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A Markov chain analysis for BIST participation index

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Abstract

This study addresses the trend estimation of the participation indices (PARTI) in the Istanbul Stock Exchange (BIST) using Markov chain (MC) theory. PARTI can be regarded as the Participation 50 Index (KAT50) and the Participation 30 Index (KATLM). Since KAT50 has only been calculated since 9th July 2014, there are only a few studies on this index. Therefore, in this study, we examine the PARTI indices. Firstly, we have employed MC method using 520 daily closing values of KATLM, between 1st July 2014 and 29th July 2016. For the KAT50 index, we used 514 daily closing values between 9th July 2014 and 29th July 2016, considering the states of these indices as increasing, decreasing or remaining stable. In order to perform a Markov chain analysis relating to prediction of the future situation, a transition probability matrix was created. Using this matrix, a steady-state analysis of the chain was performed and the future trends of KAT50-KATLM were forecasted successfully. It can be concluded that the results of this study are very helpful for individual and institutional investors' investment decisions within global economies.

***Keywords:** BIST, participation index, Markov chain analysis, trend prediction.*

BIST katılım endeksi için bir Markov zinciri analizi

Özet

Bu çalışma bir Markov zinciri (MZ) modeli ile Borsa İstanbul (BIST)'da yer alan Katılım Endekslerinin (KATLM, KAT50) hareketlerini tahmin etmeyi amaçlar. KAT50 Endeksi 9 Temmuz 2014 tarihinden bu yana işlem görmeye başladığından dolayı, literatürde bu endeks üzerinde yapılmış yeterince çalışma yoktur. Bu çalışmada ilk olarak, KATLM endeksinin 520 günlük (01.07.2014-29.07.2016), KAT50 endeksinin ise 514 günlük (09.07.2014-29.07.2016) kapanış değerleri göz önüne alınarak bir MZ

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modeli oluşturuldu. Bu modelde endekslerin artış, azalış ve sabit kalma durumları dikkate alındı. Endekslerin gelecekteki değerlerine ilişkin bir MZ analizi yapmak için geçiş olasılıkları matrisi oluşturuldu. Bu matristen yararlanılarak, kararlı durum analizi yapıldı ve KATLM-KAT30 endekslerinin gelecekteki hareketleri başarılı bir şekilde öngörüldü. Bu çalışmanın sonuçlarının, bireysel ve kurumsal yatırımcıların küresel ekonomilerdeki yatırım kararları için çok yararlı olduğu sonucuna varılabilir.

Anahtar kelimeler: *BIST, katılım endeksi, Markov zinciri analizi, eğilim tahmini.*

1. Introduction

People pay attention to financial developments on a day-to-day basis. During the last few decades especially, new algorithms and methods have been generated relating to financial modelling and simulation. Markov chain analysis (MCA) is one of the methods extensively used in the solution of real-life problems, especially in financial and economic areas. For example, this technique is used to evaluate the performance of financial shares, to detect exchange rate directions, to evaluate customer demands, to solve portfolio-selection problems, to plan workforces, to estimate stocks and indices, to forecast the bankruptcy of companies, to predict financial crises, to determine manipulative transactions, to price options, for portfolio optimization, etc.

Estimation of financial indicators (indices/prices) is a complex and quite difficult issue because they depend on many factors such as political events, financial ratios and economic variables. The psychological make-up or decision-making styles of investors or experts are also major reasons for this difficulty [1]. In addition, many economic factors influence indices. Political stalemates in the country, investors' tendencies and expectations, economic productivity, the status of foreign investments on the index, preferences of corporate investors, etc. all have a very important effect on stock market prices. There are many approaches and techniques for estimating index values, such as time series analysis techniques, genetic algorithms and multiple regression models. However, there is a notable lack of studies on the estimation of indices in Turkey. Therefore, the aim in this study is to demonstrate the predictability of the KATLM and KAT50 indices using Markov chain analysis. In addition, we have aimed to determine the estimation differences between the indices by comparing the results obtained.

2. Literature Review

Many studies have been undertaken in the last quarter of a century on stock index prediction using Markov chain analysis. Eraker [2] used Markov chain Monte Carlo (MCMC) methods to predict parameters entering the drift and diffusion functions of stochastic differential equations. His estimator uses simulation-based inference through MCMC. The results show that the MCMC method is quite successful in capturing the discretization bias associated with the weekly data. Maskawa [3] studied a multivariate Markov chain model in order to show the synchronization of the directions of stock price changes. His model included a portfolio of arbitrary size, created by a recurrence relation, and he described the direction of the stock price changes very well using the multivariate Markov chain model.

Lu and Lee [4] presented an estimation of transition matrices based on discrete- and continuous-time Markov chain models. They applied these different models to bank loans, including secured and unsecured loans, for 28 banks in Taiwan. As a result of their study, they proposed a comprehensive investigation of bank loans that is expected to be helpful for financial institutions. Wang et al. [5] incorporated Markov chain theory into the fuzzy stochastic estimation of stock indices. They determined the parameters using a fuzzy linguistic summary and defined the situations of stock indices as either rising or falling. Öz and Erpolat [6] examined the monthly changes of the US dollar buying rates and the monthly changes of the ISE National 100 Index values using a multivariate Markov chain model. Vasanthi et al. [7] used a first-order Markov chain model and tried to predict the stock index trend of various global stock indices, such as those of American stock markets (DJIA, S&P 500), European markets (FTSE, FTSH), Australian markets (AUSTA^ORD), the Chinese market (SSE), the South East Asian market (Hang Seng), Pakistan market (KSE), Indian markets (BSE, NSE), etc. They predicted the trends of these indices in the short term, medium term and long term.
Lozza et al. [8] proposed a simple way to evaluate bivariate Markov processes in portfolio, risk management, and option pricing problems. In particular, they observed that the Markovian predictions of the future have a very big influence on the correct portfolio choices. Additionally, they stated that the bivariate Markov process can be used to predict the covariance matrix at a given future time. Svoboda and Lukas [9] used Markov chain analysis (MCA) to predict the trends of the Prague stock exchange PX. Moreover, some researchers predicted successfully by using another estimation techniques the trend of financial indicators such as risk return [10], index during the financial crisis [11], banking index [12], data mining in financial markets [13], financial failure [14], etc.

3. Markov chain theory

3.1. Definition

A stochastic process $X = \{X_n : n \geq 0\}$ on a countable set S is said to be a Markov chain if, for any $i, j \in S$ and $n \geq 0$, [15]

$$P\{X_{n+1} = j | X_0, ..., X_n\} = P\{X_{n+1} = j | X_n\}, \tag{3.1}$$

$$P\{X_{n+1} = j | X_n = i\} = p_{ij}. \tag{3.2}$$

The term p_{ij} is the probability that the Markov chain jumps from state i to state j. These transition probabilities satisfy $\sum_{j \in S} p_{ij} = 1,\ i \in S,$ and the matrix

$$\mathbf{P} = (p_{ij}) = \begin{bmatrix} p_{00} & p_{01} & p_{02} & \cdots \\ p_{10} & p_{11} & p_{12} & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ p_{i0} & p_{i1} & p_{i2} & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix} \tag{3.3}$$

is the transition probability matrix of the chain.

Condition (3.1) is called the Markov property, i.e., at any time $n,$ the next state X_{n+1} is conditionally independent of the past $X_0,...,X_{n-1}$ given the present state X_n. In other words, the next state is dependent on the past and present only through the present state. The Markov property is an elementary condition that is satisfied by the state of many stochastic phenomena. Condition (3.2) states that the transition probabilities do not depend on the time parameter n; the Markov chain is therefore time-homogeneous. If the transition probabilities were functions of time, the stochastic process X_n would be a non-time-homogenous Markov chain.

3.1. Theorem

For an irreducible ergodic Markov chain, $\lim_{n\to\infty} P_{ij}^n$ exists and is independent of i [16]. Furthermore, letting $\pi_j = \lim_{n\to\infty} P_{ij}^n,\ j \geq 0$ then π_j is the unique non-negative solution of

$$\pi_j = \sum_{i=0}^{\infty} \pi_i P_{ij},\ j \geq 0,\ \sum_{j=0}^{\infty} \pi_j = 1. \tag{3.4}$$

3.2. Lemma

Chapman-Kolmogorov Equation: [16] For all $s \geq 0,\ t \geq 0,$

$$P_{ij}\left(t+s\right) = \sum_{k=0}^{\infty} P_{ik}\left(t\right) P_{kj}\left(s\right) \tag{3.5}$$

The Chapman-Kolmogorov equation provides a method for computing t-step transition probabilities. If we let $P^{(t)}$ denote the matrix of t-step transition probabilities $p_{ij}\left(t\right)$, then the Chapman-Kolmogorov equation asserts that

$$P^{(t+s)} = P^{(t)}.P^{(s)} \tag{3.6}$$

where the dot represents matrix multiplication.

3.1. Participation indices using the Markov chain

Applications of the Markov chain (MC) to financial markets are quite numerous. Most of them deal with the measurement and comparison of credit risk [4], financial-economic time series [17] and the trend forecasting of stock market indices [9]. Thus, trend predictions for KATLM and KAT50 with Markov chain theory constitute the main subject of this study. In this section of the study, the Markov chain was formed using 520 daily closing values for KATLM, between 1st July 2014 and 29th July 2016, considering the states of KATLM as increasing, decreasing or remaining stable. In addition, the Markov chain was formed using 514 daily closing values of KAT50, between 9th July 2014 and 29th July 2016, considering the states of KAT50 as increasing, decreasing or remaining stable.

When all the situations are examined for KATLM, it is observed that out of 520 index closing values, 234 were increasing, 196 were decreasing and 90 were stable. Furthermore, for KAT50, out of 514 index closing values, 206 were increasing, 168 were decreasing and 140 were stable. An increase or decrease of 0.2% in the index value compared to the previous day is considered to be in the stable category. Using these observed values, firstly, state transition matrices were generated, and using these matrices, transition probability matrices were created. The matrices formed are shown in Eq. (3.7) for KATLM and Eq. (3.8) for KAT50.

$$\mathbf{S_1} = \begin{pmatrix} \text{states} & \mathbf{1} & \mathbf{0} & \mathbf{-1} \\ \mathbf{1} & 110 & 53 & 71 \\ \mathbf{0} & 36 & 15 & 39 \\ \mathbf{-1} & 84 & 27 & 85 \end{pmatrix}, \quad \mathbf{P_1} = \begin{pmatrix} 0.470 & 0.226 & 0.303 \\ 0.400 & 0.167 & 0.433 \\ 0.429 & 0.138 & 0.434 \end{pmatrix} \tag{3.7}$$

$$\mathbf{S_2} = \begin{pmatrix} \text{states} & \mathbf{1} & \mathbf{0} & \mathbf{-1} \\ \mathbf{1} & 87 & 64 & 55 \\ \mathbf{0} & 49 & 43 & 48 \\ \mathbf{-1} & 70 & 33 & 65 \end{pmatrix}, \quad \mathbf{P_2} = \begin{pmatrix} 0.422 & 0.311 & 0.267 \\ 0.350 & 0.307 & 0.343 \\ 0.417 & 0.196 & 0.387 \end{pmatrix} \tag{3.8}$$

Using the transition probability matrices, a steady-state analysis of the Markov chain was performed, and hence the probabilities of increasing, decreasing or stable states were determined when the system is in a state of equilibrium. In order to determine these probabilities the systems are shown in Eq. (3.9) and Eq. (3.10) for KATLM and KAT50 respectively:

$$\begin{aligned} \pi_1 + \pi_2 + \pi_3 &= 1 \\ 0.470\pi_1 + 0.400\pi_2 + 0.429\pi_3 &= \pi_1 \\ 0.226\pi_1 + 0.167\pi_2 + 0.138\pi_3 &= \pi_2 \\ 0.303\pi_1 + 0.433\pi_2 + 0.434\pi_3 &= \pi_3 \end{aligned} \tag{3.9}$$

$$\begin{aligned} \pi_4 + \pi_5 + \pi_6 &= 1 \\ 0.422\pi_4 + 0.350\pi_5 + 0.417\pi_6 &= \pi_4 \\ 0.311\pi_4 + 0.307\pi_5 + 0.196\pi_6 &= \pi_5 \\ 0.267\pi_4 + 0.343\pi_5 + 0.387\pi_6 &= \pi_6 \end{aligned} \tag{3.10}$$

Solving Eq. (3.9) we obtained $\pi_1 = 0.4418,$ $\pi_2 = 0.1822$ and $\pi_3 = 0.3760.$ These results mean that the probability of an increasing state in the KATLM index is 0.4418, that of a decreasing state is 0.3760 and that of a stable state is 0.1822, in the long term. When we compare these values with real index values from after 29th July 2016, i.e., between 1st August 2016 and 31st August 2017, it can clearly be seen that the index increased with probability 0.4353, decreased with probability 0.3528 and remained stable with probability 0.2119. Similarly, by solving Eq. (3.10) we found solutions $\pi_4 = 0.4008,$ $\pi_5 = 0.2723$ and $\pi_6 = 0.3269.$ That is, the probability of an increasing state for the KAT50 index is 0.4008, that of a decreasing state is 0.3269 and that of a stable state is 0.2723 in the long term. If we compare these values with real index values from after 29th July 2016, i.e., between 1st August 2016 and 31st August 2017, we find that the KAT50 index increased with probability 0.3981, decreased with probability 0.3315 and remained stable with probability 0.2704. The results obtained with MC analysis and real index values are compared in Table 1 for KATLM and Table 2 for KAT50.

Table 1. Comparing the KATLM Index values and MC analysis findings.

Increasing			Decreasing			Remaining Stable		
Real Values	MC Values	**Abs. Error**	Real Values	MC Values	**Abs. Error**	Real Values	MC Values	**Abs. Error**
0.4353	0.4418	**0.0065**	0.3528	0.3760	**0.0232**	0.2119	0.1822	**0.0297**

Table 2. Comparing the KAT50 Index values and MC analysis findings.

Increasing			Decreasing			Remaining Stable		
Real Values	MC Values	**Abs. Error**	Real Values	MC Values	**Abs. Error**	Real Values	MC Values	**Abs. Error**
0.3981	0.4008	**0.0027**	0.3315	0.3269	**0.0046**	0.2704	0.2723	**0.0019**

According to Table 1 and Table 2 we observe that the Markov chain is a powerful and accurate method for estimating the trend of the participation index.

Predictive models such as genetic algorithm, artificial neural network, ant colony and Markov chain are able to predict the economic stochastic processes with very small error rate when the conditions in the real market are normal. However, in the case of sudden positive / negative political or economic developments, these error rates increase because such prediction models do not predict these sudden fluctuations.

In this section, we will compare our results with those of some of the studies in the literature. Although there have been no studies in the literature about prediction of the participation index to date, there are some findings about index trend estimation. Among these, Vasanthi et al. [7] estimated the trend of stocks with 85.71% accuracy using Markov chain analysis. They used American stock markets (DJIA, S&P 500), European markets (FTSE, FTSH), the Australian market (AUSTA^ORD), a Chinese market (SSE), a South East Asian market (Hang Seng), and markets from Pakistan (KSE) and India (BSE, NSE) as the data for their study. Idolor [18] tried to predict the future price movements of the eight stocks traded in the Nigerian Stock Exchange using the Markov chain method, using daily data between 2005 and 2008. The results of the study show that the Markov chain model does not give a definite result without estimating the price movements in the short term.

On the other hand, regarding different applications of the proposed methods, in [19] the authors used a Markov chain model and two neural networks to predict the profits contributed by a customer under various purchasing behaviours. The proposed framework was demonstrated with historical customer transactions from a car repair and maintenance company in Taiwan. They obtained prediction accuracies for the two neural networks of about 94% in the training sample and 92% in the testing sample. In [20], the authors modelled the management of the water network using a single-layer extreme learning machine (ELM). The developed ELM model gave results with coefficients of determination ranging from 0.67 to 0.82. This was achieved with a maximum of 50 neurons in the network hidden layer and a triangular basis function.

5. Concluding remarks

In recent years, the participation index (PARTI) has become a very well-known and commonly used index in BIST (Istanbul Stock Exchange). Turkish people especially pay increasing attention to participation banking. Therefore, it is very important to be aware of PARTI. In this study, the predictabilities of the KATLM-KAT50 participation indices during the period 1st July 2014 – 29th July 2016 were investigated using a Markov chain model. Firstly, in order to perform the Markov chain analysis in relation to prediction of the future situation, the transition probability matrix was determined. Then, taking advantage of this matrix, a steady-state analysis of the chain was performed and the future trends of KATLM-KAT50 were forecasted. If we consider the results obtained with the MC analysis, we can state that MC is a powerful and accurate method for predicting this aspect of PARTI. Moreover, MC has very low errors, between 0.0019 and 0.0297.

The results of this study show that MC can successfully predict the direction of the index values with an accuracy margin of error of less than 2.5%, even for unknown samples, thus achieving results which are very close to the real market results. This outcome is very important for investors, especially portfolio managers considering investments in these indices. The results obtained with MC are likely to be helpful with regard to individual and institutional investors’ investment decisions and their portfolio preferences.

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