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AI-ENHANCED INSIGHTS INTO YEMEN RIYAL'S EXCHANGE RATE: UNRAVELING LONG-TERM BEHAVIOR THROUGH MARKOV CHAIN ANALYSIS

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ABSTRACT

The study of foreign exchange (FOREX) markets is known as foreign currency exchange. The FOREX market is where exchange rates are determined and traded. The prices of one currency, expressed in terms of another money, are defined as exchange rates. Exchange rates provide crucial data for international monetary exchange markets. Upon using the Markov chain model and R program, this study aims to determine the behavior of the Yemeni Riyal's (YER) currency rate against the US dollar (USD) with three states observed in the study. The three different movements are three other states based on the Markov chain to develop the transition probability matrix. The results showed that the exchange rate of the Yemeni Riyal could be categorized into one of three states at the end of each day during the study period. The transition probability matrix and starting state vector were calculated. The results also showed the probability of being in one of these three states, namely 'increases,' 'remains the same,' or 'decreases,' which signify 0.3614, 0.3268, and 0.3118, respectively. Moreover, the expected number of visits and return time were obtained. This result showed that the chain will visit the state of 'de-creases' (D) in three days on average. This study has shown how the utilized Markov model can fit data with the ability to predict the trend. Therefore, this model can help researchers and investors determine and make informed business decisions in a foreign exchange market, influenced by various market factors, including market forces and psychological factors affecting inves-tors.

KEYWORDS: Markov chain, Artificial Intelligence, Foreign Exchange, Exchange rates of the Yemeni Riyal, R Program; Ex-pected Number of Visits.

رؤى معززة بالذكاء الاصطناعي حول سعر صرف الريال اليمني: كشف السلوك طويل المدى من خلال تحليل سلسلة ماركوف

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الملخص

تعرف دراسة أسواق الصرف الأجنبي (FOREX) باسم صرف العملات الأجنبية. سوق الفوركس هو المكان الذي يتم فيه تحديد أسعار الصرف وتداولها. يتم تعريف أسعار إحدى العملات، معبرًا عنها بعملة أخرى، على أنها أسعار الصرف. توفر أسعار الصرف بيانات مهمة لأسواق الصرف النقدي الدولية. باستخدام نموذج سلسلة ماركوف وبرنامج R ، تهدف هذه الدراسة إلى تحديد سلوك سعر عملة الريال اليمني (YER) مقابل الدولار الأمريكي (USD) في ثلاث دول تمت ملاحظتها في الدراسة. الحركات الثلاث المختلفة هي ثلاث حالات أخرى تعتمد على سلسلة ماركوف لتطوير مصفوفة احتمالات الانتقال. أظهرت النتائج أن سعر صرف الريال اليمني يمكن تصنيفه إلى واحدة من ثلاث حالات في نهاية كل يوم خلال فترة الدراسة. تم حساب مصفوفة احتمالية الانتقال ومتجه حالة البداية. وأظهرت النتائج أيضًا احتمالية التواجد في إحدى هذه الحالات الثلاث، وهي "الزيادة"، أو "البقاء على حاله"، أو "النقصان"، والتي تعني 0.3614، و0.3268، و0.3118، على التوالي. علاوة على ذلك، تم الحصول على العدد المتوقع للزيارات ووقت العودة. أظهرت هذه النتيجة أن السلسلة ستزور حالة "النقصان (D) " خلال ثلاثة أيام في المتوسط. وقد بينت هذه الدراسة كيف يمكن لنموذج ماركوف المستخدم ملاءمة البيانات مع القدرة على التنبؤ بالاتجاه. لذلك، يمكن لهذا النموذج أن يساعد الباحثين والمستثمرين على تحديد واتخاذ قرارات عمل مستنيرة في سوق الصرف الأجنبي، متأثرًا بعوامل السوق المختلفة، بما في ذلك قوى السوق والعوامل النفسية التي تؤثر على المستثمرين.

الكلمات المفتاحية : سلسلة ماركوف؛ الذكاء الاصطناعي، النقد الأجنبي؛ أسعار صرف الريال اليمني. برنامج البحث؛ عدد الزيارات المتوقع.

1. INTRODUCTION

The FOREX market is where exchange rates are determined and traded. The prices of one currency, expressed in terms of another money, are defined as exchange rates. This market has been investigated for years because price fluctuations can impact economic development and international trade worldwide [1]. Therefore, it has been closely monitored by governments, central banks, multinational corporations, and financial traders across the globe. One crucially important topic, among others, in policymaking and international finance involves the currency value, i.e., exchange rates, which consists of measuring a nation's currency value versus another nation's currency or its economic zone. Exchange rate fluctuations can affect the prices of various assets directly and indirectly. Therefore, investors frequently consider the impact of currency fluctuations on their international portfolios. On the other hand, governments are concerned about the export and import prices and the domestic currency value of debt payments, as evidenced by the ever-growing, heated debate over the Chinese Yuan's value in recent years [2]. Furthermore, central banks are concerned about the importance of their international reserves and the influence of fluctuations in exchange rates on nations' domestic inflation. Regarding Yemen, most of Yemen's economic woes have manifested themselves in the form of exchange rate instability, which has hampered export efforts significantly. Resources such as oil, gypsum, and natural gas exhibit a high export potential, and manufactured goods are exported to other countries. The oil industry, however, continues to be the largest source of revenue in Yemen, accounting for 95 percent of the country's total revenue. Despite a series of challenges, such as inflation and economic collapse, which threatened the economy, Yemeni's chances of success are very high. Therefore, restructuring plans in trade, finance, and production are needed, according to the IMF's proposed economic plans released in 2018, which involve conceivably easing the government's participation in private sector operations [10].

The FOREX market is the world's largest financial market, where over $5 trillion is transacted daily on average. There are numerous FOREX investors, but only a few have achieved success. Many of these traders have failed for the same reason other asset-class investors failed. Also, the market’s tremendous leverage, the borrowed capital used to maximize a viable return on investments, and the relatively small margin amounts required for trading currencies have prevented traders from making repeated low-risk miscalculations. Based on specific factors, some traders may expect better investment returns than the market's constant returns. Alternatively, they might accept further risks compared to risks in different markets due to certain aspects of currency trading [15]. The Iraqi dinar’s (IQD) exchange rate using Markov chains has been investigated [10]. In their study, the authors have probed the IQD’s exchange rate versus the US dollar utilizing Markov chains and predicted its exchange rate in the future. Based on the conducted analysis results, a significant conclusion has been disclosed, which confirmed that the exchange rate will remain stable for the upcoming period. It will start to rise due to the impact of the global crisis in Iraq.

They examined the convergence of the exchange rate in Nigeria in the long run by examining the switches of exchange rates or transitions from one state to another. Based on iterations related to the Chapman-Kolmogorov equations of the employed Markov model, the results confirmed that convergence has occurred in the long run, as shown by the Markov model. The analysis results suggested that the Nigerian currency’s appreciation and depreciation against the US dollar will remain stable, as the obtained probability values show.

In another study, according to the exchange rate determination theory, [19] tested, by using the Autoregressive Distributive Lag (ARDL) model, the long-run association between the Malaysian Ringgit (MYR) and the US dollar with the British Pound (GBP) versus different interest rates, money supply variance, the world’s crude oil prices, as well as taxes of goods and services, as the dummy variable. The results revealed a negative long-run association between the MYR and the GBP with money supply variance. Also, a positive long-run association was found about the world’s crude oil prices. With the MYR supply’s increase against the GBP, the Malaysian Ringgit has witnessed depreciation, while as the world’s crude oil prices were strengthened, the MYR has witnessed appreciation. A higher reliance on the Malaysian Ringgit on the world’s crude oil showed unfavorable signs. From the authors’ perspective, Malaysia must work more efficiently to fascinate further foreign direct investments to maintain the Ringgit value at a vigorous level.

From another perspective, [14] applied the Markov chain prediction model to predict price behavior using the difference between the typical price and the closing price of the daily exchange rates. Their study has applied the Markov model to the EUR-USD currency pair in the currency market. The model has worked well with the EUR and USD. Many models used the prediction models to predict price behavior [2, 20].

The Markov-switching method has been used by [11] in their study. The researchers identified two primary regimes for Tunisia’s inflation, including low and stable inflation schemes. These are linked to the low pass-through level, whereas the high inflation scheme is linked to the high. Therefore, results showed that the price decreased due to increased interest rates. Besides, the empirical findings established evidence that the industrial production index exerted a significant negative effect because it increased the likelihood of remaining in the inflationary scheme at the high pass-through level. According to the results, the hypothesis has been supported, stipulating that those imports have increased the likelihood of remaining in the high-inflation scheme, maintaining the high pass-through level.

Exports, however, increased the prospect of remaining in the low-inflation scheme and retaining the low pass-through level. Markov chain model has been used to investigate the long-run behavior of closing prices recorded for Nigerian bank stocks [8]. Eight Nigerian bank stocks were randomly chosen, and data regarding the daily closing prices were collected. Based on the findings, despite the current market condition, there was some hope for Nigerian bank stocks, as the steady-state likelihood results showed that some of these bank stocks tend to improve in price over time. However, such a finding has been crucially informative to stockbrokers, investors, and other regulators in the financial sector.

This result is contingent on unforeseeable factors like changes in government policy, among other conditions. The results of the current study, however, are expected to provide useful insights for investors, potential investors, and involved stakeholders in stock trading. [9] applied the A Markov chain model was used to predict the possible states of the share prices of two top banks, 'Guarantee Trust Bank of Nigeria' and 'First Bank of Nigeria', by analyzing their performance from 2005 to 2010 across six years. The researchers obtained a transition probability matrix, power of the transition matrix, and probability vector to make a long-term prediction of the share prices. This allowed them to determine whether the share prices would appreciate, depreciate, or remain unchanged regardless of the banks' current share prices. They also estimated the probability of transition between the states by analyzing the performance of both banks together. Two studies, [23] and [24], have already implemented the same Markov model to forecast China's stock market tendency. A Markov chain model was used to estimate the probability of transition between the states by taking into account the performance of both banks together. In related work, [23] and [24] used the Markov model to forecast the tendency of China's stock market. Moreover, in related work, [23] and [24] used the Markov model to forecast the tendency of China's stock market.

In Kenya, [16] utilized the Markov chain model to forecast the Safari com share’s stock market trend in the Nairobi Securities Exchange. The Markov model was used to predict the share prices of Safari com by analyzing data collected over a period ranging from April 1st, 2008 to April 30th, 2012. Instead of predicting an absolute state, the model was used to forecast the probability of a specific stock state or potential share prices. By using this method, it was possible to get a more precise assessment of the potential outcomes. This forecasted value indicated the likelihood of a particular stock state or potential share prices [25].

The results revealed that the Markov model's memoryless property and random walk capability have facilitated best fitting the data and predicting the trend. Using the Markov chain model, good results for predicting the probability of each state of shares of Safaricom were observed. [13] employed the Markov model for analyzing the share price fluctuations of five varied and randomly chosen equities in the Ghana Stock Exchange. The results concluded that applying the Markov chain model as a given stochastic analysis approach in equity price research has enhanced portfolio decisions. Therefore, the Markov chain model can be applied to enhance stock trading decisions. This method in stock analysis has improved the investors' knowledge and chances of obtaining higher returns. [3] applied the Markov model to predict potatoes' arrival market price interval in the Lanka Regulated market in Nagaon District. The forecast has been carried out over 15 consecutive days.

This study aims to introduce the Markov chain method as a simple forecasting tool to analyze the Yemeni Ryle's (YER) exchange rate versus the US Dollar. The objective of this study is to understand the exchange rate's long-term behavior, estimate the expected number of visits to specific states, and determine the expected first return time to three states. Markov chains are ideal for modeling systems that exhibit temporal dependence because they can be used to model systems where the probability of a future state depends on the current state. This study used a three-state Markov chain with the states being "increases," "remains the same," and "decreases." The focus is on utilizing the first-order Markov Chain model to many advantages, which is relatively simpler to implement and analyze, requiring fewer parameters and computations, making them more accessible and less computationally intensive.

The research gap of this study is that no studies utilize the Markov chain model to estimate the exchange rate of the Yemeni Ryle's (YER). The research objectives are to forecast and analyze the exchange rate of Yemeni Ryle's (YER) compared with USD using the Markov chain model, study the long-term behavior of the exchange rate, determine the expected number of visits to the states, and estimate the expected return time of the states. The contribution of this study is that it is the first to use a Markov chain model to forecast the exchange rate of the Yemeni Ryle's (YER) and provide insights into the long-term behavior of the exchange rate. It will also be helpful for businesses and investors who need to make informed decisions about the Yemeni Ryle's (YER).

Many different models using currency exchange rate analysis might not be suitable. In this study, we focus on the Markov chain. Using the Markov model, predicting the price interval has matched real situations. However, future price forecasts by using other methods might not be suitable. Instead, the Markov model's results are incredibly encouraging. The Markov chain model is highly effective in analyzing and predicting the stock market index, particularly the closing stock prices. This model has no-after influence and is better suited for the market mechanism. Using the Markov model in the stock markets has yielded relatively best results. Therefore, this model can be utilized in bonds and future markets.

2. MATERIALS AND METHODS

This section provides a basic definition of the Markov chain as a forecasting model.

2.1. Markov Chains

Markov chains enjoy wide-ranging and valuable applications in academic and industrial fields. They have been used in various fields, such as chemistry, statistics, operations research, economics, finance, music, and other disciplines. In this study, the exchange rate analysis is emphasized. The Markov Chain estimation technique is a type of probability forecasting method, which predicts the probability of a specific state for a future exchange rate price instead of an absolute state. It is particularly effective for forecasting foreign exchange daily closing prices under the price system due to its lack of after-effects. The Markov chain model is capable of fitting the data and predicting the tendency because of its memoryless property and random walk capability. This means that every state in the given transition matrix can be directly reached from another state.

Markov chain involves a specific stochastic process with a property whereby future probabilities depend only on a present state, regardless of a past event.

Let $\{X_t , t = 0, 1, 2, \dots ,\}$ be a specific stochastic process that takes on a specific finite or a countable number of probable values. The probable values' set of the process can be signified by the nonnegative integers' set $\{0, 1, 2, \dots\}$. When $X_t = i,\ i \geq 0$, the process is in state i at the time t. A Markov chain states that when a process is in state i, then there exists a fixed likelihood p_{ij} , which will be in state j next, i.e.,

$$P\{X_{t+1} = j / X_t = i, X_{t-1}, \dots, X_1 = i_1, X_0 = i_0\} = P\{X_{t+1} = j / X_t = i\} = p_{ij} \qquad (1)$$

2.2. Position Count and Transition Probability Matrices

One-step transition frequency matrix F can be constructed as follows:

$$F = \begin{bmatrix} f_{00} & \cdots & f_{0k} \\ \vdots & \ddots & \vdots \\ f_{k0} & \cdots & f_{kk} \end{bmatrix}, \qquad (2)$$

where f_{ij} refers to the price number of transitions from the state i to the state j in a single step, the transition count matrix then p_{ij} can be estimated by:

$$p_{ij} \frac{f_{ij}}{\sum_{j=1}^{k} f_{ij}}, \sum_{j=1}^{k} f_{ij} > 0 , \tag{3}$$

The transition probability p_{ij} can be constructed into a matrix:

$$P = \begin{bmatrix} p_{00} & \cdots & p_{0k} \\ \vdots & \ddots & \vdots \\ p_{k0} & \cdots & p_{kk} \end{bmatrix}, \tag{4}$$

This matrix P is called the Markov chain transition probability matrix, with an element p_{ij} signifying a conditional probability, whereby an element in the state i at this time will be in the state j next time. The term "one-step transition probability matrix" refers to a mathematical matrix that represents the probabilities of transitioning from one state to another in a single step. The elements in the main diagonal of the transition probability matrix represent a likelihood whereby a given probability element will remain in the same state in the future. Elements outside the main diagonal represent the probabilities of movements among the given states. Matrix P's elements are probabilities with a sum of one by rows [9].

A Markov chain possesses a preliminary state vector, represented as $(1 \times k)$ vector, describing the beginning likelihood distribution at every k probable state. Entry i of a vector illustrates the chain beginning probability at the state i, i.e.,

$$P(X_0 = i) = P(0) = \left[p_0(0)\, p_1(0)\, p_2(0) \ldots p_k(0) \right], 0 \le p_i(0) \le 1 , \tag{5}$$

where

$$p_i(0) = \frac{\sum_{j=1}^{k} f_{ij}}{\sum_{j=1}^{k} \sum_{i=1}^{k} f_{ij}}, and \sum_{i=0}^{k} P_i(0) = 1 \; for\ all\ state , \tag{6}$$

$$P(X_t = i) = P(t) = \sum_{i}^{k} P(X_0 = i) P(X_t = i) , \tag{7}$$

$$\sum_{i}^{k} P_i(0) P_{ij}(t), t > 0 , \tag{8}$$

If there is information about the starting state of a system and the matrix that describes how the system transitions after a certain number of steps, it is possible to determine the state of the system after t steps,

$$P(l+1) = P(l) \times P , \tag{9}$$

which leads to:

$$P(1) = P(0) \times P , \tag{10}$$

$$P(2) = P(1) \times P = P(0) \times P^2 , \tag{11}$$

Thus,

$$P(l) = P(l-1) \times P = P(l-2) \times P^2 = \cdots = P(0) \times P^l, \tag{12}$$

Hence,

$$P(l+1) = P(0) \times P^{l+1}, \ for\ l \geq 0, \tag{13}$$

The product of the initial probability vector and the (l+1) power of the one-step transition probability matrix is the probability vector after the (l+1) step.

2.3. The (l+1) step Probability Matrix

Let $\{X_0, X_1, ...\}$ be a Markov chain with the state space $\{1, 2, 3. ..., t\}$. Recall that transition matrix P elements are defined as:

$$p_{ij} = P(X_1 = j | X_0 = i) = P(X_{t+1} = j | X_t = i), \ for\ any\ t, \tag{14}$$

p_{ij} refers to the probability of transitioning from state i to state j in one step.

The matrix Pl+1 can provide the (l+1) step transition matrix for any l

$$P(X_{l+1} = j | X_0 = i) = P(X_{t+l+1} = j | X_t = i) = (P_{ij})^{l+1}, \tag{15}$$

2.4. Classification of States

We can say the accessibility of states from each other. When it is viable to move from state i to state j, state j can be accessible from state i, composed of $i \to j$. If $p_{ij} > 0$.

Both of these states i and j can communicate, and they are composed as $i \leftrightarrow j$, when these are reachable from one another, i.e., $i \leftrightarrow j$ signifies $i \to j$ and $j \to i$ communication refers to a corresponding association, indicating that each state can communicate with this state, $i \leftrightarrow i$ and when $i \leftrightarrow j$ and $j \leftrightarrow k$, thus $i \leftrightarrow k$. Therefore, the Markov chain states can be divided into classes that communicate, i.e., only the members of the same class can communicate with one another. In other words, states i and j fit in a similar class when and only when $i \leftrightarrow j$. The Markov chain is irreducible when it possesses a single communicating class only, i.e., the Markov chain can be irreducible when the entire states can communicate with one another.

2.5. Long-Run Behaviour of Markov Chains

Assume that the transition probability matrix P on some states' finite number, labeled 0,1, ... , k, enjoys a property that, if raised to the power t, the given matrix P^t has the entire elements precisely positive. This transition probability matrix, or a matching Markov chain, can be called regular. Thus, the most significant fact regarding the regular Markov chain involves a restricting probability distribution existence.

$$P = [p_0\ p_1 \cdots p_k], whereby\ p_j > 0, \ for\ j = 0,1,\cdots k\ and \sum_j^k p_j = 1, \tag{16}$$

Such a distribution is independent of an initial state. Strictly, as for the regular transition probability matrix P, we have this convergence, which is:

$$P_{ij}^t = p_j > 0, \ for\ j = 0,1,\cdots k, \tag{17}$$

Regarding the Markov chain $\{X_t\}$, it is written as follows:

$$P\{X_t = j | X_0 = i\} = p_j > 0, \ for\ j = 0,1,\cdots,k \quad (18)$$

The convergence indicates that in the long run (t→∞), the likelihood of obtaining a Markov chain in the state j is nearly p_j regardless of which states the chain launched at time 0 [18].

2.6. Expected Number of Visits

Upon considering the essential quantity of finite-state chains, which possess transient states. When the states are recurrent, an expected number of the chain visits to the transient state are visited repeatedly, always returned to again, a given infinite number of times.

Let $\mu_{ij}(l)$= the expected number of visits in l steps that chain visits state j given $X_0 = i$

$$\mu_{ij}(l) = E\left\{\sum_{w=0}^{l} P\{X_w = j | X_0 = i\} = \sum_{w=0}^{l} P^w\right\}, w = 1,2,\cdots l \quad (19)$$

2.7. Expected Return Time

To go from state i to state j, it is necessary to have exactly n visits at a given time $t_n = Y_1 + \cdots + Y_n$, let Y_i refers to a random variable, which counts a total number of visits to the state i, thereby a long-run proportion of the visits to the state j as per unit time is obtained by taking the reciprocal of limiting probability p_j [12].

However, whereby $i = j$, we can say that $E(Y_i|x_0 = i)$ signifies an expected return time to the state i when the Markov chain began at the state i because the Y_i the definition involves only times, which are at least 1 and, thus, it was found that there exists a simple relationship between p_i and an expected return time to I [21].

$$E(X_0 = i) = \frac{1}{p_i}, i = 1,2,\cdots,k \quad (20)$$

Since $p_i \geq 0$ for the entire state i, an expected return time to every state can be finite if p_i is a steady probability of state i.

3. DISCUSSION OF THE RESULTS

3.1. Three States Derivation

It has been observed that the exchange rate of the Yemeni Ryle can be categorized into one of three states at the end of each day during the study period. On a particular day, when the exchange rate of Yemeni Riyal goes up against the US dollar compared to the day before, it is categorized as “increases” (U). However, if it goes down, it is categorized as “decreases” (D).

Furthermore, if it does not change, it is categorized as “remain the same” (S). The data are obtained from https://markets.businessinsider.com/currencies/usd-yer from 04 August 2008 to 27 June 2022. It is observed that there are 3650 trading days within this period. The data set consists of the exchange rate’s close price for the YER against the USD based on the Markov chain, these three movements represent distinct states used to develop a transition probability matrix.

3.2. The Transition Count and Transition Probability Matrices

This study demonstrates The YER exchange rate in three states (i, j=0, 1, 2).

Table 1. The transition count matrix of the exchange rate of Yemeni Ryle against the US dollar

	Increases (U)	Remains the same (S)	Decreases (D)	Total
Increases (U)	473.55	303.45	609	1386
Remains the same (S)	282.45	718.2	252	1252.65
Decreases (D)	628.95	231	333.9	1183.85

Table 1 illustrates the number of the exchange rate of the YER price classified between "increases," "remain the same," and "decreases." The f_00= 473.55 denotes the instances where the YER price increases even though it was already increased against the USD the day before. The number of times the YER price has remained steady even though it was increased against the US dollar the day before is f_12=303.45 and so on for the rest of the elements. The transition probability matrix provides information on the Markov chain's behavior, where each element shows the probability of moving from one state to another. With YER 3650 trading days, the transition probability matrix shows that the exchange rate increased for 1386 days, remained the same for 1252.65 days, and decreased for 1183.85 days.

The transition probability matrix of the exchange rate of YER can then be constructed using Equation (1), which gives:

$$\mathbf{P} = \begin{pmatrix} 0.3588 & 0.2299 & 0.4614 \\ 0.2368 & 0.6021 & 0.2113 \\ 0.5531 & 0.2032 & 0.2937 \end{pmatrix} \tag{21}$$

It can be seen from the Eq(21) that the price of the exchange rate has moved from the "increases" state (U) to the state of "remain the same" (S) with a probability of 0.2299, and it moved from the state of "remain the same" (S) to the state of "increases" (U) with a probability of 0.2368. As a result, the states U and S communicate with each other. It is possible to go from the state of "increases" (U) to the state of "decreases" (D) with a probability of 0.4614. It is also possible to go from the state of "decreases" (D) in the exchange rate to the state of "increases" (U) with a probability of 0.5531. Consequently, the two states communicate. Furthermore, it is possible to go from a condition of the exchange rate of "remain the same" (S) to a state of "decreases" (D), with a probability of 0.2113. In contrast, the exchange rate price can go from the "decreases" state to the "remain the same" state with a probability of 0.2032. Therefore, the two states can communicate with each other. All the states communicated; thus, one class exists only, and the Markov chain is irreducible.

All states in the Markov Chain ('increases,' 'remains the same,' and 'decreases') can communicate with each other with positive probabilities. This means it is possible to transition from one state to another, directly or indirectly, through intermediate states. This confirms that the Markov Chain in the study is irreducible because there are no isolated subsets of states.

3.3. Determination of Initial State Vector

The starting state vector can also be calculated as the YER exchange rate demonstrates three different states. The initial state vector P(0) is given by:

$$\mathbf{P}(0) = [p_{\mathrm{U}}(0) \quad p_{\mathrm{S}}(0) \quad p_{\mathrm{D}}(0)] \tag{22}$$

where $p_U(0)$, $p_S(0)$, and $p_D(0)$ provide the probability that the YER exchange rate increases, remains the same, or decreases at the beginning. The computation gives:

$$\begin{gathered} p_{\mathrm{U}}(0) = 1386/3650 = 0.3797 \\ p_{\mathrm{S}}(0) = 1252.65/3650 = 0.3432 \\ p_{\mathrm{D}}(0) = 1183.85/3650 = 0.3243 \end{gathered} \tag{23}$$

Hence, the initial state vector for the exchange rate of YER is as follows:

$$\mathbf{P}(0) = [0.3797 \quad 0.3432 \quad 0.3243]. \tag{24}$$

3.4. State Probabilities for Prediction and Long Run Behaviour Exchange Rate

The Markov chain model calculates the probability of a state for different periods by adding the transition probability matrix to the initial state vector. This is done through the formula P_(l+1)=P_l*P, where P_l represents the state vector for the l^th state and P is the transition probability matrix. Using this formula, we can determine the probability of the exchange rate of YER at the end of 3650 days:

$$\begin{aligned} \mathbf{P}(1) = \mathbf{P}(0) \times \mathbf{P} = [0.3797 \quad 0.3432 \quad 0.3243] \begin{bmatrix} 0.3588 & 0.2299 & 0.4614 \\ 0.2368 & 0.6021 & 0.2113 \\ 0.5531 & 0.2032 & 0.2937 \end{bmatrix} \\ = [0.3674 \;\; 0.3762 \;\; 0.4522] \end{aligned} \tag{25}$$

The result above indicated that at the end of the 3650^{st} day, the exchange rate will most likely decrease with a probability of 0.4522. The YER exchange rate increases with a probability of 0.3674 and remains the same with a probability of 0.3762.

This limiting transition probability matrix provided the steady-state probability of exchange rate in the states of increases, remaining the same, or decreases in the future. The long-run behavior of the YER exchange rate is obtained by calculating the higher-order transition probability matrix of the exchange rate. The results are obtained as follows:

$$\mathbf{P}^2 = \begin{bmatrix} 0.4174 & 0.2928 & 0.3340 \\ 0.3234 & 0.4399 & 0.2831 \\ 0.3816 & 0.2890 & 0.3585 \end{bmatrix} \tag{26}$$

$$\mathbf{P}^3 = \begin{bmatrix} 0.3856 & 0.3558 & 0.38639 \\ 0.3256 & 0.37178 & 0.3189 \\ 0.3404 & 0.3084 & 0.3317 \end{bmatrix} \tag{27}$$

$$\vdots \tag{28}$$

$$\vdots$$

$$\mathbf{P}^{21} = \begin{bmatrix} 0.3856 & 0.3930 & 0.4738 \\ 0.3856 & 0.3930 & 0.4738 \\ 0.3856 & 0.3930 & 0.4738 \end{bmatrix}$$
$$= \mathbf{P}^{22} = \mathbf{P}^{23} = \cdots \text{ and so on.}$$

After 3650 trading days, the transition probability matrix for the YER exchange rate showed a tendency to reach steady state or equilibrium after the 21th trading day.

The likelihood of the YER exchange rate descending in the foreseeable future is 0.4522, regardless of 'increasing,' 'staying the same,' or 'decreasing' at the beginning. There is a 0.3674 chance that the YER exchange rate will increase in the long run, regardless of whether it increases, stays the same, or decreases. Whether the exchange rate initially increases, remains the same, or decreases, the probability of it staying the same in the long run is 0.3762. If the YER exchange rate opens in a particular state with an initial state vector, $P(0) = [0.3797\ 0.3432\ 0.3243]$, then,

$$\mathbf{P}_0 \times \mathbf{P}^{20} = [0.3797 \quad 0.3432 \quad 0.3243] \begin{bmatrix} 0.3856 & 0.3930 & 0.4738 \\ 0.3856 & 0.3930 & 0.4738 \\ 0.3856 & 0.3930 & 0.4738 \end{bmatrix} = [0.1465\ \ 0.1348\ \ 0.1536], \quad (29)$$

3.5. Numbers of Expected Visits

Using Equation (2) of transition probability matrices, the following exchange rate matrix shows the number of visits to each state for seven trading days, that is:

$$\boldsymbol{\mu}_{ij}(7) = \mathbf{P} + \mathbf{P}^2 + \mathbf{P}^3 + \mathbf{P}^4 + \mathbf{P}^5 + \mathbf{P}^6 + \mathbf{P}^7 = \begin{bmatrix} 2.6856 & 2.2187 & 2.4506 \\ 2.4649 & 2.7418 & 2.0565 \\ 2.8881 & 2.1731 & 2.3078 \end{bmatrix} \quad (30)$$

If the YER exchange rate begins at the 'increases' state, the expected visits' number, which the chain of the exchange rate will make to the 'increases' state out of seven trading days is $\mu_{UU}(7) = 2.6856$ (3 days), to the 'same state' is $\mu_{US}(7) = 2.2187$ (2 days), and to the state of 'decreases' is $\mu_{UD}(7) = 2.4506$ (2 days).

Similarly, if the YER exchange rate starts as decreases, the predicted visits number that the chain will make to the 'increases' state is $\mu_{DU}(7) = 2.8881$ (3 days), to the state that remains the same is $\mu_{DS}(7) = 2.1731$ (2 days), and to the state that decreases is $\mu_{DD}(7) = 2.3078$ (2 days).

3.6. Expected Return Time

It is pretty helpful to comprehend whether the YER's exchange rate will continue to increase, stay the same, or decrease in the foreseeable future. The expected time it takes to return to a particular state from a similar state can be calculated using steady-state transition probabilities. Specifically, the expected time it takes to go from an 'increases' state to another 'increases' state, for the YER exchange rate, can be determined by μ_U = 1/ 0.3674 = 2.7218 (3 days). This result indicated that, on average, the chain for the YER's exchange rate should visit the 'increases' state in three days. The parameter μ_S = 3.0628 (3 days) represents the expected time for the exchange rate of YER to remain the same, starting from the same state S. This parameter indicates that the chain will visit the state of 'remains the same' on average for three days. Similarly, the expected return time to the state of 'decreases,' starting from the state of 'decreases' is $\mu\_D= 3.2322$. This result shows that the chain will visit the state of 'decreases' (D) on average in three days.

According to daily moving prices, it is concluded that the daily closing Yemeni Riyal price against the USD exhibited a trend, in general; however, with the initial side way tendency, this indicated price volatility. For establishing the Markov model to forecast the YER's exchange rate against the US dollar, the derived initial state vector and the transition matrix can be utilized for predicting the YER price states as substantiated by a forecast of 3650 trading days. Moreover, the transition matrix's convergence to a given steady-state implied ergodicity, which characterizes the foreign exchange market, has made this model applicable, and regardless of an initial condition for the YER price, in the long run, the YER will decrease, remain the same or decrease with a probability of 0.3674, 0.3762, and 0.4522, respectively.

Out of a total of seven trading days, it is expected that the state of 'increases' will be visited 2.8881times, starting from the state of 'decreases'. Similarly, it is expected that the state of 'decreases' will be visited 2.0565times, starting from the state of 'remain the same'. However, for all the states, the expected return time of the YER against USD was the same, i.e., three days. The Markov Chain estimation technique is purely a probability forecasting technique because the predicted results express the probability of a specific state for a future exchange rate price instead of being in an absolute state. However, because it has no after-effects, it is relatively more effective for forecasting foreign exchange daily closing prices under the price system. The Markov chain model can fit the data and predict the tendency because of the memoryless property and the random walk capability, in which another state could directly reach every state in the given transition matrix.

The present study has shown how the Markov model can fit data and predict the trend with an 88 % accuracy. Therefore, this model can help researchers and investors determine and make informed business decisions in a foreign exchange market, influenced by various market factors, including market forces and psychological factors affecting investors. Consequently, no single technique predicts change accurately in a foreign exchange market, including the Markov Chain approach. Hence, combining the results of utilizing the Markov Chain for prediction with different factors might be more effective as a solid foundation for making decisions. This study represents one case study on the price of the Yemeni Ryle versus the US dollar. This study is based on the first-order Markov Chains, investigating three probable states only (increases, remains the same and decreases). Therefore, it is suggested that further research should be conducted on numerous exchange rates listed against the Yemeni Ryle's exchange rate, employing a higher-order Markov chain to obtain a better understanding of the foreign currency market's behavior.

CONCLUSION

The study of foreign exchange (FOREX) markets is known as foreign currency exchange. Exchange rates provide crucial data for international monetary exchange markets. Using a Markov chain model, this study aims to determine the behavior of the Yemeni Riyal (YER) against the US Dollar (USD). The present study has shown how the utilized Markov model can fit data with the ability to predict the trend. Therefore, this model can help researchers and investors determine and make informed business decisions in a foreign exchange market, influenced by various market factors, including market forces and psychological factors affecting investors. Consequently, no single technique predicts change accurately in a foreign exchange market, including the Markov Chain approach. Hence, combining the results of utilizing the Markov Chain for prediction with different factors might be more effective as a solid foundation for making decisions. This study represents one case study on the price of the Yemeni Riyal's (YER) versus the US dollar. This study is based on the first-order Markov Chains, investigating three probable states only (increases, remains the same, and decreases). Therefore, it is suggested that further research should be conducted on numerous exchange rates listed against the Yemeni Riyal's exchange rate, employing a higher-order Markov chain to obtain a better understanding of the foreign currency market's behavior.

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