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ALTERATION OF RISK IN ASIAN BOND MARKETS DURING AND AFTER MORTGAGE CRISIS: EVIDENCE FROM VALUE at RISK (VaR) ANALYSIS

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ABSTRACT

The bond market is an important source of corporate and national finance. In this study, we analyse the risk level of 10-year government bond yields of four leading Asian countries (South Korea, Japan, Malaysia and Singapore) for two different time intervals: during the period of the mortgage crisis, and the recovery. Risk measurement is conducted via Value at Risk (VaR) analysis, with models (GARCH (1.1) and FIGARCH (1.d.1)) in order to consider changes in variance over time. We also examine the credibility of VaR analysis via the Kupiec LR and DQ tests. According to the results, the highest risk level is seen in the Japan bond market for both periods. Another considerable implication is the significantly rising risk of the Japan bond market, even after the transition from crisis to recovery period. In addition, it is shown that the risk in the Malaysia bond market decreases during the recovery period. However, Kupiec LR and DQ backtesting results demonstrate that this finding is unverifiable.

Keywords: mortgage crisis, Asian bond market, VaR, FIGARCH, backtesting

INTRODUCTION

The Federal Fund rate was 6% as of the date of 16 May 2000, and decreased eleven times during the period of 2001, reaching it's the lowest level of 1% on 25 June 2003. Thereafter, it increased 17 times until 29 June 2006, but due to the

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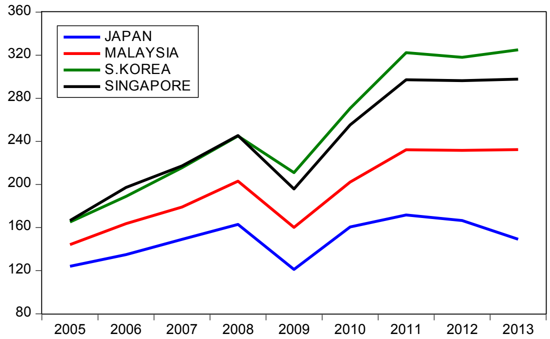
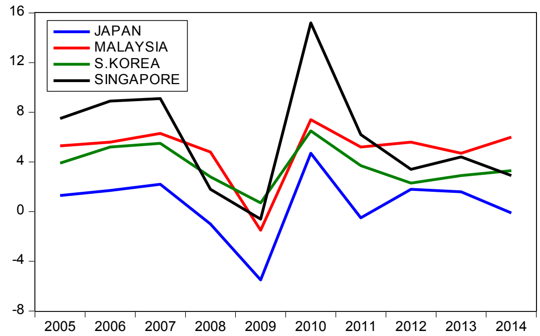
economic climate, the Federal Reserve Bank (hereafter the Fed) dropped it again to 0%–0.25% (see http://www.federalreserve.gov/monetarypolicy/openmarket.htm#calendars). As a result of the changing monetary policy of the Fed after the dot-com bubble in 2001, increases in interest rates have ruined and altered individuals and corporations' future plans and expectations. This was due to the concurrent rise in interest rates, and the sharp decrease in real estate demand and property value. The subsequent result of these developments was the wide-spread defaulting of mortgage credits, especially in sub-prime mortgages. According to the released statistics by the Chicago Fed, the default rate in sub-prime mortgage credits climbed to 25.48% in 2007, comparing to 11.19% in 2004. Spreading defaults in the securitisation market, which is one of the most important segments of the mortgage system, and doubts concerning the super high ratings of these instruments (such as risky CDO tranches), turned the real estate bubble into a financial crisis. The opacity of the financial positions of banks and other institutions causes unreliability among them, and thus triggers a liquidity crunch in the market. In addition, in the major banks search for alternative financing sources, the LIBOR rate severely and abruptly increased. The overnight LIBOR rate jumped from 2.15% to 6.44% after the collapse of Lehman Brothers. In the same period, the yearly loss of the DJI reached 19%. Eventually, in December 2008, NBER officially declared that the US economy has been in recession since December 2007. This was after they had considered the deteriorations in the statistics of the labor market and the gross domestic product. These developments have not been limited to the recession and collapses within the US economy, but they have also affected many countries' financial markets and companies from all over the world.

The mortgage crisis starts as of 31 July 2007 with the default of the two hedge funds of Bear Sterns, and peaks with the collapse of Lehman Brothers on 15 September 2008. During this period, Goldman Sachs and Morgan Stanley transform into commercial banks and Fannie Mae and Freddie Mac, which took part in the securitisation of mortgage credits, are nationalised using US$200 billion of treasury sources. The mortgage crisis shows its effect on other sectors as well. The automotive brands known as the Detroit Three (GM, Ford, and Chrysler) are saved from bankruptcy. The mortgage crisis, which now acts as a litmus test for the economic problems of Greece, has not only devastated the US economy, but it has also spread all over the world via the global integration of financial markets, including Asian markets. However, as stated by Shirai (2009) and Kawai (2009), low levels of subprime mortgage-related products in the portfolios of Asian financial institutions lead to a more stable performance during the mortgage crisis. The effect of the mortgage crisis on Asia was mostly in the real (manufacturing, industrial) sector and the export channel due to the sharp drop in demand in developed countries. These results can be seen in Figure 1.



Export value index (2000 = 100)



GDP growth (annual %)

Figure 1. Export and GDP growth of Asian countries
(Source: http://www.worldbank.org)

The bond market, which significantly indicates the borrowing cost of countries, is constantly monitored by investors as an indicator of risk perception. This study aims to analyse whether or not the mortgage crisis causes an alteration of risk in the bond markets of Asian countries: South Korea, Japan, Malaysia and Singapore. The risk structure of these countries' bond markets have been examined for two separate periods; during and after the mortgage crisis. We measure the risk level of the bond markets through Value at Risk (hereafter VaR) analysis and compare the levels in both periods to determine whether or not there is a significant difference.

LITERATURE REVIEW

As far as we have seen from the existing studies in literature, while there is a great deal of interest concerning the effect of the mortgage crisis on Asian financial markets, these studies have mostly been conducted via cointegration and volatility spillover analysis. In one of these studies, Goldstein and Xie (2009) state that the effects of the mortgage crisis on Asian countries is limited by the means of their macro-economic and balance sheet structure, and counter-cyclical monetary and fiscal policies. Likewise, Shirai (2009) argues that due to the high accumulation of savings in the past, and the lower amount of mortgage-backed structured financial instruments, damages from the mortgage crisis are relatively low in Asia compared to European countries. For example, except for South Korea, the loan-deposit ratio of banks in Asian economies remains low during the crisis. Tille (2011) states that although capital inflow to Asian countries decreases after the collapse of Lehman Brothers, this negative influence is less acute compared to other countries and it recovers quite rapidly. In parallel with previous studies, Hale and Kennedy (2012) assert that the overall effect of the mortgage crisis on Asian economies is limited and short-lived. According to the authors, countries heavily affected by the crisis are the ones that are more dependent on the international financial markets. More specifically, Ali and Afzal (2012) demonstrate that mortgage crisis increases the volatility clustering of Pakistan and Indian stock returns. Using Momentum Threshold Autoregressive (M-TAR) model, Nieh, Yang and Kao (2012) analyse the changes in the asymmetric cointegration relationship between US and Asian markets and reveal that linkage between US and China stock market is low, and therefore present suitable conditions for portfolio diversifications for this markets. Thao and Daly (2012) investigate whether or not the linkage between US and Asian stock markets has changed after the mortgage crisis by using different methods: Bivariate cointegration test, multivariate cointegration test and cointegration tests with the presence of structural breaks. According to the results, a number of bi-directional long-run relationships exist among Thailand and Indonesia; Thailand and Singapore and the Philippines and Malaysia. Dimitriou and Simos (2013) examine the volatility spillover effect of the mortgage crisis through MGARCH model in the USA, EMU, China, and Japan stock markets. Results show that Japan and EMU have the higher rate of negative influence than other countries. Laih and Liau (2013) examine the herding behaviour of six Asian countries during the period of mortgage crisis. While there is no evidence for Singapore and Hong Kong, there are significant findings for Taiwan and China stock markets. Singhania and Anchalia (2013) investigate the volatility effect of mortgage crisis in Asian stock markets and conclude that, while there is no effect in Hong Kong, there are positive findings in Japanese, Chinese, and Indian stock markets. Besides, it is shown that the Eurozone crisis has a negative effect in the volatility of Indian and Chinese stock markets. Azis, Mitra, Baluga and Dime (2013) employ the MGARCH model with BEKK specification in order to investigate significant shocks and volatility spillover from mature bond markets on selected Asian markets. Results show that although there are impressive developments in Asian bond markets, they cannot escape from the effects of the mortgage crisis. Regarding the volatility spillover between China and Indonesia stock markets, Kenani, Purnomo and Maoni (2013) analyse the integration of markets and demonstrate that, both before and after the mortgage crisis, there is a bidirectional return spillover. More recently, Hengchao and Hamid (2015) state that while investors benefited from portfolio diversification in Asian-Pacific Islamic stock markets before the mortgage crisis, this advantage has decreased since these markets moved together during the period of crisis. Kim and Ryu (2015) examine the impact of the mortgage crisis on Korean stock and future markets and determine a significant linkage and contagion effect between the US subprime market and the Korean market. In another study, Zhang and Jaffry (2015) survey volatility spillover between Chinese and Hong Kong stock markets before and after mortgage crisis through asymmetric BEKK-GARCH and VAR methods. The authors show that the mortgage crisis has increased the interaction between these two markets. As it can be seen from the literature, studies concerning the impact of the mortgage crisis on Asian economies are mostly conducted using cointegration analysis and for volatility spillover effect. Unlike existing literature, we analyse this relationship using a VaR analysis for Asian bond market.

METHODOLOGY

GARCH and FIGARCH Models

Following the study of Baillie, Bollerslev and Mikkelsen (1996) we can define the GARCH and FIGARCH models. As stated by Engle (1982), a discrete time ARCH model can be written as below:

$$\varepsilon_t \equiv Z_t \sigma_t \tag{1}$$

where $E_{t-1}(Z_t) = 0$ and $VAR_{t-1}(Z_t) = 1$. In the classic ARCH (q) model of Engle (1982), conditional variance is deemed as the linear function of lagged squared innovations. As for the GARCH model of Bollerslev (1986), it presents a more flexible lag structure:

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \tag{2}$$

where L is the backshift or lag operator. In order to ensure the stability and covariance stationary of ε_t process, all roots of [1−α (L)−β (L)] and [1−β (L)] are constrained in unit circle. For ε_t the FIGARCH (*p,d,q*) model can be presented as follows:

$$\phi(L)(1-L)^d \varepsilon_t^2 = \omega + [1-\beta(L)]v_t \tag{3}$$

Conditional variance of ε_t is as below:

$$\sigma_t^2 = \omega[1-\beta(I)]^{-1} + \{1-[\beta(L)]^{-1}\phi(L)(1-L)^d\}\varepsilon_t^2 \quad (4)$$

The biggest asset of the FIGARCH model is the distinction of long and short memories in volatility by integrating an additional parameter (d) to the GARCH model. For $d = 0$ FIGARCH model reduce to standard GARCH (p, q) model. When $0 < d < 1$ shocks to the mean occurs at a slow hyperbolic rate of decay.

Value at Risk Analysis

As stated by Taylor (2008) VaR is a maximum loss measurement of any portfolio in a given confidence level (mostly 1% and 5%) and prescribed holding period. VaR provides quantitative measures for financial risk and can yields significant and robust results against the stylized facts of the financial times series such as fat tails and long memory. As an upper bound of one side confidence interval $VaR = VaR_{t-T}$ is defined as follows:

$$Pr[\Delta P(\tau) < -VaR] = 1-\alpha \quad (5)$$

where α confidence level and $\Delta P(\tau) = \Delta P_t(\tau)$ is the return in the portfolio on time horizon τ. Besides,

$$\Delta P_t(\tau) = P(t+\tau) - P(t) \quad (6)$$

where $P(t) = \log S(t)$ and $S(t)$ is the portfolio value at current time t ($T - t = \tau$). From this point of view, we can obtain the VaR values through the distribution of portfolio returns:

$$1-\alpha = F_{\Delta P}(-VaR) = \int_{-\infty}^{-VaR} f_{\Delta P}(x)dx \quad (7)$$

where $F_{\Delta P}(x) = Pr(\Delta P \le x)$ is the cumulative the distribution function of portfolio returns in a given period of time and $F_{\Delta P}(x)$ is the probability density function of ΔP. The VaR methods in literature mostly differentiates in terms of setting $F_{\Delta P}(x)$ (Khindanova, Rachev, & Schwartz, 2001). As stated before, conditional variance term σ_t^2 defined in Equation 2 can be estimated under different GARCH family models such as FIGARCH (see Equation 4). In accordance with this approximation, VaR model is also can be defined as below:

$$VaR(1-\alpha = \bar{R} - \sigma_t z_\alpha \tag{8}$$

In this equation $\bar{R}$ is mean return, Z_α is critical value for the preferred probability distribution with tail area α. (Orhan & Köksal, 2012). For example, in this study in order to take into account fat tails of asset returns, we used student-*t* distribution in conjunction with normal distribution in the estimation of VaR values.

Kupiec (LR) Test and Dynamic Quantile (DQ) Test

One of the most important stages in the VaR analysis is the determination of the model accuracy. This is referred to as "The Backtesting" in the literature. The backtesting is a diagnostic on the VaR model. One of the most popular methods for this is the Kupiec (1995) LR test that is based on unconditional coverage. In this model, the number of the violations are investigated regarding the obtained VaR value over a given time span. If the violation number differs substantially from that of the sample, then the accuracy of the model will be called into question. Kupiec's (1995) LR test statistic for T observation is calculated as follows:

$$LR = 2\log\left(\left(\frac{1-\hat{\alpha}}{1-\alpha}\right)^{T-I(\alpha)}\left(\frac{\hat{\alpha}}{\alpha}\right)^{I(\alpha)}\right) \tag{9}$$

where $\hat{\alpha} = \frac{1}{T} I(\alpha)$ and $I(\alpha) = \sum_{t=1}^{T} I_t(\alpha)$. If the violation number $\hat{\alpha} \times 100\%$ is exactly equal to $\alpha \times 100\%$, then the LR statistic will have a value of zero. This means that there is not enough evidence for the weakness of the preferred VaR model. On the other hand, having a bigger LR statistic implies that the VaR model overstates or understates the risk of portfolios. Similar results can be obtained for the *p*-value, as well. If the *p*-value is lower than the used significance level then the null hypothesis is rejected. This situation shows that the VaR model is not credible (Campbell, 2005).

Following the studies of Kuester, Mittnik and Paolella (2006) and Chen and Lu (2012), the DQ test can be presented as below. By remarking to the importance of conditioning violations on the VaR model, Engle and Manganelli (2004) introduced a new backtesting model based on the process of hit function:

$$H_t = I_t - \alpha = \left\{ {}^{1-\lambda,\ \text{if}\ r_t}_{-\lambda\ \ \text{else}} < -VaR_t \right\} \tag{10}$$

where $\{H_t\}$ is a centered process on the target probability λ. For any $x_{t-1} \in F_{t-1}$ to be uncorrelated with H_t, the DQ test statistic takes the form

$$DQ = \frac{\hat{\beta}'_{LS} X' \hat{\beta}'_{LS}}{\lambda(1-\lambda)} \overset{\text{asy}}{:} x^2_{p+n+2} \tag{11}$$

where $\hat{\beta}'_{LS} = (X'X)^{-1} X'(H-\lambda) \overset{\text{asy}}{:} N(0,(X'X)^{-1}\lambda(1-\lambda))$.

EMPIRICAL ANALYSIS

Data Analysis

Since 2001, the Fed has carried out three different monetary policy strategies. In the first period, the Fed conducts an easy monetary policy in order to overcome economic recession emerged after the dot-com bubble. Since inflation risks appear in the market after 30 June 2004, the Fed follows a tight monetary policy and raises the interest rates until mortgage crisis begins. During the crisis period, the Fed reduces the policy interest rate 17 times in two years. These strategies and the crisis also cause side-effects in different countries' real and financial markets. The scope of this study is to examine in which level the mortgage crisis affects bond markets of leading Asian countries. Accordingly, we measure the risk level of 10-year government bond yields of four Asian countries: South Korea, Japan, Malaysia and Singapore through VaR models. The analysis consists of the period of 13 June 2007 – 2 July 2015 and 2000 data. This duration is split up into two sub-periods: 13 June 2007 – 14 June 2011 (1000 days) and 15 June 2011–2 July 2015 (1000 days). The first period is considered as the crisis period and the second one is taken into account as the recovery period. All of the data used in the study is obtained via stooq.com, and econometric analysis is conducted through four different softwares: E-views, R, Ox-Metrics and Matlab.

The descriptive statistics of the aforementioned periods are presented in Table 1. As can be seen from the results, the mean of the bond yields increases in the recovery period for all countries except Singapore. As for σ, it shows that except for Malaysia all of the countries' standard deviation statistics rise in the second period. These results can be evaluated as the preliminary, with interesting result that while the mean yield of the Malaysian bonds increases in the second period, the risk of these bonds decreases in the same period. The skewness and kurtosis statistics demonstrate that both crisis and recovery periods, and the full period, disaffirm the normal distribution assumption. While the distribution of Japanese 10 year government bond yields in the crisis period is negatively skewed, the results in the recovery period transform to a positively skewed distribution. The case for South Korea is totally different, with positive asymmetry in the first period turning negative. Kurtosis statistics for all periods are quite different from the value (3) of normal distribution as well, indicating excess kurtosis. Finally, statistically significant Jerque-Bera test value show that all periods perform quite different behaviours from the normal distributed time series. In order to display the movements of series in two periods, we present bond yields of all of the countries in Figure 2. As can be seen, even though South Korea and Singapore demonstrate a high volatile behaviour in both periods, yields of Japan and Malaysia show a relatively lower level of fluctuation.

Before proceeding to the VaR analysis, we examine the autocorrelations of the 10-year bond yields in order to obtain more information about the characteristics of the time series. Findings concerning the autocorrelation functions show that using of long memory models in the modelling of conditional variance may be suitable, as there are signs of persistence of volatility in Figure 3. Results of autocorrelation graphs provide preliminary information for the determination of a true model from the GARCH family. Besides excess kurtosis and fat tails in return distribution, another important stylised fact of financial time series is a long memory in returns and volatilities. As a diagnostic analysis, in Figure 3, we present the first 100 autocorrelations of absolute returns of all of the bond yields with a two-sided 5% critical value. As can be seen, there is a high persistence in the absolute bond yields of Japan and Malaysia. These evidences concerning the dependence structure of the series suggest that using long memory models in the modelling of conditional variance can be useful.

Table 1
Descriptive statistics

		Mean	S.D.	Skewness	Kurtosis	Jarque-Bera
Pre-crisis	South Korea	–0.00011	0.005162	0.184605	6.523230	522.8945**
	Japan	–0.000229	0.008782	–0.056901	4.689159	119.4254**
	Malaysia	5.50E-06	0.005007	1.247947	17.79105	9375.196**
	Singapore	–0.000102	0.009049	0.333387	7.726790	949.4639**
Post-crisis	South Korea	–0.000228	0.005355	–0.0865	6.536180	522.2709**
	Japan	–0.000347	0.015462	0.691919	17.10323	8367.339**
	Malaysia	7.65E-07	0.003141	1.713786	17.91497	9758.522**
	Singapore	6.62E-05	0.009192	0.611230	8.000418	1104.108**
Full Period	South Korea	–0.000169	0.005258	0.040385	6.544027	1047.221**
	Japan	–0.000288	0.012571	0.626418	20.10049	24499.69**
	Malaysia	3.13E-06	0.004179	1.437324	21.18427	28244.27**
	Singapore	–1.80E-05	0.009119	0.475998	7.874546	2055.625**

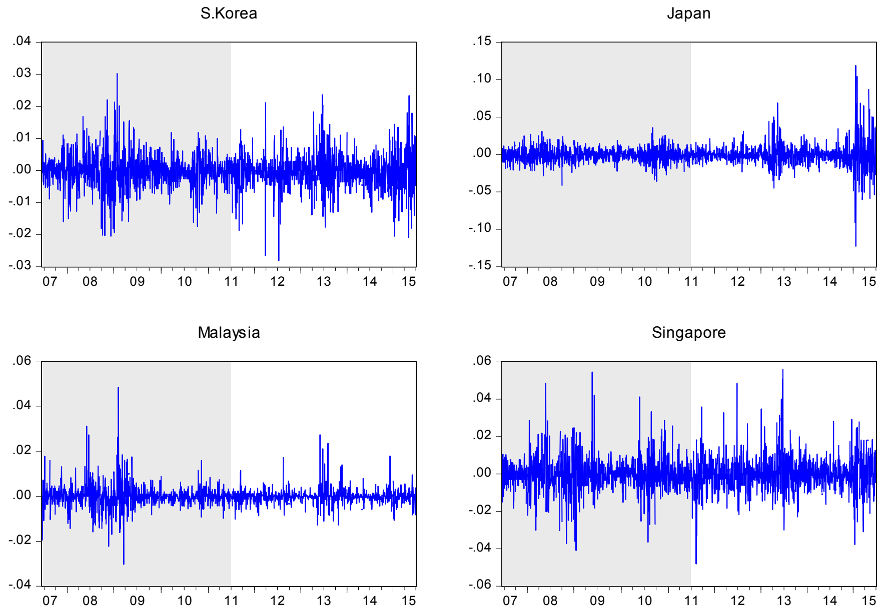


Figure 2. 10-year government bond yields

Crisis Period's Value at Risk Analysis

As stated before, risk analysis throughout the two periods will be conducted by the VaR method. By considering the stylised facts of financial time series in which variance is not stable and changes over time (heteroskedasticity), we use GARCH family models in the VaR analysis instead of constant variance VaR models such as the Parametric VaR, Historical VaR, or Monte Carlo Simulation VaR. Since autocorrelation graphs point out that there may be long memory features in the series, in conjunction with the GARCH (1.1) model we also use FIGARCH (1.d.1) model in empirical analysis. Results are presented in Tables 2 and 3.

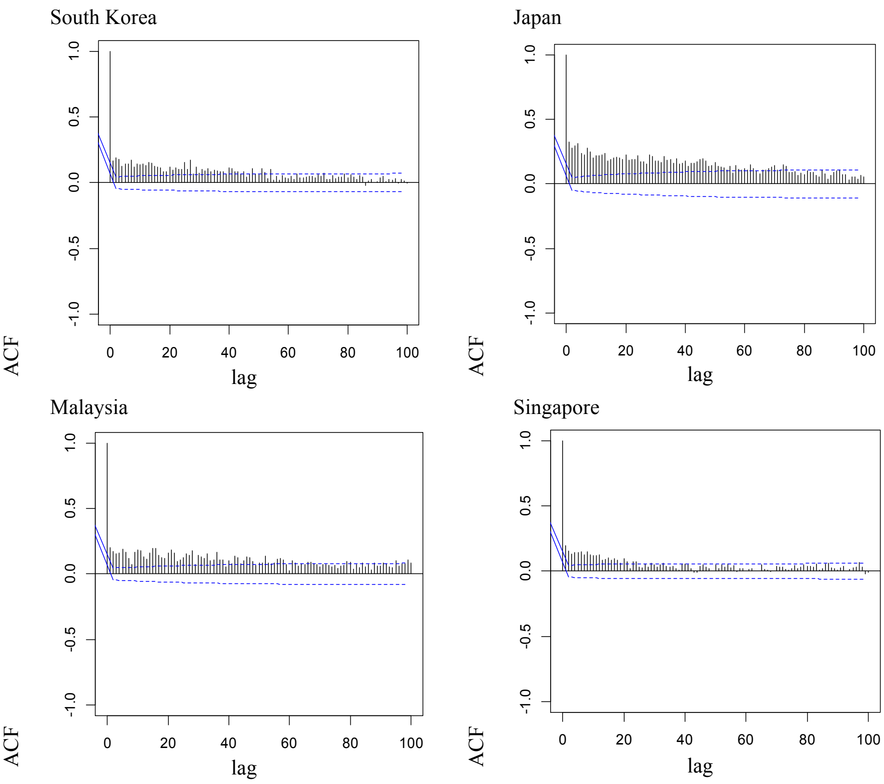


Figure 3. Autocorrelations of absolute returns

Table 2
Crisis period – GARCH (1.1) and FIGARCH (1.d.1) model (Normal distribution)

	South Korea		Japan		Malaysia		Singapore	
	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)
μ	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0001 (0.0001)	-0.0001 (0.00009)	-0.0001 (0.0002)	-0.0001 (0.0002)
ω×10^6	0.2925 (0.1632)	0.1222 (0.0885)	0.7047 (0.4495)	1.2349 (0.8811)	0.1789 (0.1151)	0.1215 (0.1296)	2.3436* (1.0124)	2.0369 (1.1059)
d	-	1.0919** (0.1629)	-	0.4645** (0.1725)	-	1.0861** (0.1996)	-	0.7186** (0.1408)
α	0.0779** (0.0219)	0.0551 (0.1403)	0.0454** (0.0125)	0.4567** (0.1248)	0.0794* (0.0320)	-0.0006 (0.1288)	0.1371** (0.0352)	0.1885 (0.1306)
β	0.9131** (0.0227)	0.9460** (0.0381)	0.9457** (0.0155)	0.7917* (0.0743)	0.9171** (0.0264)	0.9425** (0.0568)	0.8444** (0.0310)	0.7387** (0.0703)
ln(L)	3960	3963	3367	3367	4098	4099	3401	3403
AIC	-7.9133	-7.9166	-6.7276	-6.7243	-8.1880	-8.1890	-6.7951	-6.7971
SIC	-7.8937	-7.8921	-6.7080	-6.6997	-8.1683	-8.1645	-6.7755	-6.7726
Q_{20}	15.0835 [0.6562]	15.3526 [0.6376]	14.1698 [0.7179]	15.7740 [0.6083]	40.6753 [0.0016]**	48.0956 [0.0001]**	8.9924 [0.9599]	8.8182 [0.9638]

Note: Standard errors are within the parenthesis. * and ** indicates the 95% and 99% confidence level, respectively

According to the findings, the sum of the alpha and beta parameters in all of the GARCH (1.1) models is close to unity. As stated by Engle and Patton (2001), this result can be interpreted as the persistence of volatility. The sum of the alpha and beta parameters for South Korea, Japan, Malaysia, and Singapore is as follows: 0.991, 0.9911, 0.9965, and 0.9815 respectively. The most important output in the FIGARCH (1.d.1) model for us is the fractional differencing operator *d*. As stated by Baillie et al. (1996), $0 < d < 1$ this indicates stationary long memory in variance. Concerning the results of the FIGARCH (1.d.1) model, while there is long memory in the volatility of Japanese 10 year government bond yields (0.4645) and Singapore (0.7186), the volatility is no-mean-reverting (non-stationary) for South Korea (1.0919) and Malaysia (1.0861). Besides this, the AIC indicates that except for Japan, the FIGARCH (1.d.1) model fits the data better than the GARCH (1.1) model. Likewise, for the SIC statistics, the FIGARCH (1.d.1) model outperforms the GARCH (1.1) model for all of the countries except for Japan. Q_{20} presents the Ljung Box test for squared standardised residuals in 20 lags. Acceptance of the null hypothesis means no autocorrelation in the residuals. According to the Q_{20} results, there is no autocorrelation in the residuals of any models except for Malaysia. As stated in the beginning of the study, all of the series violate the normal distribution assumption. Therefore, in addition to the modelling of variance under normal distribution, we also use student-t distribution in GARCH (1.1) and FIGARCH (1.d.1) models. Results of both models have been presented in Table 3. Similar to the previous findings, the GARCH (1.1) model indicates high persistence in return volatility. The fractional differencing operator (d) of the FIGARCH (1.d.1) model is statistically significant for Japan (0.4720). However, for South Korea (1.1054) and Malaysia (1.2008), volatility has no mean reversion. As for Singapore, its volatility has long memory features. As stated by Hillebrand (2003), long memory in volatility gives clues concerning the uncertainty, or a high risk level in the market. Figure 4 presents the VaR results of GARCH (1.1) and FIGARCH (1.d.1) models for long (blue) and short (red) positions.

Subsequently, on variance modelling with the GARCH (1.1) and FIGARCH (1.d.1), we conduct VaR analysis with a non-constant variance. Heteroscedasticity is the one of most remarkable topics of financial econometrics and is currently a stylised fact for financial time series. Table 4 displays the VaR results obtained through the GARCH (1.1) and FIGARCH (1.d.1) models. One of the most interesting implications of these results is the higher VaR values of the FIGARCH (1.d.1) model compared to the GARCH (1.1) model. As stated before, this finding may arise from uncertainty which is increased by long memory in volatility. Another interesting result is having lower VaR values with the student-t distribution than those results obtained under the normal distribution. The highest VaR values among the countries are obtained for Japan, Singapore, South Korea and Malaysia, respectively.

Table 3
Crisis period – GARCH (1.1) and FIGARCH (1.d.1) model (student-t distribution)

	South Korea		Japan		Malaysia		Singapore	
	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)
μ	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0002 (0.0002)	-0.0003 (0.0002)	-0.0001 (0.00006)	-0.0001 (0.00006)	-0.0002 (0.0001)	-0.0002 (0.0001)
ω×10^6	0.3287 (0.2057)	0.1854 (0.1260)	1.0019 (0.5725)	1.6601 (1.3704)	0.3272 (0.2675)	0.0987* (0.0455)	2.2106** (1.0201)	2.4470 (1.2620)
d	-	1.1054** (0.1351)	-	0.4720** (0.2540)	-	1.2008** (0.1032)	-	0.7649** (0.1853)
α	0.0935** (0.0259)	-0.0154 (0.1278)	0.0518** (0.0148)	0.4071** (0.1666)	0.1703 (0.1035)	0.0144 (0.1049)	0.1494** (0.0392)	0.2043 (0.1246)
β	0.9042** (0.0259)	0.9430** (0.0340)	0.9360** (0.0183)	0.7617** (0.1219)	0.9101** (0.0386)	0.9651** (0.0111)	0.8442** (0.0364)	0.7606** (0.1063)
v	4.3596** (0.6104)	4.3723** (0.5991)	7.4392** (1.7503)	7.3225** (1.7920)	2.3613** (0.1787)	2.8741** (0.1671)	3.8921** (0.4927)	3.9194** (0.4005)
ln(L)	3996	3996	3380	3379	4250	4254	3468	3469
AIC	-7.9825	-7.9818	-6.7517	-6.7477	-8.4918	-8.4961	-6.9266	-6.9266
SIC	-7.9580	-7.9524	-6.7272	-6.7182	-8.4673	-8.4667	-6.9020	-6.8971
Q_{20}	14.6747 [0.6841]	14.1461 [0.7195]	13.3456 [0.7706]	14.8663 [0.6711]	38.2333 [0.0036]**	54.3857 [0.0001]**	8.7880 [0.9644]	9.4114 [0.94943]

Note: Standard errors are within the parenthesis. * and ** indicates the 95% and 99% confidence level, respectively

Table 4
Crisis period mean VaR results

		South Korea	Japan	Malaysia	Singapore
GARCH (1.1) VaR	Nor. Dist.	–0.0082	–0.0144	–0.0075	–0.0143
FIGARCH (1.d.1) VaR		–0.0084	–0.0145	–0.0076	–0.0144
GARCH (1.1) VaR	Student-t Dist.	–0.0079	–0.0141	–0.0065	–0.0135
FIGARCH (1.d.1) VaR		–0.008	–0.0143	–0.0062	–0.0135

After obtaining the VaR values, the next step is testing the credibility of VaR results or the robustness of the VaR models through a backtesting procedure. For this backtesting analysis, we use two different models in this study. First is the frequently used method in literature, the Kupiec Test, and second is as an alternative model, the DQ test. The basic logic behind the Kupiec Test is to compare the real number of violations and model prediction. As for the DQ test, it analyses whether or not VaR violations and VaR estimates are independent by performing an artificial regression (Almli & Rege, 2011). Results of the both methods can be seen in Table 5.

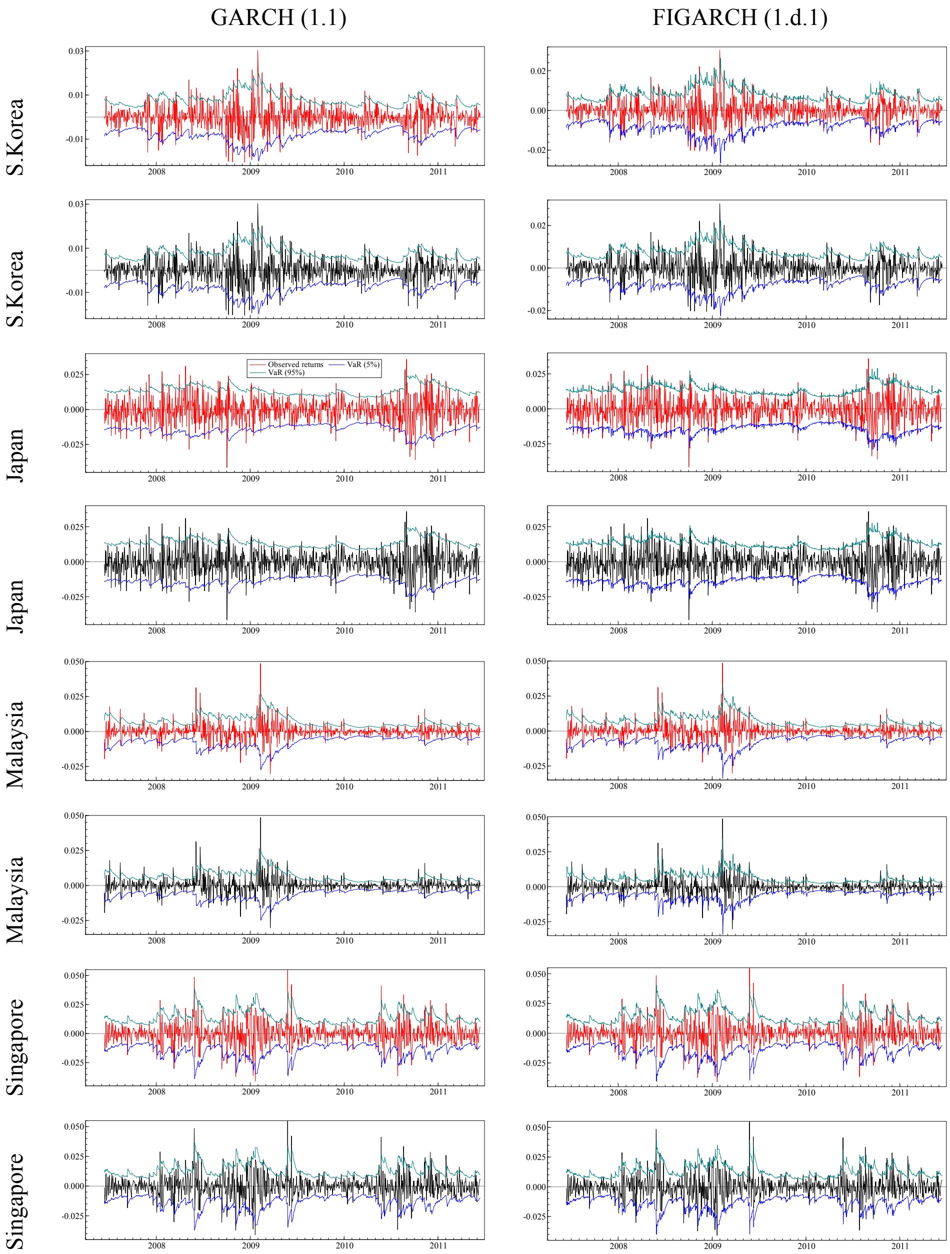


Figure 4. VaR results of the GARCH (1.1) and the FIGARCH (1.d.1) models

According to the Kupiec LR test, the FIGARCH-t (1.d.1) VaR result for Malaysia is not credible at the 99% confidence level. This means that the real violation number is different from the model prediction. Likewise, for the DQ test, the GARCH (1.1)-n VaR result for Malaysia is spurious at the 99% confidence level. This implies that the GARCH-n (1.1) and FIGARCH-t (1.d.1) models fail in predicting the true VaR value for Malaysia. As we stated before in the GARCH (1.1) and the FIGARCH (1.d.1) analysis, these two models have drawbacks in the modeling of variance for Malaysia because of the autocorrelation in the squared residuals of the model. Therefore, these results show that the backtesting and the findings of GARCH (1.1) and FIGARCH (1.d.1) models coincide with each other.

Table 5
Results of the backtesting analyses

		Kupiec LR Test			DQ Test
		FR	NV	KLRT	Stat.
South Korea	GARCH (1.1)-n	0.048	48	0.0852 (0.7702)	8.1412 (0.2279)
	GARCH (1.1)-t	0.049	49	0.0211 (0.8842)	7.6371 (0.2659)
	FIGARCH (1.d.1)-N	0.049	49	0.0211 (0.8842)	6.9827 (0.3224)
	FIGARCH (1.d.1)-t	0.051	51	0.0209 (0.8849)	6.9563 (0.3249)
Japan	GARCH (1.1)-n	0.054	54	0.3286 (0.5664)	3.7742 (0.7072)
	GARCH (1.1)-t	0.056	56	0.7307 (0.3926)	4.0985 (0.6633)
	FIGARCH (1.d.1)-N	0.051	51	0.0209 (0.8849)	3.0576 (0.8015)
	FIGARCH (1.d.1)-t	0.052	52	0.0831 (0.7730)	3.6272 (0.7269)
Malaysia	GARCH (1.1)-n	0.040	40	2.2534 (0.1333)	18.690 (0.0047)
	GARCH (1.1)-t	0.063	63	3.2988 (0.0693)	15.346 (0.0177)
	FIGARCH (1.d.1)-N	0.040	40	2.2534 (0.1333)	8.7805 (0.1863)
	FIGARCH (1.d.1)-t	0.073	73	9.8131 (0.0017)	14.856 (0.0214)
Singapore	GARCH (1.1)-n	0.046	46	0.3457 (0.5565)	5.7856 (0.4476)
	GARCH (1.1)-t	0.048	48	0.0852 (0.7702)	7.6518 (0.2647)
	FIGARCH (1.d.1)-N	0.046	46	0.3457 (0.5565)	3.2262 (0.7799)
	FIGARCH (1.d.1)-t	0.048	48	0.0852 (0.7702)	7.6518 (0.2647)

Recovery Period's Value at Risk Analysis

In this section of the empirical analysis, we follow the same procedure with crisis period's VaR analysis and conduct the same tests for the recovery period: 15 June 2011–2 July 2015. Since VaR analyses are performed by means of conditional variance, we first model volatility.

In Table 6, we present the GARCH (1.1) and the FIGARCH (1.d.1) results for the second period of the four countries' 10 years government bond yields. As can be seen from the GARCH (1.1) results, the alpha and beta parameters are statistically significant except for Malaysia. Additionally, the fractional differencing operator (*d*) in the FIGARCH (1.d.1) model is not statistically significant for South Korea. Other values of *d* indicate the existence of long memory in Japan, Malaysia, and Singapore bond markets in the recovery period. As stated before, long memory in volatility causes higher level of risk over the asset. This is due to the persistence in volatility that arises in consequence of memory is an uncertainty factor in the return of asset. According to the AIC, the GARCH (1.1) model fits the data better and outperforms the FIGARCH (1.d.1) model for all countries. Except for South Korea, the SIC supports this finding and the Ljung Box test statistics show that we cannot reject the null hypothesis. This means that there is no autocorrelation in the squared residuals of the models.In order to take fat tails in the bond yields into account, we also perform the GARCH (1.1) and the FIGARCH (1.d.1) analysis under student-t distribution. Results of these two models have been presented in Table 7. These findings also coincide with the ones obtained under normal distribution.

As can be seen from the results, the alpha and beta parameters of the GARCH (1.1) model are statistically significant for all countries except for Malaysia. In the FIGARCH (1.d.1) model, just for Singapore, there is a significant long memory feature. For the rest of the countries, volatility in bond market has no mean reversion. According to the AIC and SIC, the GARCH (1.1) model mostly fits the data better than the FIGARCH (1.d.1), which is similar to the previous results. When we examine the diagnostic statistics, the Ljung Box test indicates that there is no autocorrelation in the squared residuals of the models. This is a positive implication for the robustness of the models used. Figure 5 presents obtained VaR results of the GARCH (1.1) and the FIGARCH (1.d.1) models for long (blue) and short (red) positions.

Table 6

Post crisis – GARCH (1.1) and FIGARCH (1.d.1) models (Normal distribution)

	South Korea		Japan		Malaysia		Singapore	
	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)
μ	-0.0003	-0.0003	-0.0004	-0.0005	-0.00017	-0.0002*	-0.00001	0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.00009)	(0.00008)	(0.0002)	(0.00024)
ω×10^6	0.8458	0.1222	3.1891	0.0109	0.3192	2.1615*	4.1426	7.1263
	(0.5253)	(0.0885)	(13.541)	(0.0133)	(0.1999)	(1.0687)	(1.7918)	(7.6071)
d	-	0.3012	-	0.9708**	-	0.4404**	-	0.3064**
		(0.4827)		(0.3171)		(0.1250)		(0.1881)
α	0.0661**	0.0995	0.0924**	0.0297	0.1267	-0.5768*	0.0741**	0.2375
	(0.0204)	(1.4130)	(0.0218)	(0.1880)	(0.0759)	(0.2744)	(0.0222)	(0.1708)
β	0.9051**	0.3493	0.9101**	0.9014**	0.8592**	-.0.2912	0.8765**	0.4862**
	(0.0318)	(1.8782)	(0.0221)	(0.1327)	(0.0677)	(0.3735)	(0.0303)	(0.2702)
ln(L)	3883	3879	3127	3127	4461	4461	3330	3325
AIC	-7.7596	-7.7490	-6.2470	-6.2450	-8.9149	-8.9125	-6.6521	-6.6406
SIC	-7.7400	-7.7244	-6.2274	-6.2204	-8.8952	-8.8879	-6.6325	-6.6160
Q_{20}	5.94063	7.41123	19.1054	19.3077	8.8971	25.0905	5.56035	5.4958
	[0.9964]	[0.9861]	[0.3853]	[0.3731]	[0.9620]	[0.1224]	[0.9976]	[0.9978]

Note: Standard errors are within the parenthesis. * and ** indicates the 95% and 99% confidence level, respectively

Table 7

Post crisis – GARCH (1.1) and FIGARCH (1.d.1) models (Student-t distribution)

	South Korea		Japan		Malaysia		Singapore	
	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)	GARCH (1.1)	FIGARCH (1.d.1)
μ	-0.0001	-0.0001	-0.0009**	-0.0010**	-0.00006	-0.0001	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.00003)	(0.00006)	(0.0002)	(0.0002)
ω×10^4	0.3751	0.2729	0.0267*	0.0103	0.7264	0.0808*	1.9711	2.8004
	(0.2113)	(0.1546)	(0.0124)	(0.0148)	(0.9127)	(0.0433)	(1.1668)	(1.8904)
d	-	1.1425**	-	1.1844**	-	1.2144**	-	0.5597**
		(0.1154)		(0.2112)		(0.0972)		(0.1795)
α	0.0908**	-0.1290	0.1183**	-0.0523**	0.7409	-0.0589	0.0952**	0.2711*
	(0.0226)	(0.1029)	(0.0313)	(0.1514)	(0.7346)	(0.1211)	(0.0342)	(0.1186)
β	0.9111**	0.9437**	0.8815**	0.9562**	0.9202**	0.9639**	0.8929**	0.7059**
	(0.0204)	(0.0272)	(0.0302)	(0.0627)	(0.0234)	(0.0100)	(0.0354)	(0.1123)
v	3.7099**	3.7047**	3.6945**	3.6264**	2.0486**	2.5194**	4.0210**	4.0589**
	(0.4938)	(0.3837)	(0.5173)	(0.4125)	(0.0491)	(0.1065)	(0.5780)	(0.5393)
ln(L)	3961	3962	3183	3184	4693	4689	3402	3403
AIC	-7.9127	-7.9121	-6.3573	-6.3575	-9.3773	-9.3661	-6.7948	-6.7950
SIC	-7.8882	-7.8826	-6.3328	-6.3281	-9.3528	-9.3366	-6.7703	-6.7655
Q_{20}	6.2769	7.40038	17.6348	22.9990	8.4978	9.48904	6.1161	6.4013
	[0.9949]	[0.9862]	[0.4799]	[0.1906]	[0.9702]	[0.9473]	[0.9957]	[0.9942]

Note: Standard errors are within the parenthesis. * and ** indicates the 95% and 99% confidence level, respectively

VaR values obtained for the recovery period are presented in Table 8. As can be seen from the results, unlike the crisis period, there is no significant difference between the VaR values of the GARCH (1.1) and the FIGARCH (1.d.1) models. While for some countries, the GARCH (1.1) model's VaR results are larger, the FIGARCH (1.d.1) models display larger VaR values for other countries. If we consider the type of the distribution, it is clear that the VaR values for the student-t distribution are smaller than the ones obtained under normal distribution. Risk order for the countries does not change in the recovery period. In this period, the most risky bond market is still Japan. The order of the remaining countries is Singapore, South Korea, and Malaysia, respectively.

In order to test the credibility of the VaR analysis, we conduct the Kupiec LR and the DQ tests once again as in the crisis period's VaR analysis. According to the output of Kupiec LR test, the FIGARCH-t VaR result for Malaysia is spurious at the 99% confidence interval. This finding indicates that true violation number is different from the results of the FIGARCH-t VaR. In addition, the GARCH-t and the FIGARCH-n VaR results obtained for Singapore seem artificial. The DQ test also supports these results for Singapore.

Table 8
Post crisis mean VaR results

		South Korea	Japan	Malaysia	Singapore
GARCH (1.1) VaR	Normal Distribution	–0.0088	–0.0214	–0.0052	–0.0147
FIGARCH (1.d.1) VaR		–0.0089	–0.0213	–0.0052	–0.0148
GARCH (1.1) VaR	Student-t Distribution	–0.0082	–0.0203	–0.0040	–0.0142
FIGARCH (1.d.1) VaR		–0.0082	–0.0204	–0.0037	–0.0141

When we jointly analyse the results of the crisis and recovery periods, it seems that although in the crisis period the FIGARCH (1.d.1) models exhibit higher VaR values than the GARCH (1.1) models, for the recovery period there is no significant difference between them. For both periods, the highest VaR values are respectively as follows: Japan, Singapore, South Korea, and Malaysia. In addition, while the VaR values of Japan and Singapore are close enough to each other in the crisis period, the difference gets bigger in the recovery period. Increasing risk in Japan in the recovery period is the reason for this result. For instance, while the VaR of Japan rises 49% in the second period, this change is quite limited for South Korea and Singapore. It should be noted that the results for Malaysia are significantly different from the others. According to the findings, all of the VaR values for Malaysia decrease in the second period. However, as variance modelling and backtesting results have pointed out, we know that the VaR values obtained for Malaysia are not credible. Hence we do not take this change into account.

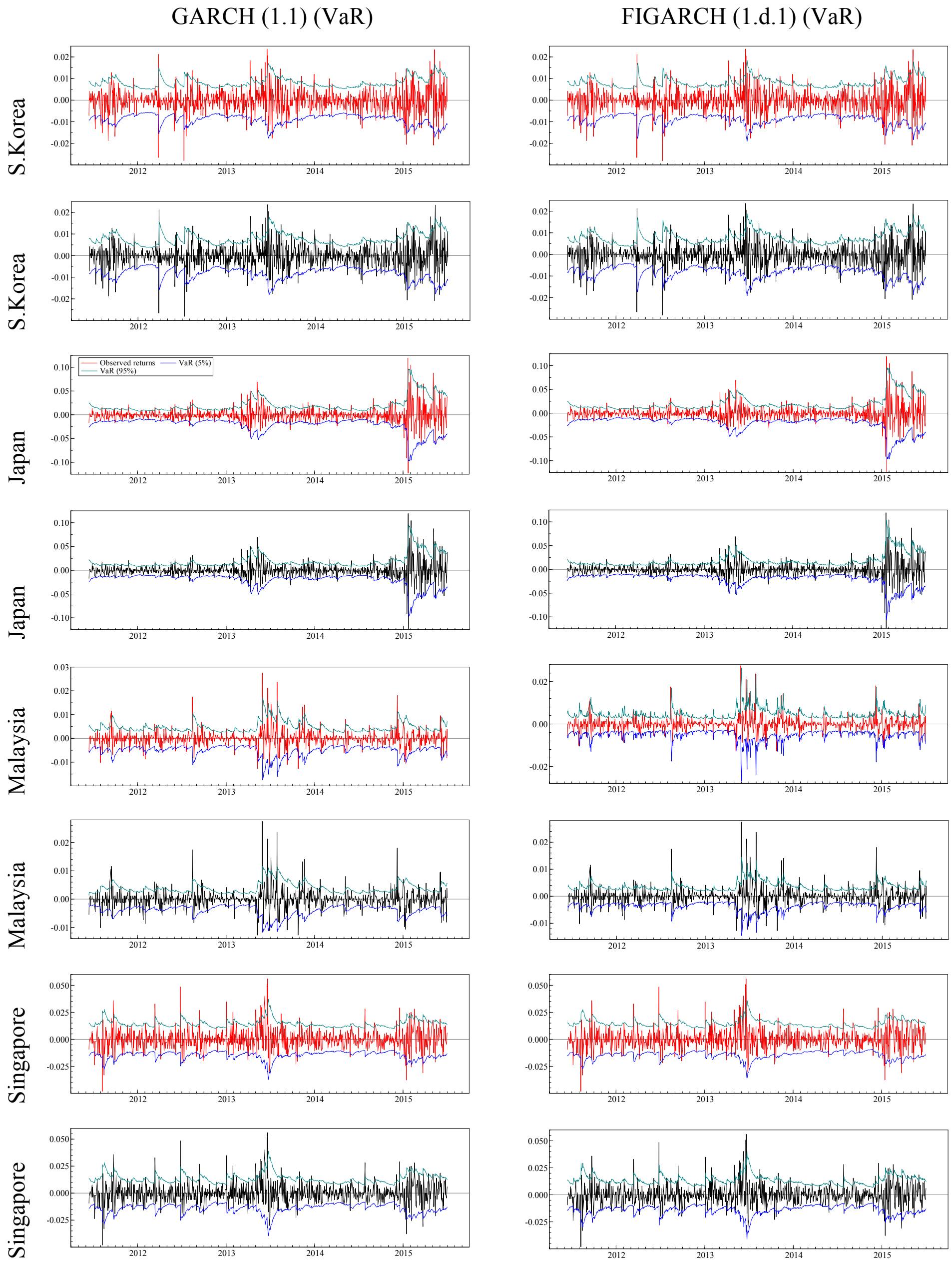


Figure 5. VaR results of the GARCH (1.1) and the FIGARCH (1.d.1) models

Table 9
Results of the backtesting analyses

		Kupiec LR test			DQ Test
		FR	NV	KLRT	Stat.
Korea	GARCH (1.1)-N	0.049	49	0.0211 (0.8842)	4.0900 (0.6644)
	GARCH (1.1)-t	0.058	58	1.2843 (0.2571)	6.7303 (0.3465)
	FIGARCH (1.d.1)-N	0.043	43	1.0807 (0.2985)	5.0044 (0.5432)
	FIGARCH (1.d.1)-t	0.057	57	0.9889 (0.3200)	8.3848 (0.2112)
Japan	GARCH(1.1)-N	0.039	39	2.7469 (0.0974)	14.270 (0.0267)
	GARCH(1.1)-t	0.040	40	2.253 (0.1333)	10.089 (0.1209)
	FIGARCH(1.d.1)-N	0.041	41	1.812 (0.1782)	11.218 (0.0818)
	FIGARCH(1.d.1)-t	0.044	44	0.7884 (0.3745)	4.9528 (0.5498)
Malaysia	GARCH (1.1)-N	0.039	39	2.7469 (0.0974)	13.963 (0.0300)
	GARCH (1.1)-t	0.061	61	2.3877 (0.1223)	11.187 (0.0827)
	FIGARCH (1.d.1)-N	0.040	40	2.2534 (0.1333)	9.0153 (0.1727)
	FIGARCH (1.d.1)-t	0.069	69	6.8301 (0.0089)	11.678 (0.0695)
Singapore	GARCH (1.1)-N	0.037	37	3.8953 (0.0484)	16.410 (0.0117)
	GARCH (1.1)-t	0.042	42	1.4215 (0.2331)	17.506 (0.0075)
	FIGARCH (1.d.1)-N	0.031	31	8.7393 (0.0031)	27.695 (0.0001)
	FIGARCH (1.d.1)-t	0.038	38	3.2937 (0.0695)	15.263 (0.0183)

CONCLUSION

Risk concept in finance theory has as great an importance as return. The accurate measurement of risk for any asset, project, or firm is absolutely vital for correct decision making. Although there are different approximations concerning the modelling and measuring of risk, the VaR model has gained a wide acceptance in literature in the measuring of market risk in the last two decades.

In this study, we analyse whether or not there is a change in the risk of selected Asian bond markets (South Korea, Japan, Malaysia, and Singapore) in the period following the mortgage crisis. In the risk analysis of 10-year government bond yields, we use two different time intervals: 13 June 2007–14 June 2011 and 15 June 2011–2 July 2015 as crisis and recovery periods respectively. Measuring of risk for all the periods has been conducted through the VaR analysis. In the modelling of variance, which is the most important and critical stage of the VaR analysis, we use the GARCH (1.1) and the

FIGARCH (1.d.1) models that consider the change of variance over time, instead of constant variance assumption. Since descriptive statistics point out fat tails in return distributions, all VaR analyses have been conducted under normal and student-t distributions. The AIC and SIC statistics show that the GARCH (1.1) models mostly outperforms the FIGARCH (1.d.1) models in modelling variance. In addition, the VaR results exhibit that in all periods, during and after mortgage crisis, the most risky bond market is in Japan among the countries analysed. The following countries in terms of risk are Singapore, South Korea, and Malaysia respectively. When we consider the type of the return distribution, we see that for both periods the VaR values obtained under student-t distribution are smaller than the ones coming from normal distribution.

In terms of financial implications, comparative VaR values from the two periods (crisis and recovery) imply that there is a significant increase in the risk of the 10-year Japanese bond market. Although there is limited rise in the risk of the South Korean and Singaporean bond markets, the increase in Japan's market is remarkable. This hike in the VaR of Japan is 49% for the GARCH-n (1.1) model and 47% for the FIGARCH-*t* (1.d.1) model. On the other hand, these rises are not so different in other models: for GARCH-t (1.1) and FIGARCH-n (1.d.1) models the numbers are 44% and 44%, respectively. In comparison with rest of the countries, the situation in Malaysia is quite different, the VaR values of this country's bond market decrease in the recovery period. However, as the Kupiec LR and the DQ backtesting statistics exhibit the weakness of the VaR results of Malaysia, we leave the decreasing risk of Malaysia out of the assessment. Overall, we see that in the recovery period of the mortgage crisis, there is a significant increase in the risk to the 10-year government bond market of Japan.

These results, in our opinion, may arise from the integration level of these bond markets with international markets. Japan and Singapore have had their own foreign currency-denominated bond markets since the 1970s leading to more significant global integration. As it is known, higher integration with global markets may cause higher volatility spillover effects in financial markets, and higher volatility would in turn cause higher required rates of return. Therefore, this interaction can affect all sides of the financial system. Policy makers in such economies, which are exposed to those effects, should take precautions against the high volatility risk.

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