

# **Evaluating the Impact of Market Reforms on Value-at-Risk Forecasts of Chinese A and B Shares\***

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## **Abstract**

This paper analyses the time-varying conditional correlations between Chinese A and B share returns using the Dynamic Conditional Correlation (DCC) model of Engle (2002). The results show that the conditional correlations increased substantially following the B share market reform, whereby Chinese investors were permitted to purchase B shares. However, this increase in correlations was found to have begun well before the B share market reform. This result has significant implication relating to the structure of the information flow between the markets for the two classes of shares. Value-at-Risk (VaR) threshold forecasts are used to analyse the importance of accommodating dynamic conditional correlations between Chinese A and B shares, and thus reflects the impact of the changes in information flow on the risk evaluation of a diversified portfolio. The competing VaR forecasts are analysed using the Unconditional Coverage, Serial Independence and Conditional Coverage tests of Christoffersen (1998), and the Time Until First Failure Test of Kupiec (1995). The results offer mild support for the DCC model over its constant conditional correlation counterpart.

**Keywords:** Chinese A and B shares, Chinese stock markets, dynamic conditional correlation, market reform, Value-at-Risk, VaR.

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## **1 Introduction**

An important feature of the shares issued by the typical state-owned enterprises in the People's Republic of China (PRC) is that they are divided into negotiable and non-negotiable blocks of scrip. The non-negotiable block is typically larger, accounting for 60-70% of issued equity, and is controlled by the PRC. The negotiable portion of issued equity can be traded in three forms, namely A, B or H shares: H shares are listed in exchanges outside mainland China, while A and B shares can be listed in either the Shanghai or Shenzhen exchanges, with dual listing not permitted. Furthermore, companies listed in the Shanghai stock exchange typically have greater market capitalization than those listed in the Shenzhen stock exchange. Prior to 28 February 2001, ownership of A shares was restricted to residents of the PRC, while ownership of B shares was restricted to foreign investors. However, starting from 28 February 2001, Chinese residents were allowed to open foreign exchange accounts to trade in B shares.

The Chinese stock market is relatively small by global standards, with the Shanghai and Shenzhen exchanges having a total market capitalisation of US\$402 billion by the end of 2005, compared to US\$13,311 billion for the New York Stock Exchange, US\$4,573 billion for the Tokyo Stock Exchange, US\$1,055 billion for the Hong Kong Stock Exchange and US\$804 billion for the Australian Stock Exchange, according to the World Federation of Exchanges. However, given the sheer size of the Chinese economy and its recent stellar growth patterns, together with the recent accession to the World Trade Organisation, the importance of the Chinese stock market is likely to increase in the coming years. Therefore, the B share market reform will have significant implications for both domestic and foreign investors as Chinese stocks begin to feature more prominently in diversified portfolios.

From a Chinese investor's perspective, the ability to trade B shares implies an increase in integration between the A and B shares market. As both classes of shares represent identical ownership in the same company, the Efficient Market Hypothesis (EMH) would suggest that both classes of shares should trade at the same price. Yet prior to the deregulation, B shares tended to trade at a significant discount to their A share counterparts. Various studies have documented this observed market

segmentation, including Bailey (1994) and Ma (1996). Subsequent papers analysed the volatility in the Chinese stock markets. For example, Su and Fleisher (1999) analysed daily data for a matched sample of 24 firms issuing both A and B shares, and found that both types of shares exhibited time-varying volatility and that A shares tend to be more volatile. Poon and Fung (2000) used threshold GARCH models to investigate the asymmetric response of A and B share volatility to positive and negative shocks, and found that A and B shares reacted asymmetrically to good and bad news. Brooks and Ragunathan (2003) analysed the information transmission between A and B shares prior to the B share market reform, and found evidence of returns spillovers, but not volatility spillovers. More recently, Chiu et al. (2005) used the Autoregressive Conditional Jump Intensity model of Chan and Maheu (2002) to investigate the impact of the B share market reform on the volatility dynamics between A and B shares. Their results suggested that deregulation led to an increase in jump intensity and frequency, and that the volatility transmission had accelerated.

All the studies mentioned above suggest that the B share market reform had a significant impact on the covariance matrix between A and B shares. The covariance matrix of a portfolio of assets is one of the most important inputs in virtually all financial applications, from risk management, asset and option pricing to portfolio construction and management, to mention but a few. Chiu et al. (2005) calculated the historical sample correlations between A and B shares for the pre- and post-deregulation periods, and concluded that all pairs of correlations increased substantially following the B share market reform.

The use of historical correlations is limited, however, as it does not allow an investigation of the time-varying structure of the dynamic correlations. Furthermore, the results presented in Chiu et al. (2005) suffer from the disadvantage that the pre-deregulation sample is roughly ten times greater than the post-deregulation sample.

As B shares are typically traded at a significant discount to their A share counterparts, the B share market reform has created substantial arbitrage opportunities for Chinese investors. These arbitrage opportunities suggest that many Chinese investors would have expanded their portfolios to include B shares. An important consideration for such investors is the degree to which A and B shares are correlated, because the

strength of the correlation between the A and B shares will determine the potential benefits of diversifying across both types of shares. Furthermore, many modern risk management practices and strategies require estimates of the variance of the portfolio as well as an understanding of the co-movements between different components of the portfolio.

Another contribution of this paper is the study of information flow between the two markets. Chui and Kwok (1998) demonstrated that the returns of B shares lead the return of A shares, due to asymmetric information and information flows, by estimating the correlation between the returns of the two shares. They argued that the domestic investors did not have the same amount of information as the foreign investors due to information restriction in China. Therefore, their investment decision depended on the information reflected by the movements of the B shares market. However, their study was conducted before the 2001 market reform and therefore does not analyse the impact of the deregulation on the information flow mechanism. This issue can be investigated through the examination of the dynamic conditional correlation between the two shares.

Therefore, the aim of this paper is to examine the impact of the recent B share market reform on the correlation dynamics between A and B shares issued in the same market, by estimating Engle's (2002) Dynamic Conditional Correlation (DCC) model. The DCC model is chosen because it models correlations and being time-varying, as opposed to the Constant Conditional Correlation (CCC) model of Bollerslev (1990), which models the conditional correlations as being constant. Two alternative conditional volatility models with time-varying conditional correlations and covariances are available, namely the Varying Conditional Correlation model of Tse and Tsui (2002) and BEKK models of Engle and Kroner (1995). Although, strictly speaking, BEKK models the conditional covariances, and hence models the conditional correlations only indirectly (see McAleer (2005) for a comprehensive discussion of alternative univariate and multivariate, conditional and stochastic volatility models). These models are not considered in this paper as they are difficult to estimate for a large number of assets, and hence have limited usefulness in modern portfolio management, where risk measures for a very large number of assets are

required. To the best of our knowledge, this paper represents that first attempt to model the dynamic nature of the correlations between A and B shares.

The results of the paper suggest that the correlations between A and B shares increased substantially over the sample period, and that this increase began well before the B share market reform. One plausible explanation would be that Chinese investors had access to B share by establishing joint venture with foreign investors. Another implication of the results is that the changes in the conditional correlation between the two returns reflect the changes in the information flow between the two markets. This extends the results of Chui and Kwok (1998) and shows the trend of information flow by examining the trend in the conditional correlations.

This paper also examines the importance of accommodating time-varying correlations when forecasting Value-at-Risk(VaR) thresholds by using both CCC and the DCC models to forecast 1000 VaR thresholds for three theoretical portfolios containing A and B shares. The empirical results suggest that accommodating time-varying correlations improves the VaR forecasts.

The plan of the paper is as follows. Section 2 describes the data used. The CCC and DCC models are presented in Section 3, and alternative estimation procedures are discussed. The empirical results are discussed in Section 4. Section 5 describes the VaR method. The economic significance of the VaR threshold forecasts arising from the two models considered are examined in Section 6. Some concluding remarks are given in Section 7.

## **2 Data**

The data used in this paper are daily returns for the Shanghai A share index (SHA), Shanghai B share index (SHB), Shenzhen A share index (SZA) and Shenzhen B share index (SZB) for the period 6 October 1992 to 10 August 2005, and are obtained from Bloomberg. At the time of data collection, this was the longest sample for which data were available for all series. All data were gathered from Datastream and converted to a single currency, namely the US dollar. Figures 1a-d plot the respective indices rebased to 100 as at 6 October 1992. Table 1 gives the sample correlations between

the various indices. The SHA and SZA indices display the greatest sample correlation at 0.952, followed by SHB and SZB at 0.833. SHB and SZA have the lowest sample correlation at 0.338, followed by SHA and SZB at 0.352.

Figures 2a-d plot the daily returns for the respective indices, with the correlations between the various index returns being given in Table 2. These results suggest that SHA and SZA index returns display the greatest sample correlation at 0.782, followed by SHB and SZB at 0.692. SHA and SZB have the lowest sample correlation at 0.288, followed by SZA and SHB at 0.319. Of particular interest is that the results show that the correlation between the same class of shares across different exchanges is typically much higher than for different classes of shares within the same exchange. This is somewhat surprising as cross listing is not permitted, so that the SHA (SHB) and SZA (SZB) indices are mutually exclusive.

**[Inset Figures 1a-d Here]**

**[Insert Table 1 Here]**

**[Inset Figures 2a-d Here]**

**[Insert Table 2 Here]**

Table 3 gives the descriptive statistics for the daily returns. All series display similar means and median, which are close to zero. The A shares consistently display a greater range than do their B share counterparts, with significantly higher maxima and significantly lower minima. Moreover, all series display excess kurtosis, with the distribution of A shares displaying significantly thicker tails than B shares. Furthermore, the SHA, SHB and SZB return series are positively skewed, while the SZA return series are negatively skewed. Finally, all series are found to be highly non-normal according to the Jarque-Bera Lagrange multiplier test statistic.

**[Insert Table 3 Here]**

### **3 Model Specifications**

Before discussing the various conditional volatility (or variance) models used in this paper, it is useful to present Engle's (1982) conditional volatility approach in which a random process may be expressed as:

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t \quad (3.1)$$

where  $y_t = (y_{1t}, \dots, y_{mt})'$  and  $E(y_t | F_{t-1})$  denotes the conditional expectation of  $y_t$ , given the information set  $F_{t-1}$ , which contains all the information to period  $t-1$ . The vector  $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{mt})'$  is the random component of  $y_t$ , or the unconditional error, which can be decomposed as:

$$\varepsilon_t = D_t^{1/2} \eta_t \quad (3.2)$$

where  $\eta_t = (\eta_{1t}, \dots, \eta_{mt})'$  is a sequence of independently and identically distributed (iid) random vectors, and  $D_t = \text{diag}(h_{1t}, \dots, h_{mt})$ , which is a diagonal matrix with the conditional variances of each asset along the diagonal.

The conditional covariance and correlation can be written as:

$$E(\varepsilon_t \varepsilon_t' | F_{t-1}) = Q_t = D_t^{1/2} E(\eta_t \eta_t' | F_{t-1}) D_t^{1/2} = D_t^{1/2} \Gamma_t D_t^{1/2} \quad (3.3)$$

$$\Gamma_t = \{\rho_{ijt}\}, i, j = 1, \dots, m,$$

in which  $Q_t$  is the conditional covariance matrix and  $\Gamma_t$  is the conditional correlation matrix.

A problem which was encountered in the early development of multivariate volatility models was that they were computationally difficult due to the large number of parameters to be estimated. This issue has been discussed in detail by McAleer and da Veiga (2005) and Asai et al. (2005). In particular, these papers show that the DCC and

CCC models, to be discussed below, are attempts to reduce the so-called “curse of dimensionality”.

## CCC

The CCC model of Bollerslev (1990) is given by:

$$H_t = W + \sum_{k=1}^r A_k \bar{\varepsilon}_{t-k} + \sum_{l=1}^s B_l H_{t-l} \quad (3.4)$$

where  $H_t = (h_{1t}, \dots, h_{mt})'$ ,  $W = (\omega_1, \dots, \omega_m)'$ ,  $\bar{\varepsilon}_t = (\varepsilon_{1t}^2, \dots, \varepsilon_{mt}^2)$ ,  $A_k$  and  $B_l$  are  $m \times m$  diagonal matrices with typical elements  $\alpha_{ij}$  and  $\beta_{ij}$ , respectively,  $\forall i = j$ .

CCC models the conditional correlations of the conditional shocks as  $E(\eta_t \eta_t' / F_{t-1}) = \Gamma$ , where  $\Gamma$  is the constant conditional correlation matrix of the unconditional shocks which is, by definition, equivalent to the constant conditional correlation matrix of the conditional shocks.

## DCC

Empirical results have often found the CCC assumption to be too restrictive, so that these restrictions are often rejected in practice. Moreover, the incorrect specification of the correlation matrix may have important practical implications in many financial applications (see McAleer and da Veiga (2005) for further details). For this reason, Engle (2002) extended the CCC model to the DCC model, where the conditional correlation matrix,  $\Gamma_t$ , is assumed to be

$$\Gamma_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2} \quad (3.5)$$

$$Q_t = (i' - \theta_1 - \theta_2) \circ Q + \theta_1 \circ \eta_{t-1} \eta_{t-1}' + \theta_2 \circ Q_{t-1} \quad (3.6)$$



where  $\circ$  denotes the Hadamard element-by-element product,  $i$  denotes an  $m \times 1$  vector of unit elements, and  $Q$ ,  $\theta_1$  and  $\theta_2$  are  $m \times m$  symmetric matrices. If  $\theta_1$  and  $\theta_2$  are restricted to be the null matrix, then (3.6) collapses to  $Q_t = Q$ , which implies that the conditional correlations are constant.

Given the dynamic conditional correlations and conditional variances, the time-varying conditional covariance matrix,  $\Omega_t$ , can then be estimated as follows:

$$\hat{\Omega}_t = \hat{D}_t \hat{\Gamma}_t \hat{D}_t'. \quad (3.7)$$

The parameters in the CCC and DCC models, as defined in equations (3.1)-(3.4) and (3.1)-(3.6), respectively, can be estimated by maximizing the likelihood function, that is,

$$\hat{\lambda} = \max_{\lambda} l(\lambda) = \max_{\lambda} \left( -\frac{1}{2} \sum_{t=1}^T \log |\Omega_t| + \varepsilon_t' \Omega_t^{-1} \varepsilon_t \right) \quad (3.8)$$

where  $\lambda$  denotes the vector of unknown parameters. If  $\varepsilon_t$  follows a conditional multivariate normal distribution, then  $\hat{\lambda}$  is called the Maximum Likelihood Estimator (MLE), otherwise it is called the Quasi-MLE (QMLE).

It is straightforward to show that the likelihood function  $l(\lambda)$  can be rewritten as

$$l(\lambda) = l_1(\lambda_1) + l_2(\lambda_1, \lambda_2) \quad (3.9)$$

where  $\lambda_1$  denotes the vector of unknown parameters in the conditional mean and the conditional variance equations, and  $\lambda_2$  denotes the vector of unknown parameters in the conditional correlation matrix for CCC, and the vector of unknown parameters in (3.5) and (3.6) for DCC. Furthermore,

$$l_1(\lambda_1) = -\frac{1}{2} \sum_{t=1}^T \log |D_t^2| + \varepsilon_t' D_t^{-2} \varepsilon_t. \quad (3.10)$$

For CCC, it follows that

$$l_2(\lambda_1, \lambda_2) = -\frac{1}{2} \sum_{t=1}^T \log |\Gamma_t| + \eta_t' \Gamma_t^{-1} \eta_t - \eta_t' \eta_t \quad (3.11)$$

whereas in the case of DCC, the likelihood function is given by

$$l_2(\lambda_1, \lambda_2) = -\frac{1}{2} \sum_{t=1}^T \log |\Gamma_t| + \eta_t' \Gamma_t^{-1} \eta_t - \eta_t' \eta_t. \quad (3.12)$$

Using the invariance principle, Bollerslev (1990) and Engle (2002) argued that the parameters in the models can be estimated in two stages for CCC and DCC, respectively. The first stage involves estimating the parameters in the conditional mean and conditional variance only. Given the parameters estimated in the first stage, the second stage estimates the parameters in the conditional correlation matrix for CCC, and the parameters in the conditional correlation equation, as defined in (3.5)-(3.6) for DCC. Formally,  $\hat{\lambda}_1 = \max_{\lambda_1} l_1(\lambda_1)$  and  $\hat{\lambda}_2 = \max_{\lambda_2} l_2(\lambda_2 | \hat{\lambda}_1)$ .

Given that  $A_k$  and  $B_l$  are both diagonal matrices,  $l_1(\lambda_1)$  can then be rewritten as

$$l_1(\lambda_1) = \sum_{i=1}^m \left( -\frac{1}{2} \sum_{t=1}^T \log h_{it} + \frac{\varepsilon_{it}^2}{h_{it}} \right) \quad (3.13)$$

which is the sum of the  $m$  likelihood functions corresponding to the GARCH process for each asset. Therefore,

$$\hat{\lambda}_1 = \max_{\lambda_1} l_1(\lambda_1) \quad (3.14)$$

$$= \max_{\lambda_i} \sum_{i=1}^m \left( -\frac{1}{2} \sum_{t=1}^T \log h_{it} + \frac{\varepsilon_{it}^2}{h_{it}} \right) \quad (3.15)$$

$$= \sum_{i=1}^m \left( \max_{\lambda_i} -\frac{1}{2} \sum_{t=1}^T \log h_{it} + \frac{\varepsilon_{it}^2}{h_{it}} \right). \quad (3.16)$$

Hence, the parameters in the conditional variance can be estimated as a univariate GARCH model one asset at a time. This is useful as the structural and statistical properties of univariate GARCH model have been fully established. In particular, Elie and Jeantheau (1995) and Jeantheau (1998) showed that the QMLE is consistent for a GARCH(1,1) model if the log-moment condition is satisfied, namely,

$$E(\log(\alpha_{i1}\eta_{it}^2 + \beta_{i1})) < 0.$$

Boussama (2000) showed that the same condition is sufficient for QMLE to be asymptotically normal. Therefore, verifying the empirical log-moment condition can be viewed as a diagnostic check regarding the validity of the model.

The practical advantage of the DCC model over the other dynamic conditional correlation alternatives, such as the Varying Conditional Correlation model of Tse and Tsui (2002), is that the parameters in the conditional variance and correlation equations can be estimated separately in a two stage procedure. This allows a large number of assets to be included without imposing many of the numerical problems suffered by other multivariate GARCH-type models. Unless otherwise stated, the DCC estimates reported in this paper were obtained through the two stage procedure, as described in Engle (2002), using EViews 5.1.

#### 4 Empirical Results

In order to analyse the dynamic correlations between A and B shares in the Shanghai and Shenzhen markets, the DCC model is estimated for the entire sample period. Structural dummy variables are included in the conditional variance and correlation equations to capture the effect of the B share market reform. The augmented conditional variance and conditional correlation equations can be found as follows:

$$H_t = W + \sum_{k=1}^r A_k \bar{\varepsilon}_{t-k} + \sum_{l=1}^s B_l H_{t-l} + CV-DUM_t$$

$$Q_t = (ii' - \theta_1 - \theta_2) \circ Q + \theta_1 \circ \eta_{t-1} \eta_{t-1}' + \theta_2 \circ Q_{t-1} + \theta_3 \circ C-DUM_t,$$

where V-DUM and C-DUM are two dummy variables, such that

$$V-DUM_t = \begin{cases} 0, & t < 28/2/2001 \\ 1, & t \geq 28/2/2001 \end{cases}$$

and

$$C-DUM_t = \begin{cases} 0, & t < 28/2/2001 \\ 1, & t \geq 28/2/2001. \end{cases}$$

Moreover,  $C$  is an  $m \times 1$  diagonal matrix with typical elements  $c_i$  for  $i = 1, \dots, m$  and  $\theta_3$  is an  $m \times m$  matrix. Therefore, the impact of the market reforms can be investigated by examining the statistical significance of the estimated elements in  $\theta_2$  and  $\theta_3$ .

The estimated parameters of the conditional mean and conditional variance equations are reported in Table 4. It is important to note that, as the specifications of the conditional mean and conditional variance equations are the same for both the CCC and DCC models, the parameter estimates reported in Table 4 apply to both models. In order to accommodate non-normality of the error terms and the possible existence of outliers, the Bollerslev and Wooldridge (1992) robust t-ratios are reported.

All series except for SZA display significant AR(1) and MA(1) coefficients. In the conditional variance equation, all series display significant ARCH (or  $\alpha$ ) and GARCH (or  $\beta$ ) effects, suggesting that all series display time-varying volatility and are affected by both the short and long run persistence of shocks. An interesting finding is that A shares tend to exhibit greater long run persistence of shocks, while B shares tend to exhibit greater short run persistence. This may be due to the fact that B

share market consists of both domestic and foreign investors and hence the market could be more sensitive to shocks in short run.

As the log-moment conditions are satisfied, the parameter estimates in the conditional variance equation are consistent and asymptotically normal. Finally, the structural dummy in the conditional variance equation is negative and significant for both the SHA and SZA series, indicating that the B share market reform led to a fall in the volatility of A shares.

The parameter estimates for the conditional correlation equation are given in Table 5. It is interesting to note that the structural dummies are not significant in the conditional correlation equation, indicating that the B share market reform may not have had a significant impact on the conditional correlation between A and B shares. Figures 3a-b plot the fitted dynamic conditional correlations between the A and B share indices in the Shanghai and Shenzhen stock markets. As can be seen, both pairs of indices display significant variability in the fitted conditional correlations, with the dynamic correlation coefficients ranging from 0 to over 0.8. More importantly, the correlation between A and B share indices appears to have increased dramatically over the sample period, and this increase began well before the B share market reform. The conditional correlations measure the correlations in risk-adjusted returns. Therefore, as the conditional correlations approach 1, portfolio managers should not be diversifying across both A and B shares, but rather should be specializing and selecting the shares that are expected to yield the greatest returns.

The increasing conditional correlations could be explained by the decreasing level of asymmetric information due to the market reform. The majority of the domestic investors no longer observed the movement of the B shares for information as suggested in Chui and Kwok (1998). This is due to the fact that the movement in B shares no longer reflect information obtained only by the foreigner since domestic investors can also participate in the market. This has two implications: (i) B share market is now too noisy for purpose of obtaining additional information from foreign investors and (ii) the participation of domestic investors in both markets accelerates the integration of the two markets and hence increases the level of the conditional correlations.

## 5 Value-at-Risk

VaR is a procedure designed to forecast the maximum expected negative return over a target horizon, given a (statistical) confidence limit (see Jorion (2000) for a useful discussion). Put simply, VaR measures an extraordinary loss on an ordinary or typical day. VaR is used widely to manage the risk exposure of financial institutions and is a requirement of the Basel Capital Accord (see Basel Committee (1988, 1995, 1996)). The central idea underlying VaR is that, by forecasting the worst expected returns for each day, institutions can be prepared for the worst-case scenario.

Formally, a VaR threshold is the lower bound of a confidence interval in terms of the mean. Suppose interest lies in modelling the random variable,  $Y_t$ , which can be decomposed as:

$$Y_t = E(Y_t | F_{t-1}) + \varepsilon_t \quad (5.1)$$

This decomposition suggests that  $Y_t$  is comprised of a predictable component,  $E(Y_t | F_{t-1})$ , which is the mean conditional on the past information set,  $F_{t-1}$ , and a random component,  $\varepsilon_t$ . In this paper,  $F_{t-1}$  is taken to be all historical prices to time  $t-1$ . The variability of  $Y_t$ , and hence its distribution, is determined entirely by the variability of  $\varepsilon_t$ . It is assumed that  $\varepsilon_t$  follows a distribution such that:

$$\varepsilon_t \sim D(\mu_t, \sigma_t) \quad (5.2)$$

where  $\mu_t$  and  $\sigma_t$  are the unconditional mean and standard deviation of  $\varepsilon_t$ , respectively. The mean  $\mu_t = 0$  by the law of iterative expectations, and  $\sigma_t$  can be estimated using numerous parametric and/or non-parametric procedures. The procedure used in this paper is discussed in Section 3. Therefore, the VaR threshold for  $Y_t$  can be calculated as:

$$VaR_t = E(Y_t | F_{t-1}) - z\sigma_t \quad (5.3)$$

where  $z$  is the critical value from the distribution of  $\varepsilon_t$  that gives the correct confidence level. Alternatively,  $\sigma_t$  can be replaced by alternative estimates of the variance (see Section 3 above).

In the case of the banking industry, or authorized deposit-taking institutions, more generally, the forecasted VaR threshold is used to calculate the capital charges that banks are required to hold. The Basel Accord stipulates that the capital charge must be set at the higher of the previous day's VaR or the average VaR over the last 60 days multiplied by a safety factor that is set by local regulators but must not be smaller than 3. A capital charge works as an insurance policy that can help avoid bank runs as it requires banks to set aside sufficient funds to cover at least three times the worst possible loss, given the chosen confidence level.

In 1995 the Basel Accord was amended, and banks were permitted to use internal models to calculate their VaR thresholds. This amendment was in response to widespread criticism that the 'standardized' approach, which banks were originally required to use to calculate their VaR thresholds, led to excessively conservative forecasts. Excessive conservatism in forecasting risk has a negative impact on the profitability of banks as higher capital charges are subsequently required.

Although the amendment to the Basel Accord was designed to reward institutions with superior risk management systems, a backtesting procedure, whereby the realized returns are compared with the VaR forecasts, was introduced to assess the quality of the internal models. In cases where the internal models lead to a greater number of violations than could reasonably be expected, given the confidence level, the safety factor is increased by a penalty  $k$ , which is a function of the number of violations in the last 250 days (see Table 6 for the penalties recommended under the Basel Accord). The Basel Committee on Banking Supervision 1996 document

“Supervisory Framework for the Use of ‘Backtesting’ in Conjunction with the Internal Model Based Approach to Market Risk Capital Requirements”, defines three zones for backtesting results, (see Table 6). Section 3a of the above document states that:

*‘The green zone corresponds to backtesting results that do not themselves suggest a problem with the quality or accuracy of a bank’s model. The yellow zone encompasses results that do raise questions in this regard, but where such a conclusion is not definitive. The red zone indicates a backtesting result that almost certainly indicates a problem with the bank’s risk model.’*

Therefore, under the internal models amendment to the Basel Accord, the capital charge must be set at the higher of the previous day’s VaR or the average VaR over the last 60 days multiplied by a factor  $(3+k)$ . Finally, if a bank’s model is found to be inadequate by leading to an excessive number of violations, the bank may be required to adopt the standardized approach, which is virtually guaranteed to lead to higher capital charges. Hence, it is vitally important that the model used does not lead to backtesting results that fall in the yellow and red zones, lest regulators find the model to be inadequate and require the bank to adopt the conservative standardized approach.

## **6 Economic Significance**

In this paper a VaR example is used to demonstrate the economic significance of accommodating the dynamic nature of the conditional correlations between A and B shares. Three portfolios are considered: the first comprises equal percentages of the Shanghai A and B share indices (SZAB), the second comprises equal percentages of the Shenzhen A and B share indices (SHAB), and the third comprises equal percentages the Shanghai and Shenzhen A and B share indices. All portfolios are assumed to be rebalanced daily, so that all weights are kept equal and constant. Both the CCC and DCC models discussed above are used to forecast the conditional variance,  $h_t$ , of the portfolio, which replaces  $\sigma_t$  in equation (5.3), to calculate the VaR thresholds for the period 11 October 2002 to 10 August 2005, corresponding to



1000 forecasts. In order to eliminate exchange rate risk, all returns are converted to US Dollars.

## 6.1 Forecast Evaluations

Christoffersen (1998) derived likelihood ratio (LR) tests of unconditional coverage (UC)<sup>1</sup>, serial independence (SI) and conditional coverage (CC). Subsequently, Lopez (1998) adapted these tests to evaluate VaR threshold forecasts. These tests are widely used in practice to evaluate competing risk models. An adequate VaR model should exhibit the property that the unconditional coverage (which is calculated as the number of observed violations divided by  $T$ ) should equal  $\delta$ , where  $\delta$  is the level of significance chosen for the VaR, and  $T$  is the number of trading days in the evaluation period. The probability of observing  $x$  violations in a sample of size  $T$ , under the null hypothesis, is given by:

$$\Pr(x) = C_x^T (\delta)^x (1-\delta)^{T-x} \quad (6.1)$$

where  $\delta$ , which is typically set at 1%, is the desired proportion of observations that should be lower than the forecasted VaR thresholds. These observations are known as

violations.  $C_x^T = \frac{T!}{x!(T-x)!}$ , where  $!$  denotes the factorial operator such that

$$T! = \prod_{i=0}^{T-1} (T-i).$$

Therefore, the LR statistic for testing whether the number of observed violations, divided by  $T$ , is equal to  $\delta$ , is given by:

$$LR_{UC} = 2[\log(\hat{\delta}^x (1-\hat{\delta})^{N-x}) - \log(\delta^x (1-\delta)^{N-x})] \quad (6.2)$$

where  $\hat{\delta} = x/N$ ,  $x$  is the number of violations, and  $N$  is the number of forecasts. The LR statistic is asymptotically distributed as  $\chi^2(1)$  under the null hypothesis of correct UC.

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<sup>1</sup> Kupiec (1995) proposed the unconditional coverage test prior to Christoffersen (1998).

However, a model that leads to the correct unconditional coverage may still be sub-optimal. For example, models that lead to serially dependant violations, implying that the forecasting model is not able to effectively adjust to unexpected extraordinary trading losses that are clustered, is sub-optimal and may lead to bank failures. The test of independence is the LR statistic for the null hypothesis of serial independence against the alternative of first-order Markov dependence.

Finally, Christoffersen (1998) proposed the conditional coverage test, which is a joint test of unconditional coverage and independence. The conditional coverage LR statistic is given as the sum of the unconditional coverage LR statistic and the independence LR statistic, which is asymptotically distributed as  $\chi^2(2)$  under the joint null hypothesis.

Kupiec (1995) developed the Time Until First Failure (TUFF) test, which is based on the number of observations until the first violation. The null hypothesis is the same as for the UC test, namely that the observed proportion of violations is given by  $\hat{\delta} = x/N = \delta$ . The TUFF LR statistic, which is asymptotically distributed as  $\chi(1)$ , is given by:

$$LR_{TUFF} = -2\ln[\hat{\delta}(1-\hat{\delta})^{\tau-1}] + 2\ln\left[\frac{1}{\tau}(1-\frac{1}{\tau})^{\tau-1}\right] \quad (6.3)$$

where  $\tau$  denotes the number of observations before the first violation.

In addition to the statistical tests described above, the forecasting performance of the two models considered is also evaluated by the following four statistics: 1) the number of violations, which gives an indication of the correct coverage; 2) the proportion of time spent out of the green zone, which gives an indication of the likely additional regulatory constraints that may be imposed on the bank; 3) the mean daily capital charge, which captures the opportunity cost of using each model; and 4) the absolute deviation of actual returns versus forecasted VaR thresholds. As VaR is a technique designed for managing risk, the magnitude of a violation is of paramount importance as large violations are of much greater concern than are small violations.

Figures 4a-f plot the forecasted conditional variances for the three portfolios using both the CCC and DCC models. The conditional variance forecasts produced by the CCC and DCC models are highly correlated, with a correlation coefficient of 0.988 for the conditional variance forecasts of the Shanghai A and B share portfolio, 0.986 for the conditional variance forecasts of the Shenzhen A and B share portfolio, and 0.971 for the conditional variance forecasts of the Shanghai and Shenzhen A and B share portfolio. Figures 5a-f plot the portfolio returns and VaR threshold forecasts, which show that the VaR forecasts are also highly correlated.

The empirical results are reported in Tables 7 and 8. All models perform well according to SI, CC and TUFF. However, the CCC model fails the UC test, as it leads to excessive violations, for both the Shanghai A and B share portfolio and the Shenzhen A and B share portfolio. Based on the number of violations and proportion of time spent out of the green zone, the DCC model always dominates CCC as it always leads to a smaller number of violations and substantially less time in the yellow zone. Figures 6a-f plot the rolling backtest results for all model and portfolio combinations, while Figures 7a-f plot the rolling capital charges. As can be seen, the DCC model always leads to the same or fewer cumulative violations than does the CCC model. These results suggest that the DCC model leads to superior VaR forecasts.

On the other hand, based on the mean and maximum absolute deviation of violations, the CCC model dominates DCC as it always leads to a lower maximum and mean absolute deviation of violations. Finally, according to the mean daily capital charge, the CCC model gives lower average daily capital charges for both the Shanghai A and B share index portfolio and the Shanghai and Shenzhen A and B share portfolio. However, the DCC model leads to lower mean daily capital charges for the Shenzhen A and B share index portfolio.

A natural question is whether the reported daily capital charges are statistically different from each other. Diebold and Mariano (1995) propose a test statistic that explicitly tests the null hypothesis of no difference in the accuracy of two competing forecasts. This statistic can easily be applied to test whether the capital charges produced by the various models used in this paper are statistically different from each

other. The original test compares the errors  $(e_{1,t}, e_{2,t})$ ,  $t = 1, \dots, n$ , produced by two competing forecasts. These forecasts are evaluated using some loss function,  $f(e)$ , and the null hypothesis is of equality of the expected forecast performance,  $E[f(e_{1,t}) - f(e_{2,t})] = 0$ .

In this paper the relevant loss function is the capital charge produced by each competing model. The original statistic proposed by Diebold and Mariano (1995) is given by:

$$S_1 = [\widehat{V}(\bar{d})]^{-\frac{1}{2}} \bar{d}, \quad (6.4)$$

where

$$d_t = f(e_{1,t}) - f(e_{2,t}); \quad t = 1, \dots, n \quad (6.5)$$

$$\bar{d} = n^{-1} \sum_{t=1}^n d_t \quad (6.6)$$

$$V(\bar{d}) \approx n^{-1} \left[ \xi_0 + 2 \sum_{k=1}^{h-1} \xi_k \right] \quad (6.7)$$

where  $\xi_k$  is the  $k$ th autocovariance of  $d_t$  and  $h$  is the number of steps ahead for forecasting. However, Harvey et al. (1997) showed that the original statistic proposed by Diebold and Mariano (1995) can be over-sized and proposed the following adjusted statistic:

$$S_1^* = \left[ \frac{n+1-2h+n^{-1}h(h-1)}{n} \right]^{\frac{1}{2}} S_1. \quad (6.8)$$

The adjusted test statistic follows a t-distribution with  $n-1$  degrees of freedom. The results of the adjusted Diebold and Mariano test, as reported in Table 8, suggest that

the daily capital charges produced by each model are statistically different from each other. These results suggest that the choice of model can have serious implications for the calculated capital charges, and ADIs should exercise great care in choosing between the alternative models.

The results presented in this paper have interesting implications for risk managers as they suggest that, while the DCC model leads to less violations and hence less time spent out of the green zone than the CCC model, the capital charges given by DCC tend to be higher. Therefore, the penalty structure imposed under the Basel Accord may not be severe enough to discourage ADIs from adopting VaR models that lead to excessive violations.

## **7 Conclusion**

The aim of this paper was to model the dynamic conditional correlations between Chinese A and B share returns for the period 6 October 1992 to 10 August 2005. Prior to 28 February 2001, ownership of A shares was restricted to residents of the PRC, while ownership of B shares was restricted to foreign investors. However, starting from 28 February 2001, Chinese residents were allowed to open foreign exchange accounts to trade in B shares. A shares typically traded at a significant discount to their B share counterparts, which represented a violation of the Efficient Markets Hypothesis as both types of shares represented identical ownership in the same company. The deregulation of the B share market created substantial arbitrage opportunities, as the price of A and B shares converged, and many Chinese investors found themselves owning portfolios containing both A and B shares.

An important question for Chinese investors is the degree to which A and B shares are correlated as this will affect the portfolio construction process. The DCC model of Engle (2002) was used to estimate the dynamic conditional correlations. It was found that the correlations between Chinese A and B share returns increased substantially over the sample period, and that this increase began well before the B share market

reform. The results presented in this paper are important because, as the correlation between Chinese A and B shares approaches 1, the benefits of diversifying across both types of shares diminishes and investors should focus on the class of shares that will yield the greatest expected returns.

Given that many financial institutions are likely to hold portfolios of both Chinese A and B shares, it is important to analyse the importance of accommodating time-varying conditional correlations on the Value-at-Risk (VaR) threshold forecasts. In order to examine this important issue, the VaR thresholds were forecasted using both the CCC model of Bollerslev (1990), which imposes the restriction of Constant Conditional Correlations, and the DCC model of Engle (2002). The forecasting performance was evaluated using a variety of standard statistical tests, including the UC, SI and CC tests of Christoffersen (1998) and the TUFF test of Kupiec (1995). Both models performed well according to the SI, CC and TUFF tests, while the DCC model appeared to dominate the CCC model according to the UC tests as it generally yielded a lower number of violations.

Three other measures were also considered to reflect the concerns of both ADI's and regulators. The first measure is the proportion of time that each model leads to 'backtesting' results that fall outside the green zone, reflecting the likely extra regulatory burden that an ADI would face given the use of each model. According to this measure, the DCC model dominates CCC as it is always found to lead to a lower proportion of time spent out of the green zone. The second measure used in this paper is the size of the average and maximum absolute deviation of violations. As VaR is a procedure designed for managing risk, by allowing ADIs to hold sufficient capital in reserves to cover extraordinary losses, the size of the violation is of extreme importance. In almost all cases, the DCC model was found to lead to lower average and maximum absolute deviations.

Finally, we compare the daily capital charges given by each model. As capital charges represent an opportunity cost, ADIs effectively face a constrained optimization problem whereby they wish to minimise capital charges subject to not violating any regulatory constraints (see da Veiga, Chan, McAleer and Medeiros (2005) for further details). According to this measure, the CCC model is found to lead to lower capital

charges, on average. The Diebold and Mariano (1995) test showed that the daily capital charges produced by each model were statistically different from each other. This result is consistent with the results reported in da Veiga, Chan, McAleer Medeiros (2005), who found that the current Basel Accord penalty structure is not sufficiently severe, and hence leads to lower capital charges for models with excessive violations than for models with the correct number of violations.

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Table 1: Sample Correlations Between Indexes

SHA	SHB	SZA	SZB
	0.375	0.952	0.352
		0.338	0.833
			0.317

Table 2: Sample Correlations Between Index Returns

SHA	SHB	SZA	SZB
	0.298	0.782	0.288
		0.319	0.692
			0.341

Table 3: Descriptive Statistics for Returns

Statistics	SHA	SHB	SZA	SZB
Mean	0.005	0.001	-0.011	0.015
Median	0.000	0.000	0.000	0.000
Maximum	30.886	12.184	29.608	13.597
Minimum	-38.790	-13.085	-40.332	-16.670
SD	2.670	2.142	2.456	2.188
Skewness	0.628	0.427	-0.470	0.369
Kurtosis	37.649	8.307	40.055	10.917
Jarque-Bera	167898	4037	191897	8830

Table 4: Conditional Mean and Variance Equations

Parameter	SHA	SHB	SZA	SZB
Conditional Mean				
C	0.013 (1.253)	-0.012 (-1.765)	<b>0.011</b> (2.876)	0.098 (1.087)
AR	<b>0.541</b> (2.441)	<b>0.368</b> (2.015)	0.582 (1.138)	<b>0.556</b> (5.330)
MA	<b>-0.537</b> (-2.403)	<b>-0.217</b> (-2.015)	-0.549 (-1.027)	<b>-0.424</b> (-3.791)
Conditional Variance				
$\omega$	<b>0.079</b> (3.150)	<b>0.200</b> (3.812)	<b>0.305</b> (4.120)	<b>0.464</b> (4.409)
$\alpha$	<b>0.093</b> (4.329)	<b>0.189</b> (5.265)	<b>0.150</b> (5.414)	<b>0.270</b> (6.178)
$\beta$	<b>0.914</b> (55.354)	<b>0.780</b> (20.000)	<b>0.839</b> (29.548)	<b>0.636</b> (14.900)
V-Dum	<b>-0.033</b> (-2.236)	-0.012 (-0.263)	<b>-0.244</b> (-3.292)	0.066 (0.680)
Log Moment	-0.017	-0.093	-0.103	-0.214
$\alpha + \beta$	1.007	0.969	0.989	0.906

Note: The two entries for each parameter correspond to the parameter estimate and Bollerslev-Wooldridge robust t-ratios, respectively.

Table 5: Conditional Correlation Equation

Parameter	SHASHB	SZASZB
$\gamma$	<b>0.075</b> (1.987)	0.002 (1.067)
$\theta_1$	<b>0.001</b> (23.842)	<b>0.007</b> (12.729)
$\theta_2$	<b>0.999</b> (63.402)	<b>0.993</b> (24.797)
C-Dum	0.093 (0.601)	0.262 (1.265)

Note: The two entries for each parameter correspond to the parameter estimate and Bollerslev-Wooldridge robust t-ratios, respectively.

Table 6: Basel Accord Penalty Zones

Zone	Number of Violations	Increase in $k$
Green	0 to 4	0.00
Yellow	5	0.40
	6	0.50
	7	0.65
	8	0.75
	9	0.85
Red	10+	1.00

Note: The number of violations is given for 250 business days.

Table 7: Unconditional Coverage (UC), Serial Independence (SI), Conditional Coverage (CC) and Time Until First Failure (TUFF) Tests

Model	UC	SI	CC	TUFF
Shanghai A and B Share Portfolio				
CCC	<b>4.091</b>	0.299	4.390	0.005
DCC	3.077	0.264	3.341	0.001
Shenzhen A and B Share Portfolio				
CCC	<b>5.225</b>	0.336	5.561	0.853
DCC	3.077	0.264	3.341	1.016
Shanghai and Shenzhen A and B Share Portfolio				
CCC	3.077	0.264	3.341	1.016
DCC	0.099	0.124	0.223	0.121

Notes:

- (1) The Unconditional Coverage (UC) and Time Until First Failure (TUFF) tests are asymptotically distributed as  $\chi^2(1)$ .
- (2) The Serial Independence (SI) and Conditional Coverage tests are asymptotically distributed as  $\chi^2(2)$ .
- (3) Entries in **bold** denote significance at the 5% level.

Table 8: Mean Daily Capital Charges and AD of Violations

Model	Number of Violations	Proportion of Time out of Green Zone	Daily Capital Charge		AD of Violations	
			Mean	Diebold and Mariano	Maximum	Mean
Shanghai A and B Share Portfolio						
CCC	17	37%	9.361%		86.56%	21.01%
DCC	16	23%	9.405%	<b>-3.120*</b>	82.85%	19.89%
Shenzhen A and B Share Portfolio						
CCC	18	30%	10.055%		82.13%	23.79%
DCC	16	11%	9.977%	<b>4.896*</b>	83.39%	20.35%
Shanghai and Shenzhen A and B Share Portfolio						
CCC	16	17%	9.072%		67.39%	25.51%
DCC	11	0%	9.227%	<b>-10.549*</b>	63.39%	25.73%

Notes:

- (1) The daily capital charge is given as the negative of the higher of the previous day's VaR or the average VaR over the last 60 business days times  $(3+k)$ , where  $k$  is the penalty. The capital charge represents the proportion of the portfolio that must be kept in reserves.
- (2) All portfolios are equally weighted.
- (3) AD denotes absolute deviation which is computed as (actual return minus the forecasted VaR) divided by the forecasted VaR.
- (4) The Diebold and Mariano statistic evaluates the null hypothesis of no difference between the two forecasted capital charges for each portfolio. This statistic is asymptotically distributed as t-distribution with n-1 degrees of freedom.
- (5) Entries in **bold** are significant at the 5% level and \* denotes significance at the 1% level.
- (6) As there are 1000 days in the forecasting period, the expected number of violations at the 1% level of significance is 10.

Figure 1a: Shanghai A Share Index

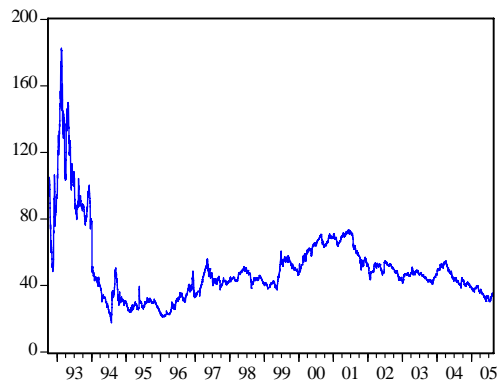


Figure 1b: Shanghai B Share Index

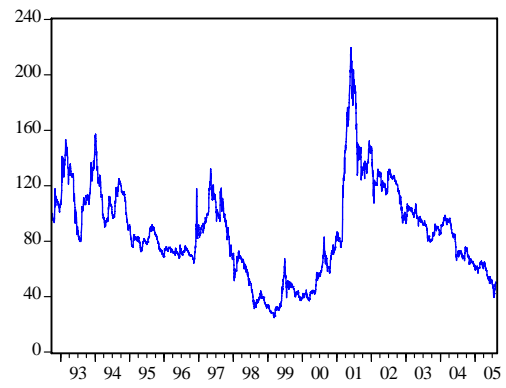


Figure 1c: Shenzhen A Share Index

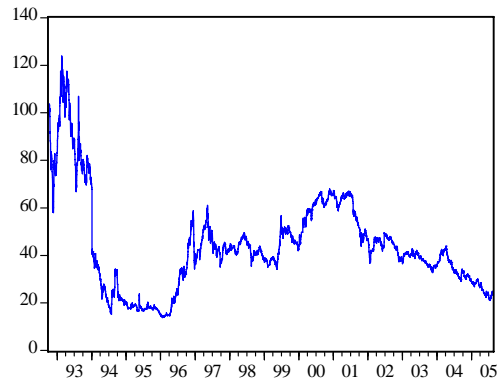


Figure 1d: Shenzhen B Share Index

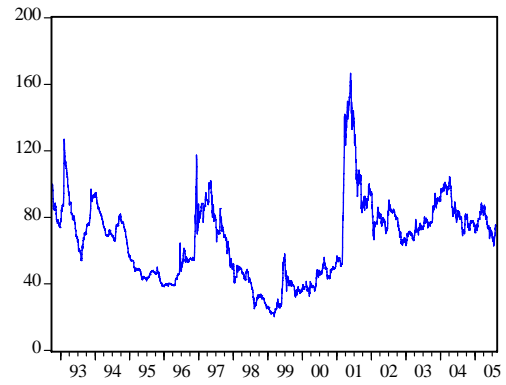


Figure 2a: Shanghai A Share Index Daily Returns

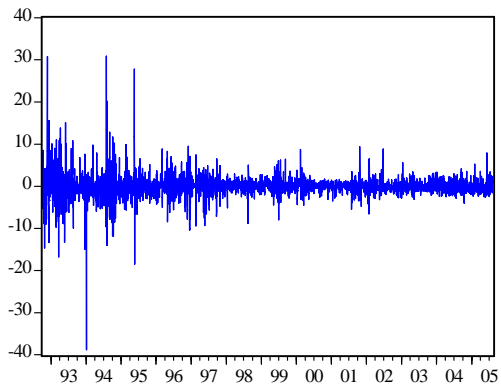


Figure 2b: Shanghai B Share Index Daily Returns

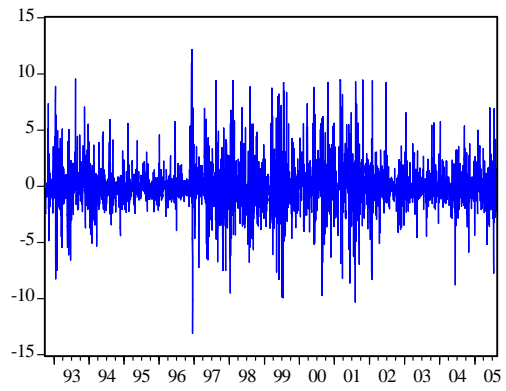


Figure 2c: Shenzhen A Share Index Daily Returns

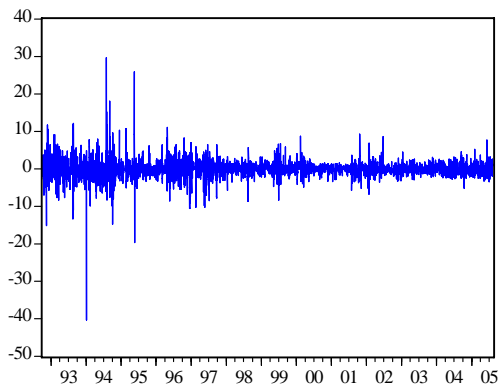


Figure 2d: Shenzhen B Share Index Daily Returns

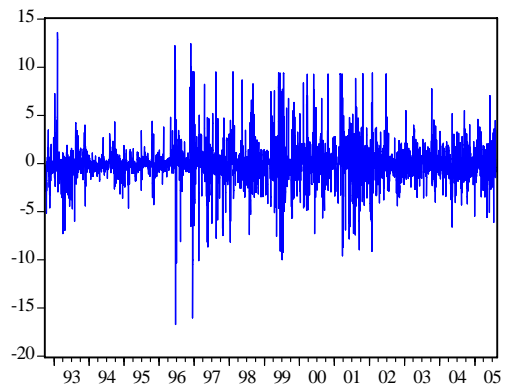




Figure 3a: Fitted DCC Between SHA and SHB

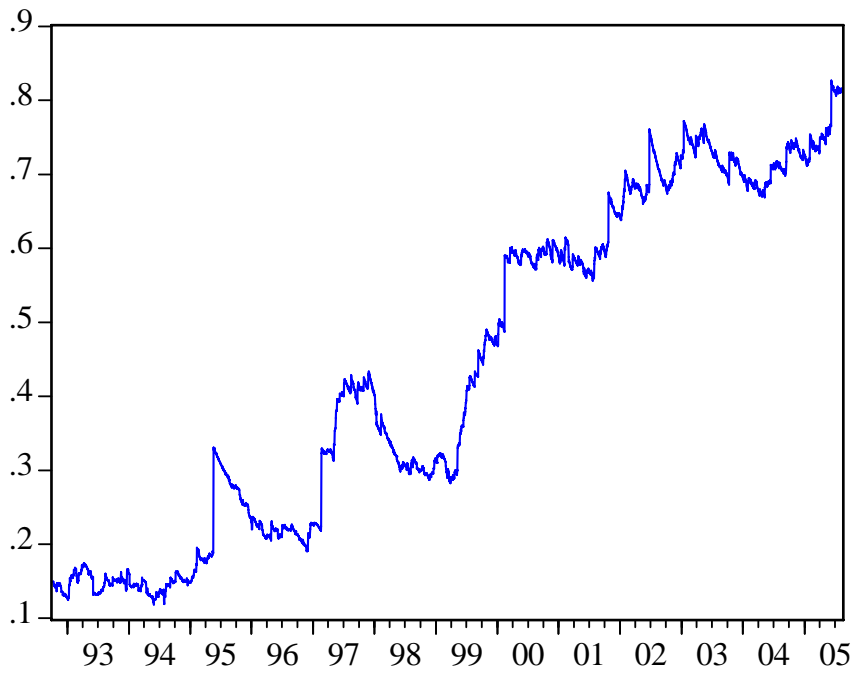


Figure 3b: Fitted DCC Between SZA and SZB

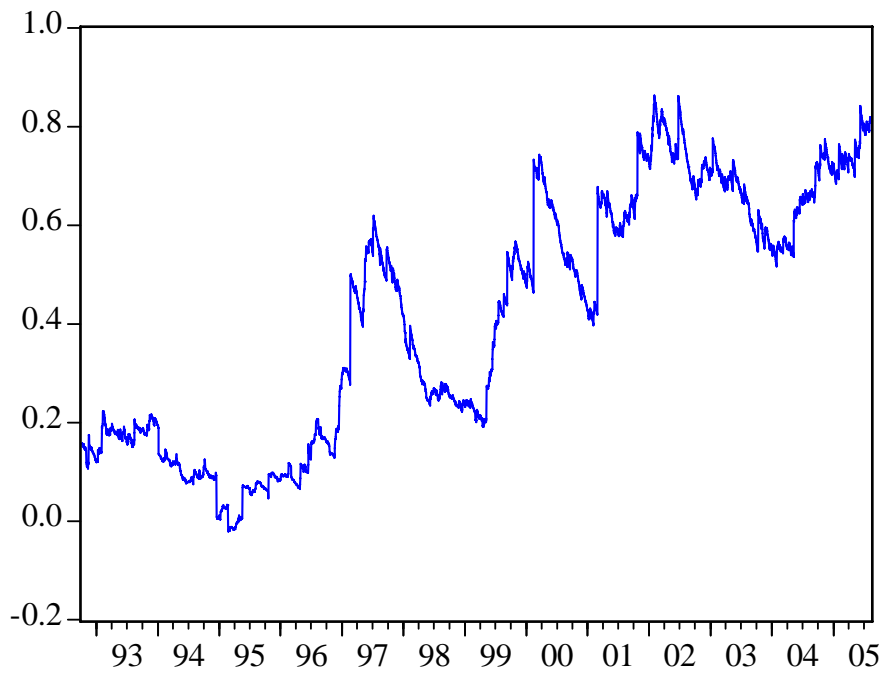


Figure 4a: Shanghai A and B Share Portfolio  
CCC Conditional Variance Forecasts

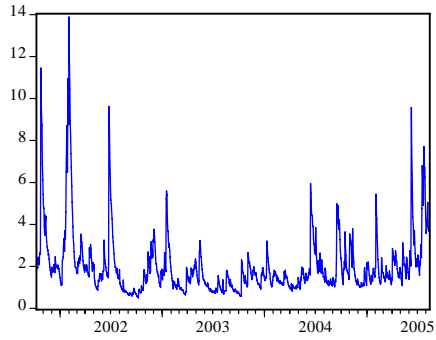


Figure 4b: Shanghai A and B Share Portfolio  
DCC Conditional Variance Forecasts

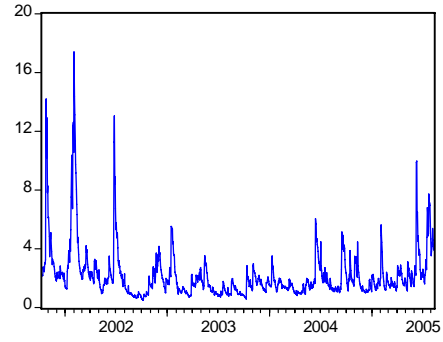


Figure 4c: Shenzhen A and B Share Portfolio  
CCC Conditional Variance Forecasts

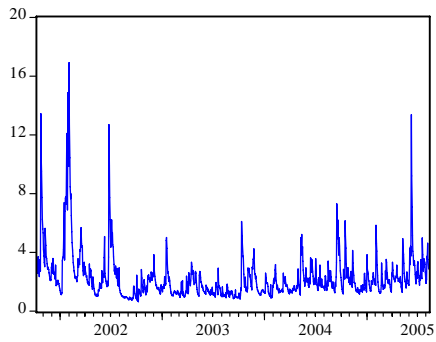


Figure 4d: Shenzhen A and B Share Portfolio  
DCC Conditional Variance Forecasts

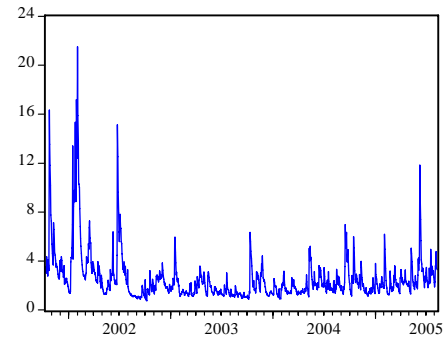


Figure 4e: Shanghai and Shenzhen A and B Share Portfolio  
CCC Conditional Variance Forecasts

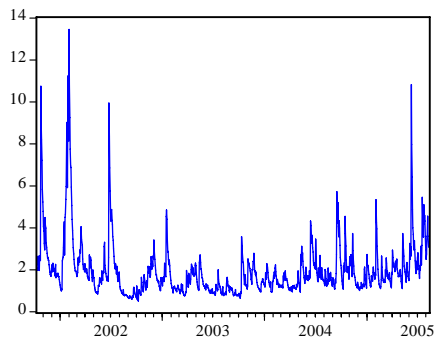


Figure 4f: Shanghai and Shenzhen A and B Share Portfolio  
DCC Conditional Variance Forecasts

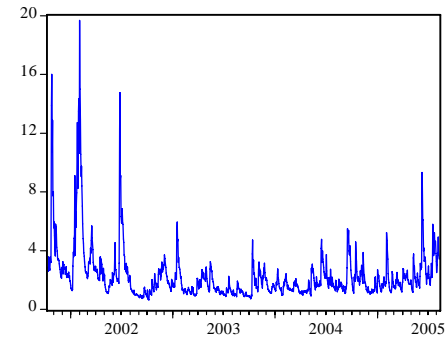


Figure 5a: Shanghai A and B Share Portfolio Returns and CCC VaR threshold Forecasts

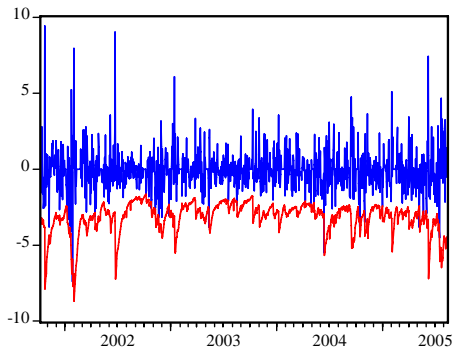


Figure 5b: Shanghai A and B Share Portfolio Returns and DCC VaR threshold Forecasts

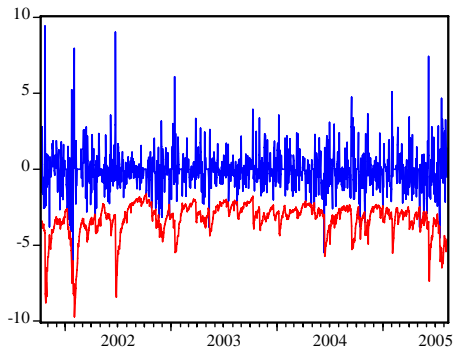


Figure 5c: Shenzhen A and B Share Portfolio Returns and CCC VaR threshold Forecasts

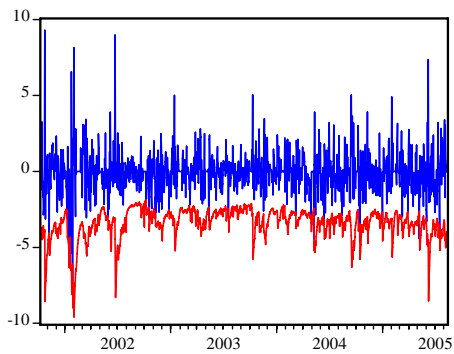


Figure 5d: Shenzhen A and B Share Portfolio Returns and DCC VaR threshold Forecasts

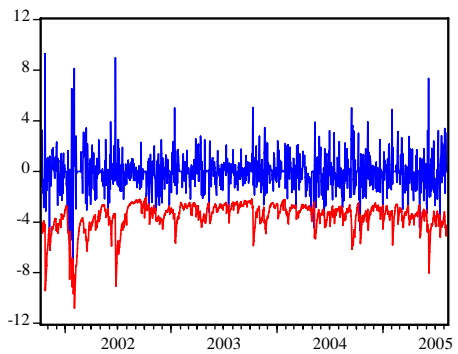


Figure 5e: Shanghai and Shenzhen A and B Share Portfolio Returns and CCC VaR threshold Forecasts

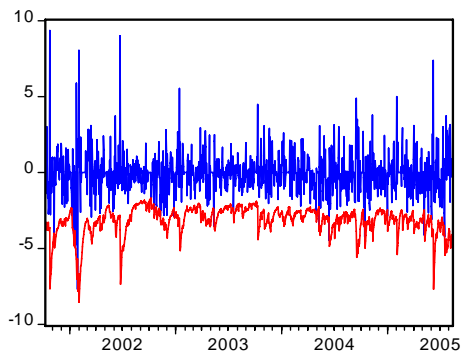


Figure 5a: Shanghai and Shenzhen A and B Share Portfolio Returns and DCC VaR threshold Forecasts

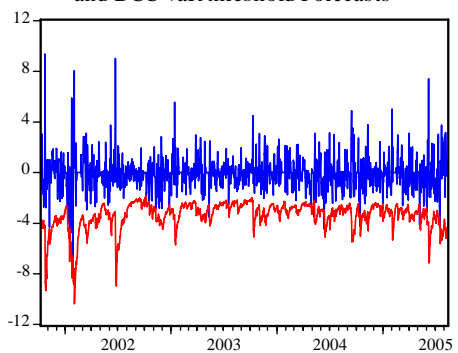


Figure 6a: CCC Rolling Backtest for Shanghai A and B Share Portfolio

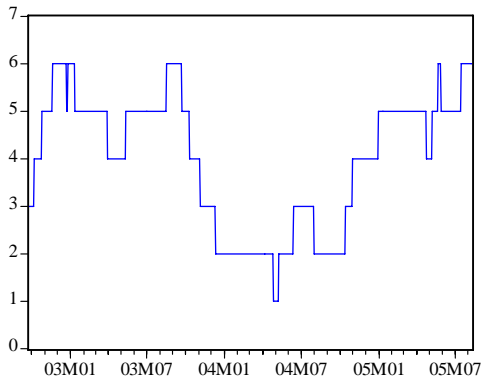


Figure 6b: DCC Rolling Backtest for Shanghai A and B Share Portfolio

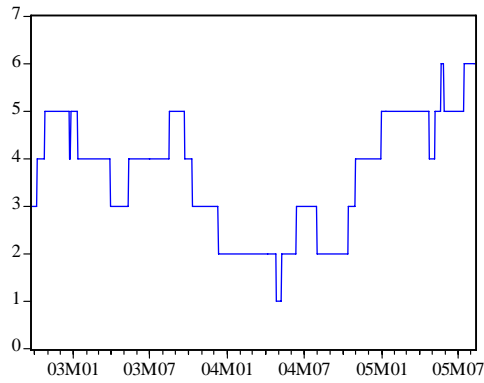


Figure 6c: CCC Rolling Backtest for Shenzhen A and B Share Portfolio

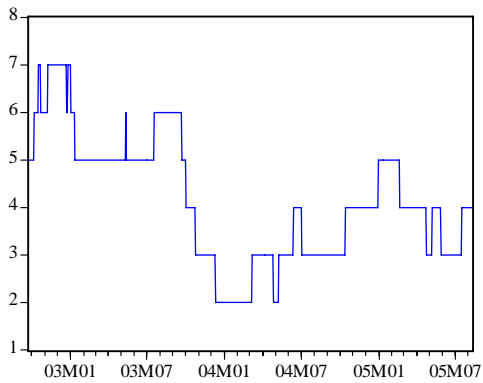


Figure 6d: DCC Rolling Backtest for Shenzhen A and B Share Portfolio

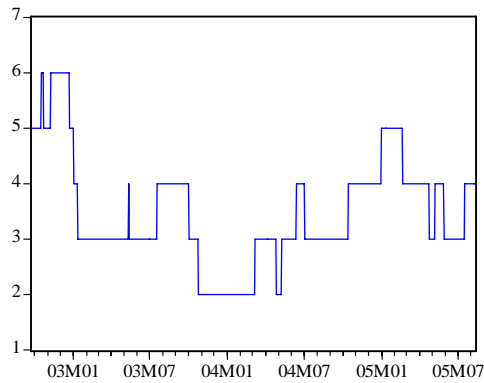


Figure 6e: CCC Rolling Backtest for Shanghai and Shenzhen A and B Share Portfolio

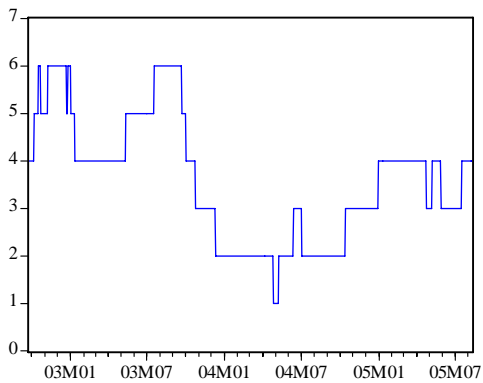


Figure 6f: DCC Rolling Backtest for Shanghai and Shenzhen A and B Share Portfolio

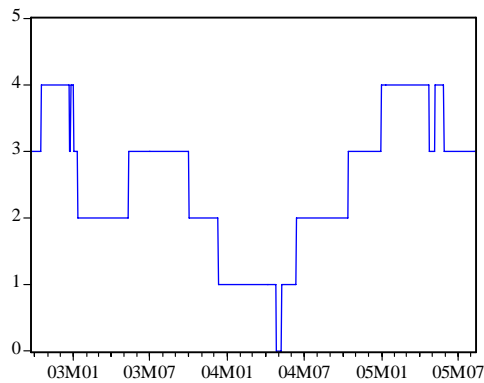


Figure 7a: Rolling CCC Capital Charges for Shanghai A and B Share Portfolio

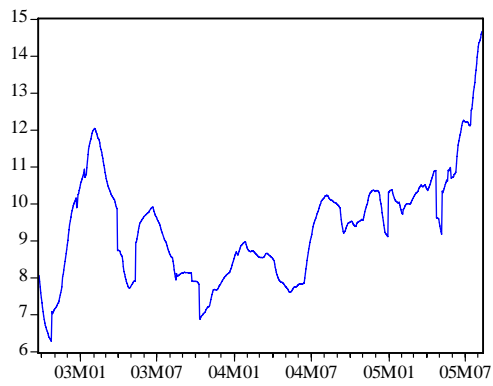


Figure 7b: Rolling DCC Capital Charges for Shanghai A and B Share Portfolio

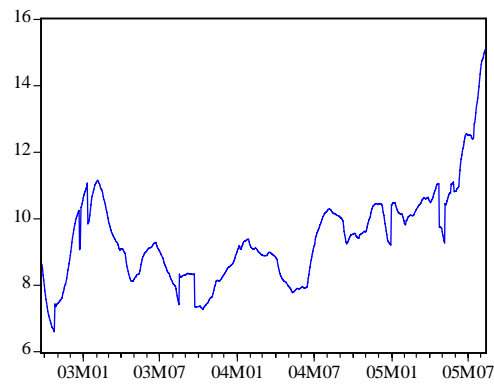


Figure 7c: Rolling CCC Capital Charges for Shenzhen A and B Share Portfolio

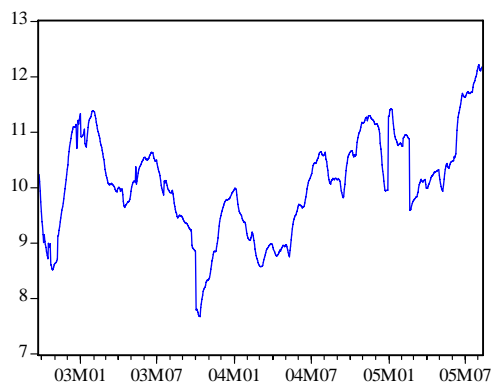


Figure 7d: Rolling DCC Capital Charges for Shenzhen A and B Share Portfolio

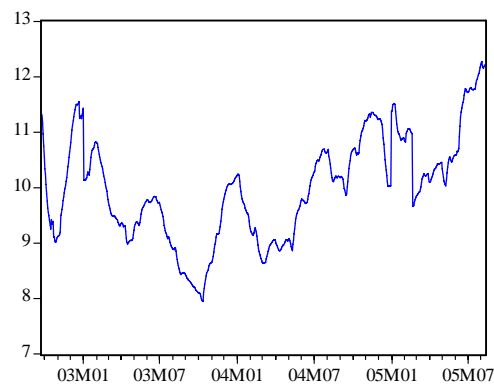


Figure 7e: Rolling CCC Capital Charges for Shanghai and Shenzhen A and B Share Portfolio

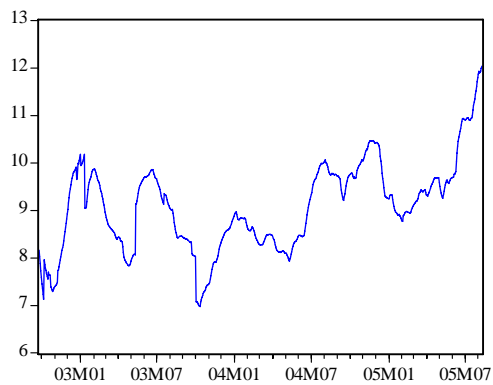


Figure 7f: Rolling DCC Capital Charges for Shanghai and Shenzhen A and B Share Portfolio

