Qiang Zhang (UK), Shabbar Jaffry (UK)

Global financial crisis effects on volatility spillover between Mainland China and Hong Kong stock markets

Abstract

The authors explore the influence of the global financial crisis on the volatility spillover between the Mainland China and Hong Kong stock markets. The data collection period is from January 04, 2002 to December 31, 2013, broken into two sub-periods: pre-crisis (January 04, 2002 to June 30, 2007) and crisis (July 01, 2007 to December 31, 2013). The authors apply asymmetric BEKK-GARCH and adopt the VAR approach as a robustness test. The results indicate that while there is no volatility spillover in the pre-crisis period, strong bi-directional volatility spillover exists in the crisis period. Meanwhile, one month 1 minute high frequency data is applied to explore intraday volatility spillover. The researchers draw three interesting conclusions: The global financial crisis enhanced the economic linkage between the Mainland China and Hong Kong stock markets; and while it did not directly influence the Mainland China market, global financial risk flowed into this region through the Hong Kong market; there exists a bi-directional daily aggregated volatility spillover, but from a microscopic view, a random volatility spillover process is concluded.

Keywords: global financial crisis, volatility spillover, asymmetric BEKK-GARCH, VAR approach, American, Mainland China and Hong Kong stock markets.
JEL Classification: G15.

Introduction

Some recent studies have investigated volatility in mature Western financial markets (Corsi, 2009; Patton, 2011; Bollerslev et al., 2012; Watcher, 2013), but few papers have examined volatility in the emerging financial markets in Mainland China (Liu and An, 2011; Yang et al., 2012). Since the economic revolution in 1979, Mainland China's economy has undergone significant development; it is currently the world's second-largest economy according to World Bank GDP data. Hence, it is interesting and important to investigate this emerging financial market's influence. Accuracy of volatility estimation and forecasting is key to optimal hedge ratio calculation, options pricing, and investment portfolio risk measurement. Since Engle (1982) created the ARCH model of conditional volatility, many have similar models developed based on it, including the GARCH, EGARCH, TGARCH, and multi-variable GARCH models. The early conditional volatility model assumes that a financial market's volatility depends only on its own market. However, many current studies indicate a dynamic volatility spillover effect between two highly linked markets (So and Tse, 2004; Chen et al., 2004; Johansson and Ljungwall, 2009). This dynamic volatility process is generally called volatility spillover or the transmission process.

One important reason to explore this dynamic volatility process is to indicate the direction in which new information flows. According to Fama's (1970) efficient market hypothesis, in an efficient market, new price movement is caused by new information. The current market price is based on all past information, and represents an equilibrium relationship between buyers and sellers. Once new information flows into the market, the old equilibrium will break and the price moves to a new equilibrium level. Outstanding new information will cause a dynamic price movement process among highly relative markets, since investors will have similar expectations of this new shock, which will lead to similar new equilibrium prices among highly relative markets.

If new information flows into different highly relative markets simultaneously, investors react to the new information at the same time, which will cause bi-directional volatility spillover. However, some empirical evidence shows that information flows into different markets at different speeds (Bhar and Nikolova, 2009; Johansson and Ljungwall, 2009). That is, in an inefficient market, if volatility transmits from one market to the other, then the lead market can acquire new information more quickly than the lag market, and vice versa. Chan et al. (1991) point out that investigating the return volatility lead-lag relationship among different markets can help to provide more information about how information flows among these markets. Another reason to investigate the volatility spillover effect is to model volatility more accurately: If volatility transmission does not exist, then one market's own market value can model its volatility. However, if a volatility transmission effect does exist, then the volatility model should be a dynamic process between these two markets.

Investigation of volatility spillover can be divided into two broad categories based on research targets. The first investigates one country's highly relative domestic markets such as spot and futures markets.

The second investigates volatility spillover among international markets. This paper will focus on the 2007 global financial crisis's influence on volatility spillover between the Mainland China and Hong Kong stock markets. This paper will contribute to the current literature in the following four ways: First, this paper is the first to investigate the global financial crisis's effect on the dynamic linkage of volatility between the Mainland China and Hong Kong stock markets. The study results will shed light on the relationship between these two stock markets and the global financial environment. Second, this study applies current data from January 04, 2002 to December 31, 2013. Third, we apply BEKK-GARCH to investigate volatility spillover and adopt the VAR approach as a robustness test. Lastly, we explore intraday high frequency volatility spillover between these two markets. The rest of the paper is organized as follows: section 1 provides a literature review, section 2 provides two markets' detailed information. Section 3 describes the data, and section 4 explains the analysis methodologies. Section 5 and 6 present the empirical results and robustness test results, section 7 discusses global financial crisis influence. Section 8 explores intraday high frequency volatility spillover and final section summarizes the paper.

1. Literature review

Volatility spillover effects comprise two categories: (1) the domestic market spillover effect, and (2) international markets spillover effects. Within the domestic market category, Kang et al. (2013) examine the volatility spillover effect between the Korean stock index futures and spot markets. They apply three high-frequency (10-minute, 30-minute and 1-hour time scales) intraday data sets using the BEKK-GARCH model. The results indicate a strong bi-directional causality relationship between the spot and futures markets, which means new information flows into the two markets simultaneously. Zhong et al. (2004) investigate the price discovery function and volatility spillover effect in the Mexican stock index futures and spot markets. The main method is based on the vector error correction model (VECM), the EGARCH model, and co-integration analysis. The results indicate that volatility transmits from the futures market to the spot market, which leads to an increase in volatility for the spot market.

Concerning research on international market spillover effects, Johansson and Ljungwall (2009) explore the linkages among the different stock markets in China, Hong Kong, and Taiwan. The data include stock prices from the three main stock markets from January 5, 1994, to December 31, 2005. The empirical findings show that there is no long-run relationship among the markets. However, the researchers find short-run spillover effects in both returns and volatility in the region. Mean spillover effects from Taiwan affect both China and Hong Kong. Volatility in the Hong Kong market spills over into Taiwan, which in turn affects the volatility in the Mainland China market. Overall, the study shows significant interdependencies and volatility spillover effects among the three markets. On the other hand, Liu and An (2011) investigate information transmission and price discovery in informationally linked markets within the multivariate generalized autoregressive conditional hetero-skedasticity and information-sharing frameworks. The results show a bi-directional relationship in terms of price and volatility spillover between American and Chinese markets, with a stronger effect from American to Chinese markets than the other way around.

Specific to Asian markets, Yang et al. (2012) investigate intraday price discovery and volatility transmission between the Chinese stock index and the newly established stock index futures markets. The results indicate that the cash market plays a more dominant role in the price discovery process, and there is no strong evidence of a volatility transmission effect between the futures and spot markets. In summary, within the domestic market category, Korean financial markets are more efficient than Mexican markets because new information flows into the futures and spot markets simultaneously. Within the greater China area, all three areas (Mainland China, Hong Kong, and Taiwan) show interdependent volatility relationships. In the intercontinental context, volatility generally flows from American to Asian markets, which indicates that new information flows first to American markets and then moves into Asian markets.

With respect to the global financial crisis's effect on volatility spillover, Choudhry and Jayasekera (2014) investigate return, volatility, and leverage spillover effects between the banking and industrial stock markets of the major economies and the smaller, stressed European Union countries from the pre-crisis period to the post-crisis period. The results indicate an increase in both means and volatility spillover between the major economies and the stressed EU economies from the pre-crisis period to the crisis period. During the pre-crisis period, there is ample evidence of spillover from Germany, the United Kingdom, and the United States to the smaller EU economies. We find little evidence of significant spillover from the smaller economies to the major economies during this period. During the crisis, however, there is clear evidence of spillover from smaller EU economies to the major economies. Focusing on Asian markets, In et al. [2001] examine dynamic interdependence, volatility transmission, and market integration across selected stock markets during the Asian financial crisis periods. The results indicate reciprocal volatility transmission between Hong Kong and Korea, and unidirectional volatility transmission from Korea to Thailand. Hong Kong played a significant role in volatility transmission to the other Asian markets.

In terms of methodologies, a variety of volatility models have been applied, including the VECM, co-integration analysis, BEKK-GARCH, VECH-GARCH, and CCC-GARCH models. Comparing VECH-GARCH and BEKK-GARCH, the advantage of BEKK over VECH is that it requires fewer parameters to estimate and ensure the positive definiteness of conditional covariance matrices, which is the most important issue for the estimation of the multivariable GARCH models (Iltuzer and Tas, 2012). However, Wu et al. (2013) point out three major disadvantages of the BEKK model: The large number of parameters in BEKK and local maxima in the likelihood function often lead to overfitting; financial markets are dynamic, and market conditions change with time, but BEKK does not naturally capture these shifts in market conditions; and the maximum likelihood fit of the BEKK parameters involves solving a non-linear optimization process, which is computationally expensive and infeasible in high dimensions. Caporin and McAleer (2012) compare two multivariate conditional volatility models − BEKK and DCC − and discuss the similarities and dissimilarities of these two models. They conclude the following: BEKK possesses asymptotic properties under untestable moment conditions, whereas DCC's asymptotic properties have simply been stated under a set of untestable regularity conditions; and BEKK could be used to obtain consistent estimates of DCCs, with a direct link to the indirect DCC model.

2. Shanghai and Hong Kong stock exchange

The most important difference in regulations between the Shanghai and Hong Kong stock exchanges is the price limits on the Shanghai stock exchange. This price limit is equal to 10% of the last trading day's settlement price. Kim (2001) made the following interesting point: More (less) restrictive on price limits will lead higher (lower) volatility in stock market. In contrast, Phylaktis et al. (1999) examined the effects of price limits on stock volatility on the Athens stock exchange. They concluded that price limits give investors time to reassess the information they have and reduce stock volatility. Exhibit 2 indicates that, for the Mainland China and Hong Kong stock exchanges, a price limit rule causes higher volatility during a pre-crisis period and lower volatility in a crisis period. Overall, a clear conclusion cannot be achieved on the effect of price limits on the volatility of a stock index.

The Shanghai stock index was compiled by the Shanghai stock exchange, and it adopted December 19, 1990, as the date from which to calculate the base point, starting with a base value of 100. The volume of shares is used as a weighting mechanism in the calculation of the index as follows:

Index value = market total value/base day market value × 100,

Market total value = listed stocks' close price × volume of share.

The Hong Kong stock index was compiled by Heng Sheng Bank, and is also weighted by share volume. The base date was selected as July 1, 1964, and the base value was 100 points. The index calculation formula is the same as the formula for the Shanghai stock index. The calculation method for these two indexes shows that a listed company with a larger share volume has a more significant influence on the index. These two indexes are the most actively traded stock indexes in Mainland China and Hong Kong, and generally represent the economic atmosphere of their respective regions.

The trading hours for the Shanghai index are divided into three parts. The first part is the auction period, from 9:15 to 9:25, and the second and third parts are continuous trading periods, from 9:30 to 11:30 and from 13:00 to 15:00. The Hong Kong index trades during four periods, including two auction periods from 9:30 to 10:00 and 16:00 to 16:10. The two continuous trading periods are 10:00 to 12:30 and 14:30 to 16:00. As of March 5, 2012, the Hong Kong stock index trading hours were modified to approach that of the Mainland China market. The first stage advanced to 9:30 to 12:00, and the second stage advanced to 13:00 to 16:00. The Hong Kong index has a total of five and a half continuous trading hours, or one and a half hours longer than that of the Mainland China market. The Hong Kong index uses the last 10 minutes of the auction period to form settlement prices, and the Shanghai index applies the volume weighted average price from the last 15 minutes of the continuous trading time to conform the settlement price. The quotation currency for Shanghai stocks is the Chinese RMB, and Hong Kong stocks have adopted the Hong Kong dollar. In this study, we do not apply a complex exchange rate to evaluate the relative value of the two markets. A continuous compound return, which represents a percentage change in stock prices, is applied to solve this currency issue.

3. Data description

The aim of this paper is to investigate the effect of the global financial crisis on volatility spillover between the Mainland China and Hong Kong stock markets. We select two representative stock indexes: the Shanghai composite index (Mainland China) and the Hang Seng index (Hong Kong). We select and match daily close values; if a market is closed, the price index of the market is the same as on the day before the market closed. The time range is from January 04, 2002 to December 31, 2013. The total sample is broken into two sub-periods: pre-crisis (January 04, 2002 to June 30, 2007) and crisis (July 01, 2007 to December 31, 2013). The Bloomberg dataset is the data source.

The daily returns are calculated as:

$$R_t = 100 \times (\log P_t - \log P_{t-1}).$$

Figure 1 shows the returns of two markets. It clearly shows that between the years 2007 and 2009, both markets were more volatile than in other periods. We find a strong volatility clustering effect in both markets. Exhibit 2 represents the basic statistical description of returns and volatility. The statistical results clearly show that the crisis period generates higher volatility than the pre-crisis period; the pre-crisis period shows positive returns on average, whereas the crisis period shoes negative returns. This result is consistent with the mature Western markets (Choudhry and Jayasekera, 2014; Coudert et al., 2011), in which the crisis period generates higher volatility and lower market returns. Meanwhile, returns and volatility are significantly different from normal distribution in the JB statistics results.

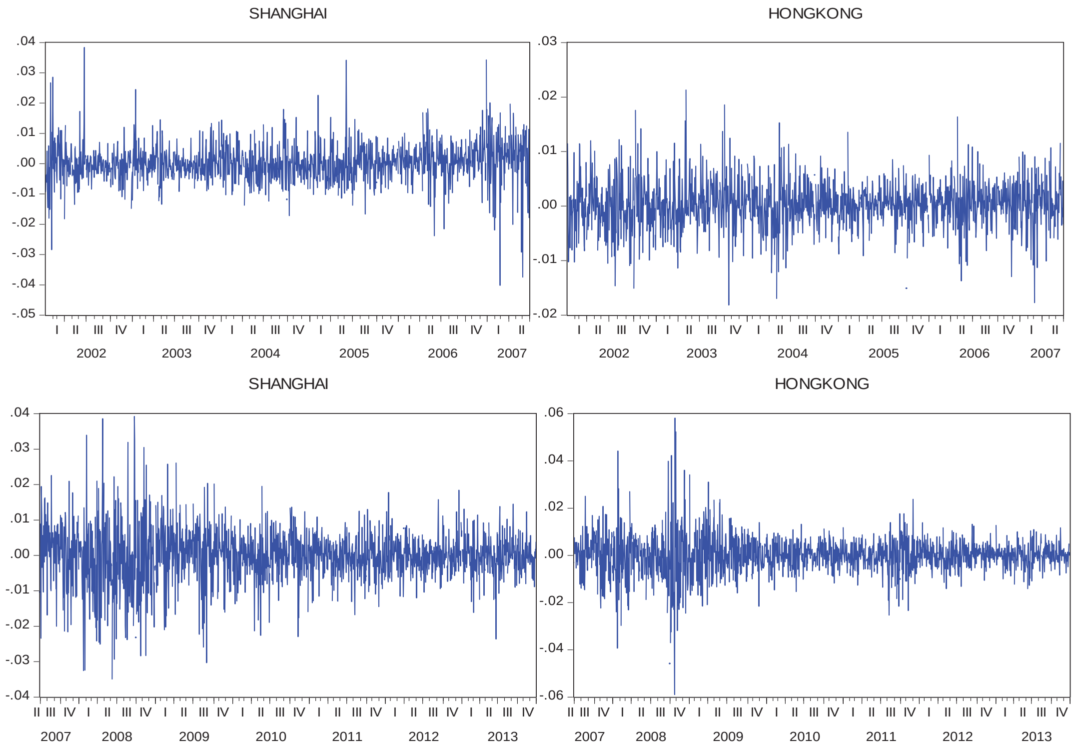

Fig. 1. Returns of two stock indexes

Table 1. Basic statistics

	Mean	Variance	Skewness	Kurtosis	JB
Pre-Crisis Period: 2002-2007					
Stock Returns					
Mainland China	0.000287	0.006614	0.036461	7.810506	1230.611
Hong Kong	0.000220	0.004543	0.042022	4.632810	142.1216
Volatility					
Mainland China	0.004644	0.004716	2.501239	13.65924	7371.249
Hong Kong	0.003331	0.003096	1.605626	6.376176	1154.286
Crisis Period: 2007-2014					
Stock Returns					
Mainland China	-0.000174	0.007789	-0.156277	5.947021	562.4538
Hong Kong	-1.71e-05	0.008263	-0.014621	10.57583	3675.607
Volatility					
Mainland China	0.005497	0.005519	2.033512	8.611247	3075.715
Hong Kong	0.005588	0.006085	3.077804	18.86688	18549.64

4. Study methodology

We apply the asymmetric BEKK-GARCH model to examine the volatility spillover effect. The advantage of the BEKK-GARCH model is that it ensures the conditional variance-covariance matrix is always positively definite (Engle and Kroner, 1995). The empirical evidence (Black, 1976; Christie, 1982) shows that financial market volatility has asymmetric effects, combined with the leptokurtic and fat tail distribution of asset returns. Volatility asymmetry refers to a negative relationship between stock returns and future volatility. This effect can be explained by two points: first, treating equity as a call option on the value of the firm's assets, when the asset value falls below liabilities, the option becomes worthless (Black, 1976; Christie, 1982); and, second, assuming a rational investor paradigm, rising volatility pushes the expected return higher, which in turn lowers the stock price, contributing to the asymmetric effect in volatility (Bollerslev et al., 1988).

The volatility spillover test models are based on bivariate VAR (1) as follows:

$$R_{i,t} = u_i + \varphi_i R_{i,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t}$ is a (2 × 1) vector referring to the two markets' returns at time t; u_i is a (2 × 1) vector representing the long-term coefficient drift; and $\varepsilon_{i,t}$ is a (2 × 1) vector referring to the random uncorrelated error terms of these two markets at time t. Thus, the equation defines H_t as the (2 × 2) conditional variance-covariance matrix of $\varepsilon_{i,t}$, and $\varepsilon_{i,t}|\psi_{t-1} \sim N(0, H_t)$ with ψ_{t-1} represents the information set at time t-1. Consequently, the conditional variance-covariance matrix H_t can be written as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\eta_{t-1}\eta'_{t-1}D. \quad (2)$$

In the conditional variance-covariance equation, C is a (2 × 2) upper triangular matrix; A is a (2 × 2) matrix representing the degree of H_t relative to the past error term in the mean equation; B is a (2 × 2) matrix referring to the relationship between current conditional variance and past conditional variance; coefficient matrix D is used to measure the impact degree of the asymmetric effect between positive and negative shocks; and asymmetric item η_{t-1} is defined as η_{t-1} = max [0, $-\varepsilon_{t-1}$].

Alternatively, we can expand the conditional variance-covariance matrix H_t as follows:

$$H_t = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \varepsilon_{t-1}\varepsilon'_{t-1} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} + \\ + \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}' \eta_{t-1}\eta'_{t-1} \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}. \quad (3)$$

We use the maximum likelihood estimation method to estimate the models, and the Berndt, Hall, Hall, and Hausman (BHHH) algorithm to optimize the method. We can represent the likelihood function $L(\theta)$ as follows:

$$L(\theta) = -\frac{TN}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}(\log|H_t| + \varepsilon'_t H_t^{-1}\varepsilon_t), \quad (4)$$

where θ denotes all the unknown parameters to be estimated; N is the number of assets; and T is the number of observations. Meanwhile, the θ in the maximum likelihood estimation is asymptotic to normal distribution.

Two aspects influence the volatility of market i: its own pervious terms, including volatility $h_{ii,t-1}$, residue $\varepsilon_{i,t-1}$, and the asymmetric term $\eta_{i,t-1}$; and market j's pervious influence and the covariance between the two markets, including covariance $h_{ij,t-1}$, residue $\varepsilon_{i,t-1}$, $\varepsilon_{j,t-1}$ and the asymmetric term $\eta_{j,t-1}$. Therefore, if

$$a_{ij} = b_{ij} = d_{ij} = 0, \ (i \neq j), \quad (5)$$

then only market i's own pervious terms influence its volatility, and no volatility spillover effect exists.

Applying the constraints of coefficients a, b, and d to test the two markets' volatility spillover effect, we propose the following hypotheses:

Hypothesis 1: No volatility spillover exists between market 1 and market 2:

$$a_{12} = b_{12} = a_{21} = b_{21} = 0, \quad (6)$$

Hypothesis 2: No volatility spillover exists from market 1 to market 2:

$$a_{21} = b_{21} = 0. \quad (7)$$

Hypothesis 3: No volatility spillover exists from market 2 to market 1:

$$a_{12} = b_{12} = 0. \quad (8)$$

Hypothesis 4: No asymmetric effect exists between market 1 and market 2:

$$d_{12} = d_{21} = 0. \quad (9)$$

5. Study results

We present the asymmetric BEKK-GARCH estimated results in Table 2.

Table 2. Asymmetric BEKK-GARCH estimated results

	Pre-Crisis Period			Crisis Period		
	Coefficient	t-Statistic	P-Value	Coefficient	t-Statistic	P-Value
Mean(1)	0.0003008	0.85543	0.39231282	-0.000194607	-1.16015	0.24598798
Mean(2)	0.0002172	0.91194	0.36180202	-0.000000778	-0.00503	0.99598947
C(1,1)	0.0066100	47.64366	0.00000000	0.000611468	5.54047	0.00000003
C(2,1)	0.0007198	2.87354	0.00405896	0.000633542	5.28883	0.00000012
C(2,2)	0.0044777	37.11401	0.00000000	0.000383889	3.24185	0.00118757
A(1,1)	0.2236068	4.23380	0.00002298	-0.147641066	-5.70459	0.00000001
A(1,2)	0.0000000	0.00000	1.00000000	-0.014215416	-0.57735	0.56370269
A(2,1)	0.0000000	0.00000	1.00000000	0.077481481	3.55431	0.00037897
A(2,2)	0.2236068	2.74558	0.00604034	0.158830052	6.69512	0.00000000
B(1,1)	0.6708204	42.37071	0.00000000	0.988478689	161.93200	0.00000000
B(1,2)	0.0000000	0.00000	1.00000000	0.017944834	2.67741	0.00741942
B(2,1)	0.0000000	0.00000	1.00000000	-0.018651637	-3.00923	0.00261913
B(2,2)	0.6708204	32.69464	0.00000000	0.947377639	147.16457	0.00000000
D(1,1)	0.0000000	0.00000	1.00000000	0.084826463	2.84028	0.00450743
D(1,2)	0.0000000	0.00000	1.00000000	-0.090980243	-2.58529	0.00972983
D(2,1)	0.0000000	0.00000	1.00000000	0.126649066	4.14664	0.00003374
D(2,2)	0.0000000	0.00000	1.00000000	0.362923758	8.79535	0.00000000

Wald Joint Coefficient Test	Pre-Crisis Period		Crisis Period	
	Chi-Squared Value	P-Value	Chi-Squared	P-Value
A(1,2)=A(2,1)=0	0.0000	1.0000	12.6518	0.0017
B(1,2)=B(2,1)=0	0.0000	1.0000	10.7108	0.0047
D(1,2)=D(2,1)=0	0.0000	1.0000	17.8002	0.0001

In the pre-crisis period, both Mainland China and Hong Kong show significant positive ARCH and GARCH effects, but no significant asymmetric effect. The ARCH and GARCH effects remain significant in the crisis period for both markets. One interesting point is that the coefficient of the ARCH term for Mainland China is negative, which indicates the first lag term shock has a negative effect on current volatility. The short-term volatility mean-revert effect can explain this phenomenon; that is, high volatility means lower volatility the next trading day for the Mainland China market. However, from a long-term point of view, the GARCH effect is still positively significant for the Mainland China market.

Asymmetric effects are significant for both markets. The asymmetric effect changes from not significant in the pre-crisis period to significant in the crisis period, which indicates investors become more risk averse. In the pre-crisis period, investors react to positive and negative shocks equally, but in the crisis period, negative shock creates more investor panic, which is reflected in negative shocks, creating larger volatility in the next trading day. The Wald joint coefficient test indicates no bi-directional volatility spillover for ARCH or GARCH and no asymmetric effect in the pre-crisis period. We find significant bi-directional volatility spillover for all three effects in the crisis period. Volatility spillover reflects information flows; strong volatility spillover indicates two markets are highly linked. The results indicate that the financial crisis increased linkage between the Mainland China and Hong Kong markets.

6. Robustness test

We apply the bivariate VAR approach and Granger causality tests as robustness tests to confirm the result. We divide the total sample period into two sub-periods: the pre-crisis period and the crisis period. We treat the daily squared logarithm return as daily true volatility. We can note the bivariate VAR as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}. \qquad (10)$$

We apply the ADF test to the two sub-periods' data stationarity and present the test results in Table 3.

From the test results, the previous conclusions are confirmed: In the pre-crisis period, no volatility spillover exists between the Mainland China and Hong Kong financial markets. In the crisis period, we find strong bi-directional volatility spillover between these two markets.

Table 3. ADF stationarity test results

	Pre-Crisis Period		Crisis Period	
	t-Statistic	P-Value	t-Statistic	P-Value
Shanghai	-9.2318	0.0000	-6.2480	0.0000
Hong Kong	-36.3538	0.0000	-5.2153	0.0000

Table 4. Granger causality test results

Pre-Crisis Period					
	Shanghai			Hong Kong	
	Chi-Squared	P-Value		Chi-Squared	P-Value
Hong Kong	0.4403	0.8024	Shanghai	3.9063	0.1415
Crisis Period					
	Shanghai			Hong Kong	
	Chi-Squared	P-Value		Chi-squared	P-Value
Hong Kong	31.6806	0.0000	Shanghai	14.4735	0.0168

7. Global financial crisis influence

We use S&P 500 stock index data to examine the global financial crisis's influence on the Mainland China and Hong Kong markets during the crisis period (June 29, 2007 to December 31, 2013). We apply BEKK-GARCH to examine the direction of volatility spillover present the test results in Table 5.

The results indicate strong ARCH and GARCH effects for the Mainland China and American markets. Both A(1,2) and B(1,2) are not significant at the 5% confidence level, which indicates no volatility spillover from the United States to the Mainland China market. However, A(2,1) and B(2,1) are significant at the 5% confidence level, which indicates that Mainland China has some degree of influence on American market volatility. Considering the Hong Kong and American markets, all the variance and covariance terms are strongly significant at the 1% confidence level, which indicates two points: Strong ARCH and GARCH effects exist for both markets; and strong bi-directional volatility spillover exists between the Hong Kong and American markets. Regarding pervious results, we find strong bi-directional volatility spillover between the Mainland China and Hong Kong markets after the global financial crisis. The Hong Kong market is a mature market directly influenced by the global financial crisis. Mainland China is still a closed market, and the American market does not influence it directly. From these results, this paper concludes that the global financial crisis influenced Mainland China through the Hong Kong market.

Table 5. BEKK-GARCH test results

	Mainland China/United States			Hong Kong/United States		
	Coefficient	t-Statistic	P-Value	Coefficient	t-Statistic	P-Value
A(1,1)	0.121618958	7.70141	0.00000000	0.201700756	7.43591	0.00000000
A(1,2)	-0.056026659	-0.96577	0.33415739	0.324246749	6.70299	0.00000000
A(2,1)	0.021466007	2.16314	0.03053053	-0.228361588	-10.59209	0.00000000
A(2,2)	0.347583439	15.92023	0.00000000	0.139671484	4.02038	0.00005811
B(1,1)	0.990803058	396.65351	0.00000000	0.800486759	36.25944	0.00000000
B(1,2)	0.006681056	0.55297	0.58028321	-0.412559603	-5.55315	0.00000003
B(2,1)	-0.007881378	-2.61902	0.00881834	0.146833859	8.42577	0.00000000
B(2,2)	0.931211959	123.93029	0.00000000	0.983745322	71.46619	0.00000000

8. Volatility spillover at intraday level

In this section, we test the volatility spillover effect between the Shanghai index and the Hong Kong index at the intraday level. Given limited access to high frequency data, the test period is for one month from November 10, 2014 to December 10, 2014. The data frequency is one-minute intervals and the total sample size is 5,761. The trading time for these two indexes is not the same; therefore, this study applies matched time data and deletes unmatched time data. The daily trading matched time is from 9:30 to 11:30 and from 13:00 to 15:00. The BEKK model is applied and Table 6 presents the tested results.

Table 6. Intraday BEKK-GARCH results

MC/HK	A(1,1)	A(1,2)	A(2,1)	A(2,2)	B(1,1)	B(1,2)	B(2,1)	B(2,2)
Coef	0.22360	0.000000	0.000000	0.223607	0.670820	0.000000	0.000000	0.670820
t-Stat	0.78172	0.000000	0.000000	0.619841	15.06923	0.000000	0.000000	15.76795
P-V	0.43430	1.000000	1.000000	0.53536	0.00000	1.00000	1.00000	0.000000

Table 6 shows that no significant volatility spillover exists between the Mainland China and the Hong Kong market at the intraday level.

Compared to daily volatility test results, the intraday volatility provides a different answer regarding the volatility spillover within the same markets. The key difference between these two results is the time interval, in this study, daily data generates an aggregate daily volatility, but intraday data provide 1-minute interval volatility. There exists a bi-directional daily volatility spillover effect between Mainland China and Hong Kong markets, but from a microscopic view, a random volatility spillover process is found and no volatility spillover is concluded between these two markets. The volatility spillover links to new information flow. Similar to volatility, within the daily level, new information flows to Mainland China and Hong Kong markets simultaneously. The expected intraday new information effect equals zero, which means that new information provides an equal effect for both markets at a 1-minute intraday level.

Study conclusion

There are three main conclusions from this study. Firstly, the global finance crisis enhanced the informational linkage between the Mainland China and Hong Kong stock markets because a strong bi-directional volatility spillover effect exists after the crisis period. After the 2007 global financial crisis, several large-cap Hong Kong stocks, such as China Petroleum (601857), China Petrochemical (600028), Industrial and Commercial Bank of China (601398), Bank of China (601988), and China Life Insurance (601628), dual-listed on the Mainland China market to diversify financial risk. The informational linkage between these two indexes rose sharply after the global financial crisis, which caused strong bi-directional volatility spillover between these two markets.

Secondly, the global financial crisis influenced Mainland China through the Hong Kong stock market. As a mature market, the Hong Kong stock market is subject to strong American market influence, as shown by the fact that strong bi-directional volatility spillover exists in the crisis period. On the other hand, no volatility spillover exists from the United States to the Mainland China market. However, we find strong bi-directional volatility spillover between the Mainland China and Hong Kong markets after the crisis. From these results, we conclude that the global financial crisis first influenced the Hong Kong market, and then the global financial risk flowed into the Mainland China market. The Mainland China stock market is still a relatively closed market. The economic integration between Hong Kong and Mainland China significantly benefits economic growth but also increases risk exposure for the Mainland China market in the case of global financial crisis.

Thirdly, this paper concludes that there is strong bi-directional daily aggregated volatility spillover effect after crisis period, but no volatility spillover effect is concluded under intraday high frequency level. That is, from a macro daily aggregated structure point of review, both two markets reflect to new information simultaneously. However, from a micro intraday high frequency level point of review, there does not have strong information linkage between these two markets. This paper concludes that volatility spillover depends on data frequency; different data structure (Micro or Macro) will provide different answer on volatility spillover in the same two markets.

References

1. Black, F. (1976). *Studies of Stock Market Volatility Change*, Proceedings of the American Statistical Association, Business and Economics Statistics Section, pp. 177-181.
2. Bollerslev, T., Engle, R.F. and Wooldridge, J.M. (1988). A Capital Asset Pricing Model With Time Varying Covariances, *Journal of Political Economy*, 96, pp. 116-131.
3. Bollerslev, T., Sizova, N. and Tauchen, G. (2012). Volatility in Equilibrium Asymmetries and Dynamic Dependencies, *Review of Finance*, 16, pp. 31-80.
4. Bhar, R. and Nikolova, B. (2009). Return, Volatility Spillovers and Dynamic Correlation in the BRIC Equity Markets: An Analysis Using a Bivariate EGARCH Framework, *Global Finance Journal*, 19, pp. 203-218.
5. Caporin, M.M. McAleer (2013). Ten Things You Should Know about the Dynamic Conditional Correlation Representation, *Econometrics*, 1 (1), pp. 115-126.
6. Chan, K.C., Karolyi, G.A. (1991). Intraday Volatility in Stock Index and Stock Index Futures Market, *Review of Financial Studies*, 4, pp. 657-684.
7. Chen, K., Fung, H. and Leung, W. (2004). Daily Volatility Behaviour in Chinese Futures markets, *Journal of International Financial Markets, Institutions and Money*, 14, pp. 491-505.
8. Choudhry, T. and Jayasekera, R. (2014). Returns and Volatility Spillover in the European Banking Industry During Global Financial Crisis: Flight to Perceived Quality or Contagion? *International Review of Financial Analysis*, 10, pp. 710-720.
9. Christie, A. (1982). The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effects, *Journal of Financial Economics*, 10, pp. 407-432.
10. Corsi, F. (2009). A Simple Approximate Long-Memory Model of Realized Volatility, *Journal of Financial Econometrics*, 7, pp. 174-196.
11. Couder, V., Couharde, C. and Mignon, V. (2011). Exchange Rate Volatility across Financial Crisis, *Journal of Banking & Finance*, 35, pp. 3010-3018.

12. Engle, R.F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, *Econometrica*, 50, pp. 987-1007.
13. Engle, R.F., Kroner, K.F. (1995). Multivariate Simultaneous Generalised GARCH, *Econometric Theory*, 11, pp. 125-150.
14. Fama, E.F. (1970). Efficient Capital Market: A review of Theory and Empirical Work, *The Journal of Finance*, 25, pp. 383-471.
15. Iltuzer, Z. and Tas, O. (2012). The Analysis of Bidirectional Causality Between Stock Market Volatility and Macroeconomic Volatility, *International Journal of Business and Social Science*, 3, pp. 12-29.
16. In, F., Kim, S., Yoon, H.H. and Viney, C. (2001). Dynamic Interdependence and Volatility Transmission of Asian Stock Markets: Evidence from the Asian Crisis, *International Review of Financial Analysis*, 10, pp. 87-96.
17. Johansson, A.C., Ljungwall, C. (2009). Spillover Effects Among the Greater China Stock Markets, *Law Finance and Economic Growth in China*, 37, pp. 839-851.
18. Kang, S.H., Cheong, C., Yoon, S. (2013). Intraday Volatility Spillovers Between Spot and Futures Indices: Evidence from the Korean Stock Market, *Physical A*, 392, pp. 1795-1802.
19. Kim, K.A. (2001). Price Limits and Stock Market Volatility, *Economics Letters*, 71, pp. 131-136.
20. Liu, Q., An, Y. (2011). Information Transmission in Informationally Linked Markets: Evidence from US and Chinese Commodity Futures Markets, *Journal of International Money and Finance*, 30, pp. 778-795.
21. Patton, J.A. (2011). Volatility Forecast Comparison Using Imperfect Volatility Proxies, *Journal of Econometrics*, 160, pp. 246-256.
22. Phylaktis, K., Kavussanos, M. and Manalis, G. (1999). Price Limits and Stock Market Volatility in the Athens Stock Exchange, *European Financial Management*, 5, pp. 69-84.
23. So, R., Tse, Y. (2004). Price Discovery in the Hang Seng Index Market: Index, Futures and the Tracker Found, *Journal of Future Market*, 24, pp. 887-907.
24. Watcher, J.A. (2013). Can Time-Varying Risk of Rare of Disasters Explain Aggregate Stock Market Volatility, *The Journal of Finance*, 68, pp. 987-1035.
25. Wu, Y., Hernandez-Lobuto, J.M. and Ghahramani, Z. (2013). *Dynamic Covariance Models for Multivariate Financial Time Series*, University of Cambridge.
26. Yang, J., Yang, Z., Zhou, Y. (2012). Intraday Price Discovery and Volatility Transmission in Stock Index and Stock Index Futures Markets: Evidence From China, *Journal of Futures Market*, 32, pp. 99-121.
27. Zhong, M., Darrat, A.F., Otero, R. (2004). Price Discovery and Volatility Spillovers in Index Futures Markets: Some Evidence from Mexico, *Journal of Banking and Finance*, 28, pp. 3037-3054.