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Fluctuations of BIST Sectoral Index Movements During High Inflation Periods: A Markov Regime Switching Analysis

Yüksek Enflasyon Dönemlerinde BIST Sektörel Endekslerinin Dalgalanmaları: Markov Rejim Switching Analizi

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Abstract

Periods of high inflation generally cause uncertainty and risks in financial markets. In Turkey, the 2017-2023 period covers a time period characterized by frequent economic and financial fluctuations. High inflation in this period affected many sectors in the country and created significant volatility in financial markets. BIST sector indices were also affected by this economic environment and exhibited different volatile performances. In particular, sectors such as energy, food and beverages are generally more affected by inflation, while sectors such as services and technology have adapted more flexibly to economic fluctuations.

In this study, BIST Sector Indices: Food and Beverages, Electricity, Tourism and Technology indices over time (2017-2023), i.e., high and low return periods, a univariate Markov Regime Switching (MRS) model is estimated. According to the findings, the Food and Beverages index is stable in a particular market regime for a long period of time and has a high probability of remaining in that regime once it is switched. For the Electricity index, the index tends to remain in a particular market regime for a long time and can adapt quickly to changes in the market. During periods of high inflation, the BIST-Tourism Index exhibited long-term stability and the low volatility period covered a large period of time. This suggests that the tourism sector is resilient to economic uncertainties and is more suitable for long-term planning. For the BIST-Technology Index, it is understood that there is a long period of stability in a particular market regime and the period of low volatility lasts almost as long as the period of high volatility. This suggests that the technology sector is resilient to economic uncertainties and maintains its long-term stability.

The contribution of this study to the literature is that it reveals sector-specific long-term stability and volatility characteristics to analyze the fluctuations of BIST sectoral indices during periods of high inflation. It provides investors with important information about the different performance characteristics across sectors, allowing them to formulate more effective strategies.

Jel Codes: *C2, E31, E44, G1*
Keywords: *Macroeconomy, Inflation, BIST, Volatility*

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Öz

Enflasyonun yüksek seyrettiği dönemler genellikle finansal piyasalarda belirsizliğe ve risklere neden olmaktadır. Türkiye'de 2017-2023 dönemi, ekonomik ve finansal dalgalanmaların sıklıkla yaşandığı bir zaman dilimini kapsamaktadır. Bu dönemde enflasyonun yüksek seyretmesi, ülkede birçok sektörü etkilemiş ve finansal piyasalarda belirgin volatilite yaratmıştır. BIST sektör endeksleri de bu ekonomik ortamdan etkilenmiş ve farklı volatil performans sergilemiştir. Özellikle enerji, gıda ve içecek gibi sektörler genellikle enflasyondan daha fazla etkilenirken, hizmet ve teknoloji gibi sektörler, ekonomik dalgalanmalara daha esnek bir şekilde adapte olmuştur.

Bu çalışmada BIST Sektör Endekslerinden: Gıda ve İçecek, Elektrik, Turizm ve Teknoloji endekslerinin zaman içerisinde (2017-2023) izlediği seyri yani yüksek ve düşük getirili dönemleri incelemek amacıyla tek değişkenli Markov Regime Switching (MRS) modeli tahmin edilmiştir. Bulgulara göre, Gıda ve İçecek endeksinin belirli bir piyasa rejiminde uzun süre kararlılık gösterildiği ve bu rejime geçildiğinde kalma olasılığının yüksek olduğu görülmektedir. Elektrik endeksi için, endeksin belirli bir piyasa rejiminde uzun süre kalma eğiliminde olduğu ve piyasadaki değişikliklere hızlı uyum sağlayabildiği anlaşılmaktadır. Yüksek enflasyon dönemlerinde BIST-Turizm Endeksi'nde uzun süreli kararlılık gözlenmiş ve düşük volatilite dönemi geniş bir zaman dilimini kapsamıştır. Bu durum, turizm sektörünün ekonomik belirsizliklere karşı direnç gösterdiğini ve uzun vadeli planlamalara daha uygun olduğunu göstermektedir. BIST-Teknoloji Endeksi için, belirli bir piyasa rejiminde uzun süre kararlılık gösterildiği ve düşük volatilite döneminin neredeyse yüksek volatilite dönemi kadar sürdüğü anlaşılmaktadır. Bu durum, teknoloji sektörünün ekonomik belirsizliklere karşı direnç gösterdiğini ve uzun vadeli istikrarını koruduğunu göstermektedir.

Bu çalışmanın literatüre katkısı, yüksek enflasyon dönemlerinde BIST sektör endekslerinin dalgalanmalarını analiz etmek amacıyla sektörlere özgü uzun vadeli kararlılık ve volatilite özelliklerini ortaya koymasıdır. Yatırımcılara sektörler arasındaki farklı performans özellikleri hakkında önemli bilgiler sağlayarak daha etkili stratejiler oluşturmalarına olanak sunmaktadır.

Jel Kodları: *C2, E31, E44, G1*
Anahtar Kelimeler: *Makroekonomi, Enflasyon, BIST, Volatilite*

1. Introduction

Currently, national economies demonstrate heightened integration with the global system compared to previous times. The basis of this integration lies in significant changes in economic policies, which have come with the globalization process. These policies prioritize the maintenance of low inflation rates, market liberalization, reduction of the public sector's scope, and promotion of cross-border flows of goods, services, and finance.

In the literature, the root causes of inflation are generally classified into three main categories: demand-pull inflation, cost-push inflation, and built-in inflation. Demand inflation occurs when aggregate demand exceeds aggregate supply. Supply inflation occurs when there is an increase in the input prices used to realize production (Taban & Şengür, 2016).

During inflationary periods, as the purchasing power of money diminishes, economic entities such as producers, consumers, and investors tend to invest in tangible assets to preserve their wealth. These assets can include various types of assets, such as commodities, real estate, and stocks. The stock market is an important issue during periods of inflation and has caused significant debate about how well investors are protected against inflation. There are two basic views in the literature on this subject.

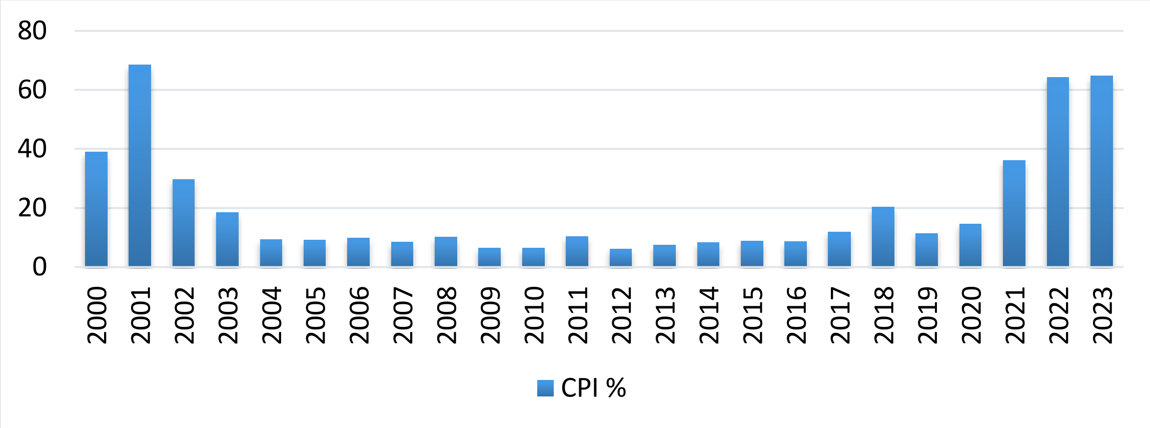
One of these perspectives is rooted in the Fisher hypothesis proposed in 1930. According to the Fisher hypothesis, the market interest rate comprises both the anticipated real interest rate and expected inflation. This hypothesis suggested that investors could protect themselves against inflation by investing in stocks during inflationary periods (Fisher, 1930; Lin, 2009; Bulmash & Trivoli, 1991; Alagidede & Panagiotidis, 2010; Ayaydın & Dağlı, 2012). This perspective posits that inflation has a positive impact on stock returns due to increases in asset prices, revenues, and profits of companies during inflationary periods.

However, in contrast to this perspective, Fama's representation hypothesis (1981) argues for a negative relationship between inflation and stock returns. That is, the agency hypothesis suggests that investors cannot protect themselves by investing in the stock market during inflationary periods (Fama, 1981; Özer, Kaya & Özer, 2011).

The main argument of the view that investors cannot be protected in the stock market during inflationary periods is that purchasing power decreases and total demand decreases as future expectations are negatively affected in these periods. This situation negatively affects the profitability of companies. It is also noteworthy that the risk premium tends to increase during periods of inflation. Increasing risk premiums causes discount rates to increase and therefore the current values of stocks to decrease (Ammer, 1994; Hatipoğlu, 2021).

The chart below shows the CPI (Consumer Price Index) rates as of the end of the year. This chart visually presents the change in inflation over time.

Figure 1: Turkish Economy Consumer Price Inflation (end of year %)



Source: CBRT, www.evds.com.tr

As can be seen from the graph, the years 2000, 2001 and 2002 point to the period of the 2001 economic crisis, when Turkey witnessed high inflation rates and deeply affected the economy. These years clearly showed the effects of the 2001 crisis. Stability-oriented economic policies taken after the crisis led to low and stable inflation rates in a period covering the period 2003-2016. However, as of 2016, a deterioration in inflation data began, and as of 2017, the periods in which this deterioration gradually deepened and inflation reached the highest levels were observed as 2021, 2022 and 2023.

In addition to these factors, events such as the Pastor Brunson crisis (2018), the US-China Trade War (2018), and the COVID-19 Pandemic (2019) have contributed to economic uncertainties and volatility in Turkey and globally. Factors such as the debates regarding the inflation-interest relationship in Turkey in 2018 have led to the emergence of uncertainties in the economic and monetary policies implemented and to be implemented on a global scale and in Turkey specifically. These uncertainties brought about variability in economic and monetary policies, distorting the country risk premium and negatively affecting many macroeconomic factors such as exchange rate, unemployment, current account deficit, interest and inflation. One of the most important of these factors is inflation. These complex interactions have complicated the planning and evaluation processes of economic actors, creating uncertainty in future economic projections.

On the other hand, the Central Bank's policies such as exchange rate interventions and inflation control play a critical role in ensuring the competitive balance between sectors. Keeping the exchange rate increases below the inflation rate aims to maintain the general stability of the economy. However, maintaining this balance brings with it the challenge of adaptation, especially in various sectors such as food and beverage, energy, tourism and technology. For example, in labor-intensive sectors, the adaptation process to rapid exchange rate increases brings with it various difficulties for sector representatives. One of the main problems faced by the sectors is the cost increases in import items. Exchange rate increases directly affect sectors that have to make purchases in foreign currency, causing costs to increase and competitive advantages to decrease. As a result, the CBRT's policy decisions and economic balancing efforts require sectors to adapt to these transitions. Sectoral representatives' understanding of the challenges that may arise in this process and developing effective strategies play a critical role in protecting the overall health of the economy. A decrease in inflation will create a perception among all actors in the economy that the issue of fighting inflation is being taken seriously, and this will be reflected in expectations over time. In this way, uncertainties in pricing will decrease and will contribute to a more controlled transition between the exchange rate and inflation.

This study uniquely employs the MRS model to analyze BIST sectoral index fluctuations during high inflation. It reveals sector-specific long-term stability and volatility patterns, contributing valuable insights to the existing literature. The study provides sector-specific findings showing that, in particular, the Food and Beverage index shows long-term stability in a certain market regime, the Electricity index can quickly adapt to changes in the market, the BIST-Tourism Index is resistant to economic uncertainties, and the BIST-Technology Index maintains its long-term stability. The results provide investors with important information about different performance characteristics between sectors, allowing them to create more effective strategies.

2. Literature Review

When reviewing research on inflation and stock returns, it is worth noting that the literature frequently contains studies that examine the relationship between inflation and stock returns. However, these studies differ in terms of the time period and countries studied. Events such as the exchange rate crisis experienced in Turkey in July 2018, the trade war between America and China, the COVID-19 pandemic and the new monetary policies implemented in 2021 represent a period of intense economic and financial fluctuations. These developments have significantly affected many macroeconomic factors, one of the most important of which is inflation. High inflation in Turkey has affected various sectors and caused significant volatility in financial markets. BIST sector indices were also affected by this economic environment and showed a variable performance. Table 1 below lists studies in national and international literature.

Table 1: Literature

Authors	Findings
Anari & Kolari (2001)	Studied the correlation between inflation and stock returns in six developed countries from 1953 to 1998. Results suggest stocks can serve as a hedge against inflation in the long term, with a positive correlation between inflation and stock returns.
Choudhry (2001)	The relationship between inflation and stock market returns was examined in high-inflation countries such as Argentina, Mexico, Chile and Venezuela. The findings suggest that stock investments can protect against inflation in these countries.
Adrangi et al. (2002)	Studied Brazil, a developing nation, to see if inflation impacted stock returns. Unlike high-inflation countries previously examined, their findings showed a negative long-term correlation. This shows that stock investments do not protect investors in developing countries such as Brazil, where inflation is high.
Rapach (2002)	Examined 15 developed economies (1957-2000) using quarterly data. The analysis did not reveal a negative impact of inflation on stock values, suggesting potential long-term protection for investors.
Karamustafa & Karakaya (2004)	Explored inflation's impact on transaction volume and quantity. The study revealed a long-term negative effect on both, but in the short term, inflation positively correlated with volume while leaving quantity unchanged.
Horasan (2008)	Investigated the impact of inflation on the Istanbul Stock Exchange using BIST 100 data and the Producer Price Index (1995-2003). The results revealed a positive correlation between inflation and the BIST 100 index.
Li et al. (2010)	Explored how inflation regimes affect the UK stock market's short- and medium-term returns (1962-2007). Unexpected inflation announcements were found to negatively impact short-term returns.
Sayılgan & Süslü (2011)	Examined (11 countries, 1999-2006) how inflation and other macroeconomic factors (exchange rate, S&P 500, interest rates, GDP, money supply, oil prices) affect stock returns. Findings suggest these factors have significant relationships with stock returns.
Khumalo (2013)	Utilized quarterly data from 1980 to 2010 to study inflation's impact on stock returns in South Africa. Results reveal a one-way causality from inflation to stock prices, with rising inflation adversely affecting them.
Ibrahim & Agbaje (2013)	Studied inflation's link to stock prices on the Nigerian Stock Exchange from 1997 to 2010. Results reveal a positive correlation, suggesting stocks as an inflation hedge for investors.
Qamri et al. (2015)	Explored inflation's effect on stock returns in the Karachi Stock Exchange, 2000-2009. Results revealed a negative correlation, implying limited inflation hedging for investors in Pakistan.
Kılıç & Dilber (2017)	The analysis, using monthly data, revealed that inflation volatility positively impacted BIST-100 volatility, while a negative correlation emerged between inflation volatility and exchange rate volatility.
Eyüboğlu & Eyüboğlu (2018)	Investigated the correlation between inflation and stock returns across 15 Borsa Istanbul sector indices from 2006 to 2016. Results indicated significant short- and long-term correlations between inflation and all 15 indices.

Şekeroğlu et al. (2019)	Examined the impact of inflation and foreign trade deficit on BIST-100 returns (2004-2017). The analysis revealed positive correlations between both inflation and the trade deficit with BIST-100 returns.
Hamad et al. (2020)	The analysis revealed no significant correlation between inflation and the BIST-100. However, it did find a one-way causal effect running from the BIST-100 index to inflation.
Ilgın & Sarı (2020)	Rising exchange rates lowered long-term stock market indices (2009-2019). Interest rates significantly impacted various sectors, while inflation lowered long-term indices. Short-term effects showed exchange rate decreases across all indices, with interest rates only affecting the BIST Bank index.
Yıldırım et al. (2020)	The study from 2013 to 2020 found a one-sided causality between interest rates and stock indices, as well as between stock indices and inflation. No significant relationship was observed between inflation and stock indices.
Hatipoğlu (2021)	The study assessed the influence of inflation on stock returns in developed nations like Germany, France, the Netherlands, Spain, Italy, Japan, Canada, and the UK using data from December 1969 to September 2020. Results showed differing relationships between inflation and stock market indices across the countries examined.
Chiang & Chen (2023)	The study spanning from January 1990 to February 2022, it found a positive relationship between inflation and stock returns. Notably, the finance, basic materials, energy, and technology sectors emerged as particularly effective in safeguarding investors against inflation.
Karagiannopoulos & Sariannidis (2023)	Analyzing data from March 2020 to August 2023, it revealed a negative long-term impact of inflation on the Greek stock market. These findings suggest that inflation does not serve as a protective mechanism for investors.

The literature review encompasses a multitude of studies conducted by diverse researchers, elucidating the diverse effects of inflation on stock returns and pinpointing critical factors influencing this association. While individual study results may diverge, together they offer an inclusive comprehension of the link between inflation and stock returns.

3. Methodology and Data Sets

The Markov Analysis technique, named after the Russian mathematician Andrey A. Markov, is designed to mathematically model state changes in processes. Initially applied by Markov in 1906 to explain the behavior of gas molecules, Norbert Wiener established the first accurate mathematical structure of Markov processes in 1923. Markov chains and processes became crucial mathematical tools in the early 20th century for understanding and modeling state changes in various processes. The MS-AR(p) model, introduced by Hamilton in 1989 for econometric analyses, is employed to comprehend changes over time. Hamilton's 1989 MS-AR(p) model, based on the Markov chain, holds a significant position in finance and econometrics literature. Works by Engel (1994), Diebold, Lee & Winbach (1994), Hamilton (1996), Kim & Nelson (1998), Krolzig (1997, 1998, 2000, 2001), and Chen (2006) emphasize the substantial contributions of the MS-AR(p) model. These studies demonstrate the model's efficacy in successfully detecting significant state changes over time in financial datasets (Damos et al., 2011: 1).

The MRS equation can be formulated as follows:

$$Y_t = \sum_{i=1}^{p} \emptyset\, S_t, iY_{t-i} + \epsilon_t \qquad (1)$$

In this equation:

Y_t, represents the value of the observed variable at time t. p, is the autoregressive degree in the model, indicating the number of autoregressive terms used. $\emptyset S_t, i$ represents the i-th autoregressive coefficient that varies depending on the regime S_t. S_t, two-state regimes, it assumes values 1 and 2. $\epsilon_t$is the error term.

The formula for the two-regime model can be articulated in the following manner:

$$Y_t = \begin{cases} C_1 + \sum_{i=1}^{p} \emptyset_{1,i} y_{t-i} + \varepsilon_{1t} & if S_t = 1, \\ C_2 + \sum_{i=2}^{p} \emptyset_{1,i} + \varepsilon_{2t} & if S_t = 2, \end{cases} \qquad (2)$$

In Equation 2, C_1 and C_2, denote constant terms when the state S_t is 1 and 2, respectively, signifying distinct constants in different regimes. The term $\sum_{i=1}^{p} \emptyset_{1,i} y_{t-i}$ represents the weighted sum of lagged values, constituting the autoregressive (AR) component where in past values influence the current value. The error term $\varepsilon_{1t}$and ε_{2t}, represent the stochastic components in two different regimes. These errors are assumed to be independent and normally distributed. If the series is in the first regime, it takes the value S_t=1, and in the second regime, it takes S_t=2. Transition probabilities in a two-regime structure are as follows:

$$P_{ij} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \qquad (3)$$

Each value in the matrix P_{ij},

$$P\left(\frac{S_{t=j}}{S_{t-1=i}}\right) = P_{ij} \qquad (i, j = 1,2) \qquad (4)$$

In accordance with Equation (4), p_{11}, represents the probability of the process remaining in the first regime after a period in which it is already in the first regime. Similarly, p_{12} signifies the likelihood of transitioning to the second regime after a period while the process in the first regime. On the other hand, p_{21} denotes the probability of transitioning to the first regime after a period while the process is ccurrently in the second regime. Additionally, p_{22} indicates the probability of the process remainin in the second regime after a period when it is already in the second regime. It is crucial to note that the sum of these transition probabilities equals one, reflecting the certainty that the process will move to one of the regimes. Furthermore, these transition probabilities must remain non-negative.

Specific formulas are employed to compute the duration of the stay in the first regime and the duration of the stay in the second regime. These formulas explain essential features of the MRS model and are important for figuring out how the system shifts between different states. Additionally, calculating these durations helps us understand how long the series stays in a specific market condition. The duration of stay in the first regime and the duration of stay in the second regime can be determined using the formulas outlined by Hamilton (1989: 360), as detailed below:

$$\frac{1}{1-P_{11}}; \frac{1}{1-P_{22}} \qquad (4)$$

This study aims to calculate how long entities stay in the first and second regimes, exploring the essential features and practical uses of the Markov Regime Switching (MRS) model. Understanding these durations is vital for grasping how long an entity operates in a particular market environment within financial markets. The formulas proposed by Hamilton (1989) are specifically designed to assess the impacts of regime changes on the MRS model, contributing to financial decision-making processes.

Understanding the durations of stay in the first and second regimes, alongside transition probabilities, is essential for gauging the MRS model's influence on market conditions and assessing financial risks. These formulas lay a robust foundation for evaluating the MRS model's effectiveness in capturing diverse scenarios in financial markets and making informed predictions.

Detailed information regarding the datasets used in the analysis is presented in Table 2.

Table 2: Data Set

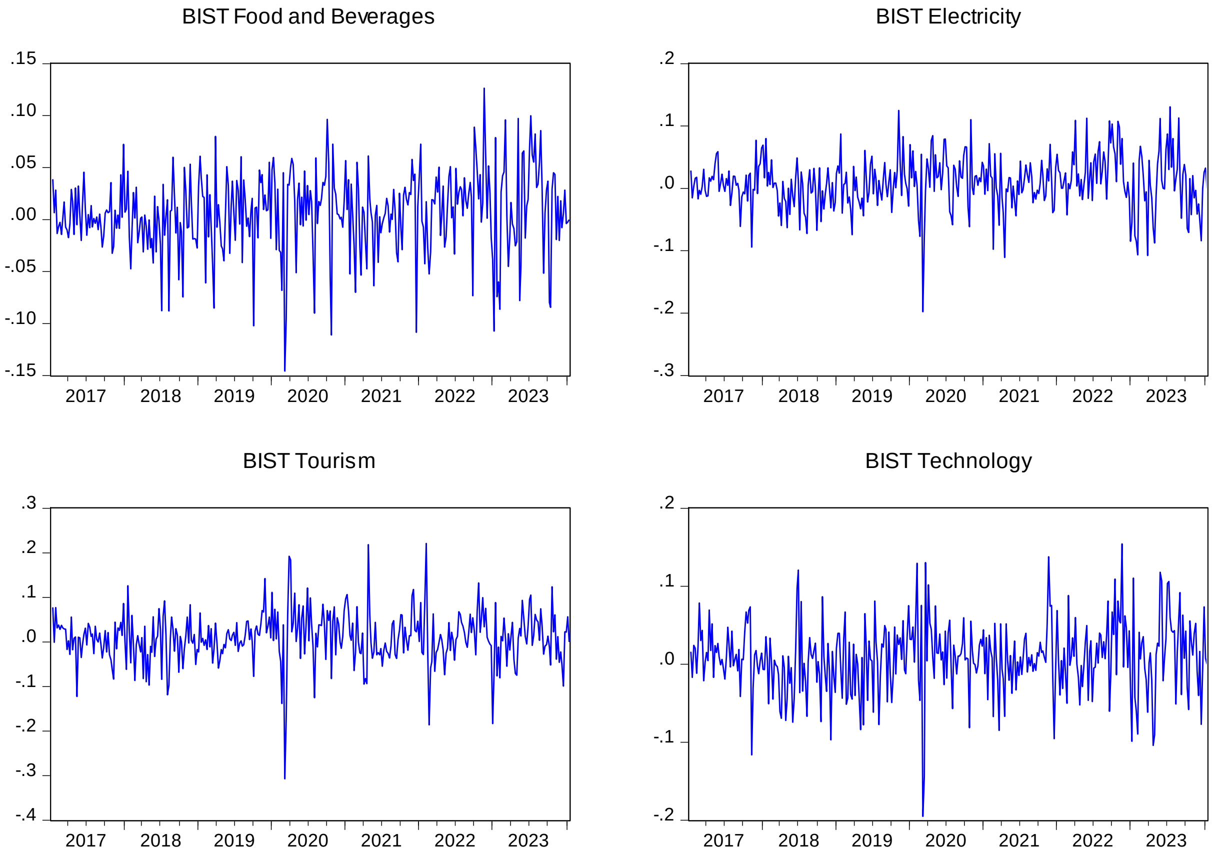
Index	Data Type	Time Range
BIST-Food and Beverage Index	Data of Returns (Adj. Closed)	2017-2023 (weekly)
BIST- Electricity Index	Data of Returns (Adj. Closed)	2017-2023 (weekly)
BIST- Tourism Index	Data of Returns (Adj. Closed)	2017-2023 (weekly)
BIST-Technology Index	Data of Returns (Adj. Closed)	2017-2023 (weekly)

Source: investing.com

Data collection process: The selected indices represent important sectors of the Turkish economy. In this way, it can be analyzed comparatively how different sectors are affected and fluctuated during the high inflation period. Indices have different risk and return profiles, volatility levels and trends. This makes your analysis more comprehensive and meaningful. Additionally, long-term data is available for BIST sector indices. This allows you to analyze over a wide time period, including periods of high inflation.

Return series are computed using the formula $r_t = (\frac{P_t - P_{t-1}}{P_{t-1}})$. Where r_t, represents the weekly return, P_t, represents the closing price of the current week, and P_{t-1}, represents the closing price of the previous week. This formula is a widely employed method for generating return series, effectively capturing the weekly price changes of indices. The return graphs for the data in Table 2 are shown below.

Figure 2: Return Graphs of BIST Sector Indices



Based on the analyzed graphs, the return series for the year 2020 appears remarkably volatile. Globally, significant uncertainties permeated financial markets due to the COVID-19 pandemic. Observable in all four graphs are rapid market declines and heightened volatility. There was an increase in cases, especially in August. The uncertainty engendered by the pandemic resulted in deteriorating economic indicators, diminished corporate profits, and an upsurge in unemployment rates. These factors collectively eroded investor confidence, precipitating declines in the markets. Furthermore, on a global scale, geopolitical events such as the U.S.-China trade war, the UK's decision to exit the EU, the Russia-Ukraine conflict, the Israel-Hamas conflict, and global food and energy crises have also instigated fluctuations in financial markets.

In Turkey, inflation ascended to double-digit figures in 2017 after an extended period of stability. The surge in the exchange rate intensified inflation even further. The rise in the exchange rate, particularly attributable to elevated import rates, exerted an inflationary effect on costs. Ensuring price stability constitutes a foundational goal of economic policies. Inflation, signifying a persistent increase in the general level of prices, results in a decline in purchasing power, heightens future uncertainties, and adversely impacts investment and savings, thereby weakening the economy. Furthermore, declarations from international rating agencies categorizing Turkey as non-investable have posed formidable challenges to the economy.

Interventions such as modifications in the central bank's monetary policy and fiscal stimulus measures implemented by the government have induced considerable volatility in the markets. Central bank interventions typically encompass diverse policy measures aimed at rectifying economic imbalances, controlling inflation, or buttressing economic growth. Alterations in interest rates can impact consumer spending, investments, and inflation. Throughout the pandemic period, the CBRT upheld low-interest rates to bolster the economy. Nonetheless, this approach contributed to inflationary pressures. Successive changes in leadership at the central bank have also contributed to uncertainties. Consequently, both internal and external adverse developments have swiftly manifested their effects on the economy, including inflation, exchange rates, a marked increase in unemployment rates, and a decline in the growth rate.

4. Empirical Findings

In this section, the descriptive statistics of BIST Food and Beverage, Electricity, Tourism, and Technology indices are explored to unveil the essential characteristics of the return series. Subsequently, the stationarity of the return series is assessed through unit root tests, namely ADF, PP, and KPSS. Additionally, the BDS test, an independence test, is employed to examine the relationships between the indices and the independence of the return series.

Following these preliminary analyses, the Markov Regime Switching (MRS) model was preferred. This model aids in understanding how indices behave in specific market regimes and assists in modeling market transitions. It provides crucial insights into the speed at which indices can adapt to different market conditions, their stability duration in a particular market regime, and aids in predicting their future performance.

The descriptive statistics for the return series are presented in Table 3.

Table 3: Descriptive Statistics

	Food and Beverage Index	Electricity Index	Tourism Index	Technology Index
Mean	0.006418	0.008712	0.009464	0.008448
Median	0.007772	0.008277	0.010150	0.008465
Maximum	0.126471	0.130521	0.221105	0.154043
Minimum	-0.145705	-0.197568	-0.307375	-0.195164
Std. Dev.	0.038612	0.042413	0.056569	0.045542
Skewness	-0.502110	-0.303277	-0.394822	-0.222560
Kurtosis	4.117879	4.739975	6.970637	4.485308
Jarque-Bera	34.43620	51.78020	249.9399	36.66515
Probability	0.000000	0.000000	0.000000	0.000000
Sum	2.348902	3.188570	3.463699	3.091874
Sum Sq. Dev.	0.544186	0.656591	1.168014	0.757048
Observations	366	366	366	366

Examining Table 3, several crucial statistical features come to light:

Mean represents the average value for each return series. The overall positive trend in average values suggests a general increase in return values throughout the examined period. The proximity of the median and average values indicates limited outlier impact and a generally balanced distribution. Positive maximum values across all indices signify profitability and positive returns in specific periods. Minimum values indicate instances of negative returns, emphasizing the inherent risks associated with investments at certain times. The positive standard deviation (Std. Dev.) highlights variability in return values compared to the expected average. Negative skewness values for all indices indicate a left-skewed distribution in the return series. Kurtosis: Values exceeding 3 suggest thicker tails than a normal distribution, emphasizing more prominent extremes in the dataset. Jarque-Bera Test: The test statistics and low probability values suggest that the return series are not normally distributed. Sum: The sum of all return values. Sum Square Deviation (Sum Sq. Dev.) measures how much each index's observations deviate from the mean value. The total number of observations for the return series of each index is 366.

Table 4: Unit Root Test

	UNIT ROOT TEST TABLE (PP)				
	At Level				
		Food and Beverage Index	Electricity Index	Tourism Index	Technology Index
With Constant	t-Statistic	-17.0071	-15.3947	-15.2130	-17.2955
		***	***	***	***
With Constant & Trend	t-Statistic	-17.1723	-15.3346	-15.2208	-17.3824
		***	***	***	***
Without Constant & Trend	t-Statistic	-16.7800	-15.3322	-15.0319	-16.9374
		***	***	***	***
	UNIT ROOT TEST TABLE (ADF)				
	At Level				
		Food and Beverage Index	Electricity Index	Tourism Index	Technology Index
With Constant	t-Statistic	-16.9867	-14.5943	-15.2397	-17.2933
		***	***	***	***
With Constant & Trend	t-Statistic	-17.2174	-14.6723	-15.2537	-17.3799
		***	***	***	***
Without Constant & Trend	t-Statistic	-16.6163	-14.1572	-14.9396	-16.8011

		***	***	***	***

Notes: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant

**MacKinnon (1996) one-sided p-values.*

When examining Table 4, it is observed that the return series used in this study were subjected to Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) unit root tests. The results of both tests indicate that the return series are stationary at the level with a 1% significance level (prob < 0.01). This implies that the mean and variance of the series remain constant over time and do not exhibit any trend.

PP and ADF tests are two widely used methods to determine whether the series contain a unit root. The ADF test adds lagged differences to correct for autocorrelation in the series, while the PP test uses a nonparametric approach to adjust for autocorrelation and heteroskedasticity. The consistent results of both tests showing no unit root at the level underscore the stable structure and reliability of the dataset used in the analysis.

This observation is critically important for the validity of the econometric models used in the study. Data without a unit root yield more reliable results in modeling and forecasting processes. Therefore, these results reinforce the robustness and accuracy of the findings obtained in the study.

In conclusion, the results of the unit root tests confirm the stationarity characteristics of the return series used in the analysis and highlight the stable structure of the dataset.

Table 5: KPSS Test

Exogenous: Constant, Linear Trend				
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel				
Kwiatkowski-Phillips-Schmidt-Shin test statistic	Food and Beverage Index LM-Stat.	Electricity Index LM-Stat.	Tourism Index LM-Stat.	Technology Index LM-Stat.
Asymptotic critical values*:	0.033482	0.051158	0.064991	0.075147
1% level	0.216000	0.216000	0.216000	0.216000
5% level	0.146000	0.146000	0.146000	0.146000
10% level	0.119000	0.119000	0.119000	0.119000

**Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)*

Table 5 displays the results of the KPSS test, showing that the return series are stationary, as the LM statistics are smaller than the 10% critical value. The stationarity of time series implies that changes over time lack a discernible structure, ensuring stability in their modeling. This characteristic significantly enhances the reliability of future predictions and analyses. The consistent and stable nature of the series over time provides a solid foundation for conducting dependable analytical work. Therefore, the obtained stationarity results mark a crucial step towards achieving more reliable outcomes within the analytical framework.

Table 6. BDS Test

	Food and Beverage Index	Electricity Index	Tourism Index	Technology Index
Dimension	BDS Statistic	BDS Statistic	BDS Statistic	BDS Statistic
2	0.026400*** (0.004401) [5.998829]	0.013346*** (0.004544) [2.937301]	0.012847*** (0.004633) [2.772725]	0.017022*** (0.004417) [3.853726]
3	0.038217*** (0.007005) [5.455711]	0.020846*** (0.007214) [2.889670]	0.027762*** (0.007355) [3.774499]	0.028741*** (0.007039) [4.083288]
4	0.043573*** (0.008355) [5.215377]	0.023650*** (0.008582) [2.755652]	0.039584*** (0.008749) [4.524121]	0.032422*** (0.008404) [3.857761]
5	0.046487*** (0.008722) [5.330112]	0.025823*** (0.008937) [2.889456]	0.040810*** (0.009110) [4.479530]	0.040196*** (0.008783) [4.576383]
6	0.046258*** (0.008424) [5.491161]	0.023737*** (0.008611) [2.756574]	0.038699*** (0.008777) [4.409115]	0.039810*** (0.008493) [4.687222]

Notes: ***, **, * indicate significances at the levels of 1%, 5%, and 10%, respectivelly. "Standard errors" are denoted by (…), and "z-Statistic" is represented by […].

Table 6 reveals that the BDS test results reject the independence hypothesis among the return series of BIST sector indices. This indicates the presence of a certain connection between the return series, suggesting that they are not independent. The table below presents the prediction results of the MRS model.

Table 7. Markov Regime Model Estimation Results

	Model 1: Food and Beverage Index	Model 2: Electricity Index	Model 3: Tourism Index	Model 4: Technology Index
C (Regime 1)	-	0.009655*** (0.003893) [2.480197]	-	0.007116* (0.004150) [1.714832]
C (Regime 2)	-	0.007373*** (0.002643) [2.789234]	-	0.010217*** (0.002854) [3.579677]
C (Common)	0.006530*** (0.001791) [3.645718]	-	0.010903*** (0.002577) [4.230762]	-
LOG(SIGMA) (Regime 1)	-2.998614*** (high volatility) (0.088340) [-33.94413]	-2.944379*** (high volatility) (0.069999) [-42.06334]	-3.104530*** (low volatility) (0.049479) [-62.74439]	-2.881139*** (high volatility) (0.073498) [-39.20029]
LOG(SIGMA) (Regime 2)	-3.743752*** (low volatility) (0.090666) [-41.29171]	-3.906900*** (low volatility) (0.118522) [-32.96357]	-2.071265*** (high volatility) (0.178169) [-11.62530]	-3.682164*** (low volatility) (0.153754) [-23.94836]
P11-C	2.460516*** (0.718760) [3.423278]	1.636723** (0.710505) [2.303603]	3.696665*** (0.645849) [5.723732]	2.557738*** (0.605099) [4.226973]
P21C	-2.590505*** (0.540333) [-4.794278]	-1.214222** (0.606596) [-2.001700]	-1.032916* (0.597034) [-1.730077]	-2.272349*** (0.677867) [-3.352205]
Mean dependent var	0.006418	0.008712	0.009464	0.008448
S.E. of regression	0.038719	0.042576	0.056743	0.045760
Durbin-Watson stat	1.767617	1.478758	1.551823	1.810283
Akaike info criterion	-3.757041	-3.550526	-3.052615	-3.415917
Hannan-Quinn criter	-3.735855	-3.525103	-3.031429	-3.390494
S.D. dependent var	0.038612	0.042413	0.056569	0.045542
Sum squared resid	0.544191	0.656192	1.168771	0.758004
Log likelihood	692.5384	655.7462	563.6285	631.1128
Schwarz criterion	-3.703726	-3.486548	-2.999300	-3.351939

Notes: ***, **, * indicate significances at the levels of the 1%, 5%, and 10%, respectively. C (common) represents the mean value of the dependent variable across all regimes. The constant C represents the mean value of the dependent variable in a specific regime. (…) shows standard errors. […] shows z-Statistic.

When examining Table 7, several crucial statistical features become apparent:

Model-1. The constant C denotes the common average value. In other words, under similar economic conditions in both regimes, the average value of the dependent variable is 0.006530. Regime 1: LOG(SIGMA):-2.998614This regime exhibits higher volatility. Regime 2: LOG(SIGMA):-3.743752 In contrast, this regime indicates lower volatility. In summary, Regime 1 signifies the high volatility, whereas Regime 2 represents the low volatility.

In Model 2 (representing the model with the BIST-Electricity index as the dependent variable), the constant term (C) values in the MRS model output signify the average value of the dependent variable in different regimes. Specifically, the C value of Model 2 in the 1st regime is 0.009655, while in the 2nd regime, it is 0.007373. This disparity between the two regimes indicates that the model exhibits changes in regimes under certain conditions, and the average values of the dependent variable vary accordingly. The higher average value in the 1st regime compared to the 2nd regime suggests that the dependent variable attains higher values in periods characterized by high volatility. In detail, Regime 1 is characterized by a LOG(SIGMA) value of -2.944379, indicating high volatility, while Regime 2, with a LOG(SIGMA) value of -3.906900, represents the low volatility.

In Model 3 (representing the model with the BIST-Tourism index as the dependent variable), the constant term (C) symbolizes the common average value. Under similar economic conditions in both regimes, the average value of the dependent variable is determined to be 0.010903. Further insights into the regimes reveal that in Regime 1, the LOG(SIGMA) is -3.104530, indicating a regime characterized by low volatility. Conversely, in Regime 2, the LOG(SIGMA) is -2.071265, signaling a regime marked by high volatility.

In Model 4 (representing the model with the BIST-Technology index as the dependent variable), the C value in the 1st regime is determined to be 0.007116, while in the 2nd regime, it is 0.010217. The observation that the average value of the 1st regime is lower than the average value of the 2nd regime suggests that the dependent variable attains higher values in periods characterized by low volatility. Delving into the regimes, we find that in Regime 1, the LOG(SIGMA) is -2.881139, indicating a regime marked by high volatility. Conversely, in Regime 2, the LOG(SIGMA) is -3.682164, signaling a regime characterized by low volatility.

The P11-C and P21-C values in the table play a crucial role in determining the duration of each regime and the probabilities of transitioning between regimes. Several statistical measures further provide insights into the model's performance: Mean dependent var: This represents the average value of the dependent variable.

S.E. of regression signifies the standard error value of the regression. Durbin-Watson stat represents the Durbin-Watson statistic and it is a measure used to evaluate the autocorrelation of error terms in regression analyses. Akaike, Schwarz, and Hannan-Quinn criteria are express the model's fit. S.D. dependent var denotes the standard deviation of the dependent variable. Sum squared residual is the sum of the squares of the residuals. Log likelihood represents the log-likelihood value of the model.The presented results affirm the model's significance, considering both coefficients and transition probabilities.

The estimation results of the two-regime and univariate Markov regime change model are presented in Table 8, which displays the Regime Transition Probability Matrix.

Table 8: Regime Transition Probability Matrix

Constant transition probabilities: P(i, k)=P(s(t)=k| s(t-1)=i) (row=i / column=j)			
Food and Beverage Index		Regime 1	Regime 2
Model 1	Regime 1	0.921327	0.078673
	Regime 2	0.069752	0.930248
Electricity Index		Regime 1	Regime 2
Model 2	Regime 1	0.837088	0.162912
	Regime 2	0.228955	0.771045
Tourism Index		Regime 1	Regime 2
Model 3	Regime 1	0.975794	0.024206
	Regime 2	0.262519	0.737481
Technology Index		Regime 1	Regime 2
Model 4	Regime 1	0.928092	0.071908
	Regime 2	0.093439	0.906561
Constant expected durations:			
Food and Beverage Index		(high volatility)	(low volatility)
Model 1		Regime 1	Regime 2
		12.71085	14.33651
Electricity Index		(high volatility)	(low volatility)
Model 2		Regime 1	Regime 2
		6.138301	4.367673
Tourism Index		(low volatility)	(high volatility)
Model 3		Regime 1	Regime 2
		41.31264	3.809245
Technology Index		(high volatility)	(low volatility)
Model 4		Regime 1	Regime 2
		13.90659	10.70217

Table 8 provides values for regime transition probabilities, representing transitions and stay probabilities in the model's market regimes. High transition probabilities suggest rapid shifts from one market regime to another, while high stay probabilities indicate prolonged durations within a particular market regime.

For Model 1, focusing on the Food and Beverage Index, the transition probabilities between regimes provide valuable insights. The high probability (92%) of transitioning from Regime 1 to Regime 1 indicates a strong tendency for the index to remain in a particular market regime for an extended period. Conversely, the probability of shifting from Regime 1 to Regime 2 is low (8%), but once this transition occurs, the probability of the index staying in Regime 2 is notably high (93%). This pattern suggests that the index tends to exhibit stability within a specific market environment, with a likelihood of persisting in that regime once entered.

The model further determines average stay times in Regime 1 and Regime 2, set at 13 and 14 weeks, respectively. These durations represent the average length of time the index remains in a particular market regime. The statistically significant probabilities (at the 1% level) for both regimes underscore the model's reliability in predicting the probabilities of transitioning between regimes. The probability of remaining in a specific regime serves as an indicator of stability in that regime and reflects the index's performance under those market conditions.

In conclusion, the Food and Beverage Index model exhibits long-term stability in a specific market regime, demonstrating a tendency to persist in that regime. The statistically significant probabilities for both regimes affirm the model's accuracy in predicting transitions and anticipating the index's performance in various market conditions.

For Model 2, focusing on the Electricity Index, the transition probabilities shed light on the index's behavior in different market regimes. The notably high probability (84%) of switching from Regime 1 to Regime 1 indicates a strong tendency for the index to persist in a particular market regime for an extended period. Conversely, the probability of transitioning from Regime 1 to Regime 2 is relatively low (16%), but once this shift occurs, the probability of the index remaining in Regime 2 is remarkably high (77%). This suggests that the Electricity Index possesses the capability to adapt swiftly and dynamically to market changes.

The model calculates average stay times in Regime 1 and Regime 2 as 6 and 4 weeks, respectively. These durations represent the average time the index remains in a specific market regime. The Electricity Index's ability to quickly adapt to sudden shocks and changes is evident, particularly reflected in its capacity to return to the former equilibrium state within a maximum of 4 weeks. This resilience signifies the index's resistance to rapid changes in the market.

Significantly, the probability values for both regimes are statistically significant at the 1% level, reinforcing the model's reliability in predicting transition probabilities between the specified regimes. In conclusion, the model for the Electricity Index provides a reliable explanation for certain market situations and transitions, showcasing the index's dynamic reaction capabilities.

In the case of Model 3, focusing on the BIST-Tourism Index, the transition probabilities offer valuable insights into the index's behavior within different market regimes. Notably, the high probability (97%) of transitioning from Regime 1 to Regime 1 indicates a strong inclination for the index to persist in a specific market regime for an extended period. Conversely, the probability of transitioning from Regime 1 to Regime 2 is low (2%), but once this transition occurs, the likelihood of the index remaining in Regime 2 is considerably high (74%). This pattern suggests that the BIST-Tourism Index is characterized by stability within a particular market environment, with a propensity to endure in that regime once entered.

The model determines average stay times in Regime 1 and Regime 2 as 41 and approximately 4 weeks, respectively. These durations represent the average length of time the index remains in a specific market regime. The extended stay duration in Regime 1, characterized by low volatility and high returns, at 41 weeks indicates that the index is more stable and exhibits low volatility during this period. In contrast, Regime 2 suggests a shorter period (4 weeks) with higher volatility. In conclusion, the model for the BIST-Tourism Index reveals long-term stability in a specific market regime, where the low-volatility period endures for a considerable duration. This implies that the index adapts to specific market conditions within the tourism sector for an extended period and tailors its performance accordingly.

In the context of Model 4, focusing on the BIST-Technology Index, the transition probabilities offer insights into the index's behavior within different market regimes. The notably high probability (93%) of transitioning from Regime 1 to Regime 1 indicates a strong inclination for the index to persist in a specific market regime for an extended period. Conversely, the probability of transitioning from Regime 1 to Regime 2 is low (7%), but once this transition occurs, the likelihood of the index remaining in Regime 2 is quite high (91%). This pattern indicates that the BIST-Technology Index demonstrates stability within a particular market environment, with a propensity to endure in that regime once entered.

The model calculates average stay times in Regime 1 and Regime 2 as 14 and 11 weeks, respectively. These durations represent the average length of time the index remains in a specific market regime. Consequently, the model for the BIST-Technology Index reveals long-term stability in a certain market regime, where the low-volatility period endures for a substantial duration of 11 weeks. This implies that the index adapts to specific market conditions within the technology sector over an extended period and tailors its performance accordingly.

Displaying regime probabilities on a date basis provides insights into the model's status at particular times. Graphics for each model are presented below.

Figure 3: Model 1: Food and Beverage Index

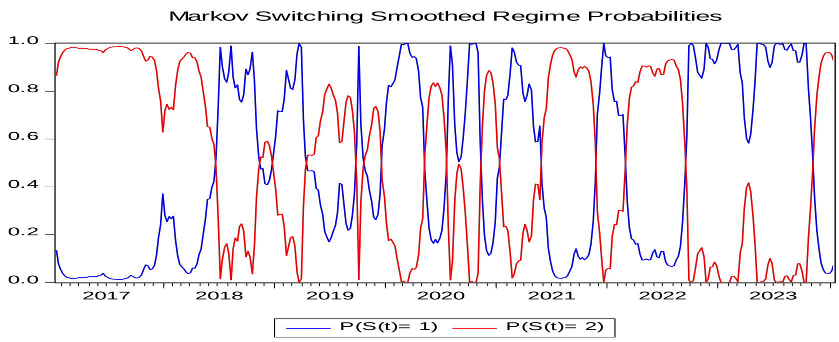


Figure 3 displays chart for the BIST-Food and Beverage index, with the blue line representing the probability of the model being in the first regime (Regime 1-High Volatility, Low Return) and the red line representing the probability of the model being in the second regime (Regime 2-Low Volatility, High Return).

Interpreting the chart: When the red line is high and the blue line is low, it indicates that the model is in the second regime (high return) during that period. Conversely, when the blue line is high and the red line is low, it indicates that the model is in the first regime (low returns) during that period. In situations where both lines on the chart take close values, it indicates periods of uncertainty or transitions in the market. Changing lines indicate that the model shifts from one regime to another at a specific point in time. The intersections of the lines mark regime changes in the model, especially when the probabilities of low volatility and high volatility regimes are equal. Fluctuations in a certain period indicate volatility in the model. The duration of the Model 1 to remain in the low volatility regime is approximately 14 weeks, while the period to remain in the high volatility regime is around 12 weeks. The close proximity of these durations suggests frequent regime changes within a certain period. However, examining the chart reveals that the BIST-Food and Beverage index experienced a highly volatile period from the last months of 2022 to the last months of 2023.

Figure 4: Model 2: BIST- Electricity Index

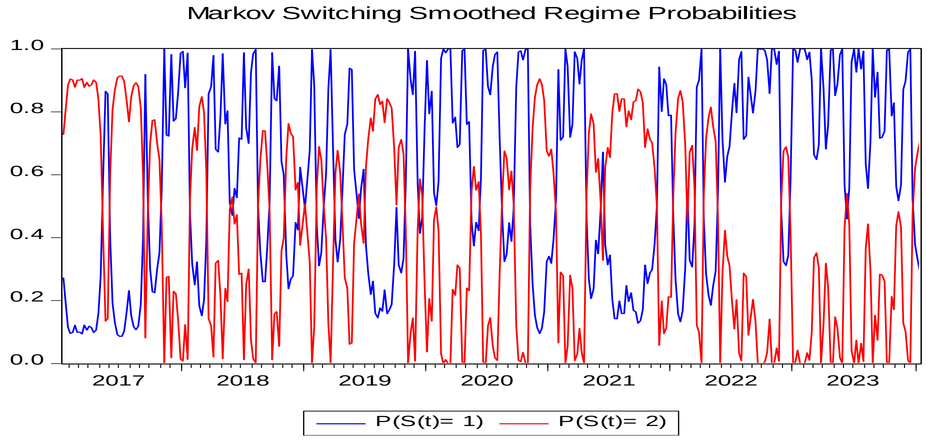


Figure 4 illustrates chart for the BIST-Electricity index, with the blue line denoting the probability of the model being in the first regime (Regime 1-High Volatility) and the red line representing the probability of the model being in the second regime (Regime 2-Low Volatility). Interpreting the chart: When the red line is high and the blue line is low, it indicates that the model is in the second regime during that period. Conversely, when the blue line is high and the red line is low, it indicates that the model is in the first regime during that period. In situations where both lines on the chart take close values, it indicates periods of uncertainty or transitions in the market. Fluctuations in a certain period indicate volatility in the model. The points where regime possibilities intersect mark transitions of the model. The duration of the BIST-Electricity index to remain in the low volatility, high return regime is approximately 4 weeks, while the period to remain in the high volatility, low return regime is around 6 weeks.

Figure 5: Model 3: BIST-Tourism Index

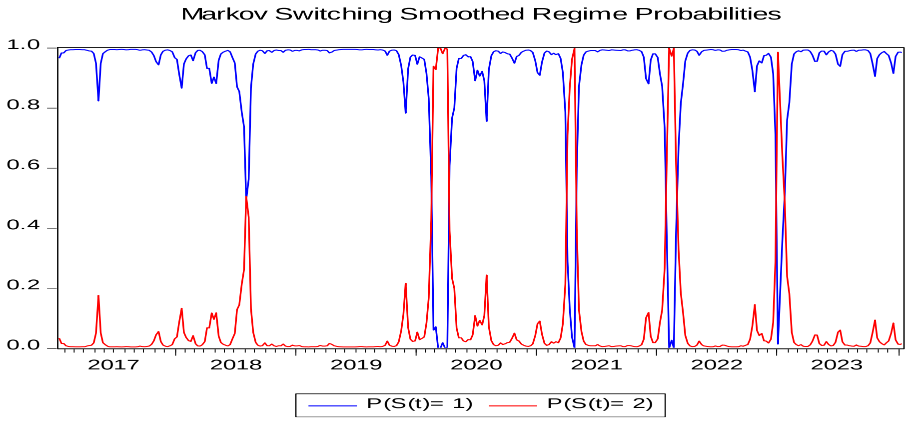


Figure 5 illustrates chart for the BIST-Tourism index, where the blue line signifies the probability of the model being in the first regime (Regime 1-Low Volatility), and the red line represents the probability of the model being in the second regime (Regime 2-High Volatility).

Interpreting the chart: When the red line is high and the blue line is low, it indicates that the model is in the second regime during that period. Conversely, when the blue line is high and the red line is low, it indicates that the model is in the first regime during that period. Close values for both lines suggest uncertainty or transition periods in the market, where determining the prevailing regime is challenging. Fluctuations in a certain period indicate volatility in the model.

The BIST-Tourism index predominantly remains in the high return regime, as evidenced by the graph. The duration of stay in Regime 1 (Low Volatility) is approximately 41 weeks, indicating a prolonged period of stability and high returns. In contrast, the duration of stay in Regime 2 (High Volatility) is around 4 weeks, representing shorter periods of volatility. Observations from the chart: Until 2020, the BIST-Tourism index predominantly stays in the high return regime for an extended period. Post-2020, the duration of the BIST-Tourism index in the high return regime shortens, suggesting a shift in market conditions.

Figure 6: Model 4: BIST-Technology Index

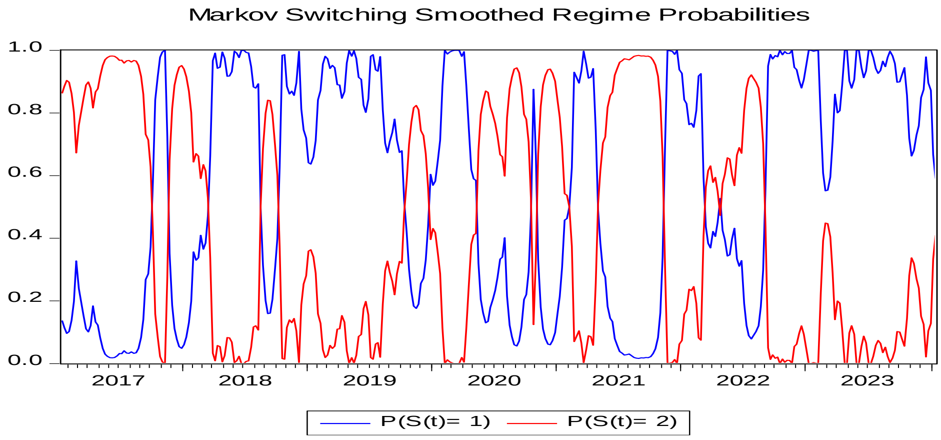


Figure 6 depicts chart for Model 4, focusing on the BIST-Technology Index. The blue line represents the probability of the model being in the first regime (Regime 1- High Volatility), while the red line signifies the probability of the model being in the second regime (Regime 2- Low Volatility).

When the red line is high and the blue line is low, it indicates that the model is in the second regime during that period. Conversely, when the blue line is high and the red line is low, it indicates that the model is in the first regime during that period. Close values for both lines suggest uncertainty or transition periods in the market, where the prevailing regime is not distinctly determined. Fluctuations in a certain period indicate volatility in the model. The BIST-Technology index has experienced both regimes for a similar duration, as indicated by the graph. The duration of stay in the low return regime is approximately 14 weeks, reflecting periods of volatility and lower returns. Conversely, the duration of stay in the high return regime is around 11 weeks, representing periods of stability and higher returns.

In summary, the BIST-Technology index exhibits periods of uncertainty and transition, with similar durations in both low and high return regimes. The chart provides insights into the dynamic behavior of the index under varying market conditions.

5. Conclusion

In Turkey, inflation ascended to double-digit figures in 2017 after an extended period of stability. Ensuring price stability constitutes a foundational goal of economic policies. Inflation, signifying a persistent increase in the general level of prices, results in a decline in purchasing power, heightens future uncertainties, and adversely impacts investment and savings, thereby weakening the economy. The CBRT's policies such as exchange rate interventions and inflation control play a critical role in ensuring competitive balance between sectors. However, maintaining this balance brings with it the challenge of adaptation, especially in various sectors such as food and beverage, energy, tourism and technology. For example, in labor-intensive sectors, the adaptation process to rapid exchange rate increases brings with it various difficulties for sector representatives. One of the main problems faced by the sectors is the cost increases in import items. Exchange rate increases directly affect sectors that have to make purchases in foreign currency, causing costs to increase and competitive advantages to decrease. The CBRT's policy decisions and economic balancing efforts require sectors to adapt to these transitions. Sectoral representatives' understanding of the challenges that may arise in this process and developing effective strategies play a critical role in protecting the overall health of the economy. A decrease in inflation will create a perception among all actors in the economy that the issue of fighting inflation is being taken seriously, and this will be reflected in expectations over time. In this way, uncertainties in pricing will decrease and will contribute to a more controlled transition between the exchange rate and inflation.

This study investigates the impact of the high inflation period in the Turkish economy from 2017 to 2023 on financial markets and sector indices. High inflation typically induces economic uncertainties, leading to increased volatility in financial markets. During this period, BIST sector indices exhibited diverse performances across different sectors, with the effects of inflation varying among them. Particularly, energy, food, and beverage sectors were more profoundly affected by inflation, whereas service and technology sectors demonstrated a more flexible adaptation to economic fluctuations. The findings obtained enrich our comprehension of the diverse impacts of inflation on sector indices, thereby improving our capacity to anticipate forthcoming financial market dynamics.

The study conducted a detailed analysis of the behavior and transitions of each index within specific market regimes, drawing insights from regime transition modeling applied to four distinct BIST sector indices. The findings from the models are summarized as follows:

Model 1 (Food and Beverage Index): The analysis indicates that transitions to a particular market regime tend to exhibit long-term stability. The Food and Beverage Index displays a consistent pattern of remaining in a specific regime for extended periods. Model 2 (Electricity Index): The study reveals that the Electricity Index is capable of quick adaptation to changes in the market, showcasing a dynamic response. The index demonstrates flexibility and responsiveness to evolving market conditions. Model 3 (BIST-Tourism Index): The trend observed for the BIST-Tourism Index suggests long-term stability during periods of low volatility, and these stable periods endure for a considerable duration. The index displays resilience and stability in the face of market fluctuations. Model 4 (BIST-Technology Index): The analysis of the BIST-Technology Index indicates that transitions to a specific market regime tend to exhibit long-term stability. Moreover, periods of low volatility in this index have an extended duration.

These results provide valuable insights into how each sector index tends to adapt to market conditions and demonstrate stability within specific market environments. Additionally, the statistically significant transition probabilities and residence times determined by the models underscore their reliability in predicting regime transitions. Overall, the developed models contribute to a deeper understanding of how these indices influence market dynamics, enabling better predictions of their future performance.

These findings coincide with similar results in other countries in the literature. For example, Horasan (2008) found a positive correlation between inflation and the BIST 100 index in the

Istanbul Stock Exchange (BIST). As in other studies in the literature, sectors in Turkey react differently during inflation periods. For example, Kılıç & Dilber (2017) found that inflation volatility positively affects BIST-100 volatility, while Eyüboğlu & Eyüboğlu (2018) found that all Borsa Istanbul sector indices have significant correlations with inflation.

This study examined each sector index individually. Subsequent research could benefit from investigating the interplay among diverse sector indices within a comprehensive economic framework, employing advanced multivariate analyses. Additionally, a more granular exploration of the impacts of key macroeconomic indicators, such as inflation, interest rates, and unemployment, on these indices would contribute to a more nuanced comprehension. Lastly, the integration of artificial intelligence and deep learning applications in future research holds the potential to significantly enhance the predictive accuracy of index behaviors.

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Çıkar Beyanı: Yazarlar arasında çıkar çatışması yoktur.

Etik Beyanı: Bu çalışmanın tüm hazırlanma süreçlerinde etik kurallara uyulduğunu yazarlar beyan eder. Aksi bir durumun tespiti halinde Fiscaoeconomia Dergisinin hiçbir sorumluluğu olmayıp, tüm sorumluluk çalışmanın yazarlarına aittir.

Yazar Katkısı: Yazarların katkısı aşağıdaki gibidir;

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Methodology: 2. author

Analysis: 2. author

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