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

The analysis of interest rate mean and volatility spillover to the industrial production index and stock markets: The case of China

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Abstract

Empirical results found the parameter estimates for the CCC-MGARCH models display that the short run persistence is positive and significant and the positive and significant ARCH and GARCH term show the ARCH and GARCH effect exist in these models. By concerning the correlations of bank reserve rate and discount rate to industrial production index, the correlation is positive and statistically significant for those variables. It indicated that China monetary policy have a positive impact to industrial production. The parameters estimates for DCC-MGARCH(1.1) model for China monetary policy to industrial production index and stock markets show the short-run persistence is positive significantly and at DCC(1.1) parameters. The sum of the DCC(1.1) parameter is less than one which implies that the model is strictly mean reverting.

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1. Introduction

China's GDP grew 11.9 percent in the second quarter of 2007, it is the fastest record in a decade. At July, 2007, the trade surplus rose 67 percent from a year earlier to $24.4 billion, the second-highest monthly total, and the money supply climbed 18.5 percent, the biggest increase in more than a year. The CPI jumped by a 10-year-high 5.6 percent in July 2007, well above the official target of 3 percent. However, the low interest rate policy has somewhat encouraged outflow of banking savings to the country's skyrocketing stock market, which has soared more than 80 percent so far this year on top of a 130 percent rally in 2006.

The monetary transmission mechanism describes how policy-induced changes in the nominal money stock or the short-term nominal interest rate impact real variables such as aggregate demand and output (Mishkin,1995). According to the traditional Keynesian interest rate channel, a policy-induced increase in the short-term nominal interest rate leads to an increase in long-term nominal interest rates, an investor act to arbitrage away differences in risk-adjusted expected returns on debt instruments of various maturities, as described by the expectation hypothesis of the term structure. When nominal prices are slow to adjust, these movements in nominal interest rates translate into movements in real interest rates as well. Then, the firms find the real cost of borrowing has increased, reduced their investment expenditure. By the way, households face high real borrowing cost cut their spending, aggregate demand and output were fall. The interest rate channel of monetary policy transmission operates within the traditional Keynesian IS-LM model and is considered as a conventional view.

Taylor (1995) argued that financial market prices are key components of how monetary policy affects real activity. In his model, a contractionary monetary policy raises short-term interest rates. Since prices and wages are assumed to be rigid, real long-term interest rate increased as well. These higher real long-term rate lead to a decline in real investment, real consumption and thereby on real GDP-in the long run, after wage and prices of goods begin to adjust, real GDP return to normal. In summary, the Keynesian view emphasizes the role of interest rates in responding to monetary policy and affecting economic activity. Thorbecke (1997) used the VAR methodology to examine the effects of monetary policy innovations on stock return data. It present evidence that monetary policy exerts large effects on ex-ante and ex-post stock returns and the results indicate that expansionary(contractionary) monetary policy cause stock return for almost every portfolio examined to increase(decrease). Rigobon and Sack (2004) show that the correlation between policy interest rate and other asset price shifts importantly on particular dates by using the simple instrumental variable regression and GMM. Empirical results indicated that increase in the short-term interest rate have a negative impact on stock prices, with the largest effect on the NASDAQ index. The results also indicate that the short-term rate has a significant positive impact on market interest rates.

Bento (2002) used EGARCH model examined the impact of unanticipated change in the federal fund rate target from Jan.1988 to Jan.2001 on the conditional mean and variance of stock prices. His study finds that the interest rate surprises have an announcement day effect on stock values and the impact of interest rate surprise on stock market volatility. Empirical analysis also showed that positive and negative surprises have an asymmetric effect on the mean and volatility of stock price. In particular, negative surprise (good news) impacted the conditional mean of stock prices, while positive surprise (bad news) impacted the conditional variance of stock price in a statistically significant manner.

Ehrmann and Fratscher (2004) had analyzed the reaction of equity markets to U.S. monetary policy in the period 1994 to 2003. In particular, this paper has focused on the relative contributions of the credit channel and the interest rate channel of monetary policy transmission. As the results of this paper, they found evidence that monetary policy affects individual stocks in a strongly heterogenous fashion. Pearce and Roley (1985) and Hardouvelis (1987) found that stock price react significantly to monetary news or unanticipated monetary policy. Much of the previous research on the effects of monetary policy on stock price has used changes in the discount rate as a proxy for changes in monetary policy. Chen (1999) also examined the effect of discount rate changes on the volatility of stock prices and on trading volume. They found that unexpected discount rate change contributed to higher, though short-lived, volatility and trading volume.

Bredin and O’reilly (2004) used the VAR to examine the effect of an exogenous temporary change in the short-term interest rate on output, price and exchange rate. In particular, it was found that a temporary monetary contraction leads to a decline in both output and prices. Secondly, a rise in the interest rate leads to immediate appreciation of the exchange rate.

There is a considerable amount of interest in understanding the interactions between asset prices and monetary policy. Rigobon and Sacks (2003) found that short-term interest rates react significantly to movements in broad equity price index, likely reflecting the expected endogenous response of monetary policy to the impact of stock price movements on aggregate demand. Much of the transmission of monetary policy comes through the influence of short-term interest rates on other assets, as it is the movements in those other asset prices-including longer-term interest rates and stock prices- that determine private borrowing costs and changes in wealth, which in turn influence real economic activity. Thorbecke (1991) documented a response of stock prices to shocks from an identified VAR, in a similar way, Jensen et al. (1996) and Jensen and Mercer (1998) examined the market’s response to discount rate changes.

The influence of monetary policy instruments on these variables is at best indirect. The most direct and immediate effects of monetary policy actions, such as changes in the federal funds rate, are on the financial markets, by affecting asset prices and returns, policy markets try to modify economic behavior in ways that will help to achieve their ultimate objectives. Understanding the links between monetary policy and asset price is thus crucially important for understanding the policy transmission mechanism. The objective of this paper, we try to analyze the relationship between interest rate variables and the industrial production index and two China stock markets by employing the Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) MGARCH-M model. Empirical results will provide us understand how the relationship between the interest rate variables and the industrial production index and stock markets.

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, the empirical analysis and discusses the results while 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：

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

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：

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

The CCC model contains N(N+5)/2 parameters. 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 mode, 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 $D_t = \mathrm{diag}\{\sqrt{\mathrm{h}_{\mathrm{it}}}\}$ 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 $\varepsilon_t \sim\sim N(0, R_t)$. We write Engle's specification of a dynamic correlation structure as below：

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

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

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; $\varepsilon_{tm}, \varepsilon'_{tm}$, 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：

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

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 of unexpected interest rate in the stock markets of the Great China area, the data consists of the monthly data of interest rate variables, the China stock markets and industrial production index. Data are collected from the Taiwan Economic Journal (TEJ) data bank. These are bank deposit reserve rate(DEP), discount rate(DIS), industrial production index(IND), Shanghai Composite index(SHC), and Shenzhen Composite index(SJC) from January1985 to July, 2007.

Table 1 present descriptive statistics for each variable series, sample means, standard deviations, skewness, kurtosis, and the Jarque-Bera statistics, the Ljung-Box statistics returns as well as squared returns, and the ARCH-LM test statistics are reported for monthly returns. The skewness statistics suggest lack of normality in the distribution of the return series. The DEP, DIS, INDEX, SHC and SJC have return distributions that are positively skewed. The values of kurtosis indicated that each of the return series is leptokurtosis compared to normal distribution. The Jarque-Bera(JB) normality test reject the null hypothesis of normally. In addition, the Ljung-Box Q(LB-Q) test statistics, for return and squared of return test the absence of autocorrelation. The significant value of the LB statistics for return series rejects the null hypothesis of white noise and indicates the presence of autocorrelation. ARCH-LM statistics are all significant at 1% level, indicating the existence of ARCH phenomena for all variable series.

Table 2 show the parameter estimates for the CCC-MGARCH(1.1) models for China adopt a contractionary monetary policy by increasing the deposit rate and discount rate to slow down the China economic growth of annually industry growth rates are reported at Table 2. The statistic reported in the parenthesis is the robust standard errors. The α_i value of the short run persistence is positive and significant and ranges series from 0.83056 for DEP to 1.8111 for IND. The positive and significant ARCH and GARCH term show the ARCH and GARCH effect exist in these models. Therefore, the results reported above show that all series exhibit time-varying conditional volatility, which can be successfully modeled using the GARCH(1,1) models. According to the panel B of Table 2, the correlations between those variables are all positive and significant. The highest correlation is 0.89962, for DEP. By concerning the correlations of DEP and DIS to INDEX, the correlation is positive and statistically significant for those variables. It indicated that China monetary policy have a positive impact to the China economic growth. The diagnostic checking of models show no return autocorrelation and heteroskedasticity effect existed.

Table 3 report the parameter estimates for the CCC-MGARCH(1,1) models for China monetary policy to two China stock markets. The value of the short run persistence is positive and significant. The ARCH term and GARCH term are negatively significant, implying that the series have a time-varying conditional volatility, that use the GARCH(1,1) model was adequate. By concerning the correlation between all series are statistically significant. The highest correlation relationship is DEP and DIS for 0.71799 and 0.744694. The correlation between DEP and SHC is positive (0.077154) but with DIS is negative (-0.15332). Turn to the SJC stock markets, the correlation between DEP and SJC is negative (-0.31415) and DIS with SJC is also negative (-0.565865). The diagnostic checking statistics value of Ljung-Box Q and ARCH-LM test indicated that no autocorrelation and heteroskedasticity exist.

Table 4 presents parameters estimates for DCC-MGARCH(1,1) model for China monetary policy to annually industry growth rate. The α_i value of the short-run persistence is positive and significant. The ARCH and GARCH term are also significant, indicated that GARCH(1,1) model is adequate. The Panel B of the Table 4 show the estimations of the positive and significant at DCC(1,1) parameters of α_i and β_i value. The sum of the DCC (1,1) parameter is less than one which implies that the model is strictly mean reverting.

Table 5 reported the parameter estimates for DCC-MGARCH(1,1) model for China interest rate to stock markets. The α_i values are all positive and statistically significant which show the short-run volatility persistence. The sum of the DCC(1,1) parameters are less than one which implies that the model is strictly mean reverting. The diagnostic checking of the model of the Ljung-Box Q statistics indicated that there is no serial correlation. The ARCH-LM test statistics show no ARCH effect in the residuals. China adopt contractionary monetary policy through the increase of interest rate variables volatility can significant affect the industrial production index and stock market at the short-run. The dynamic parameter is positive and significant indicated that the feed-back volatility correlation effect among variables.

4. Conclusion

The objective of this paper, we try to analyze the interest rate mean and volatility spillover to the industrial production index and two China stock markets by employing the Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation(DCC) MGARCH(1,1) model. The parameter estimates for the CCC-MGARCH(1,1) models for China adopt a contractionary monetary policy by increasing the deposit rate and discount rate to slow down the China economic growth of annually industry growth rates are reported at α_i value of the short run persistence is positive and significant and ranges series. The positive and significant ARCH and GARCH term show the ARCH and GARCH effect exist in these models. By concerning the correlations of deposit rate and discount rate to industrial production index and stock market, the correlation is positive and statistically significant for those variables. It indicated that China monetary policy have a positive impact to the China economic growth and stock markets. The increasing of interest rate will decrease the investment and then affect the production. Our empirical result support China's contractionary monetary policy can curb the overheating economic.

The parameters estimates for DCC-MGARCH(1,1) model for China monetary policy to annually industry growth rate and stock markets show the α_i value of the short-run persistence is positive significantly and at DCC(1,1) parameters of α_i and β_i value. China's contractionaly monetary policy affects the industry growth rate and stock market at short-run and positively significant dynamic volatility feed-back correlation among variables. The sum of the DCC (1,1) parameter is less than one which implies that the model is strictly mean reverting.

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Table 1
Descriptive Statistics

	DEP	DIS	INDEX	SHC	SJC
Mean	7.0818	3.0910	115.324	1625.43	452.6698
Median	7.5	2.9700	114.8	1518.585	423.88
Max	10.5	6.0300	133.2	4109.65	1187.51
Min	6.0	2.1600	102.1	1060.74	254.47
Std.Dev	1.0677	0.8088	5.1655	501.448	147.1026
Skewness	0.6544	1.6199	0.7221	2.4276	1.99871
Kurtosis	3.0896	7.2132	4.3974	11.0612	9.659
J.B	7.889***	129.472***	32.9817***	405.890***	276.523***
LB(6)	1545.3***	310.37***	319.42***	431.25***	435.83***
$LB^2(6)$	1287.8***	142.43***	92.027***	84.907***	61.181***
ARCH-LM(6)	452.623***	145.8***	8.7734***	296.636***	184.8108***

Note: 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 (6) 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) models for China monetary policy to industry production index

Panel A：Conditional variance equation			
	LDEP	LDIS	LINDEX
ω	0.0017***	-0.00000094	0.00009539**
	(0.0001)	(0.0001)	(0.000000268)
α	0.8305***	1.7334***	1.81111991*
	(0.0170)	(0.0109)	(0.01249927)
β	0.4480***	0.0002	-0.019056635*

Panel B：Constant Correlation Estimate			
	LDEP	LDIS	LINDEX
LDEP		0.8996623***	0.31641898*
		(0.008713)	(0.0019155)
LDIS			0.354013911*
			(0.0139756)
LIND			

Panel C：Model diagnostic checking
Log-likehood：581.8319
L-BQ^2 (12)：13.255
ARCH-LM (12) ：5.226

Note: 1. LDEP, LDIS and LINDEX is the log difference of the reserve rate, discount rate and industrial production index, respectively.

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

3. This table reports the results of the estimation of MGARCH model with t-distributed (standard errors in parentheses).

4. The CCC model is defined as：

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

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

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

Table 3
Parameter estimates for the CCC-MGARCH(1.1) models for China monetary policy to stock markets

Panel A：Conditional variance equation						
	LDEP	LDIS	LSHC	LDEP	LDIS	LSJC
ω	0.0005***	0.0001***	0.0072***	0.0002***	0.0082***	0.0078***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
α	1.7595***	0.7912***	1.2173***	0.8968***	0.4802***	0.9808***
	(0.0011)	(0.0084)	(0.0204)	(0.0385)	(0.0038)	(0.0468)
β	-0.0686***	0.1580***	-0.1158***	0.1138***	-0.1685***	-0.1362***
	(0.0001)	(0.0018)	(0.0023)	(0.0001)	(0.0064)	(0.0001)

Panel B：Constant Correlation Estimate							
	LDEP	LDIS	LSHC		LDEP	LDIS	LSJC
LDEP		0.7179***	0.0771***	LDEP		0.7446***	-0.3141***
		(0.0034)	(0.0021)			(0.0117)	(0.0001)
LDIS			-0.1533***	LDIS			-0.5658***
			(0.0135)				(0.0273)
LIND				LIND			

Panel C：Model diagnostic checking	
Log-likehood：376.217	Log-likehood：229.117
L-BQ(12)：28.617	L-BQ(12)：33.280
L-BQ^2 (12)：21.553	L-BQ^2 (12)：25.164
ARCH-LM(12)：5.4665	ARCH-LM(12)：1.1844

Note: 1. LDEP, LDIS, LSHC, and LSJC is the log difference of the reserve rate, discount rate, Shanghai Composite index, and Shenzhen Composite index, respectively

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

3. This table reports the results of the estimation of MGARCH model with t-distributed (standard errors in parentheses).

4. The CCC model is defined as：

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

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

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

Table 4
Parameter estimates for the DCC-MGARCH(1.1) models for China monetary policy to industry production index

Panel A：Conditional variance equation			
	LDEP	LDIS	LINDEX
W	0.0073***	0.0009***	0.0004***
	(0.0001)	(0.0001)	(0.0001)
α	0.5985***	0.3206***	0.2489***
	(0.0017)	(0.006)	(0.0259)
β	-0.5040***	-0.0168***	0.2871***
	(0.0001)	(0.0046)	(0.0281)
Panel B：DCC(1.1) parameter			
	α *	β *	α *+ β *
	0.5664***	0.0923	0.6587
	(0.0726)	(0.0865)	
Panel C：Model diagnostic checking			
Log-likehood：451.1954			
L-BQ(12)：23.401			
L-BQ^2 (12)：19.006			
ARCH-LM(12)：7.9081			

Note: 1. LDEP, LDIS and LINDEX is the log difference of the reserve rate, discount rate and industrial production index, respectively.

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

3. This table reports the results of the estimation of MGARCH model with t-distributed (standard errors in parentheses).

4. The DCC model is defined as：

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

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

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

Table 5
Parameter estimates for the DCC-MGARCH(1.1) models for China monetary policy to china stock markets

Panel A：Conditional variance equation						
	LDEP	LDIS	LSHC	LDEP	LDIS	LSJC
ω	0.0104***	0.0175***	0.0158***	0.0086**	0.0223***	0.0185***
	(0.0018)	(0.0073)	(0.0049)	(0.0001)	(0.0036)	(0.0072)
α	0.0158***	0.3936***	0.2174**	0.5283***	0.2109***	0.4172***
	(0.0049)	(0.0205)	(0.0372)	(0.0053)	(0.0323)	(0.0249)
β	-0.7784***	-0.1384	-0.3609***	-0.7168***	-0.1814***	-0.4724***
	(0.0997)	(0.0946)	(0.1079)	(0.0001)	(0.0658)	(0.1446)
Panel B：DCC(1.1) parameters						
	α *	β *	α *+ β *	α *	β *	α *+ β *
	0.686327***	0.318231***	0.99	0.8836***	0.0208	0.9036
	(0.05010)	(0.003354)		(0.0267)	(0.0240)	
Panel C：Model diagnostic checking						
Log-likehood：237.9909			Log-like：218.1692			
L-BQ(12)：21.0951			L-BQ(12)：30.1761			
L-BQ^2 (12)：20.3314			L-BQ^2 (12)：24.0701			
ARCH-LM (12)：2.0077			ARCH-LM (12)：4.3051			

Note: 1. LDEP, LDIS, LSHC, and LSJC is the log difference of the reserve rate, discount rate, Shanghai Composite index, and Shenzhen Composite index, respectively

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

3. This table reports the results of the estimation of MGARCH model with t-distributed (standard errors in parentheses).

4. The DCC model is defined as：

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

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

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