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CROSS CORRELATIONS BETWEEN MSCI EMERGING MARKETS INDICES AND US STOCK MARKET INDEX: EVIDENCE FROM MODWT(*)

MSCI GELİŞMEKTE OLAN PİYASALAR VE ABD PİYASA ENDEKSİ ARASINDAKİ ÇAPRAZ KORELASYONLARIN MODWT İLE İNCELENMESİ

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Abstract: MSCI Emerging Market Indices are developed for international investors to evaluate investment opportunities in developing countries and provide the investor with an opportunity for foresight. Due to the rapid globalization and contagion effects in financial markets, studies on MSCI Emerging Market Indices have attracted great interest in recent years. This study aims to investigate the long-memory characteristics of emerging market volatility and to show the existence of cross-correlations between Emerging Markets and the US stock market. For this purpose, Maximum Overlapping Discrete Wavelet Transform (MODWT), which is widely used in estimations in the field of finance, has been applied. MODWT, which can be used with all the features in the time series, is used in all scale dimensions. In addition, MODWT enables to produce asymptotically more efficient wavelet variance estimators. In the study, MSCI indices of seven emerging markets are used by considering the period between 2 May 2014 - 25 October 2018. The findings show that volatility in all emerging markets is stable and short-memory. There is also evidence of high and time-bound correlations between the US and Emerging Markets.

Keywords: MSCI index, Emerging Markets, MODWT, Cross Correlation, Long Memory

JEL: C22, C58, G15

Öz: *MSCI Gelişmekte Olan Piyasa Endeksleri, uluslararası yatırımcıların gelişmekte olan ülkelerdeki yatırım fırsatlarını değerlendirmeleri ve yatırımcıya öngörü fırsatı sunması için geliştirilmiştir. Finansal piyasalardaki hızlı küreselleşme ve bulaşma etkileri nedeniyle son yıllarda MSCI Gelişen Piyasa Endeksleri üzerine yapılan çalışmalar büyük ilgi görmektedir. Bu çalışma, yükselen piyasa oynaklığının uzun hafıza özelliklerini araştırmayı ve Gelişmekte Olan Piyasalar ile ABD hisse senedi piyasası arasında çapraz korelasyonların varlığını göstermeyi amaçlamaktadır. Bu amaçla finans alanında tahminlerde yaygın olarak kullanılan Maksimum Örtüşmeli Ayrık Dalgacık Dönüşümü (MODWT) uygulanmıştır. Zaman serisindeki tüm özellikler ile kullanılabilen MODWT, tüm ölçek boyutlarında kullanılmakta ve asimptotik olarak daha verimli dalgacık varyans tahmin edicilerinin üretilmesini sağlamaktadır. Çalışmada 2 Mayıs 2014 ile 25 Ekim 2018 arasındaki dönem dikkate alınarak yedi gelişmekte olan piyasanın MSCI endeksleri kullanılmıştır. Elde edilen bulgular tüm gelişmekte olan piyasalarda oynaklığın istikrarlı ve kısa hafızalı olduğunu göstermektedir. Ek olarak, ABD ve Gelişmekte Olan Piyasalar arasında yüksek ve zamana bağlı korelasyonun olduğu gözlemlenmektedir.*

Anahtar Kelimeler: *MSCI Endeksi, Gelişen Piyasa Endeksleri, MODWT, Çapraz Korelasyon, Uzun Hafıza*

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1. Introduction

The emerging markets have provided great investment opportunities for investors. However, with the rapid globalization and increase in financial market interactions the return expectations have been decreased greatly. Therefore, the studies on the interactions between countries have great deal of attention. During last years many studies have been implemented to identify and model how financial markets are interacted and linked. If the nature of interactions are correctly identified then, investment opportunities can be effectively evaluated (Koutmos (1996).

MSCI indices are developed to track financial markets all over the World. They are traded in US market and each index covers 80% of the financial market which belongs to. These indices provide global investors to measure the performance of financial markets. Therefore, they are called indicator indices. In this paper the interactions between seven emerging market's MSCIs in Europe, Middle East and Africa, namely Greece, Poland, Qatar, Russia, South Africa, Turkey, United Arab Emirates and US financial market index, S&P500 are investigated.

Emerging markets are linked with US and other financial market as a result of trade, investment relations and global investors (Lin et al. (1994), Cohen and Frazzini (2008), Strauss et al. (2013), Bekaert et al. (2014). Moreover, the strength and direction of interactions show different characteristics not only according to time but also according to frequency analysis (Ramsey and Lampart, 1998a). The wavelet cross correlation analysis, especially Maximum Overlap Discrete Wavelet (MODWT) for this reason, is an appropriate method for identifying these interactions (Kumar and Joshi (2011)). However, studies on financial applications of MODWT are very limited. The pioneers working in this field are Gençay, Goffe, Lampart and Ramsey. Primary and recent studies in this field are as follows. Gençay et al. (2001) examined the scaling properties of correlation between exchange rates. Kim and In (2003) investigated cross correlations between stock returns and real economic activity and they applied Granger casuality test for each time scale. Kim and In (2005) analyzed correlation between stock returns and inflation by using Wavelet analysis. Gallegati (2005) in his paper examined the interaction between MENA stock markets, namely Egypt, Israel, Jordan, Morocco and Turkey. Kim and In (2007), studied cross correlations between stock price and bond yields in the G7 countries. Lee et al. (2008) investigate the existence of correlation returns and volatility of S&P500 index by using high frequency data. Rua and Nunes (2009) analyzed interactions among international stock exchanges based on wavelet analysis. Multi-scale interactions among the interest rate, exchange rate and stock price are investigated by Hamrita et al. (2009). Gallegati (2010) tested the financial market contagion using a wavelet-based approach. Moshiri et al. (2010) examined the relationship between stock returns and inflation by using wavelet method. Nikkien et al. (2011) focused on the cross-dynamics of exchange rate expectations using different time scales. Naccache (2011) examined the relationship between oil price and MSCI index. And in this paper, wavelet cross correlation techniques and exchange rate expectations are analyzed. Bruzda (2011), analyzed interactions between the Polish business cycles and the euro zone cycles. Marius and Petre (2011) analyzed how stock markets in Germany and United Kingdom impacts Romanian stock market. Jammazi (2012) analyzed interaction between crude oil and stock returns. Madeleno and Pinho (2012) analyzed the correlations among stock markets of United Kingdom, Brazil, Japan, United States. Dacjman et al (2012) examined whether the correlations between CEE countries and developed markets present time varying dynamics by using wavelet analysis. In 2012, existence of cross correlations between Islamic and non Islamic countries were investigated by using wavelet analysis (Saiti, 2012). Fernández-Macho (2012) analyzed the correlation and the cross correlation of the Eurozone stock market returns on a scale-by-scale basis. Tiwari et al. (2013) examined the relationship among stock exchanges in Asian countries with the help of wavelet. Reboredo et al. (2013) examined the relationship between US dollar and oil price for pre- after global financial crisis periods. Alhayki (2014) applied a wavelet analysis model to examine the relationship between oil and stock returns. She also applied the Granger causality test. Khalfaoui et al. (2015) studied the relationship between oil and stock markets of G-7 countries over various time scales with both GARCH-BEKK and Wavelet analysis. Kumar et al. (2016) analyzed the stock market dynamics of BSE and NSE index by using cross correlation analysis. Martinez and Abadie (2016) examined the long term relationship of crude oil spot prices. Kumar and Kamaiah (2017) showed existence of cross correlation using Asia markets. Jena et al. (2018) examined the dynamic relationship between gold spot and futures markets.

The main purpose of this paper is to show existence of long memory in the volatilities of emerging markets and to investigate dynamics of cross correlations between US and emerging markets. For this purpose, MSCI Emerging Market Indices of six emerging markets, namely, Turkey, Greece, Poland, Qatar, United Arab Emirates and South Africa are considered. As a representation of US market, S&P500 index is used. The period from May 02, 2014 to October 25, 2018 is examined and in the analysis, the MODWT is used.

This paper contributes literature in several ways. First, although the usual belief is that the emerging market volatilities are persistent, this study provides evidences of that emerging market volatilities are not persistent. Second, most studies provide evidences of spillovers from US to Emerging markets. However, the findings of this study showed that the significant spillovers exist in the short time scales and this spillover of effect disappeared in the long term for emerging markets governed by democracy. Moreover, US affects the emerging markets governed by sharia in the long time scales, can not be observed in short time scales.

This paper is organized as follows. In Section 2, wavelet analysis is introduced and the differences between discrete wavelet transform and MODWT are explained. In Section 3, data is described and descriptive statistics and empirical results are given. Finally, in Section 4 the results are discussed and the paper is concluded.

2. Methodology

Wavelet analysis is just one of the various statistical signal extraction and filtering methods (Pollock (2006). In this section, a brief introduction to the wavelet analysis is presented and the difference between Discrete Wavelet Transform (DWT) and Maximal Overlap Discrete Wavelet (MODWT) is explained.

Wavelet transform efficiently decompose a time series by means of basis functions. Short basis is used to capture high frequency characteristics and long basis is used to capture low frequency characteristics.

DWT includes two filters which are called wavelet and scaling filters, respectively. Wavelet filter coefficients (namely, high-pass filter) are denoted by $h_\ell, \ell = 0,1,2,\ldots,L-1$ and wavelet filter has zero mean unit energy and orthogonal even shifts given in (1), respectively.

$$\sum_{\ell=0}^{L-1} h_\ell = 0\,, \qquad \sum_{\ell=0}^{L-1} h_\ell^2 = 1, \quad \sum_{\ell=0}^{L-1} h_\ell\, h_{\ell+2k}\,, \forall k \in \mathbb{Z}\,/\{0\} \tag{1}$$

(Gençay, Selçuk and Whitcher 2002)

A scaling filter coefficients, namely low-pass filter are denoted by $g_\ell, \ell = 0,1,2,\dots,L-1$ and determined by the relationship given in (2).

$$g_\ell = (-1)^{\ell+1} h_{L-1-\ell}, \qquad \forall \ell = 0,1,2,\dots,L-1 \tag{2}$$

(Gençay, Selçuk and Whitcher 2002)

DWT is an alternative to the Fourier Transform for time series. It provides wavelet coefficients that are local in both time and frequency. Moreover, unlike DWT, MODWT is not orthogonal but at each scale number of scale and wavelet coefficients are equal to the number of Percival and Mofjeld, (1997), Gençay et. al. (2001).

MODWT is superior to DWT according to the features given as follows:

i. MODWT can be used for all sample sizes.
ii. The features in the original time series can be appropriately organized with the features in the multi-resolution analysis
iii. MODWT is transition invariant which means that an integer amount of shift in the time series creates same amounts of shifts in the wavelet and scaling coefficients.
iv. MODWT generates asymptotically more efficient wavelet variance estimators (Percival, 1995).

2.1. MODWT (Maximal Overlap Discrete Wavelet Transform)

$\boldsymbol{x}$ denotes $N \times 1$ vector of observations. $\widetilde{\boldsymbol{W}}$ is a $(J+1)\,N \times N$ matrix which defines the MODWT and $\widetilde{\boldsymbol{w}}$, $(J+1)\,N \times 1$ is the vector of MODWT coefficients which is obtained from the equation given in (3).

$$\widetilde{\boldsymbol{w}} = \widetilde{\boldsymbol{W}}\boldsymbol{x}\,, \tag{3}$$

(Gençay, Selçuk and Whitcher 2002)

If the vector of MODWT coefficient is expressed by $J+1$ vectors given in (4), and if number of observations of the time series satisfies the condition $N > 2^J$, then DWT wavelet and scaling coefficients can be expressed in terms of MODWT coefficients as given in (5) and (6), respectively.

$$\widetilde{\boldsymbol{w}} = [\widetilde{\boldsymbol{w}}_{\boldsymbol{1}}, \widetilde{\boldsymbol{w}}_{\boldsymbol{2}}, \dots, \widetilde{\boldsymbol{w}}_{\boldsymbol{J}}, \widetilde{\boldsymbol{v}}_{\boldsymbol{J}}]^T \tag{4}$$

(Gencay, Selcuk, & Whitcher, 2002).

$$w_{j,t} = 2^{j/2}\, \widetilde{w}_{j.2^j(t+1)-1}\,, t = 0, 1, \dots, N/2^j - 1. \tag{5}$$

(Gencay, Selcuk, & Whitcher, 2002).

$$v_{J,t} = 2^{J/2}\, \tilde{v}_{J.2^J(t+1)-1}\,, t = 0, 1, \dots, N/2^J - 1. \tag{6}$$

(Gencay, Selcuk, & Whitcher, 2002).

where $\tilde{\boldsymbol{w}}_j$ denotes $N/2^J \times 1$ vector of wavelet coeeficients which is related with the changes on scale length of $\lambda_j = 2^{j-1}$ and $\tilde{\boldsymbol{v}}_J$ presents $N/2^J \times 1$ vector of scaling coefficients which is related with averages on scale length of $2^J = 2\lambda_J$, just like DWT (Gençay et al., 2002).

MODWT uses pyramid algorithm and requires three objects; a data vector $\boldsymbol{x}$, a rescaled wavelet filter $\tilde{h}_\ell = h_\ell/2^\ell$ and a scaling filter $\tilde{g}_\ell = g_\ell/2^\ell$, $\ell = 0,1,2,\dots,L-1$. The MODWT algorithm includes two parts which are listed as follows:

First Part of Algorithm:

Iteration 1. In order to obtain the wavelet and scaling coefficients given in (7), respectively, the data is filtered by each of the filters.

$$\tilde{w}_{1,t} = \sum_{l=0}^{L-1} \tilde{h}_\ell\, x_{t-\ell}, \qquad \tilde{v}_{1,t} = \sum_{l=0}^{L-1} \tilde{g}_\ell\, x_{t-\ell} \tag{7}$$

(Gencay, Selcuk, & Whitcher, 2002).

where $t = 0,1\dots, N-1$.

Iteration 2. In order to obtain the second level of wavelet and scaling coefficients given in (8), respectively, data is defined as scaling coefficients, $\tilde{\boldsymbol{v}}_{\boldsymbol{1}}$obtained from *Iteration 1*.

$$\tilde{w}_{2,t} = \sum_{\ell=0}^{L-1} \tilde{h}_\ell\, \tilde{v}_{1\,,t-\ell}, \quad \tilde{v}_{2,t} = \sum_{\ell=0}^{L-1} \tilde{g}_\ell\, \tilde{v}_{1,t-\ell} \tag{8}$$

(Gencay, Selcuk, & Whitcher, 2002).

where $t = 0,1\dots, N-1$.

Iteration 3 to J. Repeat the iterations up to $J = \log_2(N)$ and obtain the vector of MODWT coefficients given in (4).

Second Part of Algorithm:

Iteration 1.In order to obtain $(J-1) \times 1$ vector of scaling coefficients, $\tilde{\boldsymbol{v}}_{J-1}$, the equation given in (9) is used.

$$\tilde{v}_{J-1,t} = \sum_{l=0}^{L-1} \tilde{h}_\ell\, \tilde{w}_{J,t+\ell} + \sum_{l=0}^{L-1} \tilde{g}_\ell\, \tilde{v}_{J,t+\ell} \tag{9}$$

(Gencay, Selcuk, & Whitcher, 2002).

where $t = 0,1\dots, N-1$, and $\tilde{\boldsymbol{w}}_J$ and $\tilde{\boldsymbol{v}}_J$ are the final values obtained from the first part of algorithm.

Iteration 2. In order to obtain $(J-2)\times 1$ vector of scaling coefficients, $\tilde{\boldsymbol{v}}_{J-2}$, the equation given in (10) is used.

$$\tilde{v}_{J-2,t} = \sum_{l=0}^{L-1} \tilde{h}_\ell \, \tilde{w}_{J-1,t+\ell} + \sum_{l=0}^{L-1} \tilde{g}_\ell \, \tilde{v}_{J-1,t+\ell} \tag{10}$$

where $t = 0,1\ldots,N-1$.

Iteration 3 to J. Repeat the iterations until the first level of wavelet and scaling coefficients satisfies the condition given in (11).

$$x_t = \sum_{l=0}^{L-1} \tilde{h}_\ell \, \tilde{w}_{1,t+\ell} + \sum_{l=0}^{L-1} \tilde{g}_\ell \, \tilde{v}_{1,t+\ell} \tag{11}$$

where $t = 0,1\ldots,N-1$ and x_t is the original vector of observations.

2.2. Wavelet Variance, Covariance and Correlation

Wavelet transform can also be used to determine the variance and degree of the relationship between the two stochastic processes on a scale by scale basis. For this purpose, two processes are decomposed and for each scale λ_j wavelet weights are used to calculate wavelet variance and covariances.

The wavelet variance estimator for scale λ_j based on MODWT is defined in (12).

$$\tilde{\sigma}_X^2(\lambda_j) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \tilde{w}_{j,t}^2 \tag{12}$$

(Gencay, Selcuk, & Whitcher, 2002).

where $L_j = (2^J - 1)(L-1) + 1$ is the length of the wavelet filter for scale λ_j and $\tilde{N}_j = N - L_j + 1$ is the number of maximal overlap coefficients.

The wavelet covariance estimator for scale λ_j based on MODWT is defined as follows.

$$\tilde{\gamma}_X(\lambda_j) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \tilde{w}_{1,j,t} \, \tilde{w}_{2,j,t}, \tag{13}$$

(Gencay, Selcuk, & Whitcher, 2002).

where $L_j = (2^J - 1)(L-1) + 1$ is the length of the wavelet filter for scale λ_j and $\tilde{N}_j = N - L_j + 1$ is the number of maximal overlap coefficients.

Similarly, MODWT estimator of the cross correlation coefficients can be obtained in given equilibrium (14).

$$\tilde{\rho}_{XY(\lambda_j)} = \frac{Cov_{XY}(\lambda_j)}{\tilde{v}_X(\lambda_j)\tilde{v}_y(\lambda_j)} \tag{14}$$

(Gencay, Selcuk, & Whitcher, 2002).

The wavelet cross corelations coefficients $\tilde{\rho}_{XY(\lambda_j)}$ are between 0 and 1, like the usual unconditional cross correlation coefficients.

3. Empirical Analysis

In this study, cross correlations between the MSCI indices of emerging market (Turkey (TUR), Greece (GREK), Poland (EPOL), Qatar (QAT), United Arab Emirates (UAE), North Africa (EZA)) and S&P500 index are investigated by using the wavelet analysis. This study covers the period from May 2, 2014 to October 25, 2018. The data are collected from www.investing.com and the analysis are implemented by using R package program[1] with 'waveslim' library (Whitcher, 2020).

In the study, percentage logarithmic returns given in (15) are calculated and used in this analysis.

$$R_t = \log\left(p_t / p_{t-1}\right) * 100, i, j = 1,2,3, \dots, N. \tag{15}$$

The time series plots of MSCI index returns are demonstrated in Figure 1. According to figures all the return series show volatility clustering and some jumps at different time periods

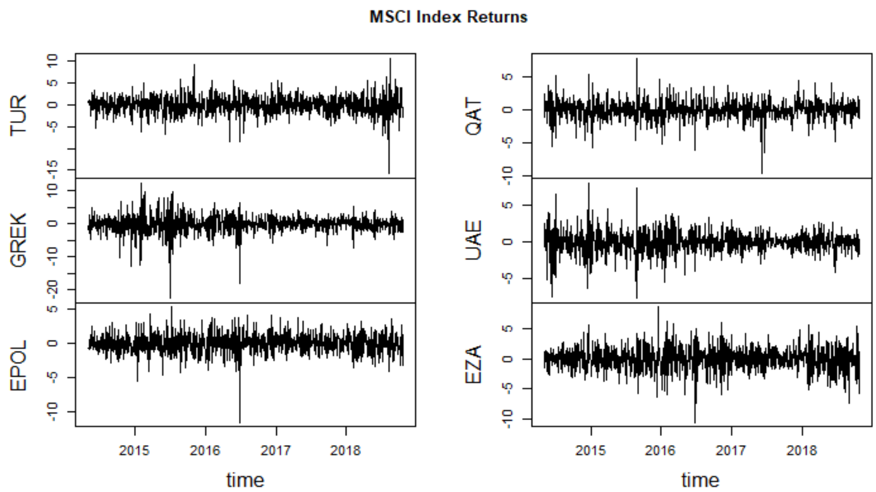

Figure 1. Time Series Plot of Percentage Log-Returns

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[1] R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

According to index return graphs, when the return graphs obtained in Figure 1 are examined, fluctuation can be seen in all series. In the MSCI series of emerging countries, the largest fluctuations belongs to Russia. The lowest fluctuation in the graphs of the yield series belongs to Qatar. Return graphs show that most fluctuations are experienced in the years 2008-2009. This fluctuation can be characterized by the fact that it was related to the 2008 crisis in that period.

Descriptive statistics, Jarque Bera test for normallity (Jarque and Bera, 1980) and Augmented Dickey Fuller test (Dickey and Fuller, 1979) for stationarity are presented in Table 1.

Table 1: Descriptive Statistics and Test Results

	Turkey	**Greece**	**Poland**	**Qatar**	**United Arab Emirates**	**S.Africa**	**S&P**
Mean	-0.074	-0.100	-0.030	-0.028	-0.048	-0.031	0.030
Median	0.023	0.000	0.000	0.000	0.000	0.033	0.038
Min.	-15.695	-22.357	-11.562	-9.536	-7.644	-10.532	-4.184
Max.	10.683	12.411	5.243	7.777	8.112	8.513	3.829
S.Deviation	2.083	2.606	1.409	1.373	1.463	1.936	0.799
Skewness	-0.552	-0.878	-0.489	-0.342	-0.136	-0.262	-0.633
Kurtosis	4.768	8.870	4.151	4.779	3.915	1.518	3.698
Jarque Bera	1134.012**	3867.542**	861.447**	1103.477**	729.683**	122.597**	723.647**
ADF	-10.779**	-11.137**	-10.472**	-10.533**	-10.775**	-11.650**	-10.871**

Note that: **, 1% significance level, *, 5% significance level

According to Table 1, within the examined period, it is observed that on average S&P500 index has the highest return and Turkey has the lowest return. Moreover, Greece is the country which shows minimum and maximum returns observed in a day. Namely, minimum return is observed as -%22.357 and maximum return is observed as %12.411. If the standard deviation is considered as a measure of risk, it can be said that S&P500 has the lowest risk and the Greece has the highest risk. Skewness coefficients are observed as negative for all index returns which means that the return distributions are left skewed. In addition, kurtosis coefficients showed that all return distributions are heavy tailed, except South Africa. Jarque-Bera test results show significant deviations from the normality and ADF test results show all return series are stationary.

MODWT (Maximal Overlap Discrete Wavelet Transform) is implemented to examine the variance, correlation and cross correlations between S&P500 and MSCI indices of emerging markets listed above. In the analysis, Daubechies 4 (d4) filter is used as a wavelet filter One advantage of using this class of wavelets is that they can be used as an effective constituent for transformations of adjacent weighted averages (Daubechies, 1992). Wavelet filter coefficient vector includes $w_1, w_2, w_3, w_4,$ and scaling factor v_1. In the analysis, $J = 8$ is selected. Since per month includes 20 working days, the scales $\lambda_j = 1 \cdots 8,$ represent the periods of 0–2 days, 2-4 days, 4–8 days, 8-16 days, 16–32 days, 32–64 days (one month to one quarter), 64–128 days (one to two quarter), 128–256 days (half year to one year), respectively.

In the analysis, firstly the wavelet variances are calculated for each scale, λ_j. Figure 2 demontrates the log-log plots of wavelet variances according to the scales.

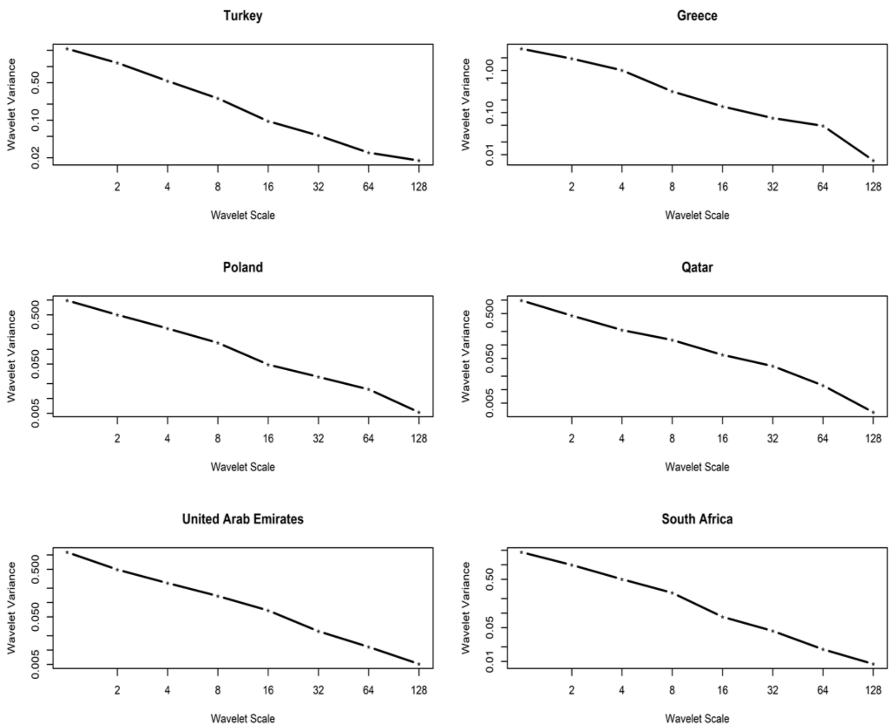

Figure 2. Wavelet Variance of MSCI Index Returns

According to Figure 2, wavelet variances of all the indices are negatively related to the scale. Overall, Greece is more volatile than other emerging markets. In addition, the log-linear relationship between wavelet variances and the scale index, $j = 1 \cdots 8$ is an indicator of long memory for variances. The coefficient of long memory, namely, Hurst exponent $H = \frac{\beta}{2} + 1$ can be obtained from the slope, β of the regression line given in (16) (Abry et al. (1995), Abry and Veitch (1996), Jensen (1999)).

$$\ln \tilde{\sigma}_X^2(\lambda_j) = \alpha + \beta \cdot j \tag{16}$$

where if $H = 0$, then the process is White Noise, if $-0.5 \leq H < 0$ then, the process is a short memory stationary process, if $0 < H \leq 0.5$ then, the process is a long memory stationary process and if $0.5 \leq H$, then the process is a long memory non-stationary process. Table 2 shows the estimated Hurst exponents of variances.

Table 2: Long Memory Coefficients of Variances

	Turkey	**Greece**	**Poland**	**Qatar**	**United Arab Emirates**	**S.Africa**
H	-0.2158	-0.3608	-0.2181	-0.2555	-0.2656	-0.2914

According to Table 2, since all the Hurst exponents are greater than -0.5 it can be concluded that the variances of all series are stationary and show short memory.

The plots of wavelet cross correlations between S&P500 and emerging markets, Turkey, Greece, Poland, Qatar, United Arab Emirates and South Africa are given in the Appendix 1-6, respectively. According to figure given in Appendix 1, in Level 1-4 wavelet correlations between S&P500 and Turkey are symmetric around zero lag. In Level 7-8 (64-128, 128-256 days) there is no significant cross correlations observed. At the first five scales (Level 1-5) the cross correlations between S&P500 and Turkey are generally very close to zero, except for only small number of lag figures shows strong correlations. For scale six (Level 6), the strong positive cross correlations are observed for lags around the zero and negative cross correlations are revealed for longer lags. According to figure given in Appendix 2, in Level 1-6 wavelet correlations between S&P500 and Greece are symmetric around zero lag. For Levels 1-7, the maximum cross correlations are about 0.5 which means weak cross correlations and all are around zero lag. For Level 8, an increase in cross correlations is observed (maximum is about 0.63) for negative lags. According to figure given in Appendix 3, in Level 1-5 wavelet correlations, between S&P500 and Poland are symmetric around zero lag. For levels 1-5, there is strong positive cross correlations around zero lag. In Level 6-7, there is no significant cross correlations observed from the figure where the maximum cross correlations are in the range of $[0.4 - 0.5]$. According to figure given in Appendix 4, in Level 1-5 wavelet correlations between S&P500 and Qatar are symmetric around zero lag. For Level 1-7, there is no significant cross correlations. For Level 8, positive cross correlations are observed for lags around 0 lag where maximum cross correlation is about 0.7. According to figure given in Appendix 5, in Level 1-6 wavelet correlations between S&P500 and United Arab Emirates are nearly symmetric around zero lag. In Level 1-7, there is no strong relationship where the maximum cross correlations are in the range $[0.3 - 0.5]$ and they are around zero lag. In Level 8, there is a positive and significant cross-correlation in the long term. According to figure given in Appendix 6, in Level 1-6 wavelet correlations between S&P500 and South Africa are symmetric around zero lag. It is observed that there are significant and strong correlations at all levels.

Moreover, in Level 8, maximum cross correlation is about 0.83 which shows the existence of stronger and positive relationship around zero lag.

4. Conclusion

The aim of this study is to examine the cross-correlations between MSCI emerging market indices and US market index. The study covers the period from May 2, 2014 to October 25, 2018. In the analysis, MODWT analysis is implemented to show evidences of wavelet covariance, correlations and wavelet cross correlations. Moreover, in this study long-term memory processes of variances are examined.

According to the results of wavelet variance obtained from all scales, the Greece is the most volatile emerging market. Cross correlations of the emerging markets (Turkey, Greece and Poland) shows that the short-term relationship with the US. In other words, spillovers from US to emerging markets (Turkey, Greece, Poland and South Africa) are extremely quick. However, the relationship between the US and other emerging markets (Qatar and United Arab Emirates) reaches a higher level in the longer term and reaches a maximum in half a year to a year. Overall, this can be interpreted as high globalization in countries causes quick spillovers. Therefore, the spillover effect exists in short time for countries governed by democracy and its effect has disappeared in the long term. On the other hand, spillover effects from US to the emerging markets governed by sharia can be observed in the long time.

The study is important because it is a reference to the investor who wants to invest in emerging markets. The findings of this study show that interactions between US and emerging markets are high but not constant. Global investors benefit from the scale differences of these relationships between US and emerging markets by adjusting their investment times to the emerging markets.

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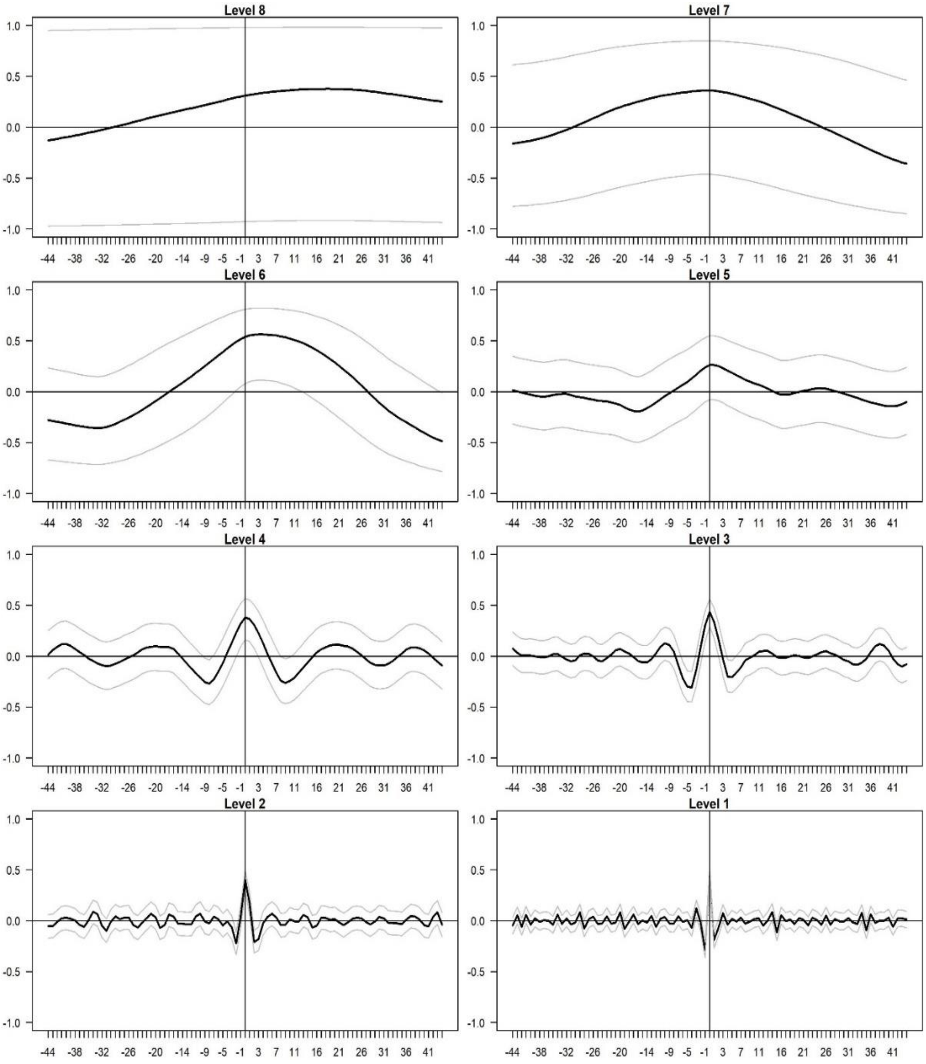
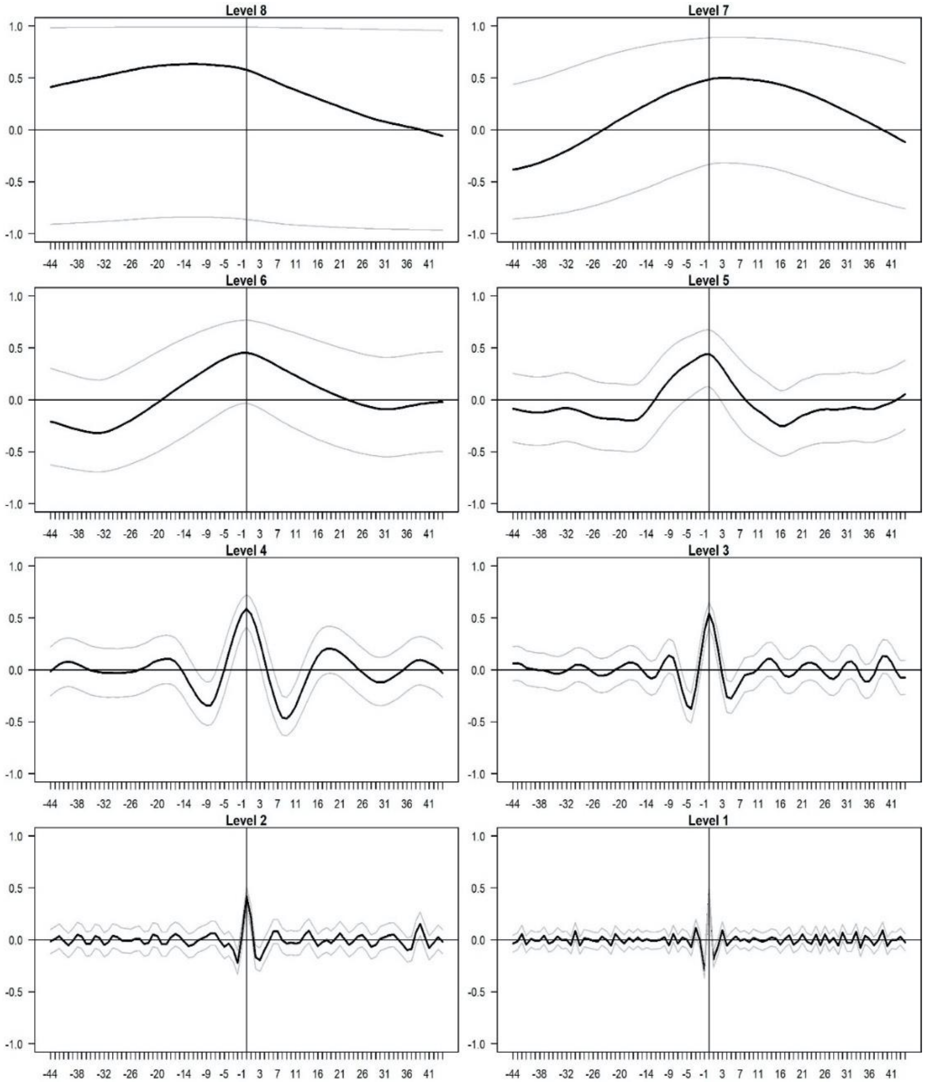
APPENDICES:

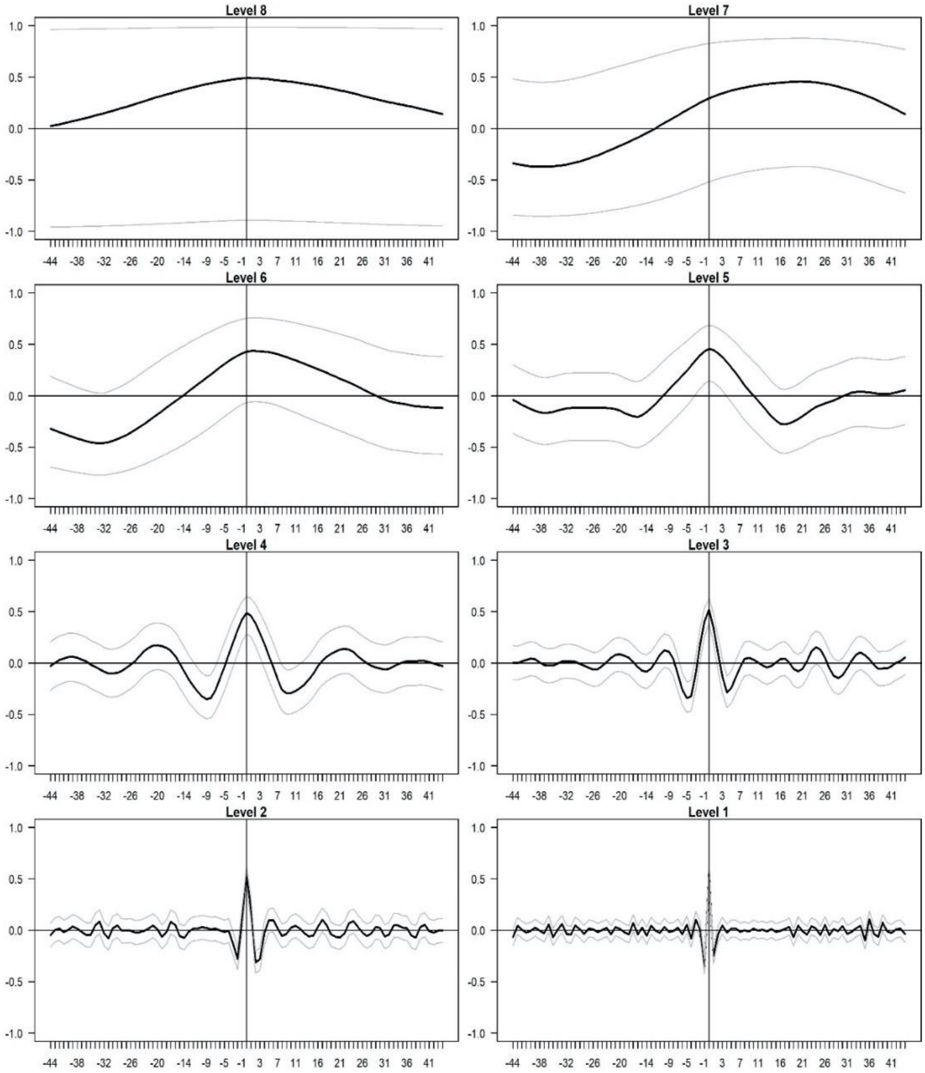
Appendix 1: Wavelet Cross Correlations Between Turkey and S&P500



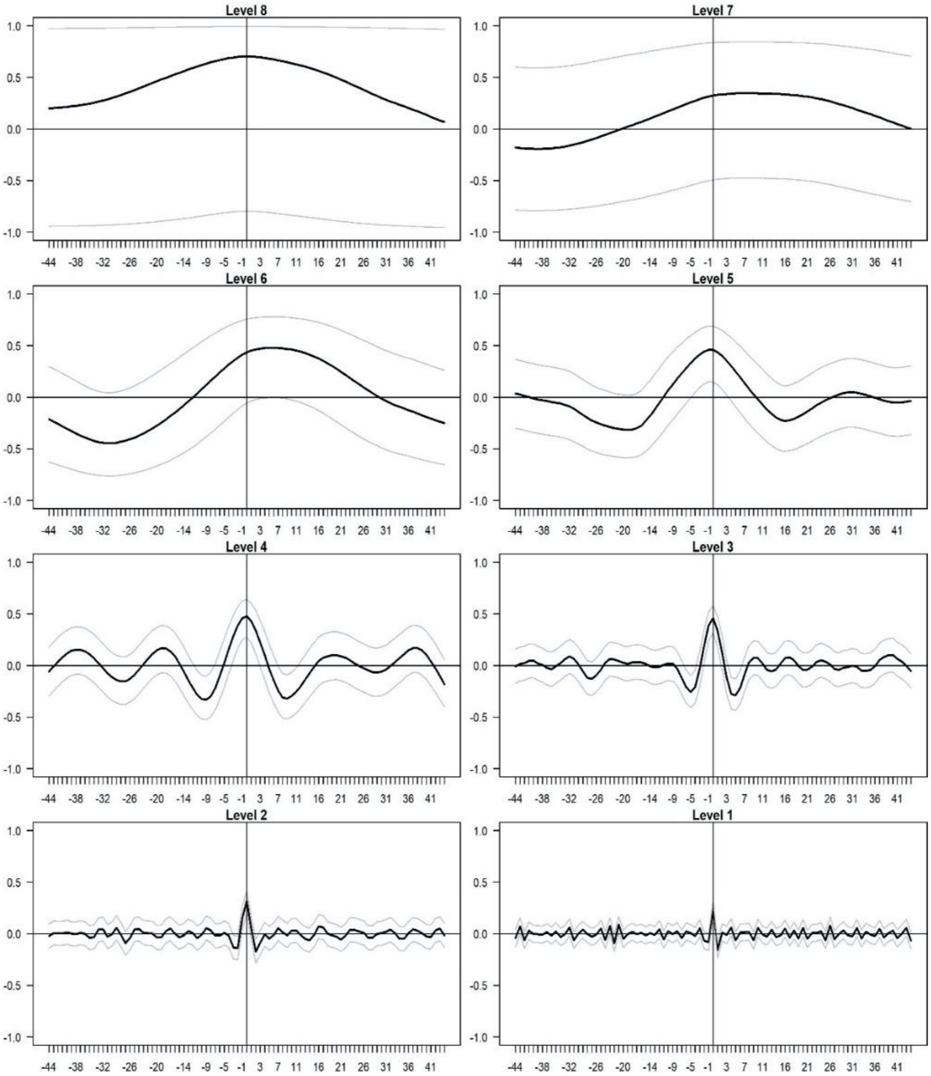
Appendix 2: Wavelet Cross Correlations Between Greece and S&P500



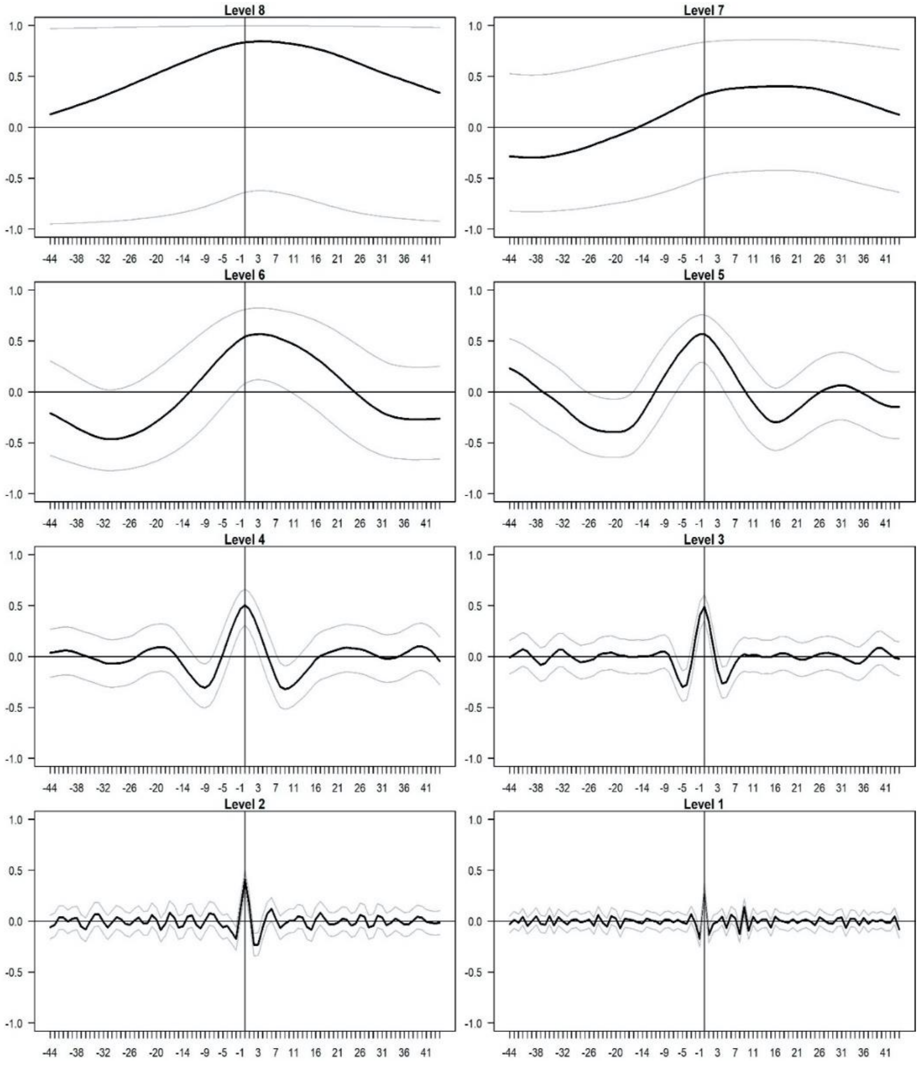
Appendix 3: Wavelet Cross Correlations Between Poland and S&P500



Appendix 4: Wavelet Cross Correlations Between Qatar and S&P500



Appendix 5: Wavelet Cross Correlations Between United Arab Emirates and S&P500



Appendix 6: Wavelet Cross Correlations Between South Africa and S&P500