International Transmission of Stock Market Movements: A Wavelet Analysis on MENA Stock Markets

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ABSTRACT

As international financial markets have become increasingly interdependent, new evidence on international spillover effects has widely been discussed around the globe. However, the MENA region has received little attention concerning international transmission of stock market movements. In this paper, we discuss international spillover effects between the major developed markets (U.S., Japan and Germany) and the emerging markets in the MENA region (Turkey and Egypt). While GARCH-type models have mainly been used to investigate international stock market spillovers in much of previous studies, we develop new testing strategies based on discrete wavelet decomposition. The basic finding is that price as well as volatility spillover effects exist from the developed stock markets to the MENA counterparts, but not *vice versa*. Also discussed is on the interdependence of the major MENA stock markets.

Keywords : MENA stock markets, Stock returns, Volatility, Spillovers, Wavelet analysis

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I. Introduction

With the development in the liberalization of capital movements and the securitization of stock markets, international financial markets have become increasingly interdependent. Advanced computer technology and improved worldwide network processing of news have improved the possibilities for domestic stock markets to react promptly to new information from international markets. As a consequence, an increasing attention has been given in recent literature to the topic of international transmission of stock market returns and volatility.

Using international stock return data, previous studies generally found evidence for spillover effects across international stock markets. Eun and Shim (1989) found a substantial multi-lateral interaction among the nine largest stock markets in the world. In particular, they documented that news originating in the U.S. market brings the most influential responses from other national markets. Hamao *et al.* (1990) provided some evidence for spillover effects from New York to Tokyo and London and from London to Tokyo, but not from Tokyo to either to New York or London.

Other studies concerning the international transmissions of stock returns and volatility include, among others, Ng *et al.* (1991), Lin *et al.* (1994), Karolyi (1995), Kim and Rogers (1995) and Booth *et al.* (1997), where new evidence on spillover effects are discussed around the globe. For example, Ng *et al.* (1991) and Ng (2000) found significant spillovers among the Pacific Rim countries, and Booth *et al.* (1997) provided evidence for price and volatility spillovers among the Scandinavian countries.

While new evidence on international spillover effects has widely been discussed around the globe, the Middle East and North African (MENA) region has received little attention. In fact, an attempt was made in Benkato and Darrat (2000) to discuss spillover effects from the major developed markets to the Turkish stock market, using monthly stock prices. In view of the recent development in information network that is capable of disseminating news instantaneously around the world, however, a shock in a national stock market can be transmitted to another market within a very short period of time. It is thus essential to use high-frequency data such as daily prices to examine spillover effects.

The main purpose of this paper is to investigate whether and to what extent the MENA markets are integrated globally with major developed markets such as the U.S., Japan and Europe. New evidence is provided on the price and volatility spillovers from the developed markets to emerging markets in the MENA region. Also discussed is on the interdependence of major MENA stock markets (Turkey and Egypt).

Another contribution of this paper is to propose new testing strategies to spillover effects. As spillover effects are expected to be completed within a short period of time [see Eun and Shim (1989)], much of previous studies on spillovers are concerned with the influence of any unanticipated shocks or innovations to one stock market on other markets. In order to extract new information in stock markets and hence to examine the relationships between short-term fluctuations in stock prices, the VAR methodology uses forecast errors from the regression model, and the GARCH methodology uses the estimated ARCH error terms. However, such approaches are subject to being sensitive to model specifications.

New testing strategies based on wavelet analysis are developed in this paper to investigate international stock market spillover effects. Wavelet analysis is a comparatively new and powerful mathematical tool for signal processing. Although wavelet analysis has recently shown diverse applications in many fields, such as medical sciences and physics, it has received little attention in econometric analysis of financial data [see, however, Ramsey and Zhang (1996)]. In particular, the discrete wavelet transform is very useful in decomposing time series data into an orthogonal set of components with different frequencies. By examining the relationships between high-frequency fluctuations in stock returns, obtained from reconstruction of the data by wavelet 'crystals', we can investigate the response of the MENA stock markets to news in the developed markets. The multiresolution decomposition of wavelet analysis is also useful in handling so-called the 'Monday effect' of stock market returns often discussed in earlier empirical studies.

The basic finding is that price as well as volatility spillover effects exist from the major developed stock markets to the MENA counterparts, but not *vice versa*. Such observations are consistent with earlier empirical and theoretical results in this area that innovations in matured stock markets are transmitted to emerging markets. In particular, much of earlier studies found that the U.S. stock market is, by far, the most influential in the world with no single foreign market being able to significantly explain the U.S. market movements. Further investigation into other MENA stock market data will provide new evidence on whether and to what extent the MENA markets are integrated globally with major developed markets. Such results will have an implication on whether the global linkage of emerging capital markets has been strengthened recently and these markets have become more vulnerable to shocks originating from foreign markets.

The paper is organized as follows. Section 2 presents some new statistical results of wavelet analysis in decomposing time series data. In section 3, we propose a new approach to testing spillovers across international stock markets, and apply this method to investigate the relationships between the U.S. and MENA stock market data, and evidence is presented for spillover effects both in stock returns and volatility. Section 4 provides a summary with brief discussions on some extensions.

II. Wavelet analysis

The study of wavelets as a distinct discipline started in the late 1980's. Wavelet theory has since inspired the development of a powerful methodology, which includes a wide range of tools such as wavelet transforms, multiresolution analysis, time-scale analysis, time-frequency representations with wavelet packets. Signal processing, data compression, medical imaging, turbulence and numerical analysis are only a few examples from a long list of disciplines in which wavelets have been successfully employed. Among others, the wavelet transforms and their modifications are becoming increasingly popular in diverse areas of applied and theoretical science.

Whilst the wavelet methodology has received little attention in time series analysis of economic and financial data, there are a few recent papers in economic application of wavelet analysis. Goffe (1994) illustrated the application of wavelets to nonstationary economic time series, and Gilbert (1995) examined the stability of economic relationships. Ramsey and Zhang (1996, 1997) used waveform dictionaries to examine the time-frequency distributions of financial data. Nason (1995), Wang (1995) and Wong *et al.* (1997) discussed the wavelet detection of jump points in economic and financial data. Based on a unified view of wavelet filtering techniques that are potentially very useful in finance and economics, Gençay *et al*. (2001) presented several empirical examples using financial time series data.

In this section, we give only a brief overview of two basic tools of wavelet analysis: discrete wavelet transform (DWT) and multiresolution analysis (MRA). Readers are referred to, *inter alia*, Chui (1992) for a thorough review of wavelet analysis and Daubechies (1992) for further technical details. Practical aspects of wavelets are discussed in Bruce and Gao (1996), and an overview on the use of wavelet analysis is given in Lee (1998). Further references can be found in more recent books by Vidakovic (1991) and Percival and Walden (2000).

2.1. Wavelets

As wavelet analysis bears points of comparison and points of contrast to Fourier analysis, recognizing both methodologies is important for understanding what wavelets can bring to the examination of time series data. Fourier analysis is the fundamental tool for understanding the frequency structure of stationary signals. However, many signals including economic and financial time series are nonstationary and their frequency behavior evolves over time. Time-frequency analysis of wavelet theory is what we need in order to study the frequency domain properties of nonstationary signals.

Wavelets are the building blocks of wavelet transformation analogous to the function e^{inx} in the ordinary Fourier transformation. Both methods involve the projection of a signal onto an orthogonal set of components; trigonometric sine and cosine functions in the case of Fourier series representations, wavelets in the case of wavelet analysis. As with a sine or cosine wave, a wavelet oscillates around zero. However, the oscillations in a wavelet function damp rapidly down to zero and it is localized in time and space, as opposed to the trigonometric functions that have constant amplitude over the entire real line. Therefore, in contrast to Fourier series that have infinite energy when extended to being defined over the entire real line, wavelet representations have finite energy over the entire real line and hence are defined within $L^2(\boldsymbol{R})$. This difference implies that the functions involved in wavelet analysis have narrow support. More importantly, they are not necessarily homogeneous over time, while the functions represented by Fourier series are assumed to be homogeneous so that the same frequencies hold at the same amplitude over any sub-segment of observed time series. Hence wavelets are a very powerful tool in handling dynamic patterns that may change rapidly over time.

In this paper, we focus on two major facets of wavelet analysis. First, wavelets are localized in time, and hence are useful in handling a variety of nonstationary signals. The nonstationarity in this case is concerned with a broader notion than the presence of unit roots. Second, wavelets can separate a signal into multiresolution components. The fine and coarse resolution layers capture, respectively, the fine and coarse scale features in the signal. We now introduce the description of a signal in terms of wavelets and define a few terms that will be used subsequently.

There are two types of wavelets defined on different normalization rules; father wavelets ϕ and mother wavelets ψ. The father wavelet integrates to 1 and the mother wavelet integrates to 0:

$$\int \phi(t)dt = 1; \ \int \psi(t)dt = 0 .$$

Roughly speaking, the father wavelets are good at representing the smooth and low-frequency parts of a signal, and the mother wavelets are useful in describing the detail and high-frequency components. Thus, they are used in pairs within a family of wavelet functions, with father wavelets used for the trend components and the mother wavelets for all the deviations from the trend. A variety of families of wavelets have been developed for use as the fundamental wavelet. Among others, four types of orthogonal wavelets are typically used in empirical analysis, namely: the haar, daublets, symmlets and coiflets. The haar wavelet is a square wave with compact support. It is the only compact orthogonal wavelet with symmetry, but it is not continuous unlike the other wavelets. The daublets are continuous wavelets, also with compact support. While the daublets are quite asymmetric, the symmlets are constructed to be as nearly symmetric as possible. The coiflets are also symmetric with additional properties that both ϕ and ψ have vanishing moments.

Except in some special cases, there is no analytical formula for computing a wavelet function. Instead, wavelets are derived using a special two-scale dilation equation. For a father wavelet $\phi(x)$, the dilation equation is defined by

$$\phi(x) = \sqrt{2}\sum_k \ell_k \phi(2x-k)\,. \tag{1}$$

The mother wavelet $\psi(x)$ can similarly be obtained from the father wavelet by the relationship

$$\psi(x) = \sqrt{2}\sum_k h_k \phi(2x-k)\,. \tag{2}$$

The coefficients ℓ_k and h_k are the low-pass and high-pass filter coefficients defined as:

$$\ell_k = \frac{1}{\sqrt{2}}\int \phi(t)\phi(2t-k)dt \tag{3}$$

$$h_k = \frac{1}{\sqrt{2}}\int \psi(t)\phi(2t-k)dt\,. \tag{4}$$

2.2. Wavelet approximation

Any function $f(t)$ in $L^2(\boldsymbol{R})$ to be represented by a wavelet analysis can be built up as a sequence of projections onto father and mother wavelets generated from ϕ and ψ through scaling and translation as follows:

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t-k) = 2^{-j/2}\phi(\frac{t-2^j k}{2^j}) \tag{5}$$

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t-k) = 2^{-j/2}\psi(\frac{t-2^j k}{2^j})\,. \tag{6}$$

The wavelet representation of the signal or function $f(t)$ in $L^2(\boldsymbol{R})$ can now be given as:

$$f(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t), \tag{7}$$

where J is the number of multiresolution components, and k ranges from 1 to the number of coefficients in the specified component. The coefficients $s_{J,k}$, $d_{J,k}, \cdots, d_{1,k}$ are the wavelet transform coefficients given by the projections

$$s_{J,k} \approx \int \phi_{J,k}(t) f(t)\,dt \tag{8}$$

$$d_{j,k} \approx \int \psi_{j,k}(t) f(t)\,dt, \text{ for } j = 1,2,\ldots, J. \tag{9}$$

The magnitude of these coefficients reflects a measure of the contribution of the corresponding wavelet function to the total signal. The basic functions $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$ are the approximating wavelet functions generated as scaled and translated versions of ϕ and ψ, with scale factor 2^j and translation parameter $2^j k$, respectively. The scale factor 2^j is also called the dilation factor and the translation parameter $2^j k$ refers to the location. Here 2^j is a measure of the scale or width of the functions $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$. That is, the larger the index j, the larger the scale factor 2^j, and hence the function get shorter and more spread out. The translation parameter $2^j k$ is matched to the scale parameter 2^j in that as the functions $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$ get wider, their translation steps are correspondingly larger.

2.3. Multiresolution analysis

The discrete wavelet transformation (DWT) calculates the coefficients of the wavelet representation (7) for a discrete signals $f_1,\ldots, f_n$ of finite extent. The DWT maps the vector $\mathbf{f} = (f_1, f_2\ldots, f_n)'$ to a vector of n wavelet coefficients $\mathbf{w} = (w_1, w_2\ldots, w_n)'$. The vector $\mathbf{w}$ contains the coefficients $s_{J,k}$, $d_{J,k}, \cdots, d_{1,k}$ of the wavelet series representation (7). The coefficients $s_{J,k}$ are called the smooth coefficients, representing the underlying smooth behavior of the signal at the coarse scale 2^J. On the other hand, $d_{j,k}$ are called the detailed coefficients, representing deviations from the smooth behavior, where $d_{J,k}$ describe the coarse scale deviations and $d_{J-1,k}, \cdots, d_{1,k}$ provide progressively finer scale deviations.

In cases when n is divisible by 2^J, there are $n/2$ coefficients $d_{1,k}$ at the finest scale $2^1 = 2$. At the next finest scale $2^2 = 4$, there are $n/4$ coefficients $d_{2,k}$. Likewise, at the coarsest scale, there are $n/2^J$ coefficients each for $d_{J,k}$ and $s_{J,k}$. Summing up, we have a total of n coefficients:

$$n = n/2 + n/4 + \ldots + n/2^{J-1} + n/2^J + n/2^J .$$

The number of coefficients at a scale is related to the width of the wavelet function. At scale 2, the translation steps are $2k$, and so $n/2$ terms are required in order for the functions $\psi_{1,k}(t)$ to cover the interval $1 \le t \le n$. By similar reasoning, a summation involving $\psi_{j,k}(t)$ requires just $n/2^j$ terms, and the summation involving $\phi_{J,k}(t)$ requires only $n/2^J$ terms. The string of coefficients can be ordered from coarse scales to fine scales as:

$$\mathbf{w} = \begin{pmatrix} \mathbf{s}_J \\ \mathbf{d}_J \\ \mathbf{d}_{J-1} \\ \vdots \\ \mathbf{d}_1 \end{pmatrix}. \tag{10}$$

Each of the sets of coefficients in $\mathbf{w}$ is called a ‘crystal’, and the wavelet associated with each coefficient is referred to as an ‘atom’.

The multiresolution decomposition of a signal can now be defined by using the product of the crystals and the corresponding wavelet atoms, namely:

$$S_J(t) = \sum_k s_{J,k}\phi_{J,k}(t) \tag{11}$$

$$D_j(t) = \sum_k d_{j,k}\psi_{J,k}(t) \quad \text{for } j = 1,2,\ldots,J. \tag{12}$$

The functions (11) and (12) are called the smooth signal and the detail signals, respectively, which constitute a decomposition of a signal into orthogonal components at different scales. Similarly to the wavelet representation (7) of a signal in $L^2(\boldsymbol{R})$, a signal $f(t)$ can now be expressed in terms of these signals:

$$f(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t) \tag{13}$$

As each terms in (13) represent components of the signal $f(t)$ at different resolutions, it is called a multiresolution decomposition (MRD).

The coarsest scale signal $S_J(t)$ represents a coarse scale smooth approximation to the signal. Adding the detail signal $D_J(t)$ gives a scale 2^{J-1} approximation to the signal, $S_{J-1}(t)$, which is a refinement of the coarsest approximation $S_J(t)$. Further refinement can sequentially be obtained as:

$$S_{j-1}(t) = S_j(t) + D_{j-1}(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_j(t)$$

The collection $\{S_J,\ S_{J-1},\ S_{J-2}, \cdots, S_1\}$ provides a set of multiresolution approximations of the signal $f(t)$.

III. Empirical results

Much of previous studies on spillovers are concerned with international transmission mechanism of any unanticipated shocks or innovations originating from one stock market to other markets. In order to examine short-term fluctuations in stock prices, the VAR methodology uses forecast errors, and the GARCH methodology uses the estimated ARCH error terms. However, such approaches are subject to being sensitive to model specifications.

In this section, we apply the tools of wavelet analysis discussed in the previous section to a real data set to investigate whether and to what extent the MENA markets are integrated globally with major developed markets. We first examine the time-scale properties of stock index returns and their volatility based on the discrete wavelet decomposition and the multiresolution analysis. In doing so, we use the Wavelet package produced by StatSci of MathSoft that was discussed in Bruce and Gao (1996). The discrete wavelet transform is very useful in decomposing time series data into an orthogonal set of components with different frequencies. By examining the relationships between high-frequency fluctuations in stock returns, obtained from reconstruction of the data by 'crystals', we can investigate the international transmission of 'news' in stock markets. The multiresolution decomposition of wavelet analysis is also useful in handling so-called the 'Monday effect' of stock market returns often discussed in earlier empirical studies. [See Lee (2001) for adjusting periodic variations in economic time series via wavelet analysis.] The haar wavelet, designated as "haar", is mainly used as the basic wavelet function. Although alternative choices for basic wavelet such as "symmlet" are tried for comparison, the results are not much affected, and hence are suppressed to save space.

3.1. Data description

The data used in the analysis to follow consist of daily composite stock market indices for two MENA countries (Turkey and Egypt) and three major matured markets (U.S., Japan and Germany). We focus on the Turkish and Egyptian markets, as they are among the largest stock markets in the MENA region. As for the developed markets, much of earlier studies found that the U.S. stock market is, by far, the most influential in the world. The Japanese and German markets are also examined to discuss the global linkage of emerging capital markets to movements in other matured markets.

The data are obtained from the website at http://finance.yahoo.com. The definitions of these stock price indices are as follows: ISE National-100 for Turkey (henceforth denoted as TK); CMA for Egypt (denoted as EG); Dow Jones Industrial Average for the U.S. (denoted as US); Nikkei 225 for Japan (denoted as JP); and DAX for Germany (denoted as GM). All stock indices are measured at closing times, in terms of local currency units. The data set ranges from August 1998 to May 2001. Time series plots in Figure A.1 show that the stock indices of these markets appear to display similar long-swing movements with their peaks around May of 2000.

These stock market indices are transformed to daily rates of return by calculating continuously compounded index returns from $R_t = 100 \times \ln(S_t / S_{t-1})$. Note that these 'daily' rates of return on a given calendar day may represent returns realized over different time intervals depending on holiday and trading day schedules. Notice also that we use close-to-close returns as in Karolyi (1995), while recent spillover studies on nonsynchronous trading environments such as Hamao *et al.* (1990) and Koutmos and Booth (1995) used open-to-close returns.[1] Because these stock markets are operating in different time zones with different holiday and trading day schedules as well as different opening and closing times, some daily observations are deleted. After matching the daily observations, we have about 550 through 680 observations depending on which pairs of countries are under investigation.

The summary statistics of daily returns are presented in Table 1. In all cases, the excess kurtosis and skewness measures are indicative of evidence against normal distribution. Time series plots in Figure 1 also show the typical phenomena of volatility clustering in stock returns. We can also see that the Turkish market shows the highest average daily return (13.5 percent) across all markets together with the highest variability as measured by the standard deviation of the returns, which is typical in most emerging markets. Figure 1 also show a noticeably large volatility in the Turkish market compared to other markets. On the other hand, the Egyptian market displays less volatility than other matured markets, whilst it exhibits higher average daily return. Such features of the Egyptian market are in contrast with the conventional wisdom of high risk and high return.

– Insert < Table 1> and <Figure 1> here. –

3.2. Price Spillovers

If the price movements of one stock market affect subsequent price movements in other markets, then the innovations of the influential market should lead to subsequent changes in the other markets. Given earlier empirical results that the U.S. market is the most influential in the world [see, for example, Eun and Shim (1989)], we first examine whether innovations in the U.S. stock market are transmitted to the MENA markets.

In order to investigate international stock market spillovers, we need to figure out the innovations in stock markets. While GARCH-type models have mainly been used to capture such innovations in much of recent empirical work, the multiresolution decomposition approach is applied here to derive high-frequency fluctuations in stock market data. Based on the reconstructions of the stock returns at different scales, we can investigate the relationships between various pairs of rescaled data to discuss about the spillover effects from the U.S. stock market returns and their volatility to the MENA counterparts.

Table A.1 in the Appendix provides the summary statistics for the wavelet crystals of the stock returns. From the energy %, which denotes the proportion of energy in the original signal accounted for by each crystal, we can first see that high-frequency detail components represent much more energy than low-frequency smooth components. Here the finest scale crystal 'd1' represents short-term variations due to shocks occurring within a day or two, and the next finest component 'd2' accounts for variations at a time scale of $2^2 = 4$ days. Such observation indicates that movements in stock returns are mainly caused by short-term fluctuations. In fact, such phenomenon is somewhat expected as stock returns cannot be predictable in advance.

[1] Although both open and close indices are available for the matured stock markets, close quotes only are available for Turkey and Egypt. In fact, although open quotes for the Turkish index are available, they are almost the same as close quotes of the previous trading day.

Figure 2 portrays the wavelet decompositions of the stock returns corresponding to the wavelet crystals in Table A.1. The high volatility in the Turkish market, as discussed above, is clearly depicted in high-frequency fluctuations such as D1 and D2. As we focus on recent movements in international stock markets, no noticeable changes in volatility are observed in the stock returns throughout the sample period.

– Insert <Figure 2> here. –

In order to investigate whether and to what extent the U.S. stock market movements are transmitted to the MENA markets, we first start with a simple regression of the Turkish return on the U.S. return of the *previous trading day*.[2] Table 2 reports the coefficient estimates from a sequence of least squares regressions using different scales of analysis obtained via the multiresolution decomposition. As for the raw data on stock returns, the slope coefficient is quite high and significant. However, such a result may not be interpreted as direct evidence on the international transmission mechanism of stock market movements. If one stock market is causally prior to other markets, the price movements of the influential market should affect subsequent price changes in other markets, but are not affected by price movements of other markets in earlier period. In order to see whether the Turkish market movements may also explain the U.S. stock prices, we estimate a reverse regression, where the U.S. return of the *same calendar day* now becomes the dependent variable. In this case, the estimated coefficient turns out to be significant (at 10 percent significance level), although it is relatively small. Such result is in contrast to earlier findings that no single foreign market can significantly affect the U.S. market.

– Insert < Table 2> here. –

In fact, spillovers are concerned with the effects of any unexpected developments in one stock market on other markets. In order to figure out the international transmission mechanism of 'news' in stock markets, we need to focus on the relationships between high-frequency fluctuations in stock returns. Based on the reconstructions of the returns data at different scales, we next examine the relationships between the finest components (D1) in stock returns. The estimate of the slope coefficient is not much affected, and still remains significant. As the next finest scale (D2) has a fairly large portion of energy in stock return movements, we also consider such fluctuations by using the sum of D1 and D2. In this case, the slope coefficient is again estimated to be significant. These results are in agreement with earlier empirical findings that innovations in the U.S. stock markets are rapidly transmitted to other markets.

In order to see whether such spillover effects are spurious, reverse regressions are estimated using the same scale data. In this case, the slope coefficient from regression of D1 scale data turns out to be far from being significant. As for the (D1+D2) scale data, the regression coefficient is again estimated to be insignificant. Such results can be interpreted as evidence that the U.S. market is not influenced by innovations in the Turkish market. Thus, unlike the results from the raw data, consistent observations are obtained to previous empirical findings when we focus on high-frequency fluctuations.

Similar observations are obtained for the relationship between the Turkish market and other matured markets considered in this paper (Japan and Germany). The regression of the TK

[2] On a calendar day, the Turkish market opens earlier than the U.S. market. Thus, if the U.S. market is causally prior to the Turkish market, 'news' in the U.S. market should be followed by a response in the Turkish market on the next trading day.

return on the JP (or GM) return leads to significant estimates at any scaled components. On the other hand, reverse regressions result in either insignificant estimates and/or wrong sign.[3]

Thus, strong evidence is found for price spillover effects from the matured stock markets to the Turkish counterpart, but not *vice versa*. However, as we use close-to-close returns, such results do not necessarily indicate that information generated in the U.S. market can be used to trade profitably in Turkey. In order to investigate whether information originating from one stock market can be used to trade profitably in other markets, we need to use open-to-close returns as in Koutmos and Booth (1995).

As for the Egyptian market, a somewhat different picture emerges. First, the slope coefficient estimated from a simple regression of the EG return on the US return of the previous trading day turns out to be insignificant. As presented in panel (a) of Table 3, further regressions of the EG return on the US return lead to insignificant estimates at any scaled components.

Although the regressions of the EG return on the JP return lead to significant estimates at all the scaled components considered here, evidence for price spillover effects from the Japanese stock market to the EG market appears to be quite weak. An analysis between the EG return and the GM return lead to insignificant estimates at any scaled components. Thus, while the EG market appears to be somewhat influenced by the Japanese market, price spillover effects are not found from the U.S. and German stock markets to the EG market. Again, reverse regressions are estimated using the same scale data, which result in either insignificant slope coefficients and/or wrong sign.

To recapitulate, little evidence is found for price spillover effects from the developed stock markets to the emerging EG counterpart, although we cannot draw too strong a conclusion from such mixed results.[4] On the other hand, there is strong evidence against spillover effects from the emerging markets to the developed markets, which is consistent with earlier empirical findings in this area.

In order to investigate interdependence of the two MENA stock markets, the regressions between the EG returns and the TK returns are estimated at various scales, the results of which are presented in panel (c) of Table 3. While significant estimates of the slope coefficient are obtained from a simple regression of the EG and TK returns, the slope coefficients from regressions of D1 and of (D1+D2) scale data turn out to be insignificant. In fact, as shown in Figure A.1, the stock indices of these two markets appear to display similar long-swing movements over the sample period. Thus, such results can be interpreted as evidence that while the two MENA markets are somewhat related with each other, no spillover effects are found between these markets.

3.3. Volatility Spillovers

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[3] As for the relationship between TK and GM, note that reverse regressions result in the same t-statistics and R^2 values as the previous ones, since returns of the same trading days are used in both regressions. See also note (3) to Table 2.

[4] Such a finding of no spillover effects from the developed market to the Egyptian market might be due to lack of enough data on the effects of 'daily news' in the U.S. market on the Egyptian market. That is, as the U.S. market opens later than the Egyptian counterpart, which opens four days a week while the U.S. market opens five days a week, innovations or 'daily news' in the U.S. market are not transmitted to the EG market as frequently as innovations in the Japanese or German market. In fact, it is only three times (Monday, Tuesday, and Wednesday) a week that 'daily' innovations in the U.S. market can reach Egypt on the very next day. On the other hand, the Japanese market opens earlier than the Egyptian counterpart. Thus, 'daily news' in the former can be transmitted on the same day to the latter, which might lead to significant influences on the latter.

As changes in variance of financial asset prices may reflect the arrival of information and the extent to which the market responds to new information, an increasing attention has been given in recent literature on volatility spillovers as well as price spillovers.[5] While GARCH-type models have mainly been used to capture unexpected movements in volatility by estimating conditional variance, the multiresolution decomposition approach is applied here to derive such unexpected changes in stock price volatility. Table A.2 in the Appendix provides the summary statistics for the wavelet crystals of the squared stock returns.[6] Unlike the stock returns in Table A.1, low-frequency smooth components have almost as much energy as high-frequency detail components, which is indicative of volatility clustering phenomenon often discussed in GARCH literature.

Based on similar approach to the previous subsection, we can test for causality in variance of stock returns to discuss about the volatility spillover effects. Again, we first start with a regression of the square of the TK return on that of the US return in the previous trading day. Table 4 reports the coefficient estimates from a sequence of least squares regressions using different scales of analysis obtained via the multiresolution decomposition. As for the raw data on squared stock returns, the slope coefficient is quite high and significant. However, such a result may not be interpreted as direct evidence for the international transmission mechanism of stock market volatility, since such significant regression estimates may simply reflect spurious spillover effects discussed in the previous subsection. In fact, the estimated coefficient from a reverse regression turns out to be significant, although it is relatively small.

As spillovers are concerned with the effects of any unexpected developments in one stock market on other markets, we next investigate the relationships between high-frequency fluctuations in stock return volatility to figure out the international transmission mechanism of 'news' in stock markets. Using the reconstructed series on the squared returns data at different scales, we examine the relationships between the finest components (D1) in stock return volatility and also between the sums of the two finest scales (D1+D2). The slope coefficients are again estimated to be significant, while the values are smaller than that obtained from the raw data. These results are in agreement with earlier empirical findings that innovations in the U.S. stock markets lead to subsequent movements in other markets.

– Insert < Table 4> here. –

In order to investigate whether such spillover effects are spurious, reverse regressions are estimated using the same scale data. In this case, the slope coefficients are far from being significant. Such results can be interpreted as evidence that the U.S. market is not influenced by innovations in the Turkish market. Thus, volatility spillover effects are found from the U.S. stock market to the Turkish counterpart, but not *vice versa*. These results agree with earlier empirical findings based on the VAR methodology and the GARCH methodology.

Similar observations are obtained for the relationship between the Turkish market and the Japanese market. The regressions of the TK volatility on the JP volatility lead to significant estimates at any scaled components except the (D1+D2) scale data. As for the relationship between the Turkish market and the German market, however, evidence for volatility spillovers

[5] Some recent studies include Engle *et al.* (1990), Hamao *et al.* (1990), King and Wadhwani (1990), Cheung and Ng (1996), Booth *et al.* (1997), Benkato and Darrat (2000), and Ng (2000).

[6] As we focus on the effects of unexpected movements in stock price volatility in one market on those in other markets, and such unexpected changes in volatility can be derived via the multiresolution decomposition approach, the squared stock returns are used here as a direct measure of volatility. As shown in Figure A.2, the squared stock returns appear to display similar pattern to the conditional variance series obtained from the GARCH approach. In fact, the results are not much affected when the GARCH variance series are used rather than the squared stock returns.

is quite weak. Although a significant estimate of the slope coefficient is obtained from the regression of the TK volatility on the GM volatility, the regressions for the finest scaled components result in insignificant estimates. Such a finding of no volatility spillover effects from the GM market to the TK market might be due to the almost synchronous trading hours of these markets. As they open and close at about the same time, innovations in volatility of the GM returns are not well transmitted to the TK market. Again, reverse regressions result in either insignificant estimates and/or wrong sign at any scaled components.

As for the volatility spillover effects between the Egyptian market and the U.S. market, very similar results to the Turkish case are obtained, which is unlike the price spillover case where a bit different picture from the Turkish market emerges. As shown in Table 5, while the slope coefficient estimated from a simple regression of the EG volatility on the US volatility of the previous trading day turns out to be insignificant, further regressions using the reconstructed series at finest scales lead to significant estimates. The slope coefficients from the regressions between the finest components (D1) and also between the sums of the two finest scales (D1+D2) in stock return volatility are significant. Note also that the estimated values are larger than that obtained from the raw data. Reverse regressions are again estimated using the same scale data to check whether such significant relations are spurious. In this case, unlike the regression of EG volatility on US volatility, the slope coefficients from regressions of the US volatility on the EG volatility using any scaled data results in insignificant estimates or wrong sign. As spillovers are concerned with the effects of any unexpected developments in one stock market on other markets, we need to focus on the relationships between high-frequency fluctuations in stock return volatility. Hence such observations can be used as evidence for volatility spillover effects from the U.S. stock market to the Egyptian counterpart, but not *vice versa*.

– Insert < Table 5> here. –

On the other hand, the regressions of the EG volatility on the JP (or GM) returns lead to insignificant estimates at finest scaled components. Thus, while the EG market appears to be influenced by the US market, volatility spillover effects are not found from the JP and GM stock markets to the EG market. Again, in order to see whether such spillover effects are spurious, reverse regressions are estimated using the same scale data, which result in either insignificant slope coefficients and/or wrong sign. Thus, while evidence of spillover effects from the Japanese and German markets is quite weak, volatility spillover effects, if any, are found from developed stock markets to the emerging EG counterpart, but not *vice versa*.

As for the interdependence of the two MENA stock markets, no spillover effects are found between them. In fact, negative (and insignificant) estimates of the slope coefficient are obtained from regressions of the EG and TK volatility and of their D1 and (D1+D2) scale data. Lack of volatility spillover effects from the GM market to the EG market or between the two MENA markets might be due to the fact that the return data of the same trading days are used. As these markets open and close at about the same time, innovations in volatility of one market are not much expected to be transmitted to other markets.

IV. Concluding Remarks

Wavelet analysis is a comparatively new and powerful mathematical tool for signal processing. In particular, the discrete wavelet transform is very useful in decomposing time series data into an orthogonal set of components with different frequencies. By examining the relationships between high-frequency fluctuations in stock returns, obtained from reconstruction of the data by 'crystals', we can investigate international transmission of news across stock markets.

An attempt is made in this paper to examine price and volatility spillover effects across international stock markets, based on the wavelet methodology in decomposing time series data. In particular, we investigate the relationships between the matured stock markets in the U.S., Japan and Germany and the emerging markets in the MENA region. Using the composite stock indices such as ISE-100 of Turkey and CMS of Egypt together with those for Dow Jones Industrial Average of the U.S., Nikkei 225 of Japan, and DAX of Germany, new evidence is found for price as well as volatility spillover effects from the developed stock markets to the MENA counterparts, but not *vice versa*. Our results confirm the importance of news from developed international stock markets in the determination of stock returns and volatility in emerging markets.

A few interesting observations can be pointed out from our empirical analysis. First, the Turkish stock market seems quite well integrated globally with the major developed markets in the world. Such an observation is in agreement with an earlier result in Benkato and Darrat (2000). On the other hand, the linkage between the Egyptian market and the global market appears to be rather weak, although evidence can be found for spillover effects from the developed stock markets to the Egyptian market. The difference in the degree of spillover effects between the two MENA countries lies in the difference in the degree of capital market liberalization between them.

Although interesting results are presented in this paper via wavelet analysis, much work remains to be done. First of all, our methodology can naturally be applied to any sets of international stock market returns to provide new evidence on spillover effects. Hence the next item on the research agenda should include an empirical investigation into international spillovers from the developed markets such as the U.S. to other emerging markets around the globe including other stock markets in the MENA region.

The current approach can also be extended to multivariate framework. Such multivariate analysis would be useful in providing new evidence on spillover effects in the context of uncertainty associated with the potential interaction among any set of stock market return series.

While the wavelet methodology is used here to just decompose time series data, the wavelet analysis is much more powerful in signal processing than what is discussed in this paper. For instance, the wavelet approach can be used to investigate whether innovations in one market may lead to asymmetric impact on other markets depending on the sign as well as the size of such shocks, as discussed in, e.g., Cheung and Ng (1992) and Koutmos and Booth (1995).

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Table 1. Summary Statistics of Stock Returns

Statistics	Turkey	Egypt	U.S.	Japan	German
Mean	0.13456	0.08652	0.00572	-0.03897	0.00954
Median	-0.09499	0.05200	0.01858	-0.08805	0.06860
Std. Dev.	4.00885	0.76337	1.26788	1.54995	1.64128
Skewness	0.00344	0.43329	-0.34928	0.07938	-0.20997
Kurtosis	5.76379	4.67905	5.21217	5.34965	4.07333

Note : The sample size for TK and US is 672, and those for EG, JP, and GM are 552, 644, and 679, respectively.

Table 2. Regressions for Turkish Stock Returns at Different Scales

(a) TK and US

Regression / Scale	R_t^{TK} on R_{t-1}^{US} (US → TK)			R_t^{US} on R_t^{TK} (TK → US)		
	Intercept	Slope	R^2	intercept	Slope	R^2
R_t	0.1312 (0.8627)	0.5832 (4.8573)	0.0340	0.0260 (0.5373)	0.0217 (1.7752)	0.0047
D1	0.0000 (0.0000)	0.4440 (4.0477)	0.0239	0.0000 (0.0000)	0.0074 (0.5901)	0.0005
D1+D2	0.0000 (0.0000)	0.5238 (4.3470)	0.0274	0.0000 (0.0000)	0.0137 (1.1214)	0.0019

(b) TK and JP

Regression / Scale	R_t^{TK} on R_t^{JP} (JP → TK)			R_t^{JP} on R_{t-1}^{TK} (TK → JP)		
	Intercept	Slope	R^2	intercept	Slope	R^2
R_t	0.1809 (1.1473)	0.4471 (4.3935)	0.0292	-0.0263 (-0.4278)	0.0105 (0.6911)	0.0007
D1	0.0000 (0.0000)	0.5079 (4.7686)	0.0342	0.0000 (0.0000)	-0.0302 (-1.9159)	0.0057
D1+D2	0.0000 (0.0000)	0.4249 (4.1568)	0.0262	0.0000 (0.0000)	-0.0037 (-0.2449)	0.0001

(c) TK and GM

Regression / Scale	R_t^{TK} on R_t^{GM} (GM → TK)			R_t^{GM} on R_t^{TK} (TK → GM)		
	Intercept	Slope	R^2	intercept	Slope	R^2
R_t	0.1340 (0.8882)	0.5244 (5.7036)	0.0459	-0.0026 (-0.0423)	0.0874 (5.7036)	0.0459
D1	0.0000 (0.0000)	0.3993 (4.3858)	0.0276	0.0000 (0.0000)	0.0692 (4.3858)	0.0276
D1+D2	0.0000 (0.0000)	0.4067 (4.4951)	0.0290	0.0000 (0.0000)	0.0713 (4.4951)	0.0290

Notes: 1) R_t^{TK}, R_t^{US}, R_t^{JP} and R_t^{GM} denote the TK, US, JP and GM index returns at calendar day *t*, respectively.
2) The figures in the parentheses denote t-statistics of the coefficients.
3) In the TK and GM case, the reverse regressions result in the same

t-statistics and R^2 values as the previous ones, since returns of the same days are used in both regressions.

Table 3. Regressions for Egyptian Stock Returns at Different Scales

(a) EG and US

Regression / Scale	R_t^{EG} on R_{t-1}^{US} (US → EG)			R_t^{US} on R_t^{EG} (EG → US)		
	intercept	Slope	R^2	intercept	Slope	R^2
R_t	0.0899 (2.7473)	0.0329 (1.2699)	0.0029	0.0145 (0.2712)	-0.0358 (-0.5152)	0.0005
D1	0.0000 (0.0000)	0.0343 (1.4511)	0.0038	0.0000 (0.0000)	-0.0666 (-0.8132)	0.0012
D1+D2	0.0000 (0.0000)	0.0290 (1.2106)	0.0027	0.0000 (0.0000)	-0.0878 (-1.1549	0.0024

(b) EG and JP

Regression / Scale	R_t^{EG} on R_t^{JP} (JP → EG)			R_t^{JP} on R_{t-1}^{EG} (EG → JP)		
	intercept	Slope	R^2	intercept	Slope	R^2
R_t	0.0875 (2.6266)	0.0474 (2.1942)	0.0090	-0.1178 (-1.8341)	0.0625 (0.7533)	0.0010
D1	0.0000 (0.0000)	0.0440 (2.2134)	0.0092	0.0000 (0.0000)	0.0879 (0.9986)	0.0019
D1+D2	0.0000 (0.0000)	0.0364 (1.7844)	0.0262	0.0000 (0.0000)	0.0728 (0.8524)	0.0014

(c) EG and GM (or TK)

Regression / Scale	R_t^{EG} on R_t^{GM} (GM ↔ EG)			R_t^{EG} on R_t^{TK} (TK ↔ EG)		
	intercept	Slope	R^2	intercept	Slope	R^2
R_t	0.0920 (2.8408)	0.0170 (0.8454)	0.0013	0.0730 (2.2393)	0.0166 (2.0846)	0.0080
D1	0.0000 (0.0000)	0.0003 (0.0176)	0.0000	0.0000 (0.0000)	0.0007 (0.1007)	0.0000
D1+D2	0.0000 (0.0000)	-0.0007 (-0.0358)	0.0000	0.0000 (0.0000)	0.0087 (1.1368)	0.0024

Notes: 1) R_t^{EG} denotes the EG index return at day *t*. See also note (1) to Table 2.
2) In the GM and TK cases, as the reverse regressions result in the same t-statistics and R^2 values as the previous ones, results on the regressions of R_t^{EG} on R_t^{GM} (or R_t^{TK}) are reported here to save space. See also note (3) to Table 2.

Table 4. Regressions for Turkish Stock Return Volatility at Different Scales

(a) TK and US

Scale \ Regression	V_t^{TK} on V_{t-1}^{US} (US → TK)			V_t^{US} on V_t^{TK} (TK → US)		
	intercept	Slope	R^2	intercept	Slope	R^2
V_t	14.5230 (9.6818)	0.9607 (2.3455)	0.0081	1.4579 (10.6493)	0.0076 (2.0629)	0.0063
D1	0.0000 (0.0000)	0.6915 (2.2612)	0.0076	0.0000 (0.0000)	0.0040 (1.0072)	0.0015
D1+D2	0.0000 (0.0000)	0.5344 (1.5080)	0.0034	0.0000 (0.0000)	0.0054 (1.3286)	0.0026

(b) TK and JP

Scale \ Regression	V_t^{TK} on V_t^{JP} (JP → TK)			V_t^{JP} on V_{t-1}^{TK} (TK → JP)		
	intercept	Slope	R^2	intercept	Slope	R^2
V_t	14.2683 (12.5780)	1.0380 (2.5465)	0.0100	2.2627 (29.6101)	0.0107 (3.0251)	0.0140
D1	0.0000 (0.0000)	1.0266 (1.7311)	0.0046	0.0000 (0.0000)	-0.0002 (-0.0664)	0.0000
D1+D2	0.0000 (0.0000)	0.1135 (0.1789)	0.0001	0.0000 (0.0000)	-0.0034 (-1.1833)	0.0022

(c) TK and GM

Scale \ Regression	V_t^{TK} on V_t^{GM} (GM → TK)			V_t^{GM} on V_t^{TK} (TK → GM)		
	intercept	Slope	R^2	intercept	Slope	R^2
V_t	13.9131 (9.0358)	0.8334 (2.9367)	0.0126	2.4461 (12.3428)	0.0151 (2.9367)	0.0126
D1	0.0000 (0.0000)	0.3246 (1.2991)	0.0025	0.0000 (0.0000)	0.0077 (1.2991)	0.0025
D1+D2	0.0000 (0.0000)	0.3834 (1.4092)	0.0029	0.0000 (0.0000)	0.0076 (1.4092)	0.0029

Notes: 1) V_t^{TK}, V_t^{US}, V_t^{JP} and V_t^{GM} denote the TK, US, JP and GM return volatility at calendar day *t*, obtained as the squares of each index returns.
2) See also notes to Table 2.

Table 5. Regressions for Egyptian Stock Return Volatility at Different Scales

(a) EG and US

Regression / Scale	V_t^{EG} on V_{t-1}^{US} (US $\rightarrow$ EG)			V_t^{US} on V_t^{EG} (EG $\rightarrow$ US)		
	intercept	Slope	R^2	intercept	Slope	R^2
V_t	0.5941 (11.8404)	0.0145 (0.5010)	0.0005	1.6238 (29.1184)	-0.1676 (-2.2970)	0.0095
D1	0.0000 (0.0000)	0.0956 (2.0462)	0.0076	0.0000 (0.0000)	0.0430 (1.5084)	0.0041
D1+D2	0.0000 (0.0000)	0.1672 (4.0295)	0.0288	0.0000 (0.0000)	0.0559 (1.7691)	0.0057

(b) EG and JP

Regression / Scale	V_t^{EG} on R_t^{JP} (JP $\rightarrow$ EG)			R_t^{JP} on R_{t-1}^{EG} (EG $\rightarrow$ JP)		
	intercept	Slope	R^2	intercept	Slope	R^2
V_t	0.7082 (16.7528)	0.0400 (2.5640)	0.0123	2.5043 (34.1187)	-0.4913 (-5.1696)	0.0478
D1	0.0000 (0.0000)	0.0061 (0.3170)	0.0002	0.0000 (0.0000)	-0.1103 (-1.1548)	0.0025
D1+D2	0.0000 (0.0000)	0.0061 (0.5195)	0.0005	0.0000 (0.0000)	-0.0752 (-0.9800)	0.0018

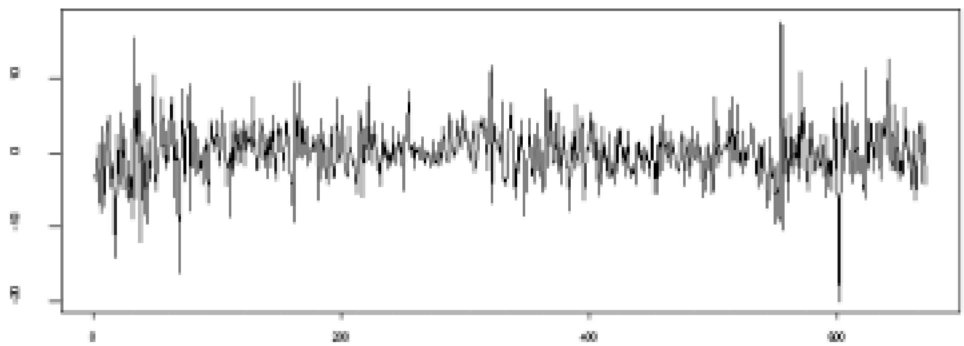
(c) EG and GM (or TK)

Regression / Scale	V_t^{EG} on V_t^{GM} (GM $\leftrightarrow$ TK)			V_t^{EG} on V_t^{TK} (TK $\leftrightarrow$ EG)		
	intercept	Slope	R^2	intercept	Slope	R^2
V_t	0.6416 (11.3376)	-0.0191 (-1.7112)	0.0052	0.6467 (20.3451)	-0.0024 (-1.6946)	0.0053
D1	0.0000 (0.0000)	-0.0159 (-1.4703)	0.0039	0.0000 (0.0000)	-0.0005 (-0.3385)	0.0002
D1+D2	0.0000 (0.0000)	-0.0165 (-1.4440)	0.0037	0.0000 (0.0000)	-0.0017 (-1.2343)	0.0029

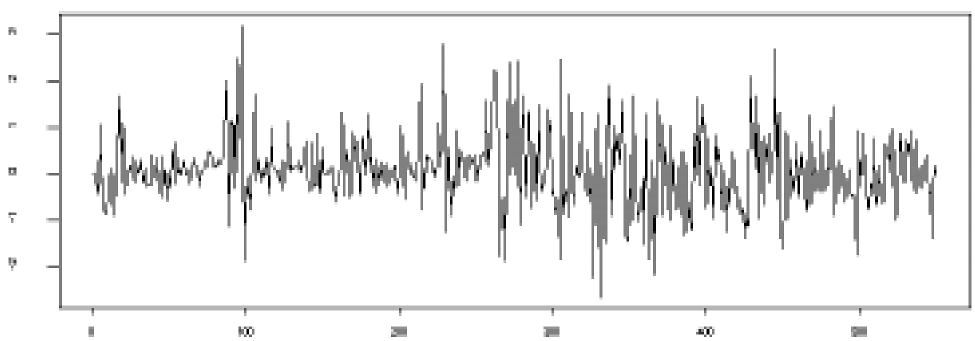
Notes: 1) V_t^{EG} denotes the EG return volatility at day *t*. See also note (1) to Table 4.
2) In the GM and TK cases, as the reverse regressions result in the same t-statistics and R^2 values as the previous ones, results on the regressions of V_t^{EG} on V_t^{GM} (or V_t^{TK}) are reported here to save space.

Figure 1. Daily Stock Index Returns

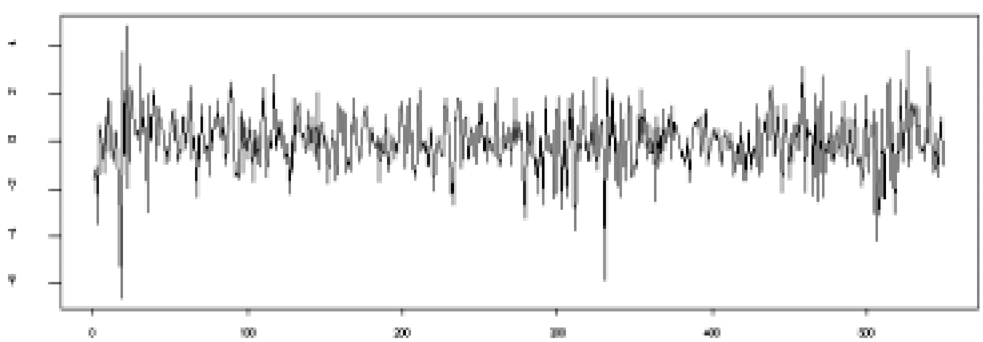
(a) TK



(b) EG



(c) US



(d) JP

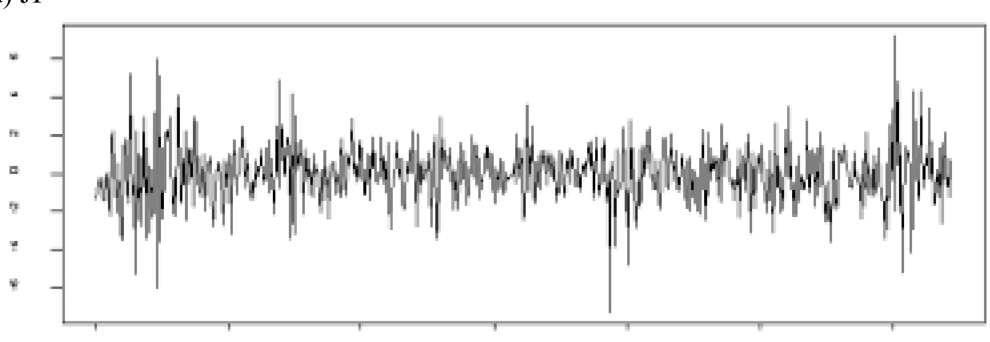
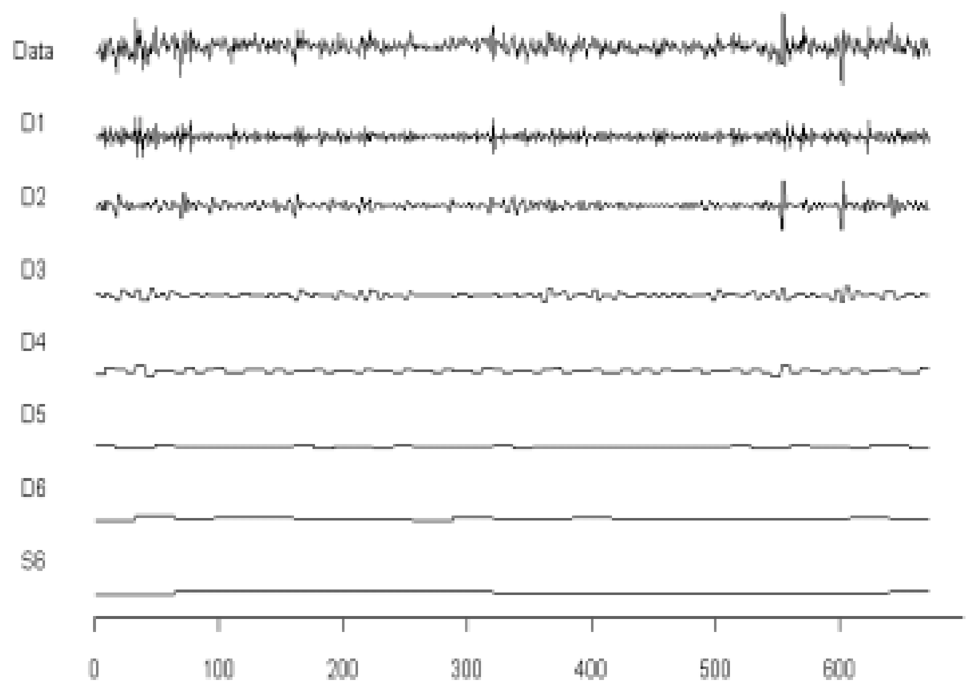


Figure 2. Multiresolution Decomposition of Daily Index Returns

(a) TK



(b) EG

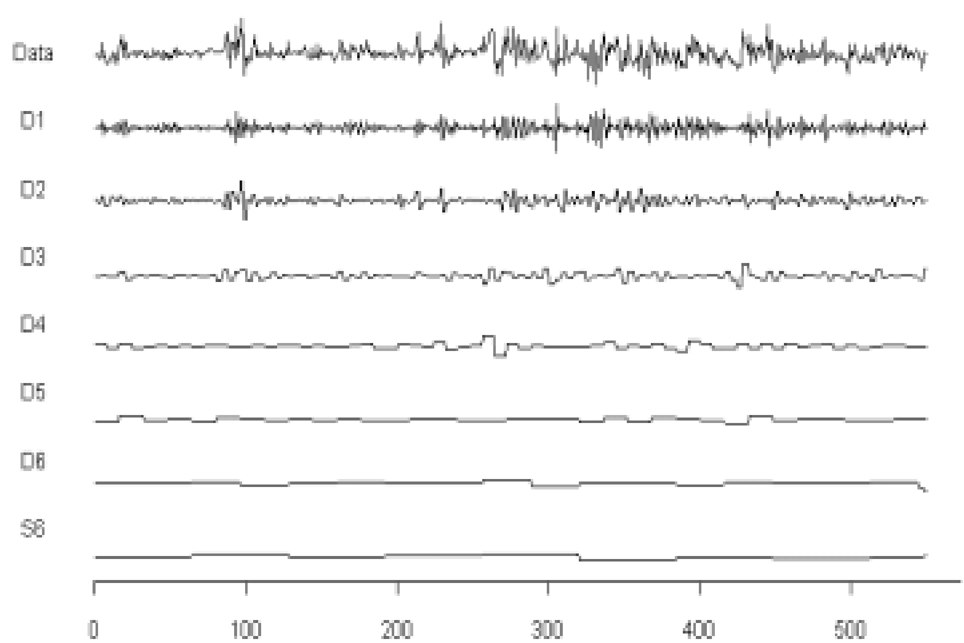


Table A.1. Summary of DWT Coefficients for Stock Returns

(a) TK

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	-1.10	-0.49	-0.16	0.46	1.64	0.04	0.77	0.59	0.01
d6	-1.90	-0.18	0.13	0.63	0.89	-0.03	0.89	0.72	0.01
d5	-2.85	-1.10	-0.06	1.01	1.99	-0.10	1.42	1.58	0.04
d4	-4.02	-0.71	-0.21	0.52	2.19	-0.17	1.13	0.90	0.05
d3	-4.70	-1.20	-0.18	0.63	2.38	-0.30	1.34	1.42	0.15
d2	-3.92	-0.78	-0.05	0.74	4.75	0.02	1.32	1.11	0.27
d1	-7.30	-0.92	-0.03	0.66	3.84	-0.13	1.24	1.19	0.48

(b) EG

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	-1.24	0.09	0.46	1.61	2.54	0.69	1.34	1.70	0.06
d6	-1.12	-0.46	0.08	0.77	1.91	0.18	0.93	1.02	0.02
d5	-2.16	-1.11	-0.30	0.28	0.53	-0.40	0.80	0.93	0.04
d4	-2.14	-0.06	0.09	0.62	3.52	0.21	0.87	0.62	0.08
d3	-3.08	-0.39	-0.02	0.41	1.98	-0.04	0.80	0.61	0.13
d2	-1.96	-0.30	0.05	0.41	3.43	0.10	0.76	0.53	0.25
d1	-3.03	-0.28	0.01	0.42	2.27	0.04	0.71	0.53	0.42

(c) US

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	-6.27	-1.05	1.09	3.09	8.66	1.03	4.06	3.39	0.02
d6	-13.43	-4.39	-0.18	1.32	3.90	-2.12	5.26	4.09	0.03
d5	-6.02	-2.50	-0.39	1.72	4.44	-0.37	3.25	3.13	0.02
d4	-10.12	-3.11	-0.51	2.64	10.17	-0.21	4.01	4.44	0.06
d3	-11.57	-2.44	0.30	2.29	8.76	-0.28	3.96	3.39	0.12
d2	-26.28	-2.35	0.06	2.49	11.15	-0.42	4.77	3.61	0.35
d1	-12.41	-1.71	0.42	2.47	15.44	0.40	3.57	3.10	0.40

(d) JP

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	-2.29	-1.44	-0.16	0.89	1.37	-0.29	1.33	1.60	0.01
d6	-2.51	-1.10	-0.15	0.88	2.41	-0.14	1.49	1.76	0.01
d5	-3.56	-1.24	-0.63	0.44	2.02	-0.53	1.39	1.58	0.03
d4	-2.68	-1.03	-0.09	0.97	2.34	-0.15	1.33	1.54	0.05
d3	-3.71	-0.98	0.03	1.15	6.81	0.11	1.72	1.62	0.15
d2	-4.38	-0.73	-0.07	1.07	6.82	0.02	1.54	1.35	0.25
d1	-5.35	-1.09	-0.13	0.87	6.47	-0.16	1.55	1.47	0.50

Note : The energy % denotes the proportion of energy in the original signal represented by each crystal.

Table A.2. Summary of DWT Coefficients for Stock Return Volatility

(a) TK

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	56.82	63.95	98.47	163.95	248.42	122.68	69.42	60.29	0.22
d6	-137.92	-30.55	7.60	21.52	84.44	-3.85	61.11	54.19	0.03
d5	-150.56	-9.69	5.71	27.61	140.99	9.30	56.36	30.02	0.07
d4	-185.87	-8.14	2.97	15.69	96.21	-2.27	48.04	18.53	0.10
d3	-101.63	-10.16	1.15	9.50	239.23	5.20	43.84	14.45	0.16
d2	-225.70	-6.78	1.01	8.29	264.32	4.33	37.25	11.16	0.24
d1	-105.66	-6.07	0.00	6.03	182.51	-0.32	23.77	8.94	0.19

(b) EG

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	0.84	3.72	7.36	12.09	22.34	8.77	6.41	6.20	0.19
d6	-3.86	-0.94	0.43	2.30	19.14	1.84	5.39	2.07	0.05
d5	-13.79	-0.72	0.17	1.11	4.90	-0.06	3.10	1.40	0.03
d4	-14.02	-0.77	-0.01	0.63	13.10	0.06	3.01	1.01	0.06
d3	-9.44	-0.58	-0.04	0.58	23.19	0.17	2.77	0.91	0.10
d2	-7.03	-0.64	-0.04	0.42	42.24	0.28	3.34	0.82	0.29
d1	-18.77	-0.53	-0.05	0.43	29.11	0.00	2.36	0.72	0.29

(c) US

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	3.88	7.66	9.85	15.54	28.74	12.26	7.24	6.99	0.24
d6	-11.28	-1.42	0.03	2.53	10.12	0.38	5.81	3.54	0.03
d5	-18.35	-1.12	-0.23	1.28	6.22	-0.66	4.48	1.86	0.05
d4	-10.74	-1.18	-0.52	1.10	7.96	-0.09	2.81	1.83	0.04
d3	-13.43	-0.95	0.12	0.95	9.70	0.05	3.02	1.43	0.08
d2	-17.17	-0.82	0.14	0.89	27.67	0.32	3.47	1.27	0.23
d1	-21.60	-0.69	-0.04	0.59	20.64	-0.03	2.99	0.94	0.33

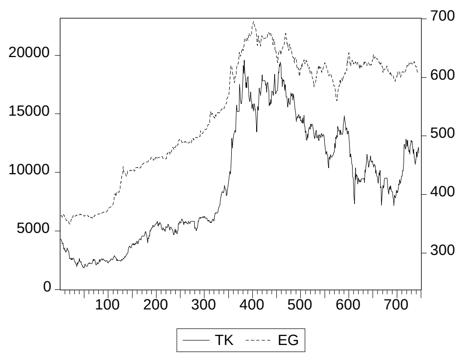
(d) JP

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	0.30	10.96	14.27	21.24	42.67	17.56	11.92	6.86	0.24
d6	-12.34	-0.21	3.27	6.70	12.66	2.86	7.13	5.72	0.03
d5	-22.64	-0.43	1.94	3.89	6.57	0.19	6.73	3.13	0.04
d4	-21.76	-2.18	-0.50	1.05	14.77	-0.50	5.83	2.34	0.07
d3	-20.05	-1.71	-0.35	1.18	19.76	0.05	4.72	2.19	0.09
d2	-24.99	-0.96	0.09	1.38	14.74	0.37	4.19	1.77	0.14
d1	-25.16	-0.98	-0.02	1.03	36.97	0.11	4.89	1.50	0.39

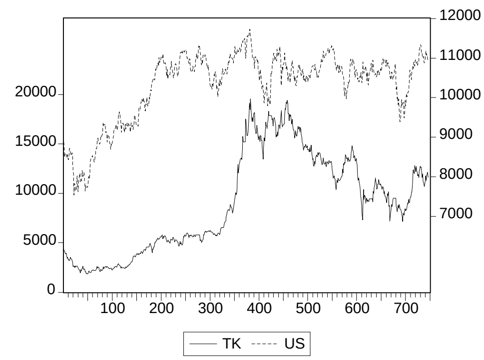
Note : See note to Table A.1.

Figure A.1. Composite Stock Indices

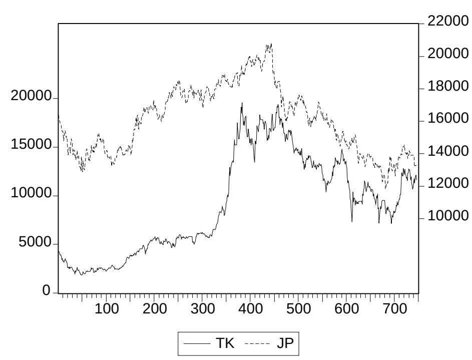
(a) TK and EG



(b) TK and US



(c) TK and JP



(d) TK and GM

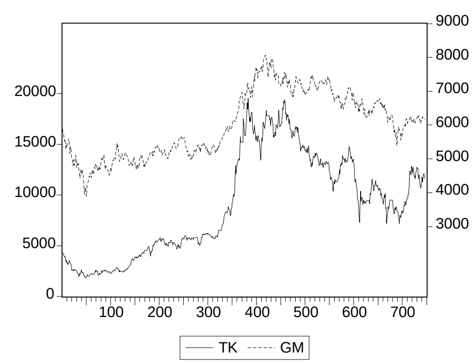
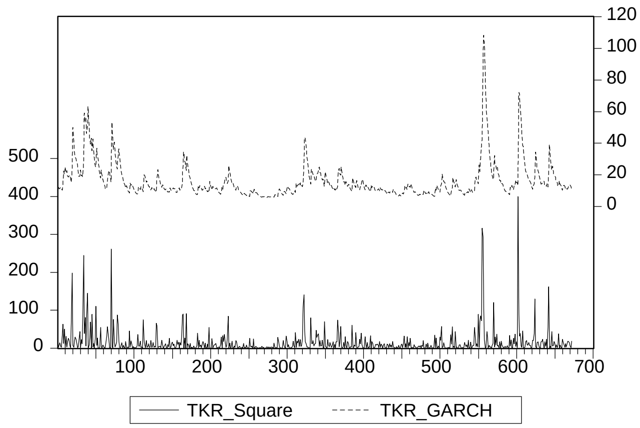


Figure A.2. Square of TK Stock Returns and GARCH Process



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500
400
300
200
100
0
100
200
300
400
500
600
700
TKR_Square
TKR_GARCH