The Effect of B Share Market Reform on Volatility Spillovers and Changes in Correlation between Chinese A and B Shares

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EXTENDED ABSTRACT

The aim of this paper is to investigate the effect of the Chinese B share market reform on the correlation and information transmission between A and B Shares issued in the Shanghai and Shenzen stock exchanges. Daily returns for the Shanghai A share index (SHA), Shanghai B share index (SHB), Shenzen A share index (SZA) and Shenzen B share index (SZB) are used for the period 6 October 1992 to 8 February 2005. The results suggest that the all pairs of correlations increase dramatically over the period analysed, but such increase begins well before the reforms to the B Share market.

1 Introduction

An important feature of the shares issued by the typical People's Republic of China (PRC) state-owned enterprises 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 A, B or H shares. H shares are listed in exchanges outside of mainland China while A and B shares can be listed in either the Shanghai or Shenzen exchanges, dual listing is not permitted. Furthermore, companies listed in the Shanghai stock exchanges have typically greater market capitalization. than those listed in the Shenzen 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.

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) analyse daily data for a matched sample of 24 firms issuing both A and B shares and find that both types of shares exhibit time varying volatility and that A shares tend to be more volatile. Poon and Fung (2000) use threshold GARCH models to investigate the asymmetric response of A and B share volatility to positive and negative shocks and find that A and B shares react asymmetrically to good and bad news. Brooks and Ragunathan (2003) analyse the information transmission between A and B shares prior to the B share market reform and find evidence of returns spillovers but not volatility spillovers. More recently Chiu et al. (2005) use the Autoregressive Conditional Jump Intensity model of Chan and Maheu (2002) to investigates the impact of the B share market reform on the volatility dynamics between A and B shares. Their results suggest 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 almost all financial applications, from risk management, asset and option pricing to portfolio construction and management to mention but a few. The aim of this paper is to examine the impact of the recent B share market reform on Value-at-Risk (VaR) thresholds forecast. Following the B share market reform, it is likely that many Chinese investors would have expanded their portfolios to also include B shares. Since the B share market reform has been shown in various papers to have led to a change in the volatility dynamics between A and B shares, a logical question is how to optimally accommodate these changes when modelling and forecasting the covariance matrix.

The Vector Autoregressive Moving Average Asymmetric Generalized Autoregressive Conditional Heteroskedasticity (VARMA-AGARCH) model of Hoti et al. (2003), is used to estimate the covariance matrix and to test for a change in the correlation between A and B shares following the reforms in the B share market. An attractive feature of the VARMA-AGARCH model is its ability to capture the asymmetric effects of positive and negative shocks on the conditional volatility, and to accommodate interdependencies (or spillovers) in returns and volatilities, which allows the existence of mean and volatility spillovers to be tested jointly.

Hence, the use of the VARMA-AGARCH model allows us to explore several empirical side issues such as returns and volatility transmission and spillovers, across the different classes of shares within markets and across markets, as well as between the same class of shares within markets. By analysing the sample before and after the reforms separately, this paper also investigates whether the transmission and spillover of volatility was affected by the reform.

2 Data

The data used in this paper are daily returns for the Shanghai A share index (SHA), Shanghai B share index (SHB), Shenzen A share index (SZA) and Shenzen B share index (SZB) for the period 6 October 1992 to 8 February 2005. All data was gathered from Datastream and converted to a single currency, namely the US dollar. Table 1 gives the descriptive statistics for the daily returns. As can be seen all series display similar means and median close to zero. The A shares consistently display greater range than their B share counterparts, with significantly higher maxima and significantly lower minima. All series display excess kurtosis, with the distribution of A shares displaying significantly thicker tails than B shares. Finally, all series are found to be highly non-normal according to the Jarque-Bera statistic.

Table 1:Descriptive Statistics for Returns

	SHA	SHB	SZA	SZB
Mean	0.007	0.007	-0.008	0.017
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	2.708	2.146	2.484	2.201
Skewness	0.616	0.435	-0.484	0.373
Kurtosis	37.014	8.373	39.772	10.967
Jarque-Bera	155479	3976	181598	8593

3 Model

Equation Chapter 3 Section 3

This paper uses the vector autoregressive moving average asymmetric generalised autoregressive conditional heteroskedasticity (or VARMA-AGARCH) model of Hoti et al. (2003) to model the time varying volatility and test for the existence of volatility spillovers and asymmetric effects. Hoti et al. (2003) derived the necessary and sufficient conditions for strict stationarity and ergodicity, sufficient conditions for the existence of the log-moment and all moments, and sufficient conditions for consistency and asymptotic normality of the quasi-maximum likelihood estimator (QMLE) under non-normality of the standardized shocks to returns. Their proofs are based on the derivation of the causal expansions, which do not require the existence of moments. The structural and asymptotic properties of all nested special cases follow by the imposition of appropriate restrictions, which allows the various special cases of the VARMA-AGARCH model to be tested. An alternative multivariate model for which asymptotic theory has been considered is the BEKK model of Engle and Kroner (1995). Comte and Lieberman (2003) showed consistency of the QMLE of BEKK using the conditions established in Jeantheau (1998), and asymptotic normality of the QMLE by assuming the existence of eighth moments. However, as the moment conditions have been assumed rather than derived, it is not possible to verify the conditions in practice.

The general multivariate model is given by:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \tag{3.1}$$

$$\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t \tag{3.2}$$

$$\varepsilon_t = D_t \eta_t \tag{3.3}$$

$$H_t = W + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-l} + \sum_{l=1}^{r} C_l I(\eta_{t-l}) \vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} B_l H_{t-l} \tag{3.4}$$

where $H_t = (h_{1t},...,h_{mt})'$, $W = (\omega_1,...,\omega_m)'$, $D_t = diag(h_{it}^{1/2})$, $\eta_t = (\eta_{1t},...,\eta_{mt})'$, $\vec{\varepsilon}_t = (\varepsilon_{1t}^2,...,\varepsilon_{mt}^2)$, A_l, C_l and B_l are $m \times m$ matrices with typical elements α_{ij}, γ_{ij} and β_{ij}, respectively, for $i, j = 1,...,m$, $I(\eta_t) = diag(I(\eta_{it}))$ is an $m \times m$ matrix, $\Phi(L) = I_m - \Phi_1 L - ... - \Phi_p L^p$ and $\Psi(L) = I_m - \Psi_1 L - ... - \Psi_q L^q$ are polynomials in *L*, the lag operator, F_t is the past information available to time *t*, I_m is the $m \times m$ identity matrix, and $I(\eta_{it})$ is an indicator function, given as:

$$I(\eta_{it}) = \begin{cases} 1, & \varepsilon_{it} \le 0 \\ 0, & \varepsilon_{it} > 0. \end{cases} \tag{3.5}$$

The time subscripts in the model correspond to calendar time. The coefficients α_{ij} and β_{ij}, $i \ne j$, measure the extent to which the lagged unconditional shock and lagged conditional variance in market *j*, respectively, influence the conditional variance in market *i*.

An attractive feature of the VARMA-AGARCH model is its ability to capture multivariate asymmetries concerning the impact of positive and negative shocks to market *i* on the conditional variance in market *i* through the coefficient γ_i. If γ_i is positive, it implies that negative shocks increase the conditional volatility in market *i* to a larger extent than do positive shocks.

Bollerslev (1990) proposed the Constant Conditional Correlation (CCC) GARCH model. The CCC model calculates the conditional correlations as $E(\eta_t \eta_t') = \Gamma$, where Γ is the constant conditional correlation matrix of the conditional shocks which is, by definition, equivalent to the constant conditional correlation matrix of the unconditional shocks. This procedure can be applied to the VARMA-AGARCH model and all its special cases to estimate the conditional correlation matrix and in turn the covariance matrix.

4 Return and Volatility Spillovers and Change in Conditional Correlation

Equation Chapter (Next) Section 4

The first issue we explore in this paper is whether the reform to the B share market substantially changed the conditional correlation between A and B shares. In order to answer this, three estimated conditional correlation matrices between A and B shares are obtained by estimating the VARMA-AGRACH model for the entire sample, the sub-sample before the reform (6/10/1992 to 28/2/2001) and the sub-sample after the reform (28/02/2001 to 8/2/2005). All estimation was undertaken using EViews 5 and full convergence was achieved. Both the asymptotic t-ratios of Weiss (1986) and the Bollerslev and Wooldridge (1992) robust t-ratios are reported, inference is based on the robust t-ratios as these are robust to the presence of outliers and non-normality.

Let ρ_1 and ρ_2 be the correlations from the first and second period, respectively. The test statistic for testing differences in correlations is then given by:

$$Z = \frac{(\rho_1 - \rho_2)}{SE} \tag{4.1}$$

$$SE = \sqrt{\frac{1}{(n_1 - 3)} + \frac{1}{(n_2 - 3)}} \tag{4.2}$$

where n_1 and n_2 are sample sizes used to calculate ρ_1 and ρ_2 respectively.

Table 2:Conditional Mean Equation 6 October 1992 - 8 February 2005

Coefficient	SHA	SHB	SZA	SZB
Constant	-0.019	-0.017	-0.054	-0.003
	-0.152	-0.203	-1.093	-0.031
	-0.487	-1.586	-1.847	-0.099
SHA(-1)	-0.007	0.016	0.107	0.002
	-0.004	0.378	2.616	0.044
	-0.003	-1.115	1.656	0.166
SHB(-1)	-0.033	**0.016**	-0.054	**0.120**
	-0.546	0.019	-2.219	2.608
	-0.964	5.388	-1.779	4.048
SZA(-1)	0.024	-0.014	-0.323	-0.002
	0.388	-0.287	-0.973	-0.036
	0.460	-0.193	-0.961	-0.168
SZB(-1)	0.046	**0.105**	**0.066**	0.011
	0.894	3.158	3.121	0.007
	1.585	2.595	3.509	0.009
MA(1)	-0.007	**0.017**	0.256	0.011
	-0.004	0.020	0.729	0.007
	-0.003	-5.332	0.696	0.009

Notes:

1. The three entries for each parameter are their respective estimate

Asymptotic and Bollerslev-Wooldridge (1992) robust t-ratio.

2. SHA(-1), SHB (-1), SZA (-1), SZB (-1) denote the lagged returns

for each index.

3. Entries in **bold** are significant at the 5% level using the robust t-ratios.

Tables 2 and 3 give the parameter estimates of the VARMA-AGARCH model for the entire sample. Evidence of returns spillover is found from SZB to both SHB and SZA, indicating that past returns of SZB affect future returns from SHB and SZA; and from SHB to SZB, indicating that past returns of SHB affect future returns to SZB. Evidence of positive volatility spillover is found from SHA to SZA. While evidence of negative spillovers is found from SZB to SZA. Positive (negative) volatility spillover suggests that a shock to one index would increase (reduce) the volatility of other indices.

Tables 4-6 give the conditional correlation matrix for the entire sample, the pre-reform sample and the post-reform sample respectively. As can be seen the calculated conditional correlations for all index pairs are significantly higher following the reform than prior to the reform. For example, the correlation between SHA and SHB prior to the reform is 0.344 while the correlation for the period following the reform is 0.704, similar results are found for all index pairs. Table 7 uses the testing procedure described above to test for differences in correlation between samples and finds all the differences in all correlations to be statistically significant at the 99% level.

Table 3: Conditional Variance Equation 6 October 1992 - 8 February 2005

Coefficient	SHA	SHB	SZA	SZB
ω	**6.933**	**3.933**	**2.321**	**4.317**
	6.171	5.268	8.543	4.614
	2.957	3.833	3.170	3.275
γ	0.043	-0.040	0.123	0.019
	1.298	-1.329	2.890	0.406
	0.262	1.523	1.457	0.264
SHAα	0.145	-0.002	-0.013	-0.003
	5.139	-1.169	-8.952	-0.541
	1.484	-1.324	-0.197	-0.926
SHAβ	**0.582**	-0.009	**0.331**	-0.010
	9.212	-0.786	6.507	-0.757
	3.775	0.173	2.936	-1.287
SHBα	-0.029	**0.125**	0.000	-0.015
	-1.451	4.277	0.084	-0.448
	-1.310	2.770	0.046	-0.716
SHBβ	-0.034	**0.549**	-0.015	-0.026
	-0.829	6.511	-1.373	-0.651
	-0.861	3.045	-0.706	-0.776
SZAα	-0.018	-0.003	0.114	-0.003
	-0.476	-1.799	5.092	-0.608
	-0.411	1.017	1.521	-1.060
SZAβ	-0.019	-0.015	0.261	-0.016
	-0.732	-1.101	2.944	-1.027
	-0.925	-0.553	1.313	-1.677
SZBα	-0.025	-0.018	-0.007	**0.140**
	-2.428	-1.806	-1.280	4.366
	-1.335	-0.154	-1.348	2.236
SZBβ	-0.064	-0.026	**-0.047**	**0.566**
	-3.704	-1.855	-5.051	5.983
	-1.621	0.419	-2.707	4.280

Notes:
1. The three entries for each parameter are their respective estimate and Bollerslev-Wooldridge (1992) robust t-ratio.
2. The parameters in the conditional variance equation associated with SHA, SHB, SZA and SZB index returns are denoted by α and β.
3. Entries in **bold** are significant at the 5% level

The results reported in Table 4 show that the existence of structural change has significant impact on the conditional correlation and the assumption of static conditional correlation may not hold. In this case, failing to accommodate the structural change can cause downwards bias in the conditional correlation. Such downward bias can have serious implications for many financial applications. For example, this downwards bias indicating a greater diversification in a portfolio is detrimental as the risk of a portfolio is underestimated by the low conditional correlation between the returns of different assets. This can then lead to suboptimal hedge ratios, poor asset allocation decisions and excessively aggressive VaR thresholds.

Table 4: Conditional Correlation 6 October 1992 - 8 February 2005

	SHA	SHB	SZA	SZB
SHA	1.000	0.344	0.785	0.327
SHB		1.000	0.390	0.671
SZA			1.000	0.414
SZB				1.000

Table 5: Conditional Correlation 6 October 1992 - 28 February 2001

	SHA	SHB	SZA	SZB
SHA	1.000	0.277	0.763	0.256
SHB		1.000	0.290	0.598
SZA			1.000	0.313
SZB				1.000

Table 6: Conditional Correlation 28 February 2001- 8 February 2005

	SHA	SHB	SZA	SZB
SHA	1.000	0.704	0.964	0.693
SHB		1.000	0.706	0.859
SZA			1.000	0.711
SZB				1.000

Table 7: Test for Differences in Correlation

Between Samples

	SHA	SHB	SZA	SZB
SHA		**11.272**	**5.309**	**11.555**
SHB			**10.998**	**6.894**
SZA				**10.510**
SZB				

The figures given are the z scores given by equation 4.1. Figures in **bold** are significant at the 1% level. using the robust t-ratio.

5 Correlation Dynamics

The VARMA-AGARCH model, like all its nested variations, imposes the assumption of constant conditional correlations. Engle (2002) and Tse and Tsui (2002) have recently proposed closely related multivariate GARCH models with time-varying conditional correlations. McAleer et al. (2004) provide a theoretical motivation for these models in terms of a vector of serially correlated standardized residuals, develop the generalized autoregressive conditional correlation (GARCC) model, and derive the theoretical and statistical properties of a wide range of dynamic conditional correlation models.

In the constant conditional correlation framework, Γ is the constant conditional correlation matrix of the standardised shocks, η_t, which are assumed to be either a vector of independently and identically distributed (iid) random variables, or a martingale difference process. However, in the dynamic conditional correlation framework, the conditional correlation matrix, Γ, is no longer constant but follows a restricted multivariate GARCH(1,1) specification. If Γ is assumed to be time varying, a more general multivariate GARCH structure would be required to generalize the iid assumption for η_t. This difficulty would render the existing proofs of consistency and asymptotic normality of the QMLE for the constant conditional correlation GARCH model invalid for its time-varying counterpart. Such deficiencies would also prevent the models from testing for the presence of volatility spillovers.

Using rolling windows approach, we can examine the time-varying nature of the conditional correlations using the VARMA-AGARCH model. Rolling windows are a recursive estimation procedure whereby the model is estimated for a restricted sample, then re-estimated by adding one observation to the end of the sample and deleting one observation from the beginning of the sample. The process is then repeated until the end of the sample. If the rolling conditional correlations are found to vary substantially over time, the assumption of constant conditional correlations may be too restrictive. Such a result may be used to motivate the estimation of dynamic conditional correlation models, and may also question the existing results based on constant conditional correlation models. In order to strike a balance between efficiency in estimation and a viable number of rolling regressions, the rolling window size is set at 1000.

Figure 1: Rolling Conditional Correlation Between SHA & SHB

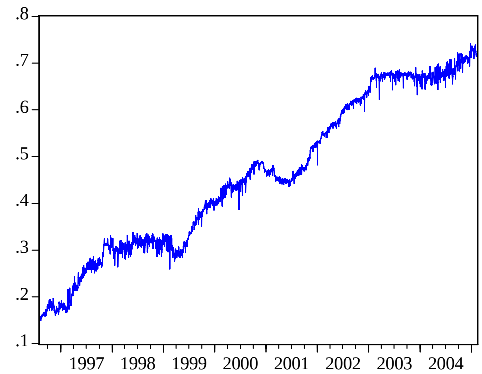


Figure 2: Rolling Conditional Correlation Between SHA & SZA

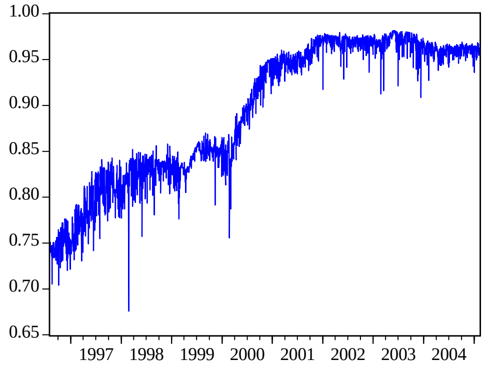


Figure 3: Rolling Conditional Correlation Between SHA & SZB

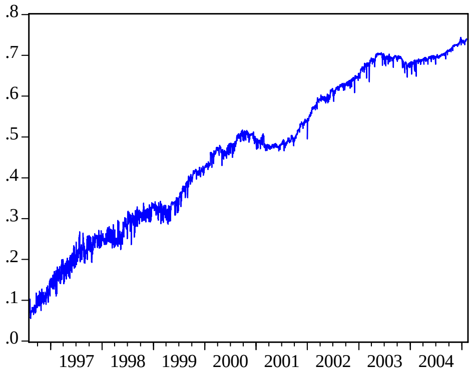


Figure 4: Rolling Conditional Correlation Between SHB & SZB

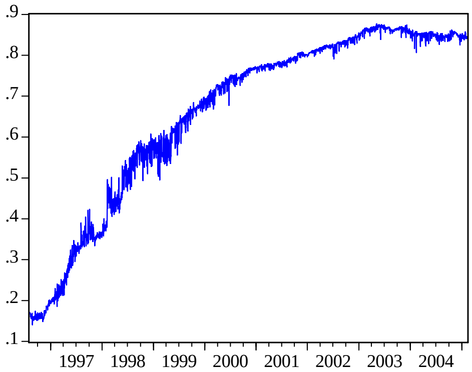


Figure 5: Rolling Conditional Correlation Between SZA & SZB

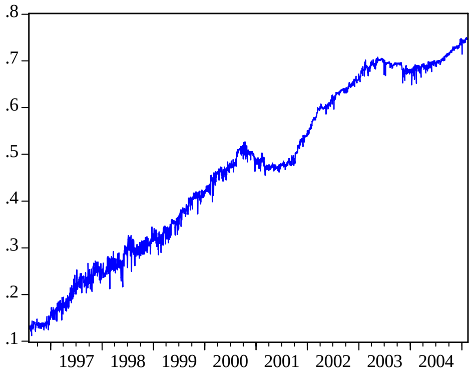
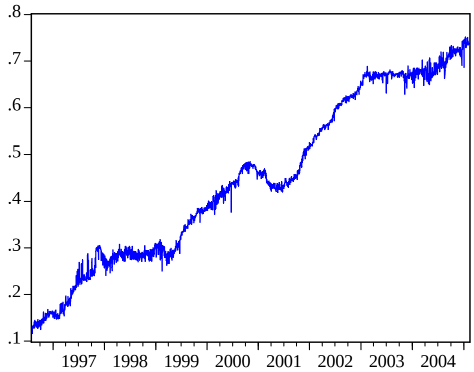


Figure 6: Rolling Conditional Correlation Between SHB & SZA



Figures 1-6 plot the dynamic paths of the constant conditional correlation matrices for the VARMA-AGARCH model using rolling windows. All the conditional correlations display significant variability. More specifically, all pairs of conditional correlations appear to increase

over time. These results suggest that the assumption of constant conditional correlations may not be valid, and hence may lead to biased inferences. It is interesting to note that all pairs of conditional correlations appear to strengthen from the beginning of the period, with all A and B share pairs displaying similar patterns where there appears to be an initial increase in the conditional correlations in 1997, which could be due to the handover of Hong Kong, a further spike in 1999 which could correspond to the hand over of Macaw and finally a spike in 2001 which is likely to be due to the reform to the B share market.

6 Conclusion

This paper examined the effect of the B share market reform on the information transmission and correlations dynamics between A and B shares listed in mainland China. The results showed that the correlation between A and B shares has increased dramatically over time, but this increase began well before the B share market reforms. The empirical results also indicated the presence of both returns and volatility spillovers between the four indices.

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