

A Wavelet Analysis of MENA Stock Markets

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Abstract

In this paper we revisit the issue of integration of emerging stock markets with each other and with the developed markets over different time horizons using weekly stock indices data from June 1997 until March 2005 of the five major MENA equity markets (Egypt, Israel, Jordan, Morocco and Turkey) and applying the discrete wavelet decomposition analysis. We decompose the weekly stock market returns of the main indices of the MENA countries into different time scale components using the *non-decimated discrete wavelet transform* and then analyze the time-scale relationship between the stock market indices of some developed areas (SP and Eurostoxx) and those of the MENA countries. The results from wavelet correlation analysis both among MENA stock markets and between these markets and some major stock markets suggests that MENA stock markets are nor regionally nor internationally integrated.

Keywords: Stock market returns, Wavelet correlation, Comovements

JEL classification: C22, E31

1 Introduction

The process of globalization determined by the trade and financial liberalization of the nineties has been further enhanced by the recent trend of the international stock market indices to become more and more integrated. Thus, as a consequence of the increased integration among national economies, both business cycles synchronization and stock returns correlations are expected to raise over time and across countries. In such a context of increased interdependence among major international stock markets the equity markets of emerging countries may represent a profitable opportunity for international investors because of the potential benefits they offer

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to international investors seeking diversification for constructing their financial portfolios (Chen *et al.*, 2002, Bekaert and Harvey, 2002, 2003, Neaime, 2002).

Given the methodologies usually employed in empirical studies¹ testing integration among international stock markets, such benefits may be generally stated only over long time horizons, that is only in the long-run, as time series analysis techniques² may separate out just two time scales in economic time series, *i.e.* *the short run and the long run*. But the stock market provides an example of a market in which the agents involved consist of heterogeneous investors making decisions over different time horizons (from minutes to years) and operating at each moment on different time scales (from speculative to investment activity). In this way, the nature of the relationship between stock returns may well vary across time scales according to the investment horizon of the traders, as the small time scales may be related to speculative activity and the coarsest scales to investment activity.

In such a context, with both the time horizon of economic decisions and the strength and direction of economic relationships between variables may differ according to the time scale of the analysis (see Ramsey and Lampart, 1998a), a useful analytical tool may be represented by wavelet analysis. Wavelets are particular types of function $\omega(x)$ that are localized both in time and frequency domain and used to decompose a function $f(x)$, *i.e.* a signal, a surface, a series, etc., in more elementary functions which include informations about the same $f(x)$. The main advantage of wavelet analysis is its ability to decompose macroeconomic time series, and data in general, into their time scale components. Moreover, because of the translation and scale properties, nonstationarity in the data is not a problem when using wavelets and prefiltering is not needed. Several applications of wavelet analysis in economics and finance have been recently provided by Ramsey and Lampart (1998a, 1999b), Ramsey (2002), In and Kim (2003), Kim and In (2003), and Lee (2004).

Empirical studies concerning emerging stock markets have received less attention to the countries of the Middle East and North African (MENA) region in comparison to, for example, the countries of the Asian and Latin

¹Empirical studies investigating the interdependence between international stock markets are based on the estimation of a correlation matrix of stock market index returns and/or on multivariate analysis techniques, such as cointegration theory and principal component analysis. Examples of application of these techniques to MENA and other emerging markets are Gunduz and Omran (2002), Neaime, (2003) and Da Costa *et al.*,(2005).

²These techniques, particularly cointegration analysis, analyze the interrelations among stock market indices by examining either their short run or long run relationships. Thus, after testing for the presence of a common stochastic trend among the returns of the stock markets the benefits of international portfolio diversification through investing in emerging stock markets may be stated only over long horizons, that is only in the long-run.

American regions. In this paper we revisit the issue of integration of emerging stock markets with each other and with the developed markets over different time horizons using weekly stock indices data from June 1997 until March 2005 of the five major MENA equity markets (Egypt, Israel, Jordan, Morocco and Turkey) and applying the discrete wavelet decomposition analysis.

The paper is organized as follows: the main properties of the wavelets and the method for calculating the wavelet correlation coefficient through wavelet variance and covariance are dealt with in section 2. Section 3 investigates the comovements among MENA stock market returns using both unconditional and wavelet correlation coefficients, while section 4 focuses on a comparison of the relationship between MENA stock markets and some mature West European stock markets (US and Euro-zone) on a scale-by-scale basis. Finally, section 5 concludes the paper.

2 Wavelet analysis

Many economic and financial time series are nonstationary and, moreover, exhibits changing frequencies over time. Much of the usefulness of wavelet analysis has to do with its flexibility in handling a variety of nonstationary signals. Indeed, as wavelets are constructed over finite intervals of time and are not necessarily homogeneous over time, they are localized in both time and scale. Thus, two interesting features of wavelet time scale decomposition for economic variables will be that, i) since the base scale includes any nonstationary components, the data need not be detrended or differenced, and ii) the nonparametric nature of wavelets takes care of potential nonlinear relationships without losing detail (Schleicher, 2002).

In this section we present first the basic concepts of wavelet analysis, then present the method for calculating the wavelet variance and covariance from the data decomposed by the *non-decimated discrete wavelet transform*. Wavelet analysis, roughly speaking, decomposes a given series in orthogonal components, as in the Fourier approach, but according to scale (time components) instead of frequencies. The comparison with the Fourier analysis is useful first because wavelets use a similar strategy: find some orthogonal objects (wavelets functions instead of sines and cosines) and use them to decompose the series. Second, since Fourier analysis is a common tool in economics, it may be useful in understanding the methodology and also in the interpretation of results. Saying that, we have to stress the main difference between the two tools. Wavelet analysis does not need stationary assumption in order to decompose the series. This is because Fourier approach decomposes in frequency space that may be interpreted as events of time-period T (where T is the number of observations). Put differently, spectral decomposition methods perform a global analysis whereas, on the

other hand, wavelets methods act locally in time and so do not need stationary cyclical components. Recently, to relax the stationary frequencies assumption it has been developed a windowing Fourier decomposition that essentially use, for frequencies estimation, a time-period M (the window) event less than the number of observations T . The problem with this approach is the right choice of the window and, more important, its constancy over time.

Going into some mathematical details we may note that there are two basic wavelet functions: the father and the mother wavelets, $\phi(t)$ and $\psi(t)$, respectively. The formal definition of the father wavelets is the function

$$\Phi_{J,k} = 2^{-\frac{J}{2}} \Phi \left(\frac{t - 2^J k}{2^J} \right) \quad (1)$$

defined as non-zero over a finite time length support that corresponds to given mother wavelets

$$\Psi_{J,k} = 2^{-\frac{J}{2}} \Psi \left(\frac{t - 2^J k}{2^J} \right) \quad (2)$$

with $j = 1, \dots, J$ in a J -level wavelets decomposition. The former integrates to 1 and reconstructs the longest time-scale component of the series (trend), while the latter integrates to 0 (similarly to sine and cosine) and is used to describe all deviations from trend. The mother wavelets, as said above, play a role similar to sines and cosines in the Fourier decomposition. They are compressed or dilated, in time domain, to generate cycles fitting actual data.

To compute the decomposition we need to calculate wavelet coefficients at all scales representing the projections of the time series onto the basis generated by the chosen family of wavelets, that is

$$\begin{aligned} d_{j,k} &= \int f(t) \Psi_{j,k} \\ s_{J,k} &= \int f(t) \Phi_{J,k} \end{aligned}$$

where the coefficients d_{jk} and s_{Jk} are the wavelet transform coefficients representing, respectively, the projection onto mother and father wavelets.

The orthogonal wavelet series approximation to a signal or function $f(t)$ in $L^2(R)$ is given by

$$f(t) = \sum_k s_{J,k} \phi_{J,k}(t) + \sum_k d_{J,k} \psi_{J,k}(t) + \dots + \sum_k d_{j,k} \psi_{j,k}(t) + \dots + \sum_k d_{1,k} \psi_{1,k}(t) \quad (3)$$

where J is the number of multiresolution components or scales, and k ranges from 1 to the number of coefficients in the specified components. The

multiresolution decomposition of the original signal $f(t)$ is given by the sum of the smooth signal S_J and the detail signals D_J, D_{J-1}, \dots, D_1 ,

$$f(t) = S_J + D_J + D_{J-1} + \dots + D_j + \dots + D_1 \quad (4)$$

where $S_J = \sum_k s_{J,k} \Phi_{J,k}(t)$ and $D_j = \sum_k d_{j,k} \Psi_{j,k}(t)$ with $j = 1, \dots, J$. The sequence of terms S_J, D_J, \dots, D_1 in (4) represent a set of signals components that provide representations of the signal at the different resolution levels 1 to J , and the detail signals D_j provide the increments at each individual scale, or resolution, level.

The restrictions of DWT, i.e. a sample size multiple of 2^J and sensitivity to circular shifts due to the downsampling approach, are overcome by the maximal overlap DWT (MODWT) which applies to any sample and is translation invariant, at the cost of giving up orthogonality. The *maximal overlap discrete wavelet transform* (MODWT) is a non-orthogonal variant of the classical discrete wavelet transform that unlike the orthogonal discrete wavelet transform, is translation invariant, as shifts in the signal do not change the pattern of coefficients. Applying a j th order nondecimated version of the orthonormal DWT, i.e. the maximal overlap DWT (MODWT), yields J vectors of wavelet filter coefficients $\widetilde{W}_{j,t}$, for $j = 1, \dots, J$ and $t = 1, \dots, \frac{N}{2^j}$, and one vector of wavelet filter coefficients $\widetilde{V}_{j,t}$ through

$$\widetilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{h}_{j,l} f(t-l) \quad (5)$$

$$\widetilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{g}_{j,l} f(t-l) \quad (6)$$

where $\widetilde{h}_{j,l}$ and $\widetilde{g}_{j,l}$ are, respectively, the rescaled wavelet and scaling filter coefficients from a Daubechies compactly supported wavelet family (Gencay *et al.* 2001).

In addition to the features stated above MODWT allows for a scale-based analysis of the variance of a stochastic process, called wavelet variance, and the covariance between two stochastic processes, called wavelet covariance, as it is an energy-preserving transform (Percival and Mofjeld, 1997). The wavelet variance is estimated using the wavelet series coefficients for scale 2^{j-1} through

$$\widetilde{v}_{f(t)}^2(2^{j-1}) = \frac{1}{\widetilde{N}_j} \sum_t \left[\mathbf{w}_{j,t}^{f(t)} \right]^2 \quad (7)$$

where the vectors \widetilde{W}_j are n -dimension vectors containing the wavelet filter coefficients w_J, \dots, w_1 of the wavelet series approximations, and $\widetilde{N}_j = \frac{N}{2^j - L_j}$ with $L_j = [(L-2)(1-2^j)]$, and thus level j wavelet variance is

simply the variance of the wavelet coefficients at that level (Gencay *et al.*, 2002). Similarly, the covariance is defined as:

$$\widetilde{Cov}_{f(t)g(t)}(2^{j-1}) = \frac{1}{\widetilde{N}_j} \sum_t \left[\mathbf{w}_{j,t}^{f(t)} \mathbf{w}_{j,t}^{g(t)} \right]^2 \quad (8)$$

Finally, analogously to its time series counterpart, wavelet based correlation coefficients are defined as the wavelet covariance $\widetilde{Cov}_{f(t)g(t)}$ between two series, standardized by the square root of their wavelet variances $\widetilde{v}_{f(t)}^2$ and $\widetilde{v}_{g(t)}^2$:

$$\widetilde{\rho}_{f(t)g(t)}(2^{j-1}) = \frac{\widetilde{Cov}_{f(t)g(t)}(2^{j-1})}{\widetilde{v}_{f(t)}^2(2^{j-1})\widetilde{v}_{g(t)}^2(2^{j-1})} \quad (9)$$

Empirically, an unbiased estimator of the true wavelet variance, covariance and correlation will be given by the variance, covariance and correlation of the boundary-unaffected wavelet based coefficients (Whitcher *et al.*, 1999).

3 Comovements among MENA equity markets

The data used in this paper consist of the weekly stock market indices of Egypt, Israel, Jordan, Morocco and Turkey, as these five stock markets stand out in the MENA region.³ Data are retrieved from Datastream for a time period from June 1997 until March 2005 and are expressed in local currencies. The use of weekly data is useful as they avoid nonsynchronous trading problems arising from different operating hours and time zones. In what follows we investigate whether MENA stock markets are integrated with each other: a) at the time series level using unconditional correlation analysis (sub-section 3.1), and b) at different scales using wavelet correlation analysis (sub-section 3.2).

3.1 Unconditional correlation analysis

The most commonly used measure to analyze comovements among international equity markets is unconditional correlation analysis. Cross-country correlations have been largely used to obtain a static estimate of the comovements of actual returns across countries (see, for example, Dumas *et al.*, 2000). In this sub-section we begin our analysis by presenting the descriptive statistics of the five MENA stock markets returns series, and then turn to the analysis of stock market returns series comovements. These stock

³With over \$62 billion in capitalization, 270 active listed companies and a daily trading volume of \$1,25 billion in 2000 Istanbul is now the most important financial market in the MENA region

market indices are transformed to compounded week-to-week stock market returns by calculating 100 times the natural logarithmic differences of the weekly stock prices, that is $100 * \ln\left(\frac{P_t}{P_{t-1}}\right)$.

Table 1: Summary statistics of weekly stock returns

	Egypt	Israel	Jordan	Morocco	Turkey
Mean	0.32	0.21	0.31	-0.04	0.64
Median	0.11	0.52	0.12	-0.06	0.81
Maximum	21.57	8.43	7.21	10.30	28.57
Minimum	-11.81	-11.05	-8.60	-6.61	-36.86
Std. Devn.	4.13	3.06	2.02	1.98	7.37
Sharp Ratio	7.75	6.86	15.34	-2.02	8.68
Skewness	0.35	-0.35	0.23	0.75	-0.15
Kurtosis	4.96	3.63	4.88	7.30	5.22

Table 1 reports the summary statistics of the percent weekly stock index returns. We may note how higher average returns be generally associated to higher volatility, according to the usual high return - high standard deviation characteristic of emerging markets. In particular, the Turkish market shows the highest performance across the MENA stock markets, with an average weekly return of .64%, but also the highest variability, with a standard deviation of 7.367%. Egypt and Israel stock markets display lower average returns than Turkish market, but even lower levels of volatility. But using a measure of stock index returns adjusted for the level of risk associated to a particular financial activity, as the return per unit of risk (indicated with the Sharp ratio in Table 1), we find that the best performance in terms of risk-adjusted returns is displayed by Israel, followed by Egypt and Turkey. On the other hand Jordan and Morocco presents features that are in contrast with the conventional wisdom of high return and high risk: indeed, both markets display levels of volatility lower than those of the other MENA stock markets, but while Jordan's average weekly returns are among the highest (about 0.30%), Morocco displays negative returns.⁴ Finally, as regards the distribution of the weekly stock market returns, the excess kurtosis and skewness measures are indicative of evidence against normal distribution in all cases.⁵

⁴Previous studies over the period between 1995 (or 1997) and 2000 (Gunduz and Omran, 2000, Hakim, 2000 and Hakim and Neaime, 2003) find lower (higher) average returns for Jordan and Turkey (Morocco) and similar values for Egypt and Israel. These differences may depend on a large increase of their stock market index returns that these countries have experienced in the last five years.

⁵For a normal distribution the skewness and kurtosis measures should be 0 and 3 respectively. A formal test for normality of the returns distribution based on such measures is represented by the Jarque-Bera statistic. The null hypothesis of normal returns is rejected for all markets of our sample.

Table 2: Cross-correlations among weekly stock index returns series

Time series	Egypt	Israel	Jordan	Morocco	Turkey
Egypt	1.00				
Israel	0,150* (0,050)	1.00			
Jordan	0,126* (0,060)	0,079 (0,043)	1.00		
Morocco	0,041 (0,048)	0,061 (0,048)	-0,055 (0,062)	1.00	
Turkey	0,011 (0,046)	0,265* (0,052)	0,030 (0,049)	0,100 (0,053)	1.00

Note: HAC standard errors (in parenthesis). * indicates significance at the 5% level.

Table 2 reports cross-correlations among stock index returns for the five MENA stock markets. The results show that MENA stock market indexes tend to have a moderate correlation among themselves, with an average correlation equal to 0.081 and a maximum correlation among all equity markets amounting to a just .265. Indeed, correlation coefficients do not significantly differ from zero only in three cases: Egypt and Israel, Egypt and Jordan, and Israel and Turkey. Thus the results of the cross-correlation analysis of the stock index returns for MENA stock markets indicate that these stock markets do not exhibit a significant degree of integration with each other.

3.2 Wavelet variance and correlation analyses

In order to analyze if the pattern of comovements across MENA equity markets is time-scale dependent, we investigate the relationships among stock market returns at different time scales using wavelet analysis, as it enables us to separate a signal into multiresolution components. We decompose the weekly stock market index returns series of the five MENA countries into their time-scale components using the *maximal overlap discrete wavelet transform* (MODWT) which is a non-orthogonal variant of the classical discrete wavelet transform.

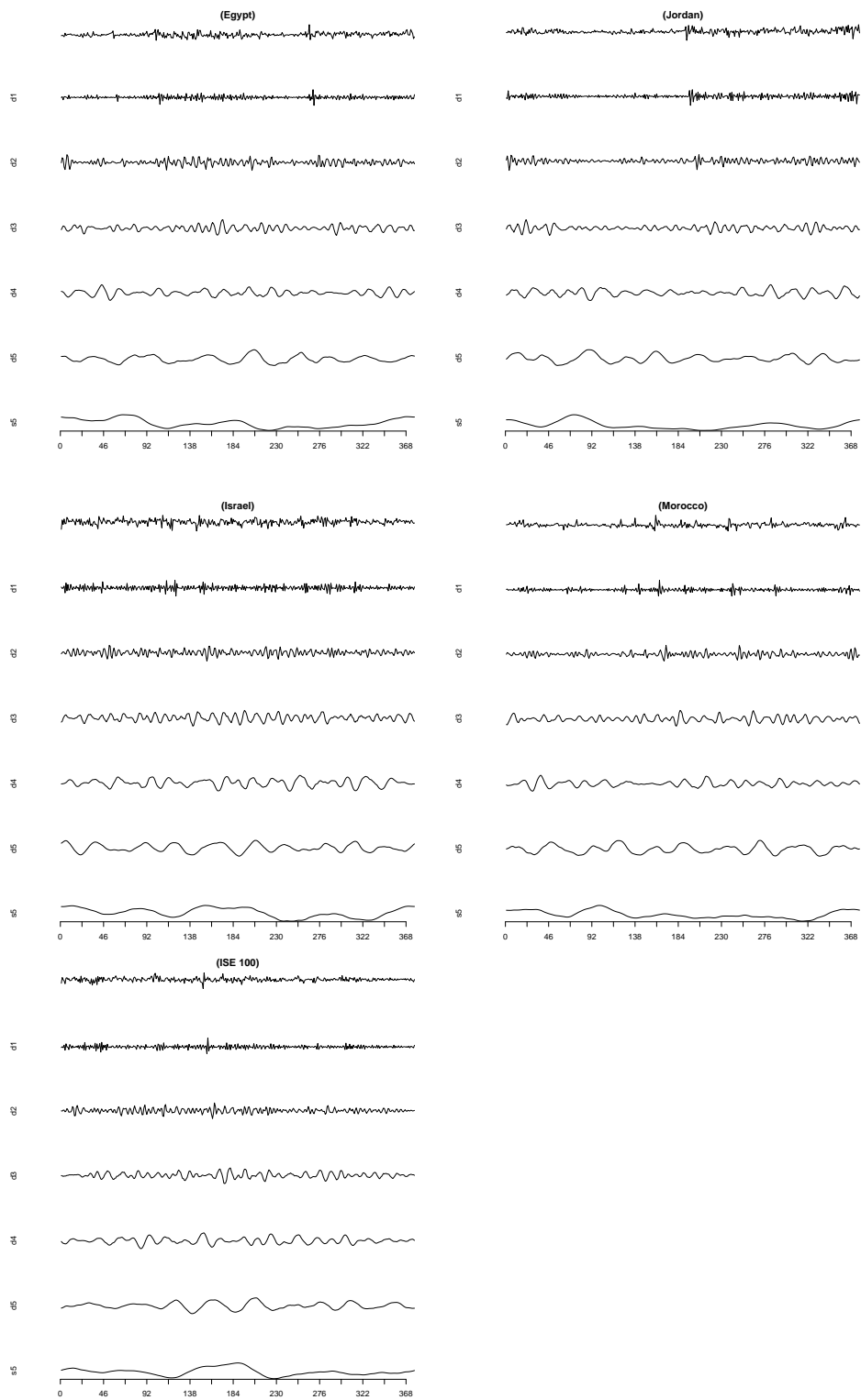


Figure 0 - Multiresolution decomposition of weekly stock returns

We apply the non-decimated discrete wavelet transform to the weekly stock index returns for the five MENA countries accomplished using the Daubechies least asymmetric (LA) wavelet filter of length $L = 8$, that is $LA(8)$, based on eight non-zero coefficients (Daubechies, 1992), with periodic boundary conditions. The application of the translation invariant wavelet transform with a number of scales $J = 5$ produces five vectors of wavelet filter coefficients, that is w_5, w_4, w_3, w_2, w_1 , and one vector of scaling coefficients, v_5 . Since we use weekly data, the wavelet filter coefficients, $w_{5,k}, \dots, w_{1,k}$, represent progressively finer scale deviations from the smooth behaviour, and correspond to 32-64, 16-32, 8-16, 4-8 and 2-4 weeks period, respectively. In figure 0 we report the multiresolution decomposition of the weekly stock index returns of Egypt, Jordan, Israel, Morocco and Turkey, respectively. The first line in each chart of Figure 0 shows the plot of the original series, the last the MODWT scaling coefficient vector, \tilde{V}_5 , that capture the trend of the series, and between them the wavelet coefficient vectors from the high-frequency, \tilde{W}_1 , to the low frequency, \tilde{W}_5 , variations.

Figure 1 shows the MODWT-based wavelet variance (the straight lines) with the 95% confidence interval of the estimate (represented by the upper, U, and lower, L, lines) of the stock index returns for the MENA countries (both individually and together). The main results emerging from wavelet variance analysis are twofold: i) a tendency for wavelet variance to decrease as the wavelet scale increases, and ii) the existence of significant differences in volatility at different scales among countries (as evidenced by the bottom right panel in Figure 1). In particular, Turkey stock market returns display the highest levels of volatility, Jordan and Morocco are the less volatile, with Egypt and Israel displaying intermediate values.

In Figures 2 to 6 we report the estimated wavelet correlations coefficients between the stock index returns of each of the five MENA countries and all the other MENA countries over different time scales. The analysis of the wavelet coefficients show that the significant relationships between the MENA countries are mostly at the longest wavelet scale, *i.e.* at scale 5,⁶ and that the number of significant relationship decreases markedly as the wavelet time scale decreases. In particular, at the longest and intermediate wavelet scales the wavelet correlations coefficients exceeds substantially unconditional correlations. At the longest wavelet scale the highest correlation is between Israel and Turkey, about .60, with both countries displaying a much lower correlation with Egypt and Jordan, between .30 and .40. On the other hand Egypt and Jordan show the highest value of wavelet correlation among themselves, with a value greater than .40. Otherwise, at all other wavelet scales there are only a limited number of significant relationships, all involving Israel. In particular, Israel displays a positive relationship with

⁶The only exception is Morocco which has a negative significant correlation with Egypt and no significant relationship with the other MENA countries.

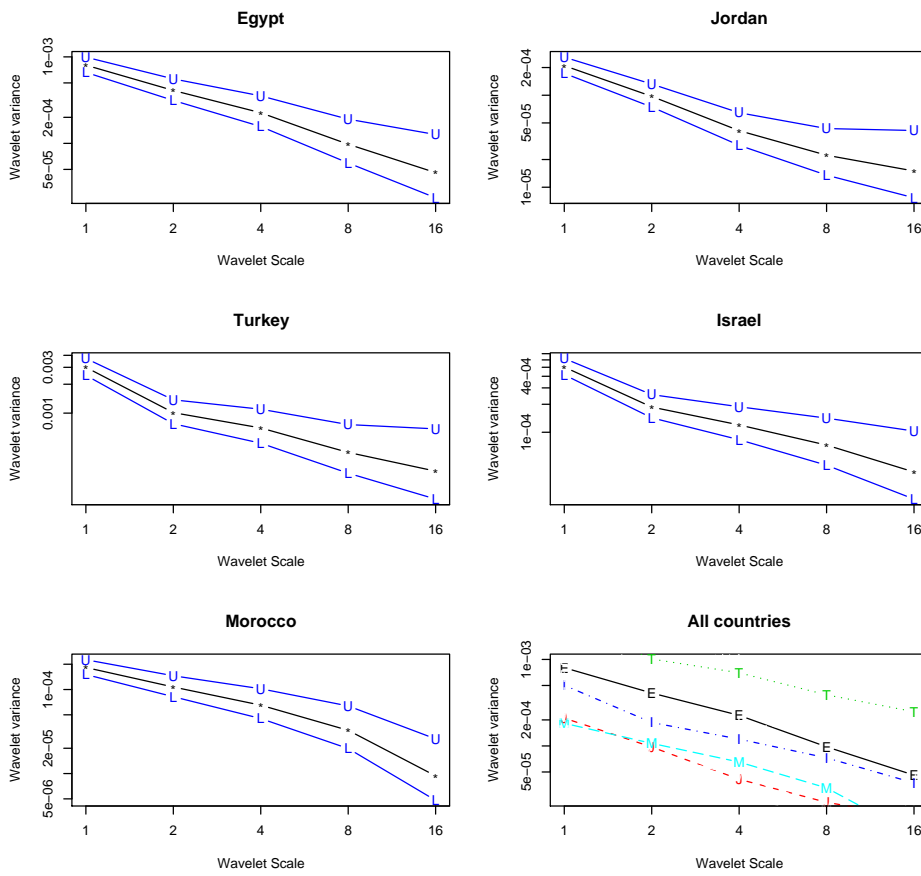


Figure 1: Estimated wavelet variance of MENA stock index returns

Turkey at scales 4 and 2, and with Egypt and Morocco at scale 3. In summary, the results suggest the existence of a low degree of integration among the equity markets of the countries of the MENA region. Such an evidence of a weak regional financial integration among the MENA stock markets finds its exception in the strong returns linkages between the stock markets of Israel and Turkey, particularly at the longest scale.

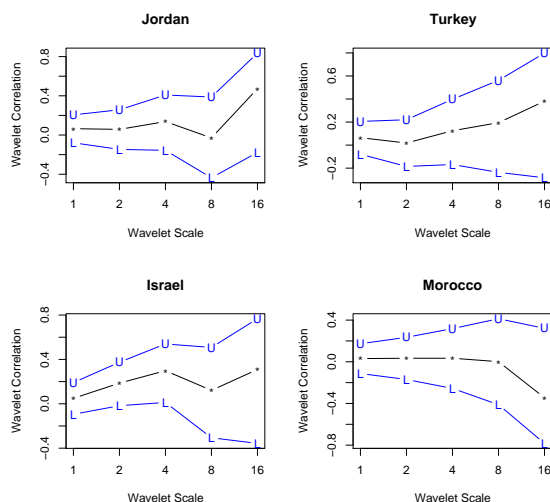


Figure 2: Estimated wavelet correlation of Egypt

4 Time-scale relationships between MENA and developed equity markets

The empirical literature about stock market correlation of developed and developing countries report two main findings: first, correlation among developed stock market returns are generally higher than correlations among developing countries; second, emerging stock markets tend to have low stock correlation with developed stock markets, a fact that makes emerging markets a good tool for the diversification of risk of global investors. Thus, in this section we complement, the analysis of the previous section examining the time-scale relationships between the equity market indices of the MENA countries and their respective counterparts in the US and the Euro-zone.⁷

In Figures 7 and 8 we report the wavelet correlation coefficients between the returns of the S&P-500 and Eurostoxx indices, respectively, and the returns of each of the stock market index of the countries in the MENA

⁷The stock market indexes representative of the US and the Euro-zone are the S&P-500 index and the Eurostoxx index.

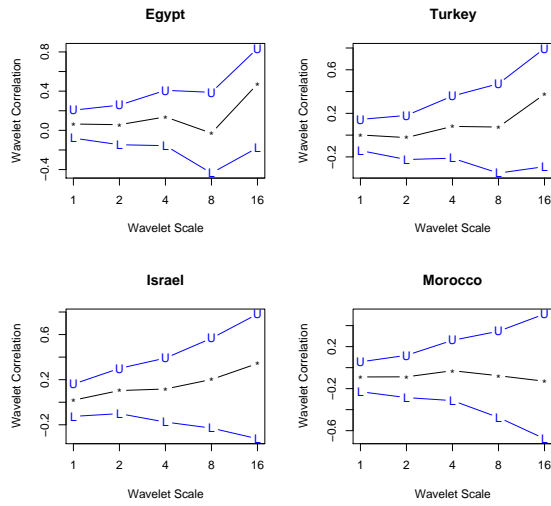


Figure 3: Estimated wavelet correlation of Jordan

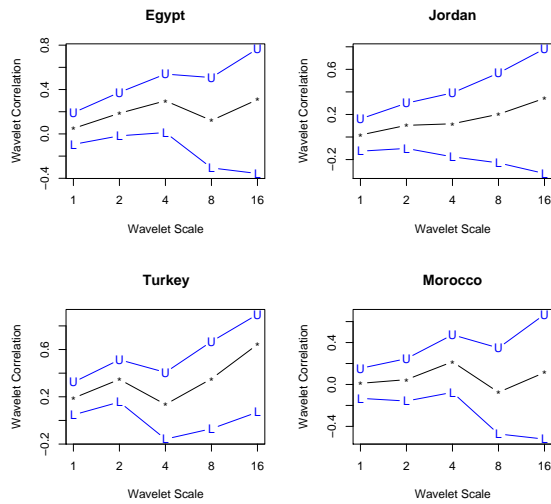


Figure 4: Estimated wavelet correlation of Israel

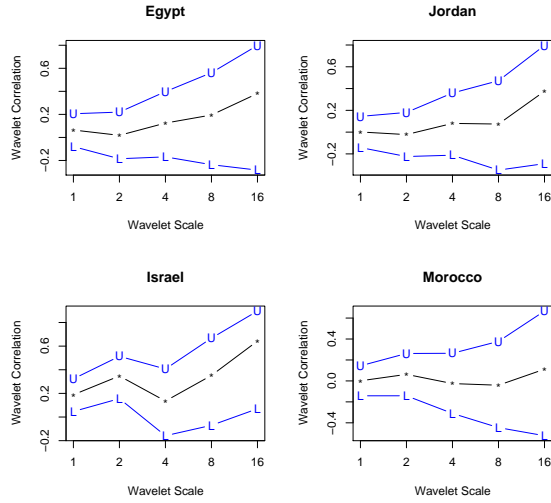


Figure 5: Estimated wavelet correlation of Turkey

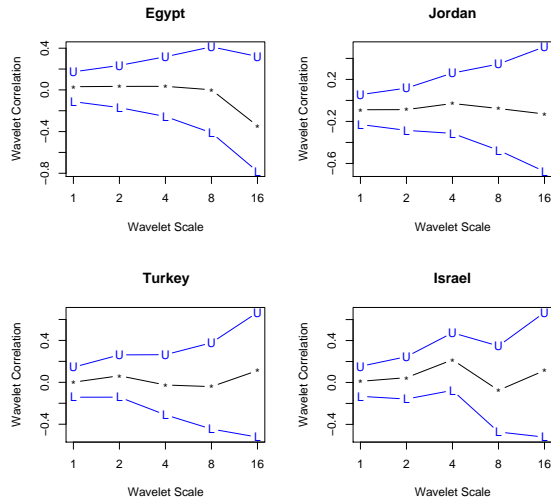


Figure 6: Estimated wavelet correlation of Morocco

region. The top left panel in both figures displays the wavelet correlation at different scales between the returns of the S&P-500 and Eurostoxx indices. The results of the wavelet correlation analysis shows that the relationship between the two indices are high and significant at all scales, with the values increasing as the wavelet scale increases, from about .60 at scale 1 to about .80 at scale 5. The patterns of comovements change radically when we look at the panels displaying the wavelet correlation between the returns of the developed stock markets and those of the MENA countries. At the lowest scales, 1 to 3, the correlation is generally not significantly different from zero (and in almost all cases it is negative at scale 1) and becomes significant only at the highest scales (scale 5). But inside this general pattern of low financial integration between MENA stock markets and their counterparts in the US and Euro-zone, MENA countries may be distinguished in two distinct groups: the first with Turkey and Israel, and the other one with Egypt, Jordan and Morocco. Indeed, while the correlation of the countries of this second group are generally not significantly different from zero at all scales (with the exception of Egypt and Morocco at the lowest scale, 5), the correlation of Israel and Turkey are positive and significant at the 4th and 5th scales, with these correlations being larger with the European than with the US stock market index (and more for Turkey than for Israel). Thus, our findings suggest that Israel and Turkish markets seems to be more internationally integrated with developed stock markets than the other MENA equity markets, especially at the longest scales.

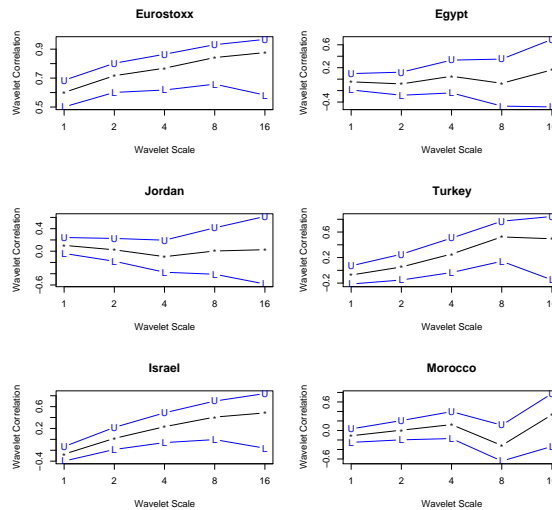


Figure 7: Estimated wavelet correlation of SP index

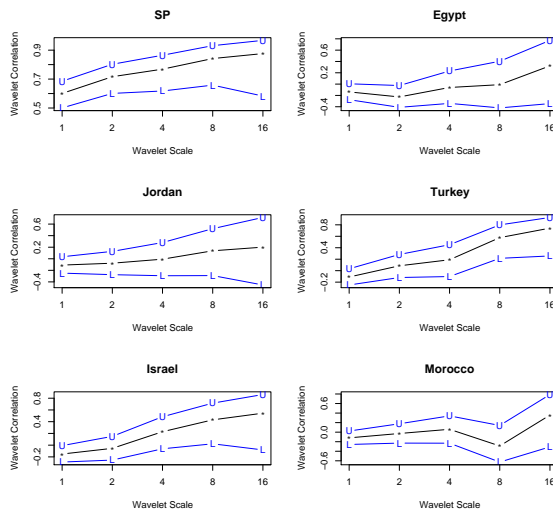


Figure 8: Estimated wavelet correlation of Eurostoxx index

5 Conclusion

In this paper we revisit the issue of integration of emerging stock markets with each other and with the developed markets over different time horizons using weekly stock indices from some countries of the MENA region (Egypt, Israel, Jordan, Morocco and Turkey) over the period June 1997 through March 2005. In particular, we investigate stock market returns comovements among MENA countries on a scale by scale basis through the application of the *maximal overlap discrete wavelet transform* (MODWT) with the Daubechies least asymmetric ($LA(8)$) wavelet filter of length $L = 8$.

The results from wavelet variance and correlation analysis indicate that wavelet variance of MENA stock markets tends to decrease and wavelet correlation among MENA stock markets tends to increase as the wavelet time scale increases (particularly at the longest scales). Indeed, the shorter the time scale (high frequencies), the smaller the number of significant comovements of MENA stock market returns with each other and with major world stock markets.

Moreover, with respect to the degree of integration both among MENA stock markets and between these markets and their respective counterparts in the US and the Euro-zone, wavelet analysis suggests that MENA stock markets, when compared with the relationship between the S&P 500 and the Eurostoxx indexes, are not regionally nor internationally integrated (with a partial exception represented by Israel and Turkey). Thus, as our findings from wavelet correlation analysis suggest that as markets' interdependence tends to become stronger as the time horizon increases (especially between

some major MENA countries), the benefits from international stock market diversification may be reduced substantially for international investors with longer horizons, but not for short term traders.

6 References

Bekaert G. and C.R. Harvey, 2002, "Research in emerging markets finance: looking to the future", *Emerging Markets Review*, 3, 429-448.

Bekaert G. and C.R. Harvey, 2003, "Emerging markets finance", *Journal of Empirical Finance*, 10, 3-55.

Chen G., Firth M. and O.M. Rui, 2002, "Stock market linkages: Evidence from Latin America", *Journal of Banking and Finance*, 26, 1113-1141.

Da Costa N. Jr, Nunes S., Ceretta P., and S. Da Silva, 2005, "Stock-market comovements revisited", *Economics Bulletin*, 7, 3, 1-9.

Dumas B., Harvey C.R. and P. Ruiz, 2000, "Are correlations of stock returns justified by subsequent changes in national outputs?", *mimeo*.

Gencay R., Selcuk F., and B. Whitcher, (2001), "Scaling properties of foreign exchange volatility", *Physica A*, 289, 249-266.

Gunduz L. and M. Omran (2000), "Stochastic Trends and Stock Prices in Emerging Markets: The Case of Middle East and North Africa Region", *mimeo*.

In F. and S. Kim, 2003, "Hedge Ratio and Correlation between the Stock and Futures Markets: Evidence from the Wavelet Analysis", *Journal of Business*, forthcoming.

Hakim S. (2000), "Price Linkages and Integration of the Cairo Stock Exchange", *mimeo*.

Hakim S. and S. Neaime (2003), "Mean-Reversion Across MENA Stock Markets: Implications for Derivative Pricing", *International Journal of Business*, 8 (3), 347-357.

Lee H.S. (2004), "International transmission of stock market movements: a wavelet analysis", *Applied Economics Letters*, 11, 3/20, 197-201

Kim S. and F.H. In (2003), "The Relationship Between Financial Variables and Real Economic Activity: Evidence From Spectral and Wavelet Analyses", *Studies in Nonlinear Dynamics and Econometrics*, 7, No. 4.

Neaime S., 2002, "Liberalization and Financial Integration of MENA Stock Markets", *mimeo*.

Percival D. B. and H.O. Mofjeld, 1997, "Analysis of subtidal coastal sea level fluctuations using wavelets", *Journal of American Statistical Association*, 92 (439), 868-880.

Ramsey J.B. and C. Lampart, 1998a, "The Decomposition of Economic Relationship by Time Scale Using Wavelets: Money and Income", *Macroeconomic Dynamics*, 2, 49-71.

Ramsey J.B. and C. Lampart, 1998b, "The Decomposition of Economic Relationship by Time Scale Using Wavelets: Expenditure and Income", *Studies in Nonlinear Dynamics and Econometrics*, 3, No. 4, 23-42.

Ramsey J.B., 2002, "Wavelets in Economics and Finance: Past and Future", *C.V. Starr Center for Applied Economics*, No. 2002-02.

Schleicher C., 2002, "An Introduction to Wavelets for Economists", *Bank of Canada Working Paper*, No. 02-3.

Whitcher B., Guttorp P. and D.B. Percival, 1999, "Mathematical background for wavelet estimators for cross covariance and cross correlation", *Technical Report no. 38*, National Research Centre for Statistics and the Environment, Seattle.