as noted by Rekik, Hachicha, & Boujelbene (2014); Qiu, Song, & Akagi (2016); Tkáč & Verner (2016); Guan, Dai, Zhao, & He (2018) (Ayub et all.,2020:674).

1. Personal intervention in selecting neural network inputs without a supporting financial model.
2. The small size of input observations.

Based on the above, the **knowledge contribution** of the current research lies in employing neural networks while addressing these two limitations: the manual selection of inputs without a financial model and the constraints posed by a limited dataset.

Second: Capital Asset Pricing Model (CAPM)

The portfolio selection model introduced by Markowitz (1959) is the foundation from which the Capital Asset Pricing Model (CAPM) emerged (Fama & French,2004:25). It is considered the first model used for pricing non-physical investment assets and was introduced in 1960 by Sharpe, Lintner, and Mossin (Manniello,2021:5). The model was first presented by Sharpe in 1960 and later developed by Lintner in 1965, leading to Sharpe receiving the Nobel Prize in 1990 for his contribution to the model (Elbannan,2015:216).

This model gained significant importance due to its ability to explain many financial aspects within modern financial theory. It has been tested in various financial markets worldwide, reinforcing its validity as a tool for estimating future returns on financial assets (Fang et all.,2020:225).

The model is built on several assumptions:

a. All investors operate within a single time horizon.
b. Investors are rational.
c. There are no transaction costs for buying and selling.
d. Information is symmetric among investors.
e. Borrowing and lending can occur at a risk-free interest rate (Ndikum,2020:2-3).

According to Fama and French, the model is the cornerstone for pricing high-risk assets, as it possesses a sound theoretical and mathematical structure, allowing for the calculation of returns and the associated risk. It also provides a tool for evaluating financial assets in terms of estimated return and expected risk for each asset (Jan,2019:4). The model introduced the concept of beta (β) as a measure of systematic risk, which affects all economic activities. This makes beta a superior comparative tool, as it measures risk uniformly across all financial assets. Accordingly, beta values are classified into three levels (Wang,2024:6):

$\beta = 1$ the financial asset moves in the same direction as the market.

$\beta > 1$ The financial asset is more volatile than the market.

$\beta < 1$ The financial asset is less volatile than the market.

According to the original formulation of the (CAPM), risk is expressed as the degree of return volatility of a financial asset. Thus, the mathematical representation of the model as in the equation (1):

$$r_a = r_f + \sigma_a(r_m - r_f) \ldots\ldots (1)$$

As r_a represents the return on assets, r_f denotes the risk-free return, r_m refers to the market return, and σ_a is the standard deviation of the security relative to the market return. Since the previous equation does not provide a clear representation of the covariances among securities, the new model of the equation was introduced by replacing the standard deviation with the β coefficient, resulting as in the equation (2) (Chen,2021:916-917):

$$r_a = r_f + \beta_a(r_m - r_f) \ldots. (2)$$

Table (1) stocks in Iraq stock exchange

stocks		
Commercial Bank of Iraq	National Bank of Iraq	Iraqi Agricultural Products
Asia Cell Telecommunication	Iraqi Islamic Bank	Mansour Hotel
Al-Ameen for Insurance	United Bank for Investment	Karbala Hotel
Al-Ahlyia for Agricultural Production	National Islamic Bank	Babylon Hotel
Iraqi Dates processing and Marketing	Metallic Industries and Bicycles	Baghdad Hotel
National for Tourist Investment	Mamoura Real-estate	Ashur International Bank
Modern Sewing	Al-Mansour Pharmaceuticals Industries	Gulf Commercial Bank
Tufted Carpets	Al-Mosul for funfairs	Iraqi Middle East Bank
Middle East for Production- Fish	AL-Nukhba for Construction	Mansour Bank
National Chemical &Plastic Industries	Ready Made Clothes	Mosul Bank
Kharkh Tour Amuzement City	Iraqi Products Marketing Meat	Iraqi Agricultural Products
Iraqi land transport	Iraq Baghdad For General	
AL- Kindi of Veterinary Vaccines	Baghdad Soft Drinks	

Accordingly, based on the new modification, the expected return on a security can be determined by the response of the difference between the market return and the risk-free return, depending on the sensitivity of β, added to the risk-free return. This forms the Security Market Line (SML), as illustrated in the figure (2) [24]:

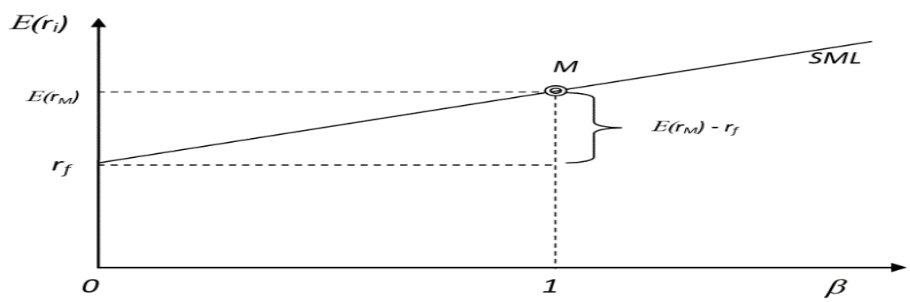

Figure (2) Security Market Line
Source: Bartosz Czekierda, "The Capital Asset Pricing Model Test of the model on the Warsaw Stock Exchange", ***Cap. Asset Pricing Model Test Model Wars. Stock Exch.*****, 2007, p. 16.**

Third: Neural Networks in the Financial Domain

Artificial intelligence has the capability to process data intelligently, which is reflected in its ability to learn from errors and overcome them during data analysis. This enhances flexibility and accuracy in executing assigned tasks. Neural networks are among the most important artificial intelligence algorithms due to their ability to process time series data, which is widely used in stock price prediction (Kusuma & Budiartha,2022:810). Over the past two decades, the use of neural networks has been developed by many financial researchers with sufficient expertise in the field. This has led to accurate estimations in financial asset return prediction (Jan,2019:5). The heterogeneity of financial data, its adherence to different statistical distributions, and the issue of autocorrelation among assets have necessitated the development of methods capable of overcoming these challenges—this is where

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neural networks play a crucial role [26]. (Cao et all.,2024:9).

Neural networks consist of a single neuron that processes input data using assigned weights, giving importance to each input. The data is then processed into new weighted outputs and forwarded as inputs to the next stage, as illustrated as in the equation (3):

$Y_t = \emptyset(X_t W_x + Y_{t-1} W_y + b)$.... (3)

As X_t represents the input values, W_x denotes the inputs with assigned weights, and Y_{t-1} refers to the reintroduced outputs, while W_y represents the outputs with new weights. This process continues iteratively until reaching the saturation point. The mechanism of the neural network's operation is illustrated in Figure (3) (Manniello,2021:14-15).

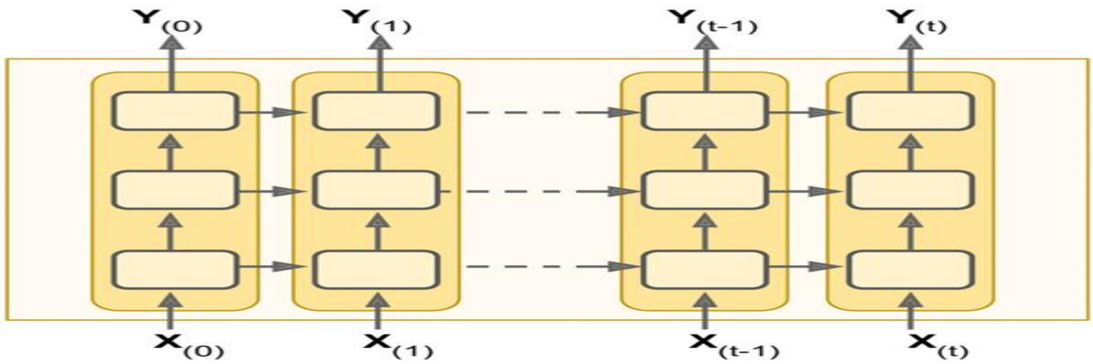

Figure (3): Neural Network Inputs

Source: R. Altieri, "Bachelor degree in Management and Computer Science, p.16.

Feed-forward neural networks consist of three layers: the first is the input layer, the second is the hidden layer, where processing and learning from errors take place, and the third is the output layer, as illustrated in Figure (4) (Agrawal et all.,2016:23)

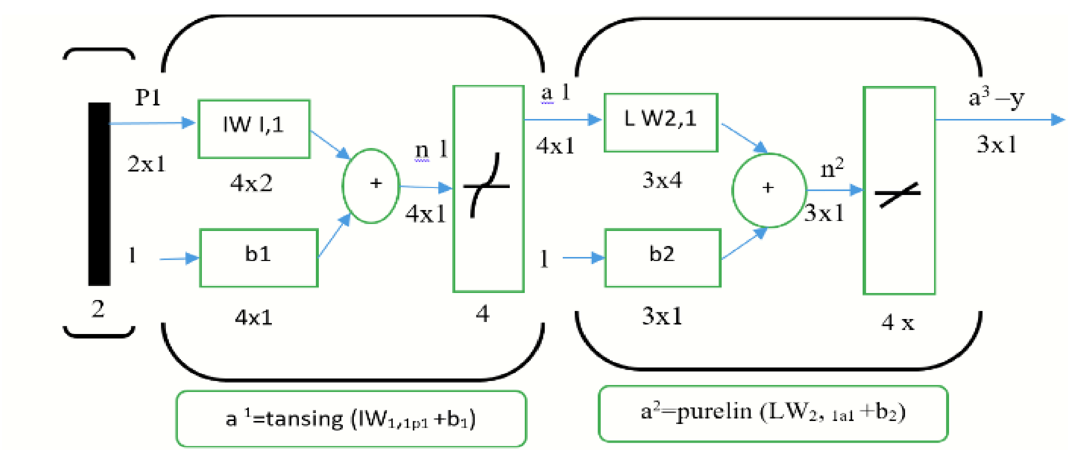

Figure (4): Layers of Feed-forward Neural Networks

Source: "S. Agrawal, D. Goyal, and P. D. Murarka, 'Implementation of Artificial Neural Network with Capital Asset Pricing Model to Predict Stock Prices of Various Sectors,' Ciência e Técnica Vitivinícola, vol. 31, no. 4, pp. 20-30, Jan. 2016", P.23.

Practical aspect

First: Estimating Returns Using the Capital Asset Pricing Model (CAPM)

In order to estimate the returns for the stocks listed on the Iraq Stock Exchange, which consists of 42 stocks as shown in table (1): After excluding those companies that experienced significant loss in closing prices due to their trading being suspended by the market for violating listing conditions, which caused the loss of many of their values within the series, the mask & pudding method was used to compensate for the missing values, provided that

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the loss percentage did not exceed 20%. Monthly closing price data was collected for the period from 1/1/2021 to 31/12/2024, resulting in 60 observations. The risk-free rate of return was 0.048, derived from data published on the Central Bank of Iraq's website, while the value of the Iraq Stock Exchange Index was 0.0125, representing the average index value for the period from 1/1/2021 to 31/12/2024. Thus, the β coefficient and returns were estimated using the CAPM model, as shown in the results in table (2).

The table (2) β coefficient and the estimated stock returns

stock	beta	Ex. return	stock	beta	Ex. return	stock	beta	Ex. return
BCOI	0.85924	0.01752	BNOI	2.47231	-0.03970	AIRP	0.96028	0.01394
TASC	0.32582	0.03644	BIIB	0.86106	0.01746	HMAN	1.88476	-0.01886
NAME	-0.05349	0.04990	BIBI	0.03688	0.04669	HKAR	0.31322	0.03689
AAHP	-0.29569	0.05849	BNAI	-0.34457	0.06022	HBAY	0.54810	0.02856
IIDP	0.12394	0.04360	IMIB	-0.38242	0.06157	HBAG	0.48150	0.03092
HNTI	0.47482	0.03116	SMRI	3.61090	-0.08009	BASH	0.70217	0.02309
IMOS	0.77434	0.02053	IMAP	0.39084	0.03414	BGUC	0.81348	0.01914
IITC	0.56330	0.02802	SMOF	-0.53043	0.06682	BIME	0.03918	0.04661
AMEF	-0.12531	0.05245	SNUC	0.43255	0.03266	BMNS	-0.19956	0.05508
INCP	-0.21118	0.05549	IRMC	-1.66187	0.10695	BMFI	0.53294	0.02909
SKTA	0.48430	0.03082	AIPM	0.38305	0.03441	AIRP	-2.00805	0.11923
SILT	23.40798	-0.78235	SBPT	-0.24707	0.05676			
IKLV	0.11698	0.04385	IBSD	0.31822	0.03671			

Using the R program, the value of β and stock returns for the companies listed in the table (1), were estimated. Based on the results shown in the table (2), the highest value of the β coefficient was for the Iraqi land transport, with a value of 23.40798, which is a very high value indicating significant volatility in the stock returns for this company. It is a positive value, indicating a correlation with the Iraq Stock Exchange index. On the other hand, the lowest value was for the **Sumer Commercial Bank**, with a value of -2.00805, indicating a negative relationship. The lowest estimated return value was for the Iraqi land transport, with a value of -0.78235, which aligns with the value of β, while the highest return value was for the **Sumer Commercial Bank**, with a value of 0.11923, which also corresponds to the value of β. These abnormal values reflect the state of instability in closing prices resulting from the instability of supply and demand for shares of certain companies. This fluctuation is attributed to the state of instability experienced by the companies issuing these shares.

Second: Estimating returns using neural network model integrated with CAPM

In order to increase the accuracy of the estimate, the CAPM was integrated with forward neural networks to estimate the β coefficient and the return on the assets listed in the table (first table). The results were as shown in Table (3)

Table (3) β coefficient and stock return estimated using neural networks

stock	beta	Ex. return	stock	beta	Ex. return	stock	beta	Ex. return
BCOI	0.09730	0.04455	BNOI	-0.11902	0.05222	HMAN	-1.06679	0.08584
TASC	-1.81669	0.11244	BIIB	5.52769	-0.14808	HKAR	-0.24263	0.05661
NAME	-27.19592	1.01272	BIBI	1.52533	-0.00611	HBAY	0.31557	0.03681
AAHP	-5.05021	0.22715	BNAI	1.50838	-0.00551	HBAG	-1.29989	0.09411
IIDP	2.51390	-0.04118	IMIB	-5.01915	0.22604	BASH	6.12529	-0.16928
HNTI	-2.97758	0.15362	SMRI	-0.93826	0.08128	BGUC	-12.15607	0.47921
IMOS	-5.23112	0.23356	IMAP	-0.16750	0.05394	BIME	-1.11199	0.08745

IITC	1.36860	-0.00055	SMOF	1.51096	-0.00560	BMNS	-7.94061	0.32968
AMEF	-3.77577	0.18194	SNUC	-0.08572	0.05104	BMFI	0.22652	0.03996
INCP	-3.28060	0.16437	IRMC	3.31625	-0.06964	IBSD	15.49553	-0.50167
SKTA	-0.43483	0.06342	AIPM	0.48028	0.03096	AIRP	8.44425	-0.25154
SILT	13.19263	-0.41998	SBPT	-6.56876	0.28101			
IKLV	0.87501	0.01696	IBSD	-0.01590	0.04856			

Noting the results shown in table (3), the highest value of the β coefficient belonged to Baghdad Bank, with a value of 15.495, which is a very large value indicating high volatility in the stock returns of this company.

Third: Comparing the results using RMSE and MBE methods

To verify the accuracy of the estimates between the neural network model and the Capital Asset Pricing Model (CAPM), the metrics of Mean Squared Error (MSE) and Mean Bias Error (MBE) will be used. This positive value indicates a positive correlation with the Iraq Stock Exchange Index. On the other hand, the lowest value was for Al-Amin Insurance Company, with a value of -27.195, which indicates a negative relationship. The lowest estimated return was for Baghdad Bank, with a value of (-0.50167), which aligns with the value of β. On the other hand, the highest return was for Al-Amin Insurance Company, with a value of 1.01272, which also corresponds to the value of β.

Table (4) Comparison of the estimated return using MSR and MBE

stock	MBE	MSE	stock	MBE	MSE	stock	MBE	MSE
BCOI	-0.02703	0.001	BNOI	-0.09192	0.008	HMAN	-0.1047	0.011
TASC	-0.076	0.006	BIIB	0.165539	0.027	HKAR	-0.01972	0.000
NAME	-0.96283	0.927	BIBI	0.0528	0.003	HBAY	-0.00825	0.000
AAHP	-0.16866	0.028	BNAI	0.06573	0.004	HBAG	-0.06319	0.004
IIDP	0.084779	0.007	IMIB	-0.16448	0.027	BASH	0.192375	0.037
HNTI	-0.12247	0.015	SMRI	-0.16137	0.026	BGUC	-0.46007	0.212
IMOS	-0.21303	0.045	IMAP	-0.01981	0.000	BIME	-0.04084	0.002
IITC	0.028566	0.001	SMOF	0.072415	0.005	BMNS	-0.2746	0.075
AMEF	-0.12949	0.017	SNUC	-0.01838	0.000	BMFI	-0.01087	0.000
INCP	-0.10888	0.012	IRMC	0.176589	0.031	IBSD	0.359887	0.130
SKTA	-0.0326	0.001	AIPM	0.003449	0.000	AIRP	0.370775	0.137
SILT	0.443458	0.197	SBPT	-0.22425	0.050			
IKLV	0.02689	0.001	IBSD	-0.01185	0.000			

Noting the results in table (4), it is clear that the MBE and MSE values were close to zero, indicating a strong alignment between the estimated values using the Capital Asset Pricing Model (CAPM) and the neural networks. The lowest estimation accuracy was observed for Al-Amin Insurance Company, due to the high volatility in the closing prices, which was reflected in the large value of β, as mentioned earlier. Meanwhile, the best estimation accuracy was for the Meat Production and Marketing Company, which indicates the effectiveness of integrating neural networks with the Capital Asset Pricing Model (CAPM) to estimate returns, provided that the monthly closing price series remains stable.

Conclusion

The current research tests the use of neural networks integrated with the capital asset pricing model (CAPM) to maximize the accuracy of parameter estimation in the CAPM model. Due to the nature of financial data, specifically the monthly closing prices, which arise from supply and demand factors, causing volatility in their values and the loss of many of those values, coupled with the significant limitations of financial mathematical models, there is a need for a tool capable of overcoming these obstacles, these obstacles are rooted in the random nature of the Iraqi Stock Exchange data, which tends towards an abnormal distribution. The research concluded with several findings, including the ability of the neural network algorithm to estimate the parameters of the CAPM model, with the MSR and MBE values close to zero. Additionally, there was a significant alignment between the accuracy of the estimates and the anomalies of the closing prices, as in the case of Al-Amin Insurance Company. This indicates the ability of the neural network to detect the instability in the monthly closing series. On the other hand, the neural network provided parameter estimation that outperformed that obtained using the CAPM model, based on the two hypotheses of the study, the study proved the superiority of the neural network tool in overcoming the limitations with linear models that are not consistent with the nature of the data of the Iraqi Stock Exchange. With regard to the second hypothesis, the performance of the capital asset pricing model improved after merging it with the neural network in a way that provided guidance for that tool.

Data Availability:

The data used to support the results of this study has been included in the article.

Conflict of Interest:

The authors declare that they have no conflicts of interest.

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