Price and Volatility Spillovers in Stock Markets : A Wavelet Analysis

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ABSTRACT

While GARCH-type models are mainly used to investigate international transmission mechanism of stock markets in much of previous studies, an attempt is made in this paper to examine price and volatility spillover effects across international stock markets via wavelet analysis. We first propose a new testing strategy to spillover effects based on discrete wavelet decomposition, which is then applied to investigate the dynamics and the potential interaction in international stock markets. Using the data on the daily stock returns of the U.S. Dow Jones index and of the KOSPI (Korea Composite Stock Price Index), strong evidence is found for price as well as volatility spillover effects from the U.S. stock markets to the Korean counterparts, but not *vice versa*. Our methodology can naturally be applied to any sets of international stock market returns to provide new evidence on spillover effects.

JEL Classification : C14, C22, G15

Keywords : Wavelet analysis, Stock returns, Volatility, Spillovers

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 world-wide 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), using an ARCH-M model, provided some evidence for spillover effects from New York to Tokyo and London and from London to Tokyo, but not from Tokyo to either 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) found significant spillovers among the Pacific Rim countries, and Booth *et al.* (1991) provided evidence for price and volatility spillovers among the Scandinavian countries.

In much of empirical studies on international stock market spillovers, the VAR (vector autoregression) methodology was used in Eun and Shim (1989) and earlier studies, and the GARCH (generalized autoregressive conditional heteroscedasticity) methodology has mainly been used in more recent work. Since spillover effects are expected to completed within a short period of time as discussed in Eun and Shim (1989), much of spillover literature is concerned with the effects of any unanticipated shocks or innovations to one stock market on other markets. In order to extract new information in stock markets, 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.

The purpose of this paper is to propose a new testing strategy to spillover effects based on wavelet analysis. 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, physics and economics, 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 ‘crystals’, we can investigate international transmission of ‘news’ in stock markets. The multiresolution decomposition of wavelet analysis is also useful in handling periodicity in stock market returns, for instance, the so-called ‘Monday effect’ often discussed in earlier empirical studies.

While our main purpose is to discuss a wavelet methodology to investigate international transmission mechanism of stock markets, an attempt is made in this paper to illustrate how to apply the approach to testing for price and volatility spillover effects across international stock markets. In particular, we investigate the relationships between the U.S. and Korean stock market returns and also between their volatility. Using the data on the daily stock returns of the U.S. Dow Jones index and of the KOSPI (Korean Stock Price Index), it is found that price as well as volatility spillover effects exist between the U.S. stock markets and the Korean counterparts. With recent boom and slowdown of IT (information & technology) industries in both U.S. and Korea, strong evidence can also be found for spillovers from NASDAQ to KOSDAQ (Korea Securities Dealers’ Automated Quotation). Such observations are consistent with earlier empirical and theoretical results on this area that innovations in developed stock markets are transmitted to emerging markets, and that the U.S. stock market is by far the most influential in the world with no single foreign market being able to explain significantly the U.S. market movements.

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 Korean 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. However, wavelet analysis has received little attention in time series analysis of economic and financial data.

Some recent papers in economic application include Goffe (1994), Gilbert (1995), Nason (1995), Ramsey and Zhang (1995, 1996), Wang (1995) and Wong *et al.* (1997). Goffe (1994) illustrated the application of wavelets to nonstationary economic time series, and Gilbert (1995) examined the stability of economic relationships. Ramsey and Zhang (1995, 1996) 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.

In this section, we give only a brief overview of two basic tools of wavelet analysis: DWT (discrete wavelet transform) and MRD (multiresolution decomposition). 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).

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 which 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:

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

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. Figure 1 illustrates four types of orthogonal wavelets typically used in empirical analysis, which are 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.

– Insert < Figure 1> here. –

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

$$\phi(x) = \sqrt{2}\sum_{k} \ell_{k}\phi(2x-k) . \tag{2.1}$$

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

$$\psi(x) = \sqrt{2}\sum_k h_k \phi(2x-k)\,. \tag{2.2}$$

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

$$\ell_k = \frac{1}{\sqrt{2}}\int \phi(t)\phi(2t-k)dt \tag{2.3}$$

$$h_k = \frac{1}{\sqrt{2}}\int \psi(t)\phi(2t-k)dt\,. \tag{2.4}$$

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:

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t-k) = 2^{-j/2}\phi(\frac{t-2^j k}{2^j}) \tag{2.5}$$

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t-k) = 2^{-j/2}\psi(\frac{t-2^j k}{2^j})\,. \tag{2.6}$$

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

$$f(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t), \tag{2.7}$$

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

$$s_{J,k} \approx \int \phi_{J,k}(t)\,f(t)\,dt \tag{2.8}$$

$$d_{j,k} \approx \int \psi_{j,k}(t)\,f(t)\,dt, \text{ for } j = 1,2,\ldots,J. \tag{2.9}$$

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^jk, respectively. The scale factor 2^j is also called the dilation factor and the translation parameter 2^jk 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 (2.7) 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 (2.7). 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:

$$\mathbf{w} = \left. \begin{matrix} \mathbf{s}_J \\ \mathbf{d}_J \\ \mathbf{d}_{J-1} \\ \vdots \\ \mathbf{d}_1 \end{matrix} \right| . \tag{2.10}$$

Each of the sets of coefficients in **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:

$$S_J(t) \;=\; \sum_k s_{J,k}\phi_{J,k}(t) \tag{2.11}$$

$$D_j(t) \;=\; \sum_k d_{j,k}\psi_{J,k}(t) \quad \text{for } j = 1,2,\ldots,J. \tag{2.12}$$

The functions (2.11) and (2.12) 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 (2.7) of a signal in $L^2(\boldsymbol{R})$, a signal $f(t)$ can now be expressed in terms of these signals:

$$f(t) \;=\; S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t) \tag{2.13}$$

As each terms in (2.13) 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, 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 consisting of the U.S. and Korean stock market returns and their volatility. We first examine the time-scale properties of stock returns and 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 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. The symmlet, designated as "s8", is mainly used as the basic wavelet function, and alternative choices for basic wavelet such as "haar" are tried for comparison, but the results are not much affected.

3.1. Data description

The data used in the analysis to follow consist of daily stock market indices of Korea and New York at closing time, in terms of local currency units. For Korea, the KOSPI (Korea Composite Stock Price Index) of the Korea Stock Exchange and the KOSDAQ (Korea Securities Dealers' Automated Quotation) are used. For the U.S., we use the indices of the DJIA (Dow Jones industrial average) and the NASDAQ. The data set for KOSPI and DJIA covers the period January 3, 1995 through August 8, 2000, and that for KOSDAQ and NASDAQ covers the period January 3, 1997 through August 8, 2000. Because the two 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 1333 observations for KOSPI and DJIA and 860 observations for KOSDAQ and NASDAQ.

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 the returns realized over different time interval 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.

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. Contrary to conventional wisdom of high risk and high return, the mean returns in Korean market are lower than in the U.S., while the variances are larger relative to the U.S. market. Such anomalies resulted from the collapse of Korean financial system after the financial crisis of Korea in November 1997 and subsequent instability of Korean stock market. Time series plots in Figure 2 also show a noticeable increase in the volatility in Korean market around the end of 1997 as well as the usual phenomena of volatility clustering in both markets [also see Figure 3].

– Insert < Table 1> and <Figure 2> 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. On the other hand, if such price movements are not affected by price changes of other markets, then future returns of the influential market should not be explained by innovations of the other markets in earlier periods. Given earlier empirical results that the U.S. market is the most influential in the world [see, e.g, Eun and Shim (1989)], we first examine whether innovations in the U.S. stock market are transmitted to Korean market, while no shocks to Korean market can significantly affect the U.S. market movements.

In order to investigate international stock market spillovers, we need to figure out the innovations in stock markets. While GARCH-M 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 Korean counterparts.

Table 2 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.

– Insert < Table 2> here. –

Figure 3 portrays the wavelet decompositions of the stock returns corresponding to the wavelet crystals in Table 2. As discussed above, the Korean financial crisis in November 1997 and subsequent instability of Korean stock market led to much increased volatility in the KOSPI returns. Such changes are more clearly depicted in high-frequency fluctuations such as D1 and D2. As for the KOSDAQ returns, a more significant increase in volatility can be observed from January 1999, when the Korea economy experienced a venture boom owing to various supporting measures of Korean government for information technology industries.[1] While the DJIA returns appear not to show such noticeable change in volatility, the NASDAQ returns display increasing volatility throughout the sample period.

– Insert <Figure 3> here. –

In order to investigate whether and to what extent the U.S. stock market movements are transmitted to Korean market, we first start with a simple regression of the KOSPI returns on the DJIA returns of the previous trading day. Table 3 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 for 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 U.S. stock prices can also be explained by the Korean market movements, we estimate a reverse regression, where the DJIA returns of the same calendar day now become the dependent variable. In this case, the estimated coefficient turns out to be significant, although it is relatively small, which is in contrast to earlier findings that no single foreign market can significantly affect the U.S. market.

– Insert < Table 3> 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

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[1] The 693rd observation indicates the KOSPI return on December 1, 1997. As for the KOSDAQ, the 262nd observation indicates return on December 1, 1997, and the 474th observation denotes return on January 5, 1999.

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. shock 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 have a wrong sign. As for the (D1+D2) scale data, the regression coefficient is far from being significant. Such results can be interpreted as evidence that the U.S. market is not influenced by innovations in Korean 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 KOSDAQ and NASDAQ returns. The regression of the KOSDAQ returns on the NASDAQ leads to significant estimates at any scaled components. On the other hand, reverse regressions result in either insignificant estimates and/or wrong sign.

Too check if such results depend on the choice of the basic wavelet, the multiresolution decomposition using the haar wavelet is also considered. The same regression models as above are estimated for the high-frequency components of stock returns that are now reconstructed via the haar wavelet. The regression estimates at different scales are also reported in Table 3, and the results turn out to be the same as those based on the symmlet. That is, the regressions of the Korean stock returns on the U.S. counterparts lead to significant estimates at any scaled components, while reverse regressions result in either insignificant estimates and/or wrong sign.

To recapitulate, price spillover effects are found from the U.S. stock markets to the Korean counterparts, 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 Korea. 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).

3. 3. Volatility Spillovers

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.[2] 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 4 provides the summary statistics for the wavelet crystals of the squared stock returns. Unlike the stock returns in Table 2, 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.

– Insert < Table 4> here. –

Figure 4 portrays the wavelet decompositions of the squares of stock returns corresponding to the wavelet crystals in Table 4. As discussed above, the Korean financial crisis in November 1997 and subsequent instability of Korean stock market led to much increased volatility in the KOSPI returns, which is depicted in high-frequency fluctuations such as D1 and D2. As for the KOSDAQ returns, more significant increase in volatility can be observed from January 1999, when the Korea economy experienced a venture boom owing to various supporting measures of Korean government for information technology industries.

– Insert < Figure 4> here. –

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

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

start with a regression of the square of the KOSPI returns on that of the DJIA returns in the previous trading day. Table 5 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 section. 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. shock markets are rapidly transmitted to other markets.

– Insert < Table 5> 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 either of wrong sign or far from being significant. Such results can be interpreted as evidence that the U.S. market is not influenced by innovations in Korean market. Thus, volatility spillover effects are found from the U.S. stock markets to the Korean counterparts, 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 KOSDAQ and NASDAQ volatility. The regression of the KOSDAQ volatility on that for the NASDAQ leads to significant estimates at all scaled components. On the other hand, reverse regressions result in either insignificant estimates and/or wrong sign. As in the previous subsection, the multiresolution decomposition via the haar wavelet is considered, which also leads to the same results as those based on the symmlet.

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.

While our main purpose is to present a wavelet methodology in decomposing time series data, based on the discrete wavelet transform, an attempt is made in this paper to examine price and volatility spillover effects across international stock markets. In particular, we investigate the relationships between the U.S. and Korean stock market returns and also between their volatility.

Using the composite indices such as KOSPI and DJIA as well as the indices for KOSDAQ and NASDAQ, new evidence is found for price as well as volatility spillover effects from the U.S. stock markets to the Korean 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.

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. For example, while new evidence on international transmission mechanism of stock returns and volatility has been widely discussed around the globe, the MENA (Middle East and North African) region has received little attention concerning spillover effects in stock markets. 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 emerging 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	KOSPI	DJIA	KOSDAQ	NASDAQ
Mean	-0.0475	0.0725	-0.0135	0.1268
Median	-0.0691	0.0956	-0.0567	0.2594
SD	2.2289	1.0528	2.4501	1.8624
Skewness	-0.0382	-0.5781	-0.2642	–0.4587
Excess Kurtosis	5.2523	8.0435	6.5125	5.9724

Note : The sample size for KOSPI and DJIA is 1332, and that for KOSDAQ and NASDAQ is 859.

Table 2. Summary of DWT Coefficients for Stock Returns

(a) KOSPI

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	-5.69	-0.98	-0.59	1.11	4.87	-0.30	2.51	1.35	0.02
d6	-2.84	-1.12	0.40	1.53	5.00	0.41	2.03	2.25	0.01
d5	-3.32	-0.89	-0.11	0.81	3.21	-0.06	1.66	1.34	0.02
d4	-4.36	-1.33	-0.26	1.10	4.27	-0.06	1.91	1.74	0.05
d3	-9.23	-1.06	0.30	1.56	7.10	0.25	2.67	1.92	0.18
d2	-8.54	-1.34	-0.06	1.41	8.07	0.01	2.44	1.99	0.30
d1	-7.42	-0.93	-0.03	1.02	10.07	0.04	2.04	1.45	0.42

(b) DJIA

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	-1.77	0.06	0.70	1.27	1.71	0.56	0.95	0.95	0.02
d6	-2.58	-0.51	-0.08	0.57	2.23	-0.04	0.99	0.96	0.01
d5	-1.83	-0.51	-0.03	0.52	2.36	0.05	0.89	0.79	0.02
d4	-2.90	-0.63	0.15	0.70	3.16	0.07	1.01	0.85	0.06
d3	-3.67	-0.66	0.04	0.69	2.12	-0.01	1.04	1.01	0.12
d2	-3.96	-0.56	0.08	0.68	4.13	0.08	1.11	0.92	0.28
d1	-5.62	-0.58	-0.01	0.60	7.52	0.02	1.05	0.88	0.50

(c) KOSDAQ

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	-6.19	-3.18	-0.02	0.98	7.19	-0.06	3.74	4.45	0.04
d6	-3.95	-1.14	0.33	1.87	6.58	0.77	3.07	2.28	0.02
d5	-13.15	-0.64	0.08	0.96	6.80	-0.18	3.36	1.17	0.06
d4	-6.23	-1.04	0.32	1.20	10.61	0.39	2.78	1.48	0.08
d3	-9.03	-0.93	-0.06	1.08	10.45	-0.07	3.00	1.54	0.19
d2	-9.98	-1.00	-0.05	0.70	8.51	0.01	2.40	1.36	0.24
d1	-11.26	-0.94	-0.02	0.73	8.55	-0.13	2.12	1.30	0.38

(d) NASDAQ

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	-1.88	-0.19	0.81	1.87	4.77	0.96	2.02	1.67	0.02

d6	-1.46	-0.78	0.63	1.27	2.61	0.37	1.29	1.82	0.01
d5	-2.52	-1.23	0.13	1.61	3.06	0.16	1.70	2.06	0.03
d4	-5.92	-1.04	0.13	0.76	5.22	-0.02	1.77	1.55	0.06
d3	-6.97	-1.32	0.01	1.02	5.81	-0.28	1.95	1.69	0.14
d2	-5.88	-0.95	0.00	0.84	10.32	-0.05	1.82	1.34	0.24
d1	-8.35	-0.96	0.03	1.02	7.99	0.00	1.89	1.47	0.51

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

Table 3. Regressions of Stock Returns at Different Scales

(a) KOSPI and DJIA

Regression / Scale		R_t^{KOR} on R_{t-1}^{US}			R_t^{US} on R_t^{KOR}		
		intercept	Slope	R^2	intercept	slope	R^2
R_t		-0.0848 (-1.4270)	0.5138 (9.1239)	0.0589	0.0739 (2.5632)	0.0274 (2.1076)	0.0033
D1	Symmlet	-0.0004 (-0.0115)	0.4331 (8.3340)	0.0496	0.0002 (0.0079)	-0.0387 (-2.7851)	0.0058
	Haar	0.0000 (0.0000)	0.4188 (7.5155)	0.0407	0.0000 (0.0000)	-0.0245 (-1.7614)	0.0022
D1+ D2	Symmlet	-0.0028 (-0.0553)	0.4661 (8.5510)	0.0521	0.0004 (0.0165)	-0.0045 (-0.3394)	0.0001
	Haar	0.0000 (0.0000)	0.5354 (9.4978)	0.0635	0.0000 (0.0000)	0.0092 (0.7076)	0.0004

Note : 1) R_t^{KOR} and R_t^{US} denote the KOSPI and DJIA index returns at calendar day *t*, respectively.
2) The figures in the parentheses denote t-statistics of the coefficients.
3) For comparison, two choices of the basic wavelet, symmlet and haar are considered for the multiresolution decomposition.

(b) KOSDAQ and NASDAQ

Regression / Scale	R_t^{KOR} on R_{t-1}^{US}			R_t^{US} on R_t^{KOR}		
	intercept	slope	R^2	intercept	slope	R^2
R_t	-0.0531 (-0.6520)	0.3120 (7.1469)	0.0562	0.1248 (1.9651)	0.0365 (1.4067)	0.0023

D1	Symmlet	-0.0008 (-0.0152)	0.2614 (7.0063)	0.0542	0.0002 (0.0041)	-0.0761 (-2.5419)	0.0075
	Haar	0.0000 (0.0000)	0.2846 (7.0414)	0.0547	0.0000 (0.0000)	-0.0395 (-1.3362)	0.0021
D1+ D2	Symmlet	-0.0035 (-0.0551)	0.2773 (7.0211)	0.0544	0.0006 (0.0109)	-0.0053 (-0.1861)	0.0001
	Haar	0.0000 (0.0000)	0.2602 (6.1239)	0.0419	0.0000 (0.0000)	-0.0173 (-0.6192)	0.0004

Note : R_t^{KOR} and R_t^{US} here denote the KOSDAQ and NASDAQ index returns at calendar day *t*, respectively.

Table 4. Summary of DWT Coefficients for Squared Stock Returns

(a) KOSPI

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	2.79	8.90	38.06	60.00	138.15	39.07	34.07	38.85	0.32
d6	-35.86	-5.35	0.82	4.86	31.58	0.40	13.81	6.31	0.02
d5	-24.31	-4.34	-0.91	0.72	33.95	-1.12	9.50	4.17	0.02
d4	-43.91	-3.32	-0.11	2.24	57.52	-0.01	13.46	4.41	0.09
d3	-34.73	-1.82	-0.07	2.64	23.23	0.42	7.62	3.09	0.06
d2	-29.14	-2.25	-0.19	2.27	115.06	0.44	10.10	3.47	0.20
d1	-52.86	-2.31	-0.30	1.32	41.73	-0.57	8.67	2.68	0.29

(b) DJIA

	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) KOSDAQ

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %
s6	0.08	5.61	15.97	77.09	194.26	45.71	57.20	22.45	0.36
d6	-11.80	-1.27	0.96	2.72	52.44	5.65	16.62	3.31	0.02
d5	-38.66	-2.47	-0.15	3.35	23.56	-0.04	12.92	4.50	0.02
d4	-84.49	-1.81	0.19	2.62	36.55	-2.19	15.97	3.30	0.07
d3	-42.26	-2.70	0.12	1.80	32.36	-0.90	10.93	3.22	0.06
d2	-79.39	-1.78	-0.22	0.79	45.73	-0.58	12.28	1.97	0.16
d1	-62.33	-1.95	-0.15	0.84	85.74	-0.33	12.06	1.93	0.31

(d) NASDAQ

	Min	1Q	Median	3Q	Max	Mean	SD	MAD	Energy %

s6	0.65	8.32	22.99	29.46	102.52	26.35	26.49	21.03	0.31
d6	-26.62	-5.92	0.77	6.02	13.92	-1.47	10.67	8.62	0.02
d5	-14.08	-5.21	0.86	3.61	50.59	2.03	12.51	5.99	0.07
d4	-34.66	-2.16	-0.87	1.75	33.03	-0.80	9.07	2.58	0.07
d3	-33.59	-1.62	-0.09	1.47	32.69	-0.01	7.22	2.29	0.09
d2	-35.01	-1.57	-0.24	1.12	29.72	-0.64	5.93	2.00	0.13
d1	-33.93	-1.42	-0.14	1.08	52.70	0.21	6.58	1.87	0.31

Note : See note to Table 2.

Table 5. Regressions of Stock Return Volatility at Different Scales

(a) KOSPI and DJIA

Regression / Scale		R_t^{KOR} on R_{t-1}^{US}			R_t^{US} on R_t^{KOR}		
		intercept	Slope	R^2	intercept	Slope	R^2
R_t		4.0176 (13.772)	0.8524 (9.1041)	0.0587	0.9479 (10.758)	0.0336 (4.3169)	0.0138
D1	Symmlet	0.0008 (0.0046)	0.5704 (5.7242)	0.0240	0.0001 (0.0018)	-0.0164 (-1.9683)	0.0029
	Haar	0.0000 (0.0000)	0.7213 (7.8720)	0.0445	0.0000 (0.0000)	-0.0340 (-4.7228)	0.0165
D1+ D2	Symmlet	0.0043 (0.0204)	0.7439 (8.2711)	0.0489	0.0003 (0.0048)	0.0016 (0.2002)	0.0000
	Haar	0.0000 (0.0000)	0.5354 (9.4978)	0.0635	0.0000 (0.0000)	0.0012 (0.1499)	0.0000

Note : 1) R_t^{KOR} and R_t^{US} denote the square of KOSPI and DJIA index returns at calendar day *t*, respectively.
2) See notes to Table 3.

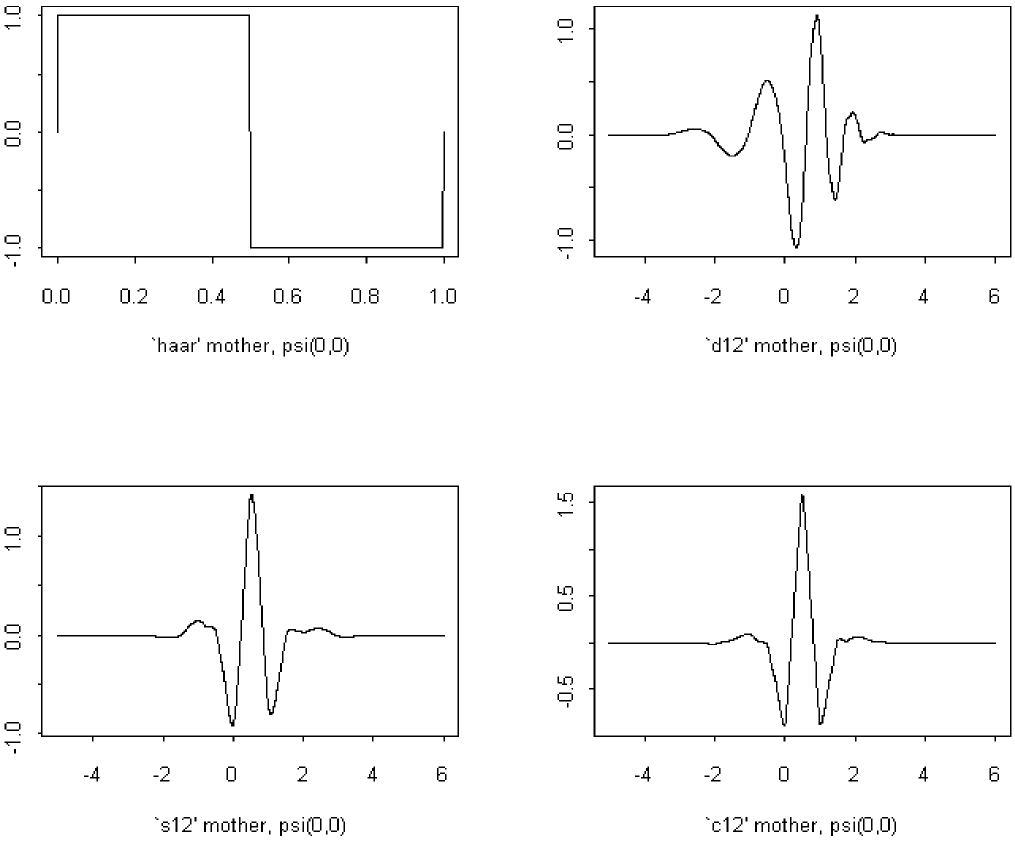
(b) KOSDAQ and NASDAQ

Regression / Scale	R_t^{KOR} on R_{t-1}^{US}			R_t^{US} on R_t^{KOR}		
	intercept	Slope	R^2	intercept	slope	R^2
R_t	3.7167 (7.5219)	0.6547 (11.124)	0.1262	2.6757 (9.7196)	0.1388 (7.4442)	0.0608

D1	Symmlet	-0.0002 (-0.0008)	0.2615 (4.2221)	0.0204	-0.0001 (-0.0008)	-0.0630 (-3.4562)	0.0138
	Haar	0.0000 (0.0000)	0.4351 (6.8632)	0.0521	0.0000 (0.0000)	-0.0628 (-3.4973)	0.0141
D1+ D2	Symmlet	0.0005 (0.0014)	0.3519 (5.5131)	0.0343	0.0007 (0.0036)	-0.0016 (-0.0835)	0.0000
	Haar	0.0000 (0.0000)	0.3512 (5.8431)	0.0383	0.0000 (0.0000)	0.0065 (0.3394)	0.0001

Note : R_t^{KOR} and R_t^{US} here denote the square of KOSDAQ and NASDAQ index returns at calendar day *t*, respectively.

Figure 1. Types of Orthogonal Wavelets : haar, daublets, symmlets, coiflets



Note : The numbers are related to the width and smoothness of the wavelet functions.

Figure 2. Daily Index Returns for KOSPI, DJIA, KOSDAQ, NASDAQ

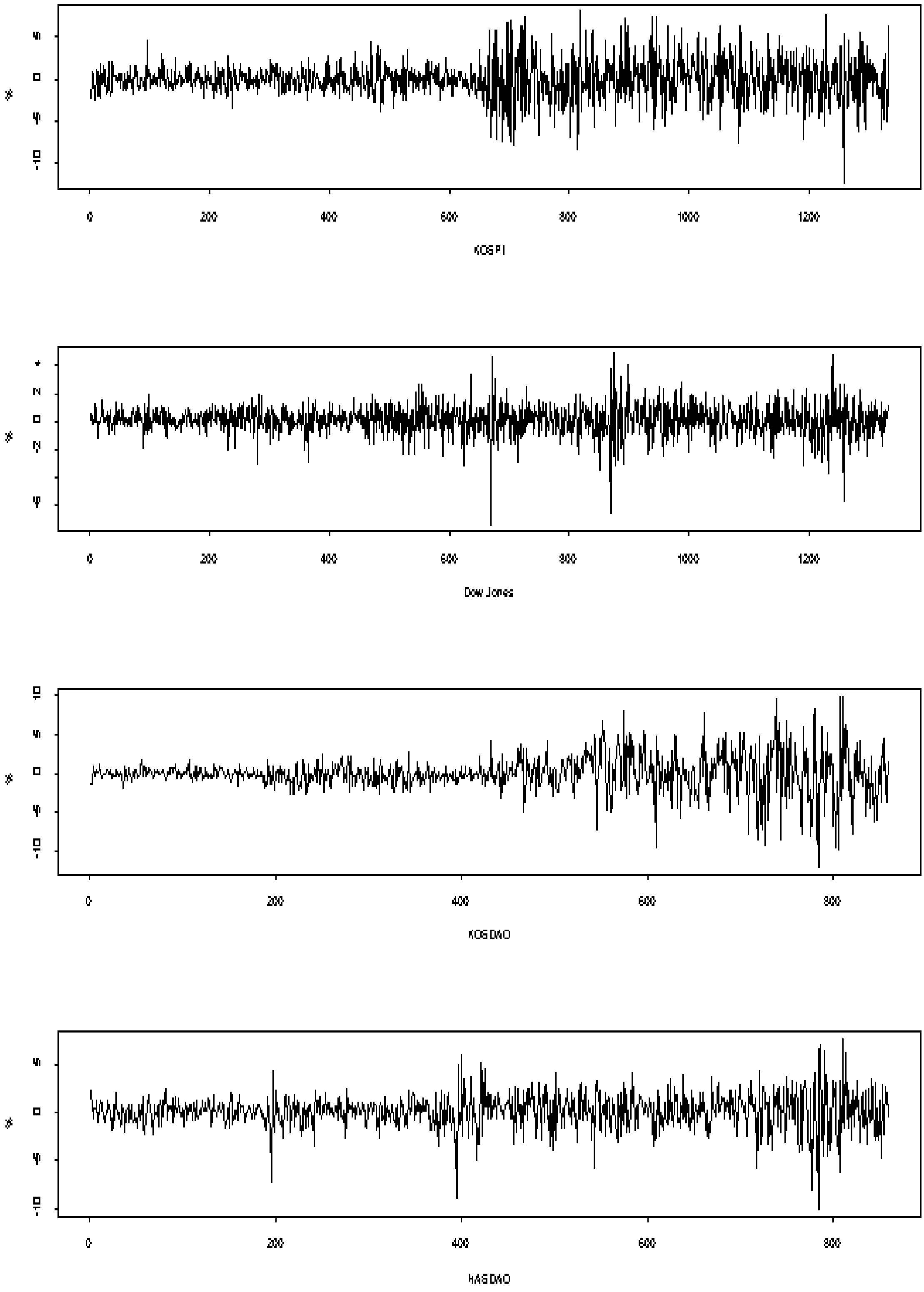
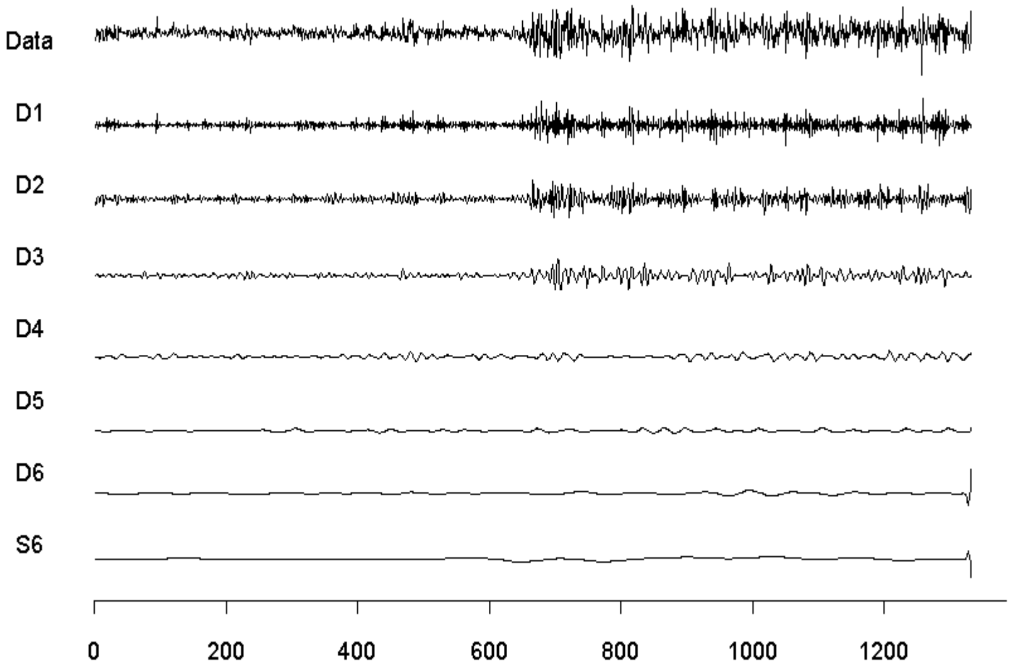


Figure 3. Multiresolution Decomposition of Daily Index Returns

(a) KOSPI



(b) DJIA

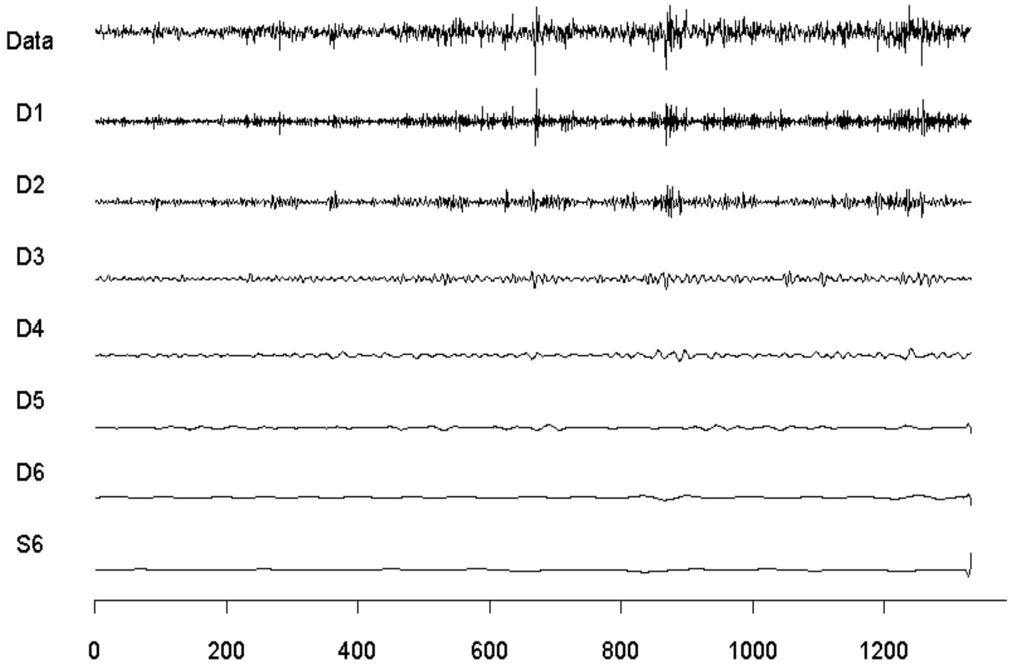
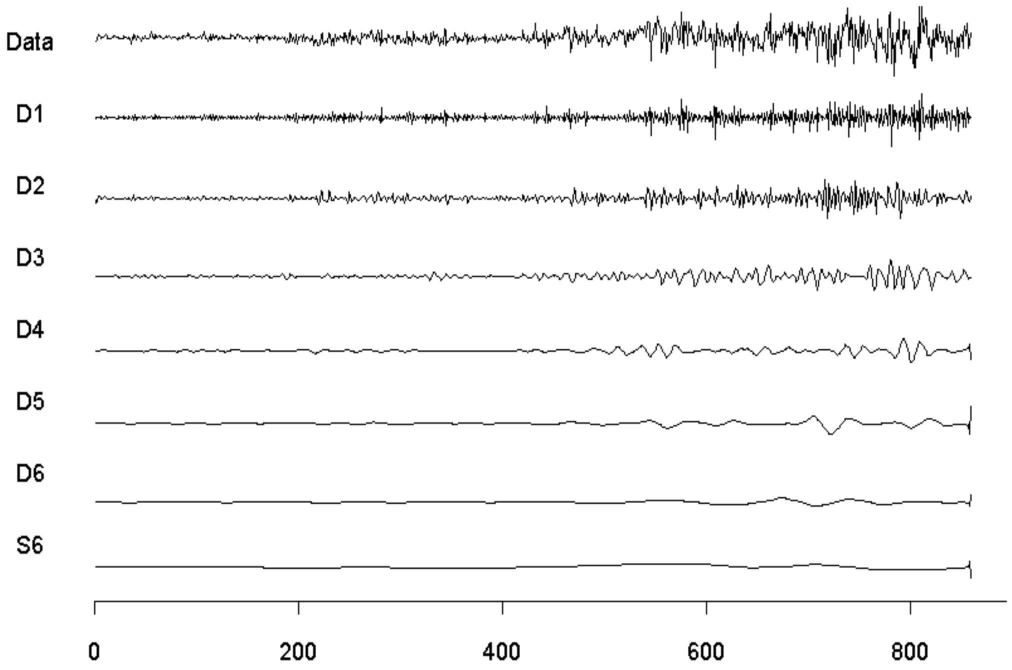


Figure 3. Multiresolution Decomposition of Daily Index Returns (Continued)

(c) KOSDAQ



(d) NASDAQ

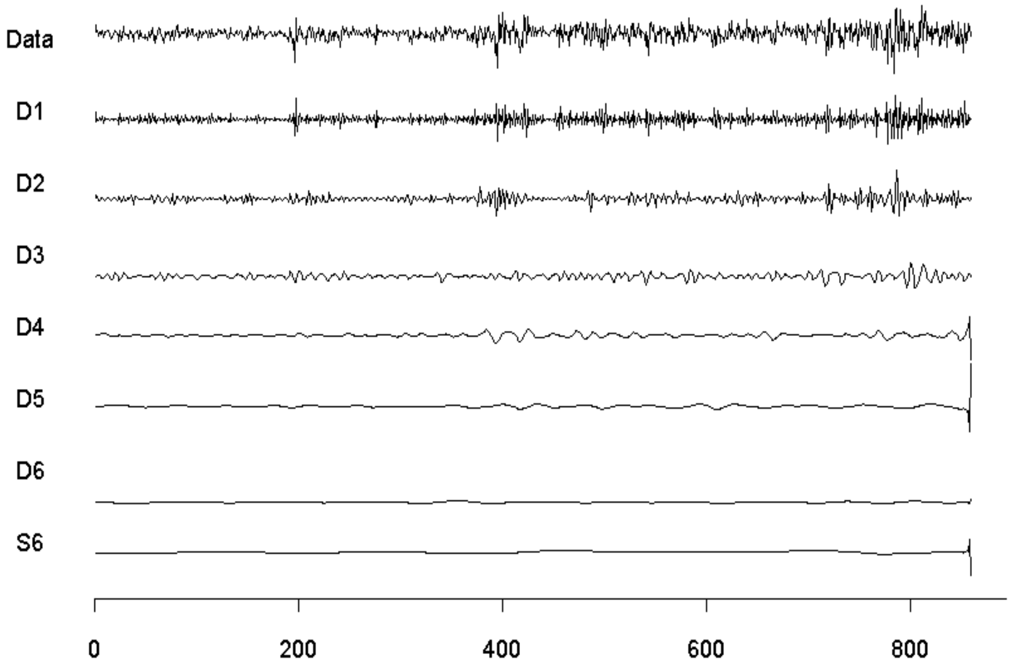
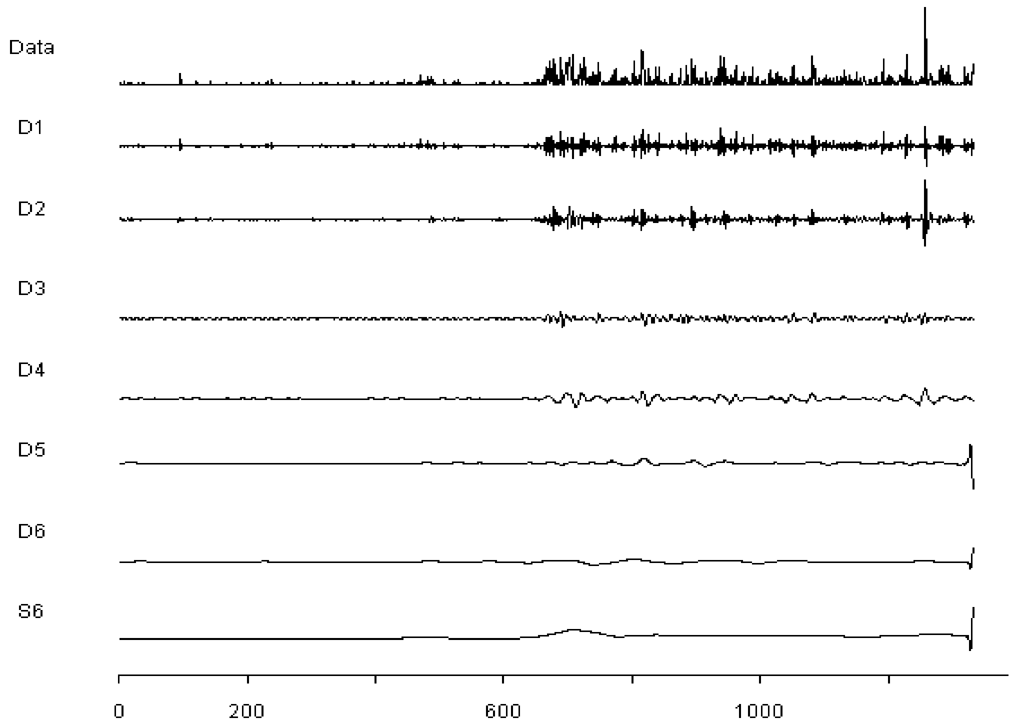


Figure 4. Multiresolution Decomposition of Squared Returns

(a) KOSPI



(d) NASDAQ