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An Empirical Analysis of the Volatility Spillover Effect between World-Leading and the Asian Stock Markets: Implications for Portfolio Management

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Abstract: This study employs the Vector Autoregressive-Generalized Autoregressive Conditional Heteroskedasticity (VAR-AGARCH) model to examine both return and volatility spillovers from the USA (developed) and China (Emerging) towards eight emerging Asian stock markets during the full sample period, the US financial crisis, and the Chinese Stock market crash. We also calculate the optimal weights and hedge ratios for the stock portfolios. Our results reveal that both return and volatility transmissions vary across the pairs of stock markets and the financial crises. More specifically, return spillover was observed from the US and China to the Asian stock markets during the US financial crisis and the Chinese stock market crash, and the volatility was transmitted from the USA to the majority of the Asian stock markets during the Chinese stock market crash. Additionally, volatility was transmitted from China to the majority of the Asian stock markets during the US financial crisis. The weights of American stocks in the Asia-US portfolios were found to be higher during the Chinese stock market crash than in the US financial crisis. For the majority of the Asia-China portfolios, the optimal weights of the Chinese stocks were almost equal during the Chinese stock market crash and the US financial crisis. Regarding hedge ratios, fewer US stocks were required to minimize the risk for Asian stock investors during the US financial crisis. In contrast, fewer Chinese stocks were needed to minimize the risk for Asian stock investors during the Chinese stock market crash. This study provides useful information to institutional investors, portfolio managers, and policymakers regarding optimal asset allocation and risk management.

Keywords: return spillover; volatility spillover; shock spillover; US financial crisis; Chinese stock market crash

JEL Classification: G10; G11; G12; G15

1. Introduction

Information transmissions from both return and volatility across national equity markets are of greater interest to both investors and policymakers, with increasing financial integration in the stock markets all over the world (Yousaf et al. 2020). If, for example, asset volatility is transmitted from one market to another during turmoil or crisis period (Forbes and Rigobon 2002; Diebold and Yilmaz 2009), then portfolio managers need to adjust their asset allocations (Baele 2005; Engle et al. 2012) and financial policymakers need to adapt their policies in order to mitigate the contagion risk. Changes in linkages between national equity markets, especially during a crisis, can also have important implications for asset allocations, business valuation, risk management, and access to finance.

Several studies have examined linkages between the equity markets during the 1997 Asian financial crisis (In Francis et al. 2001; Wan and Wong 2001; Yang et al. 2003), and the last 2008 global financial crisis (Yilmaz 2010; Cheung et al. 2007; Kim et al. 2015; Li and Giles 2015; Lean et al. 2015; Vieito et al. 2015; Zhu et al. 2019) and some studies, see, for example, Fung et al. (2011) and Guo et al. (2017), develop theories to explain that crisis. However, the linkages between equity markets during the Chinese stock market crash of 2015have been rarely examined. The Chinese stock market experienced a major crash in 2015 (Zhu et al. 2017; Yousaf and Hassan 2019; Yousaf et al. 2020; Yousaf and Ali 2020). The CSI 300 index increased before reaching 5178 points in mid-June of 2015. Then, it took a roller-coaster ride and dropped by up to 34% in just 20 days; Chinese stock market also lost 1000 points within just one week. Around 50% of Chinese stocks lost more than half of their pre-crash market value. The Chinese stock market crash affected many other commodities and financial markets, including Asian (Allen 2015) and the US stock markets (The causes and consequences of China's market crash 2015).

Despite the importance of the Chinese crash for international portfolio managers, few studies have examined how it was transmitted to other national financial markets. Xiong et al. (2018) investigate the time-varying correlation between economic policy uncertainty and Chinese stock market returns during the Chinese crash of 2015, while Yousaf and Hassan (2019) examine the linkages between crude oil and emerging Asian stock markets during this crisis. However, research on the linkages between stock markets has not been investigated yet for the 2015 Chinese crash. Therefore, this study focuses on providing useful insights about this issue for the Asian region, which has attracted considerable attention from finance practitioners and academics due to its position as the center of global economic activity in the 21st century[1]. While using the US and Chinese equity markets as the indicators of global markets, we explore whether global investors can get the maximum benefit of diversification by adding emerging Asian market stocks in their portfolios. In literature, several studies have examined the linkages between the global (US and China) and emerging Asian equity markets during the Asian financial crisis, and the US financial crisis (Yang et al. 2003; Beirne et al. 2013; Jin 2015; Li and Giles 2015), but not in the Chinese stock market crash.

We address the above-mentioned literature gap by examining the return and volatility spillover from the US and China to the emerging Asian equity markets during the Chinese stock market crash by using the VAR-AGARCH model that was developed by Ling and McAleer (2003). Moreover, we examine the ability of spillovers during the full sample period and the 2008 US financial crisis to provide comparative insights to investors about whether the impact of the Chinese crash on equity market spillovers was different from those in the other sample periods. Our findings show that return spillover was observed from the US and China to the Asian stock market during the US financial crisis and the Chinese stock market crash. Volatility was also transmitted from the US to the majority of the Asian stock markets during the Chinese stock market crash. However, volatility was transmitted from China to the majority of the Asian stock markets during the US financial crisis. Overall, as the return and volatility transmission vary across pairs of stock markets and financial crises, investors have to adjust their asset allocations from time to time to improve their profits. Therefore, we also estimate the optimal weights and hedge ratios during the full sample period, the US financial crisis, and the Chinese stock market crash. Our findings imply that fewer US stocks were required to minimize the risk for Asian stock investors during the US financial crisis compared to during the Chinese crash. In contrast, fewer Chinese stocks were needed to minimize the risk for Asian stock investors during the Chinese stock market crash as compared to during the US crisis. Overall, our findings draw several important implications for risk management and portfolio diversification that could be useful for investors and policymakers related to the US and Asian stock markets.

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[1] Source: https://www.ft.com/content/520cb6f6-2958-11e9-a5ab-ff8ef2b976c7.

The rest of the paper is organized as follows: Section 2 provides the literature review. Section 3 describes the data and methodology. Section 4 reports the findings, and Section 5 concludes the whole discussion.

2. Literature Review

The analysis of both return and volatility spillover between stock markets is crucial for investors in designing optimal portfolios. According to modern portfolio theory, the gains of international portfolio diversification decrease when the correlation of security returns increases and vice versa. Michaud et al. (1996) discuss the advantages of a low correlation between the developed and emerging markets for international portfolio diversification. Due to this trend, investors can benefit by investing in emerging markets that are weakly interconnected with developed markets. However, this correlation becomes higher during an economic crisis, suggesting low diversification benefits when diversification is most required.

2.1. Linkages between US, China, and Asian Stock Markets

Many studies have been conducted to investigate the link between different stock markets during the last three decades. Liu and Pan (1997) examine the mean and the volatility spillover from the US and Japan to Singapore, Hong Kong, Thailand, and Taiwan. The results show that the US market is more dominant than the Japanese stock market in transmitting return and volatility effects to four Asian stock markets. Huang et al. (2000) investigate the link between the US, Japan, and South China growth triangle. The US stock market significantly and dominantly affects the south Chinese growth triangle compared to the impact of Japan on China's stock market. The return spillover has been also found to be significant from the US to Hong Kong and Taiwan, and from Hong Kong to the Taiwanese stock market. Miyakoshi (2003) estimates the return and volatility spillover between the US, Japan, and seven Asian stock markets (South Korea, Taiwan, Singapore, Thailand, Indonesia, and Hong Kong). It finds a significant return spillover from the US to Asian markets, whereas no return spillover is found from Japan to Asian stock markets. Moreover, the volatility spillover from Japan to other Asian stock markets is observed to be dominant as compared to the volatility spillover from the US to Asian stock markets.

Johansson and Ljungwall (2009) examine the association between stock markets of China, Hong Kong, and Thailand. It reports a significant return spillover from Taiwan to China and the Hong Kong stock market. In contrast, volatility spillover runs from Hong Kong to Taiwan and from Taiwan to the Chinese stock market. Zhou et al. (2012) estimate the spillover between Chinese and international (the US, the UK, France, Germany, Japan, India, Hong Kong, Taiwan, South Korea, and Singapore) stock markets from 1996 to 2009. Before 2005, the Chinese stock market was affected by spillover from other international markets. After 2005, volatility spillover was significantly transmitted from China to most of the other international stock markets. Chien et al. (2015) report on the significant financial integration between China and the ASEAN-5 (Indonesia, Malaysia, the Philippines, Singapore, and Thailand) stock markets. Huo and Ahmed (2017) provide significant evidence of both return and volatility effects from China to the Hong Kong equity market.

2.2. Linkages between US, China, and Asian Stock Markets during Crisis

Many studies have examined the linkages between markets during crisis periods. Yang et al. (2003) investigate the short and long-run relationship between the US, Japan, and ten Asian stock markets, mainly focusing on the Asian financial crisis of 1997–1998. This study reports a strengthened long-run co-integration among these stock markets during the Asian financial crises. The degree of integration is found to change during crises and non-crisis periods. Beirne et al. (2013) look at the volatility spillover from developed to emerging stock markets during periods of turbulence in mature stock markets. It finds that volatility in mature markets affects the conditional variances in emerging stock markets.

Moreover, the spillover effect from developed to emerging markets is also changed during times of turbulence in mature markets.

Jin (2015) examines the mean and volatility spillover between China, Taiwan, and Hong Kong. It reveals that financial crises have a substantial and positive effect on expected conditional variances, but also that the size and dynamics of impacts vary from market to market. Li and Giles (2015) investigate the volatility spillover across the US, Japan, and four Asian developing economies during the Asian financial crisis of 1997 and the US financial crises of 2008. The results revealed that there is a presence of a volatility spillover effect from the USA to Asian developing economies and Japan. This study also finds a bidirectional volatility spillover between US and Asian markets that occurred during the Asian financial crisis. Gkillas et al. (2019) explore integration and co-movement between 68 international stock markets (including in the Asian region) during the US financial crisis.

Overall, several studies have examined the return and volatility spillover from the US to Asian markets during the Asian financial crisis of 1997 and the US financial crisis of 2008. However less has been done on both return and volatility transmission from China to the emerging Asian stock markets during the US financial crisis and the Chinese stock market crash. Moreover, no study has examined return and volatility spillovers from the US to the emerging Asian stock markets during the Chinese crash. Therefore, this study addresses these above-mentioned literature gaps.

3. Data and Methodology

3.1. Data

We based our empirical investigation on daily data of accepted benchmark stock indices of nine Asian countries and the US. The Emerging Asian stock markets include China, India, South Korea, Indonesia, Pakistan, Malaysia, the Philippines, Thailand, and Taiwan. The emerging Asian economies were selected from the list of countries, including the MSCI (Morgan Stanley Capital International) emerging market index. The data of stock indices were taken from the Data Stream database. The index is assumed to be the same on non-trading days (holidays except weekends) as on the previous trading day, as suggested by Malik and Hammoudeh (2007) and many others.[2]

This study used the full sample period from 1 January 2000 to 30 June 2018 and studies the following two sub-samples: the first sub-period from 1 August 2007 to 31 July 2010 presenting the period with the US financial crisis; and the second sub-period from 1 June 2015 to 30 May 2018 presenting the period with the Chinese Stock market crash. We note that Yousaf and Hassan (2019) also use similar time frames for the US financial crisis and the Chinese stock market crash. This study followed He (2001) and many others to use three-year data for each crisis for short-run analysis. Changes in market correlations take place continuously not only as a result of crises but also due to the consequences of many financial, economic, and political events. Moreover, Arouri et al. (2015) have also used the daily data covering periods shorter than three years to estimate the return and volatility spillover between gold and Chinese stock markets in US financial crisis by applying the VAR-GARCH model. The difference in the opening time of US and Asian stock markets was adjusted by using lags where necessary.

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[2] In time-series data, if there are missing values, there are two ways to deal with the incomplete data: (a) omit the entire record that contains information, (b) Impute the missing information. We used 10 series in this paper and if we wanted to omit the missing data for one series then the data of all other nine series needed to be removed as well for that specific day. So, if we omitted the data for days where values are missing at specific days, then we lost the data for many days, which is not good for getting realistic results. Therefore, we followed many studies, for example, Malik and Hammoudeh (2007), and imputed the missing data by using previous day data. Indeed, there are many methods used to impute the missing data and every method has pros and cons, but we used this imputation method following past literature. Moreover, our missing observations were less than one percent of overall data, therefore the imputation method should not create a larger effect than that on results.

3.2. Methodology

This study estimated the return and volatility transmissions using the Vector Autoregressive-Generalized Autoregressive Conditional Heteroskedasticity (VAR-AGARCH) model proposed by McAleer et al. (2009). Several studies have previously used the VAR-GARCH and VAR-AGARCH model to estimate spillover between different asset classes (Arouri et al. 2011; Arouri et al. 2012; Jouini 2013; Yousaf and Hassan 2019). This model includes the Constant Conditional Correlation (CCC-GARCH) model of Bollerslev (1990) as a special case. The selection of the model was based on three reasons. First, the most commonly used multivariate models are the BEKK (Baba, Engle, Kraft, and Kroner) model and the DCC (dynamic conditional correlation) model. These models often suffer from unreasonable parameter estimates and data convergence problems (Bouri 2015). The VAR-AGARCH model overcomes these problems regarding parameters and data convergence. Second, it incorporates asymmetry into the model. Third, this model can be used to calculate the optimal weights and hedge ratios.

Ling and McAleer (2003) propose the multivariate VAR-GARCH Model to estimate the return and volatility transmission between the different series. For two series, the VAR-GARCH model has the following specifications for the conditional mean equation[3]:

$$R_t = \mu + FR_{t-1} + e_t \text{ with } e_t = D_t^{1/2}\eta_t, \tag{1}$$

in which R_t represents a 2×1 vector of daily returns[4] on the stocks x and y at time t, μ denotes a 2×1 vector of constants, F is a 2×2 matrix of parameters measuring the impacts of own lagged and cross mean transmissions between two series, e_t is the residual of the mean equation for the two stocks returns series at time t, η_t indicates a 2×1 vector of independently and identically distributed random vectors, and $D_t^{1/2} = diag\ (\sqrt{h_t^x}, \sqrt{h_t^y})$, where h_t^x and h_t^y representing the conditional variances of the returns for stocks x and y, respectively, are given as

$$h_t^x = C_x + a_{11}\left(e_{t-1}^x\right)^2 + a_{21}\left(e_{t-1}^y\right)^2 + b_{11}h_{t-1}^x + b_{21}h_{t-1}^y, \tag{2}$$

$$h_t^y = C_y + a_{12}\left(e_{t-1}^x\right)^2 + a_{22}\left(e_{t-1}^y\right)^2 + b_{12}h_{t-1}^x + b_{22}h_{t-1}^y. \tag{3}$$

Equations (2) and (3) reveal how shock and volatility are transmitted over time and across the markets under investigation. Furthermore, the conditional covariance between returns from two different stock markets can be estimated as follows:

$$h_t^{x,y} = p \times \sqrt{h_t^x} \times \sqrt{h_t^y}. \tag{4}$$

In the above equation, $h_t^{x,y}$ refers to the conditional covariance between the returns of two stock markets $(x,\ y)$ at time t. Moreover, p indicates the constant conditional correlation between the returns of two stock markets $(x,\ y)$.

The VAR−GARCH model assumes that positive or negative shocks have the same impact on the conditional variance. To estimate the spillover between different markets, we estimated spillover between two stock markets by using the VAR−AGARCH Model proposed by the McAleer et al. (2009).

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[3] Several studies, for example, Hammoudeh et al. (2009), Arouri et al. (2011), and Dutta et al. (2018) have applied the VAR for the conditional mean equation.

[4] $Stock\ Returns_t = ln\left(\frac{Stock\ Index_t}{Stock\ Index_{t-1}}\right)$.

The VAR AGARCH model incorporates asymmetry in the model as well. Specifically, instead of using Equations (2) and (3), the conditional variance of the VAR AGARCH model was defined as follows:

$$h_t^x = C_x + a_{11}A\left(e_{t-1}^x\right)^2 + a_{21}A\left(e_{t-1}^y\right)^2 + b_{11}h_{t-1}^x + b_{21}h_{t-1}^y + a_{11}B\left[\left(e_{t-1}^x\right)\left(\left(e_{t-1}^x\right) < 0\right)\right], \tag{5}$$

$$h_t^y = C_y + a_{12}A\left(e_{t-1}^x\right)^2 + a_{22}A\left(e_{t-1}^y\right)^2 + b_{12}h_{t-1}^x + b_{22}h_{t-1}^y + a_{22}B\left[\left(e_{t-1}^y\right)\left(\left(e_{t-1}^x\right) < 0\right)\right]. \tag{6}$$

In the above equations, $A\left(e_{t-1}^x\right)^2$ and $B\left[\left(e_{t-1}^x\right)\left(\left(e_{t-1}^x\right) < 0\right)\right]$ as well as $A\left(e_{t-1}^y\right)^2$ and $B\left[\left(e_{t-1}^y\right)\left(\left(e_{t-1}^y\right) < 0\right)\right]$ reveal the relationships between a market's volatility and both positive and negative own lagged returns, respectively (Lin et al. 2014). Equations (5) and (6) show that the conditional variance of each market depends upon its past shock and past volatility, as well as the past shock and past volatility of other markets. In Equation (5), $\left(e_{t-1}^x\right)^2$ and $\left(e_{t-1}^y\right)^2$ explain how the past shocks of both x and y affect the current conditional volatility of x. Moreover, h_{t-1}^x and h_{t-1}^y measure how the past volatilities of both x and y affect the current conditional volatility of x. The parameters of the VAR-AGARCH model can be estimated by using the Quasi-Maximum Likelihood estimation (QMLE) and using the BFGS algorithm.[5]

The estimates of the VAR-AGARCH model can be used to calculate optimal portfolio weights. This study followed Kroner and Ng (1998) to calculate the optimal portfolio weights for the pairs of the stock market (x, y) as:

$$w_{xy,t} = \frac{h_{y,t} - h_{xy,t}}{h_{x,y} - 2h_{xy,t} + h_{y,t}} \tag{7}$$

$$w_{xy,t} = \begin{cases} 0 & if\ W_{xy,t} < 0 \\ w_{xy,t} & if\ 0 \leq w_{xy,t} \leq 1 \\ 1 & if\ w_{xy,t} > 1 \end{cases},$$

where $w_{xy,t}$ is the weight of stock(x) in a \$1 stock(x)-stock(y) portfolio at time t, $h_{xy,t}$ is the conditional covariance between the two stock markets, $h_{x,t}$ and $h_{y,t}$ are the conditional variance of stock(x) and stock(y), respectively, and 1-$w_{xy,t}$ is the weight of stock(y) in a \$1 stock(x)-stock(y) portfolio.

It is also essential to estimate the risk-minimizing optimal hedge ratios for the portfolio of different stocks. The estimates of the VAR-AGARCH model can also be used to calculate optimal hedge ratios. This study followed Kroner and Sultan (1993) to calculate the optimal hedge ratios as:

$$\beta_{xy,t} = \frac{h_{xy,t}}{h_{y,t}}, \tag{8}$$

where $\beta_{xy,t}$ represents the hedge ratio. This shows that a short position in the stock (y) market can hedge a long position in the stock (x). Lastly, RATS 10.0 software is used for estimations.

4. Empirical Results

4.1. Descriptive Analysis

Table 1 reports the summary statistics of the daily returns for the US, China, and eight emerging Asian stock markets, namely India, Korea, Indonesia, Pakistan, Malaysia, the Philippines, Thailand, and Taiwan. The average returns of the Pakistani stock market are the highest out of these markets, whereas the lowest returns are found in the US stock market during the full sample period. The unconditional volatility is lower in Malaysia and the US market and is highest in the

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[5] Arouri et al. (2011), Sadorsky (2012), and Allen et al. (2013) use the Quasi-Maximum Likelihood estimation (QMLE) and use the BFGS algorithm to estimate the parameters in the VAR-GARCH model.

Chinese stock market. The skewness is negative in all cases, kurtosis is higher than 3 for all stocks, and Jarque–Bera statistics do not accept the hypothesis of the normality for all stocks. Moreover, we applied the Ljung–Box Q test for autocorrelation to the standardized residuals and squared standardized residuals. The coefficients both Q(12) and Q^2(12) were found to be signifcant for all series. ARCH effects were also statistically significant for all series.[6]

Table 1. Summary Statistics.

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Q-Stat	ARCH Test
USA	0.00016	0.00055	0.10958	−0.09470	0.01200	−0.20353	11.57202	14802.7 ^{a}	37.24 ^{a}	206.42 ^{a}
CHN	0.00045	0.00096	0.09401	−0.09256	0.01570	−0.31725	8.21506	5547.4 ^{a}	54.64 ^{a}	180.10 ^{a}
IND	0.00050	0.00094	0.15990	−0.11809	0.01472	−0.22234	10.54239	11474.1 ^{a}	84.62 ^{a}	283.89 ^{a}
INDO	0.00046	0.00113	0.07623	−0.10954	0.01357	−0.85402	10.92376	13206.3 ^{a}	154.0 ^{a}	457.66 ^{a}
KOR	0.00028	0.00080	0.11284	−0.12805	0.01509	−0.57337	9.64860	9149.3 ^{a}	24.06 ^{a}	210.02 ^{a}
MYS	0.00020	0.00041	0.04503	−0.09979	0.00816	−0.85496	13.33067	22038.9 ^{a}	226.8 ^{a}	267.36 ^{a}
PAK	0.00081	0.00109	0.08507	−0.07741	0.01359	−0.34875	6.83764	3058.01 ^{a}	165.5 ^{a}	594.62 ^{a}
PHL	0.00038	0.00055	0.16178	−0.13089	0.01309	0.23024	19.78304	56658.3 ^{a}	96.40 ^{a}	161.15 ^{a}
TAIW	0.00018	0.00070	0.06525	−0.09936	0.01356	−0.27454	6.59593	2659.6 ^{a}	77.68 ^{a}	201.54 ^{a}
THA	0.00044	0.00064	0.10577	−0.16063	0.01316	−0.70520	12.86191	19948.5 ^{a}	70.19 ^{a}	656.27 ^{a}

Notes: ^{a} indicates the statistical significance at 1% level.

4.2. Return, Shock and Volatility Spillover Analysis

4.2.1. Stock Market Linkages between the USA and Asia from the Full Sample Period

Table 2 represents the return and volatility spillover between US and Asian stock markets during the full sample period. The lagged stock returns were found to significantly affect the current stock returns in all studied Asian stock markets except for Korea. This highlights the possibility of short-term predictions of current returns through past returns in the Asian stock markets. Moreover, the autoregressive term of the USA stock market was found to be significant as well. This depicts that past returns help to predict current returns in the American stock market.

The estimate of return spillover from one market to another market can be estimated by using the coefficient of lagged return of one market (i.e., the US) onto another market (i.e., India) and vice versa. The return spillover from the USA to all Asian stock markets is significant. This implies that US stock market prices play an important role in predicting the prices of all Asian stock markets during the full sample period. These results are in line with the findings of Huyghebaert and Wang (2010), which find a significant return spillover from the USA to Asian markets. This shows that the effect of the returns of the American stock market are significantly transmitted to the Asian stock markets. However, the return spillover from all Asian stock markets to the USA was found to be insignificant. This implies that Asian stock market prices are not helpful in predicting the prices of the US stock market during the full sample period.

[6] We applied both Augmented Dickey–Fuller (ADF), and Phillip–Perron (PP) tests to examine the stationarity of all returns series and found that all returns series are stationary, but we do not report these results in Table form for the sake of brevity.

Table 2. Estimates of bivariate Vector Autoregressive-Generalized Autoregressive Conditional Heteroskedasticity (VAR-AGARCH) for the USA and Asian stock markets during a full sample period.

	IND	USA	INDO	USA	KOR	USA	MYS	USA	PAK	USA	PHL	USA	TAIW	USA	THA	USA
								Panel A: Mean Equation								
Constant	$4.90 \times 10^{-4\,a}$ (0.001)	$2.48 \times 10^{-4\,c}$ (0.023)	$5.13 \times 10^{-4\,a}$ (0.001)	$2.40 \times 10^{-4\,b}$ (0.022)	1.55×10^{-4} (0.252)	$2.08 \times 10^{-4\,c}$ (0.059)	1.08×10^{-4} (0.195)	$2.46 \times 10^{-4\,b}$ (0.026)	$8.79 \times 10^{-4\,a}$ (0.000)	$2.07 \times 10^{-4\,b}$ (0.048)	$3.53 \times 10^{-4\,b}$ (0.030)	$2.20 \times 10^{-4\,a}$ (0.001)	1.28×10^{-4} (0.296)	$2.64 \times 10^{-4\,b}$ (0.016)	$6.11 \times 10^{-4\,a}$ (0.000)	$2.71 \times 10^{-4\,c}$ (0.010)
r^{o}_{t-1}	0.100^{a} (0.000)	-7.65×10^{-4} (0.933)	0.136^{a} (0.000)	−0.010 (0.260)	0.017 (0.241)	0.016 (0.126)	0.168^{a} (0.000)	−0.022 (0.232)	0.168^{a} (0.000)	-4.52×10^{-3} (0.648)	0.118^{a} (0.000)	-1.87×10^{-3} (0.132)	0.054^{a} (0.000)	0.014 (0.232)	0.093^{a} (0.000)	-8.99×10^{-3} (0.423)
r^{u}_{t-1}	0.231^{a} (0.000)	-0.041^{a} (0.009)	0.301^{a} (0.000)	-0.032^{b} (0.031)	0.420^{a} (0.000)	-0.037^{b} (0.017)	0.201^{a} (0.000)	-0.034^{b} (0.035)	$6.40 \times 10^{-3\,b}$ (0.017)	-0.030^{b} (0.040)	0.421^{a} (0.000)	-0.030^{b} (0.014)	0.386^{a} (0.000)	-0.037^{b} (0.021)	0.224^{a} (0.000)	-0.037^{b} (0.021)
								Panel B: Variance Equation								
Constant	$2.68 \times 10^{-6\,a}$ (0.000)	$1.72 \times 10^{-6\,a}$ (0.000)	$1.46 \times 10^{-5\,a}$ (0.000)	$1.47 \times 10^{-6\,a}$ (0.000)	$1.40 \times 10^{-6\,a}$ (0.000)	$1.71 \times 10^{-6\,a}$ (0.000)	$6.67 \times 10^{-7\,a}$ (0.000)	$1.70 \times 10^{-6\,a}$ (0.000)	$7.61 \times 10^{-6\,a}$ (0.000)	$2.30 \times 10^{-6\,a}$ (0.000)	$3.82 \times 10^{-5\,a}$ (0.000)	$-1.46 \times 10^{-6\,a}$ (0.000)	$1.11 \times 10^{-6\,a}$ (0.000)	$1.64 \times 10^{-6\,a}$ (0.000)	$4.90 \times 10^{-6\,a}$ (0.000)	$1.72 \times 10^{-6\,a}$ (0.000)
$\left(e^{o}_{t-1}\right)^2$	0.056^{a} (0.000)	0.038^{a} (0.000)	0.118^{a} (0.000)	0.057^{a} (0.000)	0.053^{a} (0.000)	0.020^{a} (0.001)	0.090^{a} (0.000)	$7.04 \times 10^{-3\,a}$ (0.002)	0.100^{a} (0.000)	$-1.84 \times 10^{-3\,a}$ (0.000)	0.125^{a} (0.000)	0.041^{a} (0.000)	0.037^{a} (0.000)	0.035^{a} (0.000)	0.080^{a} (0.000)	8.93×10^{-3} (0.315)
$\left(e^{u}_{t-1}\right)^2$	$8.17 \times 10^{-3\,a}$ (0.001)	-5.68×10^{-3} (0.401)	2.30×10^{-3} (0.538)	-0.011^{c} (0.052)	$6.81 \times 10^{-3\,b}$ (0.032)	−0.011 (0.108)	4.97×10^{-3} (0.524)	-0.011^{c} (0.073)	$5.98 \times 10^{-3\,a}$ (0.000)	$-6.98 \times 10^{-3\,c}$ (0.083)	$-4.96 \times 10^{-3\,a}$ (0.000)	-0.014^{a} (0.000)	6.71×10^{-3} (0.110)	-8.59×10^{-3} (0.228)	$7.89 \times 10^{-3\,b}$ (0.012)	-9.45×10^{-3} (0.119)
h^{o}_{t-1}	0.877^{a} (0.000)	-0.030^{a} (0.000)	0.579^{a} (0.000)	0.085 (0.130)	0.906^{a} (0.000)	−0.018 (0.290)	0.853^{a} (0.000)	2.77×10^{-3} (0.378)	0.791^{a} (0.000)	1.71×10^{-4} (0.369)	0.506^{a} (0.000)	−0.029 (0.142)	0.925^{a} (0.000)	-0.030^{a} (0.000)	0.813^{a} (0.000)	5.47×10^{-3} (0.599)
h^{u}_{t-1}	$-4.98 \times 10^{-3\,b}$ (0.031)	0.896^{a} (0.000)	6.82×10^{-4} (0.915)	0.908^{a} (0.000)	-2.59×10^{-3} (0.407)	0.900^{a} (0.000)	0.010 (0.355)	0.894^{a} (0.000)	$-7.80 \times 10^{-3\,a}$ (0.000)	0.892^{a} (0.000)	0.036^{a} (0.000)	0.903^{a} (0.000)	2.08×10^{-4} (0.968)	0.897^{a} (0.000)	$-4.67 \times 10^{-3\,c}$ (0.076)	0.900^{a} (0.000)
Asymmetry	0.098^{a} (0.000)	0.172^{a} (0.000)	0.199^{a} (0.000)	0.164^{a} (0.000)	0.068^{a} (0.000)	0.173^{a} (0.000)	0.060^{a} (0.000)	0.183^{a} (0.000)	0.143^{a} (0.000)	0.193^{a} (0.000)	0.143^{a} (0.000)	0.167^{a} (0.000)	0.051^{a} (0.000)	0.167^{a} (0.000)	0.157^{a} (0.000)	0.175^{a} (0.000)
								Panel C: Constant Conditional Correlation								
$p^{0,u}$	0.198^{a} (0.000)		0.104^{a} (0.000)		0.185^{a} (0.000)		0.082^{a} (0.000)		0.031^{b} (0.030)		0.054^{a} (0.000)		0.142^{a} (0.000)		0.134^{a} (0.000)	
								Panel D: Diagnostic Tests								
LogL	30500.4		30678.873		30692.048		33342.351		30597.4		30633.0		30931.2		30683.3	
AIC	−9.520		−9.912		−10.060		−11.074		−10.044		−10.537		−10.030		−10.174	
SIC	−9.126		−9.518		−9.671		−10.680		−9.040		−10.143		−9.780		−9.779	

Table 2. *Cont.*

	IND	USA	INDO	USA	KOR	USA	MYS	USA	PAK	USA	PHL	USA	TAIW	USA	THA	USA
Panel D: Diagnostic Tests																
JB	533.870 [a] (0.000)	381.111 [a] (0.000)	688.360 [a] (0.000)	528.060 [a] (0.000)	870.230 [a] (0.000)	391.040 [a] (0.000)	1921.200 [a] (0.000)	500.410 [a] (0.000)	3442.14 [a] (0.000)	508.010 [a] (0.000)	10842.7 [a] (0.000)	438.390 [a] (0.000)	295.380 [a] (0.000)	462.680 [a] (0.000)	20331.6 [a] (0.000)	560.990 [a] (0.000)
Q (12)	16.143 (0.185)	22.788 (0.303)	9.012 (0.702)	15.021 (0.240)	5.829 (0.924)	18.049 (0.114)	13.179 (0.356)	14.149 (0.291)	55.870 [c] (0.097)	15.244 (0.228)	21.845 [b] (0.039)	15.008 (0.241)	18.533 [c] (0.100)	19.566 [c] (0.076)	33.450 [c] (0.087)	16.279 (0.179)
$Q^2(12)$	13.026 (0.367)	9.413 (0.667)	19.566 [c] (0.076)	8.416 (0.752)	5.242 (0.949)	9.919 (0.623)	14.799 (0.253)	10.027 (0.614)	5.970 (0.918)	0.000 [a] (0.000)	1.823 (0.923)	0.000 [a] (0.000)	16.456 (0.171)	10.976 (0.531)	0.928 (0.965)	11.617 (0.477)

Notes: The number of lags for VAR was decided using SIC (Schwartz information criterion) and AIC (Akaike information criterion) criteria. JB, Q(12), and $Q^2(12)$ indicate the empirical statistics of the Jarque–Bera test for normality, while Ljung–Box Q statistics with order 12 for autocorrelation were applied to the standardized residuals and squared standardized residuals, respectively. USA, United States of America; IND, India; INDO, Indonesia; KOR, South Korea; MYS, Malaysia; PAK, Pakistan; PHL, the Philippines; TAIW, Taiwan; THA, Thailand. Values in parentheses are the *p*-values. [a],[b],[c] indicate the statistical significance at 1%, 5%, and 10%, respectively.

ARCH coefficient captures the shock dependence, while the GARCH coefficient captures the persistence of volatility in conditional variance equations. The findings reveal that the sensitivity of past own shocks (ARCH term) is significantly positive for all Asian Stock Markets in the short run. In addition, the sensitivity of past own volatility (the GARCH term) was found to be significant for all stock markets (including the Asian and American Markets), thus the ARCH (1) volatility model was determined to be more appropriate in this case. The coefficient of past own volatility was than the coefficients of past own shocks in all Asian stock markets, implying that past own volatilities are more critical for prediction of future volatility as compared to past own shocks.

The conditional volatility of India's, South Korea's, the Philippines', Pakistan's, and Thailand's stock markets was found to be significantly affected by shocks in the American stock market. These results are similar to the findings of Syriopoulos et al. (2015), which show that past shocks in the American market significantly affect the market volatility of India, Brazil, and Russia. Therefore, this implies that shock in the American stock market leads to an increase in the volatility of the majority of Asian markets. The past volatility of the American stock market significantly influenced the conditional volatility of India's, The Philippines', Pakistan's, and Thailand's stock markets. These results confirm the previous findings of Li and Giles (2015), which finds a significant volatility spillover from the USA to emerging Asian stock markets. Further, Syriopoulos et al. 2015 found a significant volatility spillover from the USA to India. In addition, the past volatility of the majority of Asian Markets (Except for India and Taiwan) has not been significantly transmitted to the American stock market. The asymmetric coefficients of all Asian stock markets are significant and positive, showing that negative news (or unexpected shocks) for the American stock market has more ability to increase the volatility of all Asian Stock markets as compared to positive news.

Besides, the asymmetric coefficient of the American stock market is positively significant, demonstrating that negative unexpected shocks in Asian Stock markets will increase the volatility more in the American Stock market as compared to a positive shock. Constant conditional correlation (CCC) is positively significant for all pairs of stock markets. However, cross-market correlation is weak in almost all pairs, indicating that investors can get substantial gains by having these pairs in the same portfolio.

4.2.2. Stock Market Linkages between China and Asia from the Full Sample Period

Table 3 reports the return and volatility spillover between the Chinese and other Asian stock markets during the full sample period. The current stock returns of Asian stock markets are significantly affected by their own lagged stock returns. This highlights the possibility of short-term predictions of current returns through past returns in the Asian stock markets. Moreover, Chinese stock returns are also significantly influenced by their own single period lagged returns. These findings depict that stock prices can be predicted in the short term in the Chinese stock market.

The return spillover is not significant from China to the majority of other Asian markets except for the Indian, Philippines, and Thai stock markets. Besides, the return transmission from Asian markets to the Chinese market is insignificant except for in the case of the Indian Stock market. Moreover, there is a presence of bi-directional return transmission between the Indian and Chinese stock markets. This implies that Chinese (Indian) stock market prices play an important role in predicting the prices of Indian (Chinese) stock markets during the full sample period. The coefficient of past own shock of all Asian markets (including China) was found to be significant; thus, past shocks affect current conditional volatility in Asian stock markets. Besides, the sensitivity of past own volatility for all Asian markets was found to be significant as well.

Table 3. Estimates of bivariate VAR−AGARCH for China's and other Asian stock markets during the full sample period.

	IND	CHN	INDO	CHN	KOR	CHN	MYS	CHN	PAK	CHN	PHL	CHN	TAIW	CHN	THA	CHN
Panel A: Mean Equation																
Constant	5.06×10^{-4} [a] (0.000)	3.25×10^{-4} [c] (0.053)	5.37×10^{-4} [a] (0.000)	3.50×10^{-4} [b] (0.022)	2.71×10^{-4} [c] (0.065)	3.26×10^{-4} [b] (0.043)	1.69×10^{-4} [b] (0.036)	3.74×10^{-4} [b] (0.023)	8.64×10^{-4} [a] (0.000)	3.39×10^{-4} [b] (0.029)	3.32×10^{-4} [b] (0.031)	3.50×10^{-4} [b] (0.030)	2.18×10^{-4} [c] (0.089)	3.51×10^{-4} [b] (0.027)	5.05×10^{-4} [a] (0.000)	2.12×10^{-4} (0.139)
r^{o}_{t-1}	0.137 [a] (0.000)	0.036 [a] (0.004)	0.152 [a] (0.000)	0.017 (0.237)	0.083 [a] (0.000)	0.011 (0.345)	0.191 [a] (0.000)	0.018 (0.456)	0.167 [a] (0.000)	6.27×10^{-3} (0.576)	0.144 [a] (0.000)	−0.028 [b] (0.048)	0.100 [a] (0.000)	0.017 (0.241)	0.125 [a] (0.000)	0.018 (0.183)
r^{c}_{t-1}	−0.018 [c] (0.096)	0.049 [a] (0.001)	-6.05×10^{-3} (0.603)	0.050 [a] (0.000)	−0.013 (0.269)	0.055 [a] (0.000)	7.11×10^{-3} (0.295)	0.053 [a] (0.000)	0.010 (0.272)	0.055 [a] (0.000)	0.025 [b] (0.043)	0.055 [a] (0.000)	2.26×10^{-3} (0.841)	0.051 [a] (0.000)	−0.020 (0.103)	0.049 [a] (0.001)
Panel B: Variance Equation																
Constant	2.14 × 10−6 [a] (0.000)	1.14 × 10−6 [a] (0.001)	4.30 × 10−6 [a] (0.000)	1.19 × 10−6 [a] (0.002)	1.00 × 10−6 [a] (0.000)	1.37 × 10−6 [a] (0.000)	5.84 × 10−7 [a] (0.000)	1.26 × 10−6 [a] (0.000)	7.29 × 10−6 [a] (0.000)	1.15 × 10−6 [a] (0.002)	1.36 × 10−5 [a] (0.000)	1.19 × 10−6 [b] (0.048)	9.17 × 10−7 [a] (0.000)	1.21 × 10−6 [a] (0.000)	1.01 × 10−6 [a] (0.001)	1.19 × 10−6 [a] (0.001)
$\left(e^{o}_{t-1}\right)^2$	0.051 [a] (0.000)	-1.95×10^{-3} (0.413)	0.074 [a] (0.000)	-1.77×10^{-4} (0.950)	0.031 [a] (0.000)	7.03×10^{-3} (0.241)	0.074 [a] (0.000)	3.80×10^{-4} (0.668)	0.100 [a] (0.000)	-9.47×10^{-4} (0.509)	0.053 [a] (0.000)	8.20×10^{-3} [b] (0.016)	0.033 [a] (0.000)	3.74×10^{-3} [b] (0.034)	0.070 [a] (0.000)	0.023 [a] (0.000)
$\left(e^{c}_{t-1}\right)^2$	-5.03×10^{-3} [c] (0.081)	0.069 [a] (0.000)	9.29×10^{-3} [c] (0.099)	0.066 [a] (0.000)	-1.32×10^{-3} (0.551)	0.070 [a] (0.000)	-6.92×10^{-3} (0.422)	0.069 [a] (0.000)	3.56×10^{-3} (0.453)	0.064 [a] (0.000)	8.77×10^{-4} (0.754)	0.068 [a] (0.000)	9.94×10^{-3} [a] (0.000)	0.069 [a] (0.000)	7.51×10^{-3} [b] (0.025)	0.062 [a] (0.000)
h^{o}_{t-1}	0.876 [a] (0.000)	9.48×10^{-3} [a] (0.001)	0.840 [a] (0.000)	0.011 [b] (0.041)	0.929 [a] (0.000)	-6.06×10^{-3} [a] (0.000)	0.871 [a] (0.000)	2.91×10^{-3} [b] (0.022)	0.792 [a] (0.000)	1.39×10^{-3} (0.458)	0.797 [a] (0.000)	2.22×10^{-3} (0.656)	0.922 [a] (0.000)	-1.34×10^{-3} (0.508)	0.878 [a] (0.000)	-8.97×10^{-3} [a] (0.001)
h^{c}_{t-1}	7.61×10^{-3} [b] (0.033)	0.920 [a] (0.000)	-4.86×10^{-3} (0.482)	0.923 [a] (0.000)	2.24×10^{-3} (0.314)	0.918 [a] (0.000)	0.010 (0.278)	0.921 [a] (0.000)	-1.29×10^{-3} (0.816)	0.923 [a] (0.000)	1.53×10^{-3} (0.816)	0.921 [a] (0.000)	-8.00×10^{-3} [a] (0.002)	0.921 [a] (0.000)	-3.06×10^{-3} (0.497)	0.919 [a] (0.000)
Asymmetry	0.105 [a] (0.000)	0.016 [b] (0.048)	0.096 [a] (0.000)	0.012 (0.138)	0.067 [a] (0.000)	0.019 [b] (0.023)	0.073 [a] (0.000)	0.016 [c] (0.055)	0.139 [a] (0.000)	0.019 [b] (0.012)	0.096 [a] (0.000)	0.018 [b] (0.035)	0.072 [a] (0.000)	0.016 [b] (0.050)	0.073 [a] (0.000)	0.030 [a] (0.001)
Panel C: Constant Conditional Correlation																
$p^{0,c}$	0.158 [a] (0.000)		0.164 [a] (0.000)		0.211 [a] (0.000)		[a] (0.000)		0.047 [a] (0.001)		0.131 [a] (0.000)		0.218 [a] (0.000)		0.146 [a] (0.000)	
Panel D: Diagnostic Tests																
LogL	28559.5		28690.5		28584.3		31339.5		28776.2		28564.8		28882.9		28821.945	
AIC	9.191		−9.543		−9.621		−10.762		−9.824		−9.920		−9.766		−9.770	
SIC	−8.797		−9.149		−9.227		−10.368		−9.430		−9.520		−9.372		−9.375	

Table 3. *Cont.*

	IND	CHN	INDO	CHN	KOR	CHN	MYS	CHN	PAK	CHN	PHL	CHN	TAIW	CHN	THA	CHN
Panel D: Diagnostic Tests																
JB	574.750 [a] (0.000)	1348.92 [a] (0.000)	1310.07 [a] (0.000)	1391.71 [a] (0.000)	1385.22 [a] (0.000)	705.970 [a] (0.000)	1651.18 [a] (0.000)	1428.96 [a] (0.000)	3079.52 [a] (0.000)	1424.88 [a] (0.000)	1248.20 [a] (0.000)	1408.79 [a] (0.000)	464.070 [a] (0.000)	1238.55 [a] (0.000)	56026.9 [a] (0.000)	1380.10 [a] (0.000)
Q (12)	17.399 (0.135)	48.803 [a] (0.000)	10.709 (0.554)	45.754 [a] (0.000)	9.252 (0.681)	46.376 [a] (0.000)	15.229 (0.229)	44.283 [a] (0.000)	54.789 [a] (0.000)	51.513 [a] (0.000)	14.166 (0.290)	50.473 [a] (0.000)	24.449 [b] (0.018)	39.022 [a] (0.000)	31.740 [a] (0.002)	48.687 [a] (0.000)
Q^2(12)	11.249 (0.508)	11.647 (0.474)	17.033 (0.148)	9.322 (0.675)	5.203 (0.951)	11.672 (0.472)	20.075 [c] (0.066)	11.915 (0.453)	6.182 (0.907)	12.065 (0.440)	4.715 (0.967)	10.218 (0.597)	11.938 (0.451)	13.649 (0.324)	2.396 (0.999)	10.561 (0.567)

Notes: The number of lags for VAR was decided using SIC (Schwartz information criterion) and AIC (Akaike information criterion) criteria. JB, Q(12) and Q^2(12) indicated the empirical statistics of the Jarque–Bera test for normality, while Ljung–Box Q statistics of order 12 for autocorrelation applied to the standardized residuals and squared standardized residuals, respectively. CHN, China; IND, India; INDO, Indonesia; KOR, South Korea; MYS, Malaysia; PAK, Pakistan; PHL, the Philippines; TAIW, Taiwan; THA, Thailand. Values in parentheses are the *p*-values. [a], [b], [c] indicate the statistical significance at 1%, 5%, and 10%, respectively.

The conditional volatility of India, Indonesia, Taiwan, and Thailand is significantly affected by shocks in the Chinese market. Also, the conditional volatility of the Chinese market is significantly impacted by the shocks in the Philippines, Taiwanese, and Thai stock markets. The past volatility of the Chinese stock market has not influenced the conditional volatility of the most of the Asian stock markets except for the Indian and Taiwanese stock markets. These findings corroborate with the results of Zhou et al. (2012), which report a significant spillover from China to the Taiwanese stock market. However, the past volatility of the majority Asian markets (except for Pakistan, the Philippines, and Taiwan) significantly affected the conditional volatility of the Chinese stock market.

The asymmetric coefficients of all Asian stock markets were found to be significant and positive, showing that negative news of the Chinese stock market has more of an ability to increase the volatility of all Asian stock markets as compared to positive news. Moreover, the asymmetric coefficient of the Chinese stock market is significant and positive, showing that negative news in Asian markets (except in Indonesia) has a greater ability to increase the volatility of the Chinese market as compared to positive news. Constant conditional correlation is positively significant for all pairs of stock markets, but CCC is weak in majority pairs.

4.2.3. Stock Market Linkages between the USA and Asia from the US Financial Crisis

Table 4 shows the mean and volatility spillover between the USA and Asian stock markets during the US financial crisis. In Asian Stock markets (except for South Korea), past lagged returns significantly influenced the current returns. This highlights the possibility of short-term prediction of current returns through past returns in the Asian stock markets. Moreover, the American stock returns were also significantly influenced by their own single period lagged returns in the majority of cases.

The return spillover effect from the USA to all Asian markets was seen to be significant during the US financial crisis. This implies that US stock market prices played an important role in predicting the prices of all Asian stock markets during the US financial crisis. These results confirm the previous findings of Glick and Hutchison (2013), who reported a significant impact of American equity returns on Asian equity returns during the US financial crisis. Moreover, no single Asian stock market transmitted the return effect to the American market during the US financial crisis. The sensitivity of past own shock was significant for the majority of Asian markets other than Indonesia, Korea, and Taiwan. The coefficient of past own shocks of the American stock market was insignificant in the majority estimations. Besides, the coefficient of own past volatility in all Asian markets was significant except in the Philippines.

The past shocks in the American stock market significantly influenced the conditional volatility of Korea, the Philippines, and Taiwan during the US financial crisis. However, past shocks in most of the Asian stock markets (Except India) have not affected the conditional volatility of the American stock market. The effect of past volatility in the USA on conditional volatility of the Asian stock markets (except Korea) was found to be insignificant. These results match with the findings of Li and Giles (2015), which observe an absence of volatility spillover from the USA to emerging Asian stock markets during the US financial crisis. Moreover, the past volatility of majority Asian stock has not significantly affected American stock market volatility. The asymmetric coefficient of all Asian markets is significant and positive. Moreover, the asymmetric coefficient of the US market is significant and positive in all cases. Constant conditional correlation is positively significant for all pairs of stock markets, but CCC is weak in majority pairs.

Table 4. Estimates of bivariate VAR−AGARCH for the American and Asian stock markets during the US Financial Crisis.

	IND	USA	INDO	USA	KOR	USA	MYS	USA	PAK	USA	PHL	USA	TAIW	USA	THA	USA
Panel A: Mean Equation																
Constant	7.60×10^{-4} (0138)	3.49×10^{-4} (0.936)	-2.0×10^{-5} (0957)	8.03×10^{-5} (0.834)	$8.5 \times 10^{-4\,c}$ (0.080)	-7.01×10^{-5} (0.865)	3.72×10^{-4} (0.123)	-1.43×10^{-4} (0.742)	$9.53 \times 10^{-4\,a}$ (0.005)	3.57×10^{-4} (0.262)	$9.83 \times 10^{-4\,a}$ (0.001)	$4.79 \times 10^{-4\,a}$ (0.066)	1.90×10^{-4} (0.684)	-2.64×10^{-5} (0.955)	6.00×10^{-4} (0.194)	-6.12×10^{-5} (0.886)
r^{o}_{t-1}	0.081^{b} (0.031)	0.016 (0.510)	0.031^{b} (0.036)	−0.024 (0.445)	0.044 (0.141)	−0.010 (0.713)	0.145^{a} (0.000)	−0.046 (0.409)	0.125^{a} (0.001)	0.015 (0.648)	0.101^{a} (0.000)	0.016 (0.523)	0.063^{c} (0.076)	0.020 (0.565)	0.065^{b} (0.027)	−0.012 (0.663)
r^{u}_{t-1}	0.293^{a} (0.000)	-0.093^{b} (0.016)	0.423^{a} (0.000)	-0.062^{a} (0.091)	0.325^{a} (0.000)	-0.079^{b} (0.041)	0.187^{a} (0.000)	-0.080^{b} (0.042)	0.175^{a} (0.000)	0.016 (0.706)	0.489^{a} (0.000)	1.60×10^{-3} (0.963)	0.383^{a} (0.000)	-0.103^{b} (0.011)	0.249^{a} (0.000)	-0.077^{b} (0.034)
Panel B: Variance Equation																
Constant	2.91×10^{-6} (0.161)	$3.39 \times 10^{-6\,a}$ (0.001)	$1.33 \times 10^{-5\,a}$ (0.000)	$5.10 \times 10^{-6\,a}$ (0.000)	$3.98 \times 10^{-5\,a}$ (0.000)	$4.34 \times 10^{-6\,a}$ (0.000)	$1.80 \times 10^{-6\,b}$ (0.038)	$3.40 \times 10^{-6\,a}$ (0.001)	$4.22 \times 10^{-6\,a}$ (0.007)	$3.93 \times 10^{-6\,a}$ (0.000)	$3.87 \times 10^{-5\,a}$ (0.000)	$2.98 \times 10^{-6\,a}$ (0.000)	1.15×10^{-6} (0.352)	$3.73 \times 10^{-6\,a}$ (0.009)	$3.72 \times 10^{-5\,a}$ (0.000)	4.59×10^{-8} (0.984)
$\left(e^{o}_{t-1}\right)^2$	0.086^{a} (0.000)	0.075^{b} (0.016)	0.198^{a} (0.000)	0.001 (0.877)	0.012^{a} (0.000)	0.077^{c} (0.078)	0.119^{a} (0.000)	-7.24×10^{-4} (0.879)	0.036^{b} (0.034)	7.53×10^{-3} (0.439)	0.283 (0.140)	0.051^{b} (0.044)	4.98×10^{-3} (0.761)	0.029 (0.230)	0.151^{a} (0.000)	0.015 (0.678)
$\left(e^{u}_{t-1}\right)^2$	$6.65 \times 10^{-3\,a}$ (0.053)	-0.01×10^{-3} (0.337)	0.011 (0.138)	-0.029^{b} (0.014)	$7.71 \times 10^{-3\,b}$ (0.052)	0.001 (0.917)	0.051 (0.213)	−0.013 (0.361)	0.018 (0.146)	-0.060^{a} (0.001)	$-4.01 \times 10^{-3\,b}$ (0.033)	-0.061^{a} (0.000)	0.026^{c} (0.056)	−0.022 (0.113)	-5.15×10^{-3} (0.690)	-6.17×10^{-3} (0.661)
h^{o}_{t-1}	-0.868^{a} (0.000)	-0.048^{b} (0.012)	0.750^{a} (0.000)	0.060 (0.208)	0.426^{a} (0.000)	−0.012 (0.330)	0.755^{a} (0.000)	0.013^{c} (0.090)	0.854^{a} (0.000)	8.26×10^{-3} (0.470)	0.099 (0.196)	0.043 (0.171)	0.951^{a} (0.000)	-0.029^{c} (0.062)	0.449^{a} (0.000)	0.110^{b} (0.024)
h^{u}_{t-1}	$2.17 \times 10^{-3\,c}$ (0.087)	0.894^{a} (0.000)	5.62×10^{-4} (0.765)	0.945^{a} (0.000)	−0.176 (0.394)	0.906^{a} (0.000)	−0.035 (0.312)	0.915^{a} (0.000)	−0.021 (0.322)	0.907^{a} (0.000)	8.49×10^{-3} (0.115)	0.906^{a} (0.000)	−0.017 (0.382)	0.910^{a} (0.000)	0.031 (0.299)	0.905^{a} (0.000)
Asymmetry	0.064^{c} (0.090)	0.179^{a} (0.000)	0.265^{a} (0.000)	0.159^{a} (0.000)	0.446^{a} (0.000)	0.161^{a} (0.000)	0.163^{a} (0.004)	0.154^{a} (0.000)	0.101^{a} (0.004)	0.237^{a} (0.000)	0.523^{a} (0.000)	0.233^{a} (0.000)	0.075^{a} (0.000)	0.169^{a} (0.000)	0.187^{a} (0.000)	0.147^{a} (0.000)
Panel C: Constant Conditional Correlation																
$p^{0,u}$	0.172^{a} (0.000)		0.280^{a} (0.000)		0.220^{a} (0.000)		0.195^{a} (0.000)		0.016^{c} (0.086)		0.065^{b} (0.044)		0.187^{a} (0.000)		0.218^{a} (0.000)	
Panel D: Diagnostic Tests																
LogL	4230.27		4320.18		4436.36		4843.96		4850.88		6628.56		4391.36		4399.67	
AIC	−10.066		−10.502		−10.394		−11.480		−11.499		−11.518		−10.601		−10.710	
SIC	−9.773		−10.209		−10.101		−11.187		−11.205		−11.224		−10.308		−10.417	

Table 4. *Cont.*

	IND	USA	INDO	USA	KOR	USA	MYS	USA	PAK	USA	PHL	USA	TAIW	USA	THA	USA
Panel D: Diagnostic Tests																
JB	513.31 [a] (0.000)	372.23 [a] (0.000)	679.01 [a] (0.000)	512.65 [a] (0.000)	843.871 [a] (0.000)	399.862 [a] (0.000)	321.220 [a] (0.000)	627.410 (0.000)	676.080 [a] (0.000)	654.370 [a] (0.000)	1598.28 [a] (0.000)	629.470 [a] (0.000)	352.580 [a] (0.000)	635.280 [a] (0.000)	330.040 [a] (0.000)	643.320 [a] (0.000)
Q (12)	14.588 (0.264)	8.939 (0.708)	11.706 (0.469)	6.002 (0.915)	12.006 (0.445)	7.401 (0.829)	11.897 (0.454)	6.280 (0.901)	17.579 (0.129)	9.780 (0.635)	9.776 (0.636)	7.878 (0.795)	14.047 (0.298)	5.797 (0.926)	13.234 (0.352)	5.468 (0.941)
Q^2(12)	7.779 (0.802)	13.979 (0.301)	5.303 (0.947)	14.983 (0.242)	6.336 (0.898)	13.673 (0.322)	5.422 (0.942)	14.540 (0.268)	6.417 (0.894)	32.448 [a] (0.001)	2.113 (0.999)	20.023 [c] (0.067)	6.158 (0.908)	13.940 (0.305)	8.596 (0.737)	14.294 (0.282)

Notes: The number of lags for VAR was decided using SIC (Schwartz information criterion) and AIC (Akaike information criterion) criteria. JB, Q(12) and Q^2(12) indicate the empirical statistics of the Jarque–Bera test for normality, while Ljung–Box Q statistics of order 12 for autocorrelation were applied to the standardized residuals and squared standardized residuals, respectively. USA, United States of America; IND, India; INDO, Indonesia; KOR, South Korea; MYS, Malaysia; PAK, Pakistan; PHL, the Philippines; TAIW, Taiwan; THA, Thailand. Values in parentheses are the *p*-values. [a], [b], [c] indicate the statistical significance at 1%, 5%, and 10%, respectively.

4.2.4. Stock Market Linkages between China and Asia during the US Financial Crisis

Table 5 reports the return and volatility spillover between China and Asian stock markets during the US financial crisis. The current stock returns of the majority of Asian stock markets (Except in South Korea) are significantly affected by their own lagged stock returns. This highlights the possibility of short-term prediction of current returns through past returns in the Asian stock markets. However, Chinese stock returns were not significantly affected by their lagged returns during the US financial crisis. Therefore, there is no evidence of Chinese stock price prediction being possible through lagged values during the US financial crisis.

The return transmission effect from China to all Asian markets was insignificant during the US financial US crisis. However, most of the Asian markets did not transmit the return effect to the Chinese stock market other than India, Indonesia, and Malaysia. The coefficient of past own shock was found to be significant in the majority of Asian markets except for Indonesia, Korea, and Pakistan. The sensitivity to past own shocks from Chinese stock markets was found to be insignificant in the majority of markets during the US financial crisis. Moreover, the sensitivity of past own volatility in all Asian markets was significant. The past shocks of China did not influence the conditional volatility of the majority of Asian stock markets (except India) during the US financial crisis. The conditional volatility of the Chinese stock market was not affected by shocks in most of the Asian stock markets (except for Indonesia and Thailand).

There is no significant evidence of volatility spillover from Chinese to Asian stock markets except in India and Taiwan. Besides, the volatility spillover was insignificant in the majority of Asian markets (except Indonesia, Pakistan, and The Philippines) to the Chinese stock market. The asymmetric coefficient of all Asian markets is significant and positive. Moreover, the asymmetric coefficient of China is asymmetric, showing that that negative news of all Asian stock markets (except Pakistan) has more ability to increase the volatility of the Chinese stock market as compared to positive news. Constant conditional correlation is positively significant for all pairs of stock markets. However, CCC has a medium level in the majority of pairs.

4.2.5. Stock Market Linkages between the USA and Asia from the Chinese Stock Market Crash

Table 6 reports the mean and volatility spillover between the USA and Asian stock markets during the Chinese stock market crash. The autoregressive term of Asian market returns (Except Korea, the Philippines, and Taiwan) can be seen to be significant in the majority of stock markets. This shows the short-term predictability in stock price changes in the Asian stock markets. In addition, stock returns of the American stock market were significantly influenced by their lagged returns during the Chinese Crisis.

Table 5. Estimates of bivariate VAR−AGARCH for China and Asian stock markets during the US Financial Crisis.

	IND	CHN	INDO	CHN	KOR	CHN	MYS	CHN	PAK	CHN	PHL	CHN	TAIW	CHN	THA	CHN
Panel A: Mean Equation																
Constant	6.04×10^{-4} (0.2680	-2.82×10^{-4} (0.671)	6.72×10^{-4} (0.220)	-2.28×10^{-4} (0.712)	-7.49×10^{-5} (0.867)	-2.18×10^{-5} (0.974)	4.34×10^{-4} (0.146)	-5.07×10^{-5} (0.943)	$7.61 \times 10^{-4\,b}$ (0.017)	1.87×10^{-4} (0.684)	2.57×10^{-4} (0.615)	-8.84×10^{-5} (0.895)	2.65×10^{-4} (0.580)	3.46×10^{-5} (0.954)	$7.98 \times 10^{-4\,c}$ (0.091)	9.09×10^{-5} (0.876)
r^{o}_{t-1}	0.147 ^{a} (0.000)	0.109 ^{a} (0.002)	0.146 ^{a} (0.000)	0.136 ^{a} (0.001)	0.052 (0.211)	8.15×10^{-3} (0.861)	0.216 ^{a} (0.000)	0.196 ^{a} (0.008)	0.117 ^{a} (0.000)	−0.032 (0.451)	0.138 ^{a} (0.001)	5.75×10^{-4} (0.990)	0.102 ^{a} (0.007)	0.017 (0.689)	0.128 ^{a} (0.000)	0.045 (0.268)
r^{c}_{t-1}	−0.044 (0.135)	0.022 (0.576)	-9.00×10^{-3} (0.728)	0.019 (0.614)	0.011 (0.675)	0.067 ^{c} (0.086)	9.47×10^{-3} (0.534)	0.030 (0.432)	0.029 (0.259)	0.031 (0.432)	-7.18×10^{-3} (0.773)	0.043 (0.282)	0.015 (0.570)	0.052 (0.183)	−0.025 (0.233)	0.054 (0.147)
Panel B: Variance Equation																
Constant	$5.43 \times 10^{-6\,c}$ (0.064)	$1.43 \times 10^{-5\,a}$ (0.002)	$3.74 \times 10^{-5\,a}$ (0.001)	3.62×10^{-6} (0.389)	3.52×10^{-6} (0.101)	$1.61 \times 10^{-5\,a}$ (0.004)	$2.63 \times 10^{-6\,c}$ (0.087)	$1.48 \times 10^{-5\,a}$ (0.004)	-2.77×10^{-6} (0.365)	$3.62 \times 10^{-6\,c}$ (0.064)	$5.69 \times 10^{-5\,a}$ (0.000)	$1.70 \times 10^{-5\,b}$ (0.043)	1.84×10^{-6} (0.223)	$1.10 \times 10^{-5\,a}$ (0.050)	$1.50 \times 10^{-5\,a}$ (0.007)	8.77×10^{-6} (0.144)
$\left(e^{o}_{t-1}\right)^2$	0.067 ^{a} (0.001)	7.41×10^{-3} (0.446)	5.31×10^{-3} (0.821)	−0.025 ^{b} (0.013)	−0.016 (0.271)	2.75×10^{-3} (0.636)	0.112 ^{a} (0.000)	-6.75×10^{-4} (0.819)	−0.018 (0.269)	5.44×10^{-3} (0.489)	0.070 ^{a} (0.001)	1.27×10^{-3} (0.870)	0.022 (0.108)	7.35×10^{-3} (0.229)	0.055 ^{b} (0.019)	−0.011 ^{b} (0.044)
$\left(e^{c}_{t-1}\right)^2$	$-7.19 \times 10^{-3\,b}$ (0.017)	-2.74×10^{-3} (0.870)	-6.98×10^{-3} (0.748)	0.027 ^{c} (0.070)	0.015 (0.398)	9.48×10^{-3} (0.587)	0.100 (0.113)	0.020 (0.265)	-7.46×10^{-3} (0.613)	0.025 ^{b} (0.047)	1.48×10^{-3} (0.864)	0.017 (0.391)	−0.018 (0.184)	0.013 (0.388)	-6.48×10^{-3} (0.704)	0.012 (0.468)
h^{o}_{t-1}	0.893 ^{a} (0.000)	−0.016 (0.210)	0.623 ^{a} (0.000)	0.073 ^{c} (0.049)	0.919 ^{a} (0.000)	-7.47×10^{-4} (0.924)	0.789 ^{a} (0.000)	3.24×10^{-3} (0.615)	0.844 ^{a} (0.000)	0.064 ^{a} (0.015)	0.726 ^{a} (0.000)	−0.042 ^{b} (0.023)	0.936 ^{a} (0.000)	-5.07×10^{-3} (0.540)	0.834 ^{a} (0.000)	4.85×10^{-3} (0.637)
h^{c}_{t-1}	0.030 ^{a} (0.002)	0.865 ^{a} (0.000)	0.060 (0.157)	0.896 ^{a} (0.000)	1.15×10^{-3} (0.952)	0.879 ^{a} (0.000)	7.69×10^{-3} (0.916)	0.865 ^{a} (0.000)	2.14×10^{-3} (0.909)	0.952 ^{a} (0.000)	0.016 (0.504)	0.867 ^{a} (0.000)	0.041 ^{c} (0.099)	0.885 ^{a} (0.000)	0.044 (0.128)	0.876 ^{a} (0.000)
Asymmetry	0.091 ^{a} (0.003)	0.151 ^{a} (0.000)	0.361 ^{a} (0.000)	0.054 ^{b} (0.044)	0.152 ^{a} (0.000)	0.120 ^{a} (0.001)	0.149 ^{a} (0.006)	0.109 ^{a} (0.001)	0.167 ^{a} (0.000)	0.010 (0.451)	0.153 ^{a} (0.005)	0.126 ^{a} (0.000)	0.059 ^{a} (0.005)	0.116 ^{a} (0.000)	0.124 ^{a} (0.001)	0.130 ^{a} (0.000)
Panel C: Constant Conditional Correlation																
$p^{0,c}$	0.307 ^{a} (0.000)		0.290 ^{a} (0.000)		0.401 ^{a} (0.000)		0.287 ^{a} (0.000)		0.103 ^{a} (0.001)		0.270 ^{a} (0.000)		0.373 ^{a} (0.000)		0.269 ^{a} (0.000)	
Panel D: Diagnostic Tests																
LogL	3980.79		4085.73		4161.31		4570.93		4646.76		4104.40		4125.88		4144.48	
AIC	−9.451		−9.746		−9.840		−10.871		−11.412		−9.940		−9.990		−10.001	
SIC	−9.158		−9.453		−9.547		−10.578		−11.118		−9.650		−9.770		−9.707	

Table 5. *Cont.*

	IND	CHN	INDO	CHN	KOR	CHN	MYS	CHN	PAK	CHN	PHL	CHN	TAIW	CHN	THA	CHN
Panel D: Diagnostic Tests																
JB	501.810 [a] (0.000)	693.810 [a] (0.000)	541.320 [a] (0.000)	686.040 [a] (0.000)	374.450 [a] (0.000)	673.900 [a] (0.000)	541.990 [a] (0.000)	694.160 (0.000)	590.770 [a] (0.000)	756.610 [a] (0.000)	1903.28 [a] (0.000)	678.760 [a] (0.000)	356.750 [a] (0.000)	671.310 [a] (0.000)	358.350 [a] (0.000)	686.450 [a] (0.000)
Q (12)	14.715 (0.257)	7.454 (0.826)	11.152 (0.516)	7.664 (0.811)	12.457 (0.410)	8.501 (0.745)	11.203 (0.512)	6.933 (0.862)	18.800 [c] (0.093)	9.775 (0.636)	11.248 (0.508)	7.940 (0.790)	13.853 (0.310)	8.794 (0.720)	12.923 (0.375)	7.812 (0.800)
$Q^2(12)$	8.980 (0.705)	13.615 (0.326)	5.438 (0.942)	14.090 (0.295)	6.297 (0.900)	14.103 (0.294)	6.502 (0.889)	14.401 (0.276)	6.331 (0.899)	20.886 [b] (0.052)	27.233 [a] (0.007)	13.701 (0.320)	5.748 (0.928)	15.255 (0.228)	6.937 (0.862)	14.507 (0.270)

Notes: The number of lags for VAR was decided using SIC (Schwartz information criterion) and AIC (Akaike information criterion) criteria. JB, Q(12) and $Q^2(12)$ indicate the empirical statistics of the Jarque–Bera test for normality, while Ljung–Box Q statistics of order 12 for autocorrelation were applied to the standardized residuals and squared standardized residuals, respectively. USA, United States of America; IND, India; INDO, Indonesia; KOR, South Korea; MYS, Malaysia; PAK, Pakistan; PHL, the Philippines; TAIW, Taiwan; THA, Thailand. Values in parentheses are the *p*-values. [a], [b], [c] indicate the statistical significance at 1%, 5%, and 10%, respectively.

Table 6. Estimates of bivariate VAR−AGARCH for American and Asian stock markets during the Chinese Stock Market Crash.

	IND	USA	INDO	USA	KOR	USA	MYS	USA	PAK	USA	PHL	USA	TAIW	USA	THA	USA
Panel A: Mean Equation																
Constant	3.17×10^{-4} (0.227)	5.16×10^{-4} [b] (0.020)	-8.21×10^{-5} [a] (0.743)	4.52×10^{-4} [b] (0.047)	2.08×10^{-4} (0.395)	5.26×10^{-4} [b] (0.013)	-5.44×10^{-5} (0.721)	4.01×10^{-4} [b] (0.055)	3.33×10^{-4} (0.225)	4.55×10^{-4} [b] (0.030)	-3.09×10^{-4} (0.341)	4.77×10^{-4} [b] (0.029)	-3.28×10^{-6} (0.988)	5.05×10^{-4} [b] (0.011)	1.19×10^{-4} (0.557)	5.36×10^{-4} [a] (0.005)
r^o_{t-1}	0.077 [b] (0.032)	−0.044 (0.166)	0.107 [a] (0.001)	−0.028 (0.359)	−0.020 (0.560)	−0.018 (0.588)	0.089 [b] (0.013)	0.022 (0.685)	0.284 [a] (0.000)	−0.020 (0.367)	0.032 (0.342)	−0.032 (0.188)	0.031 (0.359)	0.076 (0.120)	0.147 [a] (0.000)	−0.024 (0.519)
r^u_{t-1}	0.233 [a] (0.000)	−0.082 [b] (0.024)	0.241 [a] (0.000)	−0.069 [c] (0.065)	0.351 [a] (0.000)	−0.079 [b] (0.016)	0.234 [a] (0.000)	−0.070 [c] (0.080)	0.088 [b] (0.016)	−0.077 [b] (0.044)	0.416 [a] (0.000)	−0.077 [b] (0.046)	0.405 [a] (0.000)	−0.081 [b] (0.030)	0.148 [a] (0.000)	−0.054 (0.173)
Panel B: Variance Equation																
Constant	3.75×10^{-6} [b] (0.020)	4.42×10^{-6} [a] (0.000)	2.05×10^{-6} [a] (0.005)	4.16×10^{-6} [a] (0.000)	1.11×10^{-5} [a] (0.001)	-1.41×10^{-6} (0.670)	3.61×10^{-7} [c] (0.092)	3.28×10^{-6} [a] (0.004)	4.09×10^{-6} [a] (0.000)	4.13×10^{-6} [a] (0.000)	4.62×10^{-6} [b] (0.025)	1.00×10^{-6} (0.714)	2.60×10^{-6} [a] (0.008)	3.85×10^{-6} [a] (0.000)	1.12×10^{-6} [a] (0.001)	7.03×10^{-7} (0.518)
$\left(e^o_{t-1}\right)^2$	−0.034 [b] (0.037)	0.079 [a] (0.000)	2.40×10^{-3} (0.911)	0.086 [a] (0.003)	0.149 [a] (0.001)	0.073 (0.270)	0.088 [a] (0.000)	0.018 (0.110)	−0.018 (0.402)	0.011 (0.425)	0.032 (0.277)	0.063 (0.130)	−0.020 (0.271)	0.071 (0.160)	−0.023 (0.146)	0.020 (0.311)
$\left(e^u_{t-1}\right)^2$	1.73×10^{-3} (0.915)	0.051 (0.102)	-6.47×10^{-4} (0.950)	0.065 [c] (0.064)	9.22×10^{-3} (0.738)	0.020 (0.534)	−0.077 [a] (0.000)	0.046 (0.216)	4.99×10^{-3} (0.296)	0.015 (0.640)	−0.014 (0.145)	0.037 (0.343)	0.030 (0.162)	0.068 [c] (0.059)	0.061 [b] (0.046)	0.014 (0.650)
h^o_{t-1}	0.896 [a] (0.000)	−0.066 [a] (0.000)	0.891 [a] (0.000)	−0.058 (0.202)	0.511 [a] (0.000)	0.049 (0.243)	0.865 [a] (0.000)	-7.32×10^{-3} (0.556)	0.856 [a] (0.000)	−0.020 (0.155)	0.870 [a] (0.000)	−0.051 [a] (0.004)	0.890 [a] (0.000)	−0.054 [a] (0.001)	0.913 [a] (0.000)	−0.017 (0.219)

Table 6. *Cont.*

	IND	USA	INDO	USA	KOR	USA	MYS	USA	PAK	USA	PHL	USA	TAIW	USA	THA	USA
Panel B: Variance Equation																
h_{t-1}^{u}	−0.012 (0.644)	0.754 ^{a} (0.000)	0.021 (0.306)	0.696 ^{a} (0.000)	0.204 (0.149)	0.672 ^{a} (0.000)	0.303 ^{a} (0.002)	0.642 ^{a} (0.000)	−0.012 ^{a} (0.002)	0.797 ^{a} (0.000)	0.070 (0.166)	0.711 (0.290)	−0.018 (0.515)	0.726 ^{a} (0.000)	0.157 ^{c} (0.072)	0.645 ^{a} (0.000)
Asymmetry	0.126 ^{a} (0.002)	0.270 ^{a} (0.000)	0.123 ^{a} (0.001)	0.314 ^{a} (0.000)	−0.079 (0.183)	0.346 ^{a} (0.000)	0.040 (0.231)	0.317 ^{a} (0.000)	0.253 ^{a} (0.000)	0.258 ^{a} (0.000)	0.081 ^{b} (0.035)	0.338 ^{a} (0.000)	0.131 ^{a} (0.001)	0.296 ^{a} (0.000)	0.164 ^{a} (0.000)	0.343 ^{a} (0.000)
Panel C: Constant Conditional Correlation																
$p^{0,u}$	0.324 ^{a} (0.000)		0.123 ^{a} (0.000)		0.281 ^{a} (0.000)		0.146 ^{a} (0.000)		0.059 ^{a} (0.078)		0.103 ^{a} (0.001)		0.214 ^{a} (0.000)		0.224 ^{a} (0.000)	
Panel D: Diagnostic Tests																
LogL	5580.558		5500.464		5640.723		5895.388		5471.88		5390.25		5605.08		5699.52	
AIC	−13.712		−13.614		−14.028		−14.525		−13.330		−13.434		−13.877		−13.881	
SIC	−13.418		−13.321		−13.734		−14.232		−13.037		−13.140		−13.583		−13.587	
JB	72.640 ^{a} (0.000)	204.890 ^{a} (0.000)	58.520 ^{a} (0.000)	412.790 ^{a} (0.000)	134.540 ^{a} (0.000)	168.440 ^{a} (0.000)	22.680 ^{a} (0.000)	442.380 ^{a} (0.000)	30.880 ^{a} (0.000)	428.120 ^{a} (0.000)	27.070 ^{a} (0.000)	422.700 ^{a} (0.000)	84.480 ^{a} (0.000)	230.350 ^{a} (0.000)	68.060 ^{a} (0.000)	154.390 ^{a} (0.000)
Q (12)	16.833 (0.156)	8.760 (0.723)	12.383 (0.415)	9.384 (0.670)	4.583 (0.970)	10.350 (0.585)	7.511 (0.822)	9.705 (0.642)	11.341 (0.500)	10.270 (0.592)	9.383 (0.670)	12.352 (0.418)	20.039 ^{c} (0.066)	13.680 (0.322)	6.178 (0.907)	7.190 (0.845)
$Q^2(12)$	7.383 (0.831)	3.713 (0.988)	18.894 ^{c} (0.091)	8.117 (0.776)	8.144 (0.774)	5.426 (0.942)	8.099 (0.777)	5.282 (0.948)	7.532 (0.821)	5.161 (0.952)	12.838 (0.381)	7.290 (0.838)	7.271 (0.839)	8.802 (0.720)	24.298 ^{b} (0.019)	5.675 (0.932)

Notes: The number of lags for VAR was decided using SIC (Schwartz information criterion) and AIC (Akaike information criterion) criteria. JB, Q(12) and $Q^2(12)$ indicate the empirical statistics of the Jarque–Bera test for normality, while Ljung–Box Q statistics of order 12 for autocorrelation were applied to the standardized residuals and squared standardized residuals, respectively. USA, United States of America; IND, India; INDO, Indonesia; KOR, South Korea; MYS, Malaysia; PAK, Pakistan; PHL, the Philippines; TAIW, Taiwan; THA, Thailand. Values in parentheses are the *p*-values. ^{a}, ^{b}, ^{c} indicate the statistical significance at 1%, 5%, and 10%, respectively.

The return spillover from the USA to all Asian Stock markets was significant during the Chinese crisis. This implies that US stock market prices played an important role in predicting the prices of all Asian stock markets during the Chinese stock market crash. Moreover, the return spillover from Asia to the US stock market was insignificant. The coefficient of past shock was insignificant in the majority of Asian markets except for in India, Korea, and Malaysia. The sensitivity of past own shocks of the USA was insignificant in most of the cases. In addition, the coefficient of past own volatility significantly affected the conditional volatility of all Asian markets.

The conditional volatility of the majority of Asian stock markets (except Malaysia and Thailand) was not significantly affected by the shocks in the US stock market. In addition, past shocks in most of the Asian stock markets (Except in India and Indonesia) did not influence the conditional volatility of the US stock market. The volatility transmission from the USA to most of the Asian stock markets (except Malaysia, Pakistan, and Thailand) was found to be insignificant during the Chinese Crisis. On the other hand, volatility spillover from most of the Asian stock markets to the USA stock market was evidently insignificant.

The asymmetric coefficients of all Asian stock markets (except Korea and Malaysia) were significant and positive, showing that negative news from the US stock market has a greater ability to increase the volatility of all Asian Stock markets as compared to positive news. However, the asymmetric coefficient of the US stock market is significant and positive. Constant conditional correlation was positively significant for all pairs of stock markets. However, CCC was weak in the majority of pairs.

4.2.6. Stock Market Linkages between China and Asia from the Chinese Stock Market Crash

Table 7 reports the return and volatility spillover between Chinese and Asian stock markets during the Chinese stock market crash. There is significant evidence that lagged returns influence the current stock returns of Asian Stock markets (Except in Korea, the Philippines, and Taiwan). This shows the short-term predictability in stock price changes in the Asian stock markets. Moreover, Chinese stock market returns were not affected by their lags during the Chinese stock market crash.

The return spillover was found to be insignificant from China to all Asian markets. However, the return spillover was found to be insignificant from the majority of Asian markets to the Chinese market, except for India and Taiwan, during the Chinese stock market crash. The coefficient of past own shock did not significantly influence the conditional variance of the most of the Asian stock markets except in India, Malaysia, and Thailand. Moreover, the sensitivity to past own shock of the Chinese stock market was insignificant during the Chinese crash. However, the sensitivity of past own volatility was found to be significant for all Asian stock markets.

The conditional volatility of India, Indonesia, Taiwan, and Thailand was significantly affected by the shocks in the Chinese stock market. However, the shocks in the majority of Asian stock markets (except India and the Philippines) did not influence the Chinese stock market. The past volatility of China significantly impacted the conditional volatility of the stock markets of India, Indonesia, Taiwan, and Thailand. However, volatility spillover was not found from most of the Asian stock markets (except India, Taiwan, and Thailand) to the Chinese stock market during the Chinese stock market crash.

The asymmetric coefficients of all Asian stock markets (except Malaysia and the Philippines) were significant and positive, showing that negative news of the US stock market has a greater ability to increase the volatility of Asian stock markets as compared to positive news. Asymmetric coefficients of China were significant and positive in all pairs, demonstrating that negative news for any Asian markets except for India had a greater ability to increase the volatility of Chinese stock markets as compared to positive news during the Chinese crash. Constant conditional correlation was positively significant for all pairs of stock markets, but CCC was weak in the majority of pairs.

Table 7. Estimates of bivariate VAR−AGARCH for Chinese and Asian stock markets during the Chinese Stock Market Crash.

	IND	CHN	INDO	CHN	KOR	CHN	MYS	CHN	PAK	CHN	PHL	CHN	TAIW	CHN	THA	CHN
Panel A: Mean Equation																
Constant	3.32×10^{-4} (0.168)	5.74×10^{-5} (0.835)	1.10×10^{-5} (0.964)	1.39×10^{-4} (0.615)	3.28×10^{-4} (0.147)	8.49×10^{-5} (0.715)	-1.35×10^{-5} (0.933)	9.62×10^{-5} (0.715)	4.13×10^{-4} (0.145)	1.16×10^{-4} (0.663)	5.57×10^{-5} (0.875)	1.07×10^{-4} (0.699)	2.52×10^{-4} (0.310)	9.50×10^{-5} (0.714)	1.73×10^{-4} (0.359)	1.56×10^{-4} (0.561)
r^{o}_{t-1}	0.167 [a] (0.000)	0.106 [b] (0.022)	0.144 [a] (0.000)	−0.034 (0.500)	0.084 (0.350)	−0.014 (0.715)	0.125 [a] (0.000)	0.062 (0.322)	0.288 [a] (0.000)	−0.012 (0.660)	0.056 (0.141)	-1.15×10^{-4} (0.997)	0.086 (0.280)	0.106 [b] (0.014)	0.155 [a] (0.000)	0.021 [c] (0.620)
r^{c}_{t-1}	−0.029 (0.185)	0.037 (0.356)	−0.012 (0.550)	0.069 (0.330)	−0.019 (0.361)	0.062 [c] (0.077)	0.021 (0.222)	0.053 (0.181)	0.014 (0.452)	0.062 (0.120)	0.033 (0.274)	0.062 (0.113)	5.37×10^{-3} (0.836)	0.021 (0.580)	-8.57×10^{-4} (0.965)	0.070 [b] (0.052)
Panel B: Variance Equation																
Constant	3.77×10^{-6} [a] (0.000)	1.79×10^{-6} [b] (0.012)	4.23×10^{-6} [c] (0.010)	-4.44×10^{-8} (0.930)	3.43×10^{-6} (0.139)	9.89×10^{-7} (0.425)	1.42×10^{-6} (0.126)	-2.42×10^{-7} (0.768)	4.07×10^{-6} [a] (0.000)	8.60×10^{-7} [a] (0.005)	6.97×10^{-6} [b] (0.032)	1.31×10^{-6} (0.259)	9.22×10^{-6} [a] (0.000)	3.22×10^{-6} [b] (0.017)	2.64×10^{-6} [a] (0.001)	-8.98×10^{-7} [b] (0.031)
$\left(e^{o}_{t-1}\right)^2$	−0.063 [a] (0.000)	-5.50×10^{-3} [a] (0.002)	0.052 (0.119)	5.85×10^{-4} (0.901)	0.024 (0.413)	5.44×10^{-3} (0.107)	0.102 [a] (0.003)	-8.63×10^{-4} (0.677)	−0.013 (0.560)	-2.66×10^{-5} (0.986)	0.058 (0.144)	0.018 [b] (0.022)	−0.028 (0.209)	5.81×10^{-3} (0.347)	−0.039 [b] (0.021)	-2.55×10^{-3} (0.364)
$\left(e^{c}_{t-1}\right)^2$	0.070 [a] (0.000)	0.035 [b] (0.031)	−0.018 [a] (0.007)	0.012 (0.567)	8.96×10^{-3} (0.618)	0.023 (0.290)	−0.013 (0.780)	9.71×10^{-3} (0.611)	5.15×10^{-3} (0.180)	8.77×10^{-3} (0.656)	0.021 (0.137)	0.020 (0.342)	0.062 [a] (0.008)	0.027 (0.176)	−0.033 [a] (0.000)	0.017 (0.355)
h^{o}_{t-1}	0.880 [a] (0.000)	0.016 [a] (0.000)	0.789 [a] (0.000)	8.85×10^{-3} (0.176)	0.879 [a] (0.000)	-2.40×10^{-3} (0.665)	0.768 [a] (0.000)	9.26×10^{-3} (0.283)	0.841 [a] (0.000)	-1.18×10^{-3} (0.517)	0.824 [a] (0.000)	-9.03×10^{-3} (0.137)	0.659 [a] (0.000)	0.021 [b] (0.038)	0.818 [a] (0.000)	0.015 [b] (0.028)
h^{c}_{t-1}	−0.096 [a] (0.000)	0.945 [a] (0.000)	0.039 [b] (0.025)	0.940 [a] (0.000)	−0.014 (0.742)	0.944 [a] (0.000)	0.100 (0.343)	0.934 [a] (0.000)	-6.00×10^{-3} (0.109)	0.949 [a] (0.000)	−0.026 (0.341)	0.943 [a] (0.000)	−0.118 [b] (0.017)	0.944 [a] (0.000)	0.112 [a] (0.000)	0.933 [a] (0.000)
Asymmetry	0.171 [a] (0.000)	0.029 (0.145)	0.163 [a] (0.000)	0.059 [b] (0.021)	0.044 [c] (0.077)	0.045 [c] (0.058)	0.087 (0.112)	0.065 [b] (0.015)	0.263 [a] (0.000)	0.058 [c] (0.010)	0.061 (0.210)	0.048 [b] (0.045)	0.276 [a] (0.000)	0.047 [b] (0.040)	0.229 [a] (0.000)	0.049 [b] (0.029)
Panel C: Constant Conditional Correlation																
$p^{0,c}$	0.204 [a] (0.000)		0.151 [a] (0.000)		0.282 [a] (0.000)		0.166 [a] (0.000)		0.109 [a] (0.003)		0.179 [a] (0.000)		0.319 [a] (0.000)		0.202 [a] (0.000)	
Panel D: Diagnostic Tests																
LogL	5216.702		5157.83		5258.48		5520.00		5143.34		5026.77		5246.59		5354.32	
AIC	−12.108		−12.093		−12.437		−12.929		−11.856		−11.866		−12.268		−12.364	
SIC	−11.814		−11.799		−12.143		−12.635		−11.562		−11.573		−11.975		−12.070	

Table 7. *Cont.*

	IND	CHN	INDO	CHN	KOR	CHN	MYS	CHN	PAK	CHN	PHL	CHN	TAIW	CHN	THA	CHN
JB	245.340 [a] (0.000)	365.250 [a] (0.000)	212.590 [a] (0.000)	369.930 [a] (0.000)	325.490 [a] (0.000)	305.710 [a] (0.000)	214.270 [a] (0.000)	342.420 [a] (0.000)	156.230 [a] (0.000)	422.300 [a] (0.000)	216.090 [a] (0.000)	338.660 [a] (0.000)	301.330 [a] (0.000)	269.370 [a] (0.000)	227.030 [a] (0.000)	329.200 [a] (0.000)
Q (12)	31.405 [a] (0.002)	16.802 (0.157)	10.948 (0.533)	15.522 (0.214)	27.305 [a] (0.007)	16.590 (0.166)	15.069 (0.238)	16.940 (0.152)	46.439 [a] (0.000)	20.284 [c] (0.062)	26.154 [c] (0.010)	15.115 (0.235)	13.912 (0.306)	11.123 (0.518)	24.373 [b] (0.018)	15.957 (0.193)
Q^2(12)	55.871 [a] (0.000)	17.976 (0.116)	47.212 [a] (0.000)	21.484 [b] (0.044)	48.551 [a] (0.000)	17.416 (0.135)	70.480 [a] (0.000)	21.463 [b] (0.044)	70.632 [a] (0.000)	30.028 [a] (0.003)	50.180 [a] (0.000)	23.783 [b] (0.022)	44.260 [a] (0.000)	16.310 (0.177)	88.957 [a] (0.000)	31.358 [a] (0.002)

Notes: The number of lags for VAR was decided using SIC (Schwartz information criterion) and AIC (Akaike information criterion) criteria. JB, Q(12) and Q^2(12) indicate the empirical statistics of the Jarque–Bera test for normality, while Ljung–Box Q statistics of order 12 for autocorrelation were applied to the standardized residuals and squared standardized residuals, respectively. USA, United States of America; IND, India; INDO, Indonesia; KOR, South Korea; MYS, Malaysia; PAK, Pakistan; PHL, the Philippines; TAIW, Taiwan; THA, Thailand. Values in parentheses are the *p*-values. [a], [b], [c] indicate the statistical significance at 1%, 5%, and 10%, respectively.

4.3. Optimal Weights and Hedge Ratio Portfolio Implications

Table 8 indicates the optimal weights and hedge ratios for the pairs of Asia-US stock portfolios during the full sample period, US financial crisis, and the Chinese stock market crash.[7] The range of optimal weights is 0.37 for IND/USA to 0.68 for MYS/USA during the period of the full sample, indicating that for a $1 India-USA portfolio, 37 cents should be invested in Indian stocks and the remaining 63 cents in the US stock market. The average optimal portfolio weights vary from 0.38 for IND/USA to 0.80 for MYS/USA during the US financial crisis and range from 0.37 for PHL/USA to 0.69 for MYS/USA during the Chinese stock market crash. Overall, the optimal weights of US stock in Asia-USA portfolios are higher during the Chinese stock market crash compared to the US financial crisis. This implies that investors should have maintained more US stocks in their portfolio of Asia-USA during the Chinese stock market crash compared to the Asian stocks during the US financial crisis.

Table 9 presents the optimal weights and hedge ratios for the pairs of Asia-China stock portfolio during the full sample period, US financial crisis, and the Chinese stock market crash.[8] The range of optimal weights is from 0.56 for IND/CHN, KOR/CHN, PHL/CHN to 0.81 for MYS/CHN during the full sample period. The average optimal portfolio weights vary from 0.53 for IND/CHN to 0.90 for MYS/CHN during the US financial crisis and range from 0.52 for PHL/CHN to 0.82 for MYS/CHN during the Chinese stock market crash. Overall, for the majority of Asia-China portfolios, the optimal weights of Chinese stocks were almost equal or higher during the Chinese stock market crash and the US financial crisis. This suggests that portfolio managers and investors should have maintained almost the same investment in Chinese stock in their majority of the portfolio of Asia-China during both the Chinese crash and the US financial crisis.

Table 8 presents the optimal hedge ratios for the pairs of Asia-USA stock portfolio during the full sample period, US financial crisis, and the Chinese stock market crash. Regarding the hedge ratio, the range of average hedge ratio is 0.04 for PAK/USA to 0.27 for IND/USA during the period of the full sample, showing that a long position of $1 in Pakistani stocks can be hedged for a short position of 4 cents in US stocks. During the US financial crisis, the average optimal hedge ratios varied from 0.08 for PAK/USA to 0.36 for IND/USA. The average optimal hedge ratio ranged from 0.09 for PAK/USA to 0.36 for IND/USA during the Chinese stock market crash. For the majority of pairs of Asia-USA, the hedge ratios were lower in the US financial crisis compared with the Chinese stock market crash. This suggests that few US stocks were required to minimize the risk of Asian stock investors during the US financial crisis as compared to during the Chinese crash.

Table 9 provides the optimal hedge ratios for the pairs of a Asia-China stock portfolio during the full sample period, US financial crisis, and the Chinese stock market crash. The range of average hedge ratio is 0.04 for PAK/CHN to 0.21 for KOR/CHN during the period of the full sample. During the US financial crisis, the average optimal hedge ratios varied from 0.03 for PAK/CHN to 0.32 for KOR/CHN. The average optimal hedge ratio ranged from 0.09 for MYS/CHN to 0.26 for TAIW/CHN during the Chinese stock market crash. Overall, for the Asia-China pairs, the hedge ratio was lower during the Chinese stock market crash compared to the hedge ratios in the US financial crisis. This implies that fewer Chinese stocks were needed to minimize the risk for Asian stock investors during the Chinese stock market crash as compared to during the US crisis.

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7 We calculated the optimal weights by using both VAR-GARCH and VAR-AGARCH models, but we reported the optimal weights only from the VAR-AGARCH model for the purpose of brevity.

8 We calculated the optimal weights by using both VAR-GARCH and VAR-AGARCH models, but we reported the optimal weights only from the VAR-AGARCH model for the purpose of brevity.

Table 8. Optimal Weights and Hedge Ratios for Asia/USA pairs.

	IND/USA	INDO/USA	KOR/USA	MYS/USA	PAK/USA	PHL/USA	TAIW/USA	THA/USA
				Full Sample Period				
w_t^{SU}	0.37	0.41	0.40	0.68	0.41	0.42	0.43	0.41
β_t^{SU}	0.27	0.13	0.24	0.06	0.04	0.06	0.17	0.17
				US Financial Crisis				
w_t^{SU}	0.38	0.51	0.54	0.80	0.52	0.57	0.52	0.52
β_t^{SU}	0.36	0.18	0.21	0.11	0.08	0.09	0.15	0.22
				Chinese Stock Market Crash				
w_t^{SU}	0.46	0.44	0.51	0.69	0.44	0.37	0.49	0.53
β_t^{SO}	0.36	0.15	0.29	0.11	0.09	0.14	0.22	0.22

Note: w_t^{SU} and β_t^{SU} refer to the optimal weights and hedge ratios, respectively.

Table 9. Optimal Weights and Hedge Ratios for Asia/China pairs.

	IND/CHN	INDO/CHN	KOR/CHN	MYS/CHN	PAK/CHN	PHL/CHN	TAIW/CHN	THA/CHN
				Full Sample Period				
w_t^{SC}	0.56	0.57	0.56	0.81	0.57	0.56	0.59	0.59
β_t^{SC}	0.15	0.15	0.21	0.09	0.04	0.12	0.20	0.13
				US Financial Crisis				
w_t^{SC}	0.53	0.63	0.68	0.90	0.64	0.64	0.66	0.67
β_t^{SC}	0.31	0.24	0.32	0.13	0.03	0.22	0.30	0.19
				Chinese Stock Market Crash				
w_t^{SC}	0.65	0.61	0.66	0.82	0.58	0.52	0.66	0.73
β_t^{SC}	0.17	0.13	0.23	0.09	0.11	0.18	0.26	0.14

Note: w_t^{SC} and β_t^{SC} refer to the optimal weights and hedge ratios, respectively.

5. Conclusions

In this paper, we extend the previous work by examining the return and volatility transmissions from the US and China to the eight emerging Asian stock markets including India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Taiwan, and Thailand during the Chinese stock market crash by using the VAR-AGARCH model. Moreover, we also examine the spillovers during the full sample period and the 2008 US financial crisis to provide comparative insights to investors about whether the impact of the Chinese crash on equity market spillovers is different from the crashes in other sample periods. Lastly, we also estimate the optimal weights and hedge ratios during the full period and all sub-periods.

Our comprehensive analysis reveals that both return and volatility spillover vary across different pairs of stock markets and during financial crises. The findings of return spillover indicate a significant spillover from the USA to Asian stock markets during the full sample period, the US financial crisis, and the Chinese stock market crash. This implies that US stock market prices play an important role in predicting the prices of the majority of Asian stock markets during the full period and all the sub-periods. However, the return spillover is not significant from China to emerging Asian stock markets during the US financial crisis and the Chinese stock market crash, implying that Chinese stock prices cannot be used for predicting the prices of the majority of Asian stock markets during any of the crisis periods in our study.

Our volatility spillover analysis reveals that the volatility was transmitted from the US to the majority of Asian markets during the full sample period and the Chinese stock market crash, but such a conclusion cannot be drawn for during the US financial crisis. This implies that portfolio investors of Asian stock markets could have gotten the maximum benefits of diversification by holding US stocks in their portfolio during the US financial crisis. However, the volatility spillover was transmitted from China to a majority of Asian markets during the full sample period and US financial crisis, but such a conclusion cannot be reached for during the Chinese crash, implying that portfolio investors of Asian stock markets could have gotten the maximum benefits of diversification by holding Chinese stocks in their portfolio during the Chinese stock market crash.

Based on optimal weights results, the weights of the US stocks in the Asia-USA portfolios are higher during the Chinese crash compared to the US financial crisis, implying that investors should keep more US stocks in their portfolio of the Asia-USA stocks during the Chinese stock market crash, compared to the US financial crisis. For the majority of Asia-China portfolios, the optimal weights of Chinese stocks were almost equal or higher during the Chinese stock market crash and the US financial crisis. This suggests that portfolio managers and investors should have maintained almost the same investment in the Chinese stocks in their portfolio of the Asia-China majority pairs during both the Chinese crash and the US financial crisis.

Regarding the hedge ratios, for most of the Asia-USA pairs, the hedge ratios were smaller in the US financial crisis than in the Chinese stock market crash. This suggests that few US stocks were required to minimize the risk for Asian stock investors during the US financial crisis as compared to during the Chinese crash. In contrast, for the Asia-China pairs, the hedge ratio was smaller during the Chinese stock market crash compared to that in the US financial crisis. This implies that fewer Chinese stocks were needed to minimize the risk for Asian stock investors during the Chinese stock market crash as compared to the US crisis. Overall, our findings provide several important implications for risk management and portfolio diversification that could be useful for investors and for policymakers related to the US and Asian stock markets.

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