Review article

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Determining the long run behaviour of the exchange rate of Libyan Dinar using Markov chain

Abstract

The study of foreign exchange (FOREX) markets is known as foreign currency exchange. These rates provide crucial data to international monetary exchange markets. Using a Markov chain model, this study attempts to determine the behaviour of the Libyan (LYD) currency rate against the US Dollar (USD). Three states are observed. The transition probability matrix and starting state vector are calculated. The result shows that, the probability of being in one of three states, namely, increases, remain the same or decreases are 0.3614, 0.3268 and 0.3118, respectively. The expected number of visits and return time are also obtained.

Keywords: Libyan Dinar, markov chain, forex

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Introduction

The FOREX market is where exchange rates are determined and traded. The prices of one currency expressed in terms of another currency are defined as exchange rates. This market has been investigated for many years because price fluctuations can have an impact on economic development and international trade. As a result, it is closely monitored by governments, central banks, multinational corporations, and financial traders. One of the most important topics in international finance and policy making is the exchange rate, which measures the price of one currency in terms of others. Exchange rate fluctuations can affect the prices of a variety of assets both directly and indirectly. Investors consider the impact of currency fluctuations on their international portfolios. Governments are concerned about export and import prices, as well as the domestic currency value of debt payments, as evidenced by the heated debate over the Chinese Yuan's value in recent years. Central banks are concerned about the value of their international reserves as well as the impact of exchange rate fluctuations on domestic inflation. The majority of Libya'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 have a high export potential, but manufactured goods are also exported to other countries. The oil industry, on the other hand, continues to be the largest source of revenue in Libya, accounting for 95 percent of total revenue. Despite a series of challenges such as inflation and economic collapse threatening the economy, the chances of the Libyan economy rebounding to success are very high. Restructuring plans in trade, finance, and production are needed, according to the IMF's proposed economic plans released in 2014, as is possibly easing government participation in private sector operations.[1]

Since the first issuance of the LYD in 1952, Libya has followed the system of linking the value of the LYD to foreign of currency, initially to the pound sterling, then to the USD, and finally to the Special Drawing Rights (SDR), the currency that the International Monetary Fund began issuing since 1970, where the value of LYD in March 1986 was equivalent to 2.8 Special Drawing Rights. The LYD was devalued to 2.60645 Special Drawing Rights in May of that year. In 2003, the LYD was devalued by 15%, reducing the value of the currency down to 0.5175 SDR. The most recent devaluation of the LYD occurred on January 3, 2021, when the official value of the LYD was cut to 0.1555 SDR. The par value of the LYD was reasonably stable throughout the first decade of this century, not as a consequence of the government's good economic policies, but as a result of the growth in crude oil prices on international markets, where the price of a barrel of oil topped $100 at times. When oil prices collapsed in 2013, the central bank's and government's arbitrary policies were exposed jointly, exposing more issues and complications in the Libyan economy.[2] The significant split on the political and economic levels, in addition to the reduction in oil prices. The government was split into two in late 2014, one in the west and one in the east; the Central Bank was also split into two central banks with the same name, the "Central Bank of Libya," but two different governors and departments. The new division in the country has led to new problems, perhaps the most important of which is the depreciation of the LYD against the USD and other foreign currencies, as well as the inability of banks to provide cash to cover their current accounts, and the growth of the black market for foreign currencies, as the price of the USD in this market rose by more than five times its official price, increase public spending, and raise the level of inflation to unprecedented rates that in some years exceeded 28%. The Central Bank took a random step on January 3, 2021, to cut the official value of the LYD by 70%, from 0.15175 SDR units per LYD to 0.1555 units, resulting in a 220 percent increase in the value of one USD from 1.4 LYD to 4.48 Dinars. This measure will lead to the provision of cash in the short term, and to the availability of abundant funds in the public treasury as a result of the rise in the value of the USD that the government obtains from oil exports. Perhaps this is the real and undeclared reason behind the devaluation of the LYD. However, this step has not been well studied at other levels. For citizens with fixed incomes, who receive wages and salaries, their real incomes will decrease at the same rate as the value of the LYD. As for the market for goods, this will lead to an increase in smuggling, especially gasoline smuggling. What the government and the Central Bank failed to consider is that the depreciation of the LYD must be accompanied by a comprehensive transformation plan, which includes using monetary and financial policy tools to control spending in local and foreign currencies, control the money supply, combat corruption in state agencies, avoid monopoly, and encourage local investment. The International privatization, the public sector, and other needed reforms, all of which lead to income diversification, without focusing entirely on crude oil export revenues, price stability, and lowering the high unemployment rate. The par value of the LYD will then be fixed, and the parallel market and economic distortions will be removed. All of this necessitates an effective administration to manage the country's economy, which Libya now lacks.[2] The FOREX market is the largest financial market in the world, with more than $5 trillion traded on average every day. However, while there are many FOREX investors, few are truly successful. Many traders fail for the same reasons that investors fail in other asset classes. In addition, the extreme amount of leverage—the use of borrowed capital to increase the potential return of investments—provided by the market, and the relatively small amounts of margin required when trading currencies, deny traders the opportunity to make numerous low-risk mistakes. Certain factors to currency trading may lead some traders to expect higher investment returns than the market can regularly provide, or accept more risk than they would in other markets.[3] This study aims to analyze the exchange rate of Libyan Dinar against US Dollar by using Markov chain model. The specific objectives of the study are to study the long run behaviour of exchange rate, to estimate the expected number of visits to particular states and also to estimate the expected first return time to these three states.

Literature review

Hamza et al.,[4] worked on the exchange rate of the Iraqi dinar by using Markov chains. In their research, the exchange rate of the Iraqi dinar against the US dollar using Markov chains and predicting the exchange rate in the future have been investigated. The results of the analysis showed an important conclusion that the exchange rate will remain stable for the upcoming period and then begin to rise as a result of the impact of the global crisis in Iraq.

Christy et al.,[5] examined the convergence Nigerian exchange rate in the long run by looking at the exchange rate switches or transition from a particular state to another. Through the iterations of the Chapman-Kolmogorov equations of the Markov model. It was discovered that convergence occurred in the long run as shown by the Markov model. The result of the analysis suggests that appreciation and depreciation of the Nigerian currency against dollar rate would be stable as indicated by the probability values.

Quadry et al.,[6] in their study, based on the theory of exchange rate determination by using Autoregressive Distributive Lag (ARDL) model, they tested for a long run relationship between both Malaysian Ringgit (MYR) and USD and also GBP against the differential interest rate, differential money supply, price of world crude oil and Goods and Services Tax, as a dummy variable. They found a negative long run relationship between MYR and GBP and differential money supply and a positive long run relationship against the world crude oil price. As the MYR supply increased relative to the GBP, the MYR depreciated, and as the crude oil price strengthened, the MYR appreciated. A high dependency of the MYR on world crude oil implies a bad sign. In their view, Malaysia needs to work harder to attract foreign direct investment to maintain the value of the Ringgit at a healthy level.

Oduselu-Hassan[7] applied the Markov chain prediction model to predict the price action using to the difference in the typical price and closing price of the daily exchange rates. The models applied to the EUR and USD currency pair in the currency market. The model works well with the EUR and USD.

Khemiri and Ben Ali[8] used a Markov-switching approach, where the authors identified two main regimes for inflation in Tunisia during this period: a low and stable inflation regime associated with a low pass-through level and a high inflation regime associated with a high pass-through level. The results show that the price level decreases in response to an increase in interest rates. Along with this, the empirical results provide strong evidence that the industrial production index has a negative and significant effect, as it increases the probability to stay in an inflationary regime and remain at a high pass-through level. The results also show robust support for the hypothesis that the imports increase the probability to stay in a high-inflation regime and maintain a high pass-through level. However, exports increase the probability of staying in a low-inflation regime and maintaining a low pass-through level.

Onwukwe and Samson[9] examined the long run behaviour of the closing were prices recorded of the Nigerian bank stocks using Markov Chain. A total of eight Nigerian bank stocks were randomly selected and data on their daily closing prices. Finding suggested that despite the current situation in the market, there was still hope for Nigerian bank stocks as some of these bank stocks tend to experience an increase in price in the long run as shown by the results of the steady state probability. Although, this finding was very informative and crucial to investors, stock brokers and other regulator in this sector, this finding was subject to unforeseen circumstances such as change in government policy, among many other factors. it was hope that the results of this study would be very useful to investors, potential investors and other relevant stakeholders who were involve in stock trading.

Choji et al.,[10] applied Markov chain model to predict the possible states by illustrating the performance of the top two banks. Guarantee Trust Bank of Nigeria and First Bank of Nigeria. They used six years data from 2005 to 2010. By obtaining the transition probability matrix, power of the transition matrix and probability vector, they obtained the long run prediction of the share price of these banks whether they appreciated, depreciated or remained unchanged regardless of current share price of the banks. They also estimated the probability of transition between the states by taking the performance of two banks together.

Zhang and Zhang[11] implemented a Markov chain model to forecast the stock market trend in China. This study explored that the Markov chain has no after effect and this model was more appropriate to analyze and predicted the stock market index and closing stock price was more effective under the market mechanism. By applying the Markov chain model in the stock market, the researcher achieved relatively good result. They recommended that this model could be used in other fields like future market and bond market. They also suggested that the result obtained from Markov chain model for prediction should be combine with other factors having significant influence in stock market variations and the method should be used as a basis for decision making.

Otieno et al.,[12] utilized Markov chain model to forecast stock market trend of Safari com share in Nairobi Securities Exchange in Kenya. They used Markov chain model to predict the Safari com share prices using the data collected over The first of April 2008 to 30th April 2012. In this study the Markov chain prediction has been applied for a specific purpose to forecast the probability and this forecasted value indicate the probability of certain state of stock or shares prices in future rather than be in absolute state. This study also revealed that the memory less property and random walk capability of Markov chain model facilitates to the best fit the data and to predict the trend. By using the Markov chain model, they observed the good results of predicting the probability of each state of the shares of Safari com.

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Mettle et al.,[13] used Markov chain model to analyze the share price changes for five different randomly selected equities on the Ghana Stock Exchange. This study concluded that the application of Markov chain model as a stochastic analysis method in equity price studies improved the portfolio decisions. They have suggested that Markov chain model could be apply as a tool for improving the stock trading decisions. Application of this method in stock analysis improves both the investor knowledge and chances of higher returns.

Bairagi and Kakaty[1] applied Markov Chain model in the study, where attempts have been made to predict the arrival market price interval of potatoes of Lanka Regulated market of Nagaon District. The forecasting was done for the short period of consecutive 15 days. The prediction made for the price interval by the model was identical to real situations. The forecasting made for the future price by any one method may not be adequate, but the result obtained by Markov Chain model was quite encouraging.

Agbam and Samuel,[14] practiced Markov chain for forecasting Dangote cement share prices in the Nigerian Stock Exchange. It was concluded that the derived initial state vectors and the transition matrices could be used to predict the state of Dangote Cement prices accurately. Additionally, the convergence of transition matrices to a steady state implying ergodicity that is a characteristic of stock market makes the model applicable.

Methodology

Markov chains

Markov chains have a wide range of interesting applications in academic and industrial fields. It has been used in various fields such as chemistry, statistics, operations research, economics, finance, music and other disciplines too. In this study the exchange rate analysis are focused.

Markov chain is a stochastic process with the property where the probabilities of in the future depends only on the present state, are independently of the event in the past.

Let $\{X_t, t = 0, 1, 2, ...\}$ be a stochastic process that takes on a finite or countable number of possible values, the set of possible values of the process is denoted by the set of nonnegative integers $\{0, 1, 2, ...\}$. If $X_t = i$, $i \geq 0$ then the process is said to be in state i at time t. A Markov chain gives us that whenever the process is in state i, there is a fixed probability p_{ij} that it will next be in state j, that is,

$$P\{X_{t+1} = j \mid X_t = i, X_{t-1} = i_{t-1}, \ldots, X_1 = i_1, X_0 = i_0\} = P\{X_{t+1} = j \mid X_t = i\} = p_{ij}$$

Transition count and transition probability matrices

The one-step transition frequency matrix F can be constructed as:

$$\mathbf{F} = \begin{bmatrix} f_{00} & \cdots & f_{0k} \\ \vdots & \ddots & \vdots \\ f_{k0} & \cdots & f_{kk} \end{bmatrix}$$

where f_{ij} is the number of the price of transitions from state i to state j in one step.

The transition count matrix then p_{ij} can be estimated by:

$$p_{ij} = \frac{f_{ij}}{\sum_{j=1}^{k} f_{ij}}, \quad \sum_{j=1}^{k} f_{ij} > 0 \qquad (1)$$

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

$$\mathbf{P} = \begin{bmatrix} p_{00} & \cdots & p_{0k} \\ \vdots & \ddots & \vdots \\ p_{k0} & \cdots & p_{kk} \end{bmatrix}.$$

This matrix **P** is known as the Markov chain transition probability matrix, with the element p_{ij} denoting the conditional probability that an element in state *i* at the current time will be in state *j* at the next time. It is also referred to as a one-step transition probability matrix. The elements in the main diagonal of the transition probability matrix represent the likelihood that a given probability element will remain in the same state in the future. The probabilities of movements among the given states are represented by elements outside the main diagonal. Matrix **P**'s elements are probabilities with a sum of one by rows.[15]

A Markov chain has an initial state vector, represented as $(1 \times k)$ vector that describes the probability distribution of starting at each of the *k* possible states. Entry *i* of the vector describes the probability of the chain beginning at state *i*, that is

$$P(X_0 = i) = \mathbf{P}(0) = \left[p_0(0)\, p_1(0)\, p_2(0) \ldots\ldots\ldots p_k(0)\right], \; 0 \leq p_i(0) \leq 1$$

where,

$$p_i(0) = \frac{\sum_{j=1}^{k} f_{ij}}{\sum_{j=1}^{k}\sum_{i=1}^{k} f_{ij}}, \text{ and } \sum_{i=0}^{k} P_i(0) = 1 \; \textit{for all states}.$$

$$P(X_t = i) = P(t) = \sum_i P(X_t = j \mid X_0 = i) P(X_0 = i)$$

$$\sum_i P_i(0) P_{ij}(t), t > 0$$

Knowing the system's initial state and the transition matrix after *t* steps gives,

$$\mathbf{P}(\ell + 1) = \mathbf{P}(\ell) \times \mathbf{P}$$

which lead to:

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

$$\mathbf{P}(2) = \mathbf{P}(1) \times \mathbf{P} = \mathbf{P}(0) \times \mathbf{P}^2.$$

Thus,

$$\mathbf{P}(\ell) = \mathbf{P}(\ell - 1) \times \mathbf{P} = \mathbf{P}(\ell - 2) \times \mathbf{P}^2 = \ldots = \mathbf{P}(0) \times \mathbf{P}^{\ell}.$$

Hence,

$$\mathbf{P}(\ell + 1) = \mathbf{P}(0) * \mathbf{P}^{\ell+1}, \text{ for } \ell \geq 0.$$

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

The (ℓ +1) step probability matrix

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

$$P_{ij} = P(X_1 = j \mid X_0 = i) = P(X_{t+1} = j \mid X_t = i), \text{ for any } t.$$

p_{ij} is the probability of making a transition from state i to state j in a single step.

The (ℓ +1) step transition matrix are given by the matrix $\mathbf{P}^{\ell+1}$ for any ℓ

$$P(X_{\ell+1} = j \mid X_0 = i) = P(X_{t+\ell+1} = j \mid X_t = i) = (P_{ij})^{\ell+1}$$

Classification of states

We can say the accessibility of states from each other. If it is possible to go from state i to state j, it is said that the state j is accessible from state i and can be written as $i \to j$. If $p_{ij} > 0$.

Two states i and j are said to communicate, written as $i \leftrightarrow j$, if they are accessible from each other. In other words $i \leftrightarrow j$ means $i \to j$ and $j \to i$ communication is an equivalence relation. That means that every state communicates with itself, $i \leftrightarrow j$; Further if $i \leftrightarrow j$ and $j \leftrightarrow k$, then $i \leftrightarrow k$. Therefore, the states of a Markov chain can be partitioned into communicating classes such that only members of some class communicate with each other. That is, two states i and j belong to the same class if and only if $i \leftrightarrow j$.

A Markov chain is said to be irreducible if it has only one communicating class. In the other words the Markov chain is irreducible if all states communicate with each other.

The long run behavior of Markov chains

Suppose that a transition probability matrix **P** on a finite number of states labelled 0,1, …, k has the property that when raised to some power t, the matrix $\mathbf{P}^t$ has all of its elements strictly positive. Such a transition probability matrix, or the corresponding Markov chain, is called regular. The most important fact concerning a regular Markov chain is the existence of a limiting probability distribution.

$\mathbf{P} = [p_0 \quad p_1 \cdots \quad p_k]$, where $p_j > 0$ for $j = 0,1,\ldots, k$ and $\sum_j p_j =$ 1, and this distribution is independent of the initial state. Formally, for a regular transition probability matrix **P**, we have the convergence, that is:

$$\lim_{t\to\infty} \mathbf{P}_{ij}^{(t)} = p_j > 0 \text{ , for } j = 0,1, \ldots ,k$$

For the Markov chain $\{ X_t \}$, it can be written as

$$\lim_{t\to\infty} P\{X_t = j \mid X_0 = i\} = p_j > 0 \text{ , for } j = 0,1, \ldots ,k$$

This convergence means that, in the long run ($t\to\infty$), the probability of finding the Markov chain in state j is approximately p_j no matter in which state the chain began at time 0.[16]

Expected number of visits

Here consider the important quantity for finite state chains that have transient states. The expected number of visits of the chain to a transient state. If the states are recurrent, they are visited over and over, always returned to again, an infinite number of times.

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

$$\boldsymbol{\mu}_{ij}(\ell) = E\sum_{w=0}^{\ell} P\{X_w = j \mid X_0 = i\} = \sum_{w=0}^{\ell} \mathbf{P}^w,\ w = 1, 2, \ldots, \ell \qquad (2)$$

Expected return time

For a finite irreducible Markov chain the expected number of revisits to state j is precisely n visits at time $t_n = Y_1 + \ldots + Y_n$, let Y_i is be the random variable that counts the total number of visits to state i, and thus the long run proportion of visits to state j per unit time can be obtain by taking the reciprocal of limiting probability p_j .[17]

In the case where $i = j$, we say that $E(Y_i \mid x_0 = i)$ is the expected return time to i given that the chain started at i . That is because the definition of Y_i only involves times that are at least 1. It turns out that there is a simple relation between p_i and the expected return time to i.

$$\lim_{t\to\infty} E(Y_i \mid X_0 = i) = \frac{1}{p_i}, i = 0, 1, 2, \ldots, k$$

Since $p_i \geq 0$ for all states i, the expected return time to each state is finite when p_i is a steady probability of state i.

Results and discussion

Derivation of three states

It is noticed to see that the exchange rate of the Libyan dinar con be categorized into one of three states at the end of each day during the study period. In case the exchange rate of Libyan dinar goes up against US dollar compared to the day before, then it is categorized as “increase” (U). If it goes down then it is categorized as “decreases” (D). Furthermore, if it does not change is categorized as “remain the same” (S). These are observed from daily states of the LYD exchange rate to the USD. Thus, we have the as “increases” (U), “remain the same” (S) or “decreases” (D). These three different movements are treated as three different states in the Markov chain for the purposes of developing the transition probability matrix. The transition probability gives the information about the Markov chain’s transition behaviour. The elements of the transition probability matrix show the possibility of transitions from one state to another.

With LYD 3650 trading days, the transition probability matrix shows that the exchange rate increases for 1320 days, remained the same for 1193 days, and decreases for 1137 days.

The transition count and transition probability matrices

The LYD exchange rate demonstrates three different states $(i, j = 0, 1, 2)$ in this study. Table 1 shows the number of exchange rate of LYD price classified between “increases”, “remain the same” and “decreases”. The $f_{00} = 451$ denotes the number of instances in which the LYD price increases despite the fact that it was already increased against the USD the day before. The number of times the LYD price has remained steady despite the fact that it was increased against the USD before is $f_{12} = 289$ and so on for the rest of the elements.

Table 1 The transition count matrix of exchange rate of Libyan dinar against US dollar

	Increases (U)	Remain the same (S)	Decreases (D)
Increases (U)	451	289	580
Remains the same (S)	269	684	240
Decreases (D)	599	220	318

The transition probability matrix of exchange rate of LYD can then be constructed using the equation (1), which give

$$\mathbf{P} = \begin{pmatrix} 0.3417 & 0.2189 & 0.4394 \\ 0.2255 & 0.5733 & 0.2012 \\ 0.5268 & 0.1935 & 0.2797 \end{pmatrix}$$

From the matrix P above the transition diagram for the explicit presentation of transition probability of exchange rate of LYD is shown below (Figure 1).

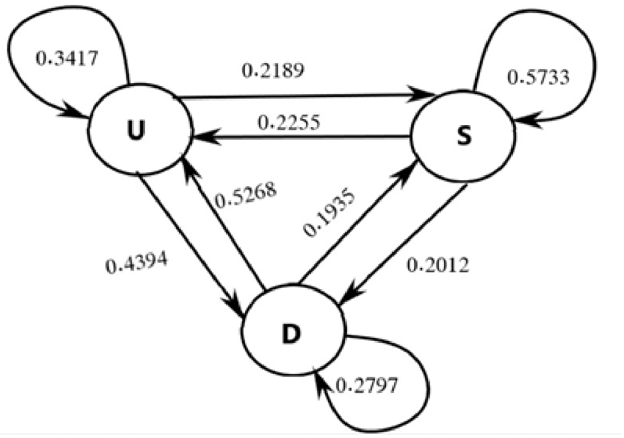

Figure 1 The transition diagram of exchange rate of Libyan dinar against US dollar.

It can be seen from the diagram that the price of exchange rate moving from the "increases" state (U) to the state of "remain the same" (S) with a probability of 0.2189 and moving from the state of "remain the same" (S) to the state of "increases" (U) with a probability of 0.2255. As a result, the states U and S communicate with each other.

It is also possible to go from the state of "increases" (U) to the state of "decrease" (D) with a probability 0.4394. It is also possible to go from the state of "decreases" (D) in the exchange rate to the state of "increases" (U) in the exchange rate with probability 0.5268. As a result, the two states communicate.

Furthermore, it is possible to go from a condition of exchange rate of "remain the same" (S) to a state "decreases" (D), with a probability of 0.2012, while, the price of exchange rate can go from "decreases" state to the state of "remain the same" with probability of 0.1935. As a result, the two states can communicate with each other.

All states communicate. As a result, there is only one class. Thus, the Markov chain is irreducible.

Determination of initial state vector

As the LYD exchange rate demonstrates three different states, the starting state vector can also be calculated. The initial state vector **P**(0) is given by

$$\mathbf{P}(0)=\left[p_U(0) \quad p_S(0) \quad p_D(0)\right]$$

where, $p_U(0)$, $p_S(0)$ and $p_D(0)$ provide the probability that the LYD exchange rate increases, stay the same or decreases, at the beginning of period. The computation gives,

$$p_U(0)=1320/3650=0.3616$$

$$p_S(0)=1193/3650=0.3269$$

$$p_D(0)=1137/3650=0.3115$$

Hence, the initial state vector for exchange rate of LYD is

$$\mathbf{P}(0)=[0.3616 \quad 0.3269 \quad 0.3115].$$

State probabilities for prediction and long run behaviour exchange rate

According to the Markov chain model, the state probability for different periods can be calculated by multiplying the transition probability matrix with the initial state vector $\mathbf{P}_{\ell+1}=\mathbf{P}_{\ell}*\mathbf{P}$. Where, $\mathbf{P}_{\ell}$ is the state vector for ℓ^{th} state and **P** is the transition probability matrix. The state probability for the exchange rate of LYD at the end of 3650 day will be

$$\mathbf{P}(1)=\mathbf{P}(0)\times\mathbf{P}=[0.3616 \quad 0.3269 \quad 0.3115]\begin{bmatrix}0.3417 & 0.2189 & 0.4394\\0.2255 & 0.5733 & 0.2012\\0.5268 & 0.1935 & 0.2797\end{bmatrix}=[0.3614 \quad 0.3268 \quad 0.3118].$$

The aforementioned conclusion indicates that at the end of the 3650^{st} day, the exchange rate will most likely decrease with a probability of 0.3118. The LYD exchange rate increases with a probability of 0.3614 and remain the same with a probability of 0.3268.

This limiting transition probability matrix provides the steady state probability of exchange rate in states of increases, remains same or decreases in the future. The long run behaviour of the LYD exchange rate is obtained by calculating the higher order transition probability matrix of the exchange rate using. The results are obtained as below:

$$\mathbf{P}^2=\begin{bmatrix}0.3976 & 0.2853 & 0.3171\\0.3123 & 0.4170 & 0.2707\\0.3710 & 0.2804 & 0.3486\end{bmatrix}$$

$$\mathbf{P}^3=\begin{bmatrix}0.3672 & 0.3120 & 0.3208\\0.3434 & 0.3598 & 0.2968\\0.3737 & 0.3094 & 0.3169\end{bmatrix}$$

$$\mathbf{P}^4=\begin{bmatrix}0.3648 & 0.3213 & 0.3139\\0.3548 & 0.3389 & 0.3063\\0.3644 & 0.3205 & 0.3151\end{bmatrix}$$

$$\mathbf{P}^5=\begin{bmatrix}0.3625 & 0.3248 & 0.3127\\0.3590 & 0.3312 & 0.3098\\0.3628 & 0.3245 & 0.3127\end{bmatrix}$$

$$\vdots$$

$$\mathbf{P}^{20}=\begin{bmatrix}0.3614 & 0.3268 & 0.3118\\0.3614 & 0.3268 & 0.3118\\0.3614 & 0.3268 & 0.3118\end{bmatrix}$$

$$=\mathbf{P}^{21}=\mathbf{P}^{22}=\cdots \text{ and so on.}$$

Since 3650 trading days, the higher order transition probability matrix for the LYD exchange rate computed above shows that the transition probability matrix tends to the steady state or state of equilibrium after the 20th trading day.

The likelihood of the LYD exchange rate descending in the near future is 0.3118, regardless of whether it increases, stays the same or decreases at the beginning. There is a 0.3614 chance that the LYD exchange rate will increase in the long run, regardless of whether it increases, stays the same or decreases. Regardless of whether the exchange rate initially increases, remain the same or decreases, the probability of it to remain the same in the long run is 0.3268.If the LYD exchange rate opens in a particular state with an initial state vector, $\mathbf{P}(0)=[0.3616 \quad 0.3269 \quad 0.3115]$, then in a steady state condition, the probability of the LYD exchange rate increases, remain the same or decreases on a given trading day can be calculated by multiplying

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the initial state vector by the higher order transition probability matrix obtained at state of equilibrium. Then,

$$\mathbf{P}_0 \times \mathbf{P}^{20} = \begin{bmatrix} 0.3616 & 0.3269 & 0.3115 \end{bmatrix} \begin{bmatrix} 0.3614 & 0.3268 & 0.3118 \\ 0.3614 & 0.3268 & 0.3118 \\ 0.3614 & 0.3268 & 0.3118 \end{bmatrix}$$

$$= \begin{bmatrix} 0.3616\ 0.3269\ 0.3115 \end{bmatrix}$$

Expected numbers of visits

The expected number of visits to any state from another state in different steps can be determined. Using (2), the following exchange rate matrix shows the number of visits to each state for seven trading days, that is

$$\mu_{ij}(7) = \mathbf{P} + \mathbf{P}^2 + \mathbf{P}^3 + \mathbf{P}^4 + \mathbf{P}^5 + \mathbf{P}^6 + \mathbf{P}^7$$

$$= \begin{bmatrix} 2.5572 & 2.1149 & 2.3279 \\ 2.3167 & 2.6760 & 2.0073 \\ 2.7221 & 2.0807 & 2.1972 \end{bmatrix}$$

If the LYD exchange rate begins at the increases state, the expected number of visits the chain for exchange rate makes to the increases state out of seven trading days is $\mu_{\text{UU}}(7) = 2.5572$ (3 days), to the same state is $\mu_{\text{US}}(7) = 2.1149$ (2 days), and to the state decrease is $\mu_{\text{UD}}(7) = 2.3279$ (2 days).

Similarly, if the LYD exchange rate starts as decreases, the predicted number of visits the chain will make to the state that increases is $\mu_{\text{DU}}(7) = 2.7221$ (3 days), to the state that remains the same is $\mu_{\text{DS}}(7) = 2.0807$ (2 days), and to the state that decreases is $\mu_{\text{DD}}(7) = 2.1972$ (2 days).

Expected return time

It will be helpful to know whether the LYD exchange rate will continue to increase, stay the same or decreases in the near future. Using steady state transition probabilities, the expected return time to a state starting from the same state is computed. The expected return time to the increases state for the LYD exchange rate, starting from the same increases state is μ_{U} = 1/ 0.3614 = 2.6760 (3 days). This result indicates that, on average, the chain for the LYD exchange rate shoulder visits the state of increases in three days. Similarly, μ_{S} = 3.05998 (3 days) is the expected return time to the state of remain the same, starting from the same state S. This means the chain for exchange rate of LYD should visits the state of remains same on an average of three days. The expected return time to the decreases state, starting from the decreases state is μ_{D} = 3.2072 . This result helps to conclude that the chain will visits the decreases state (D) on an average of three days.

Conclusion and further work

It is concluded that based on daily moving prices, the daily closing Libyan dinar price against USD had generally a trend, though with an initial side way trend, indicating volatility of price. It was to determine the Markov model for forecasting exchange rate of Libyan Dinar against USD, it is count that the derived initial state vector and the transition matrix could be used to predict the states of Libyan dinar price as confirmed by the prediction of the 3650 trading days. Additionally, the convergence of transition matrix to a steady state implying ergodicity that is a characteristic of the foreign exchange market makes the model applicable. In the long run, irrespective of the initial condition of the Libyan dinar price, the LYD will decrease, remain the same or decrease with probability of 0.3614 , 0.3268 and 0.3118 , respectively.

Out of seven trading days, the expected number of visits to the increases state starting from the state of decreases is 2.7221, and the expected number of visits to the decreases state starting from the state of remain the same is 2.0073. Unfortunately, for all states, the expected return time of the LYD against USD was the same that is three days.

The Markov Chain estimation technique is purely a probability forecasting method, as the predicted results have been simply expressed probability of a certain state of exchange rate price in the future rather than being in absolute state, but because it has no after-effects, it is relatively more effective under the price system for forecasting foreign exchange daily closing prices. Due to its memoryless property and random walk capability, in which each state may be reached directly by every other state in the transition matrix, the Markov model fits the data and is able to predict trend, this study shows how the Markov model fits the data and is able to predict trend. As a result, this model will aid both researchers and investors in identifying in general, thereby allowing them to make informed investment decisions in the foreign exchange market, which is influenced by a variety of market factors ranging from multiple market forces to psychological factors affecting investors. Therefore, no single method can accurately predict change in the foreign exchange market. Markov Chain prediction method is no exception and therefore, a combination of results from using Markov Chain to predict with other factors can be more useful as a basis for decision making. The current study was a case study on only the price of Libyan Dinar compare with US Dollar. In addition, the study was based on first-order Markov Chains just with three potential states (increases, remain the same and decreases). As a result of this research, it is suggested that more research be done on numerous exchange rates listed against the Libyan Dinar exchange rate, employing a higher order Markov chain to acquire a better understanding of the foreign currency market's behaviour.

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Conflicts of interest

The authors declare that there are no conflicts of interest.

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