Non-linear Dynamics and Recurrent Patterns in Stock Markets: A Comparison Between BIST-100 and S&P500 Indices

Hisse Senedi Piyasalarında Lineer-olmayan Dinamikler ve Düzensiz Örüntüler:BIST-100 ve S&P500 Endeksleri Karşılaştırması

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Öz

Finansal sistemler, özellikle de hisse senedi piyasaları karmaşık sistemlerdir. Bu çalışmamızda BIST-100 endeksi ve S&P500 endeksinde kaotik dinamikleri araştıracağız. 27 Mayıs 2018 ile 26 Mayıs 2022 tarihlerini kapsayan dönemde ABD Doları bazındaki günlük getiri oranları zaman serisi verisinde Lyapunov katsayılarını hesaplayacağız. İncelemeye konu olan zaman aralığı, Covid-19 pandemisi krizinin küresel finansal piyasalar üzerindeki etkilerini ve bu etkilerin uygulanan sıradışı para ve mali politikaların yansımalarını da içermektedir. Çalışmamızın sonuçlarına göre ilgili dönemde BIST-100 ve S&P 500 endeksleri kaotik davranış sergilemektedir ve eşlik eden en büyük Lyapunov katsayısı pozitif olarak hesaplanmaktadır. BIST-100 ve S&P500 endeksleri poizitif getiri değerleri etrafında denge kümesi oluşturmaktadırlar, bu durum da genişlemeci para ve maliye politikalarının etkilerini yansıtmaktadır. Ayrıca, S&P500 endeksinin pozitif getirisi BIST-100 endeksi pozitif getiri denge kümelenmesinden daha büyük değer almaktadır. ABD'de genişlemeci parasal ve mali önlemlerin birikimli miktar etkisinin çok daha büyük olması bu durumun önemli bir nedeni olarak değerlendirilebilir. S&P500 endeksinin daha fazla pozitif getiri sağlamış olması, gelişmekte olan piyasalara olan küresel yatırımcı ilgisini düşürürken, BIST-100 piyasasına olan yabancı sermaye akımını da zayıflatmaktadır. Endekslerdeki kaotik dinamikler er ya da geç piyasadaki karmaşıklık düzeyini artırırken hisse senedi piyasalarında sığ koşulda düzensiz volatilite döngülerine neden olacaktır. Bu yüzden, politika yapıcılar enflasyon hedeflemesi temelinde finansal stabiliteyi önceleyen stratejiler üretmek durumundalar. Türk ekonomis özelinde bu strateji hayata geçirilebilirse Türkiye finansal piyasalarındaki varlıklara talebin artması ve küresel sermaye akımlarının yoğunlaşması ihtimali yükselecektir. Küresel Merkez bankalarının para politikalarında sıkılaşmaya gittikleri veri kabul edilirse, bulgularımız para ve maliye politikaları ile portföy ve risk yönetimi açısından katkı sunmaktadır.

Anahtar Kelimeler Covid-19, Kaos, Lyapunov katsayısı, Piyasa verimi, BIST-100, S&P500.

Abstract

The financial systems, and particularly stock markets are complex systems. In this study, we investigate the evidence of chaotic dynamics of both BIST-100 stock market index and S&P 500 index. We compute Lyapunov

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exponents of stock market indices daily return series over the period from 27 May 2018 to 26 May 2022. The time interval under examination is chosen to reflect the effects of Covid-19 pandemic crisis on global financial markets, where extraordinary economic and financial policies have been implemented.The results of the study demonstrate that both BIST-100 and S&P500 indices exhibit chaotic behavior and associated maximal Lyapunov exponents are calculated to be positive, respectively. Both BIST-100 and S&P500 indices have equilibria around positive return values, reflecting the extraordinary effects of expansionary monetary and fiscal policies. Moreover, the magnitude of equilibria positive returns in S&P500 index is greater than that of BIST-100 index, which implies that cumulative effect of expansionary monetary and fiscal policy in U.S. economy overwhelms. The findings of the study suggest that greater positive return availability in S&P500 lowers the demand for emerging market assets and hence the capital inflow in BIST-100 stock market. The chaotic behavior eventually leads to an increase in complexity and recurrently causes volatility in stock markets. Therefore, in perspective of policy making inflation targeting should be considered as a main financial stability strategy to increase demand for Turkish assets and to enable capital inflows. Given upcoming monetary policy of global Central banks, our findings have important implications for policy making as well as portfolio and risk management.

Keywords Covid-19, Chaos, Lyapunov exponent, Market efficiency, BIST-100, S&P 500

Introduction

Recent developments in time series analysis allow proper modelling of nonlinearities in economic and financial variables. It is common knowledge that the financial systems are complex systems. This complexity is going to increase continuously (Fama&French, 1986;Hendricks et al., 2007). Beginning from 70's the literature has relied upon famous hypothesis defined by Nobel Laurate E.Fama in his famous paper (Fama, 1970). The hypothesis entitled Efficient market hypothesis (EMH) and defined a special framework in which financial markets can efficiently and optimally operate (Lehmann,1990, Barnett, &Serletis 2000). The hypothesis basically tells that the prices in markets should depend solely on available information of current events. Since the events are assumed to occur randomly, one cannot predict the forthcoming information and hence can not predict the prices by using historical data. For example, we consider the military conflict between Ukraine and Russia, which has been occurred in the date 25 February 2022. More generally, before the Russian attack, the decision makers in financial markets could not guess the military invasion. Therefore, the market prices in 24 February could not reflect any information about this event, but the prices in financial markets following 25 February fully affected by this event. Additionally, the EMH requires more assumptions. The information should be diffused in the market instantaneously, homogeneously and completely (French, & Roll, 1986; Chan & Gray, 2018). Moreover, the decision makers should rationally process the incoming information. If these conditions are satisfied the outcome of financial markets are efficient for all decision makers (Malkiel, 2003). This means that, no one can predict the prices before its occurrence, and no one can obtain (excessive) return which exceeds the risk that is taken and hence there would be no means of arbitrage in the financial system. Otherwise, the investors earn higher returns with respect to the risk they taken, which is the case for emerging market financial markets (Lo & MacKinlay, 1988; Harvey, 1995). As it can be seen, this hypothesis describes a "fair" state of financial system in allocation of sources. To realize these outcomes and to warrant the above-explained conditions the developed countries established certain economic and financial institutions for surveillance. These legislative institutions are branches of governments and monitor whether any trade-off cases occur or not (i.e., competition institutions, capital markets institutions, banking regulatory institutions and etc). Following the globalization of financial markets, these constitutional frameworks have also been accepted by emerging markets and Turkey, as well. Stock markets, foreign exchange markets, commodity markets as well as other financial markets have long been assumed to be efficient from the dominant theoretical perspective of Efficient market hypothesis.

In this study, we investigate the chaotic behavior of BIST-100 stock markets index in comparison with S&P500 stock market. The motivation behind considering S&P500 index is that: S&P500 stock market index is associated with the Volatility index (VIX) proxying capital inflows to emerging markets assets (Dawson & Staikouras 2009; Fu, Sandri,& Shackleton, 2016). The VIX measures the risk appetite of decision makers towards emerging market assets (Yoon et al., 2022) and has already shown to influence volatility in Turkish Lira (Oduncu, Akcelik, & Ermisoglu 2013). The importance of the topic of our study can be outlined as follows. From the theoretical perspective of Efficient market hypothesis, if the markets behavior becomes chaotic, then EMH will not be realized, the market equilibrium disrupts and arbitrage occurs (Brock, Lakonishok,& LeBaron, 1992; Gencay, 1998). An increase in complexity decreases the available information and leads to augmented uncertainty in the stock markets and other asset prices as well (Poon & Granger, 2005). The investor confidence decreases, systemic risk arises and capital outflows may occur. This causes volatility spillover in foreign exchange rates (Badshah et al., 2013). Because of the volatility spillover, stock markets, bond markets and other financial markets face with spillover effect (Rigobon & Sack, 2003; Ehrmann, Fratscher, & Rigobon, 2011, Badshah et al., 2013). In case of insufficient foreign reserves, the foreign exchange market can lose its depth in volume of transactions and predictability occurs. Beginning from the 2018 this is the case observed in Turkey, which disrupts the financial stability of the country. Arising systemic risks, the decision makers demand more foreign currency and the dollarization overwhelms. For a such a stress case, the actions taken by policy makers become increasingly important. Hendricks et al., (2007) reports "A detailed understanding of what constitutes systemic risk is therefore important ... Indeed, in all the roles policymakers fill in preventing systemic events and mitigating systemic risk, a proper analytical framework is crucial for defining the correct scope ...". In a similar study Chang, Feng, & Zheng (2021) report that government policy responses of strict lockdown measures and implementing fiscal measures can increase stock market returns in 20 countries.

To the best of our knowledge, this the first study focusing on the chaotic behavior of BIST-100 in comparison with S&P500 index amid Covid-19 pandemic crisis. The data covers daily observations over the period from 27/05/2018 to 26/05/2022. We reconstruct phase space in order to observe multiple equilibria embedded in financial time series, and then we compute the Lyapunov exponents (LE) of the associated dynamical system.

The sections of study can be summarized as follows: following the introduction part, a second part is a literature review with theoretical and empirical studies that shed a light on linkage between theory and application. In this part, we present literature review, the methodology and brief mathematical definition of the algorithm that is implemented. The third part introduces the background information on research and methodology. After presenting the data and the result of chaotic behavior analysis of exchange rate, we provide discussions and implications. Finally, this paper concludes with key points, recommendations, future research directions and limitations.

Literature Review

This section presents a brief and compact review for the literature focusing on non-linearity, complexity and chaos in financial markets. Table 1 tabulates a summary of the literature. These studies are also important in another respect and lead to further progress on predictability analysis, which is crucial in perspective of portfolio management and policy making (Casdagli,1989;Jegadeesh, 1990;Cutler, Poterba, & Summers,1991;Fernández-Rodríguez, Sosvilla-Rivero, & García-Artiles 1999;Atsalakis&Valavanis, 2009) Since this paper is first definitive and empirical examination of chaotic behavior in Turkish foreign exchange markets, we find it useful to present similar studies employed for other countries and financial markets. Even though the methods in the literature differ from each other in various respects, the fundamental rationale behind them is common: the patterns in market prices are assumed to recur in the future, and thus, these patterns violate the market efficiency (Scheinkman & LeBaron, 1989; Mayfield & Mizrach, 1989; Peters, 1991; Edgar, 1991; Hsieh,1993;Abhyankar et al. 1997; Panas&Ninni 2000; Hagtvedt, 2009; Ozkaya, 2015).

For the 1990 to 2005 period, Ozdemir (2008) examines the efficient market hypothesis for the Istanbul Stock Exchange National 100 price index and reports the efficiency of the stock market. The author applied linear stochastic model with structural break analysis, which is completely different from chaotic behavior investigation. On the other hand, Hasanaov & Omay (2008) allows for nonlinearity in conditional mean results in a superior model and provides good out-of-sample forecasts, which contradicts to efficient market hypothesis.

Theoretical and Conceptual Background

The mathematical foundation of the EMH is based on linear stochastic models. More specifically, the prices in a financial market exhibits random walk behavior if the market is efficient. The term efficiency can then be tested by appropriate statistical tests. Beginning from 90's and thanks to developing computational methods and tools, Efficient market hypothesis has come under serious siege (Woo,Mai, McAleer, &Wong, 2020). Rapidly growing literature on nonlinear dynamical analysis enabled researchers to establish different type of model specifications and to test the validity of EMH with respect to complexity, non-linearity, sensitivity to initial conditions and predictability (Farmer & Sidorowich 1987; LeBaron,1989; Schaffer, & Tidd, 1991; Abhyankar et al., 1997; Hagtvedt, 2009; Chu, Chen, Cheng, & Huang, 2009;Ozkaya, 2015). As the global financial integration broadens among multiple decision makers and counterparties, the complex dynamics of the financial systems strengthen and enlarge. Therefore, complex financial systems can exhibit the following dynamic features: non-linearity, path dependency and sensitive dependence to initial conditions. It is well known fact that all these features are related to chaotic dynamics of markets and can be occurred mainly in stress times.

The second aim in introducing Table 1 is to underline the methods used in the literature. We have to note that there are various methods to compute Lyapunov exponents embedded in a given time series. These methods have been initialized by the pioneering study of Wolf et al. (1985) and developed mainly in the mid 90's (Nychka et al., 1992; Rosenstein et al., 1993; Kantz, 1994). In our study we employ the methodology introduced in Kantz (1994). Kantz's method does not need the exact determination of the value of embedding dimension and enables to work with noisy data and well-operate even with short data sets. We introduce details in next section. Another point to be mentioned is that if one of the Lyapunov exponents is positive, then the system is nonlinear. Therefore, we do not in fact apply non-linearity test before examining chaotic behavior. For further details refer to Gencay and Dechert (1992). In addition, it is important to mention the VIX index, which is generally used to measure volatility and known as the fear index, took place as an explanatory variable in this model and was statistically significant. The fact that the study includes both pre-pandemic and post-pandemic, and that these periods contain local and global crises are important factors that distinguish our study from others. The factors that cause exchange rate volatility are generally searched within the country and it is emphasized how the central banks of the country react and whether these reactions are successful or not. Included in this study are the global factors that cause exchange rate volatility and only the extrinsic parameters being statistically significant are the main features that distinguish our study from the others.

Empirical Review and Hypothesis Development

Research and Methodology

Let us denote the dynamical system, $h: R^n \to R^n$, with the trajectory,

$$y_{t+1} = h(y_t) + u_{t+1}\ ,\ t = 0,1,2 \dots, T \qquad (1)$$

The dynamical system itself may be assumed to be contaminated by noise, or the observed time series φ_t given below in Eq.(3) may be assumed to convey noise. The Lyapunov exponents for such a dynamical system are measures of the average rate of divergence or convergence of a typical trajectory or orbit.

The state of the system at any period t, y_t cannot be observed and hence the actual functional form, which generates the dynamics. In the literature, the model used is the following: associated with the dynamical system in (1) there is a measurement function $f: R^n \to R$ which generates the time series,

$$\varphi_t = f(y_t) \tag{2}$$

It is assumed that all available observation is the sequence $\{\varphi_t\}$. Suppose that the target system is a dynamical system in (1), and the observed financial time series is obtained through a measurement function in Eq.(2). Takens's theorem (Takens, 1981), enables to reconstruct a trajectory which is an embedding of the original trajectory if the m value is sufficiently large. In the embedding method, we define two essential parameters, embedding dimension and time delay. One method to estimate the value of time delay is to select the frequency level that corresponds to a dominant power spectral feature. From observed time series $\{\varphi_t\}$, one can generate the data vector,

$$z_t = \left(\varphi_{t+(m-1)d}, \varphi_{t+(m-1)d}, \dots, \varphi_t\right) \tag{3}$$

where d is the time delay; this vector defines a point in m-dimensional reconstructed phase space, where m is the embedding dimension (Abarbanel, 1995). Therefore, a trajectory can be drawn in phase space by varying t. Our observation interval in time domain requires time delay d, to be equal to 1.

In order to directly compute maximal Lyapunov exponent, Wolf et al. (1985) and Kantz (1994) propose similar algorithms. Let z_t be the time evolution of some initial condition z_0 in the phase-space, R^m. Then maximal Lyapunov exponent is found with probability 1 by,

$$\lambda_{max} = \lim_{t\to\infty} \lim_{\varepsilon\to 0} \frac{1}{t} ln\left(\frac{\left|z_t - z_t^{(\varepsilon)}\right|}{\varepsilon}\right) \text{ and } \left|z_0 - z_0^{(\varepsilon)}\right| = \varepsilon \tag{4}$$

Eq.(4) is employed for almost all difference vectors $\left(z_0 - z_0^{(\varepsilon)}\right)$. To compute λ_{max} one can either apply Eq.(3) in R^m by searching for pairs of neighboring trajectories and follow how they diverge or can evaluate Eq.(3) in the tangent space. Therefore, to further progress, we define the distance between a reference trajectory z_t and one of $\varepsilon -$ neighbor(s) $z_{t+\tau}^{(\varepsilon)}$ after the iteration through τ by a function $G(.): R^m \to R$

$$G\left(z_t, z_t^{(\varepsilon)}; \tau\right) = \left|z_{t+\tau} - z_{t+\tau}^{(\varepsilon)}\right| \tag{5}$$

The Eq.(5) gives the magnitude of the difference vector $\left(z_{t+\tau} - z_{t+\tau}^{(\varepsilon)}\right)$. As given in Eq.(2), these distances are projections of the difference vectors in the true phase space onto a one dimensional subspace spanned by the observable. In order to measure the maximal Lyapunov exponent we fix t, search for all neighbors $z_t^{(\varepsilon)}$of z_t, inside an $\varepsilon -$neighborhood U_t and compute the average of the distances between all neighboring trajectories and the reference trajectory z_t as a function of τ where it is the relative time (iteration) depends on t. The logarithm of $G(.)$ is needed to smooth the output of the function. Finally, we obtain (6).

$$D(\tau) = \frac{1}{T}\sum_{t=1}^{T} ln\left(\frac{1}{|U_t|}\sum_{z_t^{(\varepsilon)} \epsilon U_t} G\left(z_t, z_t^{(\varepsilon)}; \tau\right)\right) \tag{6}$$

In Eq.(7) $|U_t|$ denotes the number of elements of set of $\varepsilon -$ neighbors of z_t. The first sum in the RHS of the Eq.(6) composed of the distance between z_t and each neighbor. Then we obtain its average and take logarithm. Since we should perform this calculation for all t , we take time average of the sum to obtain average magnitude of the principal axis of the m-dimensional ellipsoid. Finally, the slope of the curve

$D(\tau)$ gives us the maximal Lyapunov exponent. In summary, our numerical value for the maximal Lyapunov exponent is the slope of the curve $D(\tau)$ in the scaling region.

Findings and Discussions

The observed time series $\{\varphi_t\}$ is daily return of BIST-100 index in terms of US Dollar over the period from 27/05/2018 to 26/05/2022. Central Bank of Turkey (https://evds2.tcmb.gov.tr/) closing buying prices are used in computing BIST-100 index values. On the other hand, the daily return of S&P 500 is obtained from Federal Reserve St. Louis (https://fred.stlouisfed.org/). The Tisean Package in Hegger et al., (1999) is used to compute the output Eq.(6). All computations and graphs are obtained by using R programme. In Figure 1 and Figure 2, we depict the scatter plot visualization of BIST-100 and S&P500 indices in phase-space respectively. The z-axis denotes the time series, whereas y-axis denotes the series 1-lagged behind and x-axis denotes the series 2-lag behind. This is phase-space representation of exchange rate series in 3-dimensional phase-space. Figure 1 and Figure 2 shows the line graph of stock BIST-100 and S&P500 indices, respectively. This representation enables us to reveal recurrent patterns. On the other hand, we present Figure 3 and Figure 4 in order to detect multiple equilibria. Figure 3 and Figure 4 are obtained from Eq.(3) and depict the phase-space reconstruction of BIST-100 and S&P500 indices, respectively.

The results of the analysis are depicted in Figure 5 and Figure 6. Both Figure 5 and Figure 6 plot the output of Eq.(6) for BIST-100 and S&P500 indices, respectively. In Figure 5 and Figure 6, the slope of the curves gives the maximal Lyapunov exponent, $\lambda_{max}(t)$. The x-axis τ, signifies iteration number. The negative values derive from logarithm of the distances lying the interval (0,1]. The τ value(s) where the slope of the curves approximates zero is denoted by τ_{max} and signifies the last step of scaling range, implying that the dynamic system is still predictable. For BIST-100 data, τ_{max} = 6, whereas for S&P500 τ_{max} = 8. For the iterations exceeding this value $\tau^* > \tau_{max}$, the points are no more affected by the chaotic attractor, thus the system investigated is said to jump through an unpredictable state. From Figure 5 it is straightforward that the data examined show chaotic behavior associated with positive maximal Lyapunov exponent. Since the function in Figure (6) does not saturate with in maximum iteration range, and the effects of expansionary policies is powerful and persistent on S&P500 index.

Tables and Figures

Table 1: Summary of Literature Review, Source: Author

Authors	Subject	Sample Info	Method	Findings
Abhyankar et al., (1997)	The S&P 500, the DAX, the Nikkei 225, and the FTSE-100	S=10000	Lyapunov exponent (LE)	No evidence of Chaos
Vasilios et al., (2019)	BRICS countries exchange rates	S=1200, monthly	LE	Evidence of Chaos
Lim, Wang & Yao (2018).	US Markets NYSE, NASDAQ and AMEX	1927-2017	Time series momentum	Not i.i.d and No efficiency

Zhu, Wang, Xu, & Li (2007).	NASDAQ, DJIA and STI indices	weekly and daily 11.5.1997, 6. 12. 1990 and 3.1. 1989 to 10. 18. 2005	Augmented neural network	nonlinear predictables
Vamvakaris, Pantelous,& Zuev (2018)	S&P 500 index	S=5800 daily 1996–2016	Neural network Horizantal visibility graph	Chaos, nonlinear predictables
Nguyen, & Parsons (2022)	12 emerging economies stock market indices	1998-2022	(1) BDS (2)Spectral analysis	No efficiency
Borges (2010)	The stock markets of UK, France, Germany, Spain, Greece	daily and weekly 1993-2007	Testing EMH	Mixed results:weak form of efficiency
Matilla-Garcia (2007)	Energy futures (1) Natural gas (2) unleaded gas (3) light crude oil	NYMEX daily, S= 3700 3.19990-10.2005	LE	Evidence of Chaos
Hasanov&Omay(2008)	Turkish (ISE-100) and Greek stock (ASE) markets	monthly returns 1988-2005	STAR	Nonlinearity No efficiency
Peters (1991)	S&P 500 index	S not indicated	LE	(1) Nonlinearity (2) Evidence of chaos
Das&Das (2007)	Foreign Exchange Rate of Twelve countries	S=8500 daily 01.1971-12.2005	LE	(1) Nonlinearity (2) Evidence of chaos
Andreadis (2000)	S&P 500 index	Daily 12.1.1988-4.1.1998	fractional Brownian motion	No chaos

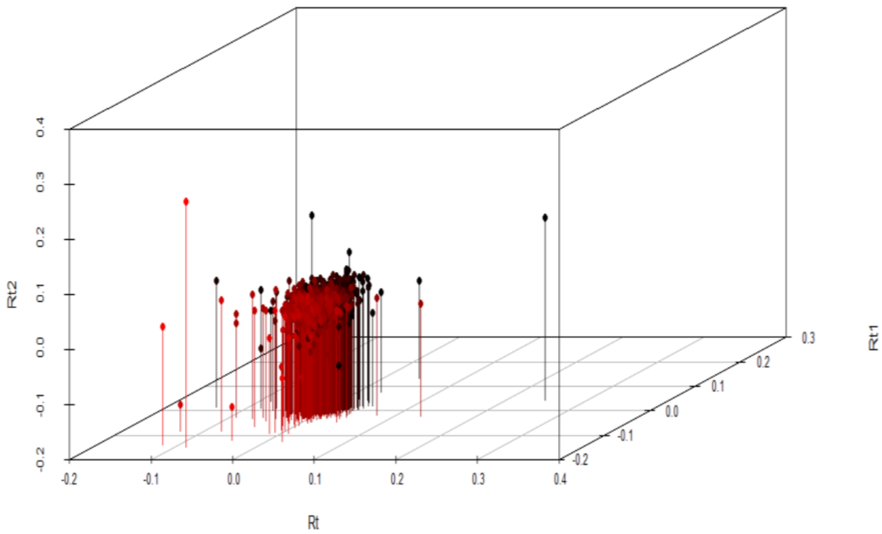

Figure 1: Phase-space representation of BIST-100; Source: Author

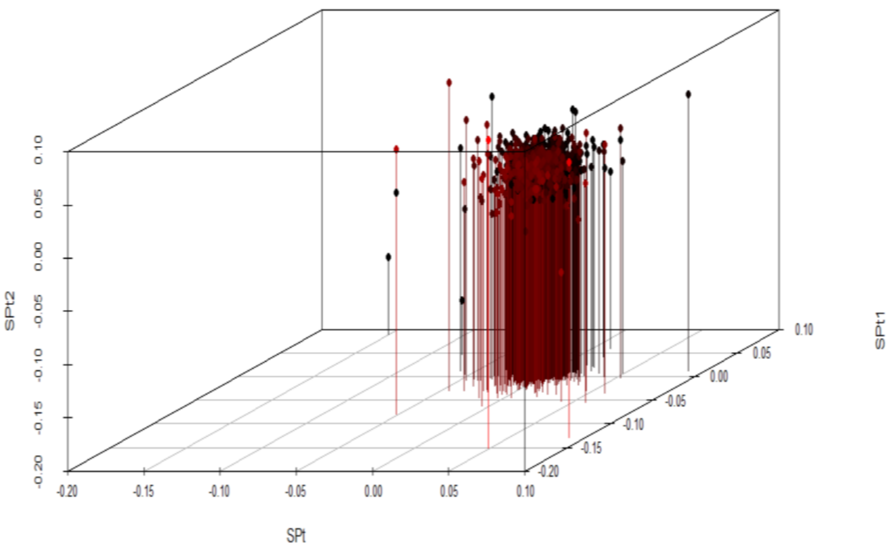

Figure 2: Phase-space representation of S&P 500; Source: Author

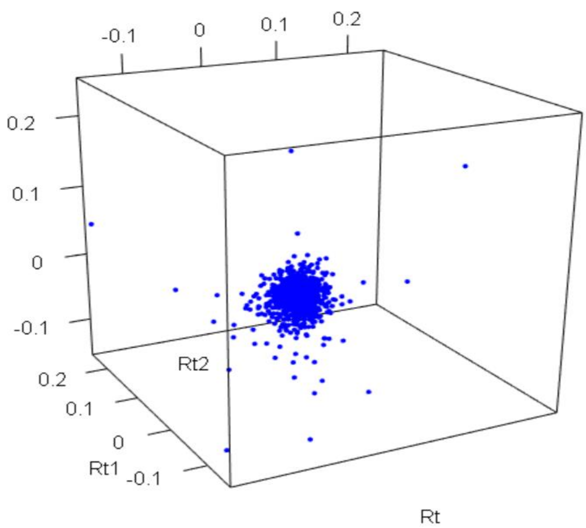

Figure 3: Spillover in 3-d embedding space in BIST-100; Source: Author

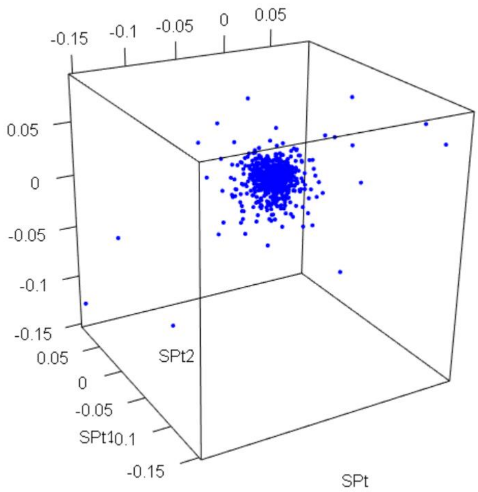

Figure 4: Spillover in 3-d embedding space S&P500; Source: Author

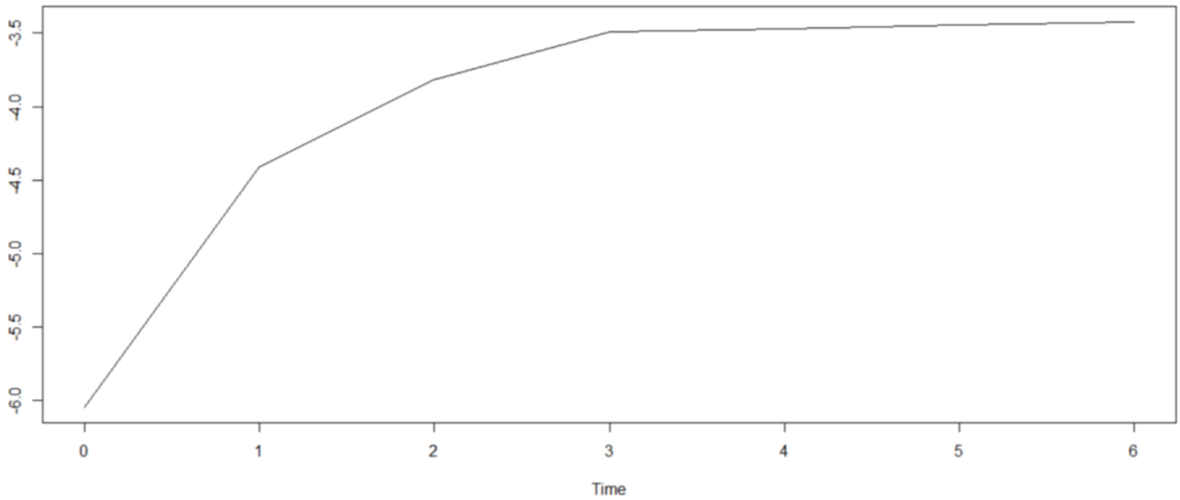

Figure 5: BIST-100 time evolution of initially nearby points – D(τ).
Source: Author

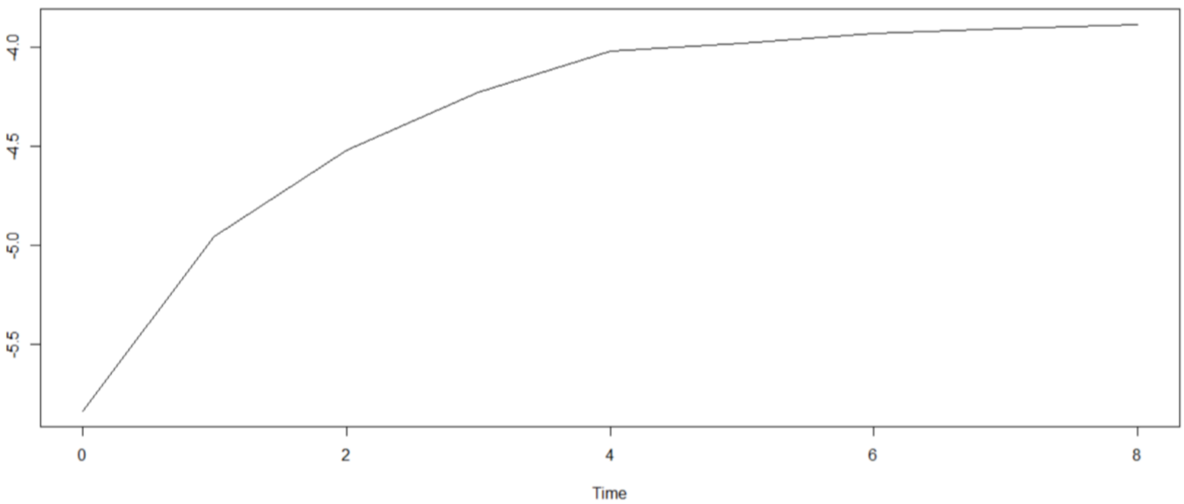

Figure 6: S&P 500 time evolution of initially nearby points – D(τ).
Source: Author

Conclusions

Over the period from May 2018 to May 2022, both BIST-100 and S&P500 stock markets give positive returns in terms of US Dollar. Both indices have equilibria around positive return values, reflecting the extraordinary effects of expansionary monetary and fiscal policies. The behavior of S&P500 index can be explained mostly by overreaction of decision makers. Moreover, the average magnitude of equilibria positive returns in S&P500 index is greater than that of BIST-100 index, which implies that cumulative effect of expansionary monetary and fiscal policy in U.S. economy exceeds the amount injected in Turkish financial system. The reason is that, at the initial stage of Covid-19 pandemics the Federal Reserve rescue plan supplied excessive money to financial markets.The findings of the study suggest that greater positive return availability in S&P500 lowers the demand for emerging market assets and hence the capital inflow in BIST-100 stock market. Overall, our examination of chaotic behavior of the BIST-100 index reveals evidence of chaos for the period under examination. This violates the EMH and excessive returns than risks become possible.This result is consistent with the findings in the related literature (Woo et al. 2020). Therefore, the stock market prices enabled arbitrage and predictability. Frankfurter&Mcgoun (2000) argue that numerous empirical researches are not consistent with the EMH, and they conclude that debate on Behavioral Finance is not rigorous enough, which has also been investigated in Ozkaya(2015). In the medium and long-run, this will disrupt efficient source allocation in productive sectors and will lower demand for stock market. Moreover, we observe certain speculative price fluctuations in financial markets in Turkey in months of August 2018, November 2020, December 2021, respectively. The sensitivity of the country to short-term capital inflows-outflows and Covid-19 pandemics crisis increased the financial vulnerability. Basically, this has augmented the need for policymakers and Central bank to intervene in the currency markets. For the actions of policy makers in case of systemic risks, Hendricks et al., (2007) reports that "... the importance of a sound method for identifying systemic risk becomes obvious. Without it, policymakers face a strong incentive to build expansive regulatory regimes capable of influencing practices that may or may not truly reduce systemic risk, because the...". On the other hand, if market-oriented systemic risks would not be eliminated, then it may develop in response to a sharp decline in the value of one particular type of asset.

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Genişletilmiş Özet

Bu çalışmanın amacını ve gündeme getirdiği soruların önemi şu şekilde özetlenebilir.Finansal sistemler, özellikle de hisse senedi piyasaları karmaşık sistemlerdir. Bu çalışmamızda BIST-100 endeksi ve S&P500 endeksinde kaotik dinamikleri araştıracağız. İncelemeye konu olan zaman aralığı, Covid-19 pandemisi krizinin küresel finansal piyasalar üzerindeki etkilerini ve bu etkilerin uygulanan sıradışı para ve mali politkaların yansımalarını da içermektedir. Bununla birlikte çalışmamız, teorik açıdan da literatürde yerleşik bir hipotez olan Verimli piyasa hipotezi (Fama,1970) bir ampirik sınamasını sunmaktadır. Verimli piyasa hipotezine göre, eğer bir piyasanın zaman içerisindeki davranışı, dinamiği kaotik olursa, o zaman o piyasa için verimli piyasa hipotezinin geçerliliğinden bahsedilemez, piyasa dengesi kaybolur, piyasa katılımcıları için adil-olmauan kazanç imkanları oluşur (Brock, Lakonishok,& LeBaron, 1992; Gencay, 1998). Böylelikle, artan derecedeki karmaşıklık, piyasada fiyatlamaya esas olan enformasyon miktarını azalatarak, belirsizliğin yükselmesine sebep olmaktadır (Poon & Granger, 2005). Bu durumun önlenmesi için kaotik davranışların test edilebilmesi önem arzeder.

Çalışmaya konu olan değişkenlere ait verilerin derlenmesi şu şekildedir: 27 Mayıs 2018 ile 26 Mayıs 2022 tarihlerini kapsayan dönemde ABD Doları bazındaki günlük getiri oranlarıdır.

Çalışmanın sunduğu niceliksel ve niteliksel analizin özellikleri şu şekildedir. 27 Mayıs 2018 ile 26 Mayıs 2022 tarihlerini kapsayan dönemde ABD Doları bazındaki günlük getiri oranları zaman serisi verisinde Faz uzaylarını yapılandırılmaktadır, çoklu-denge kümeleri araştırılmaktadır ve maximal Lyapunov katsayılarını hesaplamaktadır.Bu araştırma araçları ve hesaplamaları, piyasa karar vericilerinin beklentilerinin oluşması, uzlaşması ya da ayrışması seyri açısından bilgi verirken, bunların niceliksel değerlerini de elde etmemizi sağlamaktadır.

Çalışmanın literatüre katkısı şöyle özetlenebilir: BIST-100 endeksinin ve karşılaştırmalı olarak da S&P500 endeksinin, Covid-19 kapanma önlemlerini kapsayan zaman diliminde kaotik davranış sergileyip sergilemediğinin araştırmasını yapan ilk çalışma olmaktadır. Bununla birlikte, çalışma stres zamanlarında uygulanacabilecek ve finansal kararlılığı sağlayabilecek politikalara ışık tutarken, mevcut politikaları da değerlendirmektedir.

Çalışmanın bulguları ve elde edilen sonuçlar şu şekilde ifade edilebilir. Çalışmamızın sonuçlarına göre ilgili dönemde BIST-100 ve S&P 500 endeksleri kaotik davranış sergilemektedir ve eşlik eden en büyük Lyapunov katsayısı pozitif olarak hesaplanmaktadır. BIST-100 ve S&P500 endeksleri poizitif getiri değerleri etrafında denge kümesi oluşturmaktadırlar, bu durum da genişlemeci para ve maliye politikalarının etkilerini yansıtmaktadır. Ayrıca, S&P500 endeksinin pozitif getirisi BIST-100 endeksi pozitif getiri denge kümelenmesinden daha büyük değer almaktadır. ABD’de genişlemeci parasal ve mali önlemlerin birikimli miktar etkisinin çok daha büyük olması bu durumun önemli bir nedeni olarak değerlendirilebilir. S&P500 endeksinin daha fazla pozitif getiri sağlamış olması, gelişmekte olan piyasalara olan küresel yatırımcı ilgisini düşürürken, BIST-100 piyasasına olan yabancı sermaye akımını da zayıflatmaktadır.

Makalenin bulguları neticesinde gelecek çalışmalara ışık tutması açısından bazı husular şöyle sıralanabilir. Endekslerdeki kaotik dinamikler er ya da geç piyasadaki karmaşıklık düzeyini artırırken hisse senedi piyasalarında sığ koşulda düzensiz volatilite döngülerine neden olacaktır. Bu yüzden, politika yapıcılar enflasyon hedeflemesi temelinde finansal stabiliteyi önceleyen stratejiler üretmek durumundalar. Türk ekonomisi özelinde bu strateji hayata geçirilebilirse Türkiye’nin finansal piyasalarındaki varlıklara talebin artması ve küresel sermaye akımlarının yoğunlaşması ihtimali yükselecektir. Küresel Merkez bankalarının para politikalarında sıkılaşmaya gittikleri veri kabul edilirse, bulgularımız para ve maliye politikaları ile portföy ve risk yönetimi açısından katkı sunmaktadır. Gelecekte yapılacak olan çalışma ve analizlerde, piyasa katlılımcılarının karar-verme davranışları üzerine modeller tasarlanarak, özellikle stres zamanlarda kaotik davranışa sebebiyet veren dinamiklerin daha mikro temelleri araştırılabilir. Karar vericilerin rasyonelliğine ilişkin görüşler daha da ilerletilebilir (Ozkaya, 2015). Gelecek için çalışma ajandası oluşturacak bu konular özellikle yatırımcının güven algısının, karar verme etkinliğine katkısının modellenmesi temelinde düşünülebilir. Güven algısını ölçen çeşitli ampirik metotlar mevcuttur, bunlardan faydalanılarak başarı derecesi yüksek matematik modeller kurgulanabilir.