Is China a source of financial contagion?

Abstract

The study examines the role China plays compared with the US in transmitting contagion to South Asian countries during crisis and noncrisis periods. Dynamic conditional correlation (DCC) increases during the contractionary periods of US and Chinese business cycles. Trade intensity positively influences DCC. Results from DCC models are reinforced by those from the Diebold–Yilmaz model that US and Chinese financial firms transmitted more spillovers than they received during the global financial crisis. Results are robust to the alternative specification of business cycles, USD or local currency returns, the application of the Markov regime-switching model, and the Diebold–Yilmaz model.

Keywords: Financial contagion, spillover index, dynamic conditional correlation, business cycle, trade intensity

JEL classification: G15, G20, G21, G22, G23

I. Introduction

The global financial crisis (GFC) in 2007–2009 and the European debt crisis in 2010–2012 rekindled the debate over financial spill-over risk from developed to emerging and frontier financial markets. Most studies have focused on the financial contagion among developed markets (Alexakis and Pappas 2018; Jung and Maderitsch 2014; Rotta and Valls Pereira 2016) and there is a limited literature on the spread of financial contagion from developed or emerging markets to emerging and frontier markets (Paramati, Roca and Gupta 2016; Paramati et al. 2017; Rotta and Valls Pereira 2016).[1] These studies adopt the US market as a source of contagion, as the US is the largest economy. Although China is the second largest economy and highest exporting country (International Monetary Fund 2018a), there is a paucity of research on how the Chinese market channels financial contagion to emerging and frontier markets. Our study fills this void by investigating whether China plays a similar role as the US does in transmitting financial contagion to emerging and frontier markets, particularly South Asian markets (India, Bangladesh, Pakistan, and Sri Lanka).

Following Bekaert, Harvey, and Ng (2005), financial contagion is defined in our study as the correlation between markets beyond economic fundamentals.[2] In their seminal work, King and Wadhwani (1990) show that the correlations increased significantly between the US and another two developed markets (the UK and Japan) following the US market crash in 1987. Forbes and Rigobon (2002) observe no contagion, but interdependence in 1994 Mexican and 1997 Asian crises among developed and emerging markets. However, Corsetti, Pericoli, and Sbracia (2005) find contagion, refuting the argument of no contagion by Forbes and Rigobon (2002) on the ground that the latter imposes a restriction on the variance of errors from a crisis originating country to adjust for heteroskedasticity.

[1] The FTSE equity country classification has three main categories: developed, emerging, and frontier countries.
[2] See the various definitions of contagion in Pericoli and Sbracia (2003) and Cheung, Tam, and Szeto (2009).

Our study offers several contributions to emerging literature. First, this study is a novel attempt to investigate the spillover effects on South Asian countries from China and the US. South Asia has undergone financial reforms in recent times, and the financial liberalisation in the region has opened it up to increased capital flows as well as spillover effects from external shocks (Narayan, Smyth and Nandha 2004). South Asian countries are alike in an economic and geographical sense, and they share a strong common historical tradition. Further, the equity market characteristics of South Asian countries appear to be similar in contrast to those of developed markets (Gunasekarage and Power 2001; Narayan et al. 2004). Given these close ties and the similar equity market characteristics of South Asian countries, it is interesting to examine whether the spillover effects from the US and China to South Asian countries have similar patterns.

Second, most prior studies primarily examine the correlations and volatilities between market indices. However, financial firms play important roles in facilitating the transmission of domestic monetary policy. Financial firms mediate between savers and borrowers both within and beyond national boundaries, thereby exposing them to financial shocks from international markets. Hence, financial firms act as one of the main channels to transmit shocks across markets (De Haas and Van Horen 2012; Schnabl 2012). This study investigates whether financial firms in India, Bangladesh, Pakistan, and Sri Lanka are exposed to financial stock return shocks from the US and China.

Third, capital mobility across borders may play a role in transmitting financial shocks (Cetorelli and Goldberg 2011). In particular, Bangladesh and India typically have negative net equity flows during periods of market downturns (The World Bank Group 2019). For example, following the stock market crash in 1996 (see Hoque 2007), Bangladesh had negative net equity flows until 1999. Hence, capital mobility into and out of South Asian countries may play a role in transmitting risk by increasing cross-correlations or volatilities among financial prices across the border.

Using monthly stock return data from January 1995 to March 2018, we find time-varying correlations and spillovers among the financial firms in our sample. Our main results are summarised as follows. First, the dynamic conditional correlations (DCCs) between South Asian and US/Chinese financial stock returns appear to be low. However, during the GFC, correlations appear to be high. Second, DCCs decrease (increase) during expansionary (contractionary) periods of US and Chinese business cycles. Third, the trade intensity of India with the US is positively related to the corresponding conditional correlation, as India is its eighth highest trading partner (The US Census Bureau 2018). Fourth, Diebold and Yilmaz's (2012) spillover index model shows that US and Chinese financial firms transmitted more spillovers than they received during the GFC, indicating a source of financial contagion during crisis periods. Finally, our findings are robust irrespective of using USD or local currency returns or adopting the alternative Diebold and Yilmaz (2012) specification. Moreover, the Markov regime-switching model shows that high DCC regimes coincide with the periods of economic downturns. These results demonstrate that China is as influential as the US in transmitting financial contagion to South Asian countries. This highlights a notable contribution of our study that the role of China is equally important in transmitting financial contagion.

The paper is organised as follows. Following the introduction, Section 2 provides the model specification. Section 3 provides the data, and descriptive statistics and Section 4 provides the results. Section 5 does robustness checks, and Section 6 provides the conclusion.

II. Model specification

To investigate the financial contagion between US/Chinese and South Asian financial firms, we employ the asymmetric DCC (ADCC) model of Cappiello, Engle, and Sheppard (2006) and Diebold and Yilmaz's (2012) spillover index.

DCC Model

Building on the DCC-GARCH model of Engle (2002), extant studies (Alexakis and Pappas 2018; Kocaarslan et al. 2017) apply the ADCC model of Cappiello et al. (2006) to examine financial contagion. Cappiello et al. (2006) demonstrate that equity returns in Europe, Australasia, and North America demonstrate asymmetries in conditional volatility. Our study provides the results of the DCC-GARCH and ADCC-GARCH models to see the robustness of those results.

Let r_t be an $n \times 1$ vector of assets returns with mean zero and covariance matrix H_t:

$$r_t|\Omega_{t-1} \sim \mathrm{N}\ (0, \mathrm{H_t}) \tag{1}$$

where $\Omega_{i,t-1}$ is the information set at $t-1$.

Following Engle's (2002) two-stage procedure, we have selected the univariate model based on information criteria in the first stage and estimated DCC parameters in the second.[3] We have selected the best univariate model from the following:[4]

- GARCH (Bollerslev 1986)
- GJR-GARCH (Glosten, Jagannathan and Runkle 1993)
- EGARCH (Nelson 1991)
- IGARCH (Engle and Bollerslev 1986)
- APARCH (Ding, Granger and Engle 1993)

The DCC parameters are estimated in the second stage:

$$H_t \equiv D_t R_t D_t \tag{2}$$

where $D_t = diag\left(h_{11,t}^{1/2} \dots \dots \dots\ h_{nn,t}^{1/2}\right)$, R_t is the correlation matrix.

$u_{i,t} = \varepsilon_{i,t}\,/\sqrt{h_{ii,t}}$ is the standardised residuals.

$$R_t \equiv Q_t^{*-1} Q_t\ Q_t^{*-1} \tag{3}$$

Eq. (3) is the correlation matrix with $Q_t = \left(q_{ij,t}\right)$ and $Q_t^* = (q_{ii,t}^*) = \sqrt{q_{ii,t}}$ as a diagonal matrix.

$$Q_t = (1 - a - b)\bar{Q} + a(\mathrm{u}_{t-1}\mathrm{u}_{t-1}') + bQ_{t-1} \tag{4}$$

where $\overline{Q}$ is the unconditional variance matrix of $u_{i,t}$; a and b are nonnegative scalars with $(a + b) < 1$.

$$\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}} \quad i, j = 1,2, \dots n,\ and\ i \neq j \tag{5}$$

[3] Following Cappiello et al. (2006), we select the BIC as an appropriate information criterion, although many information criteria are available.

[4] The detailed specifications of univariate GARCH models are not provided to conserve the space.

In Eq. (5), $\rho_{ij,t}$ represents DCCs between South Asian and US/Chinese financial stock returns. Cappiello et al.'s (2006) ADCC model is built on Engle's (2002) DCC model and Glosten et al.'s (1993) asymmetric GARCH model as:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma I[\varepsilon_{t-1} < 0]\varepsilon_{t-1}^2 \tag{6}$$

In Eq. (6), the indicator function $I[\varepsilon_{t-1} < 0]$ is equal to 1 if ε_{t-1}<0 and 0 otherwise. The DCC model of Engle (2002) in Eqs. (3) and (4) has not taken asset-specific news and asymmetries into the model. Cappiello et al. (2006) describe the correlation matrix in Eq. (3) to be

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G) + A'u_{t-1}u_{t-1}'A + G'n_{t-1}n_{t-1}'G + B'Q_{t-1}B \tag{7}$$

where A, B, and G are $k \times k$ parameter matrices, $n_t = I[u_t < 0]$o u_t ($I[u_t < 0]$ is a $k \times 1$ indicator function taking the value of 1 if $u_t < 0$ and 0 otherwise, 'o' is the Hadamard product, and $\bar{N} = E[n_t n_t']$).

Eq. (7) is an asymmetric generalised DCC (AG-DCC) model (For details, see Cappiello et al. 2006). The ADCC model is a special case of the AG-DCC model if A, B, and G matrices are replaced by scalars. Cappiello et al. (2006) suggest the scalar ADCC as

$$Q_t = (\bar{Q} - a^2\bar{Q} - b^2\bar{Q} - g^2\bar{N}) + a^2u_{t-1}u_{t-1}' + g^2n_{t-1}n_{t-1}' + b^2Q_{t-1} \tag{8}$$

Finally, we have modelled the DCCs in terms of US and Chinese business cycles, trade intensity, and financial crisis dummies for the Asian financial crisis, the European debt crisis, and GFC. We investigate the influence of US and Chinese economic activities on the correlations among financial firms. We have used the Economic Cycle Research Institute (ECRI) US monthly leading index and the OECD composite leading indicators for China to identify the contractionary and expansionary periods of business cycles. The Hodrick–Prescott filter (Hodrick and Prescott 1997) is used to find the cyclical component from the Economic Cycle Research Institute leading index. Positive (negative) values indicate periods of economic expansion (economic downturns).

To examine how the bilateral trade between the US/China and South Asian countries influences the correlations, we have used Frankel and Rose's (1998) model as:

$$T_{ij,t} = \left(X_{ij,t} + M_{ij,t}\right)/\left(X_{i,t} + X_{j,t} + M_{i,t} + M_{j,t}\right) \quad (9)$$

where $T_{ij,t}$ is the trade intensity measure between the US/China and South Asian countries at time t; $X_{ij,t}$ ($M_{ij,t}$) is the exports (imports) between the US/China and South Asian countries ; $X_{i,t}$ and $M_{i,t}$ are the global exports and imports of South Asian country i, respectively; and $X_{j,t}$ and $M_{j,t}$ are the global exports and imports of the US and China, respectively.

The following model is estimated to examine the effects of economic variables on DCCs:

$$\rho_{\mathrm{ij},t} = \beta_0 + \beta_1\rho_{\mathrm{ij},t-1} + \beta_2 D_1 + \beta_3 D_2 + \beta_4 D_3 + \beta_5 C_{\mathrm{j,t}} + \beta_6 T_{\mathrm{j,t}} + e_{ij,t} \quad (10)$$

where $\rho_{ij,t}$ represents the correlations between South Asian and US/Chinese financial firm returns in month t. D_1, D_2, and D_3 are dummy variables for the periods of July 1997 to December 1998 (Asian financial crisis), July 2007 to June 2009 (GFC), and January 2010 to August 2012 (European sovereign debt crisis), respectively. The lagged DCC ($\rho_{\mathrm{ij},t-1}$) to the order of 1 in Eq. (10) is for controlling serial correlation. $e_{ij,t}$ is the residual. $C_{\mathrm{j,t}}$ are the cyclical components of the leading indices of the US and China. $T_{\mathrm{ij,t}}$ is the trade intensity measure.

Directional spillover model

We apply Diebold and Yilmaz's (2012) spillover index model to measure the return and volatility spillovers across financial firms. The Diebold and Yilmaz (2012) framework is used widely to examine the spillover effects across markets (Batten et al. 2019; Corbet et al. 2018). The Diebold and Yilmaz (2012) model measures the spillovers in a generalised vector autoregression (VAR) framework that removes the potential order-dependent results using Cholesky factor orthogonalisation (see Diebold and Yilmaz 2008).

Let us assume an N-variable VAR(p), $y_t = \sum_{i=1}^{p} \varphi_{y_{t-i}} + \varepsilon_t$, where $\varepsilon \sim (0, \Sigma)$ is a vector of i.i.d. disturbances. The moving average is represented as

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$$

where A_i is an $N \times N$ matrix that follows the following recursive pattern:

$A_i = \omega_1 A_{i-1} + \omega_2 A_{i-2} + \cdots + \omega_p A_{i-p}$ with $A_{i-p} = 0$ for $i < 0$.

Diebold and Yilmaz (2012) calculate the H-step-ahead FEVD (Forecast Error Variance Decompositions) as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\left(e_i' A_h \Sigma e_j \right) \right)^2}{\sum_{h=0}^{H-1} \left(\left(e_i' A_h \Sigma A_h' e_i \right) \right)^2} \tag{11}$$

where σ_{jj} is the standard deviation of the residual for the jth equation. e_i is a selection vector, with 1 as the ith element and 0 otherwise, and $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. Each element is normalised by the row sum:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{12}$$

with $\sum_{j=1}^{N} \theta_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$

Following the Diebold and Yilmaz (2012) model, the spillover index is estimated in Eq. (13):

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \tag{13}$$

The directional spillover to market i from all other markets j is measured in Eq. (14):

$$S_{i\cdot}^g = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \tag{14}$$

Similarly, the directional spillover to all other markets j from market i is measured in Eq. (15):

$$S_{\cdot i}^g = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^g(H)}{N} \cdot 100 \tag{15}$$

The net spillover to all other markets j from market i is measured by subtracting Eq. (15) from E. (14):

$$S_i^g = S_{\cdot i}^g - S_{i\cdot}^g \tag{16}$$

III. Data and descriptive statistics

The data were obtained from DataStream, ECRI, and the OECD from January 1995 to March 2018. Monthly return indices for the financial stock returns of India, Bangladesh, Pakistan, Sri Lanka, the US, and China were obtained from DataStream. Returns were computed from the return index: $R_{i,t} = ln(RI_{i,t}/RI_{i,t-1})$, where $R_{i,t}$ is portfolio return and $RI_{i,t}$ is the total return index.[5] The US leading index (monthly) was collected from the ECRI, while the composite leading indicator for China was obtained from the OECD. We used monthly data to avoid

[5] Mink (2015) argues in favour of using local currency-denominated returns than common currency returns.Forbes and Rigobon (2002) and Akhtaruzzaman and Shamsuddin (2016) find qualitatively similar results for contagion while using local currency and USD returns..

nonsynchronous trading issues (Scholes and Williams 1977) and settlement and clearing interruptions (Baillie and Ramon 1990).

Table 1 presents the characteristics of the Chinese, South Asian, and US equity markets. The market capitalisation to GDP ratio is the lowest (highest) in Bangladesh (India). The market capitalisation of India is the highest, followed by Pakistan, Bangladesh, and Sri Lanka. It appears from these characteristics that the Indian equity market is more advanced than its South Asian counterparts. Table 2 shows that the US is the major destination of exports from South Asia, while China is the major source of imports. Table 3 and Fig. 1 show that net equity flows to South Asian countries are associated with stock return indices (The World Bank Group 2019).

<Insert Tables 1–3>

<Insert Fig. 1>

The stock returns of India and Sri Lanka appear to have more volatility during the GFC period compared with the entire study period. However, country-specific crises are evident from the return series and stock return volatility of South Asian countries (see Figs. 2 and 3). For example, Figs. 2 and 3 illustrate that Bangladesh experienced significant volatility in stock returns following a stock market crash in 1996 (see Hoque 2007).

<Insert Figs. 2 and 3>

The mean financial stock returns of India, Bangladesh, Pakistan, and Sri Lanka are much higher than those of the US and China. The mean monthly financial stock return of Bangladesh is

1.50% over the sample period, while the US and Chinese mean monthly financial stock returns are 0.50% and 0.40%, respectively.

<Insert Table 4>

The skewness of portfolio returns deviating from zero and the kurtosis being over 4 in all cases, indicates a nonnormal distribution. Also, the Jarque–Bera test shows that return distribution is nonnormal. All portfolio return series do not have unit roots. The Box–Pierce–Ljung portmanteau test demonstrates that most returns do not have autocorrelation.

Table 5 presents the GARCH specification and Table 6 provides the selected parameters of the best GARCH models for each country.

<Insert Tables 5 and 6>

IV. Empirical results

Dynamic conditional correlations

The results from DCC and ADCC models are presented in Table 7. The Lagrange multiplier test of Tse (2000) shows that constant correlations among financial stock returns do not exist. The average correlation coefficients between South Asian financial stock returns and the US financial firm return are 0.1615 and 0.1636 for the DCC and ADCC models, respectively compared with 0.1235 and 0.1187 for the Chinese financial stock return. These results imply that the low correlation coefficients provide an opportunity for international portfolio diversification. Further, they indicate that both the US and China play limited but similar roles in channelling financial contagion to South Asian countries.

<Insert Table 7>

<Insert Fig. 4>

Determinants of DCCs

The determinants of DCCs include US and Chinese business cycles, the trade intensity measures, and financial crisis dummies. The GFC during 2007–2009 appears to increase the cross-correlations between China and Indian/Sri Lankan financial stock returns, providing evidence of contagion. Results are consistent with the literature (Kim and Kim 2013; Mellado and Escobari 2015). However, our results show that the effects of the European debt crisis and Asian financial crisis on the DCCs are mixed, having both negative and positive effects. This finding indicates that the GFC had more profound effects on the increasing time-varying correlation than the European sovereign debt crisis and the Asian financial crisis on South Asian financial stock returns.

<Insert Table 8>

The US business cycles have negative and significant effect on DCCs between the US and South Asian countries except Sri Lanka. These results indicate that DCCs between the Bangladesh, India, Pakistan, and US financial firm returns increase (decrease) during the periods of US economic downturns (upswings). These results corroborate literature (Akhtaruzzaman, Shamsuddin and Easton 2014; Ferreira and Gama 2010). Also, the Chinese business cycles have a negative effect on DCCs between the Chinese financial stock return and those of India and Sri Lanka, reinforcing the evidence that financial contagion occurs during Chinese economic downturns. These results suggest that international portfolio diversification is not optimal during economic downturns in the major markets of the world, particularly the two largest economies, China and the US.

The trade intensity of India with the US is found to have a positive effect on the DCC between Indian and US financial firm returns. However, the trade intensity with the US is not found to have significant effects on the corresponding correlations for Bangladesh, Pakistan, and Sri Lanka. Since India is the eighth highest trading partner of the US, the bilateral trade intensity between them appears to play a role in transmitting contagion.[6] The trade intensity of Bangladesh, India, and Pakistan with China does not appear to influence the conditional correlations, thereby not aiding the transmission of financial contagion to these countries via the trade channel. However, the trade intensity of Sri Lanka with China appears to be increasing the conditional correlation.

<Insert Table 9>

Return and volatility spillovers

Results in Table 9 provides the values of the net spillover indices for US, Chinese, and South Asian financial firms, indicating the net contributors and net recipients for return and volatility spillovers. The results demonstrate that across our entire sample, the return spillover is 16.3% and the volatility spillover is 17.6% on average. Both the return and the volatility spillover indices appear to be low, and these results corroborate the findings from the DCC models discussed earlier, implying that the information transmission between US/Chinese and South Asian financial firms is low. The results from the directional spillovers suggest that US

[6] The top 15 trading partners with the US as at May 2018 were obtained from the US Census Bureau (https://www.census.gov/foreign-trade/statistics/highlights/top/top1805cm.html). The data show that Bangladesh, Pakistan, and Sri Lanka are not among the top 15 trading partners of the US.

financial firms are a net contributor in transmitting volatility spillovers across the financial firms in our sample, whereas they are marginally a net recipient in transmitting return spillovers. On the contrary, Chinese financial firms appear to be net contributors for both return and volatility spillovers across financial firms. Another interesting result is that Indian financial firms appear to be a net contributor in transmitting return spillovers. This result draws attention to the role of India in transmitting financial contagion across South Asian markets.

Diebold and Yilmaz (2012) mention that the entire spillover table and index only provide a summary of volatility and cannot identify important cyclical movements in spillovers. Following Diebold and Yilmaz (2012), we thus estimate the spillover volatility using a 60-month rolling window to investigate the extent and nature of spillovers throughout the sample period.[7] Fig. 5 provides the spillover plots for returns and volatility, showing that both jumped significantly during the GFC, particularly upon the collapse of Lehman Brothers. In addition, the spillover indices rose after the US terrorist attack in September 2011. During the European debt crisis, the spillover indices appeared to be higher following the GFC. Both US recession periods and the periods of stagnation and decline identified by our study coincide with the higher spillover indices for both returns and volatility. Similarly, the Chinese periods of stagnation and decline identified by our study coincide with the higher spillover indices for both returns and volatility.

<Insert Fig. 5>

[7] Diebold and Yilmaz (2012) employ 200-day rolling windows given that the frequency of their data is daily. Since the frequency of our data is monthly, we applied 60-month rolling windows. A number of studies (Antonakakis, Chatziantoniou and Filis 2014; Klößner and Sekkel 2014) use 60-month rolling windows to construct their spillover plots. Our 60-month rolling window sample is consistent with one-quarter of the sample size (see Zhang et al. 2018).

Thus far, we have only discussed the total spillover plots, which ignore the directional information provided in the 'Directional from Others' column, measured by $S_{i\cdot}^{g}$ in Eq. (14). The 'Directional to Others' row is measured by $S_{\cdot i}^{g}$ in Eq. (15). Fig. 6 provides the directional spillover plots for both returns and volatility, which vary significantly over the sample period. These plots demonstrate that US and Chinese financial firms transmitted more spillovers than they received during the GFC, indicating a source of financial contagion during crisis periods. Again, as India is the largest economy in South Asia, Indian financial firms played a visible role in transmitting return spillovers during the GFC. Finally, Fig. 7 shows the net spillover volatility measured by S_{i}^{g} in Eq. (16). These plots for both returns and volatility reconfirm the directional spillover plots that the US and China are sources of financial contagion during crisis periods.

<Insert Figs. 6 and 7>

V. Robustness checks

We conduct some robustness checks. First, we examine whether the results from local currency returns are similar to those for USD returns. Second, we employ the NBER business cycles for US recession periods instead of using the ECRI leading index. Third, a Hamilton's (1989) Markov regime-switching model is employed to check whether high DCC regimes match with the period of economic downturns. Finally, we estimate the spillover index for a forecast horizon from 4 to 10 months with a VAR lag structure from 2 to 6 months and rolling windows of 36, 48, and 60 months.

US dollar returns

The DCC model is re-estimated using USD returns. We find that results are qualitatively similar irrespective of the use of USD returns or local currency returns (see Appendix 1).

Alternative definition of the business cycle

NBER recession periods are used as an alternative measure of economic downturns instead of using the ECRI monthly leading index in Eq. (10).[8] Overall, we find similar results that DCCs are high in both definitions of recession periods.

Markov regime-switching model

In Eq. (9), economic condition variables were employed to assess their role in changing DCCs. Alternatively, we apply Hamilton's (1989) Markov regime-switching model and find that high (low) DCC regimes coincide with the periods of economic downturns (upswings). For example, Fig. A1 provides DCCs along the regime probabilities for a pair of countries: the US and India. Fig. A1 demonstrates that regime 1 often resembles a low DCC regime associated with the periods of economic upswings (unshaded area), while regime 2 refers to a high DCC regime associated with the periods of economic downturns (shaded area).

<Insert Fig. A1>

Alternative specification of the spillover index

We construct total spillover plots for a forecast horizon from 4 to 10 months with a VAR lag structure from 2 to 6 months. We also calculate spillover plots with rolling windows of 36, 48, and 60 months. Figs. A2 and A3 provide the spillover plots for returns with a forecast horizon

[8] To save space, those results are not presented.

from 4 to 10 months and a VAR lag structure from 2 to 6 months, respectively. Figs. A4 and A5 provide the same spillover plots for volatility. Figs. A6 and A7 provide the spillover plots for returns and volatility with rolling windows of 36, 48, and 60 months, respectively. Figs. A2 to A7 show that the total spillover plots are qualitatively similar, indicating that empirical results are not sensitive to the change in VAR lag structure, forecast horizon, or size of the rolling window.

<Insert Figs. A2–A7>

VI. Conclusion

The study examines financial contagion from China and the US to four South Asian countries. The DCCs between South Asian and US/Chinese financial stock returns appear to be low. These low correlation coefficients provide an opportunity for international portfolio diversification. Moreover, lower correlation coefficients indicate that both the US and China play limited but similar roles in channelling financial contagion to South Asian countries.

The presented evidence suggests that the DCC between Chinese and Indian financial stock returns was higher during the GFC, constraining portfolio diversification for international investors. However, the effects of the European debt crisis and the Asian financial crisis on DCCs are mixed, having both negative and positive effects.

The conditional correlations between Bangladesh, India, Pakistan, and US financial firm returns increase (decrease) during contractionary (expansionary) periods of the US business cycle. Similarly, the DCCs between the Chinese financial stock return and those of India and Sri Lanka increase (decrease) during contractionary (expansionary) periods in China. The trade intensity of India with the US increases the DCC, thereby aiding the transmission of contagion. Our findings are robust to irrespective of using local currency or USD returns. Moreover, the regime-switching model shows that high DCC regimes coincide with the period of economic downturns. Thus, knowledge of DCCs may help regulators, policymakers, and international investors devise strategies to withstand external economic shocks.

The directional and net spillover plots for returns and volatility demonstrate that US and Chinese financial firms transmitted more spillovers than they received during the GFC, indicating a source of financial contagion during crisis periods. However, both the return and the volatility spillover indices appear to be low, and these results corroborate the results from the DCC models. Both the DCC models and Diebold and Yilmaz's (2012) spillover index model demonstrate that US and Chinese financial firms play limited but similar roles in transmitting financial contagion to South Asian financial firms. The empirical results suggest that India, as the largest economy in South Asia and sixth largest economy in the world (International Monetary Fund 2018b), is the main source of return spillovers across the financial firms in our sample. Future research is therefore warranted on how India plays a role in transmitting financial contagion to South Asian countries as well as to the world.

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Table 1: Characteristics of the South Asian, US, and Chinese equity markets (average values over 1995–2017)

	Bangladesh	India	Pakistan	Sri Lanka	China	US
Market capitalisation of listed companies (current USD, billions)	19.30	1,188.38	33.97	10.75	3,843.35	17,143.33
Stocks traded, total value (% of GDP)	1.36	53.46	35.61	2.65	85.99	199.49
Stocks traded, turnover ratio of domestic shares (%)	20.09	71.85	162.48	14.41	188.36	159.14
Market capitalisation of listed companies (% of GDP)	15.33	77.03	22.27	20.53	54.06	127.03
S&P Global Equity Indices (annual % change in USD price)	8.41	16.94	16.29	9.97	14.43	9.61

Note:
1. Data retrieved from the World Development Indicators database, The World Bank Group.

Table 2: Openness of South Asian countries with the US and China, December 2017
Panel A: Exports as a percentage of total exports

Destination	Bangladesh	India	Pakistan	Sri Lanka
US	12.74	15.42	15.51	26.40
China	2.11	4.75	5.47	2.51

Panel B: Imports as a percentage of total imports

Source	Bangladesh	India	Pakistan	Sri Lanka
US	2.70	6.09	4.14	1.71
China	22.41	16.33	24.01	18.38

Note:
1. Export receipts and import payments are obtained from the Direction of Trade Statistics, International Monetary Fund.

Table 3: Net equity flows (USD millions) to South Asian countries (1995–2017)

Year	Bangladesh	India	Pakistan	Sri Lanka
1995	-15	1590	10	n/a
1996	-117	3958	285	n/a
1997	-10	2556	330	n/a
1998	-4	-601	-22	n/a
1999	-1	2317	66	n/a
2000	1	2481	35	n/a
2001	-3	2950	-130	-35
2002	-1	1063	79	-53
2003	2	8216	-26	-143
2004	4	9054	49	-100
2005	20	12151	451	-216
2006	n/a	9509	1152	-304
2007	n/a	32863	1276	-322
2008	n/a	-15030	-270	-488
2009	n/a	24689	-37	-382
2010	-54	30442	511	-1049
2011	50	-4048	25	-171
2012	134	22809	178	272
2013	262	19892	111	226
2014	358	12369	762	178
2015	-105	1933	529	-60
2016	114	2337	-339	24
2017	251	5928	-389	359

Notes:
1. Net private equity flows from 1995 to 2017 were retrieved from the World Development Indicators, The World Bank Group.
2. n/a indicates not available.

Table 4: Descriptive statistics of monthly financial stock returns, January 1995–March 2018

Panel A: Financial firms portfolio

	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque–Bera	Q (12)	ADF	PP
Bangladesh	0.015	0.228	-0.407	0.060	-0.842	7.420	203.27***	18.10	-13.69***	-13.79***
India	0.013	0.392	-0.317	0.091	-0.229	5.265	48.50***	9.84	-13.19***	-13.19***
Pakistan	0.017	0.279	-0.503	0.102	-1.079	7.343	213.65***	13.05	-14.63***	-14.62***
Sri Lanka	0.013	0.369	-0.205	0.077	1.114	6.739	172.19***	21.46**	-13.04***	-13.39***
US	0.005	0.166	-0.240	0.055	-0.959	6.736	160.19***	32.12***	-12.69***	-12.75***
China	0.004	0.392	-0.297	0.085	0.291	5.844	76.55***	8.05	-13.84***	-13.94***

Notes:

The Jarque–Bera test is used to check whether the return distribution is normal. The Box–Pierce–Ljung statistic, Q (12) statistic is distributed as a χ^2 with 12 degrees of freedom. The augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) are used to check the unit root of return series.

*, **, and *** represent significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 5: Specification of the GARCH models

Country	GARCH	GJR-GARCH	EGARCH	APARCH	IGARCH
Bangladesh	-2.4444	**-2.4537**	-2.3522	-24466	-2.4484
China	-1.8610	**-1.8990**	-1.8636	-1.8938	-1.8623
India	-1.9531	**-1.9701**	-1.9206	-1.9622	-1.9466
Pakistan	-1.6634	-1.5728	**-1.6972**	-1.6617	-1.6706
Sri Lanka	-2.3176	-2.2488	**-2.3724**	-2.3600	-2.3248
US	-3.1530	-3.1543	-2.9876	-3.1551	**-3.1601**

Note:

1. The value with the lowest BIC is the best univariate GARCH model and the best models are emboldened for each country.

Table 6: Univariate GARCH models

Asset	Model selected	ω	α	β	γ
Bangladesh financial stocks	GJR-GARCH	0.0160	0.2268*	0.8484***	-0.1646**
China financial stocks	GJR-GARCH	0.0029	0.6601**	0.4370**	-0.5884
India financial stocks	GJR-GARCH	0.0099*	-0.0263	0.7635***	0.2264**
Pakistan financial stocks	EGARCH	0.0103	1.3436	0.6107***	-0.0020
Sri Lanka financial stocks	EGARCH	0.0165	2.5877	0.8013***	-0.0153
US financial stocks	IGARCH	0.0101***	0.7364**	0.1902***	

Note: This table reports the selected specifications and parameter estimates of the univariate GARCH models used to standardise each return series.

Table 7: Conditional correlations using the DCC model and ADCC model, January 1995–March 2018

Panel A: Conditional correlations of South Asian financial stock returns with US financial stock returns

	DCC					ADCC				
	Bangladesh	India	Pakistan	Sri Lanka	Average	Bangladesh	India	Pakistan	Sri Lanka	Average
Mean	0.0053	0.2477	0.1625	0.2306	0.1615	0.0025	0.2773	0.2102	0.1645	0.1636
Maximum	0.4000	0.7385	0.3044	0.4843		0.9957	0.6131	0.7446	0.4559	
Minimum	-0.9950	-0.3067	0.0167	-0.2917		-0.9900	-0.4472	-0.3412	-0.1582	
Std. dev.	0.1258	0.1740	0.0477			0.1457	0.1954	0.2006	0.1293	
LM test of Tse (2000)	84.39***	33.55***	21.21***	13.82***		32.25***	30.90***	5.56***	12.81***	
DCC/ADCC Parameters										
a	0.1124***	0.1493**	0.0351	-0.0239**		0.1052	0.4773***	0.4389***	-0.0167	
b	-0.2436***	0.5865**	0.7971***	0.9972***		0.9661***	0.0728	0.2156	1.0033***	
g						0.0368	-0.0740	-.03317**	-0.0786	

Panel B: Conditional correlations of South Asian financial stock returns with China financial stock returns

	DCC					ADCC				
	Bangladesh	India	Pakistan	Sri Lanka	Average	Bangladesh	India	Pakistan	Sri Lanka	Average
Mean	-0.0065	0.3093	0.1241	0.0671	0.1235	0.0133	0.3056	0.1092	0.0468	0.1187
Maximum	0.2428	0.4422	0.9997	0.3294		0.2986	0.7956	0.4977	0.5584	
Minimum	-0.1661	0.0062	-0.0598	-0.0873		-0.1719	0.2619	-0.5407	0.0114	
Std. dev.	0.0787	0.0317	0.0811	0.0495		0.1109	0.0716	0.1171	0.0656	
LM test of Tse (2000)	27.43***	91.73***	3.78***	55.05***		23.32***	11.74***	13.22***	10.06***	
DCC/ADCC Parameters										
a	0.0442	-0.0269	-0.0318	0.0355		0.0932*	0.0006	0.02569**	0.0113	
b	0.8250***	0.47756	0.8926	0.7055**		0.8891***	0.6677***	-0.0486	0.7655***	
g						0.0153	0.0724	-0.2207	0.0484	

Table 7: Conditional correlations using the DCC model and ADCC model, January 1995–March 2018 (Contd.)

Notes:

1. Presents the estimates of the parameters of Eq. (5):

$$\rho_{ij,t}=q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}\ i,j=1,2,\dots n,\ and\ i\neq j \qquad (5)$$

In Eq. (5), $\rho_{ij,t}$ represents DCCs between South Asian and US/Chinese financial stock returns. $q_{ii,t}$ and $q_{jj,t}$ are the conditional variance of South Asian and US/Chinese financial stock returns, respectively.

2. The Lagrange multiplier (LM) test of Tse (2000) tests the null hypothesis: H_0: $\delta_{12}=0$ for the equation: $\rho_{ij,t}=\rho_{ij}+\delta_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1}$, where $\varepsilon_{1,t-1}$ and $\varepsilon_{2,t-1}$ are the standard residuals in South Asian, US, and Chinese financial stock returns, respectively from the best fit GARCH (1,1) process.
3. a, b, and g are the DCC parameters in Eqs. (4) and (8).

*, **, and *** represent significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 8: Determinants of the conditional correlations of South Asian financial firms with respect to Chinese and US financial firms, January 1995–March 2018

Panel A: DCCs with respect to US financial firms

	Bangladesh		India		Pakistan		Sri Lanka	
	DCC model	ADCC model	DCC model	ADCC model	DCC model	ADCC model	DCC model	ADCC model
Constant	0.012	-0.013	0.019	0.103**	0.019*	0.096	0.008	0.005
Lagged DCC	-0.0379***	-0.573***	0.662	0.231***	0.796***	0.302***	0.927***	0.972***
Dummy_GFC	-0.058	0.012	0.016	-0.004	-0.005	-0.095	0.011	-0.008
Dummy_European debt crisis	-0.027**	0.003	0.017	0.020	0.007*	-0.003	0.006	-0.003
Dummy_Asian financial crisis	0.006	0.058	0.027	0.029	0.002	-0.061	-0.043**	-0.031
Trade intensity	1.261	7.798	5.578**	9.882***	8.203	38.688	10.392	2.917
US business cycle	-0.004*	-0.08**	-0.007***	-0.008***	-0.001***	0.005	0.001	0.001
Diagnostic statistics								
Q (12)	19.02*	11.90	7.65	6.04	11.65	5.12	10.50	7.77
Q^2 (12)	48.12***	18.24	14.15	20.55*	10.51	14.08	10.03	0.03

Panel B: DCCs with respect to Chinese financial firms

	Bangladesh		India		Pakistan		Sri Lanka	
	DCC model	ADCC model	DCC model	ADCC model	DCC model	ADCC model	DCC model	ADCC model
Constant	0.011	0.0143	0.198***	0.110***	0.067**	0.043*	0.008	-0.001
Lagged conditional correlation	0.809***	0.897***	0.361***	0.611***	0.475**	0.790***	0.663	0.695
Dummy for GFC	0.016	0.009	0.016*	0.042*	0.005	-0.025	0.023***	0.029**
Dummy for European sovereign debt crisis	-0.010	-0.008	-0.002	0.004	-0.007	-0.013	-0.001	-0.001
Dummy for Asian financial crisis	0.001	0.002	-0.002	0.021	-0.011	-0.015	0.009	0.017
Trade intensity	-5.39	-5.65	0.123	0.024	-0.231	-4.93	14.52*	15.04
China business cycle	0.004	-0.001	0.001	-0.006*	0.010	0.008	-0.004**	-0.007*
Diagnostic statistics								
Q (12)	5.31	7.08	2.86	26.58***	19.10*	18.34	7.04	11.71
Q^2 (12)	4.91	2.85	1.24	32.37***	7.22	5.85	4.57	0.49

Table 8: Determinants of the conditional correlations of South Asian financial firms with respect to US and Chinese financial firms, January 1995–March 2018 (Contd.)

Notes:

a) Presents the estimates of the parameters of Eq. (10).
b) Diagnostic statistics are based on standardised residuals ($\varepsilon_{i,t}/\sqrt{h_{i,t}}$). Q (12) and Q^2 (12) are the Box–Pierce–Ljung Q statistics for the standardised residuals, and squared standardised residuals of order 12, respectively.

*, **, and *** represent significant at the 0.10, 0.05, and 0.01 levels, respectively.

Table 9: Spillover index for returns and volatility from South Asian, US, and Chinese financial stock returns, January 1995–March 2018

Panel A: Spillover table for returns

To	From								
	US	China	Bangla -desh	India	Sri Lanka	Pakis- tan	Directional from Others*	Net	Conclusion
US	81.6	2.9	0.4	7.8	2.1	5.1	18.4	-1.32	net recipient
China	1.7	86.3	1.5	9.0	0.2	1.2	13.7	0.94	net contributor
Bangladesh	0.2	2.8	92.7	3.4	0.2	0.6	7.3	-2.18	net recipient
India	7.7	6.9	2.0	73.9	4.3	5.1	26.1	8.29	net contributor
Sri Lanka	4.0	0.7	0.4	7.2	83.8	3.9	16.2	-5.72	net recipient
Pakistan	3.8	1.2	0.7	7.1	3.7	83.9	16.1	-0.01	net recipient
Directional to Others**	17.1	14.6	5.1	34.4	10.5	16.1	97.8		
Directional including own	98.7	100.9	97.8	108.3	94.3	100.0	Spillover Index (97.8/600): 16.3%		

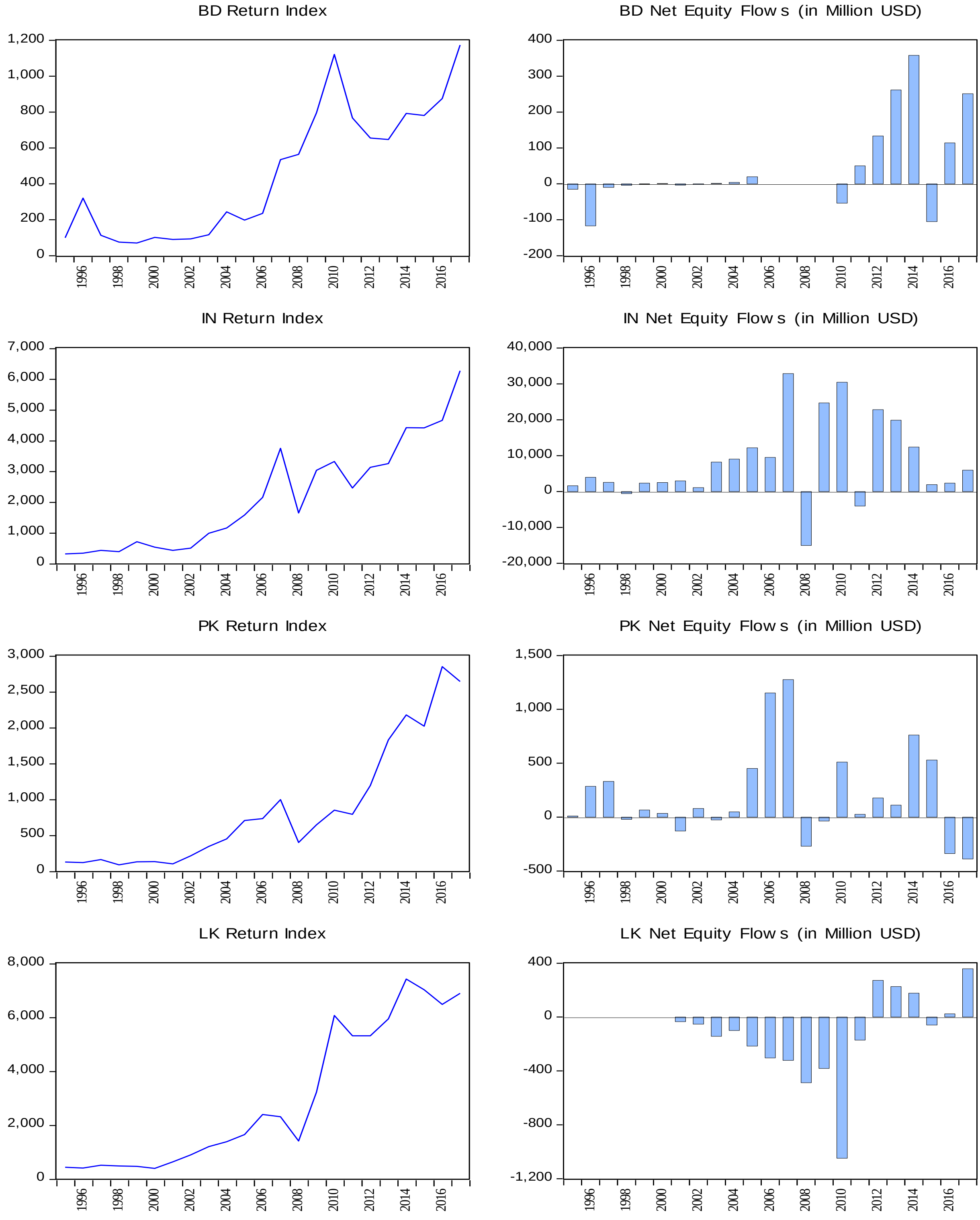
Panel B: Spillover table for volatility

To	From								
	US	China	Bangla -desh	India	Sri Lanka	Pakis- tan	Directional from Others*	Net	Conclusion
US	78.3	0.7	2.0	14.2	1.7	3.1	21.7	23.0	net contributor
China	0.8	90.2	0.2	5.3	1.4	2.2	9.8	4.7	net contributor
Bangladesh	0.7	9.9	86.8	1.8	0.3	0.4	13.2	-7.5	net recipient
India	21.1	0.9	1.2	74.4	2.3	0.1	25.6	-0.6	net recipient
Sri Lanka	17.7	0.2	1.7	3.1	73.3	4.0	26.7	-20.6	net recipient
Pakistan	4.3	2.9	06	0.5	0.5	91.2	8.8	1.0	net contributor
Directional to Others**	44.6	14.5	5.7	25.0	6.1	9.8	105.8		
Directional including own	123.0	104.7	92.5	99.4	79.4	101.0	Spillover Index (105.8/600): 17.6%		

Note:
The underlying variance decomposition is based upon a monthly VAR of order 2, using the spillover index in Diebold and Yilmaz (2012) with a generalised VAR framework (Koop, Pesaran and Potter 1996; Pesaran and Shin 1998), in which forecast error variance decompositions are invariant to the ordering of the variables. The (i, j)th value is the estimated contribution to the variance of the 10-month-ahead stock return (Panel A) and stock return volatility (Panel B) forecast error of country i coming from innovations to the stock return volatility of country j.

* Directional from Others measure spillover from all markets j to market i.
** Directional to Others measure spillovers from market i to all markets j.

Figure 1: Net capital flows and stock return indices, 1995–2017



Notes:

1. Net private equity flows from 1995 to 2017 were retrieved from the World Development Indicators, The World Bank Group. Net Equity flows are denominated in USD (millions).
2. The return indices of India, Bangladesh, Pakistan, and Sri Lanka from 1995 to 2017 were obtained from DataStream.

Figure 2: Monthly financial stock returns of Bangladesh (BD), India (IN), Pakistan (PK), Sri Lanka (LK), the US, and China (CH), January 1995–March 2018

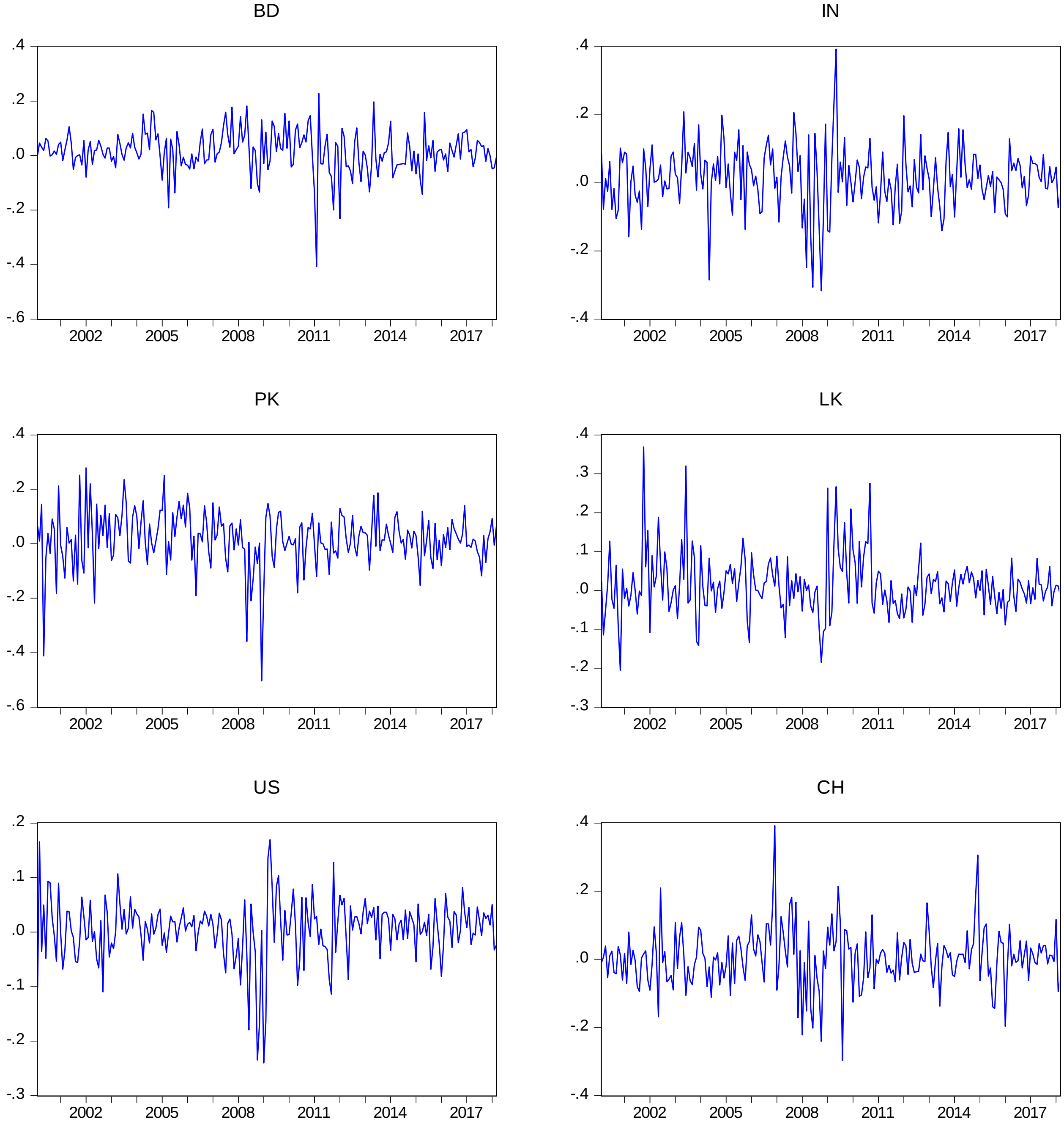
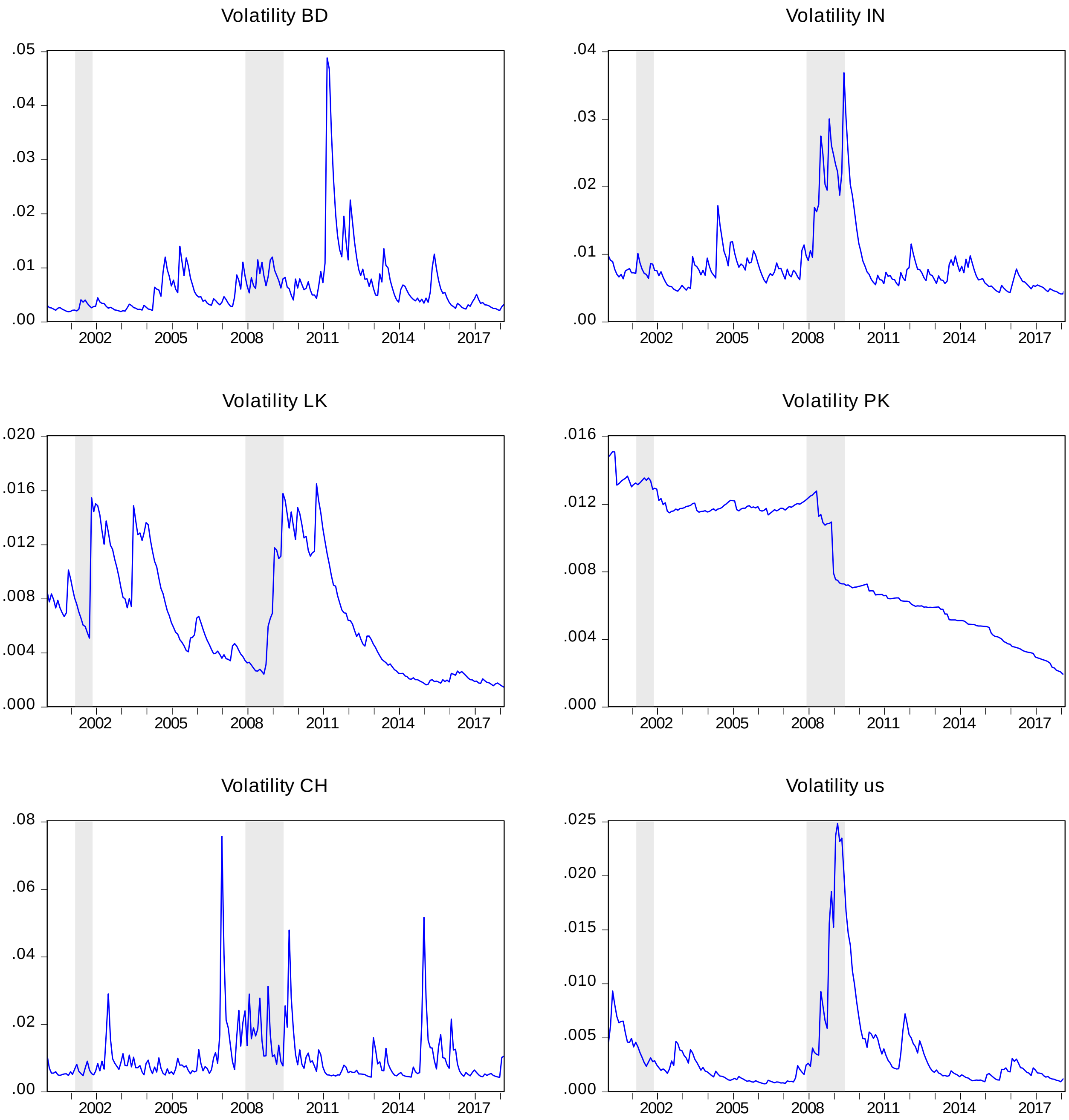


Figure 3: Conditional volatility of the stock returns

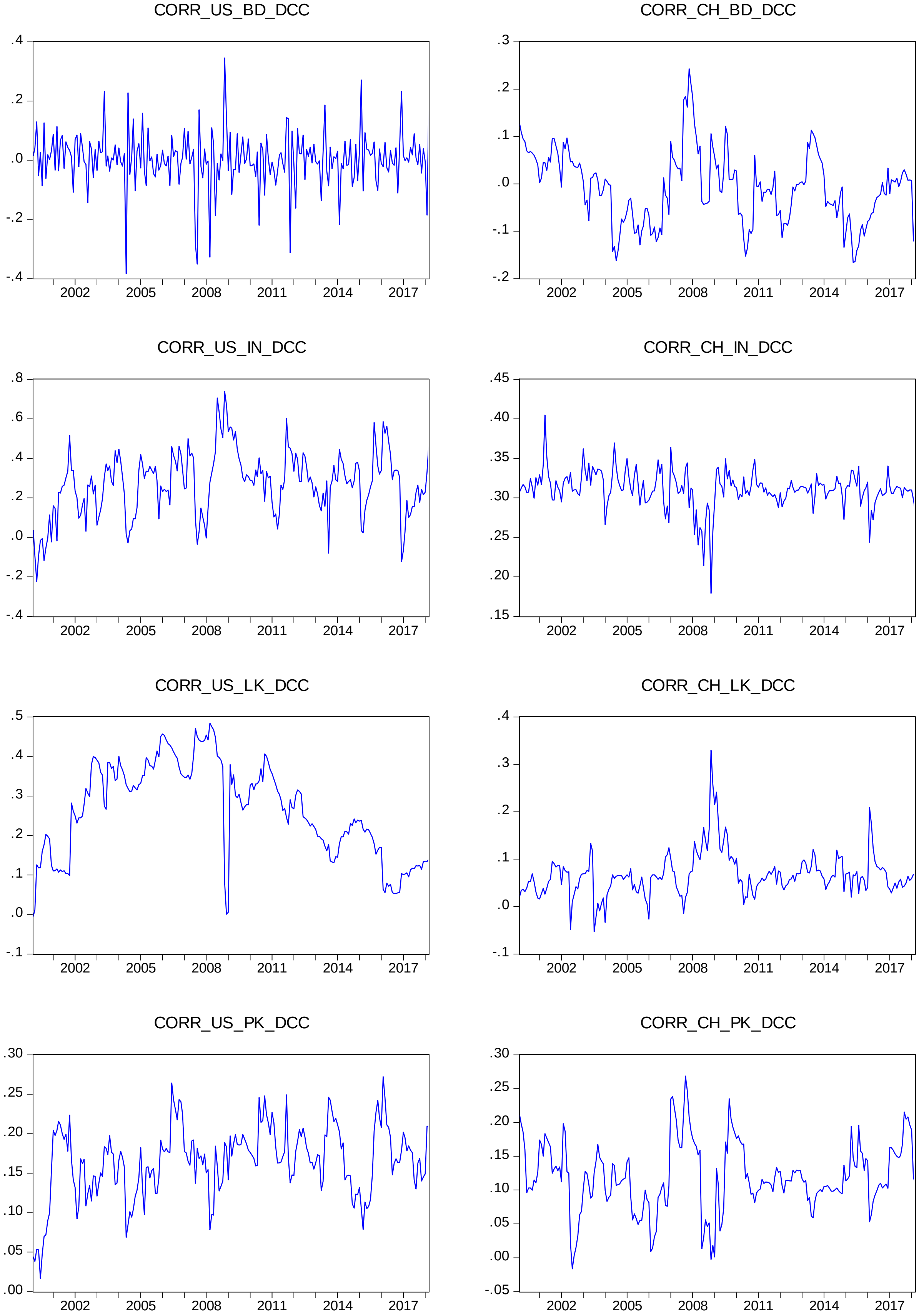


Notes:

1. The conditional volatility of each return series is generated using the best fit GARCH model with no exogenous variables (see Tables 5 and 6 for the best GARCH model for each country).
2. Shaded areas indicate NBER US recession periods.

Figure 4: Conditional correlations

Panel A: DCCs



Panel B: ADCCs

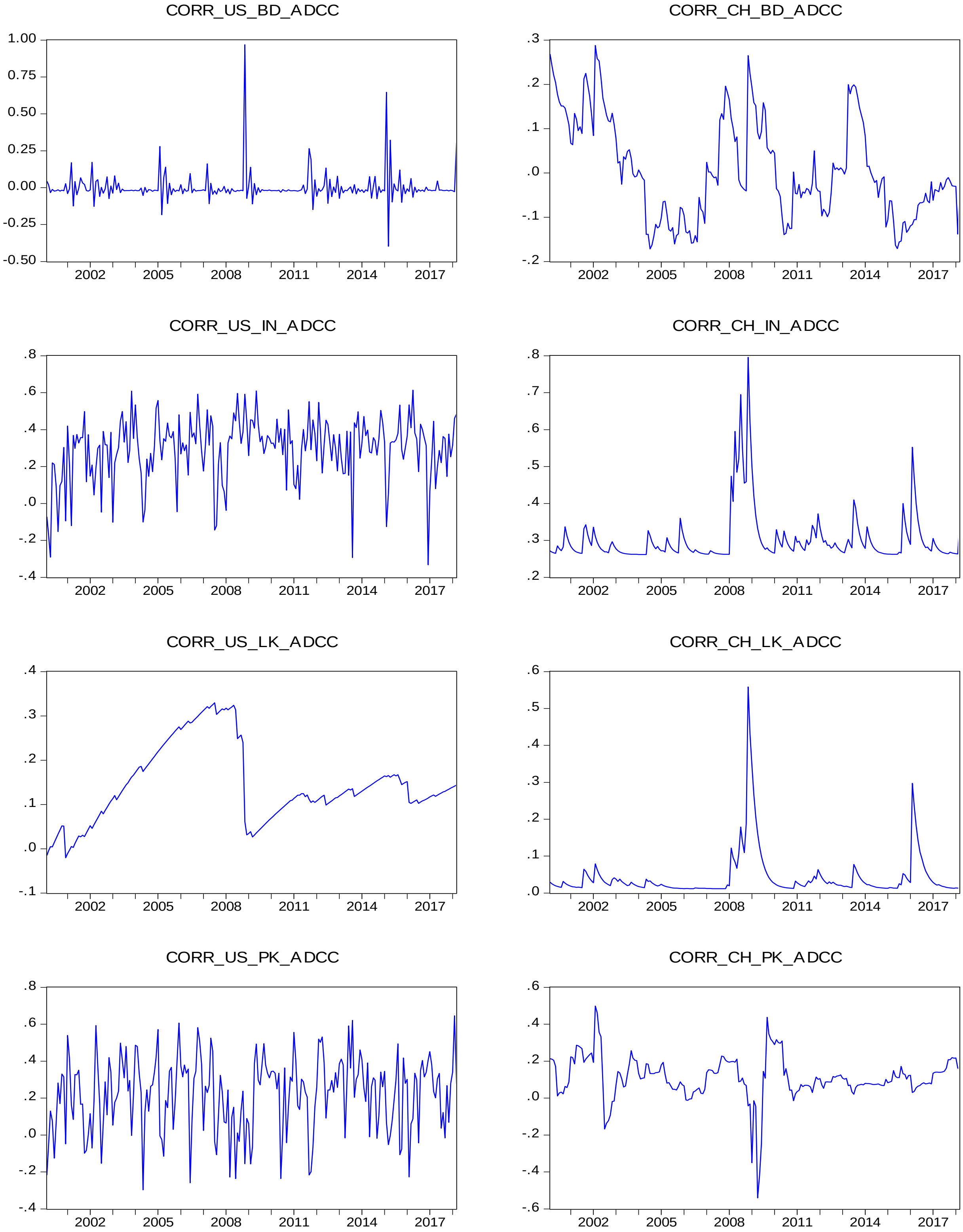
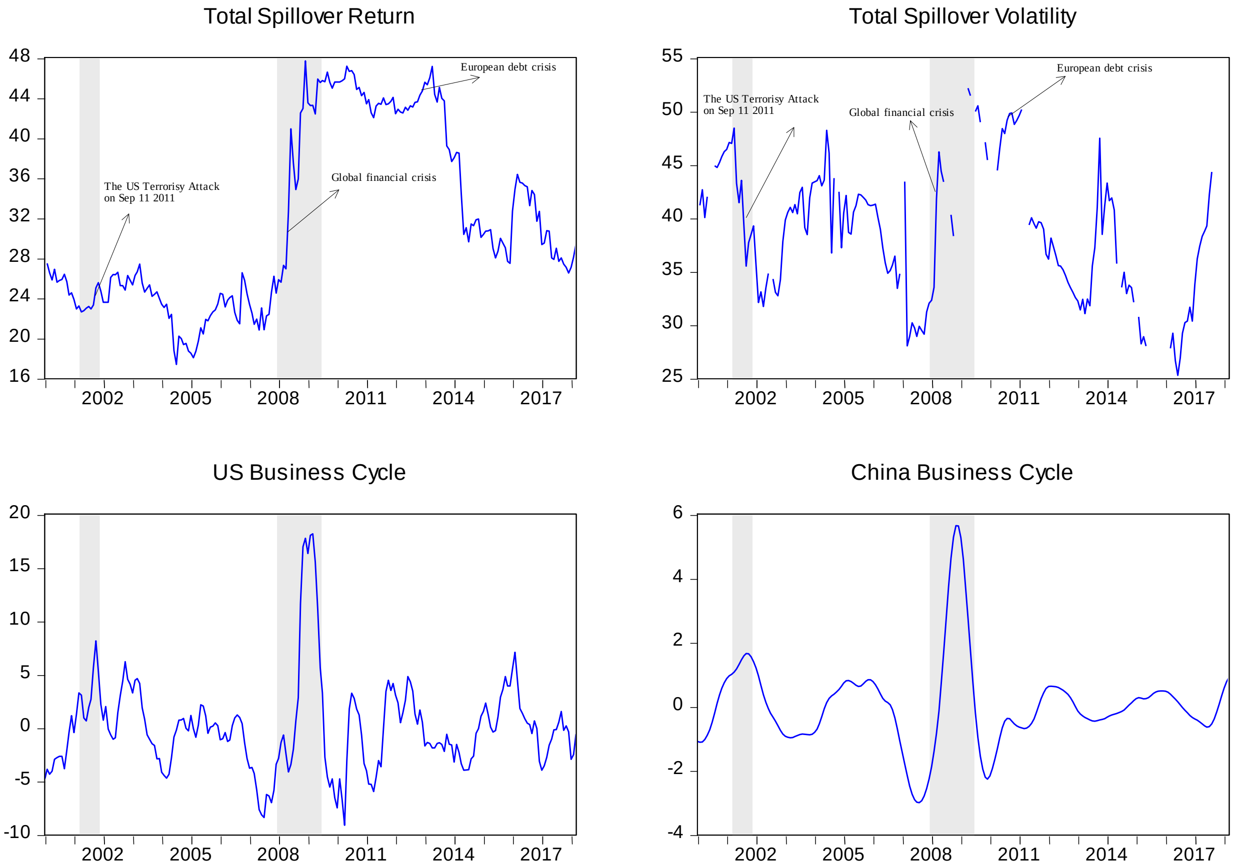


Figure 5: Spillover plots for return and volatility spillovers, January 2000–March 2018



Notes:

1. This figure is from the spillover indices for returns and volatility from South Asian, US, and Chinese financial stock returns, estimated using 60-month rolling windows. Shaded areas indicate NBER US recession periods.

Figure 6: Directional spillover plots
Panel A: Directional spillover plots: returns

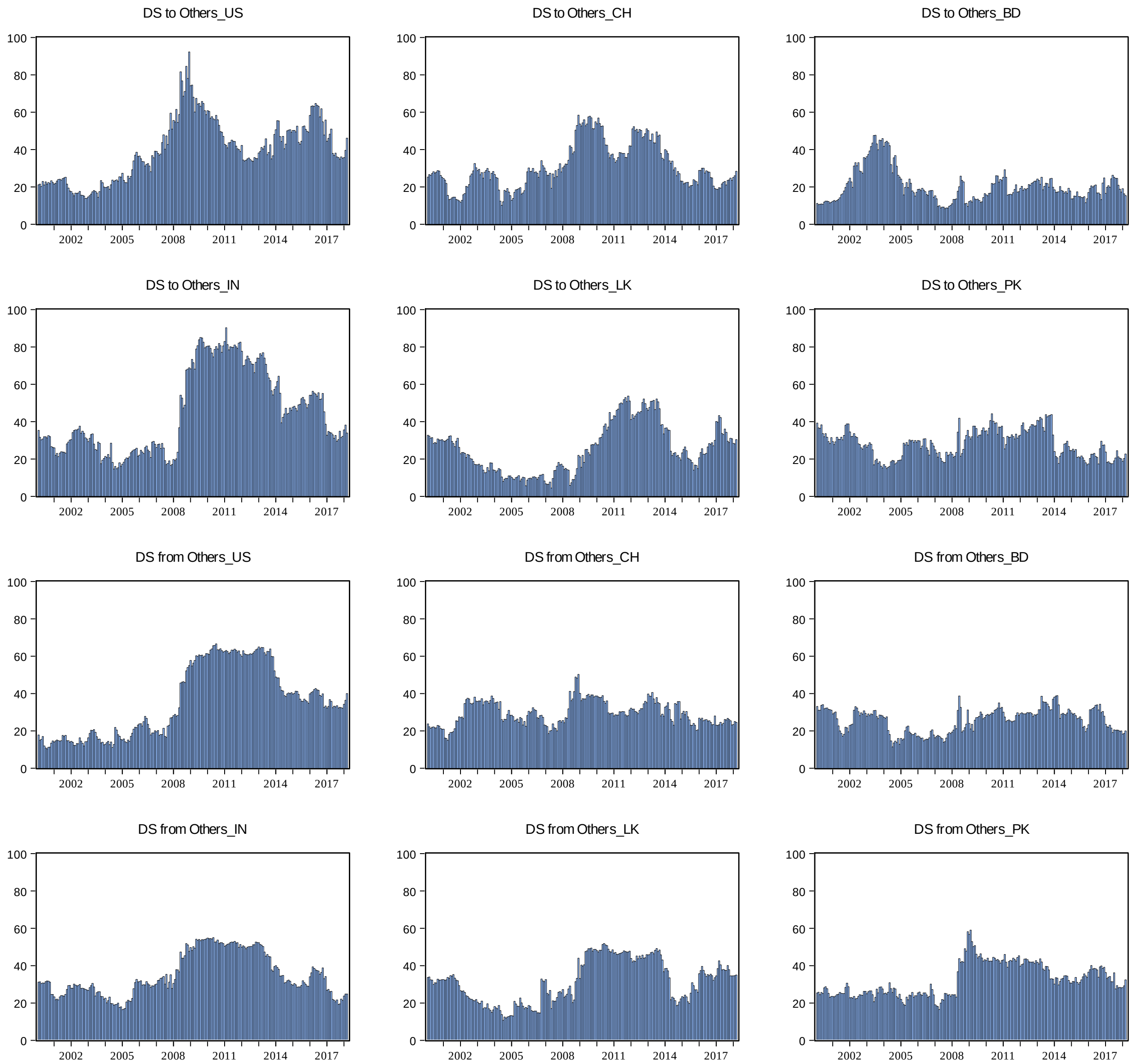
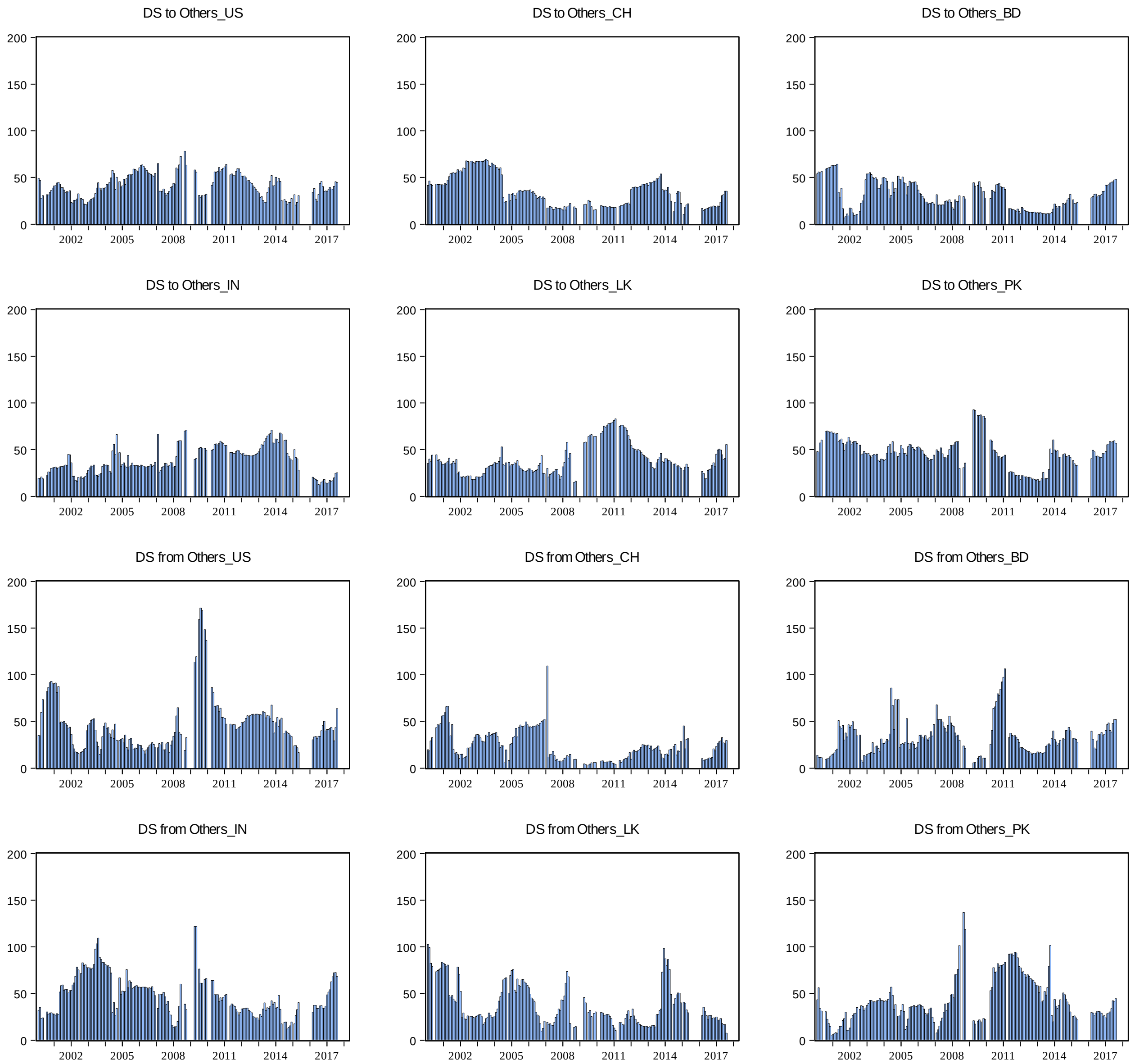


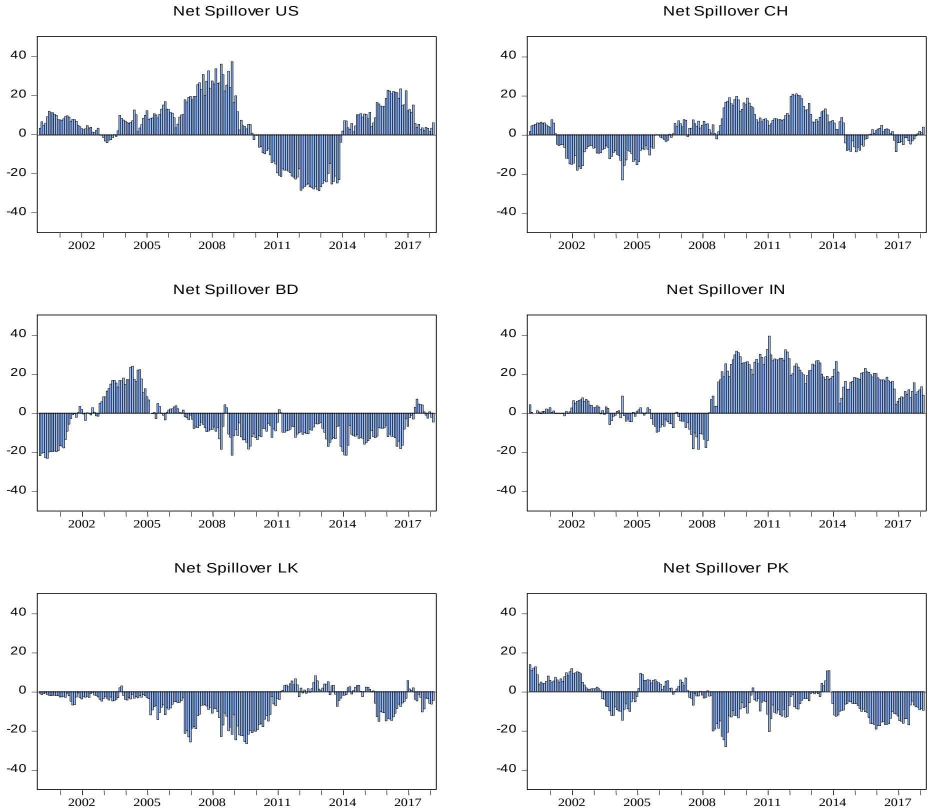
Figure 6 (continued): Directional spillover plots
Panel B: Directional spillover plots: volatility



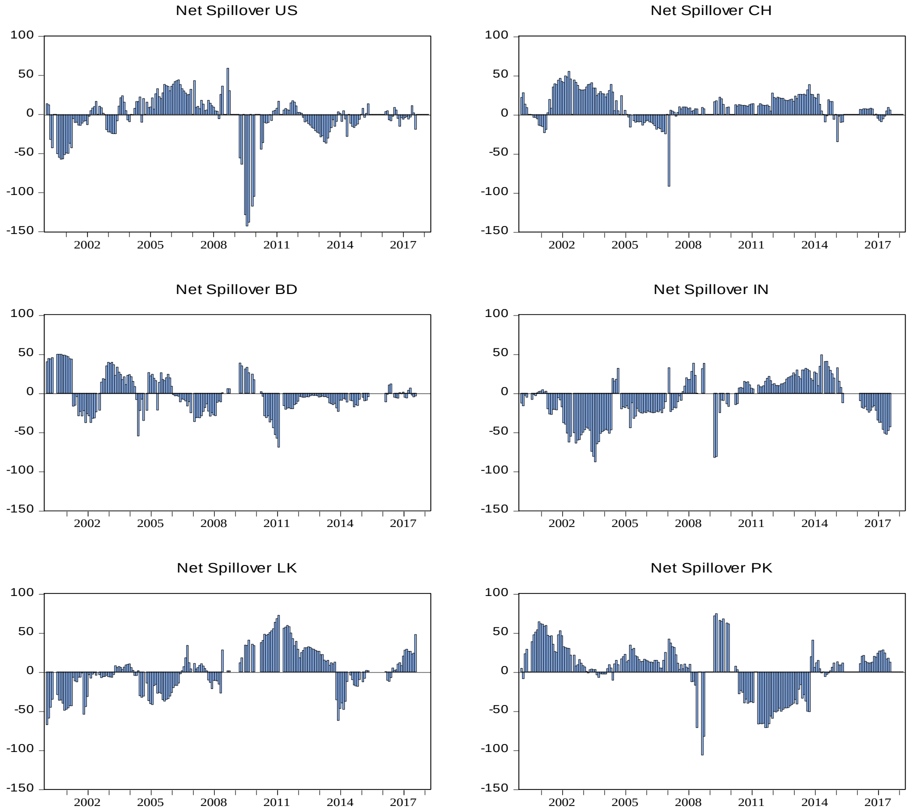
Notes:
DS stands for 'Directional Spillover' for each country. The 'Directional from Others' column is measured by $S_{i\cdot}^{g}$ in Eq. (14). The 'Directional to Others' row is measured by $S_{\cdot i}^{g}$ in Eq. (15). For example, 'DS to Others_US' indicates the directional spillovers to China (CH), Bangladesh (BD), India (IN), Sri Lanka (LK), and Pakistan (PK). 'DS from Others_US' indicates the directional spillovers from CH, BD, IN, LK, and PK to US. Panels A and B refer to the return and volatility spillovers, respectively.

Figure 7: Net spillover plots for return and volatility spillovers, January 2000–March 2018

Panel A: Net spillover plots: returns



Panel B: Net spillover plots: volatility



Notes:

Net Spillover is measured by S_i^g in Eq. (16). For example, ‘Net Spillover US’ is calculated using ‘US Directional Spillover To Others’ minus ‘US Directional Spillover From Others’.

Appendix A1: Determinants of the conditional correlations of South Asian financial firms with respect to Chinese and US financial firms, January 1995–March 2018 (returns are denominated in USD)

Panel A: DCCs with respect to US financial firms

	Bangladesh		India		Pakistan		Sri Lanka	
	DCC model	ADCC model	DCC model	ADCC model	DCC model	ADCC model	DCC model	ADCC model
Constant	0.011	0.002	0.019	0.019	0.028***	0.058	0.029*	0.003
Lagged DCC	-0.332***	-0.518***	0.643***	0.637***	0.782***	0.15***	0.925***	0.910***
Dummy GFC	-0.040	-0.019	0.018	0.016	-0.004	-0.081	0.007	0.022
Dummy European sovereign debt crisis	-0.018*	-0.008	0.031	0.031	0.006**	-0.002	0.007*	0.017
Dummy Asian financial crisis	-0.046	-0.032	0.024	0.023	0.003	-0.039	-0.018**	-0.052*
Trade intensity	-5.009	3.278	6.149**	6.325**	5.457	34.386	-10.261	13.424
US business cycle	-0.002	-0.003	-0.007***	-0.007***	-0.001***	0.003	0.001	0.002
Diagnostic statistics								
Q (12)	15.97	10.61	7.021	6.833	9.31	3.48	13.51	8.11
Q^2 (12)	17.44	12.65	13.035	13.31	10.21	13.68	31.86***	10.29

Panel B: DCCs with respect to Chinese financial firms

	Bangladesh		India		Pakistan		Sri Lanka	
	DCC model	ADCC model	DCC model	ADCC model	DCC model	ADCC model	DCC model	ADCC model
Constant	0.013	0.017	0.015***	0.070***	0.108***	0.081***	0.004	0.015**
Lagged DCC	0.835***	0.884***	0.527***	0.481***	0.028	0.193***	0.664***	0.628***
Dummy GFC	0.018	0.013	-0.013	0.035*	0.009	0.013	0.026***	0.026**
Dummy European debt crisis	-0.013	-0.011	-0.002	0.005	0.014	0.020	-0.001	0.001
Dummy Asian financial crisis	0.001	0.002	-0.001	0.018	0.025	0.023	0.011	0.015
Trade intensity	-6.54	-6.62	0.019	0.342	1.918	3.022	18.006*	14.555
China business cycle	0.004	0.002	0.001	-0.010***	-0.009	-0.010**	-0.005**	-0.007*
Diagnostic statistics								
Q (12)	5.56	7.39	6.06	24.14	22.59	23.37	13.58	12.92
Q^2 (12)	4.21	4.84	1.06	12.64	16.23	17.04	6.16	0.36

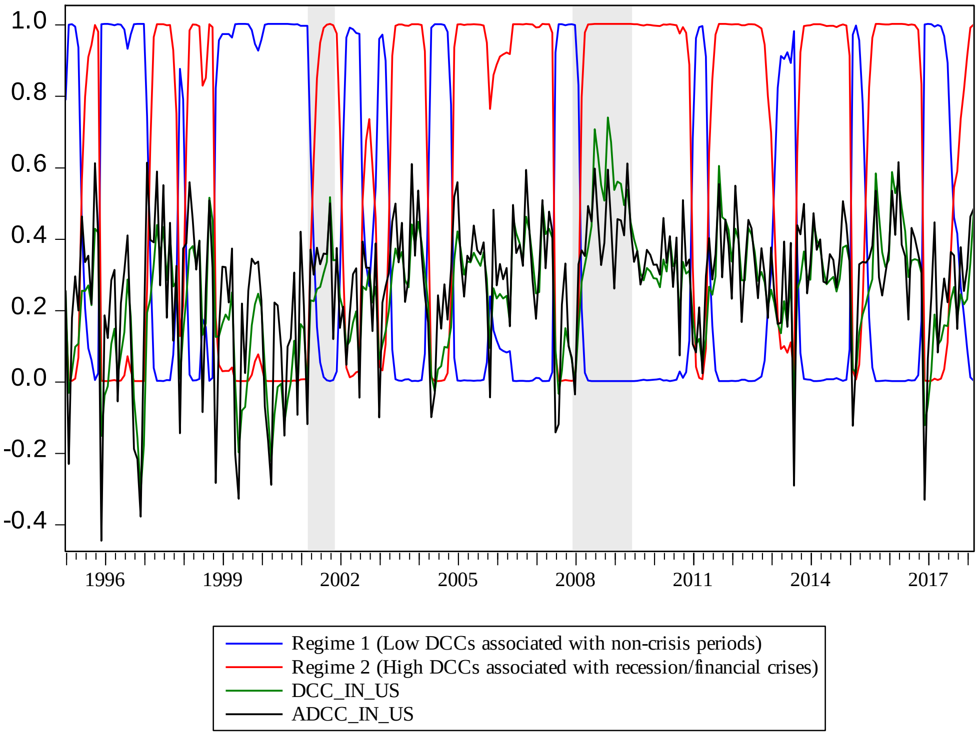


Figure A1. DCCs and filtered regime probabilities from the Markov regime-switching models (India–US): January 1995–March 2018

Notes:

a. Regimes 1 and 2 were obtained from Hamilton's (1989) Markov regime-switching model. The first-order Markov assumes that the probability of being in a regime depends on the preceding condition, so that

$$P(S_t = j|S_{t-1} = i) = p_{ij}(t) \quad \text{(A1)}$$

Probabilities can be written in a transition matrix:

$$p(t) = \begin{bmatrix} p_{11}(t) & \dots & p_{1M}(t) \\ \dots & \dots & \dots \\ p_{M1}(t) & \dots & p_{MM}(t) \end{bmatrix} \quad \text{(A2)}$$

where the ij^{th} element is the probability of moving from regime i in period $t-1$ to regime j in period t.

b. The vertical axis indicates the filtered probabilities and DCCs.

c. Shaded areas indicate NBER US recession periods and crises.

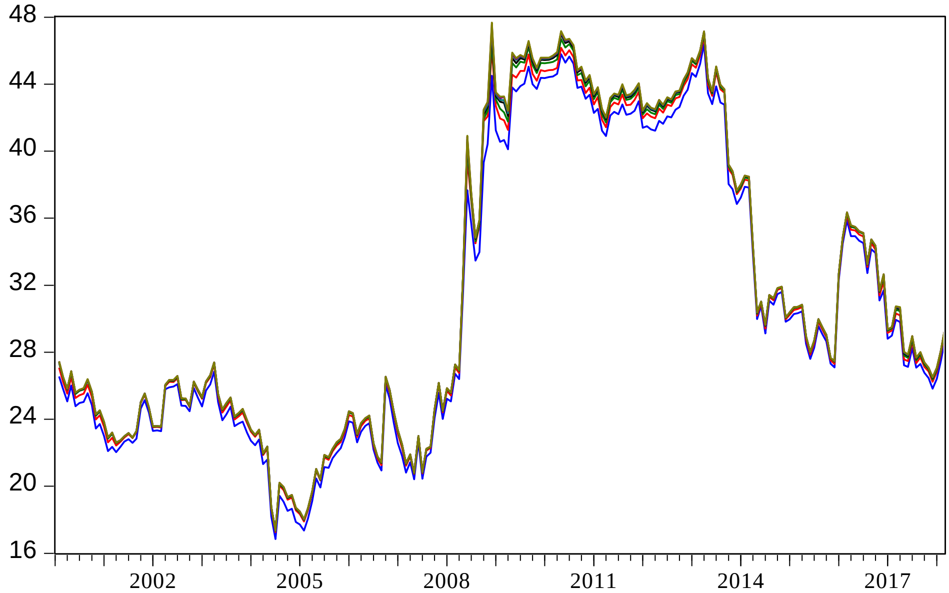


Figure A2. Sensitivity of the return spillover index to the forecast horizon (4 to 10 months): January 1995–March 2018

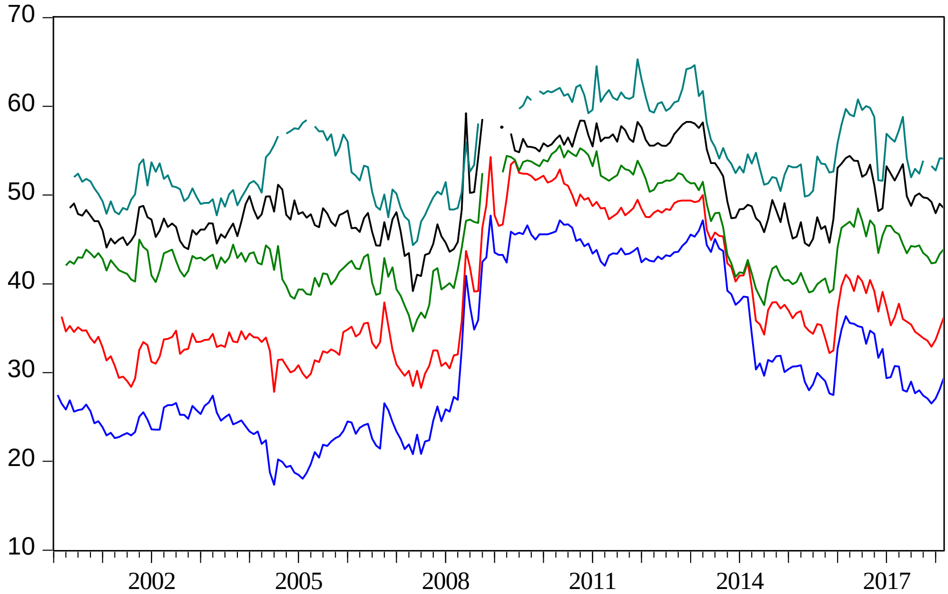


Figure A3. Sensitivity of the return spillover index to the VAR lag structure (orders of 2 to 6): January 1995–March 2018

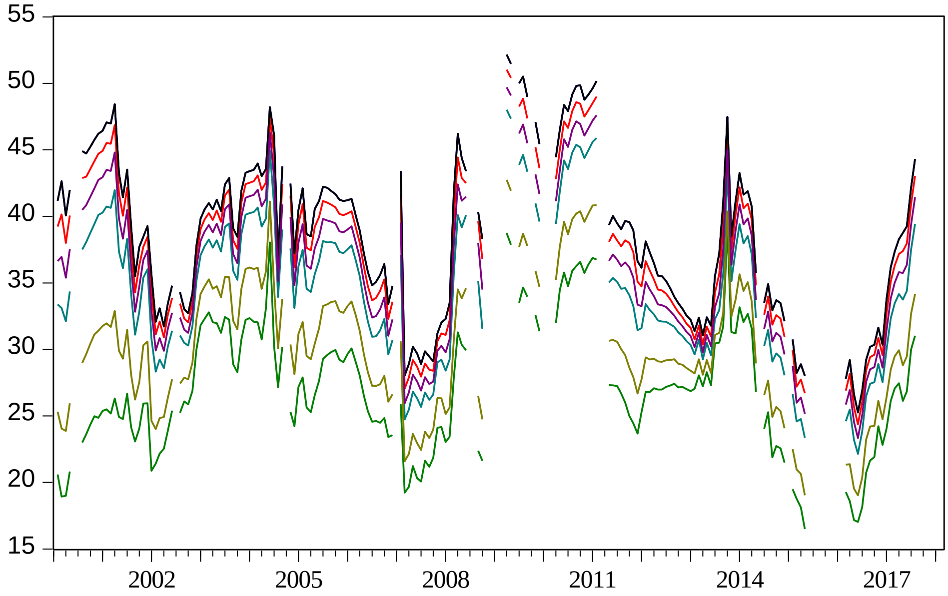


Figure A4. Sensitivity of the volatility spillover index to the forecast horizon (4 to 10 months): January 1995–March 2018

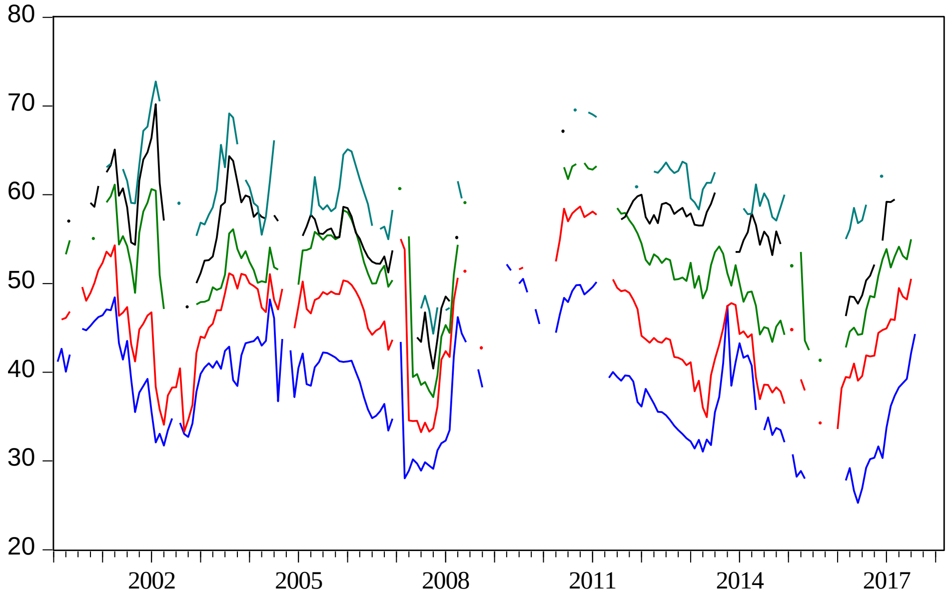


Figure A5. Sensitivity of the volatility spillover index to the VAR lag structure (orders of 2 to 6): January 1995–March 2018

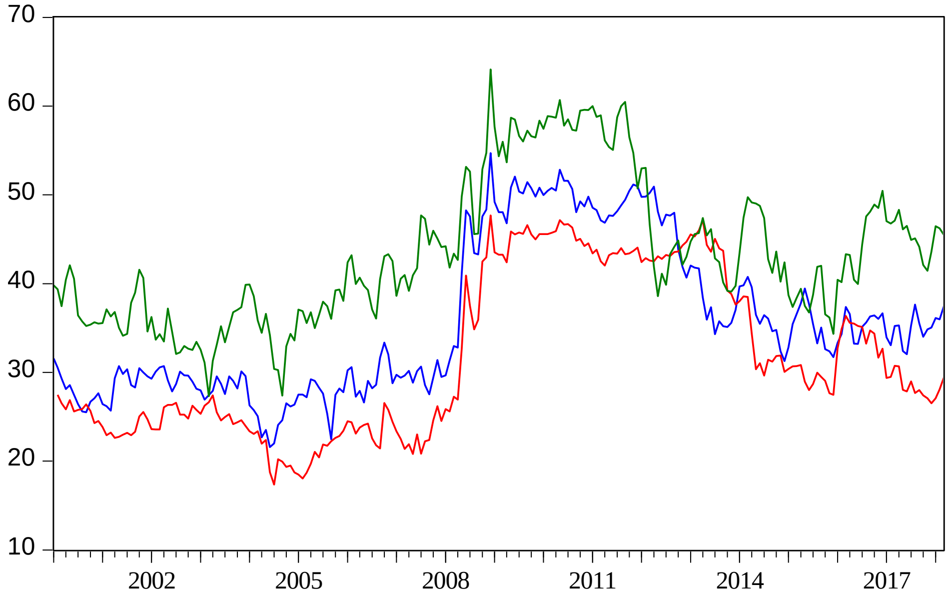


Figure A6. Sensitivity of the return spillover index to rolling windows (36, 48, and 60 months): January 1995–March 2018

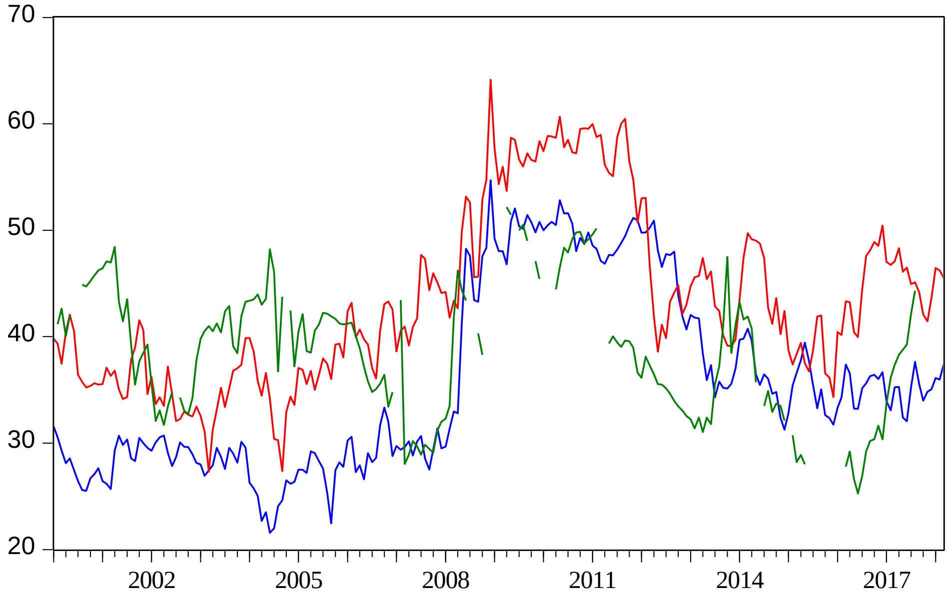


Figure A7. Sensitivity of the volatility spillover index to rolling windows (36, 48, and 60 months): January 1995–March 2018