Finance Research Letters 31 (2019) 104–109

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

The asymmetric high-frequency volatility transmission across international stock markets

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ARTICLE INFO

Keywords:
Stock markets
MHAR-DCC model
Asymmetric volatility
High-frequency data

ABSTRACT

We construct a MHAR-DCC model to investigate the high-frequency volatility transmission across international stock markets. We use the overnight volatility estimator to eliminate the effects of non-synchronous trading problem. We analyze the asymmetric volatility transmission effects across the international stock markets. The empirical results suggest that the periods when the total spillover index increases to high levels correspond to the periods when the market volatility is high. The volatility transmission effect in the US and Singapore stock markets exhibit the normal leverage effect, while the volatility transmissions of Japanese and Hong Kong stock markets exhibit the reverse leverage effect.

1. Introduction

The recent global financial crises (e.g. the Asian financial crisis, the subprime mortgage crisis and the European debt crisis) touch off the substantial concerns about the financial risk contagion across countries (Hasler and Ornthanalai, 2018).

The Multivariate Generalized Auto-Regressive Conditional Heteroskedasticity (MGARCH) model built by Bollerslev (1990) is widely extended in the literature to investigate the volatility transmission across financial markets with relative low frequency daily data (Katsiampa et al., 2019; Canh et al., 2019).

The advantages of high-frequency data have been proved by numerous of literatures (e.g., Bauer and Vorkink, 2011; Ji and Zhang, 2019), which motivates the researchers to investigate the high-frequency volatility connectedness across international financial markets based on the heterogeneous autoregressive (HAR) model of Corsi et al. (2009). Bauer and Vorkink (2011) present the multivariate HAR (MHAR) model as an extension of HAR model. Recently, some scholars have merged the MHAR model with MGARCH model. Bubák et al. (2011) construct a vector (V)HAR-GARCH model to study the dynamic high-frequency volatility spillover of the European exchange markets. Moreover, leverage effects are taken consideration into recent literature to explore the asymmetric volatility contagion effect (Barunik et al., 2016; Luo and Ji, 2018).

Based on the existing literatures, we constructs a MHAR-DCC model by integrating MHAR model with Dynamic Conditional Correlation (DCC)-GARCH model of Engle (2002), and then utilizes the intraday high-frequency data to explore the dynamic volatility connectedness of the S&P500 Index, the Nikkei225 index, the Hang Seng Index, and the Straits Times Index. We eliminate the non-synchronous problem by using the overnight realized volatilities and Bayesian data augmentation approach according to Luo and Chen (2018) and Luo et al. (2019). Considering the leverage effect of volatility, we decompose the realized volatility into the positive return volatility and the negative return volatility by employing the semi-variance estimator proposed by Barndorff-

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https://doi.org/10.1016/j.frl.2019.04.025
Received 15 January 2019; Received in revised form 1 April 2019; Accepted 11 April 2019
Available online 12 April 2019

Nielsen et al. (2010). Finally, we apply the MHAR-DCC model and the total and directional volatility spillover indices proposed by Diebold and Yilmaz (2011, 2014) to investigate the asymmetric volatility transmission.

The structure of this paper is as follows. Section 2 presents the data and variables. The methodology is described in Section 3. Section 4 analyses the results and Section 5 concludes.

2. Data and variables

We employ the 5-minutes price series of the major stock market indices in the US, Japan, Hong Kong and Singapore. The sample includes the S&P 500 Index (SPI), the Nikkei 225 index (NEI), the Hang Seng Index (HSI), and the Straits Times Index (STI), and covers a period from 1 June, 2009 to 31 May, 2014, which is from TICK database.

Particularly, The US stock market trades latter than the Asian market, thus the volatility of later trading is affected by information spillovers from the previous trading markets. Therefore, we suppose that the information in the non-trading time of each stock market can be captured by the overnight return and employ the overnight volatility estimator as the proxy of the market volatility. The overnight return can be calculated by the logarithmic difference between the opening price of the current day and the closing price of the previous day that$r_{n,t} = 100 \times (\log P_t^o - \log P_{t-1}^c)$. The overnight realized volatility (ORV) can be measured by combining the overnight return with the realized volatility (Ahoniemi and Lanne, 2013). To make full use of the 24-hours information of different stock markets, we compute the ORV as follows:

$$ORV_t = \begin{cases} \omega_1 r_{n,t+1}^2 + \omega_2 RV_t, \text{ for } NEI, HSI \text{ and } STI \\ \omega_1 r_{n,t}^2 + \omega_2 RV_t, \text{ for } SPI \end{cases} \tag{1}$$

$$RV_{t+1} = \sum_{j=1}^{n} r_{t,j}^2 \tag{2}$$

where the optimal weighted variance ω_1 and ω_2 can be obtained according to Hansen and Lunde (2005).

Furthermore, we decompose the realized volatility into the positive return and the negative return volatilities by virtue of the semi-variance estimator so that we can analyze the volatility leverage effects in international volatility spillover research.

$$RS^- = \sum_{i=1}^{n} r_i^2 I[r_i < 0], \quad RS^+ = \sum_{i=1}^{n} r_i^2 I[r_i > 0] \tag{3}$$

where $I(\bullet)$ is an indicative function, and $RV = RS^- + RS^+$.

To synchronize the volatility series due to different holidays in different markets, we delete international public holidays (e.g. Christmas, New Year and Easter), and fill in the missing values caused by different domestic holidays using Bayesian data augmentation method. Finally, we get a sample with 1286 trading days.

Table 1 reports the summarized statistics of the ORV, the negative realized semi-variance (RS^-) and the positive realized semi-variance (RS^+). According to Table 1, the stock markets of Japan and Hong Kong have much larger average ORV than those of Singapore and Japan. The RSV^-in US, Hong Kong and Japan stock markets are larger than RSV^+, which indicates that the negative volatility is larger than the positive one, thus the leverage effect is significant. Besides, according to the skewness, kurtosis and JB statistics, all volatility series exhibit the positive skewness and peak kurtosis. The Ljung-Box statistics demonstrate that all the volatility series are significantly autocorrelated and long memory. ADF statistics shows that all the volatility series are stationary.

Table 1
Summarized statistics of the realized volatility estimators.

VARIABLES	Mean	Standard deviation	Skewness	Kurtosis	JB	Ljung-Box ,Q(5)	Ljung-Box ,Q(10)	Ljung-Box ,Q(20)	ADF
ORV									
NEI	1.6149	2.4434	7.87	121.17	761,533.20	311.74	404.41	460.90	−18.03
HIS	1.5351	2.5262	10.99	203.07	2,170,644.45	458.72	669.66	939.09	−15.90
STI	0.7007	0.8837	4.72	37.56	68,766.12	1527.99	2392.55	3454.57	−12.55
SPI	0.9514	1.5387	5.32	40.07	79,708.64	989.73	1548.82	2336.73	−13.86
RSV^-									
NEI	0.6331	0.8011	6.24	61.82	193,740.89	1037.04	1664.61	2385.21	−15.52
HIS	0.3314	0.3688	5.23	44.53	98,274.04	1220.24	2044.25	2838.29	−15.59
STI	0.3035	0.3470	7.29	95.58	470,608.96	549.35	886.34	1385.69	−17.51
SPI	0.1626	0.1554	5.33	49.77	123,275.55	1065.27	1755.11	2538.61	−16.17
RSV^+									
NEI	0.5975	0.6768	5.92	58.22	170,921.17	1228.48	2043.79	2873.82	−14.70
HIS	0.3210	0.3662	6.03	54.49	149,877.66	1298.03	2104.55	2872.69	−15.30
STI	0.3080	0.2970	4.21	30.65	44,776.51	492.37	888.99	1377.17	−19.13
SPI	0.1544	0.1223	4.04	32.63	50,531.45	1075.53	2008.76	3320.86	−16.42

3. Model and methodology

3.1. MHAR-DCC model

Following Bauer and Vorkink (2011), the single-dimensional HAR can be extended to the high-dimensional version by vectoring the variables:

$$\mathbf{RV_t} = \beta_0 + \beta_1 \mathbf{RV^1_{t-1}} + \beta_2 \mathbf{RV^5_{t-1}} + \beta_3 \mathbf{RV^{22}_{t-1}} + \varepsilon_t \tag{4}$$

where $\mathbf{RV_t}^1$, $\mathbf{RV_t}^5$ and $\mathbf{RV_t}^{22}$ are the daily, weekly and monthly volatility vectors respectively, $RV_t^N = \frac{1}{N}\sum_{j=0}^{N-1} RV_{t-j}$, $\boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, $\boldsymbol{\beta}_3$ are the $k \times k$ matrices. We further employ the realized semi-variance estimator to describe the asymmetric effects of positive and negative volatility on international financial market volatility connectedness. Therefore, we build the MHAR model in (4) by covering three types volatility estimators, $\mathbf{RV_t} = [RV_{NE,t}, RV_{HI,t}, RV_{ST,t}, RV_{SP,t}]'$, $\mathbf{RS_t^-} = [RS^-_{NE,t}, RS^-_{HI,t}, RS^-_{ST,t}, RS^-_{SP,t}]'$ and $\mathbf{RS_t^+} = [RS^+_{NE,t}, RS^+_{HI,t}, RS^+_{ST,t}, RS^+_{SP,t}]'$.

Furthermore, Corsi et al. (2008) suggested specifying the error term to be heteroscedastic due to the volatility effect. Considering the conditional dependence among the financial markets, we introduce the DCC-GARCH model to model he error term in the MHAR model:

$$\varepsilon_t = H_t^{1/2} w_t,\ w_t \sim NID(0, I) \tag{5}$$

where $H_t$follows the DCC-GARCH specification according to Engle (2002), and w_t follows the multivariate normal distribution with zero mean and covariance of identity matrix.

This paper estimates the coefficients in MHAR-DCC model according to Bubák et al. (2011) as follows. First, estimate the coefficients of each equation in MHAR model by using OLS approach. To avoid the curse of dimensionality in MHAR model, the insignificant explanatory variables are sequentially eliminated until all the explanatory variables retained in the model are significant. Second, estimate the model (4) and obtain the estimated residuals, and then the coefficients in DCC-GARCH can acquired by two-step MLE approach according to Engle (2002).

3.2. Forecast error decomposition approach and volatility transmission effects

Based on the proposed MHAR-DCC model, we further study the high-frequency volatility transmission effect by employing the forecast error decomposition approach in Diebold and Yilmaz (2014). Unlike the previous studies, we employ the overnight realized volatility estimators so that we can make full use of the high-frequency data to provide more useful information on volatility spillover. Moreover, the D-Y spillover index combined with the MHAR-DCC model provides a comprehensive framework to study the dynamics and direction of volatility spillovers between stock markets.

MHAR model can be considered as the 22 orders lagged VAR model with coefficients constraints:

$$\mathbf{RV_t} = \Phi_0 + \sum_{i=1}^{22} \Phi_i \mathbf{RV_{t-i}} + \varepsilon_t \tag{6}$$

$\boldsymbol{\Phi}_i$, $i = 0, 1, \cdots, 22$ is a $k \times k$ coefficients matrix, where $\boldsymbol{\Phi}_0 = \boldsymbol{\beta}_0$, $\Phi_1 = (\beta_1 + \frac{1}{5}\beta_2 + \frac{1}{22}\beta_3)$, $\Phi_2 = \cdots = \Phi_5 = \frac{1}{5}\beta_2 + \frac{1}{22}\beta_3$, $\Phi_6 = \cdots = \Phi_{22} = \frac{1}{22}\beta_3$.

Given the stationarity of coefficients in VAR model, the VAR(22) in Eq. (6) can be written compactly as a vector move averaging (VMA) version with infinite orders:

$$\mathbf{RV_t} = \Psi_0 + \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i} \tag{7}$$

where $\boldsymbol{\Psi}_i$ is a $k \times k$ coefficient matrix in VMA model and the coefficient matrix can be obtained by iterative estimation approach, namely $\Psi_i = \sum_{j=1}^{p} \Phi_j \Psi_{i-j}$, $\boldsymbol{\Psi}_0 = I_N$, $\boldsymbol{\Psi}_i = 0$ for $i < 0$.

Diebold and Yilmaz (2014) offer an error decomposition method for studying the volatility transmission effect. The error decomposition factor $s_{ij,t}$ of volatility spillover index can be received by combining coefficients in VMA model and variance in GARCH model:

$$s_{ij,t} = \frac{\sigma_{jj,t}^{-1} \sum_{l=1}^{L-1} (\varepsilon_i' \Psi_l \mathbf{H}_t \varepsilon_j)^2}{\sum_{l=1}^{L} (\varepsilon_i' \Psi_l \mathbf{H}_t \Psi_l' \varepsilon_j)} \tag{8}$$

where $\mathbf{H_t}$ is the time-variant covariance matrix of $\varepsilon_t$based on DCC-GARCH model, $\sigma_{jj,t}$ is the j^{th} element in volatility matrix. $\boldsymbol{L}$ is the forecast horizon and equals 10 in this paper.

Then, we standardize s_{ij} by $\tilde{s}_{ij}$=100*$s_{ij}/\sum_{j=1}^{n} s_{ij}$. Summing the error decomposition factor on non-diagonal lines up can receive the total volatility spillover index as in Dielbold and Yilmaz (2011):

$$S_{overall} = 1/N \sum_{i,j=1,\ i \neq j}^{N} \tilde{s}_{ij} \tag{9}$$

Moreover, by summing the error decomposition factors except that of a specific market in the same row (column) we can obtain the volatility spillover index received from (transmitted to) other markets:

$$S_{i,from} = 1/N \sum_{i,j=1,\quad i\neq j}^{N} \tilde{s}_{ij} \tag{10}$$

$$S_{i,to} = 1/N \sum_{i,j=1,\quad i\neq j}^{N} \tilde{s}_{ji} \tag{11}$$

We also compute the net spillover index which measures how much each market contributes to the volatility in other markets:

$$S_{ij,pair} = 1/N\,(\tilde{s}_{ji} - \tilde{s}_{ij}) \tag{12}$$

Furthermore, following Barunik et al. (2016), we distinguish the positive semi-variance and the negative semi-variance, and compare the difference in total and directional volatility spillover of separate semi-variances. The asymmetric total and directional volatility spillover index can be defined as:

$$SAM_{overall} = S^{+}_{overall} - S^{-}_{overall} \tag{13}$$

$$SAM_{from} = S^{+}_{from} - S^{-}_{from} \tag{14}$$

$$SAM_{to} = S^{+}_{to} - S^{-}_{to} \tag{15}$$

4. Empirical results

We first analyze the MHAR regression results based on the ORV estimation. According to Bubák et al. (2011), we sequentially eliminate the insignificant explanatory variables until all the explanatory variables retained in the model are significant. As shown in Table 2, the lagged daily-volatility of the US stock market has a significant positive impact on the current volatility of the Asian developed stock markets (Japan, Hongkong, Singapore). Meanwhile, the Asian stock markets are connected closely, i.e., the current volatility of one Asian stock market is significantly affected by the lagged volatility of the other Asian stock markets. We also present the Ljung-Box Q test results for the residuals of each MHAR equation. The results suggest that the residuals exhibit the strong autocorrelated property for most stock markets.

Then, we analyze the overall spillover effects as shown in Fig. 1. The left graph in Fig. 1 shows the total high-frequency volatility spillover effect across international stock markets. We can find that the periods when the total volatility spillover index of the four stock markets reaches a high (low) position correspond to the periods when the stock markets have high (low) volatilities. The economic intuition behind is that the stock market becomes more correlated by volatility spillover during the volatile situations (Jebran et al., 2017).

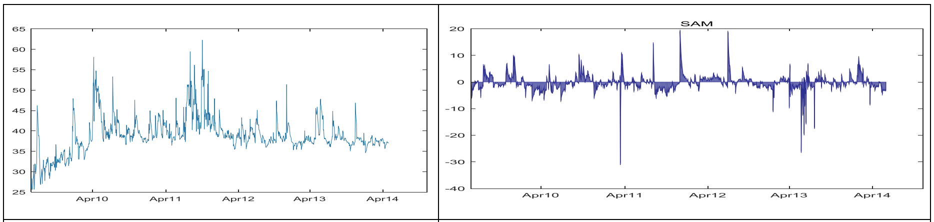
The right graph in Fig. 1 shows the asymmetric volatility spillover index across international stock markets. The spillover asymmetry measure (SAM) is mostly negative, meaning that the spillover intensity of negative volatility is higher than that of positive volatility. In addition, the periods when SAM is negative (positive) mainly correspond to the periods when the stock market is turbulent (steady). Thus, during the turbulent (steady) period, the volatility transmission effect of bad (good) news is more significant than that of good (bad) news. The previous studies have found the transmission of volatility associated with bad news is stronger than that associated with good news (e.g., Clements et al., 2015), and our results extend the findings of Corradi et al. (2012) that the volatility transmission effect of news is conditional on the volatility state of markets.

Fig. 2 shows the net pair volatility index between markets. The pair volatility spillover index between the three pairs of Asian markets and the US market (NEI-SPI, HIS-SPI and STI-SPI) are always negative over time, implying that the volatilities of the Asian

Table 2
Estimation results for different stock markets.

	NEI coefficient	*t*	HSI coefficient	*t*	STI coefficient	*t*	SPI coefficient	*t*
Constant	0.6396***	4.7112	0.6120***	4.5401	0.1129***	3.5565	0.1809***	2.4714
NEI(1)	0.2176***	2.6874	−0.1215***	−3.0849	−0.0172*	−1.7128		
HSI (1)	−0.1124***	−3.4915						
STI(1)			0.7522***	3.6334	0.1659**	2.0655	0.4038***	2.4431
SPI(1)	0.4298***	4.4468	0.6214***	3.3827	0.2137***	3.5071		
NEI(5)	0.1749**	2.2257						
HSI (5)								
STI(5)					0.2599**	2.3953		
SPI(5)							0.5120***	5.3801
NEI(22)	0.2337**	2.2654						
HSI (22)								
STI(22)					0.3924***	3.2805		
SPI(22)	−0.2846***	−2.9090			−0.1702***	−3.0605		
Ljung-Box Q(5)	0.7260		53.8845***		55.1843***		46.5883***	
Ljung-Box Q(10)	6.9298		61.2252***		63.6193***		64.7464***	
Ljung-Box Q(20)	16.3226		94.1033***		99.2794***		96.7053***	

Notes: ***, **, * indicate the 1%, 5% and 10% significance respectively.



Total volatility spillover index | Asymmetric total volatility spillover index.

Fig. 1. Overall volatility spillover index.

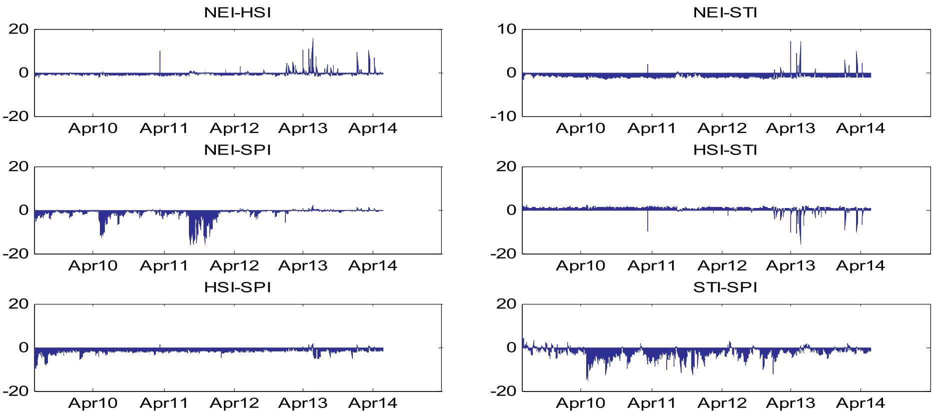


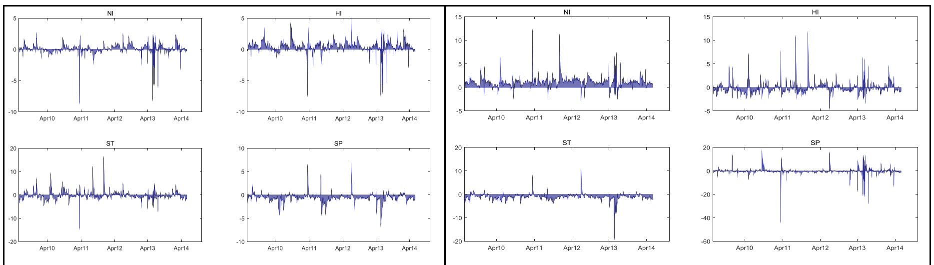
Fig. 2. Net pair volatility spillover index.

stock markets are dominated by the US stock market. In addition to the world market (US) effect on Asian markets, the regional market (Japan) causes the volatilities of Hong Kong and Singapore markets because NEI-HIS and NEI-STI are mostly positive. Thus, both regional and world factors drive the volatilities of the Asian stock markets (Ng, 2000; Li and Giles, 2015).

The left plot and the right plot in Fig. 3 shows the directional asymmetric volatility spillover index of a specific market from the other stock markets and to the other stock markets respectively. As shown in Fig. 3, the asymmetric volatility spillover indices contributing from or to the other stock markets for the Japanese and Hong Kong stock markets are mostly positive for the whole sample period, while the asymmetric volatility spillover indices of Singapore and US stock markets from or to the other stock markets are mostly negative. Generally, the leverage effect of financial market implies that market volatility caused by bad news is greater than that caused by good news. Therefore, the volatility transmissions in the US and Singapore stock markets exhibit significant leverage effects, and the Japanese and Hong Kong stock markets exhibit reverse leverage effects on the contrary according to the analysis above. The distinct asymmetric effects of different market are mainly due to the distinctions in investor structures and market policies of different stock markets (Barunik et al., 2016).

5. Conclusion

We construct the MHAR-DCC model to study the asymmetric volatility transmissions across international stock markets with the intraday high-frequency data of stock markets in the US, Japan, Hong Kong and Singapore. Besides, we employ the overnight realized volatility estimator to synchronize the volatility series of different stock markets.



from other markets | to other markets

Fig. 3. Asymmetric volatility spillover indices.

From the perspective of the total volatility transmission effect, the periods when the total volatility spillover indices reach the high point correspond to the periods when the stock market is volatile, while the periods when the total volatility spillover index stays in low level correspond to the periods when the stock market is steady. From the perspective of the asymmetric volatility transmission effect, the bad news transmission effect is more significant than the good one during the turbulent period, while during the stable period, the good news transmission effect is more significant than the bad one. The volatility transmission effect of the US and Singapore stock markets exhibit the normal leverage effect, while the volatility transmissions of Japanese and Hong Kong stock markets exhibit the reverse leverage effect.

The conclusions in this paper contribute to the discovery of the general law of volatility transmission and information spillover across international financial markets, which benefit for market investors and policy makers.

Acknowledgment

Supports from the National Natural Science Foundation of China under Grant No. 71803049, No.717774152, MOE (Ministry of Education in China) Project of Humanities and Social Sciences(No.17YJC630099), Natural Science Foundation of Guangdong Province (2018A030310400), Fundamental Research Funds for the Central Universities (2018BSXM10), Guangzhou philosophy and Social Sciences Fund (2019GZQN07), the Major Program of the National Social Science Foundation of China (16ZDA042).

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