E C O N O M I C S B U L L E T I N

Multivariate GARCH modeling analysis of unexpected U.S. D, Yen and Euro-dollar to Reminibi volatility spillover to stock markets

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Abstract

The objective of this paper, by employing the Constant Conditional Correlation(CCC) and Dynamic Conditional Correlation(DCC) MGARCH-M model using the unexpected exchange rate shock to measure the impact effect of the U.S.D, Yen and Eurodollar exchange rate shock mean and volatility spillover to stock markets. The empirical results of the CCC-MGARCH shows the negative correlation between the unexpected U.S.D-RMB at China stock markets indicate that unexpected shock will have a negative effect to the China stock markets. The positive correlation of New York Dow Jones and two China stock markets show that the increase of New York stock market index will increase the China stock market index. From the DCC-MGARCH(1,1) model, the positive and significant value of £\ and £] show ARCH and GARCH effect exist. The DCC parameters are insignificantly and the sum value of the parameters is less than one, show that model is mean reverting.

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1. Introduction

The relationships between stocks and the foreign exchange markets have been discussed by previous authors. For example, Johnson and Soenen (1998) find evidence of correlation between USD and Japanese Yen, and the stock markets in some pacific-Basic countries. Meanwhile, Abid *et al* (2003) investigated the correlations within emerging stock markets and found that volatility spillover occurs in both directions. On the other hand, several papers have investigated the transmission mechanism of innovation and volatility stock across international stock markets. For instance, mean and volatility spillover across international stock markets have been studied by Hamao *et.al* (1990), Koutmos (1996a, 1999b), and Jeong (1999).

Numerous studies have attempted to model the dynamics of the exchange rate process and the transmission of exchange rate volatility across markets within a given exchange rate system. These studies include that carried out by Kearney and Patton (2000) who used multivariate EGARCH modeling of exchange rate volatility transmission in the European Monetary System, and the one carried out by Najand and Yung (1997), who studied the transmission of volatility in the foreign exchange futures markets. Granger, Huang, and Yang (2000) adopted a series of co-integration models with structural breaks to examine the relationship between stock returns and currency markets. However, they did not find significant evidence regarding causality between the two variables. This finding is not supported by Baharumshan *et al.* (2002). Phylaktis and Ravazzollo (2005) used co-integration models to identify a significant relationship between stock returns and currency markets. Through co-integration analysis and error correction models, Ajayi and Mougoue (1996), meanwhile, found evidence of dynamic linkage between stock price and exchange rates in eight industrialized countries.

Tastam (2006) showed that the conditional correlation between the exchange rate and U.S. stock return displays a high extent of time variation, while Kanas (2000) found evidence of volatility spillover from stock returns to exchange rate changes in five of the six industrialized countries. He showed that all stock returns spillovers are symmetric, indicating that the effect of bad news is the same as the effect of good news on the exchange rate. On the other hand, Zapatero (1995) showed that there is an explicit linkage between the volatility of stock price and the volatility of the exchange rate in fully integrated financial markets.

Although numerous studies have been devoted to analyzing the impact of exchange rate changes on stock prices (Gao, 2000), little has been done to investigate the interaction between unexpected exchange rate shock and international stock markets. Thus, the objective of this paper is to use the error term (i.e., the term which derivates from the GARCH (1,1) model to become the proxy variable of the unexpected exchange rate shock) to measure the impact of the USD-, Yen- and Eurodollar-Reminbi (RMB) exchange rate shock mean and volatility spillover to the two China stock markets by employing the Constant Conditional Correlation(CCC) and Dynamic Conditional Correlation (DCC) MGARCH-M models. One advantage of the MGARCH specification is that it permits time-varying conditional variance as well as simple variance, thereby allowing for possible interaction within the conditional mean and the variance of two or more financial series.

The remainder of this paper proceeds as follows: Section 2 describes the details of our econometric methods; Section 3 provides a description of the data, fundamental statistic and volatility measurement, and the empirical analysis before finally discussing the results. Section 4 concludes the paper.

2. Methodology

2.1 Constant Conditional Correlation (CCC) MGARCH model

One advantage of the MGARCH specification is that they permit time-varying conditional variance as well as variance; thus allow for possible interaction within the conditional mean and variance of two or more financial series. Instead of modeling conditional covariance matrix directly, some other research model *Ht* indirectly through conditional correlation. The first model of this type is the Constant Conditional Correlation (CCC) model of Bollerslev(1990). He proposed a class of MGARCH models in which the conditional correlations are constant and thus the conditional variances are proportional to the produce of the corresponding conditional standard deviations. The restriction highly reduces the number of unknown parameters and this simplifies estimation. The CCC model is defined as：

$$H_t = D_t R D_t = \left| e_{ij}\sqrt{h_{iit}h_{jjt}} \right| \qquad (1)$$

where $D_t = diag\left(h_{11t}^{1/2}......h_{nnt}^{1/2}\right)$, h_t can be defined as any univariate GARCH model, and R=(e_{ij}) is a symmetric positive definite matrix with e_{ij} =1, $\forall i$ and R is the matrix containing the conditional correlation e_{ij} . The original CCC model has a GARCH(1,1) specification for each conditional variance in D_t：

$$h_{iit} = W_i + \alpha_i h_{ii,t-1} + \beta_i \varepsilon_{i,t-1}^2, \text{ i=1…N} \qquad (2)$$

where H_t is positive definite if and only if all the N conditional variances are positive and R is positive definite. This model gives positive definite and stationary conditional covariance matrix provided that the ρ_{ij} make up a well-defined correlation matrix and the parameters are all nonnegative. The estimation is done by maximizing the quasi-likelihood, assuming conditional normality.

2.2 Dynamic Conditional Correlation (DCC) MGARCH model

In the CCC model, the assumption that the conditional correlations are constant may seem unrealistic in many empirical applications. Engle (2002) propose a generalization of the CCC model by making the conditional correlation matrix time dependent. The model is then called a dynamic conditional correlation (DCC) model. The DCC model belongs to the family of multivariate GARCH models. Developments in multivariate GARCH modeling are driven by the need to reduce computational requirements while simultaneously ensuring that covariance matrices remain positive definite through suitable parameter restrictions.

To understanding the DCC-MGARCH model, we write the conditional variance covariance matrix as below：

$$r_t | \phi_{t-1} \sim N(0, H_t) \tag{3}$$

$$H_t = D_t R_t D_t \tag{4}$$

where H_t is the conditional covariance matrix; R_t is the nxn time varying correlation matrix, where $D_t = \mathrm{diag}\{\sqrt{\mathrm{h_{it}}}\}$ is a nxn diagonal matrix of time-varying standard deviation from univariate GARCH models; and $R_t = \{e_{ij}\}_t$ which is a correlation matrix containing conditional correlation coefficients. The elements in D_t follow the univariate GARCH(p,q) process in the following：

$$h_{it} = W_i + \sum_{p=1}^{p_i} \alpha_{ip} \varepsilon_{it-p}^2 + \sum_{q=1}^{\theta_i} \beta_{iq} h_{it-q}, \forall i = 1,2 \cdots n \tag{5}$$

Dividing each return by its conditional standard deviation, $\sqrt{h_{it}}$, we get the vector of standardized returns $\varepsilon_t = D_t^{-1} r_t$, where ε_t ~~ $N(0, R_t)$. We write Engle's specification of a dynamic correlation structure as below：

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{6}$$

$$Q_t = \left(1 - \sum_m \alpha_m^* - \sum_n \beta_n^*\right)\overline{Q} + \sum_m \alpha_m^* \left(\varepsilon_{t-m} \varepsilon_{t-m}^{'}\right) + \sum_n \beta_n^* Q_{t-n} \tag{7}$$

where Q_t^* is a diagonal matrix containing the square root of the diagonal entries of Q_t , Q_t is the conditional variance-covariance matrix Q_t is obtained from the first stage of equation. Where, the covariance matrix, Q_t , is calculated as a weighted average of $\overline{Q}$, The unconditional covariance of the standardized residuals; $\varepsilon_{t-m}, \varepsilon'_{t-m}$, a lagged function of the standardized residuals; and Q_{t-n} the past realization of the conditional covariance. In the DCC(1,1) specification only the first lagged realization of the covariance of the standardized residuals and the conditional covariance are used. This requires the estimation of two additional parameters, α_m^* and β_n^*. Q_t^* is a diagonal matrix whose elements are the square root of the diagonal elements of Q_t. The DCC-MGARCH model is estimated using he maximum likelihood method in which the log-likehood can be written as：

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left[n\log(2\pi) + 2\log\left|D_t\right| + \log\left|R_t\right| + \varepsilon_t^{'}R_t^{-1}\varepsilon_t\right] \tag{8}$$

where ε'_t is the standardized residual derived from the first stage univariate GARCH estimation, which is assumed to be *n.i.d.* with a mean zero and a variance, R_t. Hence, the variance matrix, R_t, is also the correlation matrix of the original zero mean return series.

The DCC model is designed to allow for the two-stage estimation of the conditional covariance matrix H_t, the first stage univariate volatility models are fitted for each of the assets and estimates of hit are obtained. In the second stage, the market returns are transformed by their estimated standard deviations resulting from the first stage and are used to estimate the parameters of the conditional correlation. The H matrix is generated by using univariate GARCH models for the variances, combined with the correlations produced by the θ_t .

3. Empirical Results

In order to investigate the mean and volatility spillover of the unexpected exchange rate to the Chinese stock markets, the data used consists of the daily data culled from five stock market indexes and three exchange rates from the Taiwan Economic Journal (TEJ) data bank. These are the New York Dow-Jones index (NYD), the Japan Nikkei 225 index (J225), the European Amsterdam AEX Stock index (AEX), the China Shanghai Composite index (SHC), and the Shenzhen Composite index (SJC), as well as the respective exchange rates of the U.S. Dollar (CAR), Japan Yen (CJR), and Eurodollar (CUR) to China RMB from July 21, 2005 to January 4, 2007. Returns in each market are calculated as the first difference in the natural logarithms of the stock market indexes. Table 1 presents the descriptive statistics for each variable series. From the table we can see that the skewness statistics suggest lack of normality in the distribution of the return series, while the value of kurtosis indicate that each of the return series is more peaked than in the normal distribution. The Jarque-Bera (JB) normality test rejects the null hypothesis of normally. The significant value of the LB-Q statistics for the squared returns suggests the presence of autocorrelation in the square of stock returns. The ARCH-LM is statistically significant at 1% level, indicating the existence of ARCH phenomena for all variable series. There are different approaches to proxy exchange rate uncertainty.[*] Here, we use the GARCH method error term as the proxy for

[*] One approach is to use the variance of the exchange rate return (Goldberg and KolstadK, 1995). Another approach is using the estimated standard

measuring exchange rate uncertainty or shocks. Due to the fact that the calculated ADF statistics are considered less than the critical value only for first difference of variables, it could be concluded that all variables have differences in terms of stationarity.

3.1 The Constant Condition Correlation (CCC) MGARCH Model

Table 2 shows the parameter estimate of the CCC-MGARCH model for the effect of the USD-RMB unexpected exchange rate shock on the China stock market. The α and β values of the unexpected exchange rate shock on the China SHC stock markets are positive and significant at 0.0705 and 0.9225, respectively. The α and β values of the unexpected exchange rate shock to the China SJC stock markets are 0.0691 and 0.9116, respectively. Both are considered positive and statistically significant at 1% level. The positive and significant ARCH term and GARCH term show that the ARCH and GARCH effects exist in these models. The reported results demonstrate that, in fact, all series exhibit time-varying conditional volatility, which can be successfully modeled using the GARCH (1,1) models. The correlation between unexpected USD-RMB shocks to the China stock markets is negative (i.e., -0.0223 for the SHC stock market and -0.0703 for the SJC stock market). This indicates that the increase of the unexpected exchange rate shock will reduce the stock market index returns.

Table 3 presents the effect of the Yen-RMB unexpected exchange rate shock to the stock markets. The unexpected exchange rate shock to the China stock markets show positive and significant α and β values. The unexpected exchange rate shock to the China stock market shows a negative correlation (-0.0608 for SHC and -0.03288 for SJC) and a positive correlation (0.0783 for SHC and 0.069772 for SJC) between the NYD and China stock markets, respectively.

Table 4 shows the parameter estimates of the unexpected Eurodollar-RMB exchange rate to the stock markets. Empirical results presented in the table show positive and significant α and β values. Based on the constant correlation estimate, the correlation values of the unexpected exchange rate shock to the China stock market are positive (0.0214 for SHC and 0.0217 for SJC), with a corresponding positive correlation (0.0517 for SHC and 0.0423 for SJC) between the AEX and China stock markets.

3.2. The Dynamic Conditional Correction (DCC) MGARCH Model

Table 5 reports on the parameter estimates for the DCC-MGARCH model for the USD-RMB exchange rate volatility to the China stock markets. The respective values of α shows that the short run persistence in volatility are positive and statistically significant (0.0880 and 0.0935). Panel B of Table 5 shows the estimations of the positive and significant parameters of the B^* value at DCC (1.1). If the sum of the DCC (1.1) parameter is less than one, this implies that the model is

GARCH model to obtain a conditional measure of volatility. GARCH methods have been used to derive measures of uncertainty (Engle, 1982).

strictly mean reverting. Table 6 displays the unexpected RMB-Yen exchange rate shock to the stock markets with positive and significant α and β values. The DCC parameters are insignificant and the sum of the parameters is less than one, implying that the model is mean reverting. Lastly, the unexpected Eurodollar-RMB exchange rate shock to the stock market is presented in Table 7, with positive and statistically significant α and β values at 1% level for the two China stock markets. The DCC parameters are insignificant and the sum value of the parameters is less than one, implying that the model is mean reverting.

4. Conclusion

According to the CCC-MGARCH (1,1) model, the α and β values of the three unexpected exchange rate shocks to the China stock markets are positive and statistically significant at 1% level. The constant correlation estimate matrix of both the USD-RMB and the Yen-RMB unexpected exchange rate shocks to the two China stock markets are negatively correlated, while that for the Eurodollar-RMB unexpected exchange rate shock is not. From the DCC-MGARCH (1,1) model, we can see the positive and significant values of α and β in the three unexpected exchange markets. Based on the DCC (1,1) parameter table, the coefficient value of the parameters are insignificant within the three unexpected exchange rate markets. Moreover, the sum of the DCC (1,1) parameter show that models are mean reverting. Based on empirical results, the negative correlation between the unexpected exchange rate shock and stock markets indicate that the unexpected shock will have a negative effect on the China stock markets. Therefore, China needs to face the unexpected exchange rate transmission effect from other countries because it's gradually opening and depending. This is especially true for the USD-RMB exchange rate market. Moreover, the volatility transmitted effects to the stock markets have been found in the three unexpected exchange rate markets.

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Table 1

Data Summary Statistics

	CAR	CJR	CUR	NYD	J225	AEX	SHC	SJC
Mean	0.1091	14.7528	0.1003	11297.71	15614.20	5811.692	1664.964	407.945
Mediam	0.1088	14.7486	0.0993	11124.37	15960.62	5850.8	1589.54	396.770
Maximum	0.1123	16.2096	0.1069	12786.64	18215.35	6444.4	3197.54	841.480
Minimum	0.1068	13.5931	0.0949	10215.22	11695.05	5142.1	1020.63	240.370
Std.Dev.	0.0015	0.5788	0.0030	686.7813	1548.216	325.1345	580.9623	144.193
Skewness	0.5959	0.3340	0.3071	0.6051	-0.8981	-0.1500	1.1249	1.24147
Kurtosis	2.2923	2.9739	1.8562	2.2302	3.0088	2.0124	3.1670	3.85270
Jarque-Bera	32.7460	9.2088	28.7239	35.0627	54.9815	18.1557	86.7374	117.450
ARCH-LM(12)	94.286***	21.544**	11.844***	2.366****	3.969***	8.1103***	7.368***	12.016***
LB(12)	113.13***	22.22***	35.252***	25.746****	116.12***	28.16***	24.854**	40.766***
$LB^2(12)$	191.29***	51.57***	43.273***	27.981***	107.63***	197.96***	96.396***	158.66***

1. The significant value of the LB-Q statistics for the squared returns suggests the presence of autocorrelation in the square of stock returns. ARCH-LM statistics proposed by Engle (1982) aimed to detect ARCH. In fact the values of ARCH-LM (12) are all significant at 1% level, indicating the existence of ARCH phenomena for all variable series.

2. ***, ** and * indicated at least significant at 1%, 5%, and 10 % level.

Table 2

Parameter estimates for the CCC-MGARCH (1.1) model for U.S.D-RMB volatility spillover to NYD and China Stock Markets

$H_t = D_t R D_t = \left| e_{ij} \sqrt{h_{iit} h_{jjt}} \right|$ $h_{iit} = W_i + \alpha_i h_{ii,t-1} + \beta_i \varepsilon_{i,t-1}^2$, i=1…N

Panel A：Variance Equation						
	DLNYD	DLSHC	G1	DLNYD	DLSJC	G1
ω	1.230e-05***	2.44e-06	8.314e-11***	2.363e-06***	5.439e-06**	9.668e-11***
	(-4.04e-06)	(-1.71e-06)	(-3.38e-12)	(-7.97e-07)	(-2.87e-06)	(-6.00e-12)
α	0.0411	0.0705***	0.1167***	0.0419**	0.0691***	0.1193***
	(-0.0312)	(-0.017)	(-6.99e-03)	(-0.0203)	(-0.0182)	(-0.0111)
β	0.6055***	0.9225***	-0.3994***	0.8993***	0.9116***	-0.3688***
	(-0.1036)	(-0.0174)	(-0.0171)	(-0.0314)	(-0.0217)	(-0.0254)

Panel B：Constant Correlation estimates							
	DLNYD	DLSHC	G1		DLNYD	DLSJC	G1
DLNYD		0.02440	-0.0223	DLNYD		0.03480	-9.51e03
		(-0.0482)	(-0.0477)			(-0.0544)	(-0.0495)
DLSHC			-0.0675	DLSHC			-0.0703
			(-0.0479)				(-0.0545)
G1				G1			
Log-like：	6855.2141			Log-like：	6822.0157		

1. The statistic reported in the parenthesis is the robust standard errors.

2. DLNYD, DLSHC and DLSJC are the difference log of the New York Dow-Jones stock index, Shanghai composite stock index and Shenzhen composite stock index.

3. G1 is the U.S.D-RMB unexpected exchange rate shock which derived from GARCH(1.1) error term.

4. ***, ** and * indicated at least significant at 1%, 5%, and 10% level.

Table 3

Parameter estimates for the CCC-MGARCH (1.1) model for Yen-RMB volatility spillover to J225 and China Stock Markets

$H_t = D_t R D_t = \left| e_{ij} \sqrt{h_{iit} h_{jjt}} \right|$ $\qquad h_{iit} = W_i + \alpha_i h_{ii,t-1} + \beta_i \varepsilon^2_{i,t-1}$, i=1…N

Panel A：Variance Equation

	DLJ225	DLSHC	G2	DLJ225	DLSJC	G2
ω	1.2041e-04***	1.8586e-06***	3.3674e-11***	2.152e-06***	3.61e-06***	5.39e-12***
	(-9.13e-06)	(-8.39e-08)	(-1.07e-12)	(-1.31e-06)	(-2.77e-06)	(-3.29e-11)
α	0.0547***	0.0710***	0.9353***	0.0834***	0.0790***	1.3035***
	(-0.0156)	(-6.12e-03)	(-0.027)	(-0.2596)	(-0.0223)	(-0.0261)
β	0.022	0.9281***	-0.1384***	0.8724***	0.9276***	-0.0114
	(-0.552)	(-6.52e-03)	(-6.76e-04)	(-0.0389)	(-0.0195)	(-0.0233)

Panel B：Constant Correlation estimates

	DLJ225	DLSHC	G2		DLJ225	DLSJC	G2
DLJ225		0.0783*	-0.0498	DLNYD		0.0698	-0.0494
		(-0.0434)	(-0.0468)			(-0.0490)	(-0.0473)
DLSHC			-0.0608	DLSHC			-0.0329
			(-0.0502)				(-0.0461)
G2				G2			
Log-like：	7144.044			Log-like：	6899.572		

1. The statistic reported in the parenthesis is the robust standard errors.

2. DLJ225, DLSHC and DLSJC are the difference log of the Japan Nikkei 225 stock index, Shanghai composite stock index and Shenzhen composite stock index.

3. G2 is the Yen-RMB unexpected exchange rate shock which derived from GARCH(1.1) error term.

4. ***, **, * indicated at least significant at 1%,5%, and 10% level.

Table 4

Parameter estimates for the CCC-MGARCH model for Eurodollar-RMB volatility spillover to AEX and China Stock Markets

$$H_t = D_t R D_t = \left| e_{ij} \sqrt{h_{iit} h_{jjt}} \right| \qquad h_{iit} = W_i + \alpha_i h_{ii,t-1} + \beta_i \varepsilon_{i,t-1}^2 \text{, i=1…N}$$

Panel A： Variance Equation

	DLAEX	DLSHC	G3	DLAEX	DLSJC	G3
ω	5.480e-06***	3.14e-06	8.229e-16***	3.37e-06***	2.81e-06***	8.115e-10***
	(-1.60e-06)	(-2.38e-06)	(-4.48e-11)	(-1.65e-06)	(-9.75e-07)	(-6.18e-11)
α	0.1063***	0.0803***	0.2612***	0.1197***	0.0597***	0.2346***
	(-0.023)	(-7.81e-03)	(-0.0172)	(-0.0343)	(-0.0176)	(-0.0277)
β	0.7056***	0.9125***	-0.4962*	0.8107***	0.9348***	-0.4229***
	(-0.064)	(-0.0166)	(-0.0354)	(-0.0524)	(-0.0156)	(-0.0586)

Panel B： Constant Correlation estimates

	DLAEX	DLSHC	G3		DLAEX	DLSJC	G3
DLAEX		0.0517	0.0395	DLNYD		0.0423	0.0555
		(-0.0457)	(-0.0444)			(-0.0472)	(-0.0507)
DLSHC			0.0214	DLSHC			0.0127
			(-0.0544)				(-0.0552)
G3				G3			
Log-like：	6884.360			Log-like：	7095.185		

1. The statistic reported in the parenthesis is the robust standard errors.

2. DLAEX, DLSHC and DLSJC are the difference log of the Amsterdam stock index, Shanghai composite stock index and Shenzhen composite stock index.

3. G3 is the Eurodollar-RMB unexpected exchange rate shock which derived from GARCH(1.1) error term.

4. ***, **, * indicated at least significant at 1%,5% and 10% level.

Table 5

Parameter estimates for the DCC-MGARCH model for U.S.D-RMB exchange rate volatility to NYD and China Stock Market

$$r_t|\phi_{t-1} \sim N(0, H_t) \qquad H_t = D_t R_t D_t \qquad h_{it} = W_i + \sum_{p=1}^{p_i} \alpha_{ip}\varepsilon_{it-p}^2 + \sum_{q=1}^{\theta_i} \beta_{iq} h_{it-q}, \forall i = 1,2\cdots n$$

Panel A：Variance Equation						
	DLNYD	DLSHC	G1	DLNYD	DLSJC	G1
ω	3.6546e-05***	2.07e-04	8.2805e-11***	3.5999e-05***	2.2094e-04***	8.5307e-11***
	(-1.87e-06)	(-9.18e-06)	(-2.42e-12)	(-1.59e-06)	(-1.01e-05)	(-1.98e-12)
α	-0.0138	0.0880*	0.0677***	-9.85e-03	0.0935***	0.0696***
	(-0.03)	(-0.04)	(-2.60E-03)	(-0.02)	(-9.24e-03)	(-7.64e-04)
β	0.0314	0.0112	-0.3503***	0.0197	-0.012	-0.3610***
	(-0.04)	(-0.04)	(-0.01)	(-0.03)	(-0.02)	(-7.52e-03)
Panel B：DCC (1.1)parameter						
	$\hat{\alpha}*$	$\hat{\beta}*$	$\hat{\alpha}*+\hat{\beta}*$	$\hat{\alpha}*$	$\hat{\beta}*$	$\hat{\alpha}*+\hat{\beta}*$
	5.56e-16	0.3801***	0.3801	1.05e-11	0.4943***	0.4944
	(-1.57e-03)	(-0.08)		(-4.37e-03)	(-0.10)	
Log-like：	6788.9285			Log-like：	7034.4284	

1. The statistic reported in the parenthesis is the robust standard errors.

2. DLNYD, DLSHC and DLSJC are the difference log of the New York Dow-Jones stock index, Shanghai composite stock index and Shenzhen composite stock index.

3. G1 is the U.S.D-RMB unexpected exchange rate shock which derived from GARCH(1.1) error term.

4. ***, **, * indicated at least significant at 1%,5% and 10% level.

Table 6

Parameter estimates for the DCC–MGARCH model for Yen-RMB volatility spillover to J225 and China Stock Markets

$$r_t|\phi_{t-1} \sim N(0, H_t) \qquad H_t = D_t R_t D_t \qquad h_{it} = W_i + \sum_{p=1}^{p_i} \alpha_{ip}\varepsilon_{it-p}^2 + \sum_{q=1}^{\theta_i} \beta_{iq} h_{it-q}, \forall i = 1,2\cdots n$$

Panel A：Variance Equation						
	DLJ225	DLSHC	G2	DLJ225	DLSJC	G2
ω	7.8563e-05***	1.4268e-04***	1.4984e-11***	3.4164e-05***	1.2498e-04***	1.8756e-11***
	(-1.18e-05)	(-2.26e-05)	(-7.20e-12)	(-1.13e-06)	(-1.67e-05)	(-2.98e-12)
α	0.0847**	0.1437***	0.4371***	0.2416***	0.4202***	0.6057***
	(-0.03)	(-0.03)	(-0.04)	(-0.02)	(-0.06)	(-0.02)
β	0.3255***	0.3068***	0.4175***	0.5517***	-0.2468***	0.2389***
	(-0.02)	(-0.05)	(-0.10)	(-0.01)	(-0.04)	(-0.04)
Panel B：DCC(1.1)parameter						
	$\hat{\alpha}*$	$\hat{\beta}*$	$\hat{\alpha}*+\hat{\beta}*$	$\hat{\alpha}*$	$\hat{\beta}*$	$\hat{\alpha}*+\hat{\beta}*$
	0.0526	1.27e-14	0.053	6.80e-15	0.0359	0.036
	(-0.03)	(-0.08)		(-0.02)	(-0.05)	
Log-like：	7086.3121			Log-like：	7079.1711	

1. The statistic reported in the parenthesis is the robust standard errors.

2. DLJ225, DLSHC and DLSJC are the difference log of the Japan Nikkei 225 stock index, Shanghai composite stock index and Shenzhen composite stock index.

3. G2 is the Yen-RMB unexpected exchange rate shock which derived from GARCH(1.1) error term.

4. ***, **, * indicated at least significant at 1%, 5% and 10% level.

Table 7

Parameter estimates for the DCC-MGARCH model for Eurodollar-RMB volatility spillover to AEX and China Stock Markets

$$r_t|\phi_{t-1} \sim N(0, H_t) \qquad H_t = D_t R_t D_t \qquad h_{it} = W_i + \sum_{p=1}^{p_i} \alpha_{ip}\varepsilon_{it-p}^2 + \sum_{q=1}^{\theta_i} \beta_{iq} h_{it-q}, \forall i = 1,2\cdots n$$

Panel A：Variance Equation						
	DLAEX	DLSHC	G3	DLAEX	DLSJC	G3
ω	1.694e-05***	2.13e-06	8.904e-10***	3.9549e-05***	2.19e-04	7.659e-10***
	(-1.35e-06)	(-1.76e-06)	(-6.04e-11)	(-3.73e-06)	-1.41e-05	-6.44e-11
α	0.1035***	0.0710*	0.2075***	0.1861***	0.2186***	0.1521***
	(-0.02)	(-0.01)	(-0.02)	(-0.02)	(-0.03)	(-0.02)
β	0.6253***	0.9287***	-0.4727***	0.0934***	0.0146***	-0.3383***
	(-0.02)	(-0.01)	(-0.04)	(-8.54e-03)	(-0.04)	(-0.04)
Panel B：DCC(1.1)parameter						
	$\hat{\alpha}*$	$\hat{\beta}*$	$\hat{\alpha}*+\hat{\beta}*$	$\hat{\alpha}*$	$\hat{\beta}*$	$\hat{\alpha}*+\hat{\beta}*$
	0.0213	0.3178	0.3391	6.44e-03	1.58e-14	0.0006
	(-0.96)	(-0.64)		(-0.02)	(-0.13)	
Log-like:	6972.12			Log-like:	6914.24	

1. The statistic reported in the parenthesis is the robust standard errors.

2. DLAEX, DLSHC and DLSJC are the difference log of the Amsterdam stock index, Shanghai composite stock index and Shenzhen composite stock index.

3. G3 is the Eurodollar-RMB unexpected exchange rate shock which derived from GARCH(1.1) error term.

4. ***, **, * indicated at least significant at 1%, 5%, and 10% level.