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Article

Intraday Volatility Spillover between the Shanghai and Hong Kong Stock Markets—Evidence from A+H Shares after the Launch of the Shanghai-Hong Kong Stock Connect

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Abstract: Using minute data of eligible A+H stocks under the Shanghai-Hong Kong Stock Connect (SHHKSC), we investigate the volatility spillover between the Shanghai and Hong Kong stock markets based on a generalized autoregressive conditional heteroskedasticity-X (GARCH-X) model with four exogenous variables, namely, volatilities of the corresponding stocks on the other market, volatilities of the indexes of both stock markets, and volatilities of the correlated stocks, which are selected using the dynamic conditional correlation model and bootstrap approach. Results show that after the launch of the SHHKSC, volatility spillovers are significant in both directions almost all the time, and the volatility spillover between the two stock markets tends to be larger when bidirectional capital flows under the SHHKSC increase or when important financial events occur. We also analyze the influences of the volatilities of correlated stocks and industries on the volatility spillover and volatilities of A+H stocks. The bidirectional volatility spillovers between Shanghai and Hong Kong stock markets do not change qualitatively after incorporating the volatilities of correlated stocks and industries in the GARCH-X model. Moreover, the average volatilities of the correlated stocks are shown to have significant influences on the volatilities of individual A+H stocks, and the influences increase when the local stock market shows a sharp rise or fall. Compared with the market indexes, the correlated stocks could be regarded as a more important and indispensable factor for individual A+H stocks' volatilities modeling, which may carry more information than the industry.

Keywords: Volatility spillover; Shanghai-Hong Kong Stock Connect; DCC model; GARCH-X model; High-frequency data

1. Introduction

With rapid economic development and implementation of a series of financial reforms and innovations—for instance, the issue of increases in A+H shares as well as launches of the qualified domestic institutional investor (QDII) mechanism, RMB qualified foreign institutional investor (RQFII) mechanism, and Shanghai-Hong Kong Stock Connect (SHHKSC), mainland China's stock markets have become remarkably correlated and more integrated with the Hong Kong stock market. The problem of volatility spillover between the Shanghai and Hong Kong stock markets has aroused wide attention from scholars. In particular, launch of the SHHKSC further promotes the opening up of Chinese stock markets and broadens the channels for bidirectional trading between the Shanghai and Hong Kong stock markets. Under this circumstance, the linkage between the two stock markets will be strengthened unprecedentedly, and the volatility spillover and risk transmission process will experience enormous changes.

Investigation of the volatility spillover between the Shanghai and Hong Kong stock markets after such a groundbreaking event needs urgent attention, as it has the following crucial implications: it helps to better understand the efficiency of both markets and their new pattern of relationship; it gives advice on international asset allocation and risk diversification, since the SHHKSC broadens the investment portfolio and improves the market structure on both sides; it provides references for financial policymaking under more marketable and internationalized circumstances; and it promotes healthy and sound development of the Shanghai and Hong Kong stock markets.

After the launch of the SHHKSC, researchers resumed the study of volatility spillover between the Shanghai and Hong Kong stock markets, and most studies were conducted based on daily data. Feng and Duan (2016) pointed out that implementation of the SHHKSC has reinforced the linkage between the two markets, and the volatility spillover from the Shanghai to the Hong Kong stock market has been significantly enhanced. Xu et al. (2017) demonstrated that the SHHKSC program enhanced the degree of bidirectional volatility spillovers between the industries in both markets, particularly the spillover from Shanghai to Hong Kong.

Although a small number of studies investigate the volatility spillover between the Shanghai and Hong Kong stock markets using high-frequency data, they mainly focus on market indexes. For instance, Lin (2017) reported that the causality of volatility was bidirectional both before and after the SHHKSC program, but the unidirectional feature of shock spillover from the Hong Kong market to Shanghai did not change in essence. Huo and Ahmed (2017) indicated that the SHHKSC program has increased the conditional variance of both stock markets, and after the program, the Shanghai stock market played a leading role over the Hong Kong stock market in terms of both mean and volatility spillover effects.

Currently, the stock exchanges have piled up large amounts of high frequency data, which makes it possible to uncover the essence of volatility spillover. Since the vigorous development of information science and technology has greatly promoted the speed of capital flows and information transfer, low-frequency data seem inadequate to fully reflect the volatility spillover mechanism. On the other hand, high-frequency data of individual stocks contain more detailed information, which may help us better understand the volatility spillover behavior in a smaller time scale. The relevant results could be used to develop better investment strategies for investors and provide more effective risk prevention advice to policymakers. Therefore, it is essential to investigate the volatility spillover between stock markets using high-frequency data of individual stocks.

In previous studies, several types of models were proposed to investigate volatility spillover. Among these, multivariate generalized autoregressive conditional heteroskedasticity (GARCH) type models are commonly used, such as the Glosten, Jagannathan, and Runkle (GJR) GARCH model (Choudhry and Jayasekera, 2014); Baba, Engle, Kraft, and Kroner (BEKK) GARCH model (Huang et al., 2012; Li, 2007); and dynamic conditional correlation (DCC) GARCH model (Dong and Wu, 2008; Tsiaplias and Chua, 2013). These multivariate GARCH models have one thing in common: they mainly account for the historical information of the series itself when modeling the conditional volatilities. To consider other factors that have significant influences, many additional economic or financial variables, denoted as X, are included in the GARCH model, which is thus known as the GARCH-X model (Brenner et al., 1996). Nana et al. (2013) suggested that the inclusion of exogenous variables helps to better understand market behavior, further improve the prediction of market reactions, and thus resist future risks.

In empirical studies that use the GARCH-X model to estimate conditional volatility, the choice of exogenous variables spans a wide range of economic or financial indicators, such as stock volumes, interest rates, and realized volatilities. Lamoureux and Lastrapes (1990) showed that the daily trading volume had significant explanatory power on the variance of daily returns, and it was therefore included in the GARCH model. Sharma et al. (1996) introduced stock volume into the GARCH (1, 1) model and found that volume does contribute significantly to explaining the GARCH effects. Similarly, the correlations between the trading volume and conditional market variance were investigated by Marsh and Wagner (2005) using a GARCH-X model. Engle and Patton (2001) and Glosten et al. (1993) put three-month US Treasury bill rates into a GARCH-M model for modeling the stock volatility, and Gray (1996) added interest rates to explain the conditional variance using a regime-switching GARCH model. Engle (2002) first introduced the realized volatility into a GARCH-X model. Similar studies include Cipollini et al. (2007), Engle and Gallo (2006), Hansen et al. (2012), Hwang and Satchell (2005), and Shephard and Sheppard (2010). In addition, many other variables such as forward-spot spreads (Hodrick, 1989), implied volatilities (Blair et al., 2001; Day and Lewis, 1992; Lamoureux and Lastrapes, 1993), bid-ask spreads (Bollerslev and Melvin, 1994), and futures open interest (Girma and Mougoue, 2002) are considered as exogenous variables.

Since the volatility of a certain stock would unavoidably be influenced by the overall circumstances and regional factors of the stock market, it is necessary to consider them when modeling the volatility of individual stocks. The overall circumstances of the stock market can be well represented by the market indexes. However, the influence of regional factors is not solely from the industries or plates. In fact, we find that not only do stocks in the same industry or plate tend to have strong correlations, but the stocks in different industries or plates such as those issued by companies that have business dealings with each other also may have significant influences on each other. Therefore, we identify stocks that have strong correlations with a certain stock as correlated stocks to accurately measure the influence of the regional factor on this stock. Based on this idea, we first include a new variable called the volatility of correlated stocks in our GARCH-X model for modeling the volatility of an eligible A+H stock on the Shanghai (Hong Kong) stock market, together with three other variables, namely the volatility of the Shanghai Composite Index (SCI), volatility of the Hang Seng Index (HSI), and volatility of the corresponding stock on the Hong Kong (Shanghai) stock market. The influences of industries on individual stocks have been considered in the literature. We incorporate the volatilities of industries into our model and compare the influences of correlated stocks and industries on the volatility spillover and volatilities of eligible A+H stocks.

A DCC model is used to detect the correlated stocks of each A+H stock in this study. In early studies on stock correlations, hierarchical clustering methods such as minimum spanning tree (MST) and planar maximally filtered graph (PMFG; Huang et al., 2008; Zhang et al., 2014) were commonly used to identify the static correlation between individual stocks. To study the variance of their correlations over time, researchers started to use hierarchical clustering methods in rolling windows (Aste et al., 2010; Huang et al., 2014), which may have caused multifarious results due to the arbitrary choice of parameters, including the length and drift of the estimation window, which undermined the objectivity and reasonability of the research conclusions to some extent (Forbes and Rigobon, 2002). The DCC model is a successful method to detect time-varying correlations, which can not only overcome chaos in selecting parameters of the estimation window by directly offering full-sample correlation estimates but also obtain higher robustness with respect to the heteroscedasticity matter (Engle, 2002; Caporale et al., 2005; Cappiello et al., 2006). It has been used widely to investigate the dynamic conditional correlations among stocks. Lyócsa et al. (2012) constructed the MST of S&P 100 constituents using the DCC model. Yiu et al. (2010) estimated the dynamic correlations between 11 Asian stock markets and the US stock market using an asymmetric DCC model, and Mensi et al. (2017) used the DCC model to analyze the dynamic conditional correlations between the BRICS stock markets.

In this study, we introduce a GARCH-X model with four exogenous variables and use the minute data of individual stocks to investigate the volatility spillover between the Shanghai and Hong Kong stock markets after the launch of the SHHKSC based on this new model. Our work has four contributions: First, using minute data, we not only accurately and promptly reveal the intraday volatility spillover behavior but also study the dynamics of volatility spillover between the Shanghai and Hong Kong stock markets on different trading days. Our results show that the volatility spillover between the two stock markets is strengthened when capital flows under the SHHKSC increase or important financial events occur; this is in contrast with the bidirectional results of previous studies based on low-frequency data during a certain sample period. Second, using the minute data of individual A+H stocks rather than the market indexes, we investigate the volatility spillover from the perspective of individual stocks, which means that our study can be compared in detail with previous studies based on the high-frequency data of market indexes. Third, we assume that the volatility of an A+H stock would be influenced by the overall circumstances and regional factors of the stock market. Moreover, we introduce exogenous variables such as the volatilities of market indexes and correlated stocks to construct a new GARCH-X model, based on which we can not only analyze the volatility spillover but also simultaneously measure the influences of stock indexes and correlated stocks on the volatility of individual stock. Fourth, our study is of practical value to investors in the Shanghai and Hong Kong stock markets and policymakers. Investors in the two markets could refer to our interpretation regarding the increase in volatility spillover and take proactive measures to allocate their stock assets and control the potential risks in advance. Our results also offer valuable references for policymakers, with which they could foresee the possible aftermath of implementating a policy and take preemptive measures to prevent financial risks.

The remainder of this paper is organized as follows: Section 2 presents the data and introduces the methods. Section 3 addresses the empirical results, and Section 4 is the conclusion.

2. Data and Methods

2.1. Data

In this study, we use the one-minute closing prices of 832 eligible A+H stocks (these include 568 Shanghai

Stock Exchange stocks that are eligible for trading by Hong Kong and overseas investors as well as 264 eligible Hong Kong Stock Exchange stocks that mainland investors are able to trade) under the SHHKSC to study the volatility spillover between the Shanghai and Hong Kong stock markets. To model the volatilities of A+H stocks listed on the Hong Kong stock market, the correlated stocks are selected from the eligible Hong Kong Stock Exchange (HKSE) securities under the SHHKSC; correspondingly, the correlated stocks are filtered from the eligible Shanghai Stock Exchange (SSE) stocks under the SHHKSC for modeling the volatilities of individual A+H stocks on the Shanghai stock market. Therefore, under the SHHKSC, the one-minute closing prices of 264 eligible H-shares for southbound trading and 568 eligible A-shares for northbound trading, as well as the SCI and HSI, are used in our study. All data are retrieved from the Bloomberg database.

SSE stocks that are eligible for trading by Hong Kong and overseas investors include all constituent stocks of the SSE 180 Index and the SSE 380 Index, as well as other SSE-listed A-shares that have corresponding H-shares listed on the HKSE; among these, stocks that are not traded in RMB or are under risk alert are excluded. At the beginning of the SHHKSC, there were 568 eligible SSE stocks in total, and those shares accounted for most of the market capitalization of all SSE-listed A-shares. Eligible stocks listed on the HKSE that mainland investors are able to trade include all constituent stocks of the Hang Seng Composite Large Cap Index (HSLI), Hang Seng Composite Mid Cap Index (HSMI), and other H-shares that have corresponding shares in the form of A-shares listed on the SSE. Stocks that satisfy the conditions described below are filtered out: (a) Hong Kong shares that are not traded in HKD; (b) H-shares that have corresponding shares listed and traded on any exchange in mainland China other than the SSE; and (c) H-shares that have corresponding A-shares put under risk alert. At the beginning of the SHHKSC, the total number of eligible HKSE stocks was estimated to be 264, and it accounted for about 80% of all HKSE securities in terms of market capitalization and trading volume.

The sample period of our study is from 17 November 2014 to 5 July 2016, which is more than one and a half years. According to the holiday arrangement of the SHHKSC, investors are allowed to trade on the other market on days when the Hong Kong and Shanghai markets are both open for trading. Therefore, other than weekends and holidays, we also exclude the days when only one stock exchange is open, and thus we select 384 trading days for the SHHKSC.

The SSE usually trades from 9:30 am (Beijing time) to 11:30 am and from 1:00 pm to 3:00 pm. On the other hand, the trading hours of the HKSE are 9:30 am to 12:00 am and 1:00 pm to 4:00 pm. In our study, we investigate the intraday volatility spillover during the period when there are simultaneous operations on both markets. Thus, we only use data from 9:30 am to 11:30 am and from 1:00 pm to 3:00 pm on each trading day, which is 240 minutes a day in total.

The one-minute returns are calculated as the difference in natural logarithms of the closing prices using the following formula:

$$r_i(t) = ln\, P_i\,(t) - ln\, P_i\,(t-1), \tag{1}$$

where i refers to a stock or a market index, and $P_i(t)$ denotes the closing price of stock (index) i at time t.

2.2. GARCH-X Model

The GARCH-X model is an extended GARCH model. The GARCH model was proposed by Bollerslev (1986) and has been widely used to estimate the volatility of financial series, since it can well characterize the volatility clustering features of financial series. For a time series of r_t, the framework of a univariate GARCH can be formulated as follows:

$$r_t = E(r_t|\Omega_{t-1}) + \varepsilon_t , \tag{2}$$

$$\varepsilon_t|\Omega_{t-1} \sim N(0, h_t), \tag{3}$$

$$h_t = \omega + \sum_{k=1}^{q} \alpha_j \varepsilon_{t-k}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}, \tag{4}$$

where Ω_{t-1} refers to the information set at time $t-1$, ε_t is the error term on past information set Ω_{t-1}, h_t is the conditional variance of r_t that also known as the volatility, and p and q are the orders of the GARCH term h_{t-j} and the autoregressive conditionally heteroscedastic (ARCH) term ε_{t-k}^2, respectively. Equation (2) is called the mean equation, and Equation (4) is the conditional variance equation.

The standard GARCH model only relates the volatility of the time series to the information contained in their own history; additional variables are introduced into the GARCH model to consider the influences of other important factors for modeling the volatilities of economic and financial time series (Engle and Patton, 2001; Hansen et al. 2012; Sharma et al. 1996). Given its popularity, we use the GARCH (1, 1) model to specify the volatility equation of the GARCH-X model as follows:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \pi x_{t-1}, \tag{5}$$

where ε_t is the error term conditional on the past information set, h_t is the conditional variance at time $t-1$, and x_{t-1} denotes the exogenous variables that have influence on the volatility h_t.

In this study, we specifically construct the following GARCH (1, 1)-X models to investigate the volatility spillover from the Shanghai stock market to the Hong Kong stock market and vice versa:

$$\begin{aligned} V_{i,H}(t) = \theta_H + \alpha_H \varepsilon_{i,H}^2(t-1) + \beta_H V_{i,H}(t-1) + \gamma_{1H} V_{i,A}(t-1) \\ + \gamma_{2H} V_{i,CS\_H}(t-1) + \gamma_{3H} V_{HSI}(t-1) + \gamma_{4H} V_{SCI}(t-1), \end{aligned} \tag{6}$$

$$\begin{aligned} V_{i,A}(t) = \theta_A + \alpha_A \varepsilon_{i,A}^2(t-1) + \beta_A V_{i,A}(t-1) + \gamma_{1A} V_{i,H}(t-1) \\ + \gamma_{2A} V_{i,CS\_A}(t-1) + \gamma_{3A} V_{SCI}(t-1) + \gamma_{4A} V_{HSI}(t-1), \end{aligned} \tag{7}$$

where $V_{i,H}(t)$ and $V_{i,H}(t-1)$ represent the volatilities of individual A+H stocks on the Hong Kong stock market at time t and $t-1$, respectively. Similarly, $V_{i,A}(t)$ and $V_{i,A}(t-1)$ are the volatilities of individual A+H stocks on the Shanghai stock market at time t and $t-1$, respectively. $V_{i,H}(t-1)$ and $V_{i,A}(t-1)$ are also known as the GARCH terms, and $\varepsilon_{i,H}^2(t-1)$ and $\varepsilon_{i,A}^2(t-1)$ denote the ARCH terms of A+H stocks on the Hong Kong and Shanghai stock markets, respectively. $V_{HSI}(t-1)$ and $V_{SCI}(t-1)$ are the volatilities of the HSI and the SCI at time $t-1$, respectively. The average volatilities of correlated stocks listed on the Hong Kong and Shanghai stock markets, denoted as $V_{i,CS\_H}(t-1)$ and $V_{i,CS\_A}(t-1)$, are calculated by taking the equal weight average of the volatilities of the correlated stocks, which are detected by the DCC model and the bootstrap approach. The subscript i, CS_H represents the correlated stocks of A+H stocks on the Hong Kong stock market, which are selected from the 264 eligible HKSE stocks under the SHHKSC. Similarly, the subscript i, CS_A stands for the correlated stocks of A+H stocks on the Shanghai stock market, which are filtered from the 568 eligible SSE stocks under the SHHKSC.

The above-mentioned volatilities of individual stocks or indexes are all conditional volatilities estimated by the univariate GARCH (1, 1) model. Notice that Equations (6) and (7) are estimated through panel regression for the 384 trading days. We can now analyze the dynamics of volatility spillover by investigating the estimated results over different days.

In Equation (6), γ_{1H} is the coefficient of $V_{i,A}(t-1)$, which can be used to illustrate the dynamics of the volatility spillover from the Shanghai stock market to the Hong Kong stock market. The coefficients γ_{2H}, γ_{3H}, and γ_{4H} help to explain how the average volatility of the correlated stocks, HSI, and SCI influence the volatilities of A+H stocks on the Hong Kong stock market, respectively. Similarly, the coefficient γ_{1A} in Equation (7) can be used to illustrate the dynamics of the volatility spillover from the Hong Kong stock market to the Shanghai stock market, and the coefficients γ_{2A}, γ_{3A}, and γ_{4A} help to analyze how the average volatility of correlated stocks, SCI, and HSI influence the volatilities of individual A+H stocks on the Shanghai stock market, respectively.

2.3. DCC Model

The DCC model was widely used to estimate the multivariate dynamic conditional correlations, and in our study, it is used to detect the correlated stocks for the individual A+H stocks. According to the work by Engle (2002), the DCC estimator has the flexibility of univariate GARCH but not the complexity of conventional multivariate GARCH. By parameterizing the dynamic conditional correlations directly, the DCC model is naturally estimated in two steps. The first step is the estimate of a series of univariate GARCH models. The second step uses the maximum likelihood estimate (MLE) approach to estimate the correlation matrix based on the residuals and conditional variances obtained from the univariate GARCH.

For the return series $r_{i,t}$ of stock i, the mean equation and conditional variance equation can be respectively written as

$$r_{i,t} = E\left(r_{i,t} \middle| \Omega_{t-1}\right) + \varepsilon_{i,t}, \tag{8}$$

$$h_{ii,t} = \omega_i + \sum_{j=1}^{q} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^{p} \beta_{ij} h_{ii,t-j}. \tag{9}$$

Suppose there are N stocks, and N series of stock returns comprise the return matrix R_t. The residuals of R_t are assumed to be multivariate normally distributed with a zero mean and a time-varying covariance of H_t.

$$\boldsymbol{\varepsilon_t} | \Omega_{t-1} \sim N(0, H_t), \tag{10}$$

where $\Omega_{t-1}$is the information set of R_t at time $t-1$. H_t can be decomposed as

$$H_t = D_t P_t D_t, \tag{11}$$

$$D_t = diag\{\sqrt{h_{ii,t}}\}, \tag{12}$$

where D_t is a diagonal matrix of time-varying conditional standard deviation from the univariate GARCH model, and P_t represents a time-varying conditional correlation matrix with diagonal elements equal to one. Since $\boldsymbol{\varepsilon_t} = D_t^{-1} P_t$, P_t can be obtained directly as

$$P_t = D_t^{-1} H_t D_t^{-1} = E_{t-1}(\boldsymbol{\varepsilon_t} \boldsymbol{\varepsilon_t'}). \tag{13}$$

Thus, the elements of $P_t = \{\rho_{ij,t}\}$, $i = 1, \cdots$, N, and $j = 1, \cdots$, N can be calculated as

$$\rho_{ij,t} = \frac{\sum_{s=1}^{t-1} \lambda^s \varepsilon_{i,t-s} \varepsilon_{j,t-s}}{\sqrt{(\sum_{s=1}^{t-1} \lambda^s \varepsilon_{i,t-s}^2)(\sum_{s=1}^{t-1} \lambda^s \varepsilon_{j,t-s}^2)}}. \tag{14}$$

According to the derivation by Engle (2002), the correlation estimator $\rho_{ij,t}$ can be written as

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}, \tag{15}$$

where $q_{ij,t}$ is the element of the covariance matrix Q_t, which is a weighted average of a positive definite matrix Q_{t-1} and a positive semidefinite matrix $\boldsymbol{\varepsilon_{t-1}\varepsilon'_{t-1}}$.

$$Q_t = (q_{ij,t}) = (1-\lambda)\boldsymbol{\varepsilon_{t-1}\varepsilon'_{t-1}} + \lambda Q_{t-1} \tag{16}$$

Q_t can also be written as

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\boldsymbol{\varepsilon_{t-1}\varepsilon'_{t-1}} + \beta Q_{t-1}, \tag{17}$$

$$\bar{Q} = T^{-1}\sum_{t=1}^{T}\boldsymbol{\varepsilon_{t-1}\varepsilon'_{t-1}}, \tag{18}$$

where $\bar{Q}$ is the unconditional variance covariance matrix of $\boldsymbol{\varepsilon_t}$, and α and β are the coefficients of the DCC model that satisfy these conditions: $\alpha > 0$, $\beta > 0$, and $\alpha + \beta < 1$.

The work by Engle (2002) suggests that the DCC (1, 1) model is most appropriate for financial time series fitting, where the orders p and q are set as 1. Following this work, we also assign the value 1 to p and q in Equation (9).

In this study, the DCC model is used to identify the correlated stocks together with the bootstrap approach. The DCC model is used to calculate the dynamic conditional correlations between stocks within one day by adopting the minute data of each trading day. For modeling volatilities of SSE stocks in Equation (6), the correlated stocks are selected from the eligible SSE stocks under the SHHKSC, and the correlated stocks in Equation (7) are filtered from the eligible HKSE stocks. If a stock is specially treated, suspended, or inactively traded on a particular day, it will be excluded from the estimation of that day. In short, the general screening criteria are as follows: if more than 30% of the minute prices of a stock are missing, it will be excluded; if less than 30% are missing, the missing prices will be assigned with the nearest minute price. Using these criteria, about 150 eligible HKSE stocks and 332 eligible SSE stocks are selected for the correlation estimation each day on average. Since the number of SSE eligible stocks selected by using these criteria is much larger than the number of minute data in a day, which will lead to invalid estimations of the dynamic conditional correlation matrices, we choose the 200-most liquid SSE stocks with the largest turnover rates for calculating the dynamic conditional correlations. On each trading day, a series of correlation estimator $\rho_{ij,t}$ are generated by the DCC model for t = 1,…, 240 minutes. To determine whether stocks i and j are stably correlated within one day, we need to test if these two stocks are correlated on average over different minutes. Specifically, if the average correlation between the two stocks within one day satisfies the condition $|E(\rho_{ij,t})| \geq \theta$, we say that those two stocks are stably correlated on that day.

The bootstrap approach is used to determine the value of the threshold θ (Clauset et al., 2009; Efron, 1992; Ren and Zhou, 2009). We first generate 1,000 synthetic matrices, and each matrix contains 200 series with the same length of minute returns within one day. The choice of the number of synthetic matrices and series is based on the principle that there are sufficient samples to generate results that are statistically significant. Further increase of these two parameters will not change the results, and thus we choose 1,000 synthetic matrices and 200 series for calculation. Each series comprises a sequence of random numbers evenly distributed between −0.1 to 0.1 due to the price fluctuation limit of $\pm 10\%$ for SSE stocks. We also use the DCC model to estimate the dynamic conditional correlations for the 1,000 synthetic matrices, similar to what we have done for the empirical stock return series. Next, we calculate the probability distribution of the dynamic conditional correlations between the synthetic series that are generated randomly; those in the 95th percentile are recognized as the threshold θ used to distinguish strong and weak dynamic conditional correlations. If the average correlation $\left|E(\rho_{ij,t})\right|$ of the empirical data is greater than the 95th percentile of the correlation coefficients of the random matrices, meaning that the average correlation is significantly stronger than the correlation of the random series, stocks i and j are stably correlated on that day. We also check the identified correlated stocks for the threshold θ generated by 99th percentile, and the results are robust for large enough percentiles.

3. Empirical Results

Using the minute data of individual stocks, we investigate the volatility spillover of the A+H stocks between the Shanghai and Hong Kong stock markets based on a GARCH-X model with four exogenous variables: volatility of the corresponding stock on the other market, average volatility of correlated stocks, volatility of the local stock market index, and volatility of the index of the other stock market.

The major content of our study is as follows: First, the DCC model is used to estimate the dynamic correlations between stocks, and the bootstrap approach is applied to determine the threshold value of the correlations, based on which the correlated stocks are detected. Next, using the volatilities of individual stocks and indexes estimated by the univariate GARCH (1, 1) model, we estimate the coefficients of the GARCH-X model and the associated p-values. Using daily minute data, the estimations are carried out for the 384 trading days based on an ordinary least square regression. In doing so, we can investigate the dynamic behavior of the volatility spillover between the Shanghai and Hong Kong stock markets. Finally, the influence of the average volatility of correlated stocks and volatilities of the market indexes on the volatilities of individual A+H socks can be analyzed in a similar fashion.

3.1. Descriptive Statistical Analysis

Table 1 reports the general descriptive statistics of the conditional volatilities involved in the GARCH-X models, including the mean, median, maximum value, minimum value, and standard deviation. These volatilities, denoted as $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{i,CS_H}, V_{SCI}, and V_{HSI}, are all estimated using the GARCH (1, 1) model, and they represent the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the correlated stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the SCI, and volatility of the HSI, respectively. We can see that the conditional volatilities of individual stocks are generally larger than those of the market indexes.

Table 1. Descriptive Statistics of the Variables in the GARCH-X Models

Variables	Mean	Median	Max	Min	S.D.
$V_{i,A}$	2.76E-06	1.82E-06	7.45E-04	8.20E-08	7.43E-06
$V_{i,H}$	2.71E-06	1.68E-06	4.96E-04	3.07E-07	7.35E-06
V_{i,CS_A}	9.95E-06	8.15E-06	1.10E-04	1.88E-06	8.32E-06
V_{i,CS_H}	2.70E-06	1.62E-06	7.45E-04	8.20E-08	8.25E-06
V_{SCI}	7.82E-08	5.13E-08	5.16E-07	3.19E-08	7.77E-08
V_{HSI}	8.71E-08	7.32E-08	3.98E-07	5.75E-08	4.53E-08

Notes: Table 1 reports the mean, median, maximum value, minimum value, and standard deviation of the volatilities in the GARCH-X models represented by Equations (6) and (7), that is, $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{i,CS_H}, V_{SCI}, and V_{HSI}, which in turn denote the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the correlated stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the SCI, and volatility of the HSI, respectively.

General statistics of the coefficients estimated by GARCH-X models represented by Equations (6) and (7) are shown in Table 2, including the mean, median, maximum value, minimum value, and standard deviation. These coefficients are estimated by an ordinary least square regression using daily minute data. The coefficients in Equation (6), that is, α_H, β_H, γ_{1H}, γ_{2H}, γ_{3H}, and γ_{4H}, are the coefficients of the GARCH term, coefficients of the ARCH term, coefficients of the volatilities of individual A+H stocks on the Shanghai stock market, coefficients of the average volatility of correlated stocks on the Hong Kong stock market, coefficients of the volatility of the HSI, and coefficients the volatility of the SCI, respectively. The coefficients in Equation (7) have similar meanings to those in Equation (6). We can see from Table 2 that the estimated coefficients of the GARCH terms, namely, β_H and β_A, are the largest among these coefficients. Among the coefficients of the four exogenous variables, γ_{1H} (γ_{1A}) and γ_{2H} (γ_{2A}) are obviously larger than γ_{3H} (γ_{3A}) and γ_{4H} (γ_{4A}), which indicates that the volatility of the corresponding stock and average volatilities of correlated stocks have much larger influences than the volatility of the local stock market index and corresponding stock market index on the volatilities of the individual A+H stocks.

Table 2. Descriptive Statistics of the Estimated Coefficients in the GARCH-X Models

Coefficients	Mean	Median	Max	Min	S.D.
α_H	5.63E-03	3.29E-03	5.29E-01	−1.79E-01	3.35E-02
β_H	7.73E-01	8.15E-01	9.53E-01	1.14E-01	1.44E-01
γ_{1H}	2.47E-02	1.26E-02	3.79E-01	−4.21E-02	4.20E-02
γ_{2H}	1.84E-02	1.29E-02	1.69E-01	−3.66E-02	2.17E-02
γ_{3H}	1.14E-02	7.78E-03	1.97E-01	−1.93E-01	2.72E-02
γ_{4H}	4.30E-05	2.70E-04	9.65E-02	−6.87E-02	7.78E-03
α_A	1.08E-02	7.40E-03	3.54E-01	−1.75E-01	3.86E-02
β_A	7.29E-01	7.71E-01	9.53E-01	2.16E-01	1.39E-01
γ_{1A}	9.25E-02	4.66E-02	9.07E-01	−7.87E-02	1.32E-01
γ_{2A}	1.82E-02	3.35E-03	3.98E-01	−9.42E-02	4.96E-02

Table 2. *Cont.*

Coefficients	Mean	Median	Max	Min	S.D.
γ_{3A}	5.35E-03	2.10E-03	1.10E-01	−4.40E-02	8.90E-03
γ_{4A}	2.42E-02	7.60E-03	6.67E-01	−7.50E-02	6.04E-02

Notes: General statistics such as the mean, median, and standard deviation are reported in Table 2 for the coefficients estimated by Equations (6) and (7), that is, α_H, β_H, γ_{1H}, γ_{2H}, γ_{3H}, γ_{4H}, α_A, β_A, γ_{1A}, γ_{2A}, γ_{3A}, and γ_{4A}. Equation (6) is formulated as $V_{i,H}(\mathrm{t}) = \theta_H + \alpha_H \varepsilon_{i,H}^2(\mathrm{t}-1) + \beta_H V_{i,H}(\mathrm{t}-1) + \gamma_{1H} V_{i,A}(\mathrm{t}-1) + \gamma_{2H} V_{i,CS\_H}(\mathrm{t}-1) + \gamma_{3H} V_{HSI}(\mathrm{t}-1) + \gamma_{4H} V_{SCI}(\mathrm{t}-1)$, and Equation (7) is formulated as $V_{i,A}(\mathrm{t}) = \theta_A + \alpha_A \varepsilon_{i,A}^2(\mathrm{t}-1) + \beta_A V_{i,A}(\mathrm{t}-1) + \gamma_{1A} V_{i,H}(\mathrm{t}-1) + \gamma_{2A} V_{i,CS\_A}(\mathrm{t}-1) + \gamma_{3A} V_{SCI}(\mathrm{t}-1) + \gamma_{4A} V_{HSI}(\mathrm{t}-1)$. $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{i,CS_H}, V_{SCI}, and V_{HSI} denote the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the correlated stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the SCI, and volatility of the HSI, respectively.

3.2. Significance of Regression Models and Estimated Coefficients

The goodness of fit of the GARCH-X models, presented by the R-squares of regression Equations (6) and (7), for the 384 trading days are plotted in Figure 1. As shown in Figure 1 (a), the R-squares of regression Equation (6) for most days range from 0.6 to 0.8, although a few of them have relatively small values. The R-squares of regression Equation (7) show similar behaviors, as shown in Figure 1 (b). These results indicate that Equations (6) and (7) have high goodness of fit for most days. Therefore, the GARCH-X models represented by both equations can well fit the volatilities of the individual A+H stocks.

To gain a general understanding of the significance of the estimated coefficients over different days, we calculate the percentage of the coefficients that are significant at the 5% significance level, measured by the ratio of the days on which the coefficient is significant among the total number of trading days. Table 3 presents the percentage of the significant coefficients estimated by the GARCH-X models. The estimated coefficients, β_H and β_A, are 100% significant. Percentages of the significant coefficients for γ_{3H} and γ_{3A} are 60.94% and 57.07%, respectively, which means that just over half the coefficients are significant. The percentages of the significant coefficients for γ_{4H} and γ_{4A} are much smaller, even less than 50%. This implies that after considering the influence of the volatilities of the corresponding stocks and average volatility of the correlated stocks, the influences from the volatilities of the local stock market index and corresponding stock market index are less significant.

We can also see from Table 3 that 82.29% of γ_{1H} and 92.93% of γ_{1A} are significant at the 5% significance level, which indicates that for A+H shares, the volatility spillover is significant between the Shanghai and Hong Kong stock markets for most days. γ_{2H} and γ_{2A} are significant for 76.56% and 62.04% of the days, respectively, implying that the average volatility of the correlated stocks also has a remarkable influence on the volatilities of the eligible A+H stocks for most days. For the importance of these significant coefficients, we will analyze in detail the coefficients γ_{1H}, γ_{1A}, γ_{2H}, and γ_{2A} in the following.

Associating the percentages of the significant coefficients in Table 3 with the average values of the coefficients in Table 2, we can see that for the coefficients of the four X-exogenous variables, those with higher significant percentages usually have large mean values. For instance, γ_{1H} and γ_{1A} are significant for 82.29% and 92.93% of the days, respectively, and have mean values of 2.47E-02 and 9.25E-02. In contrast, the estimated coefficients γ_{4H} and γ_{4A}, which have mean values of 4.00E-05 and 2.40E-04, are significant only for 29.69% and 48.69% of the days, respectively.

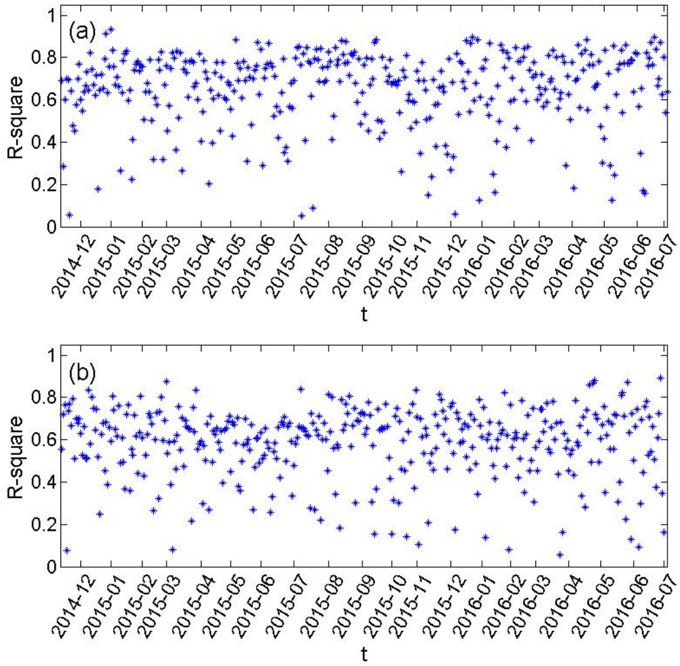

Figure 1. R-squares of the GARCH-X Models.

Notes: These are estimated R-squares that reflect the goodness of fit of the GARCH-X models for the least square regressions in the 384 trading days. Figure 1(a) shows the R-squares of Equation (6): $V_{i,H}(\mathrm{t}) = \theta_H + \alpha_H V_{i,H}(\mathrm{t}-1) + \beta_H \varepsilon_{i,H}^2(\mathrm{t}-1) + \gamma_{1H} V_{i,A}(\mathrm{t}-1) + \gamma_{2H} V_{i,CS\_H}(\mathrm{t}-1) + \gamma_{3H} V_{HSI}(\mathrm{t}-1) + \gamma_{4H} V_{SCI}(\mathrm{t}-1)$. Figure 1(b) displays the R-squares of Equation (7): $V_{i,A}(\mathrm{t}) = \theta_A + \alpha_A V_{i,A}(\mathrm{t}-1) + \beta_A \varepsilon_{i,A}^2(\mathrm{t}-1) + \gamma_{1A} V_{i,H}(\mathrm{t}-1) + \gamma_{2A} V_{i,CS\_A}(\mathrm{t}-1) + \gamma_{3A} V_{SCI}(\mathrm{t}-1) + \gamma_{4A} V_{HSI}(\mathrm{t}-1)$, in which $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{i,CS_H}, V_{SCI}, and V_{HSI} denote the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the correlated stocks on the Shanghai stock market, average volatility of the-correlated stocks on the Hong Kong stock market, volatility of the SCI, and volatility of the HSI, respectively.

Table 3. Percentages of the Significant Coefficients Estimated by the GARCH-X Models

Coefficients	Significant percentages	Coefficients	Significant percentages
α_H	69.79%	α_A	80.37%
β_H	100.00%	β_A	100.00%
γ_{1H}	82.29%	γ_{1A}	92.93%
γ_{2H}	76.56%	γ_{2A}	62.04%
γ_{3H}	60.94%	γ_{3A}	57.07%
γ_{4H}	29.69%	γ_{4A}	48.69%

Notes: The percentages of the significant coefficients are estimated by the GARCH-X models as represented by Equations (6) and (7). These coefficients are estimated by the least squares regression using minute data for each trading day, and for a specific coefficient, the percentage refers to the percentage of the days when the coefficient is significant among the total number of trading days. Equation (6) is formulated as $V_{i,H}(\mathrm{t}) = \theta_H + \alpha_H V_{i,H}(\mathrm{t}-1) + \beta_H \varepsilon_{i,H}^2(\mathrm{t}-1) + \gamma_{1H} V_{i,A}(\mathrm{t}-1) + \gamma_{2H} V_{i,CS\_H}(\mathrm{t}-1) + \gamma_{3H} V_{HSI}(\mathrm{t}-1) + \gamma_{4H} V_{SCI}(\mathrm{t}-1)$, and Equation (7) is formulated as $V_{i,A}(\mathrm{t}) = \theta_A + \alpha_A \varepsilon_{i,A}^2(\mathrm{t}-1) + \beta_A V_{i,A}(\mathrm{t}-1) + \gamma_{1A} V_{i,H}(\mathrm{t}-1) + \gamma_{2A} V_{i,CS\_A}(\mathrm{t}-1) + \gamma_{3A} V_{SCI}(\mathrm{t}-1) + \gamma_{4A} V_{HSI}(\mathrm{t}-1)$. $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{i,CS_H}, V_{SCI}, and V_{HSI} denote the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the correlated stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the SCI, and volatility of the HSI, respectively. The statistical significance level is 5%.

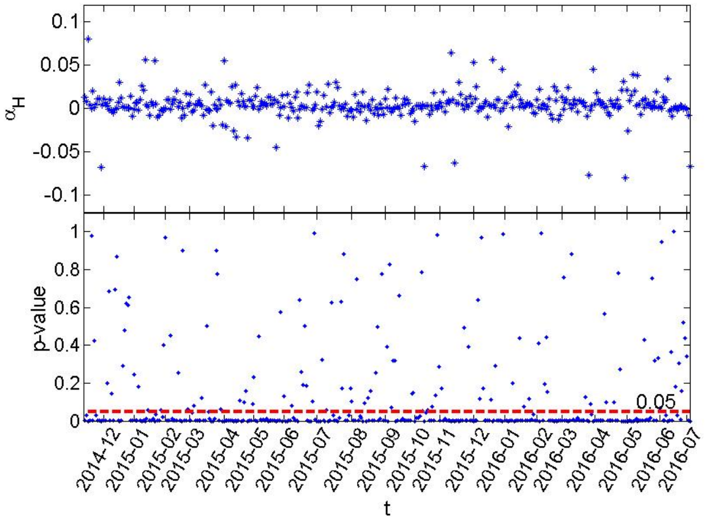

Figure 2. Estimated Coefficients α_H in Equation (6) and their *p*-values.

Notes: Estimated coefficients α_H in Equation (6) are estimated by the least square regressions for the 384 trading days, together with the corresponding *p*-values. The upper panel shows the estimated coefficients α_H in Equation (6): $V_{i,H}(\mathrm{t}) = \theta_H + \alpha_H V_{i,H}(\mathrm{t}-1) + \beta_H \varepsilon_{i,H}^2(\mathrm{t}-1) + \gamma_{1H} V_{i,A}(\mathrm{t}-1) + \gamma_{2H} V_{i,CS\_H}(\mathrm{t}-1) + \gamma_{3H} V_{HSI}(\mathrm{t}-1) + \gamma_{4H} V_{SCI}(\mathrm{t}-1)$, in which $V_{i,H}$, $V_{i,A}$, V_{i,CS_H}, V_{HSI}, and V_{SCI} denote the volatilities of individual A+H stocks on the Hong Kong stock market, volatilities of individual A+H stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the HSI, and volatility of the SCI, respectively. The lower panel plots the *p*-values of the estimated coefficients α_H, and the 5% significance level is depicted by the red dashed line.

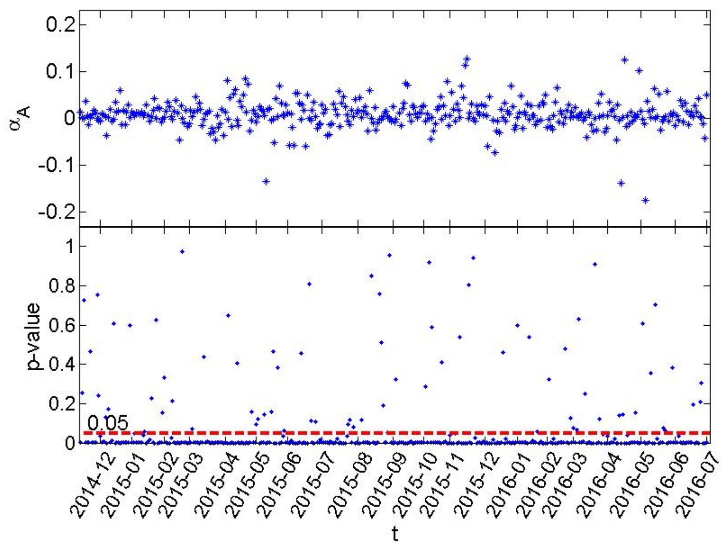

Figure 3. Estimated Coefficients α_A in Equation (7) and their *p*-values.

Notes: Estimated coefficients α_A in Equation (7) are estimated by the least square regressions for the 384 trading days, together with the corresponding *p*-values. The upper panel shows estimated coefficients α_A in Equation (7): $V_{i,A}(t) = \theta_A + \alpha_A \varepsilon_{i,A}^2(t-1) + \beta_A V_{i,A}(t-1) + \gamma_{1A} V_{i,H}(t-1) + \gamma_{2A} V_{i,CS\_A}(t-1) + \gamma_{3A} V_{SCI}(t-1) + \gamma_{4A} V_{HSI}(t-1)$, in which $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{SCI}, and V_{HSI} denote the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the-correlated stocks on the Hong Kong stock market, volatility of the SCI, and volatility of the HSI, respectively. The lower panel plots the *p*-values of the estimated coefficients α_A, and the 5% significance level is depicted by the red dashed line.

To better understand the dynamics of the estimated coefficients over different days, we further analyze their values and corresponding *p*-values obtained from the regressions for the 384 trading days. Figures 2 and 3 show the evolutions of α_H and α_A in the upper panels and the corresponding *p*-values in the lower panels. The values of α_H and α_A are slightly larger than zero and fluctuate around the mean values of 5.63E-03 and 1.08E-02, as shown in Table 2. The *p*-values of α_H and α_A for most days are significant at the 5% significance level, with the significance percentages of 69.79% and 80.37%, respectively, as shown in Table 3.

Figures 4 and 5 illustrate the evolutions of β_H and β_A in the upper panels and the corresponding *p*-values in the lower panels. The values of β_H and β_A are relatively large. Most of them are close to 1 and fluctuate around the mean values of 7.73E-01 and 7.29E-01, as shown in Table 2. The *p*-values of β_H and β_A are 100% significant at the 5% significance level, as shown in Table 3. Moreover, the sums of the coefficients of the ARCH and GARCH terms, namely $\alpha_H + \beta_H$ and $\alpha_A + \beta_A$, are close to 1 for most days, reflecting the significant high persistence of the A+H stocks' volatilities.

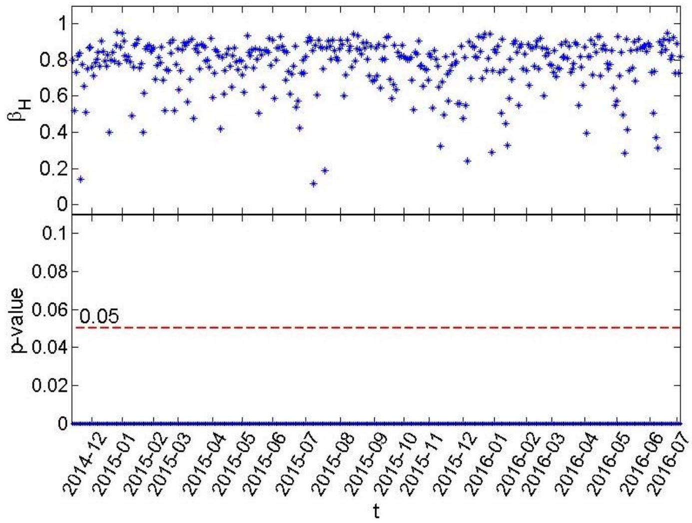

Figure 4. Estimated Coefficients β_H in Equation (6) and their *p*-values.

Notes: Estimated coefficients β_H in Equation (6) are estimated by the least square regressions for the 384 trading days, together with the corresponding *p*-values. The upper panel shows estimated coefficients β_H in Equation (6): $V_{i,H}(t) = \theta_H + \alpha_H V_{i,H}(t-1) + \beta_H \varepsilon_{i,H}^2(t-1) + \gamma_{1H} V_{i,A}(t-1) + \gamma_{2H} V_{i,CS\_H}(t-1) + \gamma_{3H} V_{HSI}(t-1) + \gamma_{4H} V_{SCI}(t-1)$, in which $V_{i,H}$, $V_{i,A}$, V_{i,CS_H}, V_{HSI}, and V_{SCI} denote the volatilities of individual A+H stocks on the Hong Kong stock market, volatilities of individual A+H stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the HSI, and volatility of the SCI, respectively. The lower panel plots the *p*-values of the estimated coefficients β_H, and the 5% significance level is depicted by the red dashed line.

From the significance of the estimated coefficients shown in Table 3, we can see that for most days, γ_{3H}, γ_{3A}, γ_{4H}, and γ_{4A} are insignificant. The mean values of these coefficients are rather small and close to zero, as shown in Table 2. We therefore do not show the evolution of these coefficients and their *p*-values here.

The values of γ_{1H}, γ_{1A}, γ_{2H}, and γ_{2A} are obviously larger than those of γ_{3H}, γ_{3A}, γ_{4H}, and γ_{4A}, and they fluctuate around the mean values of 2.47E-02, 9.25E-02, 1.84E-02, and 1.82E-02, respectively, as shown in Table 2. γ_{1H}, γ_{1A}, γ_{2H}, and γ_{2A} reflect the volatility spillover between the Shanghai and Hong Kong stock markets and the influence of the average volatilities of the correlated stocks, and they are significant for 82.29%, 92.93%, 76.56%, and 62.04% of the days, respectively, as shown in Table 3. This indicates that the volatilities of the corresponding stocks and average volatility of correlated stocks have remarkable influences on the volatilities of individual A+H stocks for most days. Therefore, we will mainly introduce their evolutions over time and offer possible interpretations for their variances in the following subsections 3.3 and 3.4.

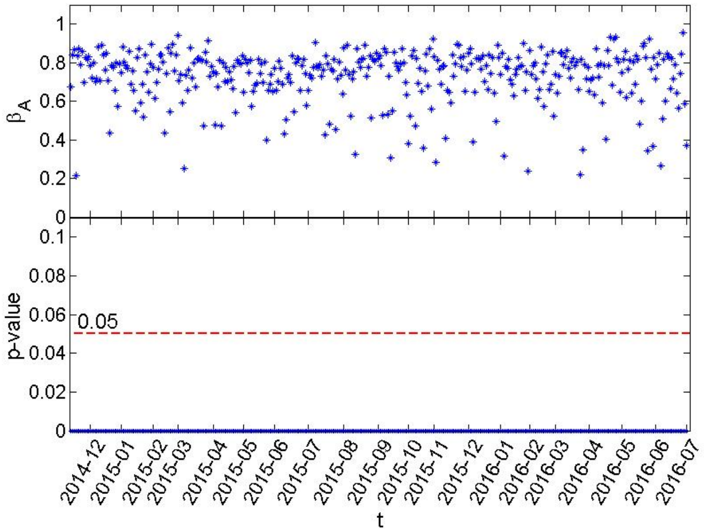

Figure 5. Estimated Coefficients β_A in Equation (7) and their *p*-values.

Notes: Estimated coefficients β_A in Equation (7) are estimated by the least square regressions for the 384 trading days, together with the corresponding *p*-values. The upper panel shows estimated coefficients β_A in Equation (7): $V_{i,A}(t) = \theta_A + \alpha_A \varepsilon_{i,A}^2(t-1) + \beta_A V_{i,A}(t-1) + \gamma_{1A} V_{i,H}(t-1) + \gamma_{2A} V_{i,CS\_A}(t-1) + \gamma_{3A} V_{SCI}(t-1) + \gamma_{4A} V_{HSI}(t-1)$, in which $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{SCI}, and V_{HSI} denote the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the-correlated stocks on the Hong Kong stock market, volatility of the SCI, and volatility of the HSI, respectively. The lower panel plots the *p*-values of the estimated coefficients β_A, and the 5% significance level is depicted by the red dashed line.

3.3. Discussion on the Volatility Spillover Dynamics

3.3.1. Analysis of the Volatility Spillover from Shanghai Stock Market to Hong Kong Stock Market

In this subsection, we discuss the volatility spillover from the Shanghai stock market to the Hong Kong stock market based on the results shown in Figure 6. Figure 6(a) illustrates the estimated coefficients γ_{1H} obtained from the regressions of Equation (6) for the 384 trading days. γ_{1H} is in general larger than zero for most days and fluctuates around the mean of 2.47E-02, as shown in Table 2. It is worth noting that γ_{1H} show obviously large values during several periods of time, such as at the beginning of the SHHKSC, from early February 2015 to early March 2015, from the end of March 2015 to the end of April 2015, in the beginning of January 2016, and in the second season of 2016. During these time periods, the volatility spillovers from the Shanghai stock market to the Hong Kong stock market are obviously stronger.

Figure 6(b) shows the corresponding *p*-values of γ_{1H}, and most *p*-values are below the significance level of 0.05, implying that γ_{1H} are significant for most days. The percentage of the significant coefficients for γ_{1H} is 82.29%, as listed in Table 3, which further confirms the results in Figure 6(b). It is worth to note that most of the data points that have large values of γ_{1H} have significant *p*-values.

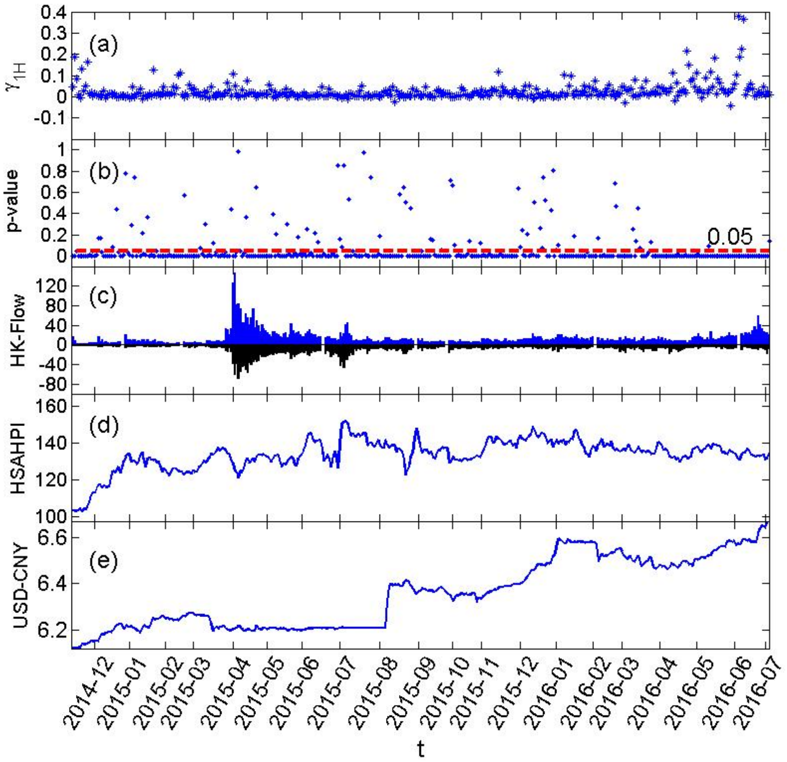

Figure 6. Estimated Coefficients γ_{1H} in Equation (6) and Their *p*-values, Together with the Plot of Three Indicators Used to Explain the Evolution of γ_{1H}.

Notes: Figure 6(a) shows the dynamics of estimated coefficients γ_{1H} in Equation (6): $V_{i,H}(t) = \theta_H + \alpha_H \varepsilon^2_{i,H}(t-1) + \beta_H V_{i,H}(t-1) + \gamma_{1H} V_{i,A}(t-1) + \gamma_{2H} V_{i,CS\_H}(t-1) + \gamma_{3H} V_{HSI}(t-1) + \gamma_{4H} V_{SCI}(t-1)$, which reflects the dynamics of the volatility spillover from the Shanghai to the Hong Kong stock market after the SHHKSC. $V_{i,H}$, $V_{i,A}$, V_{i,CS_H}, V_{HSI}, and V_{SCI} denote the volatilities of individual A+H stocks on the Hong Kong stock market, volatilities of individual A+H stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the HSI, and volatility of the SCI, respectively. Figure 6(b) displays the *p*-values of γ_{1H}, and the significance level of 5% is depicted by the red dashed line. Figure 6(c) illustrates the capital that flows in or out of the Hong Kong stock market through the SHHKSC. Figures 6(d) and 6(e) show the evolution of the Hang Seng China AH Premium Index (HSAHPI) and USD-CNY exchange rate after the launch of the SHHKSC.

To give a possible interpretation for the increase of γ_{1H} shown in Figure 6(a), we first try to analyze it from the perspective of capital flows through the SHHKSC. Figure 6(c) plots the capital that flows in or out of the Hong Kong stock market through the SHHKSC, from which we can see that capital flows were obviously large during the periods from the end of March 2015 to the end of April 2015 and in the second quarter of 2016. This phenomenon is consistent with the increase of γ_{1H} during these two periods. Specifically, from the end of March 2015 to the end of April 2015, capital flows increased significantly through the SHHKSC, mainly caused by the China Securities Regulatory Commission permitting Chinese public funds on 27 March 2015, which allowed Chinese mutual funds to invest in Hong Kong stocks through the SHHKSC without recourse to the QDII. This policy greatly stimulated the southbound trade of the SHHKSC from April 2015 to May 2015 and further catalyzed the rise of the Hong Kong stock market. During the second quarter of 2016, the net capital inflow into Hong Kong was 2 billion HKD in April 2016. It surged to 26.8 billion HKD in May, and further boosted to 44 billion HKD in June. Since capital flows carry much information on the stocks that will promote the volatility spillover, we assume the southbound capital flows through the SHHKSC are one reason why the volatility spillover from the Shanghai stock market to the Hong Kong stock market became stronger during these two periods. Furthermore, there are two more reasons for the strengthened volatility spillover in the second quarter of 2016. First, after the official launch of the Mutual Fund Connect between Hong Kong and the mainland on 18 December 2015, mutual funds issued by Hong Kong financial institutions sold very well. In contrast, mutual funds issued by mainland financial institutions enjoyed less popularity. This situation was even more obvious in the second quarter of 2016. At the end of April 2016, the northbound sales volume was 25 times that of the southbound sales volume, and this number further increased to 37 times by the end of May 2016. Second, after the report of the government of the National People's Congress, which discussed the Shenzhen-Hong Kong Stock Connect on 5 March 2016, this hot topic flared up again many times during the second quarter of 2016, which motivated investors to buy Hong Kong securities in advance for asset allocation.

For the interpretation of the increase of γ_{1H} in the beginning of the SHHKSC, we plot the Hang Seng AH premium index (HSAHPI) in Figure 6(d). The HSAHPI increased rapidly in the beginning of the SHHKSC and has maintained a high level afterwards. It is clear that before the launch of the SHHKSC, both domestic and foreign investors strongly expected to profit from investing on the Shanghai and Hong Kong stock markets based on this bull news. According to the China Securities Depository and Clearing Company Limited, more than 200,000 new stock accounts were opened from 10 November 2014 to 14 November 2014, making the number of newly opened stock accounts hit the highest point since April 2012. On the other hand, there was a net foreign capital inflow of USD 152 million into China from 5 November 2014 to 5 November 2014, which ended the outflow of eight continuous weeks according to the Emerging Portfolio Fund Research (EPFR). However, the HSAHP has been rising rapidly since 10 April 2014, when the SHHKSC was announced. It rose from 93 to 102 on the eve of the SHHKSC launch, which meant that the A-shares were no longer discounted compared with H-shares at the time when the SHHKSC was launched. Mainland investors already bought A+H shares that were relatively discounted in advance. Therefore, at the time the SHHKSC was launched, investors who already had their profit withdrew their money. The great drop in valuation differences between A-shares and H-shares discouraged the trading of the SHHKSC and enlarged the remaining quota of the SHHKSC. As a result, the hope that the SHHKSC would support the upside movement of the market indexes was lost, and both the Shanghai and Hong Kong stock markets started to fall at the beginning of the SHHKSC. The SCI and HSI fell for three consecutive days when the SHHKSC was first launched, and the HSI even plunged more than 1% on 17 November 2014, and 18 November 2014, which led to the strengthened bidirectional volatility spillover between the Shanghai and Hong Kong stock markets.

Figure 6(e) shows the trend of the USD-CNY exchange rate after the SHHKSC, which can be used to explain the strengthened volatility spillover from Shanghai to Hong Kong during the periods from early February 2015 to early March 2015 and the beginning of January 2016. Figure 6(e) shows that the USD-CNY exchange rate rose to a high level from February 2015 to March 2015, which prompted investors to invest in overseas stock markets, including the Hong Kong stock market. In addition, the volatility spillover from the Shanghai stock market to the Hong Kong stock market from early February 2015 to early March 2015 was also promoted by the permission of short selling on a total of 414 SSE stocks through the SHHKSC on 2 March 2015, and the circulation of restricted shares, which exerted great pressure of capital outflow on the A-share market. In the beginning of January 2016, the USD-CNY exchange rate reached a peak over the past half year, motivating the investment in Hong Kong. This is one reason for the strengthened volatility spillover. The key reason may, however, be the first implementation of a circuit-breaker mechanism at the beginning of January 2016, causing a slump in the A-share stock markets. Thousands of stocks dropped to the 10% fluctuation limit, and the SCI plunged 22.65% in January 2016, which further caused the jump of 11.8% for the HSI.

3.3.2. Analysis of the Volatility Spillover from Hong Kong Stock Market to Shanghai Stock Market

The volatility spillover from the Hong Kong stock market to the Shanghai stock market is analyzed based on the results shown in Figure 7. Figure 7(a) illustrates the estimated coefficients γ_{1A} obtained from the regressions of Equation (7) for the 384 trading days. γ_{1A} is in general larger than zero for most days and varies around the mean value of 9.25E-02, as shown in Table 2. Similar to the increasing behavior of γ_{1H} analyzed in subsection 3.3.1, γ_{1A} also had obviously large values at the beginning of the SHHKSC and from April 2015 to October 2015. That means the volatility spillover from the Hong Kong stock market to the Shanghai stock market was obviously stronger during these two periods.

Figure 7(b) plots the corresponding p-values of γ_{1A}, and the dashed line at the 5% significance level is also plotted for comparison. It can be easily seen that γ_{1H} are smaller than 5% and significant for most days. The percentage of the significant coefficients for γ_{1A} is 92.93%, as shown in Table 3, which further confirms the results in Figure 7(b).

To interpret the possible reasons for the increase in γ_{1A} displayed in Figure 7(a), we tackle this issue from the perspective of capital flows through the SHHKSC. Figure 7(c) shows the capital that flows in or out of the Shanghai stock market through the SHHKSC. From Figure 7(c), we observe that a large amount of capital flows in or out of the Shanghai stock market 0from April 2015 to early July 2015, which is in accord with the rise of γ_{1A} during this period. Specifically, in April 2015, the sharp increase of the HSI ended, while the SCI was on a rapid rise, which attracted a large amount of overseas capital to invest in the Shanghai stock market through the SHHKSC. However, since the bubble of the Shanghai stock market burst in June 2015, most capital was gradually withdrawn from the Shanghai stock market. Since the capital flows carry much information on the stocks, we assume that the large amount of capital flows is the reason for the enhancement of the volatility spillover from the Hong Kong stock market to the Shanghai stock market during this period. The possible reasons may be different for the increase of γ_{1A} from July 2015 to October 2015, during which both the Shanghai and Hong Kong stock markets suffered an obvious decline. The continuing drop of both markets further promoted the irrational expectations and behaviors of investors; their overreaction sped up the volatility contagion. This suggests that the enhanced volatility spillover was mainly caused by the poor performance of both markets. The capital flows further showed an increase near the end of August 2015, which also promoted the volatility spillover in this period.

We now use the HSAHPI to explain the increase of γ_{1A} in the beginning of the SHHKSC. The evolution of HSAHPI after the launch of the SHHKSC is plotted in Figure 7(d). The interpretation is the same as in subsection 3.3.1, which is that the rapid increase of HSAHPI in the beginning of the SHHKSC discouraged the trading of the SHHKSC and caused the poor performance of both the Shanghai and Hong Kong stock markets, thus leading to the strengthened bidirectional volatility spillover.

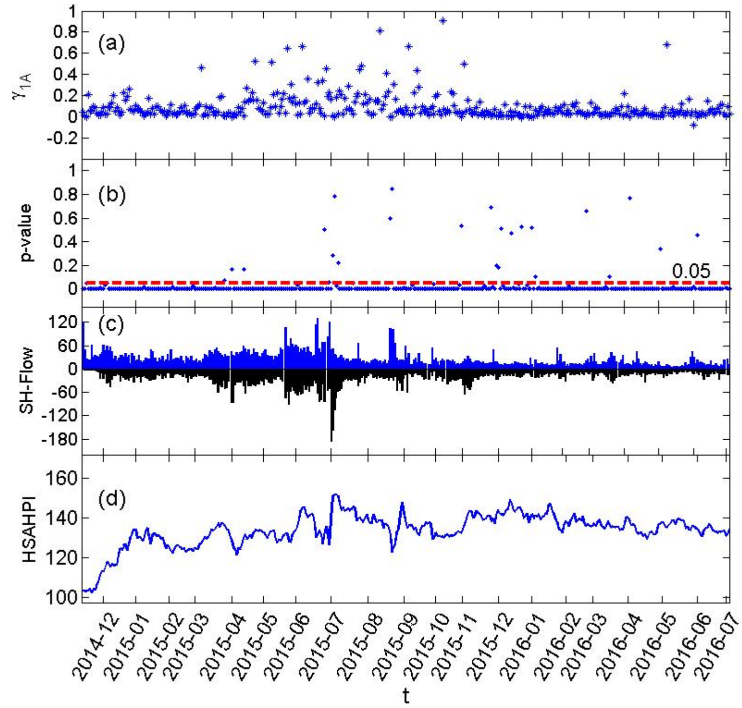

Figure 7. Estimated Coefficients γ_{1A} in Equation (7) and the *p*-values, Together with the Plot of Two Indicators Used to Explain the Evolution of γ_{1A}.

Notes: Figure 7(a) shows the dynamics of estimated coefficients γ_{1A} in Equation (7): $V_{i,A}(t) = \theta_A + \alpha_A \varepsilon_{i,A}^2(t-1) + \beta_A V_{i,A}(t-1) + \gamma_{1A} V_{i,H}(t-1) + \gamma_{2A} V_{i,CS\_A}(t-1) + \gamma_{3A} V_{SCI}(t-1) + \gamma_{4A} V_{HSI}(t-1)$, which reflects the dynamics of the volatility spillover from the Hong Kong to the Shanghai stock market after the launch of the SHHKSC. $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{SCI}, and V_{HSI} denote the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the correlated stocks on the Shanghai stock market, volatility of the SCI, and volatility of the HSI, respectively. Figure 7(b) displays the *p*-values of γ_{1A}, and the significance level of 5% is depicted by the red dashed line. Figure 7(c) illustrates the capital that flows in or out of the Shanghai stock market through the SHHKSC. Figure 7(d) shows the evolution of HSAHPI after the launch of the SHHKSC.

During the period from April 2015 to October 2015, although the volatility spillover is significant in both directions, one may wonder why the spillover from the Hong Kong stock market to the Shanghai stock market is much stronger, but not vice versa. A possible reason could be that the volatilities of A+H shares on the Hong Kong stock market led the volatilities of the corresponding stocks on the Shanghai stock market during this period. We will demonstrate this in the following. Using the intraday conditional volatilities of A+H stocks from 1 April 2015 to 31 October 2015, we calculate the correlation between the volatility of each A+H stock on the Shanghai stock market at time t and the volatility of the corresponding A+H stock on the Hong Kong stock market at $t - \Delta t$ for each day using the Pearson's correlation coefficient; for each stock, the correlation is averaged over the 384 trading days. Let Δt vary from −10 to 10 minutes. We thus have 21 averaged correlations for each A+H stock, and the value of Δt corresponds to the maximum value of the 21 averaged correlations. Denoted as the lagged time ΔT, which is the average number of minutes the volatility of an A+H stock on the Hong Kong stock market led the corresponding volatility on the Shanghai stock market. Our results show that ΔT varies from −6 to 2 minutes, and Figure 8 shows the distribution of the number of eligible A+H stocks with respect to the lagged time ΔT. The distribution shown in Figure 8 is right skewed to the side with positive lagged time ΔT; that is, for most of the eligible A+H stocks, the volatility on the Hong Kong stock market led its volatility on the Shanghai stock market. Therefore, the volatility spillover from the Shanghai stock market to the Hong Kong stock market is shown to be unobvious from April 2015 to October 2015.

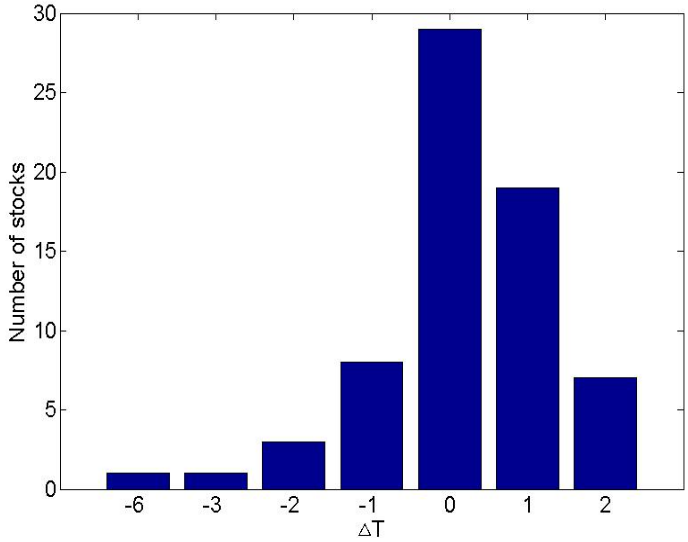

Figure 8. Number of Eligible A+H Stocks *vs.* the Lagged Time ΔT.

Notes: The lagged time ΔT denotes the average number of minutes that the volatility of an eligible A+H stock on the Hong Kong stock market led the corresponding volatility on the Shanghai stock market during the period from 1 April 2015 to 31 October 2015. We calculate the correlation between the volatility of each A+H stock on the Shanghai stock market at time t and the volatility of the corresponding A+H stock on the Hong Kong stock market at $t - \Delta t$ for each day using the Pearson's correlation coefficient: $\mathrm{corr}[V_{i,H}(\mathrm{t}-\Delta\mathrm{t}), V_{i,A}(\mathrm{t})] = \frac{cov[V_{i,H}(\mathrm{t}-\Delta\mathrm{t}), V_{i,A}(\mathrm{t})]}{\sqrt{var[V_{i,H}(\mathrm{t}-\Delta\mathrm{t})]var[V_{i,A}(\mathrm{t})]}}$; for each stock, the correlation is averaged over the 384 trading days. Let Δt vary from −10 to 10 minutes; thus, we have 21 averaged correlations for each A+H stock, and the value of Δt at the maximum value of the 21 averaged correlations, denoted as the lagged time ΔT, is the average number of minutes the volatility of an A+H stock on the Hong Kong stock market led the corresponding volatility on the Shanghai stock market.

From the above discussion on the results shown in Figures 6 and 7, we point out that there exists a bidirectional volatility spillover between the Shanghai and Hong Kong stock markets. The volatility spillover from the Shanghai stock market to the Hong Kong stock market was obviously enhanced in the beginning of the SHHKSC, from early February 2015 to early March 2015, from the end of March 2015 to the end of April 2015, at the beginning of January 2016, and in the second season of 2016. The volatility spillover from the Hong Kong stock market to the Shanghai stock market was enhanced in the beginning of the SHHKSC and from April 2015 to October 2015. In addition, we find that the volatility spillover between the Shanghai and Hong Kong stock markets is remarkably influenced by the bidirectional capital flows through the SHHKSC and the occurrence of important financial events.

3.4. Discussion on the Influence of Correlated Stocks

In this section, we will analyze how the average volatility of the correlated stocks influences the volatilities of A+H stocks and the volatility spillover effect. We first study the influence of the average volatility of the correlated stocks on the volatilities of A+H stocks. Figure 9(a) illustrates γ_{2H} obtained from the regressions of Equation (6) for the 384 trading days. γ_{2H} is in general larger than zero for most days and fluctuates around the mean value of 1.84E-02, as shown in Table 2. Note that γ_{2H} shows obviously large values during the following periods: from April 2015 to October 2015 and from January 2016 to February 2016. This means the average volatility of the correlated stocks selected from eligible HKSE stocks has a remarkable influence on the volatilities of A+H stocks on the Hong Kong stock market.

Figure 9(b) shows the corresponding p-values of γ_{2H} , and most of the p-values are smaller than the 5% significance level, implying that γ_{2H} is significant for most days. The percentage of the significant coefficients for γ_{1H} is 76.56%, as listed in Table 3, which further supports the results in Figure 9(b).

In order to give a possible interpretation for the increase in γ_{2H} shown in Figure 9(a), we analyze it based on the evolution of the HSI as displayed in Figure 9(c). We find that the average volatility of correlated stocks has a large influence on the volatilities of A+H stocks on the Hong Kong stock market when the HSI shows sharp rises or falls in regions framed by red dashed boxes.

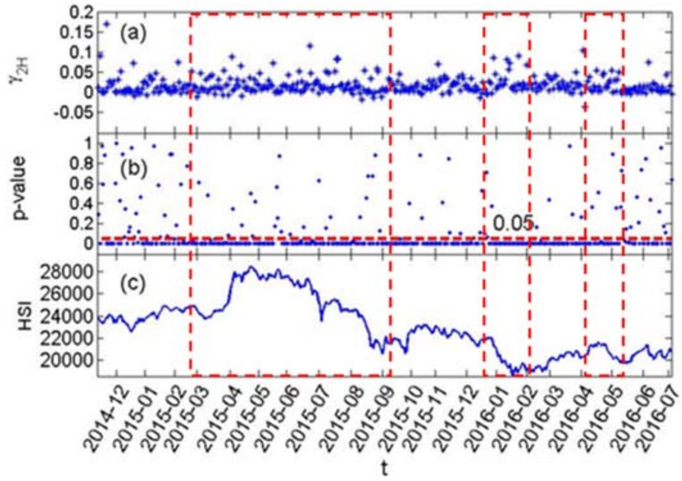

Figure 9. Estimated Coefficients γ_{2H} in Equation (6) and their p-values, as well as the Evolution of the HIS.

Notes: Figure 9(a) shows the dynamics of the estimated coefficients γ_{2H} in Equation (6): $V_{i,H}(t) = \theta_H + \alpha_H \varepsilon_{i,H}^2(t-1) + \beta_H V_{i,H}(t-1) + \gamma_{1H} V_{i,A}(t-1) + \gamma_{2H} V_{i,CS\_H}(t-1) + \gamma_{3H} V_{HSI}(t-1) + \gamma_{4H} V_{SCI}(t-1)$, which reflects the influence of the average volatility of the correlated stocks on the individual A+H stocks' volatilities on the Hong Kong stock market. $V_{i,H}$, $V_{i,A}$, V_{i,CS_H}, V_{HSI}, and V_{SCI} denote the volatilities of individual A+H stocks on the Hong Kong stock market, volatilities of individual A+H stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the HSI, and volatility of the SCI, respectively. Figure 9(b) displays the p-values of γ_{2H} together with the significance level of 5% depicted by the red dashed line. Figure 9(c) plots the evolution of the HSI.

Figure 10(a) shows the estimated coefficients γ_{2A} obtained from the regressions of Equation (7) for the 384 trading days. Similarly, the coefficient γ_{2A} for the Shanghai stock market is in general larger than zero and fluctuates around the mean value of 1.82E-02, as listed in Table 2, indicating that the average volatility of the correlated stocks selected from eligible SSE stocks also has a remarkable influence on the volatilities of A+H stocks on the Shanghai stock market. The corresponding p-values of γ_{2A} are also plotted in Figure 10 (b), and γ_{2A} is significant under the 5% significance level for most days.

We next investigate why the average volatility of correlated stocks shows a large influence during the volatile periods on the volatilities of A+H stocks on both markets. A possible explanation is that the correlations between the stocks become stronger during the volatile periods, and the increased correlations will further strengthen the influence of the volatilities of the correlated stocks.

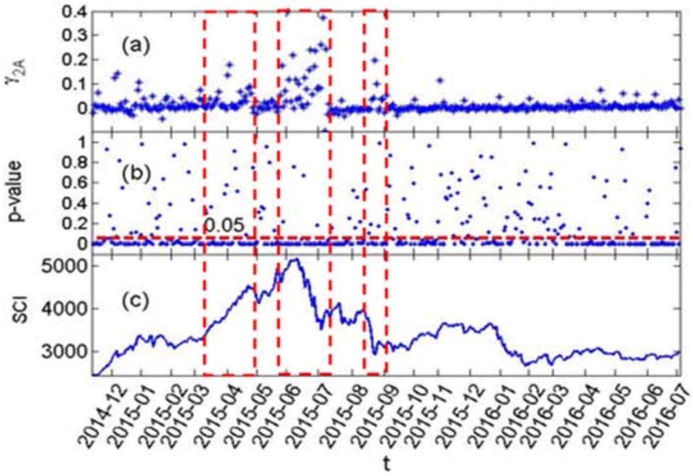

Figure 10. Estimated Coefficients γ_{2A} in Equation (7) and their *p*-values, as well as the Evolution of the SCI.

Notes: Figure 10(a) shows the dynamics of the estimated coefficients γ_{2A}in Equation (7): $V_{i,A}(t) = \theta_A + \alpha_A \varepsilon^2_{i,A}(t-1) + \beta_A V_{i,A}(t-1) + \gamma_{1A} V_{i,H}(t-1) + \gamma_{2A} V_{i,CS\_A}(t-1) + \gamma_{3A} V_{SCI}(t-1) + \gamma_{4A} V_{HSI}(t-1)$, which reflects the influence of the average volatility of the correlated stocks on the A+H stocks' volatilities on Shanghai stock market. $V_{i,A}$, $V_{i,H}$, V_{i,CS_A}, V_{SCI}, and V_{HSI} denote the volatilities of individual A+H stocks on the Shanghai stock market, volatilities of individual A+H stocks on the Hong Kong stock market, average volatility of the correlated stocks on the Shanghai stock market, volatility of the SCI, and volatility of the HSI, respectively. Figure 10(b) displays the *p*-values of γ_{2A} together with the significance level of 5% depicted by the red dashed line. Figure 9(c) plots the evolution of the SCI.

To better understand the importance of the correlated stocks, we compare the models before and after introducing the average volatility of correlated stocks. Specifically, we estimate Equation (19) and Equation (20) for each trading day to further analyze the influence of the volatilities of correlated stocks on the volatilities of A+H stocks, when the average volatility of the correlated stocks is removed. The results of Equations (19) and (20) are compared respectively with those of Equations (6) and (7). We should mention that all these four equations pass the multi-collinearity tests.

$$V_{i,H}(t) = \theta_H + \alpha_H \varepsilon^2_{i,H}(t-1) + \beta_H V_{i,H}(t-1) + \gamma_{1H} V_{i,A}(t-1) + \gamma_{3H} V_{HSI}(t-1) + \gamma_{4H} V_{SCI}(t-1), \quad (19)$$

$$V_{i,A}(t) = \theta_A + \alpha_A \varepsilon^2_{i,A}(t-1) + \beta_A V_{i,A}(t-1) + \gamma_{1A} V_{i,H}(t-1) + \gamma_{3A} V_{SCI}(t-1) + + \gamma_{4A} V_{HSI}(t-1). \quad (20)$$

In order to measure the contribution of each variable to the R-square of the regression equation, we calculate the LMGs of each volatility sequence in Equations (6), (7), (19), and (20) for the 384 trading days, which is known as the averaging over orderings approach proposed by Lindeman et al. (1980). According to Johnson and Lebreton (2004), LMG is the most successful indicator to measure the relative importance of each variable in multivariate regressions. The comparisons between the estimated results of models with or without the average volatility of correlated stocks, namely the comparisons between Equation (6) and Equation (19) and between Equation (7) and Equation (20), are displayed in Table 4.

Table 4. Comparison between the Estimated Results of Models with and without the Average Volatility of Correlated Stocks

Table 4A

	Equation (6)				**Equation (19)**		
Coefficients	γ_{1H}	γ_{2H}	γ_{3H}	γ_{4H}	γ_{1H}	γ_{3H}	γ_{4H}
Mean	2.47E-02	1.84E-02	1.14E-02	4.30E-05	2.56E-02	1.38E-02	2.81E-04
Percentages	82.29%	76.56%	60.94%	29.69%	82.03%	70.05%	30.21%
LMG	3.30E-04	1.71E-04	7.88E-05	1.16E-05	2.35E-03	2.07E-03	1.96E-03
R-square	0.6517				0.6506		

Table 4B

	Equation (7)				**Equation (20)**		
Coefficients	γ_{1A}	γ_{2A}	γ_{3A}	γ_{4A}	γ_{1A}	γ_{3A}	γ_{4A}
Mean	9.25E-02	1.82E-02	5.35E-03	2.42E-02	9.42E-02	5.70E-03	2.78E-02
Percentages	92.93%	62.04%	57.07%	48.69%	93.75%	57.81%	52.60%
LMG	4.16E-04	1.17E-04	8.80E-05	6.34E-05	5.20E-04	9.37E-05	9.61E-05
R-square	0.6200				0.6219		

Notes: Table 4 reports the comparisons between the estimated results of Equations (6) and (7) and of Equations (19) and (20), including the mean values of estimated coefficients γ_{1H}, γ_{2H}, γ_{3H}, γ_{4H} and γ_{1A}, γ_{2A}, γ_{3A}, and γ_{4A}; the mean values of R-squares estimated by the least squares regression using the minute data of the 384 trading days; and the averaged LMGs of the following independent variables: $V_{i,H}(t-1)$, $V_{i,A}(t-1)$, $V_{i,CS\_H}(t-1)$, $V_{i,CS\_A}(t-1)$, $V_{HSI}(t-1)$, and $V_{SCI}(t-1)$. LMG is an indicator that represents the contribution of each variable to the R-square of the regression equation. It is calculated based on the averaging over orderings approach proposed by Lindeman et al. (1980). For a specific coefficient, the percentage refers to the percentage of the days the coefficient is significant among the total number of trading days. $V_{i,H}$, $V_{i,A}$, V_{i,CS_H}, V_{HSI}, and V_{SCI} denote the volatilities of individual A+H stocks on the Hong Kong stock market, volatilities of individual A+H stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, volatility of the HSI, and volatility of the SCI, respectively.

From Table 4, we can see that after we include the average volatility of the correlated stocks, the estimated coefficients γ_{1H} and γ_{1A} in Equations (6) and (7) are still significant for most days and have values close to the results of Equations (19) and (20). This means there still exists significant bidirectional volatility spillover between the Shanghai and Hong Kong stock markets.

We can further infer from Table 4 that correlated stocks play an important role in the explanation of the volatilities of individual A+H stocks. The mean values of the estimated coefficients for the average volatilities of correlated stocks are relatively larger than those of the stock market indexes, and the percentages of significant coefficients for γ_{2H} and γ_{2A} are obviously larger than those of γ_{3H}, γ_{3A}, γ_{4H}, and γ_{4A}, which indicate that the average volatilities of correlated stocks have stronger and more significant influences than the volatilities of market indexes. Since the mean values of γ_{3A} in Equations (7) and (20) are negative and very close to zero, we just list the mean values of the significant coefficients in Table 4 for comparison. Moreover, the LMGs of the average volatilities of correlated stocks are much larger than the volatilities of the market indexes, implying that the average volatilities of the correlated stocks contribute more to the total R-squares of the regression models. These results jointly demonstrate that it is important to consider the influences of correlated stocks when modeling individual A+H stocks' volatilities, which probably contain more information than the market index does, and thus exert stronger and more significant influences than the market indexes on the volatilities of A+H stocks.

3.5. Discussion on the Influence of Industries

Since the influences of industries on individual stocks are widely considered in literature, we here compare the models before and after introducing the volatilities of industries. Specifically, we use the following Equations (21) and (22) to analyze the influence of the volatilities of industries on the volatilities of individual A+H stocks for each trading day,

$$V_{i,H}(t) = \theta_H + \alpha_H \varepsilon_{i,H}^2(t-1) + \beta_H V_{i,H}(t-1) + \gamma_{1H} V_{i,A}(t-1) + \gamma_{2H} V_{i,CS\_H}(t-1) + \gamma_{3H} V_{HSI}(t-1) + \gamma_{4H} V_{SCI}(t-1) + \gamma_{5H} V_{i,IND\_H}(t-1), \quad (21)$$

$$V_{i,A}(t) = \theta_A + \alpha_A \varepsilon_{i,A}^2(t-1) + \beta_A V_{i,A}(t-1) + \gamma_{1A} V_{i,H}(t-1) + \gamma_{2A} V_{i,CS\_A}(t-1) + \gamma_{3A} V_{SCI}(t-1) + \gamma_{4A} V_{HSI}(t-1) + \gamma_{5A} V_{i,IND\_A}(t-1), \quad (22)$$

where the volatility of a certain industry, denoted as $V_{i,IND\_H}(t-1)$ and $V_{i,IND\_A}(t-1)$, respectively, for the Hong Kong and Shanghai stock markets, is calculated by averaging the volatilities of the eligible stocks under the SHHKSC that belong to this industry; the classification of the industry is in accordance with the China Securities Regulatory Commission's industry classification standard. The regression results of Equations (21) and (22) are reported in Table 5, and these two equations also pass the multi-collinearity tests.

From Table 5, we can see that after we include the volatility of the industry, the estimated coefficients γ_{1H} and γ_{1A} in Equations (21) and (22) are still significant for most days and have values close to the results of Equations (6) and (7). This means there still exists significant bidirectional volatility spillover between the Shanghai and Hong Kong stock markets, and its variations over time are similar to Figures 6 and 7, which are not shown here.

We can also infer from Table 5 that the volatility of correlated stocks is a necessary variable in the explanation of the volatilities of individual A+H stocks after we introduce the volatility of industry, and it may reveal additional information that the volatility of the industry does not contain. For the volatilities of eligible A+H stocks on the Hong Kong stock market, the mean values of the estimated coefficients for the average volatilities of correlated stocks are a little smaller than those of the industry but larger than those of the stock market indexes. Moreover, the percentages of the significant coefficients for γ_{2H} are roughly equal to those of γ_{5H} and obviously larger than those of γ_{3H} and γ_{4H}; this indicates that the average volatilities of correlated stocks have influences comparable with the volatility of industry and have more significant influence than the volatilities of market indexes. Although the LMGs of the average volatilities of correlated stocks are smaller than those of the industries, they are still larger than those of the market indexes, implying that the average volatilities of the correlated stocks do make a considerable contribution to the total R-squares of the regression models. For the volatilities of eligible A+H stocks on the Shanghai stock market, although the percentages of the significant coefficients for γ_{2A} show a decline after introducing the volatilities of industries, we should not ignore the fact that the mean value of γ_{2A} and the corresponding LMG are still larger than those of the market indexes on the whole. We find that the correlations among stocks of the same industry on the Shanghai stock market are stronger, in which case the identified correlated stocks of a certain A+H stock have high coincidence with the stocks of the corresponding industry, apparently different from the Hong Kong stock market. This could explain why the percentages of the significant coefficients for γ_{2A} decrease, and the mean value of γ_{2A} and the corresponding LMG become smaller. The results in Table 5 therefore imply the necessity and importance of considering the influences of correlated stocks when modeling individual A+H stocks' volatilities.

Table 5. Estimated Results of the Models with the Inclusion of the Volatility of Industry

			Equation (21)		
Coefficients	γ_{1H}	γ_{2H}	γ_{3H}	γ_{4H}	γ_{5H}
Mean	2.33E-02	1.63E-02	7.00E-03	3.00E-04	5.37E-02
Percentages	78.65%	73.18%	51.30%	28.65%	78.39%
LMG	3.70E-05	7.29E-05	7.05E-05	3.59E-05	3.33E-04
R-square			0.6518		
			Equation (22)		
Coefficients	γ_{1A}	γ_{2A}	γ_{3A}	γ_{4A}	γ_{5A}
Mean	8.66E-02	9.80E-03	7.84E-03	9.60E-03	1.41E-01
Percentages	91.88%	51.57%	68.85%	35.86%	85.08%
LMG	3.97E-04	1.07E-05	1.81E-06	4.03E-05	3.84E-03
R-square			0.6248		

Notes: Table 5 reports the estimated results of Equations (19) and (20), including the mean values of estimated coefficients γ_{1H}, γ_{2H}, γ_{3H}, γ_{4H}, and γ_{5H} as well as γ_{1A}, γ_{2A}, γ_{3A}, γ_{4A}, and γ_{5A}; mean values of R-squares estimated by the least squares regression over 384 trading days; and averaged LMGs of the following independent variables: $V_{i,H}(t-1)$, $V_{i,A}(t-1)$, $V_{i,CS\_H}(t-1)$, $V_{i,CS\_A}(t-1)$, $V_{HSI}(t-1)$, $V_{SCI}(t-1)$, $V_{i,IND\_H}(t-1)$, and $V_{i,IND\_A}(t-1)$. LMG is an indicator that represents the contribution of each variable to the R-square of the regression equation. It is calculated based on the averaging over orderings approach proposed by Lindeman et al. (1980). For a specific coefficient, the percentage refers to the percentage of days when the coefficient is significant among the total number of trading days. $V_{i,H}$, $V_{i,A}$, V_{i,CS_H}, V_{i,CS_A}, V_{HSI}, V_{SCI}, V_{i,IND_H}, and V_{i,IND_A} denote the volatilities of individual A+H stocks on the Hong Kong stock market, volatilities of individual A+H stocks on the Shanghai stock market, average volatility of the correlated stocks on the Hong Kong stock market, average volatility of the correlated stocks on the Shanghai stock market, volatility of the HSI, volatility of the SCI, volatility of the industry on the Hong Kong stock market, and volatility of the industry on the Shanghai stock market, respectively.

4. Conclusions

The launch of the SHHKSC significantly strengthened the linkage between the Shanghai and Hong Kong stock markets. Therefore, the investigation of the volatility spillover between the Shanghai and Hong Kong stock markets after such a groundbreaking event needs urgent attention. In this study, we introduce a GARCH-X model with four exogenous variables and use this new model to investigate the intraday volatility spillover between the Shanghai and Hong Kong stock markets based on the minute data of eligible A+H stocks under SHHKSC. The influence of the average volatility of correlated stocks, volatilities of the industries, and volatilities of the market indexes on the volatilities of individual A+H socks are also analyzed, in which the correlated stocks are selected using the DCC model and the bootstrap approach. Our results show that after the launch of the SHHKSC, the volatility spillovers are significant in both directions nearly all the time, and the volatility spillovers between these two stock markets are stronger when the bidirectional capital flows increase or when important financial events occur. The volatilities of individual A+H stocks are significantly influenced by the average volatility of correlated stocks for most days, and the influence is strengthened when the local market index undergoes rapid rise or fall. The volatilities of the local stock market index and the corresponding stock market index have relatively smaller and less significant influences on the volatilities of individual A+H stocks compared with the average volatility of correlated stocks. Moreover, the influence of correlated stocks is comparable with that of the industries, particularly on the Hong Kong stock market, and should be taken as an important and indispensable factor for modeling the volatilities of individual A+H stocks.

In contrast from previous studies, we not only investigate the intraday volatility spillover between the Shanghai and Hong Kong stock markets but also analyze how the volatility spillover changes over time. Furthermore, we explain its dynamic feature from the perspective of capital flows and important financial events. Our results help investors to better understand the new pattern of the relationship between the Shanghai and Hong Kong stock markets, which further optimizes their international asset allocation and risk management strategies. This study also provides advice to the government for making proper policies under more marketable and internationalized circumstances. In addition, we emphasize the importance of introducing the volatilities of correlated stocks for modeling the volatilities of individual stocks, and we point out that it not only is a more important and indispensable factor than the market indexes but also carries more information than the volatility of the industry. Further investigation that looks into the volatility spillover among multiple individual stocks would be helpful to better understand the detailed risk transmission mechanism in stock markets.

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