Volatility Spillovers in Asian Bond Market:
A Wavelet Analysis

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Volatility Spillovers in Asian Bond Market: A Wavelet Analysis

Abstract

This paper uses wavelets method to decompose the bond return and study the volatility spillovers from other bond markets into the Asian local currency bond markets. Instead of using the popular method GARCH to estimate volatility, this paper uses wavelet to derive volatility from the data. Similar to Lee (2004), the decomposed data were used as proxies for volatilities. Nevertheless, the square of return was not used as volatility. Instead, "noise" (volatility) derived from mother wavelets was squared and used as volatility. The advantages of such method are (1) no assumption is made on how volatility (variance) should behave and (2) volatility spillover effects can be investigated for more than one time scale. Result show that US bond market has a higher effect on Asian Bond Market compared to Japan bond market. Despite the Asian exchange rate system, the magnitude of volatility spillovers from Japan and US to Asian Bond is limited, hence providing portfolio diversification for international investors. The results in this paper also show that the Asian bond markets can affect the more developed bond markets.

1. Introduction

Financial markets have become more integrated over the years due to financial market deregulation, advances in information technology and the development of standardised regulations. As a result, they have become more interdependent and new information in the financial markets can be accounted for more rapidly in the asset's price.

Volatility is an important component in the asset-pricing model of Sharpe (1964) and the option-pricing model of Black and Scholes (1973). It is important to understand market volatility spillover (or linkage) because of the high degree of market interdependence. Previous studies on financial markets have found that the second moment of financial markets provide more insight into the behaviour of the market. As indicated by Kyle (1985), much of the information is revealed in the volatility of the price of stocks, rather than the prices themselves. Indeed, Kirchgassner and Wolters (1987) noted that instantaneous relations among bond yield innovations are probably more important than simple Granger causal relations.

Most cross-border volatility spillover studies have reported that information flows between markets causes volatility linkages between them. Ross (1989) used a no-arbitrage model to show that information transmission is primarily related to the volatility of stock prices. Studies that are based on the relation between volatility and information include Harvey and Huang (1991), Ederington and Lee (1993), and Fleming, Kirby and Ostdiek (1998). A related study by Engle and Ng (1993) measured how new information is incorporated into volatility estimates.

Studies which show the importance of market linkages include Milunovich and Thorp (2006). They find that accounting for volatility spillovers in conditional covariance forecasts leads to improvements in portfolio efficiency. Findings in Brzesczynski and Welfe (2007), based on Poland's stock market, also suggest that there may be benefits to investors who use a trading strategy which exploits return spillovers from major to emerging stock markets. In contrast, the empirical results of McAleer and da Veiga (2008) suggest that the inclusion of spillover effects is not important in forecasting the Value at Risk (VaR) threshold even though the spillover effects are statistically significant. Following the Asian financial crisis, the Asian governments wanted to develop their local currency bond markets as an alternative source of funds for the region. The Asian governments generally believed that the over reliance on short-term foreign borrowing resulted in the vulnerability of the overall financial system in Asia, thus attributing to the Asian financial crisis. The regional governments believed that with a developed local currency bond market, the effect of the Asian crisis could be mitigated as the Asian bond markets would act as the alternative source of funds when funding from other sources dried up. However, if there are strong linkages between the Asian bond and other financial markets, the Asian bond markets may not have served the purpose of mitigating the effects of other financial crises.

The objective of this paper is to study how, and to what extent, volatility in the Asian local currency bond market is influenced by the global and regional bond markets. The study of the emerging bond market is important because first of all, it is denominated in local currency. With the regions' monetary policies, it offers a good opportunity to study bond market linkages. The impact of US bond market on Asian bond markets is likely to be affected by the region's monetary policy because the Asian central banks manage their currency against a basket of currencies, with the US dollar playing the most important role. Instead of using the popular method GARCH to estimate volatility, this paper uses wavelets to derive volatility from the data. The advantages of such method are (1) no assumption is made on how volatility (variance) should behave and (2) spillover effects can be investigated for more than one time scale. The limitation of this study is the data was collected in 2006 and data has not been extended. Nevertheless, the data provide some interesting insight about the East Asian Emerging bond market.

To date, there are few studies that apply wavelet in the study of volatility spillovers between financial markets. Lee (2004) applies the discrete wavelet transform (DWT) and multiresolution decomposition (MRD) to investigate the return and volatility spillover effects between the US and Korean stock markets. The wavelet transform was used to decompose stock market returns into an orthogonal set of components with different frequencies. The data was then reconstructed using 'crystals'. Transmissions between the markets were investigated by examining the relationships between high-frequency fluctuations in the stock market data. The result showed that movements in stock returns are mainly caused by short-term fluctuations. To study the short-term variations, only scale D1 (1-2 day time scale) and D2 (2-4 day time scale) were examined. Fernandez (2004) examines return spillovers in the stock markets using different time scales, a similar methodology adopted by Lee (2004). This study examines eight indices of the G7 countries, namely, Emerging Asia, Europe, Eastern Europe, the Middle East, Emerging Far East, Latin America, North America, and the Pacific regions for the period 1990-2002. The results suggest evidence of price spillovers from the G7 countries to Europe, Eastern Europe, the Middle East, Emerging Asia, Europe, Latin America, and North America. Wavelet correlation was also used to examine integration of emerging stock markets. Gallegati (2005) used weekly stock market returns to study market integration of MENA8 with developed markets in the US and Europe. The wavelets correlation analysis showed that the stock markets become more correlated as the time horizon increases. Recent papers on wavelet application in volatility spillover study include the work of Huang (2011), Graham and Nikkinen (2011) and Madaleno and Pinho (2011).

Wavelets have also been applied to study systemic risk. For instance, Gencay et al. (2005) and Fernande (2006) apply wavelet analysis to the study of the Capital Asset Pricing Model (CAPM). Masih et al. (2010) applies wavelet based CAPM to analysis of the Gulf stock markets.

The paper is organized as follows. Section two briefly discusses wavelet theory and how it can be applied in this paper. Section three provides a preliminary analysis of the data and the methodology used to examine volatility spillover effects. Section four discusses the empirical results and the implications of results. Section five concludes.

2. Wavelet Theory and application in volatility study

The main feature of wavelet analysis is that it enables the researcher to break down a signal into its constituent multiresolution components. Among all wavelet classes, the Haar wavelet is the least smooth and is therefore, useful in representing the time path of a Poisson process. In this case, the Haar wavelet can best be used to analyse financial data. Short-term traders evaluate the market at a higher frequency and have a shorter memory than long-term investors.

The origin of wavelets can be tracked back to the Fourier analysis which provides the foundation of modern time-frequency analysis. For a brief historical review of wavelet theory, see Meyer (1993), Daubechies (1992), Graps (1995), and Hubbard (1998). The development of wavelets is mainly in 3 fields at the beginning, mathematics, signal-processing and image analysis. Due to the statistical properties of wavelets, they have been developed and applied in other field recently, example in nonparametric regression, nonparametric density estimation, time series modeling and forecasting.

Unlike Fourier analysis which is localized only on the frequency domain, wavelet analysis is better for handling financial time series because firstly, wavelets are localised in both time and frequency domain, and hence, more useful in handling non-stationary data and secondly, wavelets can separate the financial data into multiresolution components. Basically, wavelets can 'cut up' the data into different frequency components.

In general, there are two basic wavelet functions: father and mother wavelets which are denoted in $\varphi(t)$ and $\psi(t)$.

$$\varphi_{j,k} = 2^{-\frac{1}{2}}\varphi\left(\frac{t-2^{j}k}{2^{j}}\right) \tag{1}$$

$$\psi_{j,k} = 2^{-\frac{1}{2}}\psi\left(\frac{t-2^{j}k}{2^{j}}\right) \tag{2}$$

The father wavelet integrates to 1 and the mother wavelet integrates to 0.

$$\int \varphi(t)dt = 1 \tag{3}$$

$$\int \psi(t)dt = 0 \tag{4}$$

Father wavelets are good at representing the smooth and low frequency part of a signal, whereas mother wavelets are good at describing those detailed and high frequency components i.e., noise. They are used in pairs within a family of wavelet functions, with the father wavelets used for the "trend" components and the mother wavelet used for the "deviation" from trends. The wavelet representation of the signal or function $f(t)$ in $L^{2}(R)$ can be given by

$$f(t) = \sum_k s_{J,k}\varphi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \ldots + \sum_k d_{j,k}\psi_{j,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t) \tag{5}$$

where J is the number of multiresolution components or scales, and k ranges from 1 to the number of coefficients in the specified components. The coefficients $s_{J,k}, d_{J,k}, \ldots, d_{1,k}$ are the wavelet transform coefficients, the magnitude of which reflects a measure of the contribution of the corresponding wavelet function to the total signal.

The smooth coefficients $s_{J,k}$ capture the smooth behavior of the signal at the coarsest scale 2_J. The detail coefficients $d_{1,k}, \ldots, d_{j,k}, \cdots d_{J,k}$, capture the deviations from the smooth signal, and provide progressively finer scale deviations. Each set of the coefficients $s_{J,}d_{J},d_{J-1},...,d_1$ is called crystal. The multiresolution decomposition of the original signal $f(t)$ is given by the following expression:

$$f(t) = S_J + D_J + D_{J-1} + ... + D_j + ... + D_1 \qquad (6)$$

where $S_J = \sum_k s_{J,k}\varphi_{J,k}(t)$ and $D_j = \sum_k d_{J,k}\psi_{J,k}(t)$ with j=1…J. The sequence $S_J, D_J, ..., D_j, ..., D_1$ represents the set of signal components at different resolution levels 1 to J., and detail signals D_j show the increment at each individual scale, or resolution level. The high-frequency components can be observed using the small window and the low-frequency components can be observed using the large window.

In wavelet analysis, Discrete Wavelets Transform (DWT) is commonly used to calculate the coefficients in (6). Although DWT is popular, it requires the original data to have a sample size N equal to the power of two in order achieve an exact orthogonal. An alternative, the Maximal Overlap Discrete Wavelet Transform (MODWT) can handle any sample size N[1] and it is used in this research to avoid preconditioning the data to a power of two. Other than skipping the downsampling of the data, the MODWT-based Multiresolution Analysis (MRA) process is the same as the DWT-based MRA. Another advantage of using MODWT is that when MODWT-based MRA is applied, the type of wavelet used will have less effect on the pattern of the data. To distinguish the properties between DWT and MODWT, see Percival and Walden (2000).

[1] See Percival and Mofjeld (1997) for properties that distinguish DWT and MODWT.

2.1 Applying Wavelet Multiresolution Analysis (MRA) to Bond Data

The idea of volatility spillover test using the wavelet multiresolution decomposition approach is to derive the unexpected changes in price volatility using mother wavelets. The success of wavelets in detecting data structure breaks makes it a very attractive tool to study volatility spillover (see Fernandez, 2005). By using wavelet analysis, rapid changes in volatility will stand out at the smallest scale, and as the scale increases, the changes tend to be smoothed out. The volatility spillover effect can then be obtained by examining the relationship between high fluctuations in the data.

The data in the present study was decomposed into different time scales using the chosen type of wavelet. The first level of decomposition examined data based on a time scale of 1-2 weeks. The second level of decomposition examined data based on a time scale of 2-4 weeks. The higher the level of decomposition, the lower the time frequency will be. See Figure 1 on decomposition of bond data up to level 3. In contrast to other econometric methodologies, wavelet does not estimate volatility. Instead wavelet derives volatility by placing the data in a small window where the smallest scale of the data (high frequency data) can be examined. Rapid changes in volatility stand out at the smallest scales (i.e. highest frequencies); therefore by decomposing the data into different time scales, volatility is derived from data at the smallest time scale. In doing so, no assumption about the properties of the data will be made. Wavelets are especially useful in detecting signals that last for a finite time and showing different behaviours in different time periods. Wavelets are well suited to detect discontinuities and sharp spikes (For a comprehensive application of wavelets to time series, refer to Percival and Walden, 2000). At the first level of decomposition, A1 (approximation at first level), which is the overall trend of the data, and a D1 (detail at first level), which is the "noise" from week 1-2. At second level of decomposition, we get A2 (approximation at second level), and a D2, which is the "noise" from week 2-4.

3. Background of the Asian Bond Markets and Preliminary Analysis of Data

The development of local currency bond markets is fairly mixed, with some countries having more success and some at a very nascent stage[2]. Bonds in Asian bond markets are denominated in local currency and also in foreign currencies such as the US dollar, Euro and Yen, with the Asian dollar bond having the biggest market share. The issuance of local currency bonds is limited due to the lack of demand from investors and the lack of supply, which is a result of the Asian corporations' reliance on equity and bank financing. After the Asian crisis in 1998, large corporations have started issuing local currency bonds but most of the issuers are government-linked corporations. Asian governments and blue chip corporations issue bonds in foreign currencies in the US and European markets, and a smaller proportion of bonds is issued in Hong Kong and Singapore markets.

Since the Asian crisis, regional governments have sought to mitigate over-reliance on the banking sector and develop the region into a more efficient regional financial market by encouraging bonds as an alternative source of financing. Also, the governments of Hong Kong, Malaysia and Singapore were encouraged to develop local currency bonds as potential investment instruments for their growing pension funds and insurance institutions. The value of the East Asian emerging local currency bond markets

[2] Most of the Asian central banks' official websites provide information on their local currency bond market development.

reached approximately US$2.4 trillion[3] by the end of 2005 and the market size is expected to increase with the growing economies. Asian governments were also keen to promote the development of local currency bonds to keep Asian savings within the region. To assist the process, the Asian Bond Fund was launched in 2003 with contributions of foreign reserves from various Asian countries. The fund is used to purchase local currency bonds. The Emerging East Asian bond market excluding PRC was reported to be US$1,794 billion in third quarter 2009. This is a huge increase compared to fourth quarter 1996 where the bonds issued were US$475 billion.

Most of the bond markets in the Asia are mainly denominated in their local currency, except for Japan, Hong Kong and Singapore which is financial centre and has their own foreign currency bond markets since the 1970s. With most transactions carried out over the counter (OTC), the secondary markets are not very active. Usually the largest holders of bonds are the institutional investors. Very often financial institutions, insurance companies and mandatory saving funds are required to invest a certain percentage of their funds in the government bonds and high quality corporate bonds, including bonds issued by state enterprises. In general, these institutional investors buy and hold the bonds until maturity, thus contributing to the illiquidity of Asian bond markets. Among the Asian countries except Japan, Korea has the largest bond market in terms of size. The Korean bond market surpasses its equity market and has probably the largest number of public and private bond issues.

As far as the credit ratings of Asian bonds are concerned, Hong Kong and Singapore rely on international credit rating agencies while South Korea, Malaysia and Thailand have domestic rating agencies that are affiliated to their governments. Hence,

[3] Asian Bond Monitor Complete Report, Nov 2006, Asian Development Bank. See http://www.adb.org.

international rating agencies, which offer objective analyses with regard to Asian bonds, play a significant role in the Asian bond markets. The bonds issued by the state enterprises, government-linked corporations and statutory boards are implicitly guaranteed by their local governments. Therefore, they have the same rating as the government bonds. Most of the corporate bonds are short to medium term and this has become a popular trend in the post-crisis period.

The data used are weekly bond data obtained from Reuters and DataStream. All data for bonds, except the US bond data, were obtained from the Reuters Fixed Income Database; and data for the US Treasury bonds were obtained from the DataStream database. Benchmark issues of the Asian government bonds were used. The data for stock indices and foreign exchange markets were all from DataStream. Indonesia is omitted from this study due to lack of sufficient data.

The starting date of the sample was dictated by the availability of the data. The sample period for all data ended on 24 December. The difficulty of data collection was complicated by the fact that most of the trading of these Asian bonds takes place over the counter and the bond market is illiquid.

The cross-border study is applied to the fixed income data from Asian bond markets, the Japanese bond market and the US bond market. Weekly data rather than daily data were chosen for this study for a number of reasons. Weekly data are used to avoid the problem of nonsynchronous trading and the day-of-the-week effects. The Asian bond markets have overlapping trading hours with the Tokyo market, the analysis of daily data would introduce information resulting from half day's news; this would result in non-simultaneous observation. Another reason is that daily data for Asian local currency bonds would not be easily available.

There were some missing data for Asian bonds. With the exception of Singapore 2-year bonds (SG2), the missing data was filled with the yield for the previous week when the missing data are no more than two consecutive weeks. It was assumed that the missing data was due to inactive trading. This assumption is not unreasonable because trading in Asian local currency bond markets is sparse and hence the markets are illiquid. However, in the case of SG2, the missing gap was too big to be accounted for by inactive trading (7-weeks data from 8 April 2001 to 20 May 2001 were missed). For this period, official data from the Monetary Authority of Singapore were used instead.

3.1 Preliminary Analysis

Table 1 shows the descriptive statistics for the return of Asian bonds in the cross-border study.

<Insert Table1>

Table 1 shows the benchmark issued by the Asian governments. Trading in these markets is sparse and liquidity may be an issue in these markets. The mean showed Taiwan 5-year bond, TW5, has the highest negative return followed by Taiwan 10-year bond, TW10. TW5 has a mean return of –0.241 and TW10 has a mean return of –0.221. Thai 7-year bond, TH7, has the highest positive return at 0.077. All the Hong Kong bonds, Korean bonds and Taiwan bonds have negative returns. In Malaysia bond market, the MY3 has negative mean return while MY10 has positive return. For Singapore bond market, all the bonds have negative mean returns except SG2. SG2 has a positive mean return. In Thai bond market, TH” and TH5 have negative mean returns while TH7 and TH10 have positive mean returns. Overall, most of the Asian bonds have negative returns.

Hong Kong 2-year bond, HK2, has the highest standard deviation at 7.129. In term of country, Thailand has the highest standard deviation for most of it bonds except TH7. TH2, TH5 and TH10 have standard deviation of over 6. All the Asian bonds are positively skewed except MY3 and TH10. MY3 has a skewness of –3.171 and TH10 has a skewness of -0.296. TW2 has the highest skewness at 2.408, followed by INDO3 at 1.906. All Hong Kong bonds and Korean bonds have skewness of lower than 1. HK5 has the lowest skewness at 0.035, followed by HK10 at 0.107. Huang and Yang (2000) and Tay and Zhu (2000) have documented positive and / or negative skewness in the Asian stock markets.

All the kurtoses are higher than 3 indicating that the returns are leptokurtic. For most Asian bond markets, the short-term bonds (2-year and 3-year bonds) have the highest kurtosis. TH2 has the highest kurtosis at 44.799, followed by MY3 at 35.841. HK3 has the lowest kurtosis at 4.033, followed by KR10 at 4.055. Comparing the bond markets, on average the Hong Kong and Korean bond markets have lower kurtoses than the other markets. These kurtoses showed that Asian bonds are of normal distribution. Bekaert and Harvey (1999) find excess kurtosis in the Asian stock markets. Hence, it is not surprising that returns from Asian bond markets have a high kurtosis. The results of Jarque-Bera (J-B) test and Kolmogorov-Smirnov (K-S) test showed that Asian bond returns are not normally distributed. The null hypothesis for the

J-B test and K-S test is the bond returns are normally distributed. The zero P-value indicates that the null hypothesis is rejected at 1% significant level for all Asian bonds.

3. Methodology

Instead of making a paired comparison between the volatilities as in Lee (2004) and Fernandez (2004), a regression was run on all the independent variables. But similar to Lee (2004), the decomposed data were used as proxies for volatilities. Nevertheless, the square of return was not used as variance. Instead, the wavelet derived from “noise” (volatility) was squared and used as volatility. The square returns were omitted in the study because they are a very noisy, though unbiased measure of volatility (Anderson and Bollerslev 1998).

The equations for cross-border spillover study using regression and wavelets at D1 scale are as follows:

$$R\_D1^2_{A,t} = c_A + \delta_A R\_D1^2_{A,t-1} + \gamma_A R\_D1^2_{JP,t-1} + \lambda_A R\_D1^2_{US,t-1} + \varepsilon_{A,t} \qquad (7)$$

$$R\_D1^2_{JP,t-1} = c_{JP} + \gamma_{JP} R\_D1^2_{JP,t-1} + \delta_{JP} R\_D1^2_{A,t-1} + \lambda_{JP} R\_D1^2_{US,t-1} + \varepsilon_{JP,t} \qquad (8)$$

$$R\_D1^2_{US,t} = c_{US} + \lambda_{US} R\_D1^2_{US,t-1} + \delta_{US} R\_D1^2_{A,t-1} + \gamma_{US} R\_D1^2_{JP,t-1} + \varepsilon_{US,t} \qquad (9)$$

D1 represents volatility at the smallest scale, 1-2 weeks. The individual bond market lagged effect was included. To take into account the effect of reverse causality, a reverse regression was run. The parameters δ_A, γ_{JP} and λ_{US} show own market lagged volatility. γ_A and λ_A represent the volatility spillovers from the Japanese and US bond markets to the Asian bond market; δ_{JP} and λ_{JP} from the Asian and US bond markets to the

Japanese bond markets, and δ_{US} and γ_{US} from the Asian and Japanese bond markets to the US bond markets. This model is denotes as Model 1.

Next, we consider volatility at D1+D2 scale, which is measured by components (D1+D2).

$$R\_(D1+D2)^2_{A,t} = c_A + \delta_A R\_(D1+D2)^2_{A,t-1} + \gamma_A R\_(D1+D2)^2_{JP,t-1} + \lambda_A R\_(D1+D2)^2_{US,t-1} + \varepsilon_{A,t}$$

(10)

$$R\_(D1+D2)^2_{JP,t} = c_{JP} + \gamma_{JP} R\_(D1+D2)^2_{JP,t-1} + \delta_{JP} R\_(D1+D2)^2_{A,t-1} + \lambda_{JP} R\_(D1+D2)^2_{US,t-1} + \varepsilon_{JP,t}$$

(11)

$$R\_(D1+D2)^2_{US,t} = c_{US} + \lambda_{US} R\_(D1+D2)^2_{US,t-1} + \delta_{US} R\_(D1+D2)^2_{A,t-1} + \gamma_{US} R\_(D1+D2)^2_{JP,t-1} + \varepsilon_{US,t}$$

(12)

D1+D2 represents volatility at 1-4 week time scale. The parameters δ_A, γ_{JP} and λ_{US} are the effects of its own lagged volatility (D1+D2). γ_A and λ_A represent volatility (volatility at 1-4 week time scale) spillover from the Japanese and US bond markets to the Asian bond market; δ_{JP} and λ_{JP} from the Asian and US bond markets to the Japanese bond market, and δ_{US} and γ_{US} from the Asian and Japanese bond markets to the US bond markets. The advantage of using this model is to understand the extent of volatility spillover over different time scales. The decomposed data shows that most of the data fluctuations concentrated on level 1 and 2; hence we keep our study to volatility at 1-2 week time scale (D1) and 1-4 week time-scale (D1+D2). This model is denotes as Model 2.

4. Empirical Results

The parameter for the spillover effect from the Japanese bond market is γ_A and the parameter for US volatility spillover effect is λ_A. There is a volatility spillover from Japan if $\gamma_A \neq 0$ and the estimated spillover effect is statistically significant at 1%, 5% or 10%. There is volatility spillover from US if $\lambda_A \neq 0$ and the estimated effect spillover effect is statistically significant at 1%, 5% or 10%. While δ_A refers to Asian own market lagged volatility effect.

4.1.1 Volatility Spillovers from Japan and US to Asian Bond Markets

Table 2 shows the spillover effects to Hong Kong bond market. As indicated in the result at the 1-2 week time scale, the own volatility effects are high, ranging from 0.351 to 0.540, all the effects are statistically significant at the 1% level. This effect is similar to the ARCH effect demonstrated in the GARCH model. The volatility spillover effects from the Japanese bond market do not show a clear trend and the parameters are not statistically significant. Therefore, no volatility spillover from Japan is found. However, volatility spillovers from the US bond market to HK2, HK3 and HK10 are observed. These spillover effects are statistically significant at the 10% level but the effects are rather small. The spillover effects are positive for HK2 (0.150) and HK3 (0.085) but negative for HK10 (-0.054). In Model 1b, the own lagged volatility spillovers are statistically significant at the 1% level for HK2 and HK10 but at the 5% level for HK5. The effects of own volatility spillover are lower in the 1-4 week time scale. The volatility spillover from Japan bond market to HK10 is 0.014 (statistically significant at the 10% level), and that from US bond market to HK2 is 0.164 (statistically significant at the 10% level). To sum up, it is observed that the Hong Kong bond market is affected by its own lagged volatility and the volatility effects from the US bond market is higher for HK2, a short-term bond. Here the US volatility spillover effect is found to be greater than that of Japan. All the results related to the Hong Kong market indicate that the volatility spillovers occur at the shortest time scale.

<Insert Table 2>

For the Korean bonds, as indicated in Table 3, the own volatility of the Korean bond market is statistically significant at the 1% level for all bonds. The effect of its own volatility increases as the bond maturity gets longer. It ranges from 0.341 for KR2 to 0.553 for KR10. There is a volatility spillover from the Japanese bond market to KR2 but the effect is negligible although the spillover is statistically significant at the 10% level. The US volatility spillover to KR10 is 0.161 (statistically significant at the 1% level). In equation at the 1-4 week time scale, the own lagged volatility of all the Korean bonds are statistically significant at the 1% level and the effects are about 0.3, except for KR2. There is no own volatility spillover effect for KR2. The Japanese volatility spillover to KR2 is statistically significant at the 10% level but the effect is small at 0.001. The US volatility spillovers to KR2 and KR10 are at 0.022 (statistically significant at the 5% level) and 0.099 (statistically significant at the 10% level) respectively. It is found that the US volatility spillover effect is greater than that of Japan. Korea's own bond market volatility dominates.

<Insert Table 3>

Table 4 shows that most of the cross-border spillover effects to the Malaysian market are negative and none of the spillover is statistically significant at either the 1%, 5% or 10% levels. There is no volatility spillover from the Japanese and US bond markets. Malaysian bond market volatility is mainly due to its own lagged volatility. Malaysia own volatility effects in a 1-2 week time scale at 0.217 for MY3 and 0.525 for MY10. Both effects are statistically significant at the 1% level. As shown in the result for 1-4 week time scale, MY10's own volatility is at 0.281 and statistically significant at the 1% level. The result indicates that most of the volatility effects concentrate on the shortest time scale. The own volatility in Malaysian bond market dominates.

<Insert Table 4>

Table 5 presents the results of spillovers to Singapore bond market. In result for 1-2 week time scale, Singapore's own lagged volatility is statistically significant at the 1% level, with effects ranging from 0.201 to 0.504. SG2's own volatility effect has the highest at 0.504. SG5, SG7 and SG10 are all affected by volatilities from the Japanese bond market. Although the spillover effects are small (below 0.1), they are statistically significant at the 1% level. There is no volatility (1-2 week time scale) spillover effect from US bond market to Singapore. SG2 is not affected by volatility from the Japanese and US bond markets. In 1-4 week time scale, only SG2's own lagged volatility is statistically significant at the 1% level, while its own volatility effect is not statistically significant for other benchmarks. Similar to the results found in 1-2 week, Japanese volatility spillovers to SG5, SG7 and SG10 are observed (statistically significant at the 1% level). US volatility spillover to SG7 is observed (effect at 0.134 and statistically significant at the 5% level). The own volatility of Singapore's bond market dominates. Overall, the Singaporean bond market is more exposed to the Japanese bond market even though the spillover effect is small but the effects are highly statistically significant. The results also show that volatility spillovers occur at the 1-2 week time scale.

<Insert Table 5>

Table 6 shows the spillover effects to Thai bond market. In 1-2 week time scale, Thailand's own lagged volatility is statistically significant at the 1% level. The effects are very high, ranging from 0.390 to 0.627 at the 1-2 week time scale. The US volatility spillover to TH10, which is statistically significant at the 1% level, is observed. The spillover effect is very high at 4.361. For 1-4 week time scale, Thailand's own lagged volatility is statistically significant at the 1% level for all bonds except TH7. The own lagged volatility is statistically significant at the 5% level for TH7. All the own lagged volatility effect is lower in 1-4 week time scale. The US volatility spillover for TH10 has a magnitude of 3.279 which is significant at the 1% level. Most of the Japanese volatility spillover effects are negative but the spillover parameters are not statistically significant. The Thai bond market volatility depends on its own lagged volatility. Except for TH10 there is no volatility spillover from other bond markets to the Thai bond market.

<Insert Table 6>

Table 7 presents the results of spillovers to Taiwan's bond market. In Model 1 at a 1-2 week time scale, Taiwan's own lagged volatility is statistically significant at the 1% level. The effects range from 0.310 to 0.616. Volatility spillovers from Japan to TW2 and TW5 are observed, which is 0.115 at the 1% significant level for TW2 and 0.012 at the 10% significant level for TW5. The volatility spillover effect from the US bond market to TW10 is –0.119 and statistically significant at the 10% level. In Model 2, Taiwan's own lagged volatility is statistically significant at the 1% level. The volatility spillover effect from Japanese bond market to TW2 is 0.154 and statistically significant at the 1% level, which is higher than the effect at the 1-2 week time scale. The findings indicate that the Taiwanese bond market is more exposed to Japan's bond market. Overall speaking, Taiwanese bond market's own volatility dominates.

<Insert Table 7 >

From Table 2 to 7, we can see that most of the spillover effects are positive and the cross-border spillover effects are rather small, with the effect of the US being higher than that of Japan. The highest volatility spillover is from US to TH10 at 4.361 (1-2 week time scale) which is statistically significant at the 1% level. Most of the Asian 10-year bonds are affected by the US 10-year bonds. In conclusion, the volatility of most Asian bonds is affected by its own lagged volatility. The volatility effect is more evident at the 1-2 week time scale. Comparatively speaking, it is found that the Hong Kong bond market is more exposed to the US bond market while the Singapore bond market is more affected by Japan than by US. Thai bond market is not affected by the Japanese bond market but the Korean and Taiwanese bond markets are more affected by both Japan and US though the spillover effects are very low. In general, Japan and US bond markets do not affect the Malaysian bond market.

Phylaktis's (1997) study of real interest rates in the Pacific-Basin region shows that the US exercises a stronger influence than Japan. However, her later study using another method shows an opposite result (Phylaktis, 1999). Though the Asian bond markets are affected by volatility from the Japanese and US bond markets, the spillover effects are small or negligible for most of them. While the Indonesian and Korean bond markets do not show any specific trend, results show that the Korean bond market is more independent, which is consistent with So et al. (1997) who studied the volatility in Southeast Asian stock markets.

Similarly, empirical results from the present study also show that volatility from Asian bond markets affect the bond markets in Japan and the US[4]. This can be due to several reasons. Firstly, there are high level of trade linkages between these Asian countries and Japan and the US; secondly, the Asian central banks hold most of their foreign reserves in US Treasury bond; and lastly, international investors rebalance their international portfolios for risk management purpose. The argument that volatility spillovers are greater from more developed markets to less developed ones is not always true. Results from Suilman (2005) study on US interest rate volatility and contagion effects suggest that the US nominal interest rates were affected by Mexican devaluations during period 1994-1998.

The results show no clear indication of whether the Japanese bond market or the US bond market has greater influence on the Asian bond markets but generally most of the results show that effect of volatility spillovers from Japan and US move in

[4] Tables on volatility spillover effects to Japan and US bond markets are available from author.

opposite direction. The US bond markets has a positive effect volatility spillover effect on the Asian bond markets could be because the Asian central banks hold most of their foreign reserves in the form of US Treasury bonds. Other explanations for these asymmetric effects are the countries' trade relations and exchange rate system. Ng (2000) study finds that the exchange rate changes and trade with Japan cause the volatility spillovers from Japan stock market to most Asian stock markets to be negative. While trade with US has a positive effect on the volatility spillovers from the US stock market. Durand et al. (2001) study on Asian stock market has also found that US shock has a positive effect on the Asian stock markets.

The empirical results from this cross-border study suggest that exchange rate system has no effect on the magnitude and direction of volatility spillover effects. Countries which fix their currencies against the US dollar do not show greater linkage with the US market. Similarly, countries that manage their exchange rates against the US dollar do not receive greater influence from the US bond market. This is consistent with the study by McCauley and Jiang (2004) which that shows that co-movement of Asian bonds and US Treasury notes does not seem to be related to the exchange rate policy.

5. Conclusion

One of the limitations of this research is the availability of data. Due to the short period of development of the Asian bond markets, data for some countries are limited. However, this set of Asian data offers some interesting results, showing, for example, that exchange rate systems do not seem to explain the volatility spillover patterns in the markets. We have also found that, despite these countries managing their currency against a basket of currencies (including the US dollar and Japanese Yen), there is no strong volatility spillover from the Japanese and US bond market. Another limitation is the study is restricted to unilateral study, it could be interesting to find out would the result differ when multivariate model is used for estimation of spillover effects.

Direction for future studies could include a comparison with other methods of volatility estimation and the predictability of wavelet-based volatility. With the increased in market volatility, it would be challenging to estimate volatility. Wavelets provide an alternative to the traditional method of volatility estimation.

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Figure 1: Wavelet decomposition process up to level 3 using MODWT

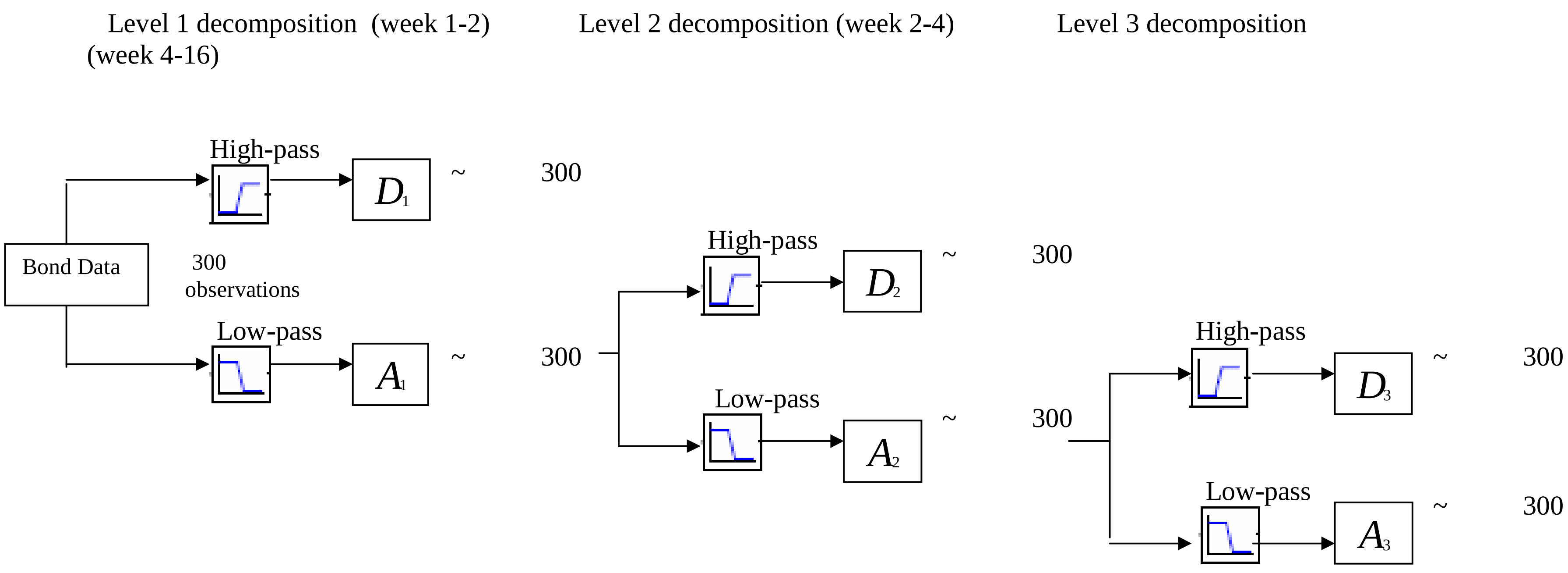

Table 1: Descriptive Statistics for Cross-border Data

	HK2	HK3	HK5	HK7	HK10	KR2	KR3	KR5	KR10
Starts	7/4/1999	9/9/2001	2/14/1999	5/23/1999	8/2/1998	3/3/2002	3/3/2002	3/3/2002	3/23/2003
End	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006
No. of Obs	391	277	411	397	439	252	252	252	197
Mean	-0.150	-0.043	-0.140	-0.152	-0.216	-0.071	-0.081	-0.128	-0.004
Std Dev	7.129	5.639	3.703	3.181	2.331	2.310	2.793	3.105	2.556
Skewness	0.653	0.596	0.035	0.315	0.107	0.318	0.765	0.933	0.567
Kurtosis	8.294	4.033	5.619	4.592	4.642	5.698	5.498	5.614	4.055
JB test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
K-S test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	MY3	MY10	SG2	SG5	SG7	SG10	TH2	TH5	TH7	TH10	TW2	TW5	TW10
Starts	1/20/2002	12/30/2001	7/11/1999	7/8/2001	5/23/1999	10/7/2001	5/9/1999	12/30/2001	6/13/2004	12/30/2001	1/27/2002	3/7/1999	1/10/1999
End	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006	12/24/2006
No. of Obs	258	261	390	286	397	273	399	261	133	261	257	408	416
Mean	-0.076	0.011	0.072	-0.070	-0.066	-0.074	-0.109	-0.175	0.077	0.024	-0.096	-0.241	-0.221
Std Dev	3.027	2.617	5.491	4.021	3.428	3.264	6.437	6.181	2.498	6.101	6.099	3.419	3.375
Skewness	-3.171	1.355	1.198	0.858	1.067	0.632	0.942	1.258	0.825	-0.296	2.408	0.869	0.353
Kurtosis	35.841	10.065	10.265	8.687	9.394	6.959	44.799	27.417	4.947	9.782	33.427	9.160	6.424
JB test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
K-S test	0.008	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: All data except HK2, HK5, HK7, HK10, SG2, SG7, TW5 and TW10, were collected in 2006.
For HK2, HK5, HK7, HK10, SG2, SG7, TW5 and TW10, data prior to 3 October 2004 were collected in 2004.
The results for Jarque-Bera (J-B) test and Kolmogorov-Smirnov (K-S) test are in P value. H0: data is normal distribution.

Table 2: US and JP on HK

	constant	HK_D1(-1)^2	JP_D1(-1)^2	US_D1(-1)^2	constant	(HK_D1(-1)+HK_D2(-1))^2	(JP_D1(-1)+JP_D2(-1))^2	(US_D1(-1)+US_D2(-1))^2
HK2	6.347*	0.525*	-0.001	0.150***	22.701*	0.187*	0.006	0.164***
	(3.180)	(11.785)	(-0.142)	(1.936)	(4.892)	(3.628)	(0.810)	(1.696)
HK3	4.440*	0.351*	0.002	0.085***	15.924*	0.045	0.005	0.054
	(4.288)	(5.828)	(0.331)	(1.799)	(6.519)	(0.707)	(0.699)	(0.936)
HK5	2.313*	0.407*	0.003	0.031	6.702*	0.125**	0.012	0.016
	(4.217)	(8.601)	(0.348)	(0.708)	(5.390)	(2.379)	(1.253)	(0.293)
HK7	1.790*	0.408*	-0.004	0.025	5.412*	0.088	-0.001	0.052
	(5.427)	(8.244)	(-0.605)	(0.645)	(7.118)	(1.626)	(-0.092)	(1.126)
HK10	1.306*	0.540*	0.003	-0.054***	3.731*	0.188*	0.014***	-0.005
	(5.284)	(11.943)	(0.428)	(-1.681)	(7.084)	(3.681)	(1.744)	(-0.123)

* denotes 1% statistically significant, ** denotes 5% statistically significant, *** denotes 10% statistically significant

Table 3: US and JP on KR

	constant	KR_D1(-1)^2	JP_D1(-1)^2	US_D1(-1)^2	constant	(KR_D1(-1)+KR_D2(-1))^2	(JP_D1(-1)+JP_D2(-1))^2	(US_D1(-1)+US_D2(-1))^2
KR2	1.045*	0.341*	0.001***	0.007	2.459*	0.075	0.001***	0.022**
	(4.348)	(5.723)	(1.648)	(0.843)	(4.397)	(1.170)	(1.704)	(1.962)
KR3	1.365*	0.421*	0.003	0.010	2.815*	0.253*	0.004	0.028
	(3.005)	(7.294)	(1.303)	(0.489)	(3.136)	(4.102)	(1.551)	(1.242)
KR5	1.969*	0.487*	0.001	-0.013	4.295*	0.277*	0.008	-0.016
	(3.477)	(8.647)	(0.116)	(-0.319)	(3.943)	(4.514)	(1.191)	(-0.378)
KR10	0.657**	0.553*	-0.005	0.161*	2.159*	0.275*	0.009	0.099***
	(2.238)	(8.982)	(-0.540)	(3.253)	(3.893)	(3.943)	(1.006)	(1.857)

* denotes 1% statistically significant, ** denotes 5% statistically significant, *** denotes 10% statistically significant

Table 4: US and JP on MY

	constant	MY_D1(-1)^2	JP_D1(-1)^2	US_D1(-1)^2	constant	(MY_D1(-1)+MY_D2(-1))^2	(JP_D1(-1)+JP_D2(-1))^2	(US_D1(-1)+US_D2(-1))^2
MY3	1.496*	0.217*	-0.002	-0.001	3.756*	0.048	-0.002	-0.008
	(4.248)	(8.610)	(-0.888)	(-0.073)	(4.817)	(1.354)	(-0.893)	(-0.408)
MY10	1.468*	0.525*	-0.008	-0.037	3.446*	0.281*	-0.006	0.007
	(2.974)	(9.829)	(-0.524)	(-0.440)	(3.638)	(4.661)	(-0.399)	(0.085)

* denotes 1% statistically significant, ** denotes 5% statistically significant, *** denotes 10% statistically significant

Table 5: US and JP on SG

	constant	SG_D1(-1)^2	JP_D1(-1)^2	US_D1(-1)^2	constant	SG_D1(-1)+SG_D2(-1))^2	(JP_D1(-1)+JP_D2(-1))^2	(US_D1(-1)+US_D2(-1))^2
SG2	5.737*	0.504*	0.005	-0.033	15.170*	0.234*	0.003	0.013
	(3.641)	(10.590)	(1.158)	(-0.520)	(4.733)	(4.699)	(0.419)	(0.256)
SG5	1.391**	0.204*	0.085*	0.015	5.832*	0.025	0.077*	0.014
	(1.994)	(3.758)	(9.569)	(0.297)	(3.411)	(0.406)	(6.322)	(0.201)
SG7	1.420*	0.348*	0.038*	0.034	4.895*	0.051	0.031*	0.134**
	(3.130)	(7.300)	(4.688)	(0.640)	(4.665)	(0.977)	(3.147)	(2.106)
SG10	1.854*	0.201*	0.061*	0.031	5.936*	-0.052	0.046*	0.067
	(4.841)	(3.343)	(5.094)	(0.528)	(6.206)	(-0.822)	(3.154)	(0.906)

* denotes 1% statistically significant, ** denotes 5% statistically significant, *** denotes 10% statistically significant

Table 6: US and JP on TH

	constant	TH_D1(-1)^2	JP_D1(-1)^2	US_D1(-1)^2	constant	TH_D1(-1)+TH_D2(-1))^2	(JP_D1(-1)+JP_D2(-1))^2	(US_D1(-1)+US_D2(-1))^2
TH2	5.784	0.601*	-0.004	0.283	14.176	0.487*	0.001	0.143
	(0.827)	(14.941)	(-0.186)	(1.067)	(1.238)	(11.054)	(0.042)	(0.603)
TH5	4.375	0.625*	-0.045	0.636	16.385	0.505*	-0.032	-0.118
	(0.677)	(12.832)	(-0.589)	(1.326)	(1.564)	(9.345)	(-0.463)	(-0.215)
TH7	0.914*	0.390*	-0.004	-0.022	1.971*	0.180**	0.014	0.058
	(2.972)	(4.705)	(-0.286)	(-0.275)	(3.094)	(2.004)	(0.915)	(0.663)
TH10	-4.467	0.627*	-0.095	4.361*	-0.295	0.478*	-0.089	3.279*
	(-1.299)	(13.610)	(-0.818)	(7.243)	(-0.050)	(8.708)	(-0.908)	(6.040)

* denotes 1% statistically significant, ** denotes 5% statistically significant, *** denotes 10% statistically significant

Table 7: US and JP on TW

	constant	TW_D1(-1)^2	JP_D1(-1)^2	US_D1(-1)^2	constant	TW_D1(-1)+TW_D2(-1))^2	(JP_D1(-1)+JP_D2(-1))^2	(US_D1(-1)+US_D2(-1))^2
TW2	0.757	0.310*	0.115*	-0.084	-2.619	0.159*	0.154*	-0.050
	(0.175)	(6.409)	(11.254)	(-0.534)	(-0.375)	(3.863)	(17.804)	(-0.347)
TW5	1.217**	0.616*	0.012***	-0.008	3.591*	0.351*	0.007	0.043
	(2.332)	(15.414)	(1.711)	(-0.200)	(3.563)	(7.383)	(0.859)	(1.001)
TW10	1.813*	0.603*	-0.002	-0.119***	5.523*	0.189*	-0.010	-0.034
	(4.670)	(14.692)	(-0.126)	(-1.859)	(6.931)	(3.692)	(-0.693)	(-0.484)

* denotes 1% statistically significant, ** denotes 5% statistically significant, *** denotes 10% statistically significant