

Research Article

The Co-Movement between International and Emerging Stock Markets Using ANN and Stepwise Models: Evidence from Selected Indices

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In the past two decades, especially after the financial crisis of 2007–09, the literature for examining the availability of integration between the stock exchanges in developed and developing markets has grown. The importance of this topic stems from the significant implications of the linkage between exchange markets on various decisions taken by interested parties, such as policymakers and investors, in the decisions for portfolio diversification. This study examines the relationship between a developing stock exchange index, Amman Stock Exchange Index (ASEI), and the number of international indices, including S&P 500, NASDAQ, Nikkei, DAX, CAC, and HSI for 2008–2019. To validate the availability of the linkage between the indices, the author includes various tests of a correlation coefficient, stepwise regression analysis, and artificial neural network (ANN). Despite the results indicating that the ANN is more efficient than linear regression in investigating the availability of the relationship between ASEI and international indices, stepwise regression and neural network support this relationship. Furthermore, ANN results revealed that the S&P 500 index and year have the most substantial relationship with ASEI. Our research is theoretically and practically important; policymakers and investors can benefit from our findings. Future studies may explore the effect of different international stock market indices on ASEI or other developing markets. Further studies can use macroeconomic factors to build prediction models for stock market indices.

1. Introduction

Financial markets are the key role players in the financial system of countries because of their ability to facilitate the flow of saving and investing decisions in the economy. Financial markets are also considered the most profitable and riskiest field for investors because they need accurate expectations of stock indices' movement to help them take the appropriate profitable investment decisions [1–4]. However, making these right decisions is a complicated mission because many macroeconomic variables and international factors interact to influence the movement of stock markets indices and subindices into unanticipated levels. [5–8].

Globalization increased the degree of cross-country movements among countries, especially with U.S. financial exchanges playing the prominent dominant role across all

countries. Thus, exploring various aspects and economic development of these financial markets and understanding the integration of international and national financial markets are important. Accordingly, finding the relationship between international stock indices caught the attention of many academics, investors, policymakers, and other parties. Reference [9] developed a network for 83 international stock indices to probe the correlation and the flow of information from one stock index to another. Transfer entropy is an effective way to quantify the flow and interaction of information between indices.

The main goal of understanding these relationships is to analyze the availability of linkages between various financial exchanges in developed and developing countries. Thus, linking different exchanges makes predicting financial market movements easy and helps take many actions on investors' and policymakers' levels. This interest grew even

more significant after the 2007-08 global financial crisis to assess and recognize the degree of interdependence relationship across the exchanges. Researchers have attempted to predict stock market indices using different statistical models such as fractional co-integration, multivariate time series, and ARIMA model [5, 6, 10]. However, many scholars have found that different generations of neural networks and artificial neural networks (ANNs) are the best prediction models for indices. These models have high accuracy and help stakeholders make accurate decisions [7, 11–13].

In this study, the author aimed at investigating the existence of the relationship between the Amman Stock Exchange Index (ASEI) and the number of main indices worldwide from 2008 to 2019. This period covers many significant events that sharply affected the economic conditions, stability, and exchange markets of the whole world in general (i.e., financial crisis 2007-08) and Jordan in specific (i.e., an increasing number of refugees because of Arab spring in many neighboring countries). To accomplish our objective, the researcher picks up an appropriate indicator that properly reflects the stock market's functioning of the stock exchange index. Indices represent the performance of the stock exchange market, echo investors' sentiments towards its economy, and give a clear indication of the overall healthiness of the financial and economic conditions. Indices are a crucial part of global investment because of their relationship with the investment decision process.

Jordan is an emerging market economy and "upper-middle-income country" as ranked by World Bank. IMF ranked Jordan's banking sector as "highly developed" along with GCC economies and Lebanon. The Index of Globalization ranked Jordan as the most globalized country in the MENA region. Recently, Jordan has been facing severe structural problems because the country lacks natural resources, water is scarce, and the population is snowballing. Other challenges in Jordan are high unemployment rates, waves of refugees from neighboring countries, and low rates of tourism return. Furthermore, Jordan has one financial market: Amman Stock Exchange (ASE) was established in March 1999 as an independent nonprofit institution and is authorized to operate as a regulated market for trading securities. In 2017, ASE became a public shareholding company wholly owned by the Jordanian government and an emerging stock market that plays a crucial role in the economy. Moreover, ASE is an active member in many national and international federations and organizations such as Arab Federation of Exchange and the World Federation for Exchange. ASE signed many memorandums of understanding (MOUs) with many stock exchange and financial markets: Middle East Investor Relations Association (MEIRA) and NASDAQ Stock Exchange. Accordingly, Jordan's economy in general and ASE face many challenges, and they have become of interest to many scholars.

Many researchers have studied the prediction of stock markets using different macroeconomic factors and feature issues [14–16]. However, few researchers tried to predict the performance of stock markets through the integration between different international and national markets' indices [10, 17, 18]. Besides, limited scholars focused on integrating with international markets on either developing markets or

Jordan's financial market (ASE) [6, 19, 20]. In investigating the expected integration between stock markets, most researchers applied regression analysis models and other advanced models. However, researchers rarely used neural network models to specify the ability to build robust prediction systems. These prediction systems play a key role in helping investors to diversify their portfolios and assisting policymakers in making the appropriate decisions. Furthermore, these prediction models appear strongly on their ability to specify the best parameters for future prediction.

Our study makes the following contributions to the previous literature. First, our study focuses on studying the integration between specific international markets and developing countries (i.e., Amman Stock Exchange). Second, the international markets in this study are picked according to their connection with Jordan's economy and ASE. These indices are the financial markets of France (CAC40), Germany (DAX), the USA (NASDAQ and S&P 500), Japan (Nikkei 225), and Hong Kong (HSI). Third, the author uses stepwise regression and ANN models to build a prediction model for ASEI using international stock markets' indices. Fourth, the author highlights the most critical relative literature that studied the integration of different international and national markets.

The study's structure contains the following: Section 2 reviews the theoretical framework and the primary literature regarding this topic. Section 3 explains and outlines the data in the sample. Section 4 shows the steps of the methodology and the process of building the models. Section 5 explains and discusses the test results. Section 6 shows the conclusions. Section 7 provides the practical implication. Section 8 discusses the limitations and possible avenues for further study.

2. Theoretical Framework and Previous Studies

The financial market's index is one of the vital indicators for any country. Understanding the index fluctuation is crucial because of the interaction between multi-economic and noneconomic factors that walk in line and across one another [6, 7]. Thus, the accurate prediction of financial markets and the integration between financial markets are the master key of extra profit. Reference [9] developed a network for 83 international stock indices to probe the correlation and the flow of information from one stock index to another. Transfer entropy is an effective way to quantify the flow and interaction of information between indices.

Researchers have used different economic factors and features to study their effect on the stock index prediction. Reference [21] focused on the role of the publicly disclosed information on the stock market index, and [22] found strong evidence that market competition product affects the stock market index. Reference [23] examined the causal effects between the sentiment index and U.S. industry returns using wavelet Granger causality and frequency domain causality approaches. The results confirmed the causality from FEARS to stock returns in short and medium terms. The sentiment index has causal effects on and stronger correlation with the overall stock market index and subsector indices.

2.1. Prediction of Developed and Developing Indices Using Macroeconomic Indicators. Many researchers investigated the prediction power of different macroeconomic indicators in predicting the financial markets' indices. Reference [24] examined the integration between five markets of BRICS, oil, and gold. They used the wavelet approach. The results showed co-movements between oil and the stock market at low frequencies. Gold is a safe haven. The most substantial effect of co-movements was captured during the onset of the financial crisis. Reference [16] revealed that changes in the U.S. economic policy uncertainty index negatively affected the co-movement between China's A/B stock markets and the U.S. market.

Reference [15] applied econophysics methodology to analyze one stock index that consists of firms producing clean energy (S&P Global Clean Energy Index). Besides, they compare it with New York Stock Exchange (NYSE) as a stock market benchmark and the price of crude oil. The results showed that the clean energy index has higher time-series dependence and less exposure to oil price than the NYSE. Reference [14] investigated the integration between BRICS financial markets and oil and natural gas indices. The findings revealed a strong interrelationship between oil and BRICS indices after removing the effects of natural gas price returns. Reference [25] found significant co-movements between oil price and Saudi Stock Market Index (TASI) over time and across frequencies.

2.2. Integrations between International Financial Markets. According to much recent research, the integrations between international financial markets are apparent. For example, [26] examined the co-movements and volatility in Pacific-developed markets. They found that the integration between these markets is so high, the expected benefits from diversification are limited, and the co-movements between these markets are intensely strong during the financial crisis. Likewise, [27] findings revealed that the skew phenomenon exists in the global stock markets and that the SGBM model works better than the traditional GBM model.

Reference [28] implemented the stock index, trading volume, and the daily difference in two stock market indices to build a multifactor fuzzy time-series fitting model. The evaluation of this proposed model was for the NASDAQ Stock Market (NASDAQ), the Taiwan Stock Exchange Index (TAIEX), and the Hang Seng Index (HSI). The results show that the proposed model is better than the other models. Besides, [29] applied technical features and macroeconomic indicators for the three major U.S. stock indices. The findings revealed that the improved stacking method outperforms state-of-the-art ensemble learning algorithms and deep learning models, achieving a higher level of accuracy.

Reference [30] investigated the impact of the U.S.-China trade war on the co-movements between the U.S. and Chinese stock markets. They applied event study analysis to study the effect of news and announcement regarding this trade war. They found that the co-movements among mainland China, Hong Kong, and the USA are positively affected by new releases. They revealed that this war had reduced the benefits of portfolio

diversification in managing risk. Similarly, [31] examined the volatility and co-movement between China, Hong Kong, and U.S. markets. Their findings showed a different sensitivity to the same event. The returns' correlation between China and Hong Kong increased sharply after 2007. Although the co-movements for return rates among these three stock markets possess mutual dynamic synchronization features, deviations are usually due to emotional transfers of funds in the international market when a significant economic or financial event occurs. Reference [32] examined the effect of two stock markets' connecting programs of Shanghai-Hong Kong stock connect and Shenzhen-Hong Kong stock connect on the co-movements among Mainland China, Hong Kong, and U.S. stock markets. The two connect programs' combined effects significantly enhance the weekly co-movements between three stock markets after the Shenzhen-Hong Kong stock connect program with an insignificant effect on the Hong Kong-U.S. pair. The structural breakpoint test of the dynamic correlation coefficient among the stock markets easily appears during the subprime crisis. Furthermore, [33] measured the cross-correlations between the U.S. and eight stock markets (G7, China, and Russia). The results show that the correlation levels with U.S. stock markets decreased in the period before the crisis. The results show a contagion effect postcrisis.

2.3. Integrations between International Financial Markets and Domestic Financial Markets. Several researchers have discussed the relationship and integrations between many international and national stock markets' indices. Reference [17] explored the integration between many developed and developing stock markets using the VAR-AGDCC-GARCH approach. He found that the correlation between the stock return shocks of Central and Eastern European countries has increased significantly during the financial turmoil, the U.S. subprime crisis, and the Euro area sovereign debt crisis. Reference [10] examined the interaction between five Asian countries with U.S. and China stock market indices through applying fractional co-integration methods. They revealed that all stock indices exhibit long memory, and the Asian stock market indices were more integrated with the U.S. stock markets indices than China stock indices. Many study findings have proven the linkage among different indices worldwide. Reference [18] studied the predictability of the Saudi Stock Market Index (TASI) and international indices and found that U.S. volatility risk indices are dominant in forecasting Saudi stock exchange.

Reference [34] investigated the financial combination between three stock indices (Dubai, Abu Dhabi, and the FTSE NASDAQ Dubai UAE 20 index). They found that the three UAE stock markets are strongly related. Reference [35] studied the relationship between TASI and U.S. stock market indices (S&P 500 and Dow Jones) and exhibited a long-run relationship between those indices. Likewise, [6] studied the estimation power of six international financial market indices on TASI using the ARIMA model. They found that S&P 500, Nikkei, CAC, and HSI of international indices' closing prices can predict the opening price of the TASI.

Reference [36] proposed a model for stock market prediction based on a large amount of historical data and a machine learning approach for the Dhaka Stock Exchange and Chittagong Stock Exchange. The linear regression approach of machine learning predicts individual stock securities. Reference [37] investigated the integration and contagion between major African stock markets and developed stock markets during the global financial and Eurozone sovereign debt crisis. Their findings showed limited evidence of integration but high and positive dynamic correlation through the crisis period. Accordingly, the study interpreted the observed co-movements caused by the contagion between these financial markets. Nevertheless, [38] studied the relationship between several stock market indices and the Ukrainian stock index by applying Granger causality and co-integration. The output supports that world stock exchange indices influence the Ukrainian index. According to [39], they examined the volatility, cross-market correlation, and co-movements between developed (Spain, the UK, Germany, and France) and emerging (Poland, Hungary, Croatia, and Romania) stock markets in the European Union. The findings show significant existence of volatility clustering among all the eight markets except for Croatia and Poland. They also reveal that both recent and past news affect the present volatility.

2.4. Prediction of Amman Stock Exchange Index (ASEI) and ASE Subsectors. Few scholars study the prediction of index and volatility for ASE and ASE subsectors using different models [40, 41]. Reference [20] reveals that the fuzzy neural network models are superior in predicting ASEI using trading volume as an input variable. Nevertheless, [42, 43] examined the ARIMA model's ability to forecast the Jordanian banking sector index (JBI) and ASEI, respectively; both papers found that the ARIMA model has significant results in short-term prediction of JBI and ASEI, respectively.

Reference [44] proved that the banking sector index can be predicted using five financial ratios: debt ratio, stock turnover, return on assets, price-to-book value, and return on equity. Few researchers have tried to estimate the relationship between international stock market indices and Amman Stock Exchange Index (ASEI) and predict one of the ASE subindices. Reference [19] showed that the co-integration and causal relationship exists among ASEI, U.S. stock markets, and the U.K. market.

Furthermore, [45] investigated the effect of short- and long-run corruption on predicting ASEI. References [46, 47] used many accounting and market indicators to predict ASEI. References [4, 48] also applied interest rates and different macroeconomic factors (i.e., interest rate, exchange rate, and oil). Both findings exhibited an inverse effect of the macroeconomic factors on ASEI prediction power and revealed a negative impact on the prediction.

3. Data

The goal of this study was to investigate the availability of integration between many international indices and the

Amman Stock Exchange Index (ASEI) for 2008–2019. The period of this study does not cover the COVID-19 period, so the findings will not be affected by this pandemic. The international markets' indices taken under consideration in this study were chosen after checking Jordan's international policies, trade balance, and memorandums of understanding (MOUs) between Jordan and different developed countries. Also, these indices are considered the key financial market indices applied [6, 7]. Accordingly, this study put into action the following financial market indices: France (CAC40), Germany (DAX), the USA (NASDAQ and S&P 500), Japan (Nikkei 225), and Hong Kong (HSI). Reference [6] found that the previous indices are significant in building a prediction model for emerging stock market indices (i.e., TASI). The data were collected from investing.com and exchange's websites and then arranged to fit into similar timing (i.e., day, month, or year) to prepare for the next step in the analysis process.

The description of our sample for the stock market indices is shown in Table 1.

Table 2 presents the statistical description of our sample. The included timing of the collected data is represented by day, month, and year. It covers daily trading sessions for 12 months from 2008 to 2019. Furthermore, the statistical measurements encompass the standard deviation that reflects the fluctuations of the indices during the study period. The preprocessing results showed that Nikkei, HSI, and DAX indices have higher volatility and mean (index return) than other international indices. The maximum index return is recorded for the HSI, and the minimum index return is recorded for S&P 500.

4. Methodology

This study investigates the relationship between the international indices and ASEI using the Pearson correlation analysis. Stepwise linear regression is used to build prediction models. Finally, the best prediction model from the previous step is applied with a neural network to improve the performance of the stepwise linear regression model.

The methodology is designed to feed the neural network model using the output of the stepwise linear regression model. The stepwise linear regression is used to find the most important variables that can be used to build an artificial neural network model that can accurately predict the output of the Amman Stock Exchange Index. This step aims to select the critical features that can be used to improve neural network prediction. Therefore, the study extracts the crucial features and feeds them to the neural network instead of using all the used features.

Many statistical measurements are applied to investigate the availability and shape of the relationship between the selected indices and ASEI. This section covers the Pearson correlation coefficient and stepwise linear regression. *The first step is to calculate the Pearson correlation coefficient and sketch the figures that indicate the power and direction of the relationship between ASEI and international indices. Pearson's correlation function is as follows:*

TABLE 1: Description of our sample for the stock market indices.

Index	Name of exchange	Description	Country
S&P 500	Standard and poor's 500 index	Market capitalization-weighted index of the 500 largest U.S. publicly traded companies	USA
NASDAQ	USA general index National Association of Securities Dealers Automated Quotations	Market capitalization-weighted index for U.S. technology stocks	USA
Nikkei 225	Japan stock market	Market capitalization-weighted index of Tokyo's top 225 companies traded on the Tokyo stock exchange	Japan
CAC40	French stock market index (Cotation Assistée en Continu)	Market capitalization-weighted index of the 40 most significant stock caps on the Euronext Paris	France
DAX	German stock market index (Deutscher Aktienindex)	Market capitalization-weighted index of 30 industrial companies in Germany	Germany
HSI	Hang Seng Index (HSI)	Market capitalization-weighted index of a selection of the largest companies in Hong Kong	Hong Kong
ASEI	Amman Stock Exchange Index	Market capitalization-weighted index of a selection of the largest 100 firms traded in Amman exchange	Jordan

TABLE 2: Statistical description of date and general indices worldwide.

	No.	Range	Minimum	Maximum	Mean	Std. deviation	Variance
Day	2019	30.00	1.00	31.00	16.0530	8.53394	72.828
Month	2019	11.00	1.00	12.00	6.4344	3.37322	11.379
Year	2019	11.00	2008.00	2019.00	2013.4547	3.42357	11.721
NASDAQ	2019	7405.59	1299.59	8705.18	4253.5325	1970.84674	3884236.854
S&P 500	2019	2471.08	682.55	3153.63	1805.8806	626.65186	392692.550
Nikkei	2019	17215.64	7054.98	24270.62	14901.4053	4924.29275	24248659.073
CAC40	2019	3375.24	2554.55	5929.79	4311.8027	772.81795	597247.590
DAX	2019	9868.88	3690.72	13559.60	8869.1848	2645.40609	6998173.376
HSI	2019	21951.05	11015.84	32966.89	23028.1739	3726.58847	13887461.657
ASEI	2019	3266.08	1777.62	5043.70	2302.4732	575.83374	331584.497

$$\text{Pearson} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{(n-1)S_x S_y}, \quad (1)$$

where \bar{x} , \bar{y} , S_x , S_y , and n are the sample mean for the first variable, the sample mean for the second variable, the standard deviation for the x variable, the standard deviation for the y variable, and the number of samples, respectively.

The second step illustrates which of these indices has the strongest effect on ASEI. Stepwise linear regression is applied [49]. The stepwise model is a combination of forward and backward regression selection methods, and it depends on adding and removing variables from the suggested model to reach the optimal model. Thus, to avoid an infinite loop while adding and removing, cutoff point probability for adding (i.e., 0.05) and removing (i.e., 0.10) is needed. Subsequently, this process generated various models. Therefore, the next stage is to pick up the best model containing the most affecting indices on ASEI using the P value for Pearson's correlation coefficient (R-square), error, and the P value of F-test and t-test. Their formulae are as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2},$$

$$\text{Error} = \frac{1}{N} \sum_{i=0}^N |y_i - \hat{y}_i|,$$

$$F\text{-value} = \frac{SS_B / (k-1)}{SS_W / (N-K)}, \quad (2)$$

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}},$$

$$p\text{ value} = 2xP(T > t).$$

The third step is to build an artificial neural network model. In this step, the best stepwise linear regression model is considered to build an artificial neural network. The artificial neural network model was divided into three layers: input, hidden, and output. The input layer contained the selected international indices and dates. The main task of the

input layer is to receive the input variables that will be used as independent variables, where the output layer stores the information about the dependent variables (ASEI). In comparison, the hidden layer creates a mathematical relationship between the input and the output variables using weight and bias variables, as shown in Figure 1.

A prediction model is built using an artificial neural network. The first step is to feed the independent and dependent variables to a network with random weights and biases. The created neural network begins training until the preset goals are achieved or the predefined time is reached. Then, a validation process improves predictability by feeding additional data into the network that has not previously been used in the original data. The last process is not essential for creating a neural network model. At the end of this step, the network is ready to be used in a prediction system. The trained network can be used to predict a new value using the following equation:

$$\text{Amman Stock Exchange Index} = f\left(\sum_{j=1}^J O_j w_{jk} + b_k\right), \quad (3)$$

where O is selected indices, K is the number of nodes in the output layer, $f(\cdot)$ is the transfer function, w_{jk} is the weight from the hidden output layer, and b_k is the bias. Based on the literature review, the optimum parameters to implement neural network predictors are shown in Table 3.

The neural network forwarded the inputs to the hidden layers from the previous layers (mainly, input or hidden layer) to calculate the Amman Stock Exchange index. For each node in the hidden layer, the neural network will use the sigmoid activation function as follows:

$$f(x) = \frac{1}{1 + e^{-x}}, \quad (4)$$

where x is the input of the node. Afterward, in the output layer, the neural network used an identity activation function as follows:

$$f(x) = x. \quad (5)$$

The combination between sigmoid and identity activation functions is selected after experimental analysis of the Amman stock market dataset.

As shown in Table 4, the data are divided into the following phases: training 2008–2017 and testing 2018 and 2019. The range for the mean and standard deviation for the training phase is 7,934 and 1,883, respectively. The testing data have a range of mean and standard deviation as 11,469 and 631, respectively.

Figure 2 summarizes the adopted steps in applying the methodology.

5. Results and Discussion

This section explains the outcomes of the main parts discussed in the former section to validate the research methodology in this study. The results include the Pearson correlation coefficient, graphical representation between

international and ASEI, running stepwise regression model, and building prediction model using ANN.

5.1. Correlation Test. Firstly, the Pearson correlation is discussed, as shown in Table 5. Table 5 represents the output of correlation coefficient and their P values between day, month, and year of trading and international indices (S&P 500, NASDAQ, Nikkei, CAC, DAX, and HSI) with ASEI. For the day, it is the only variable with a negative statistical insignificant relationship with ASEI. The month, year, and all international indices, including S&P 500, NASDAQ, Nikkei, CAC, DAX, and the HSI, have a significant negative relationship with ASEI. Four of eight have the highest negative relationship with ASEI, which are year, NASDAQ, S&P 500, and DAX with the following amounts -0.617 , -0.456 , -0.425 , and -0.421 , respectively. On the other hand, month, CAC, HSI, and Nikkei have a lower correlation with ASEI equal to -0.112 , -0.069 , -0.218 , and -0.259 , respectively. Therefore, all the prominent stock market indices applied in this study have a negative correlation indicating an inverse relationship. If these international indices increase, the ASEI is expected to decrease.

Visual graphs and correlation tests were built to understand the behaviour of each independent variable (i.e., international exchange indices with ASEI and specify the nature of the relationship between them, as presented in Table 6 and Figures 3 and 4. Regarding the variables that refer to timing, day has no significant relationship; month in the first six months of the year is upward sloping, and the next six months is downward sloping, where the year variable shows downward sloping with other month variables. However, the other figures consisting of all the international indices show mixed data; part of it is on the line, and the others are outliers. Thus, the figures cannot give clear affirmative support towards the linear relationship between the indices and ASEI. Therefore, to overcome this issue, the study will apply linear and nonlinear analysis through building stepwise analysis and neural networks, respectively.

5.2. The Stepwise Linear Regression Model. The stepwise linear regression model is applied with all selected variables to build a linear regression model. Tables 5–7 contain the output results of running stepwise regression for ASEI with the international indices. Stepwise regression determines which selected predictors significantly contribute to the dependent variable. Thus, the process requires multiple phases to add and remove variables until the regression reaches the cutoff point. Table 6 represents all the values of R^2 and error for all the developed models by stepwise. R^2 is the amount of variance in the outcome accounted for by the predictor variables; it also measures the strength of the relationship between the independent variables (i.e., international indices) and the dependent variable (ASEI) in the regression model. Thus, the rule of thumb applied is that the best model among all the developed models stepwise is the one that has the highest R^2 and lowest error. Thus, the best model is the last model with the number 8 containing month, year, NASDAQ, CAC, DAX, Nikkei, S&P 500, and

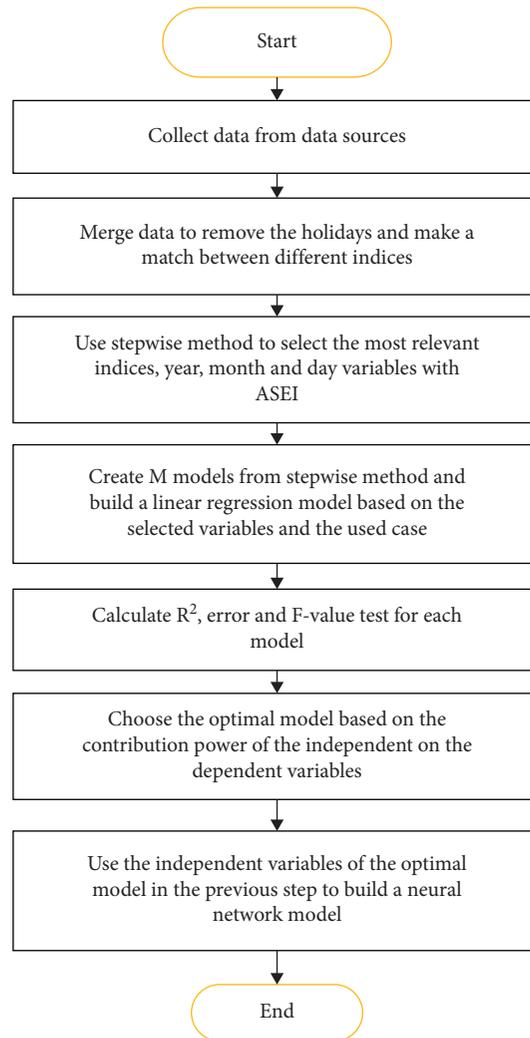


FIGURE 2: Flowchart of the proposed methodology.

HSI with the highest R^2 of 0.988 and the lowest error of 266. Table 6 summarizes the overall significance of all the concluded models through measuring the F-test. All models are found statistically significant with an F significance value of 0.000, indicating that our sample data provide sufficient evidence to conclude that our regression model fits the data better than the model without independent variables.

As shown in Table 7, the stepwise regression developed eight models, and they were all found to be statistically significant with a significance value of 0.000. Therefore, according to the stepwise regression analysis, the best model is Model 8, including month, year, NASDAQ, CAC, Nikkei, S&P 500, and HSI.

In Table 8, the findings revealed that Nikkei, S&P 500, and CAC positively affect ASEI. On the other hand, the rest of the variables (i.e., month, NASDAQ, DAX, and HSI) negatively affected ASEI. As for the standardized beta, it specifies the predictors with the most substantial contribution on the dependent variable in which it has the highest value of beta. In our case, they are in respective order from highest to lowest as follows: CAC, S&P 500, and Nikkei.

Although most of the previous tests' outcomes support a relationship between international indices (independent variables) with ASEI (dependent variable), the figures sketched did not provide precise support to the linear relationship between the dependent and all the independent variables adopted in this study. Consequently, this study will extend this analysis to another level by applying nonlinear models that the neural networks are efficient in building financial models to study the availability of relationships between various financial indicators, especially for financial markets.

5.3. Artificial Neural Network. The last step here is to run a neural network model. The outputs confirmed that the model could efficiently predict ASEI using the international stock indices with the highest R^2 (0.989) and lowest error (62). Figure 5 shows the relationship between the predicted and real values of the stock index. The plot showed that the two dimensions are semi-identical, which indicates the capability of the proposed model in predicting the movement of ASEI. Furthermore, the results highlighted that the

TABLE 5: Correlation between ASEI and international indices.

	Day	Month	Year	NASDAQ	S&P 500	Nikkei	CAC40	DAX	HSI
Correlation	-0.012	-0.112**	-0.617**	-0.456**	-0.425**	-0.259**	-0.069**	-0.421**	-0.218**
Sig.	0.590	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000

**Significant at 0.05.

TABLE 6: Stepwise linear regression models using general index based on international indices and date without using a constant.

Model	Predictors	R ²	Error
1	Year	0.941	578
2	Year, NASDAQ	0.953	514
3	Year, NASDAQ, CAC40	0.977	357
4	Year, NASDAQ, CAC40, DAX	0.984	301
5	Year, NASDAQ, CAC40, DAX, Nikkei	0.986	276
6	Year, NASDAQ, CAC40, DAX, Nikkei, S&P 500	0.987	269
7	Year, NASDAQ, CAC40, DAX, Nikkei, S&P 500, HSI	0.987	266
8	Year, NASDAQ, CAC40, DAX, Nikkei, S&P 500, HSI, month	0.988	266

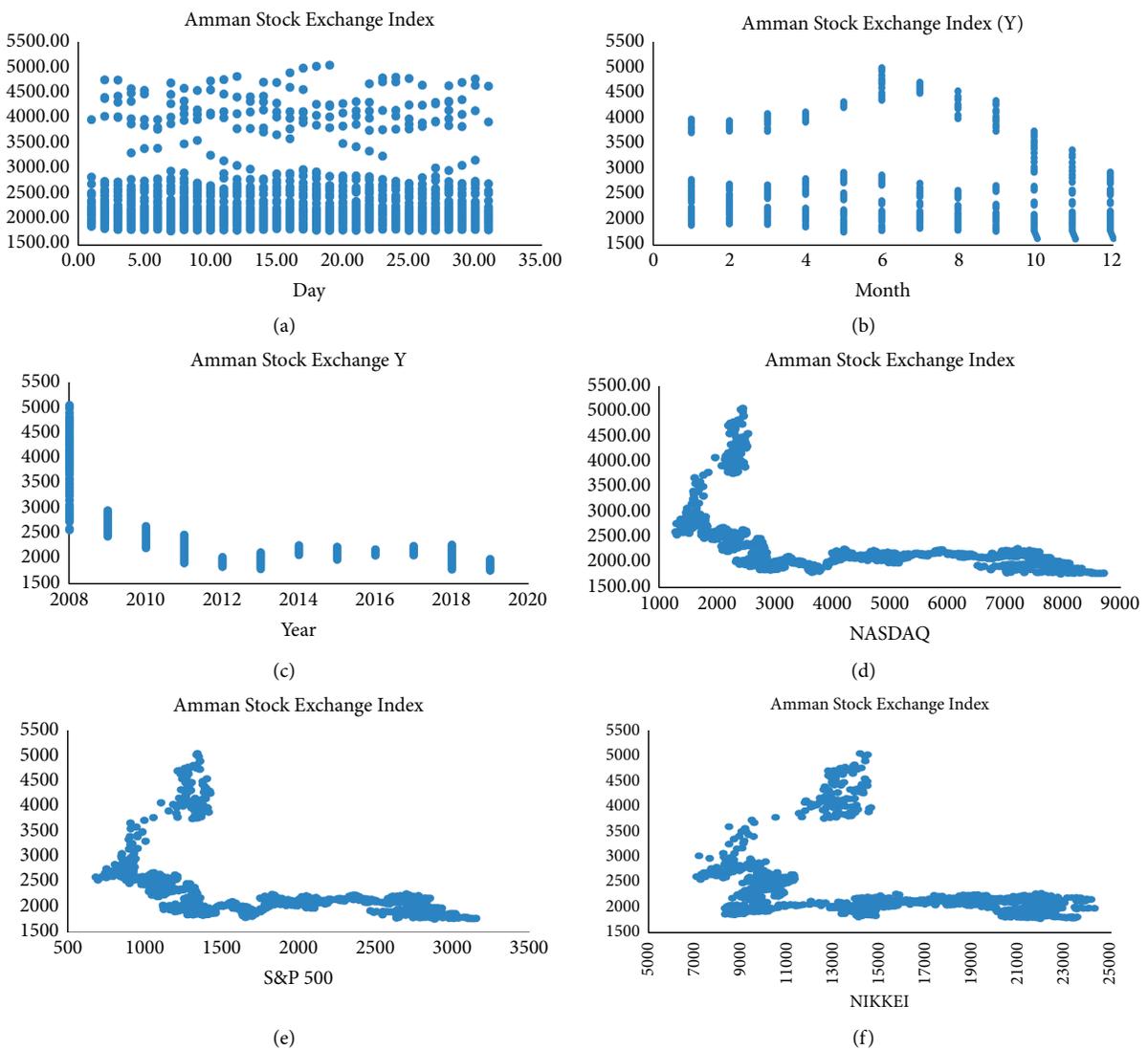


FIGURE 3: Relationship between ASEI and (a) day, (b) month, (c) year, (d) NASDAQ, (e) S&P 500, and (f) Nikkei.

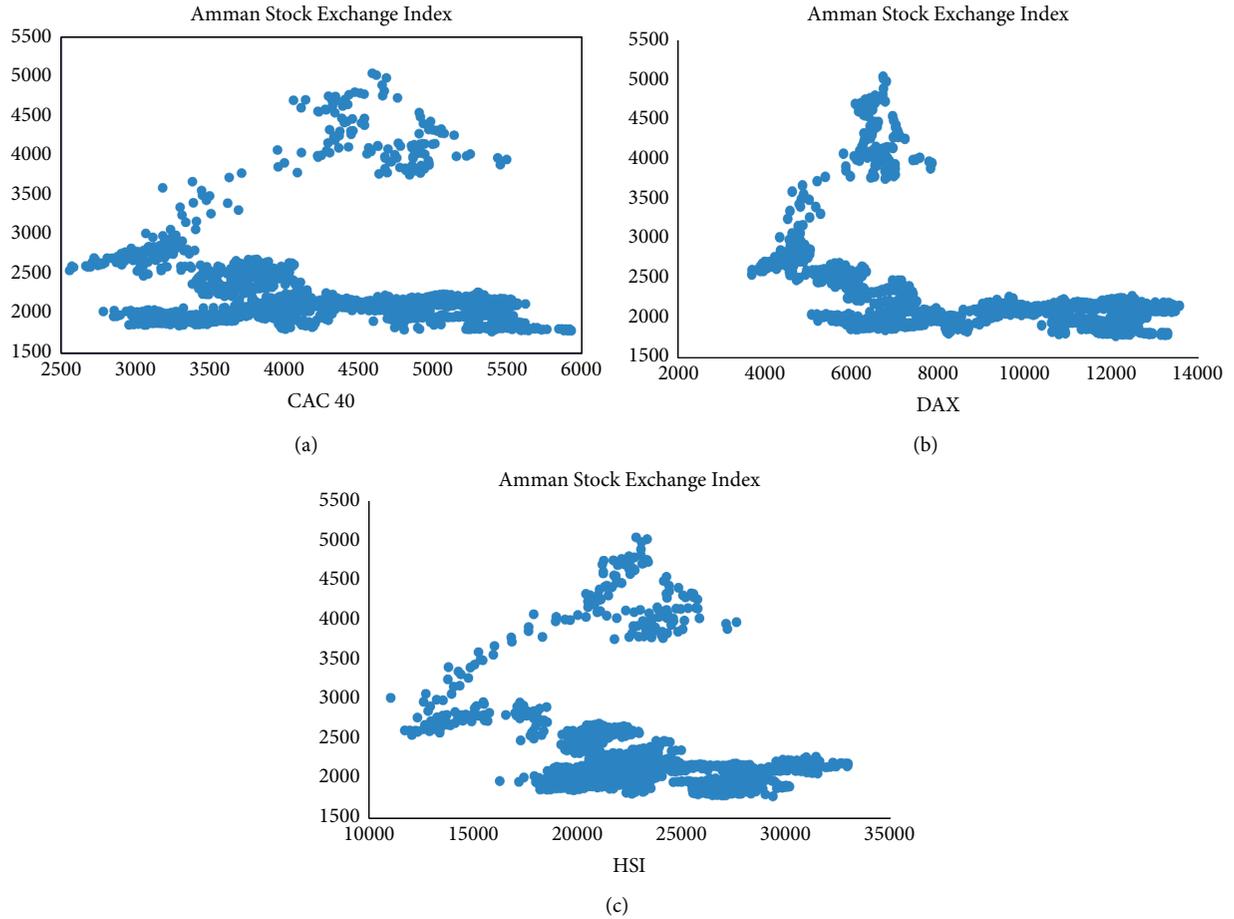


FIGURE 4: Relationship between ASEI and (a) CAC40, (b) DAX, and (c) HSI stock market indices.

TABLE 7: Analysis of variance of different stepwise linear regression models without using a constant.

Model		Sum of squares	Df	Mean square	F	Sig.
1	Regression	10697845705.588	1	10697845705.588	31992.834	0.000
	Residual	674784004.340	2018	334382.559		
	Total	11372629709.927	2019			
2	Regression	10840356220.377	2	5420178110.189	20539.252	0.000
	Residual	532273489.550	2017	263893.649		
	Total	11372629709.927	2019			
3	Regression	11115762815.256	3	3705254271.752	29080.402	0.000
	Residual	256866894.671	2016	127414.134		
	Total	11372629709.927	2019			
4	Regression	11190472184.137	4	2797618046.034	30946.843	0.000
	Residual	182157525.791	2015	90400.757		
	Total	11372629709.927	2019			
5	Regression	11218710896.697	5	2243742179.339	29358.963	0.000
	Residual	153918813.230	2014	76424.436		
	Total	11372629709.927	2019			
6	Regression	11227005398.306	6	1871167566.384	25865.601	0.000
	Residual	145624311.621	2013	72341.933		
	Total	11372629709.927	2019			
7	Regression	11230221665.956	7	1604317380.851	22666.462	0.000
	Residual	142408043.972	2012	70779.346		
	Total	11372629709.927	2019			
8	Regression	11230776334.593	8	1403847041.824	19901.792	0.000
	Residual	141853375.335	2011	70538.725		
	Total	11372629709.927	2019			

TABLE 8: Coefficients using stepwise linear regression models without using a constant.

Model		Unstandardized coefficients		Standardized coefficients	T	Sig.
		B	Std. error	Beta		
1	Year	1.143	0.006	0.970	178.865	0.000
2	Year	1.429	0.014	1.213	105.432	0.000
	NASDAQ	-0.135	0.006	-0.267	-23.239	0.000
3	Year	0.080	0.031	0.068	2.610	0.009
	NASDAQ	-0.452	0.008	-0.893	-57.052	0.000
	CAC40	0.943	0.020	1.740	46.492	0.000
4	Year	0.125	0.026	0.106	4.840	0.000
	NASDAQ	-0.211	0.011	-0.418	-19.757	0.000
	CAC40	1.231	0.020	2.272	62.153	0.000
	DAX	-0.266	0.009	-1.036	-28.748	0.000
5	Year	0.343	0.026	0.291	13.052	0.000
	NASDAQ	-0.292	0.011	-0.576	-27.284	0.000
	CAC40	0.977	0.022	1.803	43.413	0.000
	DAX	-0.334	0.009	-1.304	-36.277	0.000
	Nikkei	0.108	0.006	0.713	19.222	0.000
6	Year	0.220	0.028	0.186	7.840	0.000
	NASDAQ	-0.590	0.030	-1.164	-19.846	0.000
	CAC40	0.937	0.022	1.729	42.171	0.000
	DAX	-0.390	0.010	-1.521	-37.642	0.000
	Nikkei	0.104	0.005	0.689	19.055	0.000
	S&P 500	1.238	0.116	0.997	10.708	0.000
7	Year	0.284	0.029	0.241	9.694	.000
	NASDAQ	-0.561	0.030	-1.108	-18.908	0.000
	CAC40	1.035	0.026	1.910	39.226	.000
	DAX	-0.380	0.010	-1.481	-36.645	0.000
	Nikkei	0.093	0.006	0.617	16.514	0.000
	S&P 500	1.189	0.115	0.957	10.377	0.000
	HSI	-0.022	0.003	-0.220	-6.741	0.000
8	Year	0.310	0.031	0.263	10.104	0.000
	NASDAQ	-0.558	0.030	-1.102	-18.813	0.000
	CAC40	1.029	0.026	1.900	38.965	0.000
	DAX	-0.381	0.010	-1.485	-36.787	0.000
	Nikkei	0.094	0.006	0.622	16.663	0.000
	S&P 500	1.185	0.114	0.955	10.364	0.000
	HSI	-0.023	0.003	-0.223	-6.829	0.000
	Month	-4.977	1.775	-0.015	-2.804	.005

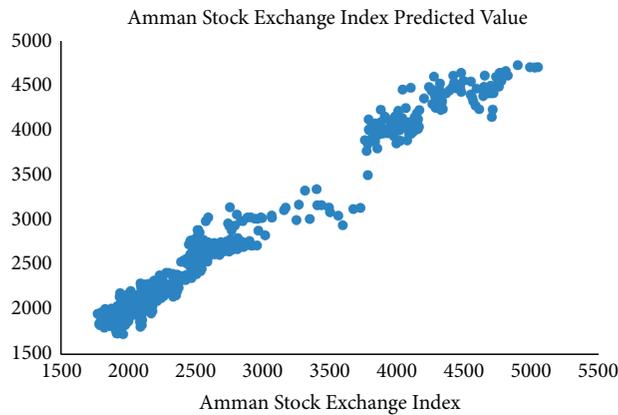


FIGURE 5: Relationship between predicted index and real ASEI.

importance level of two variables, including year and S&P 500 index, is above 50%, and the rest of the international indices (NASDAQ, CAC, DAX, Nikkei, and HSI) with

month are less than 50%. Thus, S&P 500 is the most critical index connected to ASEI, as shown in Figure 6. This result is related to that Jordan that has been a close major non-NATO

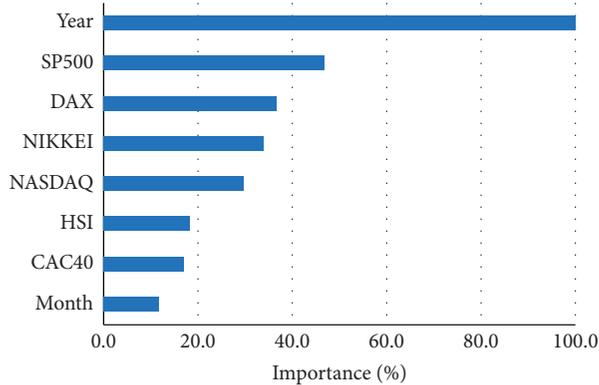


FIGURE 6: Importance analysis of the artificial neural network.

ally of the USA. The relationship between USA and Jordan has been strong for several decades, given that U.S. policy seeks to reinforce Jordan's commitments to peace, stability, and moderation. Furthermore, many MOUs were signed between Jordanian and American governments in different fields as MOUs between ASE and NASDAQ Stock exchange.

The neural network model is efficient in predicting the movement of ASEI using the international markets indices. The outcomes of this study are in line with the findings of many previous studies that provide evidence of domestic-international stock market integration. References [10, 17] found the integration between five Asian countries with U.S. and China stock market indices through applying fractional co-integration methods. Reference [18] found that U.S. volatility risk indices are dominant in forecasting TASI. Reference [35] found a long-run relationship between TASI and U.S. stock market indices (S&P 500 and Dow Jones). Likewise, [6] found that S&P 500, Nikkei, CAC, and HSI are highly integrated with TASI. Our findings show that the U.S. stock market index (S&P 500) is crucial in the ASEI prediction model. This result is consistent with [19], who found integration and causal relationship between ASEI and U.S. stock markets. Finally, financial markets tend to behave similarly, especially during the financial crisis, health crisis, and political instability such as the Arab spring revolutions.

6. Conclusions

In the past two decades, especially after the financial crisis of 2007-08, the literature for examining the availability of integration between stock exchanges in developed and developing markets has been growing. The importance of this topic stems from the significant implications of the linkage between exchange markets on various decisions taken by interested parties such as policymakers, investors, and academics.

Accordingly, this study aims to determine the relationship between ASEI and international indices between 2008 and 2019. The international indices applied in this study are S&P 500, NASDAQ, Nikkei, DAX, CAC, and HSI. The study used correlation coefficient, stepwise regression, and neural network. The correlation

coefficient determined the relationship between international indices and ASEI. The outcome showed a significant relationship between these indices. The stepwise regression model proposes the best fit model by determining which of the selected indices significantly affect the dependent variable (ASEI). The outcome suggests that all the indices are part of the best model. Furthermore, a nonlinear model is an applied artificial neural network to enhance the robustness of the results. The outcome supported the previous results showing a relationship between ASEI and international indices. S&P 500 has the highest importance level among other selected indices with ASEI. Thus, these conclusions are consistent with previous studies and can be utilized to build prediction models for ASEI, which will help take the appropriate investment and regulatory decisions. Therefore, integrations exist between stock exchange markets at different developed and developing markets, shading light on socioeconomic connections that deliver beneficial information for domestic and foreign investors of financial markets [48].

7. Practical and Theoretical Implications

Our study is theoretically and practically important. Our findings are significant for investors, managers, and policymakers to understand the nature of stock markets as these markets respond directly and randomly to any internal or external shocks. Also, this study is considered an addition to the existing literature in focusing on the financial market theory, modern portfolio theory, and efficiency theory.

Apart from theoretical contribution, policymakers can benefit from our findings as they shed light on the importance of being more exposed to international markets and applying the techniques of the developed markets. Also, policymakers should enhance the efficiency levels and the effective R&D activities of the financial markets to keep these markets competitive for all investors. This enhancement cannot be achieved without working hard to minimize the rumors and assure that only correct information is directed to investors who will rebuild the resilience of these financial markets.

Our study sheds light on socioeconomic connections that deliver beneficial information for domestic and foreign investors of financial markets. Thus, investors can benefit from the study results on diversifying their short- or long-term investments in their international portfolios and could grab the chance of applying appropriate hedging strategies. Investors can also benefit from arbitrage activity between these financial markets, but the opportunity of achieving abnormal returns is questionable. Besides, our findings will enhance the awareness of the integration between financial markets, encouraging investors to turn to other less risky investments (i.e., bonds or gold).

8. Limitations and Future Studies

This study has limitations. Limitations are existed, especially regarding the time frame and data availability. As

in the data collection process, we used only the international markets directly related to Jordan's economy, and we skipped all other indices. Besides, data were rearranged to make different weekends and holidays of these different countries alike. Finally, the data were limited to the period before COVID-19. This limitation mitigates the effect of this pandemic on the integration between ASEI and international market indices. Furthermore, only a few papers studied the integration between emerging and international markets and ASEI and international markets.

Future studies may explore the effect of other international stock market indices on ASEI or compare different advanced models in investigating the integration of the financial markets' indices. Future research can use macroeconomic factors, oil prices, and gold to build prediction models for ASEI. Studying the integration between subsector indices in emerging and developed financial markets would be attractive. Further research may investigate the effect of the financial markets' volatility and trading volume on integrating the financial markets' indices.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this study.

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