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Explaining international stock correlations with CPI fluctuations and market volatility

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ABSTRACT

This paper investigates the dynamic correlations among six international stock market indices and their relationship to inflation fluctuation and market volatility. The current research uses a newly developed time series model, the Double Smooth Transition Conditional Correlation with Conditional Auto Regressive Range (DSTCC-CARR) model. Findings reveal that international stock correlations are significantly time-varying and the evolution among them is related to cyclical fluctuations of inflation rates and stock volatility. The higher/lower correlations emerge between countries when both countries experience a contractionary/expansionary phase or higher/lower volatilities.

1. Introduction

International stock market correlations have attracted more attention with the integration and globalization of financial markets. A wealth of qualitative literatures devoted to the intriguing connection between financial markets and economic fundamentals provide sufficient evidences that co-movement of business-cycle fluctuations impact international financial market correlations. However, the controversy continues. Debates on whether economic fundamentals such as business cycle indicators significantly affect international financial correlations, surfaced in the early 1990s, and have not yet reached a consistent agreement.

Erb et al. (1994) found that correlations between two equity markets vary according to both countries' economic cycles that economic fundamentals significantly affect stock market correlations. They show that among the G-7 countries, the highest correlations appear when both countries stand in the contractionary phase and lowest correlations appear when both countries are in the expansionary phase. Correlations vary between these two extreme states when they are out of phases. Dumas et al. (2003) highlighted the statistical evidence that output correlations and stock market correlations are positively related. Forbes and Chinn (2004) showed that direct trade is the predominant factor of the world's largest markets that affect financial markets. Yang et al. (2009) investigated dynamic interdependence between international stock and bond markets affected by real economy (represented as the business cycle, the inflation environment and monetary policy stance). Furthermore, they supplied evidence that higher stock-bond correlation coincides with higher short rates and higher inflation rates.

On the contrary, other literatures maintain skeptic upon such association between real economic linkages and financial-market linkages. King et al. (1994) suggested that co-variances between international stock markets are difficult to interpret by observable economic variables, and can reverse by unobservable variables. Ammer and Mei (1996) discovered that contemporaneous co-movement in macroeconomic variables influence co-variances between international stock markets. However, they ignore this relationship because the real linkages are much stronger in the long-run than a short-run perspective. Kizys and Pierdzioch (2006) supported Ammer and Mei, showing that the linkage between monthly conditional international equity correlations and co-movement of business-cycle fluctuations is not significant enough.

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Recent researches have also focused on the linkages between international stock correlations and market volatility. Longin and Solnik (2001) found that correlation increased in bear markets, but not in bull markets and international integration tightens the financial linkage progressively. Connolly et al. (2007) offered plentiful evidence that international stock linkages are likely higher/lower when the level of implied volatility (as a measure of stock uncertainty) stays higher and its variation is larger. Aydemir (2008) indicated that the higher the risk aversion periods, the higher the tendency for market correlations and high market volatility to emerge at the same time.

Besides, Ferreira and Gama (2007) showed that sovereign debt ratings news tends to increase the international stock market correlations. Another literature focuses on the factors explaining the stock-bond correlations. For example, see Kim et al. (2006), Li and Zou (2008) and Panchenko and Wu (2009).

Motivated by earlier conflicting reports, this research restudies the relationship between economic fundamentals as well as global stock volatility and international stock market interdependence. The current work employs a range-based multivariate volatility model by Chou and Cai (2009). The smooth transition in conditional correlation is controlled by some exogenous variables. The model maintains a parsimonious structure while allowing flexibility in specifying the dynamic evolutions of conditional correlations.

This paper is organized as follows. Section 2 introduces the model including model specifications, dynamics and tests. Section 3 discusses the data set used for the empirical research. Section 4 provides empirical results. Section 5 concludes this paper.

2. The model

Following Chou and Cai (2009), consider the Double Smooth Transition Conditional Correlation-Conditional Autoregressive Range (DSTCC-CARR) model. It is an extension of the Dynamic Conditional Correlation (DCC) model of Engle (2002). Two main features of this model are the additional efficiency in using range data (see Chou, 2005; Chou et al., 2009) and the consideration of a flexible mechanism in the correlation dynamics.

2.1. The DSTCC-CARR model

Specifically, the DSTCC-CARR model is constructed with two steps: the CARR specification for estimating volatilities and the smooth transition structure of the conditional correlation allowing more than one explanatory (or transition) variable. For the bivariate case, the CARR specification is defined as Eq. (1):

$$\begin{aligned} \Re_{i,t} &= \lambda_{i,t}\varepsilon_{i,t}, \quad \varepsilon_{i,t}|I_{t-1} \sim f(1;), \quad t = 1,2,\ldots,T;\ i = 1,2, \\ \lambda_{i,t} &= \varpi_i + \alpha_i \Re_{i,t-1} + \beta_i \lambda_{i,t-1}, \end{aligned} \tag{1}$$

where the high/low range in logarithm type, of the ith asset during time t is denoted as $\Re_{i,t}$, with a conditional mean of the range $\lambda_{i,t}$. The distribution of the disturbance term $\varepsilon_{i,t}$ is assumed to be distributed with a density function $f(\cdot)$ with a unit mean. Next, the unconditional standard deviation $\bar{\sigma}_i$ and the sampling mean of the estimated conditional range $\bar{\hat{\lambda}}_i$ are used to construct an adjustment term (adj) as a ratio. The ratio is used to scale the conditional standard deviation $\lambda^*_{i,t}$ from $\lambda_{i,t}$, the expected range from the CARR model. In other words, denote the i^{th} asset return as $r_{i,t}$ and let $z^*_{i,t}$ be defined as the standardized return:

$$z^*_{i,t} = r_{i,t}/\lambda^*_{i,t}, \quad \text{where } \lambda^*_{i,t} = adj_i \times \lambda_{i,t},\ adj_i = \bar{\sigma}_i/\bar{\hat{\lambda}}_i. \tag{2}$$

In the second stage, the standardized returns are then used to compute the conditional correlations. In Engle (2002)'s DCC model, the conditional correlations are allowed to vary according to a GARCH type dynamics. In our formulation of DSTCC, however, the correlations are governed to move smoothly among four regimes. Specifically, let s_{it} be some exogenous variable, the smooth transition structure of the conditional correlation is defined as following:

$$\begin{aligned} \boldsymbol{P_t} &= (1 - F_{L1}(s_{1t}))\boldsymbol{P}_{(1)\boldsymbol{t}} + F_{L1}(s_{1t})\boldsymbol{P}_{(2)\boldsymbol{t}}, \\ \boldsymbol{P}_{(j)\boldsymbol{t}} &= (1 - F_{L2}(s_{2t}))\boldsymbol{P}_{(j1)} + F_{L2}(s_{2t})\boldsymbol{P}_{(j2)}, \quad j = 1,2, \end{aligned} \tag{3}$$

where both transition functions are logistic:

$$F_{Lj}(s_{it}) = (1 + e^{-\gamma_j(s_{jt}-c_j)})^{-1}, \quad \gamma_j > 0,\ j = 1,2. \tag{4}$$

Two parameters, named as location parameter c_j and speed parameter γ_j, are used to control the transition from one state to the other. The larger γ_j is, the faster the correlation changes from one state to the other. If $\gamma_j \to \infty$, the transition function becomes a step function. For details, see Chou and Cai (2009).

Therefore, a DSTCC-CARR model supposes that conditional correlation has four extreme states, and switches among these four states ($\boldsymbol{P}_{(11)}, \boldsymbol{P}_{(21)}, \boldsymbol{P}_{(12)}$ and $\boldsymbol{P}_{(22)}$) smoothly under the control of two exogenous transition variables.

Once$\gamma_j = 0, j = 1 or 2$, a DSTCC-CARR model reduces to an STCC-CARR model. Taking $\gamma_1 = 0$ for example, Eq. (3) should be rewritten as Eq. (5):

$$\boldsymbol{P_t} = (1 - F_{L2}(s_{2t}))\boldsymbol{P}_1 + F_{L2}(s_{2t})\boldsymbol{P}_2, \tag{5}$$

where

$$\boldsymbol{P}_1 = \frac{1}{2}(\boldsymbol{P}_{(11)} + \boldsymbol{P}_{(21)}), \quad \boldsymbol{P}_2 = \frac{1}{2}(\boldsymbol{P}_{(12)} + \boldsymbol{P}_{(22)}).$$

To complete the model, we follow Silvennoinen and Teräsvirta (2005, 2007) in assuming a Gaussian distribution for the joint density function of the standardized returns. Quasi-maximum likelihood methods are used for estimation of the parameters and covariance matrices. The Gaussian assumption may be relaxed to allow more fat-tailed conditional density functions. Further more, more flexibility can be obtained by using the copula density functions. We do not pursue these approaches in the current study to maintain the tractability of our model.

2.2. Model specification tests

Since estimating a model with unnecessary parameters causes inefficiency, specification tests are useful before estimating the DSTCC-CARR model. The tests may help determine whether the exogenous variables are useful as transition variables. Note that some of the model parameters are not identified under the null hypothesis. Luukkonen et al. (1988) adopt a linearization by first-order Taylor expansion around speed parameters to construct the test statistics. Their strategy is followed here. The detailed specification shows as Eq. (6):

$$F_{Li} \cong 1/2 + 1/4(\gamma_i(s_{it} - c_i)) + o(\cdot), \tag{6}$$

$o(\cdot)$ is the error term above the second-order.

2.2.1. Tests for CCC against a STCC-CARR model

Based on the structure of the STCC-CARR model as in (5), this work performs a first-order Taylor approximation around $\gamma_2 = 0$ to the transition function F_{L2}. The dynamic conditional correlations could be written as (7):

$$\boldsymbol{P}^*_{\boldsymbol{t}} = \boldsymbol{P}^*_1 + s_t \boldsymbol{P}^*_2 + o(\cdot). \tag{7}$$

Under the hypothesis: $H_0 : \gamma_2 = 0$, the STCC-CARR model becomes a CCC-CARR model. The current study constructs an LM test for conditional correlation constancy against an STCC-CARR model, and the LM statistics are shown as (8):

Table 1
Specification of original six stock markets indices dataset.

Country/region	Data name	Time zone	Opening hours
France/FR	CAC 40 (CAC)	GMT + 02:00	07:30 a.m.–15:00 a.m.
Germany/GER	DAX (GDAXI)	GMT + 02:00	07:30 a.m.–15:00 a.m.
Hong Kong/HK	Hang Seng (HSI)	GMT + 08:00	02:00 a.m.–04:30 a.m., 06:30 a.m.–08:00 a.m.
Japan/JP	Nikkei 225 (N225)	GMT + 09:00	00:00 a.m.–02:00 a.m., 03:00 a.m.–06:30 a.m.
UK	FTSE 100 (FTSE)	GMT + 01:00	07:30 a.m.–15:00 a.m.
USA	500 Index (GSPC)	GMT-04:00	Daylight saving time: 01:30 p.m.–07:30 p.m. Winter time: 02:30 p.m.–08:30 p.m.

Notes: Time zone distribution and opening hours of stock markets are in Greenwich Mean Time.

$$\mathrm{LM}_{\mathrm{CCC1}} = T^{-1}\left(\sum_{t=1}^{T}\frac{\partial l_t(\hat{\boldsymbol\theta})}{\partial \boldsymbol\rho_2^{*\prime}}\right)[\hat{\boldsymbol I}_{\boldsymbol T}(\hat{\boldsymbol\theta})]^{-1}_{(\rho_2^*,\rho_2^*)}\left(\sum_{t=1}^{T}\frac{\partial l_t(\hat{\boldsymbol\theta})}{\partial \boldsymbol\rho_2^{*\prime}}\right). \tag{8}$$

The derivation of (8) is given in Appendix A.

2.2.2. Tests for CCC against a DSTCC-CARR model

Based on the structure of the DSTCC-CARR model represented as (3), this study carries out a first-order Taylor approximation around $\gamma_1 = 0$ and $\gamma_2 = 0$ to the transition function F_{L1} and F_{L2} respectively. The dynamic conditional correlations could be shown as (9):

$$\boldsymbol P_{\boldsymbol t}^* = \boldsymbol P_{(1)}^* + s_{1t}\boldsymbol P_{(2)}^* + s_{2t}\boldsymbol P_{(3)}^* + s_{1t}s_{2t}\boldsymbol P_{(4)}^* + o(\cdot). \tag{9}$$

Under the hypothesis:$H_0 : \gamma_1 = \gamma_2 = 0$, the DSTCC-CARR model simplifies as a CCC-CARR model. The LM test for constant conditional correlations against a DSTCC-CARR model is listed as (10):

$$\begin{aligned}\mathrm{LM}_{\mathrm{CCC2}} = T^{-1}&\left(\sum_{t=1}^{T}\frac{\partial l_t(\hat{\boldsymbol\theta})}{\partial(\boldsymbol\rho_{(2)}^{*\prime},\boldsymbol\rho_{(3)}^{*\prime},\boldsymbol\rho_{(4)}^{*\prime})}\right)[\hat{\boldsymbol I}_{\boldsymbol T}(\hat{\boldsymbol\theta})]^{-1}_{(\rho_{(2-4)}^*,\rho_{(2-4)}^*)}\\ &\times\left(\sum_{t=1}^{T}\frac{\partial l_t(\hat{\boldsymbol\theta})}{\partial(\boldsymbol\rho_{(2)}^{*\prime},\boldsymbol\rho_{(3)}^{*\prime},\boldsymbol\rho_{(4)}^{*\prime})}\right).\end{aligned} \tag{10}$$

The derivation of (10) is also given in Appendix A. Note that we do not consider the test of the DSTCC-CARR against a DCC model. Unlike the CCC-CARR model which is a special case of the DSTCC-CARR model, the DCC model is not nested by the DSTCC-CARR model. Comparisons of the two models will rely on other types of test statistics and are not pursued here. In this paper, we purposefully preclude the conditional correlations to fluctuate too wildly (as DCC would allow). A smoother and more tractable dynamic structure is given by our DSTCC specification, although its null of CCC may be "too" simple.

3. Data

The current study chooses six international stock markets to cover primary financial markets in the world: the US, UK, France and Germany, as representatives of developed western countries in this study, and Hong Kong and Japan, who play irreplaceable roles as Asian financial centers.[1] The data consists of three groups: a series of stock market indices, consumer price index rates and a CBOE volatility index (VIX).

3.1. Stock indices, returns and ranges

Our stock market data include daily "high, low and close" price of six stock indices. The original data was extracted from the website Yahoo, China. Table 1 presents the original dataset specification, ranging from February 2, 1991 to May 31, 2007.

Stock returns and ranges are computed by $100 \times \log(p_t^{close}/p_{t-1}^{close})$ and $100 \times \log(p_t^{high}/p_t^{low})$ respectively. To compare the correlations among different indices, this work revises the dataset by the following rules. (1) Delete daily data when some markets have missing values; (2) cut off the outliers to avoid probable estimation problem; and (3) set daily range to the mean value when there is no change during the day. Details are given in Panel A and B of Table 2 and Figs. B.1–B.3.[2] All returns and ranges exhibiting excess kurtosis and Jarque-Bera tests clearly reject the null of a Gaussian distribution in all cases, so it is appropriate to use the CARR model proposed by Chou (2005).

3.2. CPI rates

Movements in Consumer Price Index (CPI) imply whether the economy goes through inflation or not. As financial markets are absolutely influenced by macro economy trends, CPI may be a meaningful variable to build up correlations between two stock markets.

Six countries' (regions) CPI's are downloaded from the IFS[3] database. Annualized CPI rates are calculated by the formula $rate_t^{\mathrm{CPI}} = 100 \times (\mathrm{CPI}_t - \mathrm{CPI}_{t-12})/\mathrm{CPI}_{t-12}$. The sample range is from 1991.1 to 2007.4. Panel C of Table 2 and Fig. B.4 give the details of the sample. At first glance, all six countries (regions) have been in expansion phase since the early 1990s, except the USA, and all have gone through a contraction phase since the end of the 20th century. This suggests that the economy is receding in most developed countries. Hong Kong appears as having the largest volatility in the past 17 years, while France holds the most stable state among them.

For solving mismatch between monthly CPI data and daily stock market indices data, monthly CPI data are converted into daily data. We simply allow the CPI to remain constant across the whole monthly days.

3.3. Stock volatility

Since international investors are always reacting to information (including market volatility) obtained in open markets, linkages among international markets are connected with market volatility. Out of variables from past observations such as lagged returns, lagged absolute returns and so on, VIX outperforms other variables for measuring market risk. VIX is the ticker symbol for the Chicago Board Options Exchange (CBOE) volatility index, which represents market volatility expectations over the next thirty days, as well as the popular measure of implied volatility for the S&P 500 index option. Since its introduction in 1993, VIX has become the world's

[1] An older version of the study employs three other markets, including Singapore, Taiwan, and China. As two members of four little dragons in Asia, Singapore and Taiwan are selected for their contributions to the world's economy. China is involved due to its remarkable journey of becoming an open financial market since joining the WTO in 2001. For brevity, the results are not reported here but can be obtained from the authors upon requests.

[2] For the sake of brevity, we put figures of indices, returns and ranges in Appendix B.

[3] Unfortunately, CPI data of Germany in 1991 is missing, and we make use of the values from "Wind Information database, China" and generate a series of CPI rates in the same way.

Table 2
Summary statistic of the data.

	FR	GER	HK	JP	UK	USA
Panel A: return series of the six stocks (1991.2.2-2007.5.31)						
Mean	0.009	0.010	0.027	−0.020	0.003	0.022
Median	0.016	0.057	0.041	−0.022	0.023	0.041
Maximum	7.002	7.553	17.247	7.655	5.904	5.574
Minimum	−7.575	−9.871	−10.000	−7.234	−5.589	−7.113
Std. Dev.	1.296	1.371	1.559	1.428	1.005	0.982
Skewness	−0.081	−0.243	0.064	0.116	−0.104	−0.116
Kurtosis	5.839	6.841	11.461	5.244	6.366	6.806
Jarq-Bera	1111.048	2060.346	9839.907	699.267	1562.606	1997.487
Panel B: range series of the six stocks (1991.2.2-2007.5.31)						
Mean	1.506	1.456	1.568	1.609	1.211	1.206
Median	1.275	1.113	1.315	1.406	0.992	1.009
Maximum	8.795	10.872	13.724	8.929	9.937	8.479
Minimum	0.297	0.131	0.243	0.291	0.173	0.177
Std. Dev.	0.893	1.184	0.987	0.899	0.802	0.766
Skewness	2.272	2.185	2.760	2.011	2.593	2.263
Kurtosis	11.461	10.359	18.850	9.976	15.520	12.607
Jarq-Bera	12675.570	10067.950	38707.380	8911.111	25235.190	15498.620
Panel C: the six monthly annual CPI rates (1991.1-2007.4)						
Mean	1.766	2.125	3.105	0.392	2.905	2.745
Median	1.793	1.757	2.139	0.000	2.883	2.762
Maximum	3.711	6.320	12.480	4.000	8.954	5.651
Minimum	0.159	0.204	−6.159	−1.573	0.697	1.067
Std. Dev.	0.673	1.337	5.253	1.165	1.210	0.819
Skewness	0.019	1.384	0.054	1.060	1.790	0.518
Kurtosis	3.579	4.337	1.586	3.518	9.835	3.855
Jarq-Bera	2.754	77.199	16.417	38.900	486.161	14.759

Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	J-Bera
Panel D: VIX-volatility implied index (1991.2.2-2007.5.31)							
18.555	17.090	45.740	9.820	6.364	1.087	4.082	809.773

premier barometer of investor sentiment and market volatility, and is often referred to as the "investor fear gauge". Index values exceeding 30 usually relate to a large amount of volatility, attributed to investor fear or uncertainty. Contrarily, the index falling below 20 indicates less stressful, even complacent times in the markets. Panel D of Table 2 and Fig. B.5 show the details.

4. Model testing and estimation results

According to modeling specification discussed in Section 2, the current work applies DSTCC-CARR models with "Aver_CPI"[4] and "VIX" as transition variables for estimation.

4.1. Transition variables

This work mainly focuses on how correlations between two stock markets vary with different inflation cycles and worldwide stock volatility. Therefore, two transition variables are adopted: (1) "Aver_CPI": average value of both countries' CPI rates, is defined by Aver_CPI = (CPI1 + CPI2)/2; and (2) "VIX": is used as a common indicator of the worldwide stock volatility.

Empirically, varying stock interdependence may be decomposed into two parts. One is high frequency changes related to the micro level of stock market movements, e.g., investor decision in terms of adverse selection, inventory costs, market power, and transaction costs. The other is low frequency (medium frequency) movements dominated by global macroeconomic shocks e.g., shifts in fundamentals, economic trends or preference changes, etc. To accommodate both of these two types of changes, the current research employs the above mentioned two transition variables. The variable VIX is a forward looking indicator of market risk. This index updates nearly every day as feedback for investors' expectations of future market uncertainty, so that it is a response to the high frequency variation of international stock correlations. On the other hand, CPI reflects both countries' recent inflation and contains the information spread from real economy to financial markets. Macroeconomic influences usually penetrate gradually and evolve over time. As a result, it is more likely to capture low (medium) frequency changes, sometimes lasting several months or more.[5] Other variables such as GDP and interest rates may also be considered. However, the CPI variable turns out to be more useful empirically. To maintain the model tractability, this study does not pursue cases with more than two transition variables.

Table 3
Results for CCC tests against STCC-CARR (DSTCC-CARR) models.

	Aver_CPI (p-value)	VIX (p-value)	VIX and Aver_CPI (p-value)
FR_GER	**0.000**	**0.000**	**0.000**
FR_HK	**0.013**	**0.006**	**0.000**
FR_JP	**0.001**	0.333	**0.001**
FR_UK	**0.001**	**0.000**	**0.000**
FR_USA	**0.022**	**0.098**	**0.001**
GER_HK	0.682	0.278	**0.001**
GER_JP	**0.000**	**0.001**	**0.000**
GER_UK	**0.000**	**0.000**	**0.000**
GER_USA	**0.000**	**0.000**	**0.000**
HK_JP	**0.000**	**0.000**	**0.000**
HK_UK	**0.001**	**0.000**	**0.000**
HK_USA	**0.006**	0.258	**0.039**
JP_UK	**0.006**	0.354	**0.020**
JP_USA	**0.019**	**0.013**	**0.000**
UK_USA	0.223	0.909	0.634

[4] We also try the transition variables forming of multiplying CPI rates, and the similar results are obtained. Results are available upon request.

[5] In a previous version of this paper, a time trend is considered as a transition variable. However, combined with the specification of the logistic transition function, such a model implies that the correlation between two stock markets should increase or decrease with calendar time monotonously. Hence it is not realistic in describing the real markets.

Table 4
LR test for STCC-CARR model against DSTCC-CARR model.

Log likelihood of the models			LR statistics			
STCC CARR (CPI)	STCC CARR (VIX)	DSTCC CARR	LR_{CPI}	P_{CPI}	LR_{VIX}	P_{VIX}
−8014.186	−8017.458	−7979.180	76.557	0.000	70.012	0.000
−9030.749	−9073.163	−9012.655	121.017	0.000	36.188	0.000
−8973.813	−8974.783	−8964.619	20.329	0.000	18.388	0.000
−10604.381	−10599.835	−10590.678	18.314	0.000	27.406	0.000
−10659.538	−10661.627	−10651.779	19.697	0.000	15.518	0.000
−8524.653	−8564.267	−8519.952	88.631	0.000	9.404	0.002
−8039.480	−8039.222	−8029.962	18.520	0.000	19.037	0.000
−9664.087	−9666.138	−9652.363	27.551	0.000	23.448	0.000
−9721.289	−9723.546	−9710.277	26.539	0.000	22.024	0.000
−9037.163	−9048.484	−9015.496	65.975	0.000	43.334	0.000
−10614.404	−10614.447	−10591.438	46.018	0.000	45.932	0.000
−10711.365	−10722.819	−10704.922	35.794	0.000	12.886	0.000
−9505.333	−9508.165	−9495.682	24.966	0.000	19.303	0.000
−9528.893	−9531.991	−9525.459	13.063	0.000	6.867	0.009
−10844.897	−10879.522	−10828.210	102.623	0.000	33.374	0.000

Table 5
Estimation results of DSTCC-CARR with Aver_CPI and VIX as transition variables.

Part I	Range parameters (former)			Range parameters (latter)										
	ϖ_1	α_1	β_1	ϖ_2	α_2	β_2	ρ_1	ρ_2	ρ_3	ρ_4	c_1	c_2	γ_1	γ_2
FR_GER	0.120	0.126	0.778	0.166	0.095	0.765	0.989	0.783	0.426	0.728	0.884	11.451	0.612	0.101
	(0.024)	(0.020)	(0.037)	(0.028)	(0.015)	(0.038)	(0.035)	(0.012)	(0.079)	(0.024)	(0.215)	(0.457)	(0.267)	(0.043)
FR_HK	0.075	0.140	0.797	0.020	0.108	0.867	0.217	0.090	0.476	0.341	5.499	16.071	0.685	0.314
	(0.017)	(0.024)	(0.036)	(0.008)	(0.014)	(0.018)	(0.098)	(0.050)	(0.047)	(0.022)	(0.269)	(0.659)	(0.321)	(0.211)
FR_JP	0.095	0.171	0.750	0.043	0.142	0.824	−0.630	0.102	0.473	0.199	1.119	20.557	384.195	1.208
	(0.021)	(0.029)	(0.044)	(0.013)	(0.017)	(0.022)	(0.247)	(0.095)	(0.083)	(0.019)	(0.011)	(0.235)	(26.659)	(0.775)
FR_UK	0.061	0.092	0.857	0.064	0.105	0.826	0.838	0.662	0.598	0.916	2.558	17.929	3.190	0.016
	(0.015)	(0.016)	(0.027)	(0.011)	(0.013)	(0.023)	(0.018)	(0.036)	(0.029)	(0.024)	(0.048)	(0.392)	(1.030)	(0.004)
FR_USA	0.092	0.153	0.770	0.026	0.114	0.852	0.249	0.397	0.785	0.412	2.329	11.423	7.420	0.612
	(0.020)	(0.025)	(0.039)	(0.007)	(0.014)	(0.019)	(0.070)	(0.037)	(0.065)	(0.022)	(0.063)	(0.285)	(2.826)	(0.329)
GER_HK	0.125	0.107	0.788	0.012	0.105	0.875	0.251	0.402	0.866	0.221	2.353	16.014	0.077	500.000
	(0.022)	(0.018)	(0.035)	(0.006)	(0.012)	(0.016)	(0.431)	(0.030)	(0.126)	(0.079)	(0.661)	(0.021)	(0.068)	(23.472)
GER_JP	0.126	0.103	0.790	0.045	0.141	0.825	0.430	−0.011	0.989	0.317	4.067	31.905	0.113	3.863
	(0.023)	(0.018)	(0.036)	(0.013)	(0.017)	(0.022)	(0.779)	(0.046)	(0.223)	(0.109)	(0.707)	(0.106)	(0.097)	(1.182)
GER_UK	0.142	0.092	0.790	0.076	0.120	0.799	0.988	0.713	0.047	0.514	1.621	10.631	0.479	0.145
	(0.024)	(0.015)	(0.034)	(0.014)	(0.016)	(0.028)	(0.076)	(0.014)	(0.248)	(0.035)	(0.159)	(0.983)	(0.175)	(0.083)
GER_USA	0.134	0.101	0.786	0.026	0.119	0.847	0.792	0.741	0.244	0.443	1.689	15.815	32.344	0.042
	(0.024)	(0.017)	(0.037)	(0.007)	(0.015)	(0.020)	(0.079)	(0.047)	(0.036)	(0.032)	(0.016)	(0.652)	(8.623)	(0.025)
HK_JP	0.013	0.108	0.872	0.039	0.124	0.846	0.594	0.151	0.968	0.518	5.234	20.209	0.276	75.587
	(0.006)	(0.013)	(0.017)	(0.011)	(0.014)	(0.019)	(0.211)	(0.041)	(0.020)	(0.017)	(0.206)	(0.023)	(0.094)	(1.063)
HK_UK	0.023	0.110	0.863	0.045	0.123	0.825	−0.178	0.430	0.572	0.114	1.453	15.933	0.069	7.094
	(0.008)	(0.014)	(0.019)	(0.009)	(0.016)	(0.023)	(0.183)	(0.028)	(0.088)	(0.062)	(0.318)	(0.074)	(0.026)	(1.057)
HK_USA	0.017	0.104	0.873	0.020	0.111	0.862	−0.758	0.803	0.487	0.346	7.822	16.759	2.837	0.271
	(0.007)	(0.014)	(0.018)	(0.006)	(0.015)	(0.020)	(0.214)	(0.183)	(0.041)	(0.018)	(0.110)	(0.225)	(1.274)	(0.092)
JP_UK	0.042	0.140	0.827	0.047	0.126	0.820	0.873	0.453	−0.259	0.199	1.265	17.544	396.768	4.952
	(0.012)	(0.016)	(0.021)	(0.010)	(0.017)	(0.025)	(0.172)	(0.068)	(0.136)	(0.018)	(0.009)	(0.133)	(3.141)	(2.785)
JP_USA	0.037	0.136	0.834	0.018	0.105	0.870	0.761	0.398	0.109	0.329	1.551	11.057	496.311	0.234
	(0.011)	(0.016)	(0.020)	(0.006)	(0.014)	(0.018)	(0.145)	(0.083)	(0.059)	(0.028)	(0.009)	(3.458)	(5.911)	(1.135)
UK_USA	0.052	0.126	0.815	0.022	0.116	0.854	0.184	0.852	0.384	0.416	3.622	16.441	14.242	0.070
	(0.010)	(0.016)	(0.024)	(0.006)	(0.015)	(0.020)	(0.091)	(0.172)	(0.033)	(0.022)	(0.098)	(0.384)	(5.346)	(0.034)

4.2. Time zone and CCC tests

Obviously, stock markets in the current model locate in different regions and time zones. Table 1 shows Greenwich Mean Time as the benchmark for measuring stock market opening hours. Stock market opening hours in Asia do not overlap with NYSE's, while those in Europe overlap with NYSE's one hour and a half. Asian and European markets present a similar situation.

This work accounts for time zone effect and makes the adjustment[6] described above for cases without overlap. Reversely, this work neglects time zone effect as long as two markets have concurrent opening hours.[7]

4.3. Model specification test

Are "Aver_CPI" and "VIX" competent for this research? Does the DSTCC-CARR model with inflation cycle and global volatility indicators as transition variables outperform the STCC-CARR model with these two indicators separately? Answering these questions requires some preliminary tests.

This study introduces the CCC tests for the constant conditional correlation null hypothesis in the STCC-CARR model and DSTCC-

6 Taking the case "US_HK" for example, the series of stock markets in Hong Kong open 12 h earlier than American markets, so returns and ranges are lagged one period in estimation.

7 Via this channel, for the cases of "FR_JP", "UK_JP", "GER_JP", "USA_HK" and "USA_JP", both returns and ranges of the latter stock markets are lagged one period, taking time zone effect into account. Appendix C provides more details.

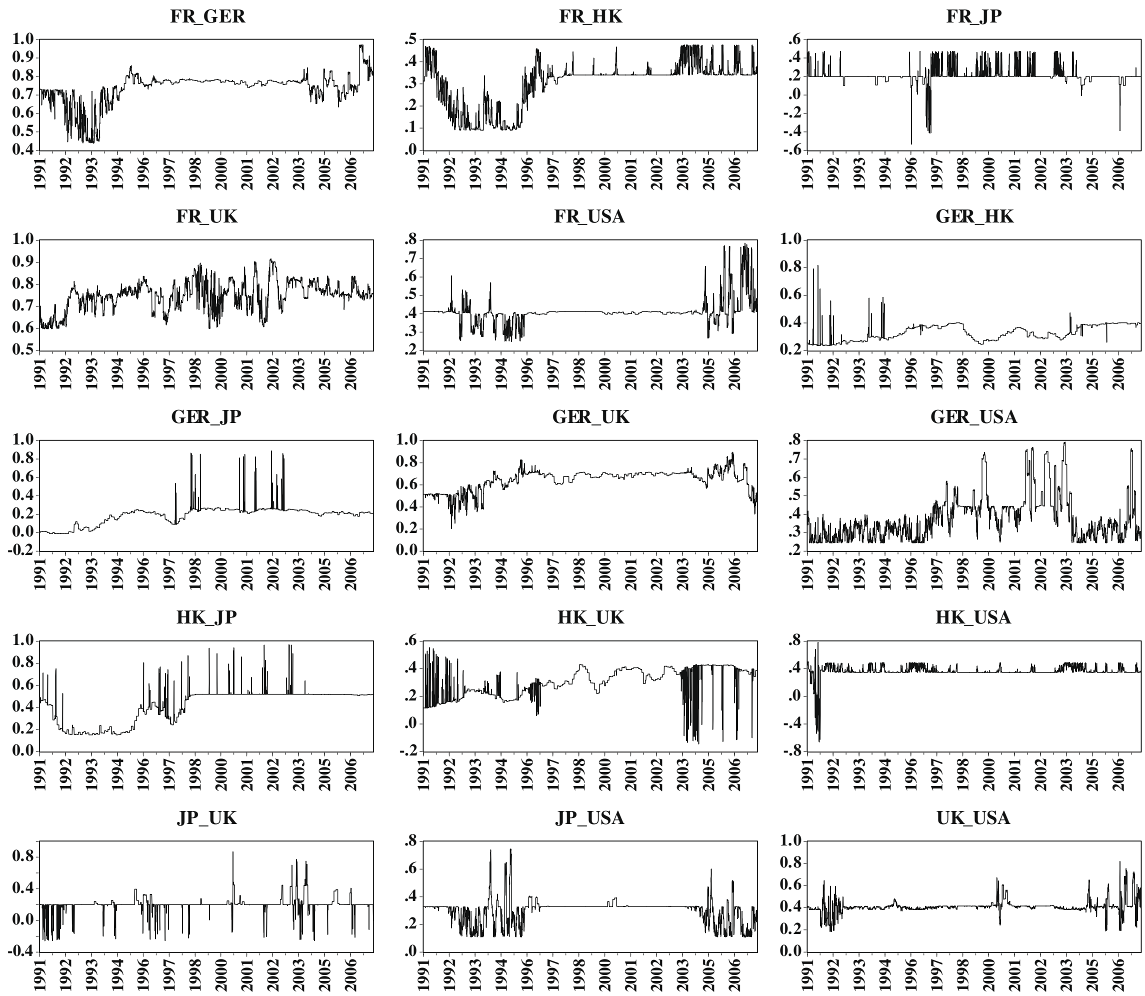

Fig. 1. Conditional correlations under DSTCC-CARR model with "Aver_CPI" and "VIX" as transition variables.

CARR model and gives the LM statistics in Eqs. (8) and (10). Results reported in Table 3 indicate that 13 out of 15 cases reject the CCC null hypothesis against the STCC-CARR model with "Aver_CPI" as the transition variable at a remarkable level of 5%,[8] and nine out of 15 cases reject the constant conditional correlation null hypothesis against the STCC-CARR model with "VIX" as the transition variable at a remarkable level of 5%. After introducing both transition variables to construct a DSTCC-CARR model, all the components except for the "UK_USA" case reject the CCC null hypothesis at the significant level of 5%. As examined above, the correlations between two stock markets truly have changed with inflation cycle and market volatility.

To testify whether the DSTCC-CARR model outperforms the STCC-CARR model, this work applies the LR tests. Table 4 gives LR statistics. Looking over 15 pair wise instances, all cases prefer the DSTCC-CARR models, implying that "Aver_CPI" and "VIX" both have indispensable effects on stock correlations. Ignoring either of their influence may make the model less convictive.

To sum up, modeling specifications should mention three points. Firstly, it's important to account for time zone effect for those components without overlapping opening hours. Secondly, "Aver_CPI" and "VIX" are useful in explaining the variations in conditional correlations between international stock market indices. Finally, compared to the STCC-CARR models, the DSTCC-CARR model proves to be more appropriate for the current application.

4.4. Model estimation

Table 5 reports the estimation results and Fig. 1 provides relevant conditional correlations.

The DSTCC-CARR model's estimation results show that coefficients in conditional range equations are significant, and the revealed characteristics are consistent with what earlier literatures report concerning the range-based volatility model. The detailed content is described in Chou (2005). As expected, most coefficients of the four extreme correlation states are significant at a 95% level. The states are different from each other, suggesting that stock correlations could be attributed to changing inflation cycles and market volatility. This paper uses speed coefficients to suggest how fast correlations transit from one state to the other. With "Aver_CPI" and "VIX" as transition variables, speed coefficients are small but significant, implying that transitions are smooth. This research cites location coefficients to indicate the sensitivity of asymmetries to inflation cycle and volatility phases. If the coefficients are larger than mean values of transition variables, the correlations between stock markets will remain stable in the state with low inflations or low volatilities. Both countries experiencing large inflations or suffering from a strong fluctuation would make stock correlations move towards high inflations or high volatilities. By contrast, correlations would stay steady with high inflation or high volatilities for a longer time. Combined with estimating results, this research

[8] By multiplying CPI rates instead of their mean value, this study constructs another transition variable to replace the "Aver_CPI". The tests are repeated and similar results are obtained. For the sake of brevity, the results are not reported but can be obtained from the authors.

Table 6
Average correlations grouped by inflation cycle and stock volatility.

	Inflation cycle			Stock volatility	
	Expansion	Out of phases	Contraction	High volatility	Low volatility
FR_GER	0.633	0.742	**0.789**	**0.769**	0.713
FR_HK	0.226	0.318	**0.349**	**0.333**	0.280
FR_JP	0.210	0.204	**0.217**	**0.236**	0.190
FR_UK	0.730	**0.762**	0.743	**0.754**	0.744
FR_USA	0.421	0.382	**0.429**	0.407	**0.412**
GER_HK	0.272	**0.364**	0.335	0.324	**0.328**
GER_JP	0.048	0.189	**0.244**	**0.227**	0.156
GER_UK	0.500	0.639	**0.707**	**0.676**	0.621
GER_USA	0.303	0.327	**0.468**	**0.459**	0.317
HK_JP	0.270	0.363	**0.521**	**0.482**	0.358
HK_USA	0.348	**0.369**	0.366	0.354	**0.368**
HK_UK	0.218	0.319	**0.353**	**0.333**	0.283
JP_UK	0.169	0.202	**0.225**	**0.212**	0.196
JP_USA	0.277	0.306	**0.307**	**0.331**	0.276
UK_USA	**0.414**	0.410	0.405	**0.421**	0.401

divides the 15 pair-wise cases into several groups. The values of c_1 demonstrate that linkages of components "FR_GER", "GER_UK", "GER_USA" and "HK_UK" tend to adhere to states with high inflations, while linkages of components "FR_HK", "HK_JP", "HK_USA" and "UK_ USA" are likely to stay at the state with low inflations. The remaining cases are not sensitive to either of the states. The values of c_2 indicate that only "GER_JP" is sensitive to high volatilities while "FR_GER", "FR_USA", "GER_UK" and "JP_USA" are sensitive to low volatilities. The remaining cases stay neutral.

To investigate how the correlations vary with different inflation cycle phases and volatilities, the current work distinguishes contraction from expansion by comparing daily CPI rates with their mean CPI. If daily CPI rate is above its mean, it is in expansionary phase, otherwise, it is in contractionary phase. Three symbols are defined to represent these phases. "Up–up" means both countries are in expansionary phase and "Down–down" means both countries are in contractionary phase. If one country is in expansionary phase and the other is in contractionary phase, the symbol "Out of phases" is denoted. Average correlations in these three phases are computed and saved in Table 6 and this study analyzes the results. Observations show that 11 out of 15 cases appear in highest correlation if both countries are in contractionary phase, while 12 out of 15 cases present the lowest correlation if they are in expansionary phase. Ten out of 15 cases show moderate correlations when two countries are out of phases. Although measured by a different economic fundamental indicator, the results are consistent with Erb et al. (1994).

Moreover, this work calculates the average correlation in the periods with high and low volatilities according to whether the value of "VIX" is larger than its mean or not. Table 6 shows strong support for the fact that higher correlation goes with higher volatility, which is identical with the literature mentioned above. Twelve out of 15 cases show higher correlation when volatility exceeds its average level.

Estimation results affirm that interdependence between international stock markets is related to the inflation cycle as well as stock volatility. In the literature, several other factors are proposed in explaining the stock market interdependence. First, low correlations across international stock markets may attribute to global portfolio diversification. To reduce their total portfolio risk, investors are willing to diversify across national markets with low correlation of returns. Solnik et al. (1996) proves that the linkage occurring between correlation and market volatility is bad news for global money managers. Investors may insist on diversifying whenever both countries are in the booming period. Aydemir (2008) finds counter–cyclical variation between international financial and fundamental linkages for risk sharing. Secondly, a constant relative risk aversion (CRRA) investor may make out-of-sample portfolio decisions with skewness and asymmetric dependence effects. Patton (2004) has found evidence that these characteristics may impact on portfolio decisions. As a result, investors may make different decisions on international stock portfolios from downturns to upturns, which would induce international stock correlations to vary according to real sector adjustments. Finally, emerging equity markets could impact on real economy. Bekaert and Harvey (2003) in related literature cited a quantity of cases approving that liberalization in financial markets brings on real economic growth. Interdependence of international financial markets from the world economic relationship cannot be separated.

5. Conclusions

This paper investigates the relationship between real and financial linkages. We use average CPI rates and VIX as transition variables in our model. Empirical results prove the DSTCC-CARR model to be effective. CCC models are rejected in favor of STCC-CARR and DSTCC-CARR formulations. The tests also indicate that the DSTCC-CARR model with both transition variables to outperform the STCC-CARR model with either of the two variables alone.

By analyzing the estimated results, this study collects ample evidence on varying correlations among different inflation cycle phases. Our results are consistent with those of Erb et al. (1994) that highest correlations appear when both countries are in the contractionary phase and lowest correlations emerge when both countries are in the expansionary phase. Correlations are also violent during periods with different volatilities, coinciding with Connolly et al. (2007). Future research could employ other indicators of economic fundamentals such as output and interest rates in our model. Other extensions like considering a richer specification with both countries' inflation rates as transition variables would also be useful.

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Appendix A. Hypothesis testing

A.1. Tests for CCC against a STCC-CARR model

Suppose structure of the STCC-CARR model is described as Eq. (5). It is a CCC-CARR model under the hypothesis: $H_0 : \gamma_2 = 0$. We make a first-order Taylor approximation around $\gamma_2 = 0$ to the transition function F_{L2}. After the linearization, the dynamic correlations matrix can be given as (A.1):

$$\boldsymbol{P}_t^* = \boldsymbol{P}_1^* + s_t \boldsymbol{P}_2^*,$$
$$\boldsymbol{P}_1^* = \frac{1}{2}(\boldsymbol{P}_1 + \boldsymbol{P}_2) + \frac{1}{4}c(\boldsymbol{P}_1 - \boldsymbol{P}_2)\gamma, \quad \boldsymbol{P}_2^* = \frac{1}{4}(\boldsymbol{P}_1 - \boldsymbol{P}_2)\gamma. \tag{A.1}$$

Thus we construct an auxiliary null hypothesis: $H_0^{aux} : \boldsymbol{\rho}_2^* = \boldsymbol{0}$, which stands for the constant correlation. This null hypothesis can be tested by an LM test.

Let $\boldsymbol{\rho}^* = (\boldsymbol{\rho}_1^{*\prime}, \boldsymbol{\rho}_2^{*\prime})$ be the vectors holding unique off-diagonal elements in the two matrices $\boldsymbol{P}_1^*, \boldsymbol{P}_2^*$, where $\boldsymbol{\rho}_i^* = \boldsymbol{vecl}(\boldsymbol{P}_i^*), i = 1, 2$. Therefore, $\boldsymbol{\theta} = (\omega_1', \ldots, \omega_N', \boldsymbol{\rho}^{*\prime})'$ is denoted as the full parameter vector and $\boldsymbol{\theta}_0$ the corresponding vector of true parameters under the null hypothesis.

After the linearization, the log-likelihood function could be rewritten as:

$$l_t(\boldsymbol{\theta}) = -\frac{N}{2}\log(2\pi) - \frac{1}{2}\sum_{i=1}^{N}\log\lambda_{it} - \frac{1}{2}\log|\boldsymbol{P}_t^*| - \frac{1}{2}\boldsymbol{z}_t^{*\prime}\boldsymbol{P}_t^{*-1}\boldsymbol{z}_t^*.$$

Therefore, we construct the LM statistics based on the partial derivatives of log-likelihood function with respect to $\boldsymbol{\omega}_i$ and $\boldsymbol{\rho}^*$. One could find the details in Chou and Cai (2009) and Silvennoinen and Teräsvirta (2007). The LM statistic is listed as (A.2):

$$\mathrm{LM}_{\mathrm{CCC1}} = T^{-1}\left(\sum_{t=1}^{T}\frac{\partial l_t(\hat{\boldsymbol{\theta}})}{\partial \boldsymbol{\rho}_2^{*\prime}}\right)[\hat{\boldsymbol{I}}_T(\hat{\boldsymbol{\theta}})]^{-1}_{(\boldsymbol{\rho}_2^*,\boldsymbol{\rho}_2^*)}\left(\sum_{t=1}^{T}\frac{\partial l_t(\hat{\boldsymbol{\theta}})}{\partial \boldsymbol{\rho}_2^{*\prime}}\right). \tag{A.2}$$

$\hat{\boldsymbol{I}}_T(\hat{\boldsymbol{\theta}})$ is a consistent estimator of the asymptotic information matrix, and $[\hat{\boldsymbol{I}}_T(\hat{\boldsymbol{\theta}})]^{-1}_{(\boldsymbol{\rho}_2^*,\boldsymbol{\rho}_2^*)}$ is the south-east $\frac{N(N-1)}{2} \times \frac{N(N-1)}{2}$ block of the inverse of $\hat{\boldsymbol{I}}_T$. The LM statistic has an asymptotic χ^2 distribution with $\frac{N(N-1)}{2}$ degrees of freedom. For the bivariate case, $N = 1$.

A.2. Tests for CCC against a DSTCC-CARR model

As the same way, suppose structure of the STCC-CARR model is described as Eq. (3). It is a CCC-CARR model under the hypothesis: $H_0 : \gamma_1 = \gamma_2 = 0$. We make the first-order Taylor approximation around $\gamma_1 = 0$ and $\gamma_2 = 0$ to the transition function F_{L1} and F_{L2} respectively. After the linearization, the dynamic correlations matrix can be given as (A.3):

$$\boldsymbol{P}_t^* = \boldsymbol{P}_{(1)}^* + s_{1t}\boldsymbol{P}_{(2)}^* + s_{2t}\boldsymbol{P}_{(3)}^* + s_{1t}s_{2t}\boldsymbol{P}_{(4)}^*, \tag{A.3}$$

where the four correlation states can be illustrated as follows:

$$\begin{aligned}
\mathbf{P}_{(1)}^* &= 1/4(\mathbf{P}_{(11)} + \mathbf{P}_{(12)} + \mathbf{P}_{(21)} + \mathbf{P}_{(22)}) \\
&\quad + 1/8c_1\gamma_1(\mathbf{P}_{(11)} + \mathbf{P}_{(12)} - \mathbf{P}_{(21)} - \mathbf{P}_{(22)}) \\
&\quad + 1/8c_2\gamma_2(\mathbf{P}_{(11)} - \mathbf{P}_{(12)} + \mathbf{P}_{(21)} - \mathbf{P}_{(22)}) \\
&\quad + 1/16c_1\gamma_1c_2\gamma_2(\mathbf{P}_{(11)} - \mathbf{P}_{(12)} - \mathbf{P}_{(21)} + \mathbf{P}_{(22)}), \\
\mathbf{P}_{(2)}^* &= -1/8\gamma_1(\mathbf{P}_{(11)} + \mathbf{P}_{(12)} - \mathbf{P}_{(21)} - \mathbf{P}_{(22)}) \\
&\quad - 1/16c_2\gamma_1\gamma_2(\mathbf{P}_{(11)} - \mathbf{P}_{(12)} - \mathbf{P}_{(21)} + \mathbf{P}_{(22)}), \\
\mathbf{P}_{(3)}^* &= -1/8\gamma_2(\mathbf{P}_{(11)} - \mathbf{P}_{(12)} + \mathbf{P}_{(21)} - \mathbf{P}_{(22)}) \\
&\quad - 1/16c_1\gamma_1\gamma_2(\mathbf{P}_{(11)} - \mathbf{P}_{(12)} - \mathbf{P}_{(21)} + \mathbf{P}_{(22)}), \\
\mathbf{P}_{(4)}^* &= -1/16\gamma_1\gamma_2(\mathbf{P}_{(11)} - \mathbf{P}_{(12)} - \mathbf{P}_{(21)} + \mathbf{P}_{(22)}).
\end{aligned}$$

Under the null hypothesis there are: $\mathbf{P}_{(1)}^* = 1/4(\mathbf{P}_{(11)} + \mathbf{P}_{(12)} + \mathbf{P}_{(21)} + \mathbf{P}_{(22)})$, $\mathbf{P}_{(2)}^* = \mathbf{0}_{N\times N}$, $\mathbf{P}_{(3)}^* = \mathbf{0}_{N\times N}$ and $\mathbf{P}_{(4)}^* = \mathbf{0}_{N\times N}$. Thus we construct the auxiliary null hypothesis: $H_0^{aux} : \boldsymbol{\rho}_{(2)}^* = \boldsymbol{\rho}_{(3)}^* = \boldsymbol{\rho}_{(4)}^* = \mathbf{0}$. The null hypothesis can be tested by an LM test. Let $\boldsymbol{\rho}^* = (\boldsymbol{\rho}_{(1)}^{*\prime}, \boldsymbol{\rho}_{(2)}^{*\prime}, \boldsymbol{\rho}_{(3)}^{*\prime}, \boldsymbol{\rho}_{(4)}^{*\prime})'$ be the vectors holding unique off-diagonal elements in the four matrices $\boldsymbol{P}_{(1)}^*, \boldsymbol{P}_{(2)}^*, \boldsymbol{P}_{(3)}^*$ and $\boldsymbol{P}_{(4)}^*$, where $\boldsymbol{\rho}_{(\mathbf{i})}^* = \boldsymbol{vecl}(\boldsymbol{P}_{(\mathbf{i})}^*), i = 1, \ldots, 4$. Therefore, $\boldsymbol{\theta} = (\omega_1', \ldots, \omega_N', \boldsymbol{\rho}^{*\prime})'$ is denoted as the full parameter vector and $\boldsymbol{\theta}_0$ the corresponding vector of true parameters under the null hypothesis.

Therefore, we construct the LM statistics based on the partial derivatives of log-likelihood function with respect to $\boldsymbol{\omega}_\mathbf{i}$ and $\boldsymbol{\rho}^*$. One could check Chou and Cai (2009) and Silvennoinen and Teräsvirta (2007) for the details. The LM statistic is represented as (A.4):

$$\begin{aligned}
\mathrm{LM}_{\mathrm{CCC2}} = T^{-1}&\left(\sum_{t=1}^{T}\frac{\partial l_t(\hat{\boldsymbol{\theta}})}{\partial(\boldsymbol{\rho}_{(2)}^{*\prime}, \boldsymbol{\rho}_{(3)}^{*\prime}, \boldsymbol{\rho}_{(4)}^{*\prime})}\right)[\hat{\boldsymbol{I}}_T(\hat{\boldsymbol{\theta}})]^{-1}_{(\boldsymbol{\rho}_{(2-4)}^*,\boldsymbol{\rho}_{(2-4)}^*)} \\
&\times\left(\sum_{t=1}^{T}\frac{\partial l_t(\hat{\boldsymbol{\theta}})}{\partial(\boldsymbol{\rho}_{(2)}^{*\prime}, \boldsymbol{\rho}_{(3)}^{*\prime}, \boldsymbol{\rho}_{(4)}^{*\prime})}\right).
\end{aligned} \tag{A.4}$$

$\hat{\boldsymbol{I}}_T(\hat{\boldsymbol{\theta}})$ is a consistent estimator of the asymptotic information matrix, and $[\hat{\boldsymbol{I}}_T(\hat{\boldsymbol{\theta}})]^{-1}_{(\boldsymbol{\rho}_{(2-4)}^*,\boldsymbol{\rho}_{(2-4)}^*)}$ is the south-east $\frac{3N(N-1)}{2} \times \frac{3N(N-1)}{2}$ block of the inverse of $\hat{\boldsymbol{I}}_T$. The LM statistic has an asymptotic χ^2 distribution with $\frac{3N(N-1)}{2}$ degrees of freedom.

Appendix B. Data description

(See Figs. B.1–B.5).

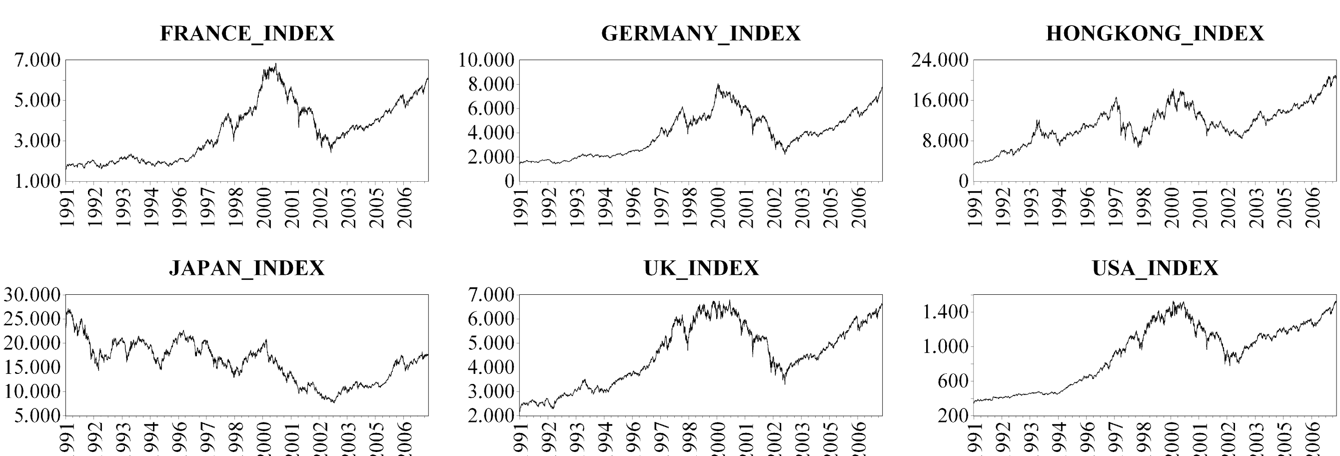

Fig. B.1. Six indices (1991.2.1-2007.5.31).

Appendix C. Time zone effects

We divide six stock markets into three groups according to the continent they locate in. Respect to the inner-group cases, time zone effect is supposed to be ignored, because the markets almost open at the same time. Correspondingly, the cross-group cases are likely to be affected by time zone, as we purpose, of which there are totally 11 cases probably involved in for analysis.

The results are reported in Table C.1. We make a comparison between the results with and without time zone effect taken into account, and the answer is straightforward. Correlations between American and Asian markets are found to increase largely if we take time zone effect into account, and the statistical value of CCC tests in both cases are improved intensely. Contrarily, after being adjusted for sake of time zone effect, correlations between American and European countries decline significantly, with no

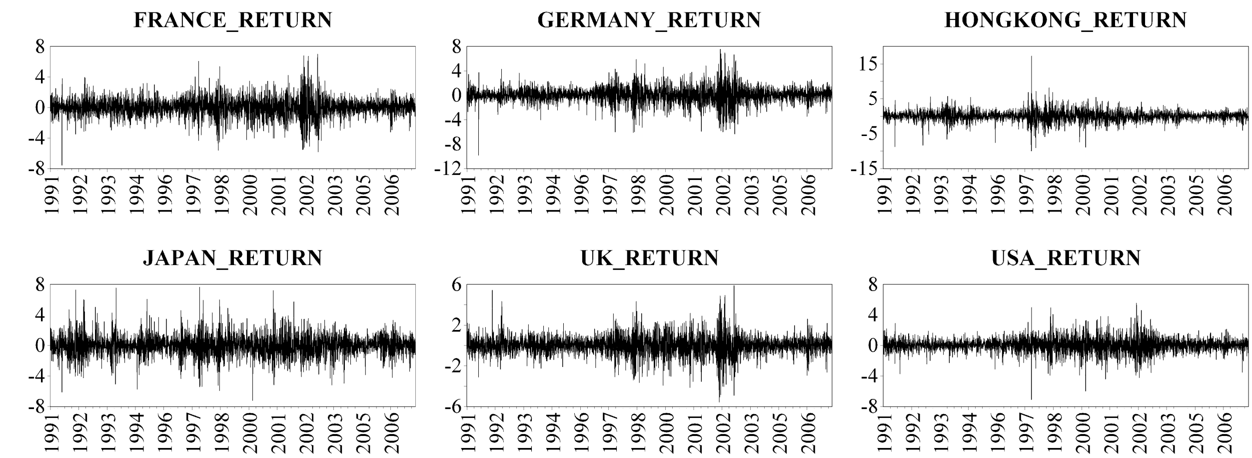

Fig. B.2. Six return (1991.2.2-2007.5.31).

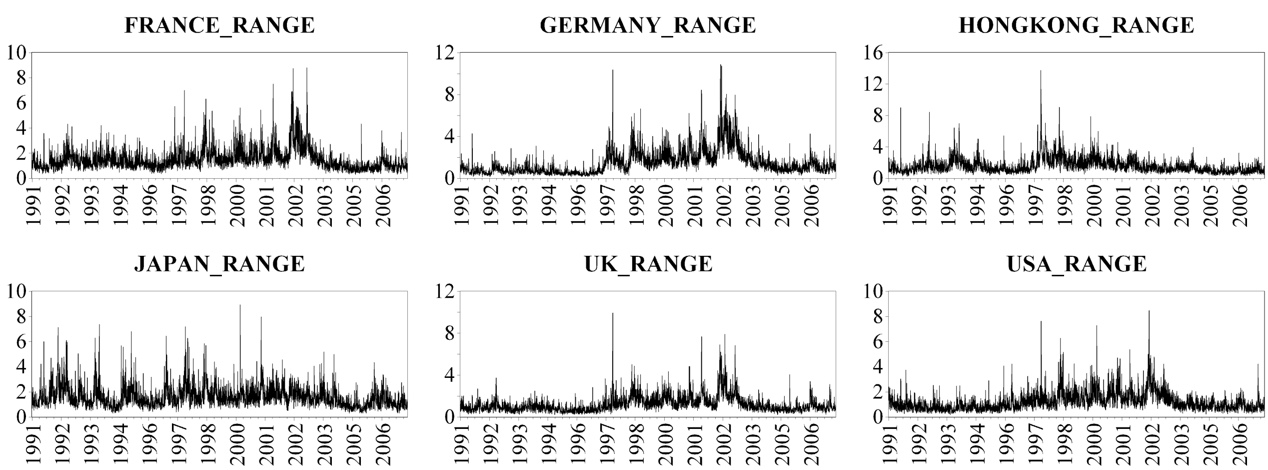

Fig. B.3. Six ranges (1991.2.2-2007.5.31).

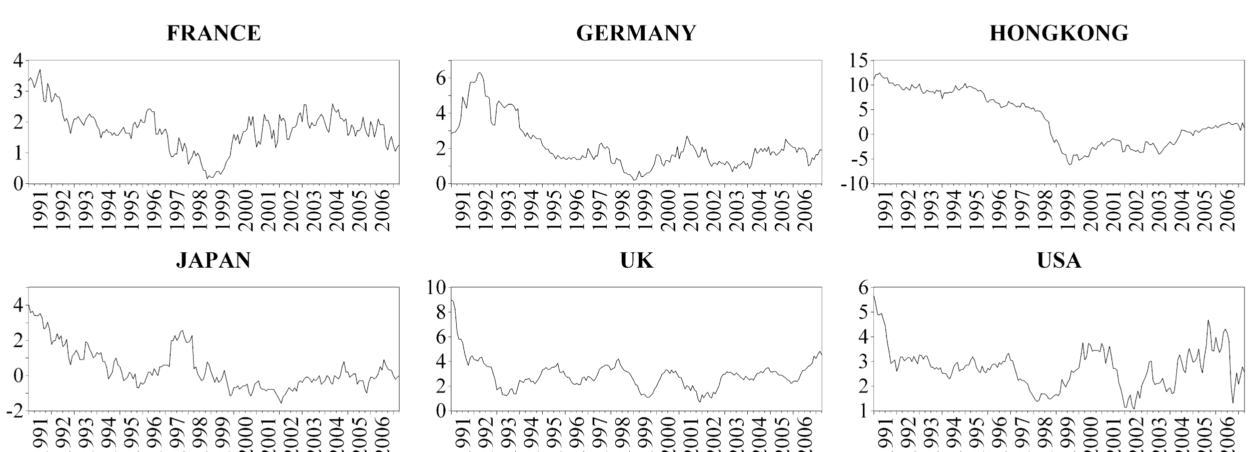

Fig. B.4. Six monthly annual CPI rate (1991.1-2007.4).

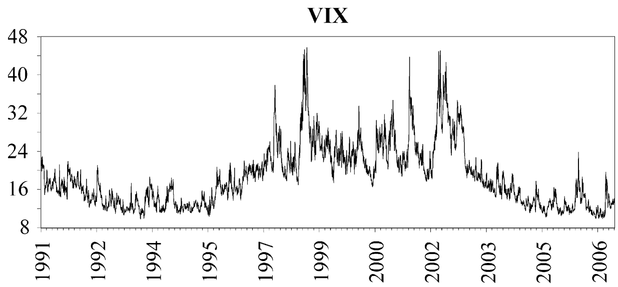

Fig. B.5. Index of VIX (1991.2.1-2007.5.31).

Table C.1
Constant Conditional Correlations with and without time zone taken into account.

	Overlap time	Without time zone considered		With time zone considered	
		Correlation	Test	Correlation	Test
FR_USA	1:30*	0.411	**0.001**	0.238	0.260
FR_HK	0:30	0.308	**0.000**	0.186	0.252
FR_JP	0:00	0.282	**0.077**	0.206	**0.001**
UK_USA	1:30*	0.408	0.634	0.242	0.444
UK_HK	0:30	0.304	**0.000**	0.223	**0.050**
UK_JP	0:00	0.278	0.405	0.203	**0.020**
GER_USA	1:30*	0.391	**0.000**	0.251	**0.000**
GER_HK	0:30	0.281	**0.001**	0.151	**0.000**
GER_JP	0:00	0.280	**0.000**	0.177	**0.000**
USA_HK	0:00	0.118	0.785	0.357	**0.039**
USA_JP	0:00	0.118	0.037	0.304	**0.000**

Notes: For the cases between USA and European countries emphasized by "*", overlapping time is one and half an hour in daylight saving time while half an hour in winter time.

improvement but even worse result in CCC tests. We also become conscious of the indeed increasing correlations between Japanese and European markets and the statistics of CCC test become significant with considering the effect. But the cases of Hong Kong and European countries tell the almost reversed results as shown in Table C.1.

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