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Investigation of Serial Dependence Asymmetry and Time Irreversibility in Stock Market Returns of MIST Countries Using the Quantile Periodogram

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ABSTRACT

The stock market indices of the countries are indicators that provide information about the countries' economies and financial stability. The aim of the study is to determine the similarities and differences in the stock market index return behaviors for Mexico, Indonesia, South Korea and Türkiye, which constitute the MIST country group. For this purpose, the spectral density kernel estimator "Quantile Periodogram" was used. The reason why this estimator is preferred is that it allows the investigation of serial dependence at different quantiles-frequencies and it is robust to outliers frequently encountered in return series, heavy-tailed distribution and changes in the distribution at high moments. The asymmetry of the serial dependence in different quantiles-frequencies and time-irreversibility which gives information about whether the financial series behavior is predictable or not, were analyzed with the quantile periodogram. According to the findings, Türkiye is the most preferred country by financial investors among MIST countries, while Mexico is the least preferred. Secondly, it is seen that the long-term behavior predictability of the returns has increased. This means that returns are more stable in the long run. When the findings are evaluated collectively, it is concluded that MIST countries are attractive for long-term financial investment.

Keywords: Stock Market, MIST Countries, Quantile Periodogram, Asymmetry, Time-Irreversibility, Predictability.

JEL Classification Codes: C14, C58, G14

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INTRODUCTION

In 2011, Goldman Sachs Research Institute researchers brought together the country group Mexico, Indonesia, South Korea and Türkiye as emerging economies, under the name of MIST. The economies of MIST countries which has similar characteristics in terms of economic growth and population structures are the largest among the country group in the Next-11 stock fund (O'Neill, 2011). MIST countries are also similar in terms of markets, exports and being G-20 members. Çolak (2012) in his article titled "Countries Like MIS(T)" stated that O'Neill's criterion for the abbreviation MIST is that the bonds and stocks of these countries provide high returns to their investors. Yalvaç (2016) in his study titled "The Rise of New Regional Powers in the World System: Comparison of Türkiye, BRICS and MIST Countries" stated that the MIST country group consists of four countries with an upward trend in the Goldman Sachs Equity Fund and although they have differences in terms of political regimes, these countries show similarities in terms of their economic potential and future.

There are different degrees of persistence (asymmetric dependencies) in different quantiles while the financial returns are not persistent on average. For this purpose, the "Quantile Periodogram" method, which can detect dynamic features such as robustness to outliers and heavy tails, extreme dependence, time irreversibility and serial dependence asymmetry was used.

The aim of this study is to examine the stock market index returns of MIST countries and to determine the serial dependency structures of the series in different quantiles and frequencies, whether they are time irreversible and their predictability degrees. In the second section of the study, a literature review on the subject is included. In the third section, the properties of the data set and the variables are introduced. In the fourth section, the "quantile periodogram" estimator is discussed with its various aspects. In the fifth section, the empirical findings are evaluated. In the sixth and last section, the findings are interpreted.

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LITERATURE

In this section, studies on asymmetry, time-irreversibility and quantile periodogram are reviewed and summarized.

Ramsey and Rothman (1993), in their study, examined the relationship between time irreversibility and business cycle asymmetry. For this purpose, they used time-domain time-reversibility (TR) test for business cycle indicators. As a result, "time irreversibility" was determined in the series and it was concluded that the U.S. business cycles were asymmetrical.

Hinich and Rothman (1998) proposed the "REVERSE test", which is the first frequency domain test based on bispectrum for time reversibility. This test is more powerful than the TR test against time-irreversible alternatives. Based on the knowledge that business cycle asymmetry can vary depending on whether macroeconomic fluctuations are time-irreversible or not, they used the frequency domain test for business cycle asymmetry. The imaginary part of the polyspectra is zero for time-reversible stochastic processes. As a result, they concluded that time irreversibility is the rule rather than the exception for the macroeconomic time series of five OECD countries. For the representative set of international monthly macroeconomic time series, business cycle asymmetry is the rule rather than the exception.

Cajueiro and Tabak (2004) analyzed the efficiency and long-term dependencies of 11 emerging markets as well as stock market indices of the U.S.A. and Japan, based on the daily closing prices of the 1992 – 2002 period with the "Rolling Sample Approach" and "Long Range Dependence Measures". It is concluded that the efficiencies of developed markets are stronger than the efficiencies of emerging markets.

Psaradakis (2008) examined the time reversibility of weakly dependent stochastic processes over the weekly index returns of major stock exchanges (Amsterdam, Frankfurt, Hong Kong, London, New York, Paris, Singapore, Tokyo) of eight countries during the 1986-1997 period. It was concluded that the return series are "time irreversible".

Eom et al. (2008) investigated the relationship between the degree of efficiency and predictability in financial time series. In the study, 60 stock market indices were examined. "Hurst Exponent" was used to measure the degree of efficiency and "Hit Rate" was used for predictability. It has been determined that predictability is stronger in market indices with low efficiency.

Lim et al. (2008) recommended the "trispectrum-based time reversibility" test, which is more comprehensive than the bispectrum-based time reversibility test. Between 1996 and 2006, returns were calculated based on 2870 stock market daily closing values of 23 developed and 25 emerging countries. They determined that the stock market index return series of 48 countries are not time reversible. It has been concluded that "time irreversibility" is a rule rather than an exception for stock market indices, stock prices do not follow a random walk process and the non-linearity of the series is often effective on time irreversibility.

Li (2012) analyzed a well-known time series of annual sunspot numbers, with a "quantile periodogram". He revealed that the secondary peaks around the dominant peak were more pronounced in the middle and high quantiles, while they were much weaker in the low quantiles. He recommended "the quantile periodogram" method to detect such quantile-dependent spectral features.

Li (2014) investigated the properties of time series with time dependent variance. There is a stronger view at high and low quantile levels compared to middle quantiles for the time series with zero central position. In the case of stationarity, the appropriate smoothed quantile periodogram can be used to alleviate this problem.

Dette et al. (2015) compared traditional spectral analysis of returns and their squares based on the daily logarithmic returns of the S&P 500 stock index between 1963 -2009 and smoothed rank-based periodograms. As a result, it is seen that the classical approach cannot detect the serial structure. Smoothed periodograms peak at the extreme quantiles and low frequencies, indicating long-range dependence (or non-stationarity) in the tails. In addition, it is determined that the values in the imaginary parts of the smoothed rank-based periodograms are absolutely smaller than the values in the real parts and this gives information about "time reversibility". The fact that the values in the imaginary parts are not zero is an indication of "time irreversibility".

Kley (2016) used S&P 500 stock market index daily closing values between 2007 and 2010 to introduce the quantile periodogram method in the R program. Thus, in order to reveal undetectable features of returns when classical instruments are used, the "quantile periodogram" was proposed in this data range, which includes the 2008 global crisis. A linear serial dependence is not detected while looking at the correlograms of the return series. After examining the correlograms of the squared return series, it appears that the nonlinear dependence is striking. Therefore, it is not possible to detect nonlinear serial dependence with the classical periodogram based on covariances. Copula spectral density was estimated with quantile periodogram and smoothed quantile periodogram. As a result, serial dependence was detected in the extreme quantiles (0.05 and 0.95).

Kley et al. (2016) focused on quantile spectral processes in their work. They established asymptotic confidence intervals for the smoothed copula rank – based periodogram used in the estimation of copula spectral density kernels.

Flanagan and Lacasa (2016) examined the stock prices time reversibility of 35 companies from NYSE and NASDAQ with the “visibility algorithm” during the 1998 - 2012 period. It was concluded that all the analyzed series were “time irreversible”, also some series are more irreversible and the degree of reversibility changes over time.

Birr et al. (2017) introduced a quantile-based spectral approach for locally stationary variables. Based on S&P500 daily returns and a meteorological data set for the 1962 – 2013 period, they found that the copula-based spectra captures the serial dependency in more detail than the classical approach.

Lim and Oh (2021) studied about the spectral analysis of the variables with long-memory properties and the use of quantile periodograms for a non-Gaussian distribution. For this purpose, S&P 500 and NASDAQ stock market volatility data was used. At the end of the study, it was seen that the method was successful in estimating the long memory parameter.

Li (2021) introduces spectral measures based on the quantile periodogram. As a result of the application carried out using S&P 500 index daily return data, it is revealed that the quantile frequency analysis provides extra contributions, compared to the classical methods, to understanding the goodness of fit with regard to financial models, serial dependence and regime shifts in financial stochastic processes.

Jin (2021) developed tests aiming to detect the dynamics of different time series using the Laplace periodogram. For the vibration-based damage detection of a mechanical system, four vibration variables were used. It was concluded that these tests showed high performance against fat-tailed time series and were robust in the comparison of local stationary processes.

DATA

The closing values pertaining to 5930 days between 05 January 1998 and 31 December 2019, regarding the stock market indices of MIST countries were taken from the website named “Yahoo Finance”. All analyzes were performed using the “R program”. Stock market indices, their symbols and definitions are given in Table 1.

Since the index series are non-stationary, the analysis was continued with the return series obtained by taking the logarithmic difference and accepted to be stationary. Descriptive statistics for each index return series are given in Table 2.

Looking at the minimum and maximum values of the return series, it is seen that the smallest negative and the largest positive return belong to the BIST100 index and that the smallest negative and largest positive returns of the other three series are close to each other. When the standard deviations of the returns are examined, it is seen that the standard deviation of the BIST100 index is slightly larger than the others. The skewness values indicate that only the distribution of the IPC index return is slightly positive - skewed, while the others are slightly negative - skewed and the index return with the lowest skewness is related to BIST100. The kurtosis values show that the sharpest return series are related to the JAKARTA and BIST100 indices. Looking at the median values, the central positions of the series are close to each other.

Table 1: MIST Countries Stock Market Indices, Symbols and Definitions

Stock Market Indices (Symbols)	Definitions
IPC MEXICO (^MXX)	Mexico Stock Market Index
JAKARTA COMPOSITE INDEX (^JKSE)	Indonesia Stock Market Index
KOSPI COMPOSITE INDEX (^KS11)	South Korea Stock Market Index
BIST100 INDEX (XU100.IS)	Türkiye Stock Market Index

Table 2: Descriptive Statistics on MIST Countries Index Return Series

	Minimum	Maximum	Median	Standard Deviation	Skewness	Kurtosis	ADF Stats / Probs
^MXX Return	-0.103	0.121	0.00058	0.014	0.133	9.24	-17.353 prob.<0.01
^JKSE Return	-0.127	0.131	0.00095	0.015	-0.207	11.67	-16.005 prob<0.01
^KS11 Return	-0.128	0.113	0.00070	0.017	-0.198	8.90	-17.042 prob<0.01
XU100.IS Return	-0.199	0.177	0.00086	0.023	-0.036	10.364	-15.916 prob<0.01

Histograms of returns and box plots in Figure 1 were used to visualize the data in Table 2. Box plotting was introduced by statistician John Tukey in 1977 to describe data sets. After examining these graphs together, it is possible to have an idea about the central position, variance, skewness, kurtosis of each return series and the

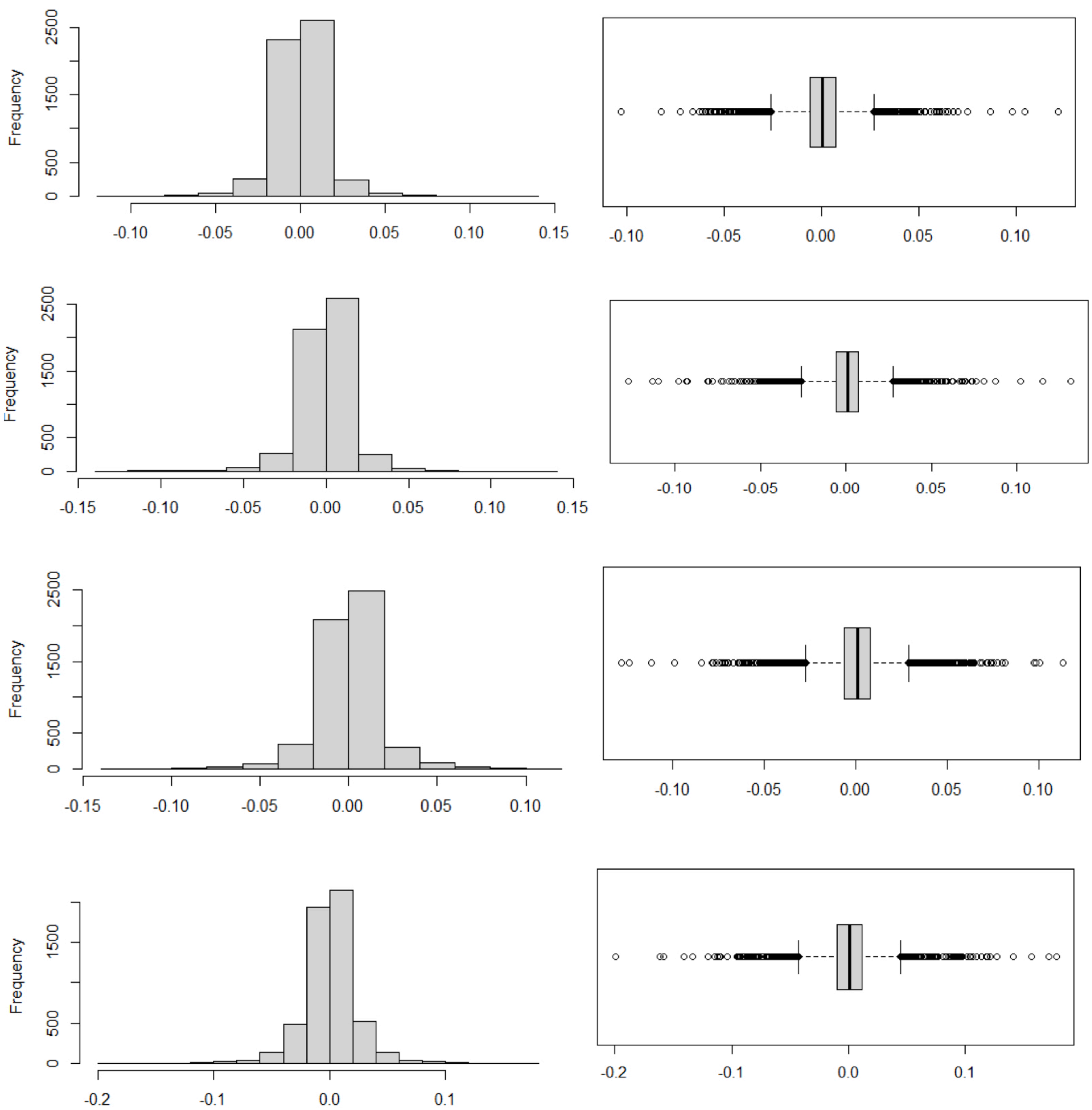

Figure 1: Histograms and Box Plots of IPC, JAKARTA, KOSPI and BIST100 Index Returns from Top to Bottom

existence of outliers. It is evident from the vertical dark line inside the box that the central position of each return series is very close to zero. Considering the starting (minimum) and end (maximum) points of the dashed lines on the left and right of the boxes, it is seen that the length between the minimum and maximum points is very close to each other for each return series. This shows that the variances of the return series are very close to each other.

Since the width of the boxes does not take up much space in the whiskers indicated by the dashed line, it is understood that the series are sharp and also the distribution of the series is close to symmetrical since the lengths of the whiskers on the right and left of the boxes are very close to each other. The points outside the whiskers give the outliers in each return series. Looking at the histograms, the graphs support the impressions obtained from the box plots. The leptokurtic (heavy-tailed and sharp) distribution of returns, which is one of the features frequently encountered in financial analysis, is a common feature in all histograms.

METHOD

Spectral methods are model independent and completely non-parametric (Birr et al., 2017, p.1620). Spectral analysis and frequency domain methods play a central role in the nonparametric approach to time series (Kley et al., 2016, p.1770). The concept of periodogram was first used by Schuster (1898) in the analysis of "hidden periodicities" in the series of meteorological events with a 26-day period.

In periodogram analysis, it takes a long time to complete one full cycle because wavelengths are long at low frequencies. As wavelengths get shorter towards higher frequencies, the frequency of the cycles will increase. The frequencies control the oscillation rate of the curve. In summary, while low-frequency spikes indicate long-term dependence, high-frequency spikes indicate short-term dependency. In addition, there is a relationship between low frequency spectral peaks at the 0.01 quantile level and financial crises & recession periods. These peaks are also an indicator of slowly decreasing positive autocorrelation (long range dependence) (Li, 2014, p.324). When there is a clustering in the return series, low-frequency peak is observed and while there is no clustering in the series, high-frequency peak is observed. In the middle quantiles, this provides information about the short-run behavior of small returns in case of large spikes at higher frequencies.

Periodic movements of a time series can be expressed by writing the autocovariance function as the sum of sine and cosine waves. This approach is known as "Ordinary Spectral Analysis". If a stochastic process is non-Gaussian, ordinary spectral analysis suffers from the weaknesses of its methods (based on conditional mean and variance), i.e. there is a lack of robustness to outliers and heavy tails. In this case, important dynamic features such as changes in skewness and kurtosis, time irreversibility, extreme dependency cannot be detected because only series with second moment can be analyzed here (Kley, 2016, p.1).

The ordinary periodogram applied to nonlinear transformations cannot reveal the asymmetric nature of the serial dependence observed in some financial time series. For this reason, "Ordinary Spectral Analysis" has been replaced by "Quantile Based Spectral Analysis". Thus, serial dependence at any quantile level of the marginal distribution can be detected with the quantile periodogram (Li, 2021, p.272).

At a fixed quantile level, the quantile periodogram has similar asymptotic statistical properties to the ordinary periodogram (Li, 2021, p.277). The quantile periodogram is also used to determine the latent periodicity in quantiles but the "Laplace periodogram" calculated for only 0.50 quantile level and the "ordinary periodogram" based on OLS estimates cannot detect latent periodicity (Li, 2012, p.766). Serial dependence in the frequency domain can be revealed in series without latent periodicity (Li, 2012, p.766).

"Laplace Cross - Covariance Kernel (LCK)", which is used in the quantile-based approach to spectral analysis and "Copula Cross - Covariance Kernel (CCK)" can be expressed as follows:

$$\gamma_k(q_1,q_2) = Cov\left(I\{X_t \le q_1\}, I\{X_{t-k} \le q_2\}\right) \quad q_1,\ q_2 \in R, \qquad k \in Z$$

$$\gamma_k^U(\tau_1,\tau_2) = \left(I\{F(X_t) \le \tau_1\}, I\{F(X_{t-k}) \le \tau_2\}\right) \tau_1,\tau_2 \in [0,1]\ , \quad k \in Z$$

Here, $I\{.\}$ is the indicator function, while F is the marginal distribution function. k represents the lag degree and is an element of the set of integers Z. q is the value of the marginal distribution of X_t corresponding to the quantile τ. CCK is invariant to monotonous transformations, so serial features can be extracted from marginal features. In these measures, there is no requirement to make assumptions about the moments. In case the stochastic process is not Gaussian and quantile-based measures of serial dependence are considered functions with arguments q_1, q_2 or τ_1, τ_2 (quantile levels), quantile-based approaches provide a richer picture of pairwise dependence than autocovariances (Kley, 2016, p.2). The covariances are replaced by the joint distributions and copulas, while the L^2 loss function is replaced by the L^1- based loss function in quantile-based approaches (Dette et al., 2015, p.783).

Respectively, the "Laplace Spectral Density Kernel" and the "Copula Spectral Density Kernel" are as follows:

$$f_{q_1,q_2}(\omega)=\frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_k(q_1,q_2)e^{-ik\omega},$$

$$q_1,\ q_2\in R,\ \omega\in R$$

$$f_{q_{\tau 1},q_{\tau 2}}(\omega)=\frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_k^U(q_1,q_2)e^{-ik\omega},\ \tau_1,\tau_2\in[0,1],\ \omega\in R$$

$q_\tau = F^{-1}(\tau)$ equality applies here. ω represents the frequency value and R is the set of real numbers. Rank-based Laplace periodograms are robust estimators of the "Copula Spectral Density Kernel" because they do not require distributional assumptions. Copula rank based periodogram method is superior to classical methods both in terms of efficiency (detection of nonlinear features) and robustness (finite variance assumption is not required) (Kley et al., 2016, p.29). Laplace periodogram is not an asymptotic unbiased estimator of copula spectral density (Dette et al., 2015, p.27).

Two different estimators can be used for quantile-based spectral analysis of time series. These estimators are called "Quantile regression based periodograms" and "Clipped time series based periodograms". The linear trigonometric quantile regression solution for the quantile regression based periodograms is as follows (Li, 2012, p.765): $\hat{\beta}_n(\omega)=\arg\min_{\beta\in\sim^2}\sum_{t=1}^{n}\rho_\tau\left(Y_t-\lambda-x_t^T(\omega)\beta\right)$ $\rho_\tau(.)$ represents the check function and $\hat{\beta}_n(\omega)$ is an argument named β that minimizes the error variance. Here, $\omega=2\pi f\in(0,\pi)$ is the frequency variable and the equality $x_t(\omega)=[\cos(\omega t),\sin(\omega t)]^T$ is valid. λ is the τ - quantile of $\{Y_t\}$. In this case, "Quantile Periodogram I" can be written as shown below:

$$Q_{n,I}(\omega)=\frac{1}{4}n\left\|\hat{\beta}_n(\omega)\right\|_2^2$$

Here $\|.\|_2^2$ is the l_2 vector norm. The "Quantile Periodogram II" is as follows:

$$Q_{n,\pi}(\omega)=\sum_{t=1}^{n}\left\{\rho_\tau(Y_t-\lambda)-\rho_\tau\left(Y_t-\lambda-x_t^T(\omega)\hat{\beta}_n(\omega)\right)\right\}$$

The two-quantile periodogram also measures the contribution of the trigonometric regressor. The quantile periodogram I measures the total power of the trigonometric regressor, while the quantile periodogram II measures the net effect of the trigonometric regressor on the cost function (Li, 2012, p.766).

"Rank based copula periodogram ($I_{n,R}$)", one of the clipped time series - based periodograms, is written as follows:

$$I_{n,R}^{\tau_1,\tau_2}(\omega)=\frac{1}{2\pi n}d_{n,R}^{\tau_1}(\omega)d_{n,R}^{\tau_2}(-\omega),\quad \omega\in R,\ \tau_1,\tau_2\in[0,1]^2$$

$$d_{n,R}^{\tau}(\omega)=\sum_{t=0}^{n-1}I\left\{\hat{F}_n(X_t)\le\tau\right\}e^{-i\omega t}=\sum_{t=0}^{n-1}I\left\{R_{n;t}\le n\tau\right\}e^{-i\omega t}$$

Here, $\hat{F}_n(x)$ is the empirical marginal distribution function and $R_{n;t}$ denotes the rank of X_t in X_0,............., X_{n-1}. $[0,1]^2$ is the set of quantile pairs. Since the rank-based copula periodogram is not a consistent estimator of the copula spectral density kernel, the smoothed version of $I_{n,R}$, "$\hat{G}_{n,R}$" is used for estimation. Smoothed rank based copula periodogram is written as follows (Kley et al., 2016, p.1776):

$$\hat{G}_{n,R}(\tau_1,\tau_2;\omega)=\frac{2\pi}{n}\sum_{s=1}^{n-1}W_n(\omega-2\pi s/n)I_{n,R}^{\tau_1,\tau_2}(2\pi s/n)$$

Here W_n is the set of weight functions. Different kernel functions can be used to perform the smoothing process. In this study, the efficient (minimizing the variance) "Epanechnikov Kernel Function" is used. The estimation variance and bias can be reduced along with the size of the local neighborhood if a large amount of data is available (Tschernig, 2004, pp.244-245).

Copula rank based periodogram (CR) used in the study was preferred for estimation because it is more efficient in detecting nonlinear features compared to quantile regression based copula periodogram. Rank based estimators are robust to outliers, heavy tails, changes in higher moments of the distribution. While obtaining the clipped time series, the indicator function takes a value of zero or one depending on whether the values of the time series are above or below a certain threshold value. For instance, the graphs for $\left(I\{X_t\le 0.5\}\right)_{t\in}$ and $\left(I\{X_t\le -1\}\right)_{t\in}$ are as follows (Dette et al., 2015, p.10):

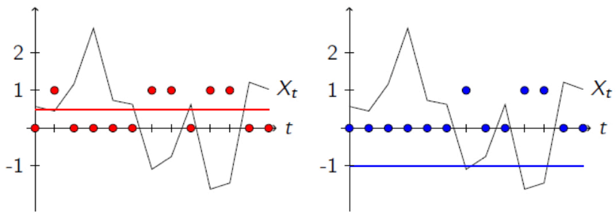

Figure 2: Clipped Time Series for $\left(I\{X_t \le 0.5\}\right)_{t\in}$ and $\left(I\{X_t \le -1\}\right)_{t\in}$

On the red graph in Figure 2, it is seen that the indicator function takes a value of one when X_t takes a value below the red threshold line and a value of zero otherwise. The same is true for the blue graph.

"Fast Discrete Fourier Transform" is preferred because of its performance in the Fourier transform of clipped time series.

EMPIRICAL FINDINGS

While stock market returns are not persistent on average, there are different degrees of persistence (asymmetric dependencies) in different quantiles. For this reason, in the study, the similarities and differences between the return series calculated based on the daily stock market index closing values of the MIST group countries with the emerging economies were analyzed by using the "Quantile Periodograms". Analysis was carried out on the basis of the period between January 5, 1998 and December 31, 2019. Thus, the ongoing pandemic period was excluded from the analysis. The time path graphs of the stock market indices of the MIST group, which consists of Mexico, Indonesia, South Korea and Türkiye, are seen in Figure 3, respectively:

When the time path graphs of the indices are examined, the effect of the 2008 global crisis made itself felt in all indices and caused serious decreases. Also, the effects of regional or national crises are seen in the graphics. For example, the effect of the 1997 Southeast Asian Crisis was detected in the graphics for Indonesia and South Korea. The graph also shows that the 2000 - 2001 crisis in Türkiye had a negative impact on BIST100. In addition, important events in the social, political and economic lives of the countries have caused significant decreases in the indices. In all time plots based on daily closing values of the stock market indices for MIST countries, the "gain-loss asymmetry", which is often seen in financial series, shows itself in the form of large downs and smaller ups. The logarithmic return series, in which stationarity is achieved to a large extent, were calculated using stock market index values.

Figure 3: IPC Mexico Index (IPCEND), KOSPI Composite Index (KOSPICI), Jakarta Composite Index (JCI) ve BIST100 Index (BIST100END) Time Path Plots, From Top Left to Bottom Right

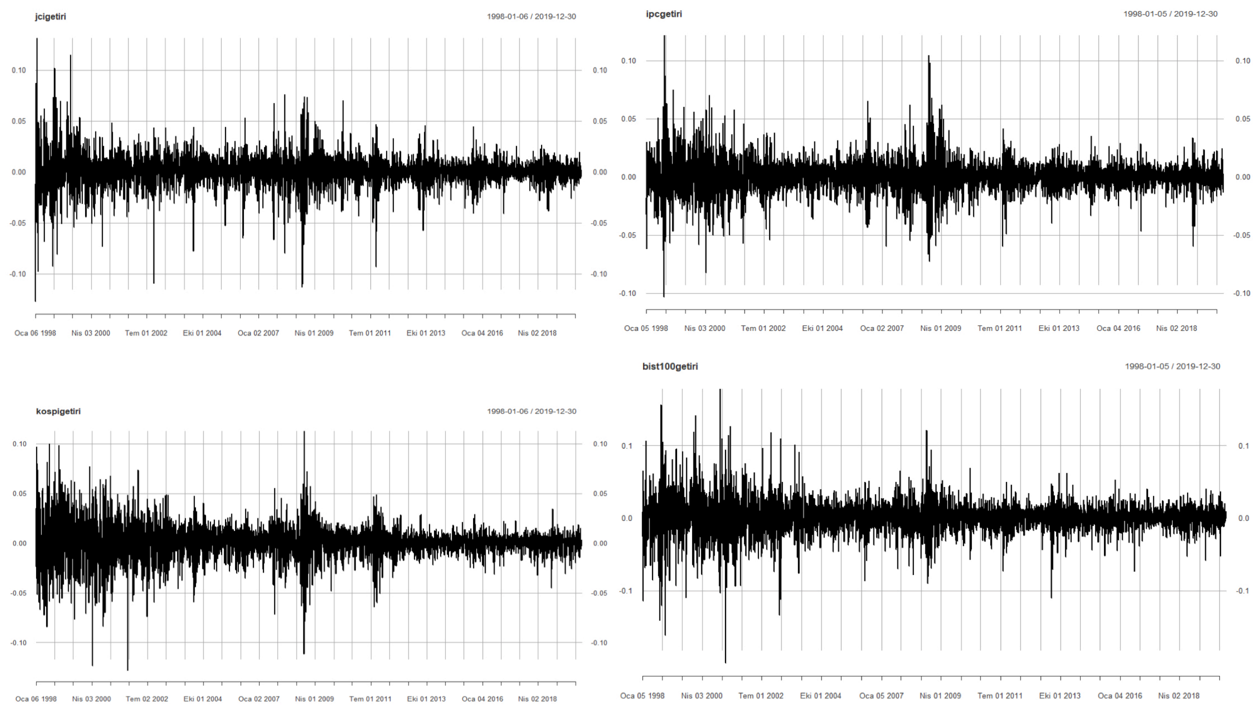

Figure 4: Jakarta Composite Index (JCI), IPC Mexico Index (IPCEND), KOSPI Composite Index (KOSPICI) ve BIST100 Index (BIST100END) Return Graphs, From Top Left to Bottom Right

In Figure 4, it is seen that the volatility clusters in the series differ. According to the correlograms, the return series reflects the "White Noise Process" characteristics, which is one of the stationary stochastic processes, but this situation has disappeared when the correlogram of the squared returns is examined. Although no linear relationship is observed between the returns, slowly decreasing positive autocorrelations are detected from the correlogram of the squared returns and a nonlinear relationship between the returns is striking. This situation

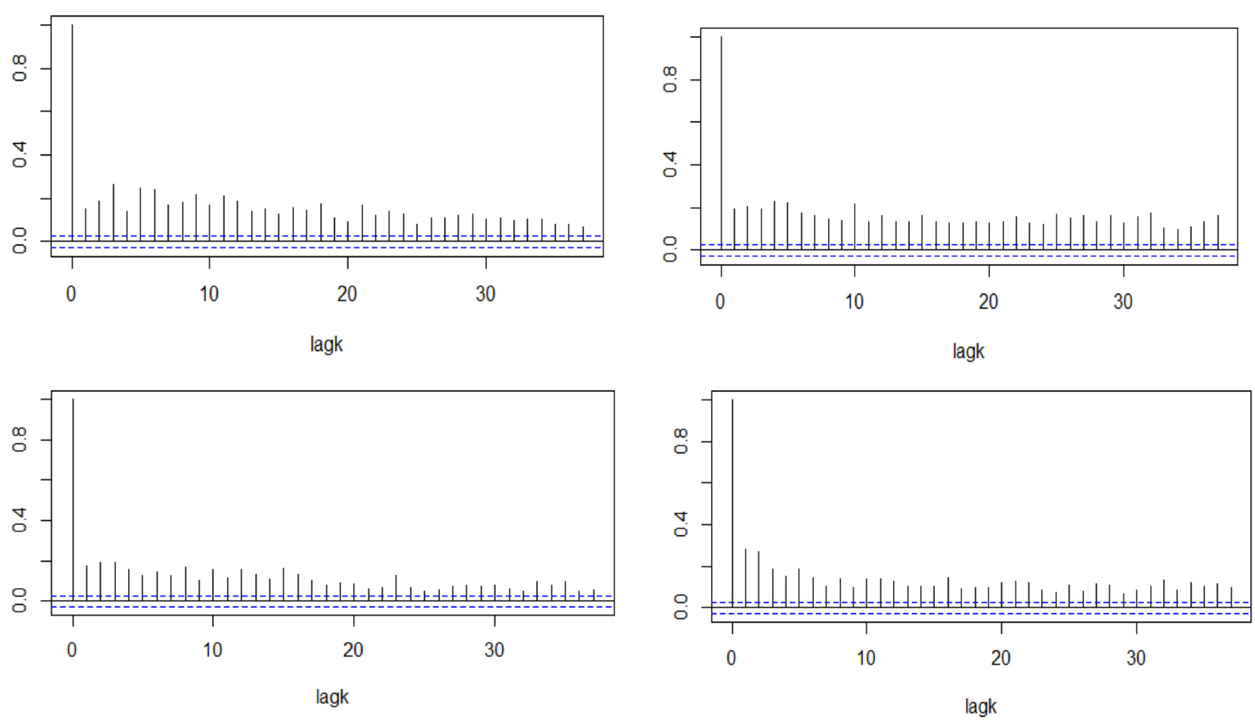

Figure 5: Correlograms of IPC Mexico Index (IPCIND), KOSPI Composite Index (KOSPICI), Jakarta Composite Index (JCI) and BIST100 Index (BIST100IND) Squared Returns, From Top Left to Bottom Right

is also evaluated as a sign of long-term dependence and volatility clustering in the series.

The "Quantile Periodogram" method is also used to reveal interesting behaviors in financial crises because traditional spectral analysis does not say much about the serial dependency structure of the data. Classical spectral methods take into account only covariance - related serial dependencies (Birr et al., 2017, p.1619). Copula spectral density is estimated from the data using the "quantile periodogram" and "smoothed quantile periodogram". The quantile periodogram shows the oscillating behavior of the series around the tau-quantile level (Li, 2021, p.274). As the Bootstrapping method, "Moving Blocks Bootstrap" was used. In this method, each block consisting of consecutive observations is deleted once and the variance of the sampling distribution of the statistical values is calculated (Kunsch, 1989, p.1217). The efficient estimator named "Epanechnikov Kernel" is used for smoothing. The bandwidth value of 0.07 used in the study of Kley (2016) was taken as a reference value and sCR plots were made according to the various bandwidths obtained from different cross - validation selectors (AMISE, UCV, MLCV, MCV) to compare with the sCR plots made with 0.07. According to some plots drawn with bandwidths less than 0.07, calculated by the cross - validation selectors, fluctuating estimates were reached. Moreover, over-smoothed estimates were obtained in some plots based on bandwidths greater than 0.07. For this reason, analyzes were carried out with bw=0.07, which is thought to be more suitable for the bias – variance balance.

In the figures on the following pages are the "Smoothed Quantile Periodogram (sCR)" graphics that give consistent estimates of spectral density functions in the 0 – 0.5 frequency range based on the return data of each stock market index. Small negatives have a stronger dependency structure than big positives due to the asymmetric behavior of actors in financial markets. The difference between extremal and central dependency structures can be seen when looking at smoothed periodograms that contain at least one extreme quantile (0.05 and/or 0.95) together with those in the middle quantiles ($\tau_1=\tau_2=0.5$). The peak at the origin in the extreme quantiles indicates the long-term memory of the extreme events and the non-zero imaginary parts above the diagonal indicate the time irreversibility (Dette et al., 2015, p.805). If the joint distribution of a time series like $\{X_1,X_2,......,X_n\}$ differs from the joint distribution of $\{X_n,X_{n-1},......,X_2,X_1\}$, the series is "irreversible". Strong irreversibility indicates that stock prices do not follow a "random walk" process in return series, because the higher the degree of irreversibility, the less the market efficiency. Non-linear and non-Gaussian linear models are "irreversible (directional)".

Hinich and Rothman (1998) suggested bispectrum-based time reversibility test (REVERSE test) in their study. This test is the first frequency domain test for time reversibility. This method tests whether the imaginary part of the estimated bispectrum is equal to zero. Here, it is based on the knowledge that the bispectrum is zero for time reversible stochastic processes. The null hypothesis is as follows :

H_0: Time Reversibility

I.I.D. process is a time-reversible process. Therefore, the time reversibility test is one of the ways to examine the random walk behavior of stock prices. If there is strong irreversibility in the return series, there are significant deviations from the i.i.d. behavior. In this manner, it is determined that stock prices do not follow a "random walk process" (Lim et al., 2008, p.8).

Moving on to the analysis of stock market index returns with "Quantile Periodogram", the smoothed rank - based copula periodogram (sCR) plots for IPC stock index returns are seen in Figure 6:

Judging by the sCR plots that give consistent estimates, there are low frequency dynamics for large positive returns when $\tau=0.95$. The same is true for small negative returns when $\tau=0.05$. Also, the peak at $\tau=0.05$ is larger than the peak at $\tau=0.95$. This shows that there is a stronger clustering effect (dependency in extreme values) in small negative returns than in clustering in large positive returns, that is, the serial dependence at the extremes has an asymmetric structure. Behind this lies the asymmetric and sometimes irrational reactions of economic agents to negative and positive shocks, that is the greater response of financial series to bad news, known as the "Leverage Effect". In the middle quantile, it is seen that the peaks are larger at low and medium frequencies. This indicates that small returns have more medium-term dependency. It is also concluded that the "stochastic time dependent variance" is in question in the series, since the dependence in the middle quantile (0.50) is stronger than the dependence in the extreme quantiles (0.05 and 0.95).

After re-examining Figure 6, considering the information about the REVERSE test and the imaginary parts of the sCR above the diagonal, a "quasi-reversible" structure is seen at high frequencies, while the degree

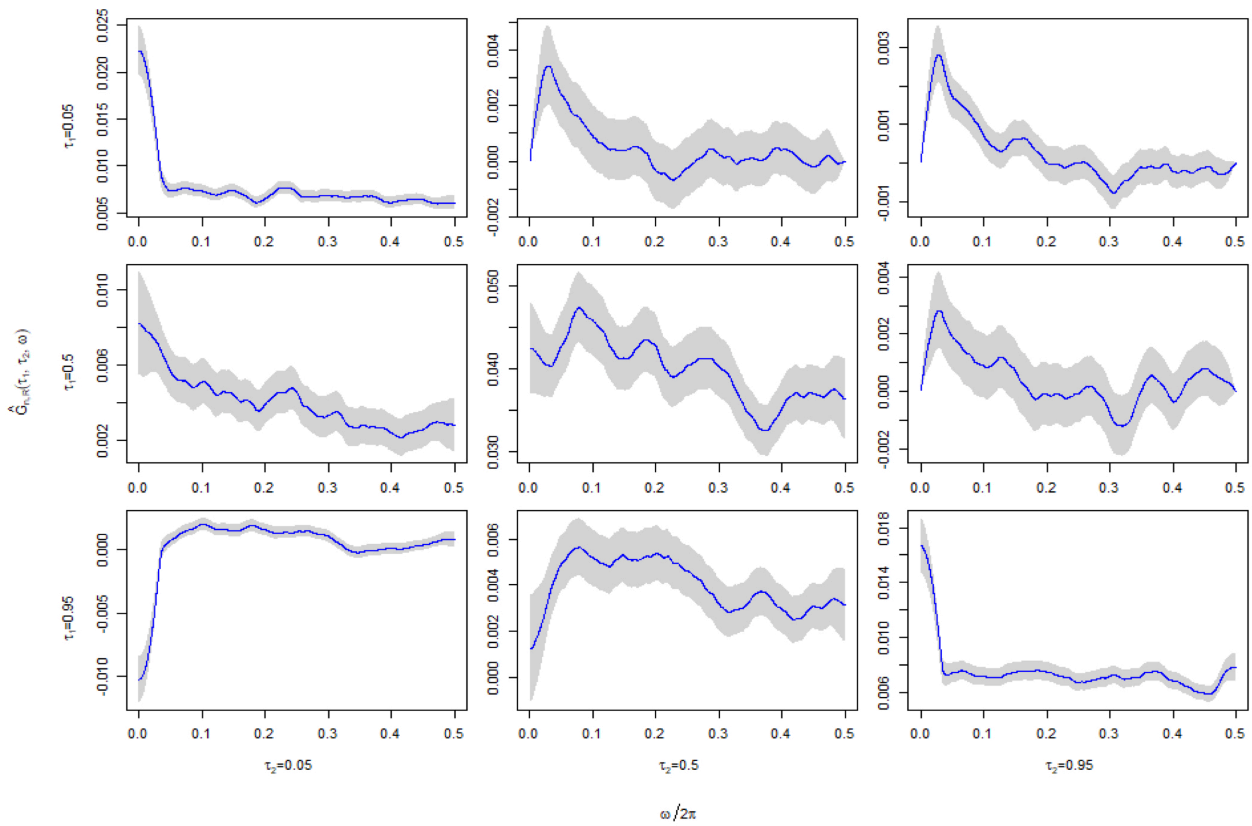

Figure 6: sCR (Epanechnikov Kernel, bw=0.07) Plots

of irreversibility increases towards low frequencies. Especially at low frequencies, that is, in the long run, market efficiency decreases, the series moves away from the random walk process and the predictability of the long-term (one business year) behavior of the series increases. This shows that the IPC index is more stable in the long term than in the short (five working days) and medium term (one working month). The peak at the origin in the extreme quantiles (0.05 and 0.95), that is, in the tails, indicates the long-term memory, that is persistence of the extreme events. The smoothed CR (sCR) plots for JCI index returns are shown in Figure 7.

Looking at the sCR plots that give consistent estimates, there are low frequency dynamics for large positive returns when τ=0.95. The same is true for small negative returns when τ=0.05. Also, the peak at τ=0.05 is almost the same length as the peak at level τ=0.95. This shows that the clustering effect in small negative returns and large positive returns is at the same level, that is, the dependency structure at extreme values seems close to symmetrical. In the middle quantile, the peak is larger at high and medium frequencies and is smaller at very high freqs. This indicates that small returns have more medium and short-term dependencies. It is also concluded that stochastic time dependent variance is in question in the series, since the dependence in the middle quantile (0.50) is stronger than the dependence in the extreme quantiles (0.05 and 0.95).

When Figure 7 is re-examined considering the information about the REVERSE test and the imaginary parts of the sCR above the diagonal, different degrees of irreversibility are observed at all frequencies, while the degree of irreversibility increases towards the middle and low frequencies. Especially at low frequencies, that is, in the medium and long term, market efficiency decreases, the series moves away from the random walk process, and the predictability of the medium and long-term behavior of the series increases. This shows that the JCI index is more stable in the long term than in the short (five working days) term. The peak at the origin in the extreme quantiles (0.05 and 0.95), that is, in the tails, indicates the long-term memory, that is, the persistence of the extreme events. The smoothed CR (sCR) plots for KOSPI index returnsare shown in Figure 8.

Looking at the smoothed periodogram plots, it is concluded that clustering is stronger in small negative returns. In the middle quantile, the peaks are more pronounced, especially at low frequencies. This indicates that small returns have medium-term dependence. It is

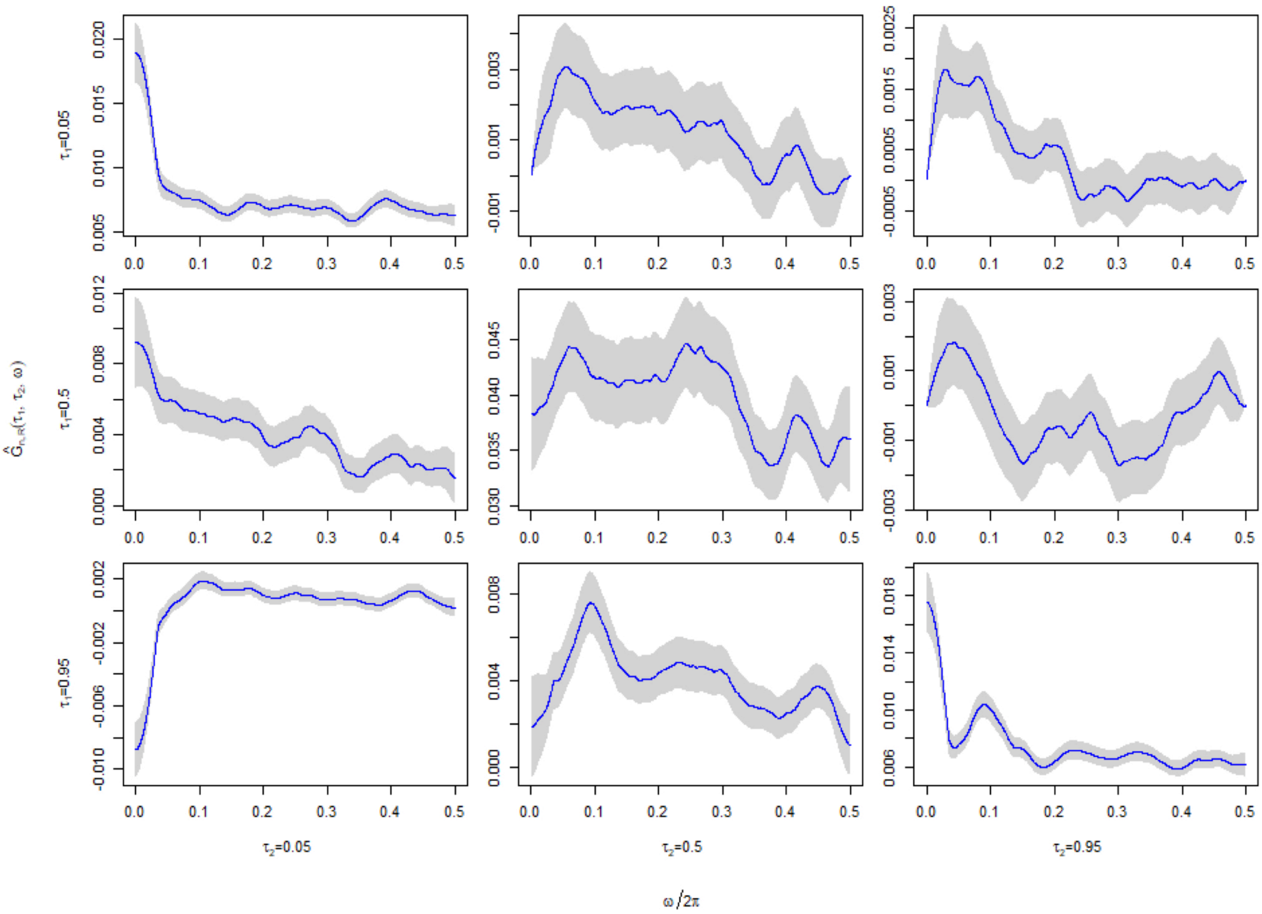

Figure 7: sCR (Epanechnikov Kernel, bw=0.07) Plots

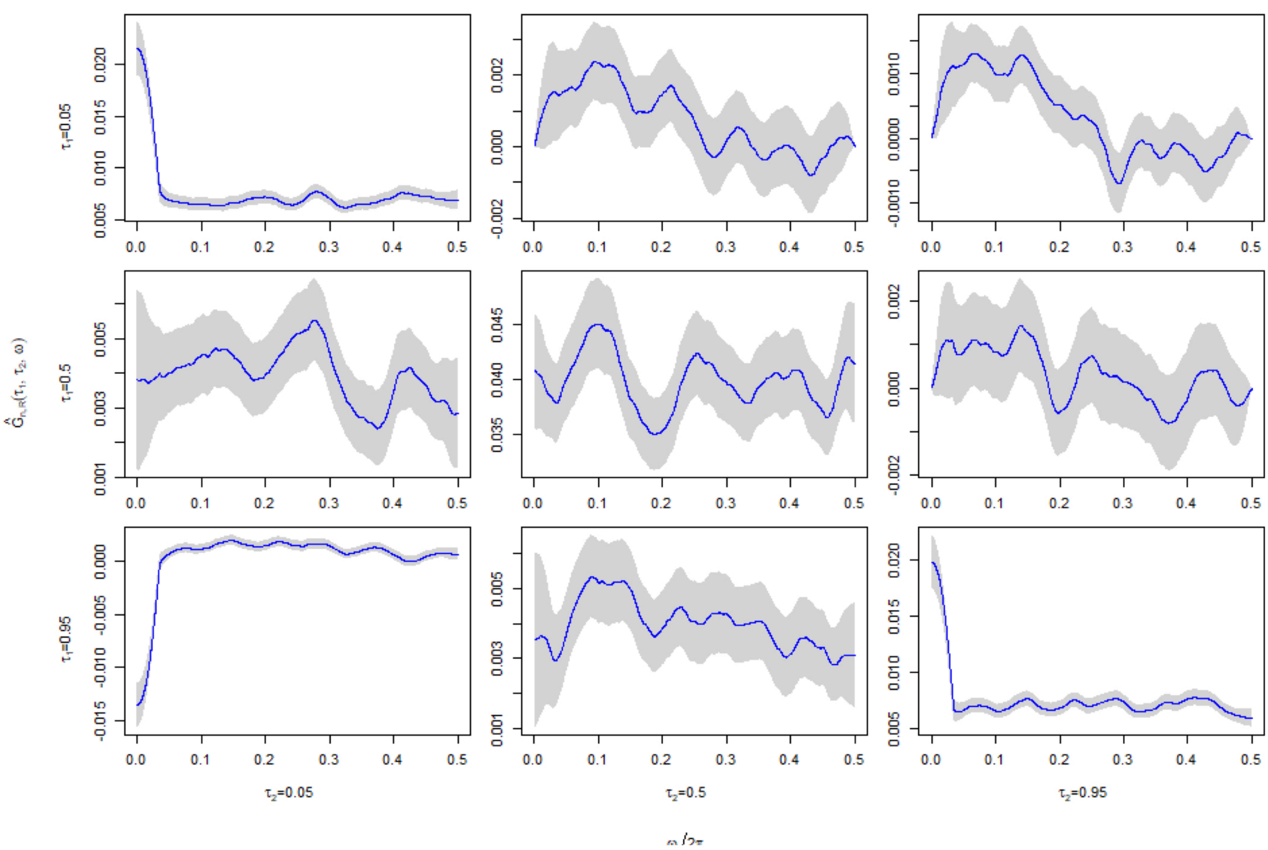

Figure 8: sCR (Epanechnikov Kernel, bw=0.07) Plots

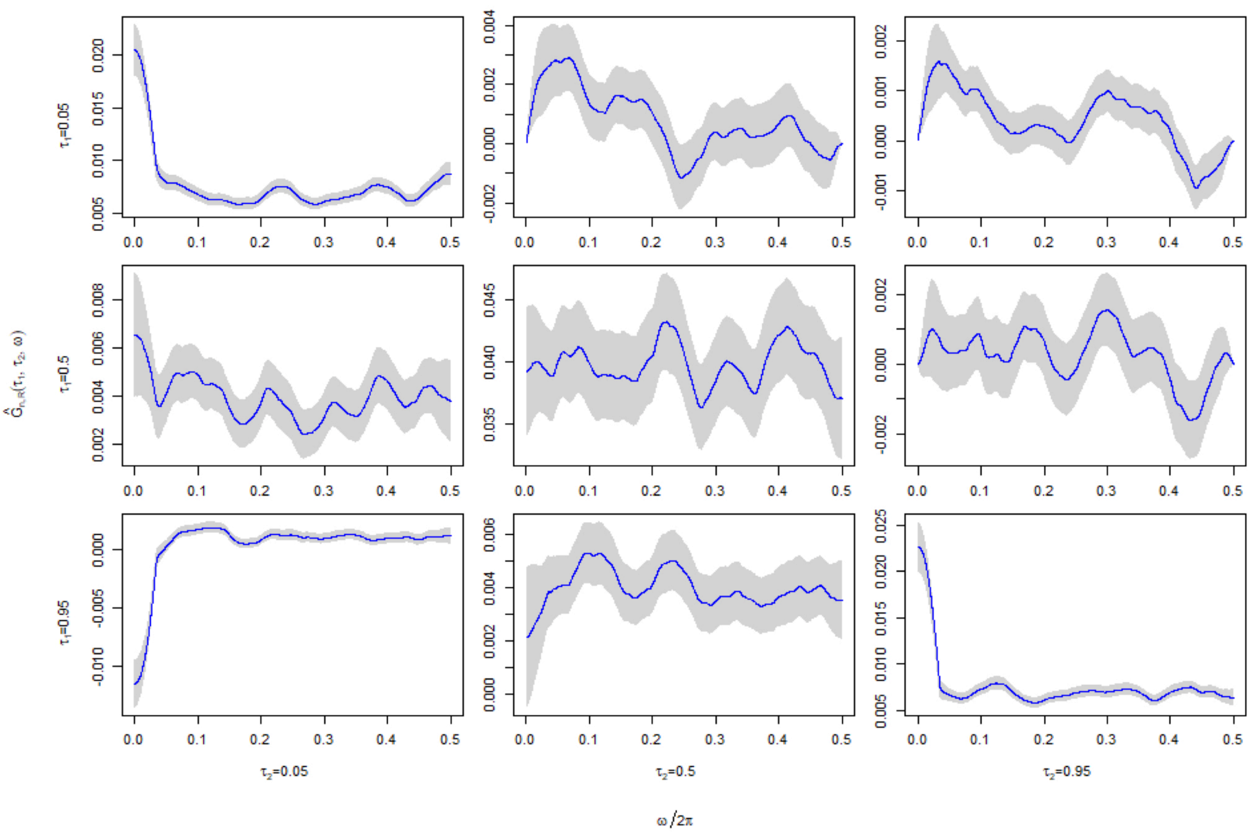

Figure 9: sCR (Epanechnikov Kernel, bw=0.07) Plots

also concluded that stochastic time dependent variance is in question in the series, since the dependence in the middle quantile (0.50) is stronger than the dependence in the extreme quantiles (0.05 and 0.95). After re-examining Figure 8, considering the information about the REVERSE test and the imaginary parts of the sCR above the diagonal, different degrees of time irreversibility are seen at all frequencies, while the degree of irreversibility increases towards low frequencies. Especially towards low frequencies, that is, in the medium term, market efficiency decreases, the series moves away from the random walk process and the behavior predictability of the series in the mid-term increases. This shows that the KOSPI index is more stable in the medium term than in the short (5 working days) and long term (one working year). The peak at the origin in the extreme quantiles (0.05 and 0.95), that is, in the tails, indicates the long-term memory, that is, the persistence of the extreme events. Finally, the smoothed CR (sCR) plots for BIST100 index returns are seen in Figure 9:

Looking at the sCR plots that give consistent estimates, there are low frequency dynamics for large positive returns when τ=0.95. The same is true for small negative returns when τ=0.05 Also, the peak at τ=0.95 is significantly larger than the peak at τ=0.05. This shows that there is a stronger clustering effect in large positive returns than clustering in small negative returns. Unlike other index returns, it is seen with the help of the quantile periodogram that clustering is more effective in large positive returns in the BIST100 index return series. This asymmetrical behavior cannot be explained by the ordinary periodogram of absolute or squared returns. In the mid-quantile, on the other hand, the peaks are greater at the high and very high freqs. This indicates that small returns have more short-term dependencies. It is also concluded that stochastic time dependent variance is in question in the series since the dependence in the middle quantile (0.50) is stronger than the dependence in the extreme quantiles (0.05 and 0.95).

Here as well, when Figure 9 is re-examined considering the information about the REVERSE test and the imaginary parts of the sCR above the diagonal, different degrees of irreversibility are seen at all frequencies, while the degree of irreversibility increases towards low frequencies. Especially towards low frequencies, that is, in the medium term, market efficiency decreases, the series moves away from the random walk process and the behavior predictability of the series in the mid-term increases. This shows that the BIST100 index is more stable in the medium term compared to the short and

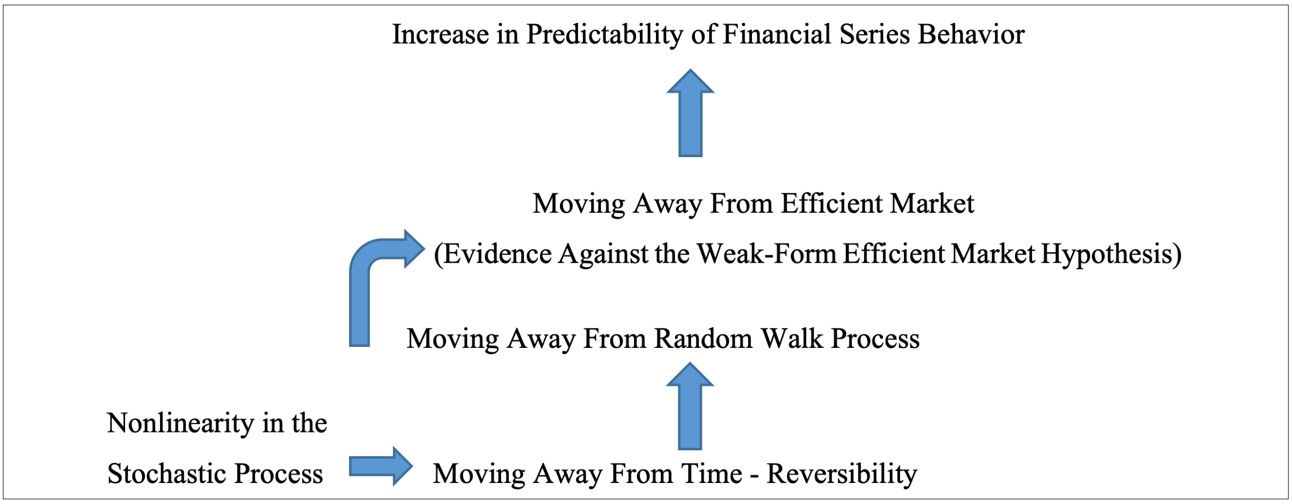

Figure 10: Flowchart from Nonlinearity to Predictability in Emerging Economies

long term. The peak at the origin in the extreme quantiles (0.05 and 0.95), that is, in the tails, indicates the long-term memory, that is, the persistence of the extreme events. In the light of the findings obtained in this study and in the literature, it is seen that the path from the non-linearity of the stochastic process to the behavior predictability of the process, shown in Figure 10, is far from being an exception for the financial series of emerging countries, but close to being the rule.

CONCLUSION

In the study, the "Quantile Periodogram" method was used to analyze the stock market indices of MIST countries. The existence of crises in these countries in the examined period necessitated the use of the "quantile periodogram" method, which enables the analysis of important dynamic features such as the asymmetry of serial dependence in the tails and to detect whether the financial series behaviors are irreversible. When the small negative returns of all stock index return series are analyzed, the effects of both global and local crises in the analysis period are evident. After analyzing the Mexican (IPC) and South Korean stock market index (KOSPI) returns, it is seen that the reaction of economic agents to negative shocks in the tails is greater than the response to positive shocks. When the Indonesian stock market index (JCI) returns are analyzed, the response to negative and positive shocks in the tails is close to symmetrical. Finally by analyzing the Turkish stock market index (BIST100), it has been found that the response of economic agents to positive shocks in the tails is greater than the response to negative shocks. Mexico is the country most affected by negative shocks in the tails and it is followed by South Korea, Türkiye and Indonesia. While Türkiye is the country most affected by positive shocks in the stock market index, it is followed by South Korea, Indonesia and Mexico. According to these results, it is seen that Türkiye is the most preferred country by financial investors among MIST countries, while Mexico is the country that can be preferred least by them.

Looking at the small returns in the indices, there is a medium-term dependency in the IPC and KOSPI stock market indices. Again, in small returns, short and medium term dependency is more common in BIST100 stock market index, while medium and short term dependency is detected in JCI. This situation reveals that Türkiye is the country where the persistence in returns other than small negative and large positive returns is weaker compared to the stock market index returns of other countries.

After evaluating the stock index return series in the context of time irreversibility, it has been determined that the stock index returns of MIST countries are "time-irreversible". This result is in line with other studies in the literature stating that "time-irreversibility" is a rule rather than an exception in financial return series. In the medium and long term, market efficiency decreases, the series moves away from the random walk process and the predictability of the long-term behavior of the series increases.

The long memory in the tails (mostly due to herd behavior) of stock index returns of MIST countries shows that financial investors can make excessive profits by analyzing the past behavior of the series. There is no long memory on small returns, that is, small returns follow a more stationary process than returns in the tails. Evaluating all the results together, it is concluded that the MIST is a preferred country group by financial investors / speculators to earn larger returns.

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