Risk, Return and Regulation in Chinese Stock Markets

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Abstract

This paper studies the dynamic behavior of risks and returns in Chinese stock markets. We characterize the time-series properties of stock-market return and volatility and test the market efficiency hypothesis. We estimate an empirical model that captures the effect of local and global information variables on the conditional mean of stock-market returns and characterize the second order conditional moments using three error generation processes. We find that stock-market volatility is time-varying, mildly persistent, and is best described by a fat-tailed distribution such as the Stable distribution. We also find that government's market liberalization policies have contributed to high stock-market volatility in China.

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1 Introduction

There are two stock markets in China, the Shanghai Securities Exchange having been inaugurated in December 1990 and the Shenzhen Securities Exchange in April 1991. Since then, more than 50 trading centers have been created in major cities across the nation, the number of listed stocks has reached about 400, the public demand for new shares has been tremendous, and market capitalization relative to GDP reached about 11% by the end of August 1996.

The extraordinary expansion and rapid growth of the Chinese stock markets have been accompanied by some difficulties. Problems include high initial public offering (IPO) underpricing, market segmentation and high stock-market return volatility. Our article examines the risk and return behavior in Chinese stock markets with focus on government regulation and stock-market volatility.

Understanding stock-market risk and return behavior is very important, because in a market consisting of risk-averse investors, greater volatility (risk) would lead investors to demand a higher risk premium, creating higher cost of capital, which impedes investment and slows economic development. The purposes of our paper are: (1) to characterize the risk and return behavior in Chinese stock markets; (2) to analyze how well Chinese stock markets function relative to other developed and emerging markets; and (3) to identify causes of the high volatility of stock-market returns in China.

In section 2, we lay out the basic pattern of returns and volatility in Chinese stock markets. In Section 3, we examine the market efficiency hypothesis using variance ratio tests and residual-based cointegration tests. In Section 4, we establish an empirical model that captures the effects of local and global information variables on the conditional mean of weekly stock-market returns. We characterize the conditional variance of returns using three alternative formulations of the error-generating process. In Section 5, we present the econometric results. We then apply the best-fitted model to examine the effect of exogenous government policy variables on stock-market return volatility in section 6. We conclude the article with a summary of findings in Section 7.

2 Stock-Market Return and Volatility Pattern

There are two categories of shares traded in Chinese stock markets: A shares are available only for Chinese citizens and B shares can be purchased only by foreign investors. Both A- and B shares are traded in the two official exchanges in China, Shanghai and Shenzhen. A shares dominate Chinese stock markets in terms of market capitalization and level of activity. (The number of B shares listed on the two exchanges is less than one-third of the number of A shares. B shares amount to less than 3% of the A shares' market capitalization and 2% of the A shares' annual trading value.) Additional categories of shares include H shares and N shares, which are available only to foreign investors and are traded in Hong Kong and the New York Stock Exchange, respectively. The analysis in our paper is based on the A and B shares data from the first-day of market trading until March 18, 1996.

We first analyze stock-market volatility and returns to investors using data of daily stock market indices for A and B shares for both the Shanghai and Shenzhen securities exchanges. We relate trading in these shares to daily market indices representing more mature stock markets, including indices of the MSCI world market, the NYSE and the Hong Kong Stock Exchange. The daily market indices are based on value-weighted portfolios of securities and do not reflect dividends.

Table 1 presents some sample distributional statistics for the stock-market indices included in this paper. Statistics include the daily and weekly risk-unadjusted sample mean returns, Sharpe ratio[1], coefficients of skewness and kurtosis, and Ljung-Box portmanteau statistics. The coefficients of skewness and kurtosis are jointly estimated with the mean and variance. The Ljung-Box Q(12) statistic is used to test the significance of serial correlation up to lag 12.

We find that: (1) Mean returns and Sharpe ratios on both share categories in both Chinese stock exchanges are relatively low compared with other Asian, U.S., and world indices. (2) Mean returns for A shares in the Shanghai Securities Exchange have been much higher than in the Shenzhen Securities Exchange. (3) Returns on B shares have been lower than those on A shares for both exchanges[2]. (4) Coefficients of kurtosis are generally higher in Chinese stock markets than those in more developed equity markets, suggesting that "big surprises" are more

[1] The Sharpe ratio is the sample mean stock return divided by the sample standard deviation.

[2] International investors who bought heavily into B shares in the first two years after B shares were listed and traded in 1992 have become disillusioned by the low returns and have started moving their investment elsewhere.

frequently observed in Chinese markets.

Next, we characterize volatility and risk patterns in Chinese stock markets. Daily A- and B share market indices for Shanghai and Shenzhen stock exchanges are plotted in figures 1 and 2. We also calculate estimates of the variance of daily stock returns over the entire sample period. Important features of the markets' volatility include: (1) The volatility of stock-market returns is higher in China than in other developed markets; (2) A share markets in Shanghai and Shenzhen exhibit far greater volatility than B share markets. (3) Extreme price volatility exists in both exchanges. For example, the Shanghai A share index more than doubled in a single day, from 636.56 on May 22, 1992 to 1341.11 on May 23, 1992; by November 17, 1992, it had fallen by over 70%, to 369.94. More recently, the Shanghai A share index rose from about 400 in July 1994 to more than 1,000 in September. (4) The size of price "jumps", measured by the percentage change in the price index, are smaller for Shenzhen A shares than for Shanghai A shares.

Third, we use the daily values of A and B share market indices to estimate the monthly variance of stock market returns in Shanghai and Shenzhen. Our monthly variance estimates use only non-overlapping sample returns in that month, and allow us to explore time-varying volatility change.

Because of the existence of autocorrelation, we follow Merton (1980) in estimating the variance of the monthly return for the A and B share market indices as the sum of the squared daily returns plus twice the sum of the products of the adjacent returns,

$$\sigma_{j,t}^2 = \sum_{i=1}^{N_t} r_{i,t}^2 + 2 \sum_{i=1}^{N_{t-1}} r_{i,t} r_{i+1,t}, \tag{1}$$

where there are N_t daily returns, $r_{i,t}$, in month t. We do not subtract the sample mean from each daily return in calculating the variance because the adjustment is very small.

Figures 3 and 4 contain plots of the monthly standard deviation estimates for A and B share returns in Shanghai and Shenzhen. These figures highlight the variation of estimated volatility in China's stock markets. As suggested in these figures, (1) there is strong evidence of time-varying volatility change in both share categories in both exchanges; (2) periods of high and low volatility tend to cluster, and volatility shows mild persistence; (3) "big surprises" are often observed in these markets; (4) the mean and standard deviation of the stock-market return standard deviation estimates are higher for A shares than for B shares.

We briefly summarize the price and return behavior of Chinese stock markets as follows:

- Risk-adjusted returns to investors are low;
- The degree of variability of these returns as evidenced by a conventional measure of volatility is very high;
- Volatility is time-varying and is mildly persistent. Volatility of A share markets is far greater than that of B share markets in both Shanghai and Shenzhen;

3 Market Efficiency Hypothesis

The fundamental insight of the market efficiency hypothesis is that security prices reflect optimal use of all available information. It is well known that the Chinese government intervenes its domestic stock markets in an unpredictable way from time to time. For example, the Chinese government suddenly removed the 1% daily price change limit on May 2, 1992 and removed the 5% daily price change limit on May 22, 1992. The Shanghai A share index doubled on May 23, 1992. In July 1994, the China Securities Regulatory Committee (CSRC) announced a series of "market support" policies to restrict the new supply of shares. The Shanghai A share index nearly tripled in two months. More recently, the CSRC announced the imposition of a 10% limit in the daily movement of any individual share price. If stock markets in China are efficient now, then there is probably no reason to change current security market regulations. But if inefficiencies exist, then policies designed to influence the stock markets may be inappropriate and the government should change or reduce its control or intervention in the stock markets.

The following two conditions describe efficient stock markets:

- Stock prices (in logarithmic form) follow a random walk with drift, i.e., any new information arriving between this and next period creates only a random deviation from this period's best forecast so that price will vary randomly around trend;
- Stock prices (in logarithmic form) between markets (e.g., Shanghai and Shenzhen security exchanges) are not cointegrated, i.e., no historical information on past stock prices at one market can improve the forecastability of stock prices in the other market.

3.1 Random Walk Hypothesis

The random walk hypothesis says that stock price sequences vary randomly over time around trend, and new information has no predictable components.

$$\ln P_{j,t+1} = \alpha_j + \ln P_{j,t} + \epsilon_{j,t} \tag{2}$$

or equivalently,

$$r_{j,t} = \alpha_j + \epsilon_{j,t} \tag{3}$$

where $r_{j,t}$ is the rate of return on jth market index. Equation (3) implies that the increments of the variance of stock-market returns are proportional to the observation interval. That is, the variance of $p_t - p_{t-s}$ is s times as much as the variance of $p_t - p_{t-1}$. Therefore we can test the random walk hypothesis using a variance ratio test. The null hypothesis is that the disturbances $\varepsilon_{j,t}$ are uncorrelated, allowing for quite general forms of heteroskedasticity[3]. Table 2 contains values of the variance ratio test statistics $\mathcal{VR}_j(q)$ with heteroskedasticity-robust standardized test statistics $\mathcal{Z}_j(q)$ in parentheses.

For Chinese stock markets, the random walk null hypothesis is strongly rejected at the 5% level of significance when daily observations are used and at the 10% level when weekly observations are used. Strong rejection of the random walk hypothesis using variance ratio

[3]Lo and MacKinlay (1988) have a detailed discussion of the statistical properties of the heteroskedastic increments null hypothesis. They show that the variance ratio statistic is asymptotically equivalent to the following expression:

$$\mathcal{VR}_j(q) = 1 + M_j(q) \stackrel{a}{=} 1 + \sum_{l=1}^{q-1} \frac{2(q-l)}{q} \hat{\rho}_j(l)$$

where q is the observation interval of alternative variance estimators and is any integer greater than 1 and $\hat{\rho}_j(l)$ denotes the lth-order autocorrelation coefficient estimator of $r_{j,t}$. $M_j(q)$ is an unbiased variance ratio estimator and is asymptotically zero under the random walk null hypothesis. Therefore, we only need to compute the standardized asymptotic variance of $M_j(q)$ to derive statistical inference.

The heteroskedastic-consistent standardized test statistic is:

$$\mathcal{Z}_j(q) \equiv \frac{\sqrt{nq} M_j(q)}{\sqrt{\hat{\theta}_j(q)}}$$

where $\hat{\theta}_j(q)$ is the asymptotic variance of $M_j(q)$. Despite the presence of general heteroskedasticity, the standardized test statistic $\mathcal{Z}_j(q)$ is still asymptotically standard normal.

tests suggests that Chinese stock markets are inefficient[4]. By comparison, for major world equity market indices, such as the MSCI, NYSE and Hong Kong indices, random walk is rejected, but not strongly, for daily observations and can not be rejected at any reasonably level of significance for weekly observations.

3.2 Cointegration-Based Market Efficiency

Central to the cointegration-based test of market efficiency is the relationship between cointegration and error correction models. Denote the logarithm of stock prices for Shanghai A shares market and Shenzhen A shares market as $p^{sh}_{a,t}$ and $p^{sz}_{a,t}$, respectively. If $p^{sh}_{a,t}$ and $p^{sz}_{a,t}$ are cointegrated, then there must exist an error correction representation of the following form (Engle and Granger, 1987, and MacDonald and Kearney, 1987):

$$\begin{pmatrix} \Delta p^{sh}_{a,t} \\ \Delta p^{sz}_{a,t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \left(p^{sh}_{a,t-1} - \beta_2 p^{sz}_{a,t-1} \right) + \sum_{k=1}^{K} \Gamma_k \begin{pmatrix} \Delta p^{sh}_{a,t-k} \\ \Delta p^{sz}_{a,t-k} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} \tag{4}$$

and $\alpha_1 + \alpha_2 \neq 0$.

The intuition behind the error-correction equations is that if stock prices in Shanghai and Shenzhen are cointegrated, knowledge of the lagged linear combination of price levels in Shanghai and Shenzhen must improve the forecastability of returns in at least one of the markets. If stock prices are determined in efficient markets, then they should have incorporated all available information. Hence, given the past stock prices in Shanghai (Shenzhen), no other information should be of use in explaining the changes in its stock prices. In particular,

$$E(p^{sh}_{a,t} \mid \Omega^{sh}_{t-1}) = E(p^{sz}_{a,t} \mid \Omega^{sh,sz}_{t-1})$$

where

$$\Omega^{sh}_{t-1} = \{p^{sh}_{a,t-1}, p^{sh}_{a,t-2}, p^{sh}_{a,t-3}, \cdots\cdots\}.$$

$$\Omega^{sh,sz}_{t-1} = \{p^{sz}_{a,t-1}, p^{sz}_{a,t-2}, p^{sz}_{a,t-3}, \cdots\cdots, p^{sh}_{a,t-1}, p^{sh}_{a,t-2}, p^{sh}_{a,t-3}, \cdots\cdots\}.$$

We test for cointegration as follows: first, we test the null hypothesis of a unit root in the time series of $p^{i}_{j,t}$ $(i = sh, sz; j = a, b)$ against the stationary alternative using Phillips-Perron

[4] The rejection of random walk hypothesis using variance ratio test also indicates that stock-market returns in China are mean-reverting, which is another piece of evidence of market inefficiency. See Fama and French (1988), Poterba and Summers (1988).

unit root tests. The test results in table 3 show that unit root hypothesis can not be rejected for any of the daily price time-series. Therefore $p^i_{j,t}$ is $I(1)$, $\forall i$ and j.

Next, we test the null hypothesis of no pairwise cointegration in stock prices between Shanghai and Shenzhen security exchanges for both A and B shares. The first step involves estimating the following cointegration regression by OLS:

$$p^{sh}_{j,t} = \alpha_{j,0} + \alpha_{j,1} p^{sz}_{j,t} + \mu_{j,t} \tag{5}$$

The estimation results in table 4, panel (I) indicate that the slope coefficient for the cointegration regression is mildly large and significantly positive for A-share markets, but is close to zero for B-share markets.

The second step is to conduct an Augmented Dickey-Fuller (ADF) unit root test on the estimated residuals, $\hat{\mu}_{j,t}$, as a proxy for the true residuals, using the following regression:

$$\Delta\hat{\mu}_{j,t} = \gamma_{j,0} + \gamma_{j,1}\hat{\mu}_{j,t-1} + \sum_{k=1}^{K} \gamma_{j,k}\Delta\hat{\mu}_{j,t-k} + \nu_{j,t} \tag{6}$$

The specific hypothesis is:

$$\begin{aligned} H_0 &: \gamma_{j,1} = 0 \\ H_A &: \gamma_{j,1} \neq 0 \end{aligned}$$

Table 4, panel (II) gives the ADF test statistic with $K = 5$ for A-share markets. The null hypothesis of no cointegration between Shanghai and Shenzhen A-share prices is rejected at 5% level of significance. The Ljung-Box portmanteau statistic $Q(5)$ is not significant at the 10% level, indicating that $\nu_{a,t}$ is white noise. Therefore, we conclude that Chinese A-share markets are inefficient. For B-share markets, ADF fails to generate a t-statistic with white noise $\nu_{b,t}$. Therefore, there is no evidence that Shanghai and Shenzhen B-share markets are cointegrated. International investors can not use past B-share price information on one exchange to predict B-share price movement on the other.

4 An Empirical Model of the Chinese Stock Market

In this section, we explore the distributional characteristics of the stock-market variance process. We establish an empirical model that captures the deterministic components of the variation in the stock-market returns and characterize the second order conditional moments using three error generation processes. We specify a baseline Generalized Autoregressive Conditional Heteroskedasticity model, or GARCH(1,1) model, that expresses the time series of weekly stock-market returns, $r_{j,t}$ on a set of local and global information variables $\mathbf{Z_{t-1}}$. Then we combine the baseline model with three types of error distributions in formulating a conditional variance process for Chinese stock markets. Finally, we specify a set of local and global information variables to explain the variation of the conditional mean in our baseline model.

4.1 Model Specification

Let $r_{j,t}$ denote the return on a market index at time t and $\mathbf{Z_{j,t-1}}$ represent a set of local and global information variables that affect the conditional mean,

$$r_{j,t} = \delta_{\mathbf{j}}' \mathbf{Z_{j,t-1}} + \epsilon_{j,t}, \tag{7}$$

$$\epsilon_{j,t} = \sigma_{j,t} z_{j,t} \tag{8}$$

$$z_{j,t} | \mathbf{\Omega_{t-1}} \sim \phi(0, 1, \nu), \tag{9}$$

$$\sigma_{j,t}^2 = \omega_j + \alpha_j \sigma_{j,t-1}^2 + \beta_j \epsilon_{j,t-1}^2, \tag{10}$$

where $\sigma_{j,t}^2$ is the conditional variance, $z_{j,t}$ is the standardized residual formed by dividing the residual, $\epsilon_{j,t}$ by the standard deviation, $\sigma_{j,t}$, $\mathbf{\Omega_{t-1}}$ is the set of information available at the beginning of time t, $\phi(\cdot)$ denotes a conditional density function, and ν denotes a vector of parameters besides conditional mean and conditional variance that may be needed to fully characterize the probability distribution. Since equation (10) defines a variance, a nonnegativity constraint must be imposed on α and β, and the sum $(\alpha + \beta)$ must be less than 1 for the volatility process to be covariance stationary (Bollerslev, 1986).

Our GARCH(1,1) model has a distinctive feature, i.e., a set of local and global information is used to explain the returns on a market index, and at the same time, conditional variance is modeled to capture volatility clustering and temporal dependence of market returns. As Nelson (1991) points out, a possible misspecification of the mean equation (7) is not of great concern, because the conditional variance estimates obtained from a GARCH model are robust to an incorrect specification of conditional mean.

4.2 Characterizing Variance in Chinese Stock Markets

The exact form of the error distribution plays an important role in estimating the GARCH(1,1) formulation. Our findings in Section 2 indicate that the time series of stock returns in China are not independent processes; large changes tend to be followed by large changes of either sign, and small changes tend to be followed by small changes. To capture this type of volatility clustering and temporal dependence of stock returns, we consider three different functional forms of the conditional density $\phi(\cdot)$. They are: Gaussian normal distribution, standardized Student t-distribution, and Stable distribution[5].

4.2.1 Normal Distribution

Under a Gaussian standard normality assumption, (9) becomes:

$$z_{j,t}|\mathbf{\Omega_{t-1}} \sim N(0,1), \tag{11}$$

The Gaussian GARCH model can accommodate volatility clustering, but it is not sufficient to account for all the leptokurtosis that appears in the Chinese data. The number of very high and very low returns observed suggests that a fatter-tailed distribution might better characterize the error process for Chinese stock market-returns.

4.2.2 Standardized t-distribution

The conditional density function for $z_{j,t}$, under the standardized Student t-distribution with mean 0, variance 1 and degrees of freedom ν, can be written as:

$$\begin{aligned} z_{j,t}|\mathbf{\Omega_{t-1}} &= \Gamma\left(\frac{\nu+1}{2}\right)\Gamma\left(\frac{\nu}{2}\right)^{-1}(\nu-2)^{-1/2} \\ &\quad \times\left(1+z_{j,t}^2(\nu-2)^{-1}\right)^{-(\nu+1)/2}, \\ &\qquad\qquad \nu > 2, \end{aligned} \tag{12}$$

[5]Other possible parametric densities include normal-Poisson mixture distribution in Jorion (1988), the power exponential distribution in Baillie and Bollerslev (1989), the normal-lognormal mixture distribution in Hsieh (1989a), and the generalized error distribution, or GED, in Nelson (1991). The application of these densities in our empirical models is beyond the scope of this study.

It is well known that the parameter ν can be interpreted as the degree of leptokurtosis. Large values of ν are associated with the absence of leptokurtosis while small values are associated with some degree of leptokurtosis. As $1/\nu$ approaches 0, the Student t -distribution approaches a standard normal distribution, but when $1/\nu > 0$, the t-distribution has "fatter tails" than the corresponding normal distribution.

4.2.3 Stable Distribution

Under the Gaussian normal distribution, the length and height of the extreme tails are fixed. Assuming a stable distribution density function for the error term in our baseline model allows us to explicitly estimate the tail length and height. Moreover, McCulloch (1995) argues that the stable non-Gaussian distribution generalizes the Central Limit Theorem to cases where the second moments of the underlying variables do not exist. It is especially useful in modeling financial asset returns that exhibit strong leptokurtosis.

We first standardize the residual by using the following transformation:

$$\epsilon_{j,t} = (\sigma_{j,t}^2)^{1/\nu} z_{j,t}, \tag{13}$$

where $z_{j,t}$ is specified to have a symmetric standard stable density with both a skewness parameter and location parameter equal to zero. Since the standard Stable distribution does not have a simple mathematical description, we use the log of the characteristic function instead:

$$\log[E(e^{iXt})] = -|t|^{\nu}, \tag{14}$$

where ν ($\nu \in (0, 2]$) is the characteristic exponent to be estimated from the model. When $\nu = 2$, the standard stable distribution becomes the stable standard normal distribution. When $\nu < 2$, absolute moments of order less than ν exist, but those of order greater than or equal to ν do not, so that variance is infinite. For example, when $\nu = 1$, the stable distribution becomes the Cauchy distribution, for which the mean is also infinite.

4.3 World Versus Local Factors in Volatility

In our baseline model, $r_{j,t} = \delta_{\mathbf{j}}^{\prime}\mathbf{Z_{j,t-1}} + \epsilon_{j,t}$, weekly market returns, $r_{j,t}$, are regressed on a set of local and global information variables that may influence the conditional mean of market index returns.

Local information variables include:

- lagged one-week market return, $r_{j,t-1}$;
- lagged change in the exchange rate between Chinese *renminbi yuan* and U.S. dollar, $\Delta RMBUS_{t-1}$;
- lagged change in exchange rate between Hong Kong dollar and U.S. dollar, $\Delta HKUS_{t-1}$;
- lagged change in weekly turnover rate, $\Delta TO_{j,t-1}$;

World information variables include:

- lagged MSCI world index return in excess of the 30-day U.S. Treasury Bill rate, $MSCI_{t-1}$;
- lagged Hong Kong Hang Seng index return in excess of the 30-day U.S. Treasury Bill rate, HS_{t-1};
- lagged NYSE index return in excess of the 30-day U.S. Treasury Bill rate, $NYSE_{t-1}$;
- lagged change in term structure spread (The yield on Long-term U.S. Government Security minus the 30-day U.S. Treasury Bill rate), TS_{t-1};
- lagged change in the 30-day U.S. Treasury Bill rate, ΔTB_{t-1}.

First, we include only local information variables in our baseline model, assuming GARCH(1,1), TGARCH(1,1) and SGARCH(1,1) error generation processes in estimating the parameters. In doing this, we treat the market as fully segmented in the sense that common shocks to world equity markets do not influence the stock markets in China and there are no covariance dynamics. To test the hypothesis that global as well as local factors influence the conditional mean returns in Chinese stock markets, we subsequently include both local and world information variables in our baseline model and estimate all the parameters again. We use Aptech System's constrained maximum likelihood (CMLE) application module with Sequential Quadratic Programming method in estimating the model.

5 Estimation and Empirical Results

We first estimate the GARCH(1,1) model under three alternative formulations of error-generation process. Then we conduct the residual diagnosis tests, including the Ljung-Box Q(8) statistics and the likelihood ratio test statistics and choose the best-fitted error distribution assumption. Finally we analyze the parameter estimates under the best-fitted model. In the next section, we apply the best-fitted model to examine the impact of exogenous government policy changes on the stock-market return volatility.

5.1 Model Comparison

We estimate the Gaussian GARCH(1,1), TGARCH(1,1) and SGARCH(1,1) models, with and without global information variables[6]. To choose among the alternative error-distribution formulations for the best fit to Chinese stock-market data, we first compare the Ljung-Box portmanteau test statistics for serial correlation with 8 lags on standardized residuals ($\hat{z}_{j,t} = \hat{\epsilon}_{j,t}\hat{\sigma}_{j,t}^{-1}$) for each time series and test the null hypothesis of no autocorrelation up to lag 8. The purpose of this test is to evaluate whether each model fully accounts for all autocorrelation of stock-market returns.

As the results in table 5 show, there is evidence of serial correlation for all time series under the Gaussian normal GARCH assumption, as the Ljung-Box Q(8) statistics are significant at the 5% level. The Bera-Jarque test for normality strongly rejects the null hypothesis of normally distributed standardized residuals under the Gaussian normal GARCH model. The skewness and kurtosis in the standardized residuals indicate the inappropriateness of the assumption of conditional normality in the error distribution. Under TGARCH and SGARCH assumptions, there is no evidence of serial correlation in the residuals, as the Ljung-Box Q(8) statistics are not significant even at the 10% level for most of the return series. Moreover, the Ljung-Box Q(8) statistics are not significant at the 5% level for six out of eight time series under the SGARCH formulation, while they meet this level of significance for only three out of eight time series under the TGARCH formulation. This indicates that the SGARCH model outperforms the TGARCH model.

The second phase of residual diagnosis is to determine whether the results under the as-

[6] For brevity, we only include the estimation results for the best-fitted model. Estimation results on other models are available upon request.

sumption of the t- and stable distributions are statistically different from those obtained under the normal distribution. To do this, we calculate likelihood ratio statistics to test the null hypothesis that the tail-thickness parameter $1/\hat{\nu} \to 0$ against the one-sided alternative that $1/\hat{\nu} > 0$ for the TGARCH formulation, and we test the null hypothesis that the tail thickness and length parameter $\hat{\nu} = 2$ against the one sided alternative that $\hat{\nu} < 2$ for the SGARCH formulation. The values for the likelihood ratio test statistics are reported in table 5.

Under the null hypothesis that $1/\hat{\nu} \to 0$ in the TGARCH formulation, $LR_{1/\hat{\nu}\to 0}$ is distributed as $\chi^2(1)$. All the $LR_{1/\hat{\nu}\to 0}$ statistics are highly significant. Under the null hypothesis that $\hat{\nu} = 2$ in the SGARCH model, $LR_{\hat{\nu}=2}$ is also distributed as $\chi^2(1)$. Almost all of the $LR_{\hat{\nu}=2}$ statistics are highly significant except the Shenzhen B-share series. Therefore, the TGARCH(1,1) and SGARCH(1,1) formulations provide better fit for the time series of returns data than the Gaussian normal GARCH formulation. Since the TGARCH and SGARCH models are not nested, a likelihood ratio test can not be used to distinguish these two models. However, the Ljung-Box portmanteau statistics seem to support SGARCH formulation better than TGARCH formulation.

Summing up, our residual diagnosis tests indicate that the GARCH model with conditional normal errors does not fully capture the leptokurtosis and the serial correlation of the standardized residuals. The GARCH model with Stable error distributions fits the time-series data the best[7].

5.2 Parameter Estimates

The parameter estimates for the SGARCH(1,1) model is presented in table 6. When only local variables are included in the model, lagged one-week return exhibits a strong influence on market return. This is probably because of nonsynchronization of trading and clearing and thinness of the markets. The constant terms in the conditional mean equations are all very small and not statistically significant at any level. The coefficient estimates for the lagged change in weekly turnover rate are also small and insignificant for all the series. Furthermore, the coefficient estimates for the lagged change in the U.S. dollar-Chinese yuan and U.S. dollar-Hong Kong dollar exchange rates are both statistically insignificant.

[7]It remains an open question whether other conditional error distributions would provide a better fit. Another interesting question is whether higher order GARCH models might provide an even better description. We leave the answers to all of these questions for future research.

When the global information variables are added to the conditional mean, the coefficient estimates for the lagged change in the U.S. dollar-Hong Kong dollar exchange rate become statistically significant in three out of the four series. Since both China and Hong Kong enforce fixed exchange rate regimes, we are puzzled by this result[8]. Among the global information variables, the lagged Hong Kong Hang Seng weekly index return variable is significant for the Shanghai B-share return series. The MSCI world weekly index return variable is significant for the Shenzhen A-share return series. The lagged NYSE weekly return variable is significant for both Shanghai and Shenzhen A-share return series. The coefficient estimates for the lagged change in the U.S. 30-day Treasury Bill rate are large in two cases, but none of the estimates is statistically significant. Neither do the U.S. term structure spread variables have any explanatory power.

To test the importance of the set of world factors in the conditional mean equation, we use likelihood ratio statistics to test the joint hypothesis that the estimated coefficients for the global information variables are all zero. For the Shanghai A share, Shanghai B share, Shenzhen A share and Shenzhen B share series, the $LR_{\hat{\delta}_{j,5}=\hat{\delta}_{j,6}=\hat{\delta}_{j,7}=\hat{\delta}_{j,8}=\hat{\delta}_{j,9}=0}$ statistics are 3.48, 12.15, 3.84 and 7.06 under the SGARCH formulation. The critical values for the 1%, 5% and 10% level of significance are 15.09, 11.07 and 9.24, respectively. Hence, the joint null hypothesis that the estimated coefficients for the global information variables are all zero can not be rejected at the 1% significance level, but it can be rejected for the Shanghai B share series at the 5% level of significance.

We conclude that local and global information variables do explain some of the variation in Chinese stock-market returns, but evidence that China's stock markets are integrated into the world financial network is at present rather weak.

The empirical results shown in table 6 indicate that A-share returns in Shanghai and Shenzhen tend to respond similarly to common news and economic factors, as the coefficient estimates in our empirical models are very similar in terms of the values and statistical significance. For example, the coefficient estimates for lagged one-week return, lagged change in the exchange rate between U.S. dollar and Hong Kong dollar, and the lagged NYSE excess return are 0.268, 0.342 and -0.31 for Shanghai A shares and 0.153, 0.744 and -0.35 for Shenzhen A

[8]The exchange rate between Hong Kong dollar and U.S. dollar fluctuates within a 1% narrow range, while the exchange rate between Chinese yuan and U.S. dollar seldom fluctuates over our sample period, except that a few "jumps" are observed.

shares. These coefficient estimates are all significant at the 5% level according to the Wald confidence limits. This implies that:

1. Even though the Shanghai and Shenzhen securities exchanges are still largely regional exchanges, there is currently potential for them to become a fully integrated national stock market.

2. The dissimilarity of coefficient estimates for the information variables between the A and B share market return series imply that domestic and international investors have very different investment sentiment and risk-aversion.

6 Explanations of Stock-Market Return Volatility

We now apply our best-fitted empirical model to study the high stock-market return volatility in China. We observe that Chinese stock markets are very sensitive to government regulations. For example, the Chinese government has expressed the belief that the volatility of "hot money" introduces "excessive" volatility in stock market prices. It therefore imposed price ceilings and floors on daily stock price movements in order to insulate the domestic stock market from "fickle" foreign capital movements prior to May 5, 1992, when it suddenly removed a 1% daily price change limit. A 5% limit was removed on May 22, 1992, which was followed by a doubling of the Shanghai A share index in one day.

Another price jump followed the "market support" policies announced by the China Securities Regulatory Committee (CSRC) on July 29, 1994. These "market support" policies included: (1) A ban on new listings of A shares for the rest of 1994; (2) easier credit availability for brokers in Shanghai through a special line of credit, in particular, the provision of a 1.15 billion U.S. dollar credit line for qualified security firms to encourage trading; (3) supporting the establishment of new mutual funds and possible foreign participation in the domestic A share market; (4) promised merger of the A and B share categories within five years. Within two months following the announcement of these policies, the Shanghai A share index nearly tripled.

We test the hypothesis that the government's stock-market liberalization policies adopted in May, 1992 led to increased stock-market volatility[9]. We include a policy dummy variable in

[9]Since the impact of the stock-market liberalization policy in May 1992 lasted for a long time, and we are

our best fitted model—SGARCH(1,1) formulation, so that the conditional variance equation becomes

$$\sigma_{j,t}^2 = \omega_j + \eta_j P_{j,t} + \alpha_j \sigma_{j,t-1}^2 + \beta_j \epsilon_{j,t-1}^2, \tag{15}$$

where $P_{j,t}$ is a policy dummy variable,

$$P_{j,t} = \begin{cases} 0 & : \text{ before the removal of the 5\% daily price change limit} \\ 1 & : \text{ after the removal of the 5\% daily price change limit.} \end{cases}$$

Under the assumption that the conditional volatility process is covariance stationary, i.e., $(\alpha_j + \beta_j) < 1$, equation (10) implies that the unconditional variance of $\epsilon_{j,t}$ is equal to $\frac{\omega_j}{1-\alpha_j-\beta_j}$ before the market liberalization policies were announced. If the unconditional variance of stock returns changed with the government's market liberalization policies, then the coefficient η_j should be statistically significant and the unconditional variance should become $\frac{\omega_j+\eta_j}{1-\alpha_j-\beta_j}$.

Another test of the hypothesis that a change in policy regimes led to increased stock-market return volatility is to divide the sample into two sub-periods, one containing the observations before the announcement of market liberalization and the other representing the post-announcement period. We then use an SGARCH(1,1) framework to estimate these two sub-samples separately. If market liberalization policies affected stock-market volatility, then the unconditional variance $\frac{\omega_j^1}{1-\alpha_j^1-\beta_j^1}$ should be smaller than $\frac{\omega_j^2}{1-\alpha_j^2-\beta_j^2}$.

The results of the two tests, shown in table 7, indicate that the coefficient of the dummy variable, η_j is statistically significant for both the Shanghai and Shenzhen A share market returns[10]. Likelihood ratio test results in tables 7 and 8 also indicate that the null hypothesis $\hat{\eta}_j = 0$ is strongly rejected at any reasonable level of significance for Shanghai A shares while it can be rejected for Shenzhen A shares at the 5% level of significance. The null hypothesis of the second test, $\frac{\hat{\omega}_j^1}{1-\hat{\alpha}_j^1-\hat{\beta}_j^1} = \frac{\hat{\omega}_j^2}{1-\hat{\alpha}_j^2-\hat{\beta}_j^2}$, is also rejected at any significance level for both the Shanghai and Shenzhen sub-samples. We conclude that the government's market liberalization policy did lead to higher stock-market volatility in China [11].

unable to separate this effect from the impact of the stock-market support policy in July 1994, we do not conduct a formal test on whether the stock-market volatility increased after the July announcement.

[10]We do not use the B share market return data because it starts on February 21, 1992, which is too close to the market liberalization date, May 22, 1992.

[11]In order to curb stock-market volatility, the CSRC reimposed a 10% daily price change limit on any individual stock on December 13, 1996. This serves as anecdotal evidence for our argument that stock-market volatility was higher after the government announced the stock-market liberalization policy in May 1992.

Other possible explanations for the high stock-market volatility include market segmentation and high IPO underpricing. We briefly discuss our conjecture. Rigorous tests on these hypotheses are beyond the scope of this article.

(i) Market segmentation and stock-market return volatility

There are two types of stock-market segmentation in China–by geographical location and by nationality of investors. Geographically, there are separate stock markets in the cities of Shanghai and Shenzhen, and dual listings are not permitted. Whereas the Shanghai Securities Exchange tends to list well-established large state-owned enterprises, the Shenzhen Securities Exchange tends to list joint-venture enterprises which, by definition, are linked to foreign companies.

Segmentation by investor type occurs, as separate classes of shares are available to Chinese citizens and non-Chinese citizens, to individual investors and institutional investors, and to domestic and foreign exchanges. Both kinds of market segmentation almost certainly lead to price distortion across markets, illegitimate transactions, thinner markets, reduced liquidity, and hence to a smaller investor pool overall.

Evidence of low market liquidity in China relative to other markets can be shown by the average daily trading volume and turnover ratio. The average daily trading volume in Shanghai in 1995 was 1162.3 million U.S. dollars, and in Shenzhen 910.2 million US dollars, which was thin compared with the NYSE (23648.7 million U.S. dollars) and other more developed emerging markets such as Taiwan (8475.4 million U.S. dollars), South Korea (2973.2 million U.S. dollars) and Malaysia (2636.4 million U.S. dollars). In 1995, the turnover ratio, defined as the average daily turnover (value) divided by outstanding market capitalization, was only 4.72% and 0.4% for Shanghai A and B shares, 4.5% and 0.28% for Shenzhen A and B shares, respectively, compared to 19.2% for the NYSE, 31.3% in Taiwan, 15.6% in South Korea, and 11.6% in Malaysia. With such illiquid stock markets in China, it is very likely that even "small" capital inflows and outflows are destabilizing. Therefore, we believe that market segmentation and reduced liquidity have probably contributed to the high stock-market return volatility in China.

(ii) IPO underpricing and stock-market return volatility

One of the most interesting facets of Chinese stock markets is the larger than average IPO underpricing of new share issues compared to other countries. A noteworthy measure is that the mean IPO initial returns, defined as the difference between the first-day market closing price minus the IPO price divided by the IPO price averaged over a sample of 308 domestic A shares that went public before January 1, 1996 is 948.59%! In other words, the first-day market closing price is on average almost eleven times as high as the initial price offered to the domestic Chinese investors (Su and Fleisher, 1997). By comparison, the average degree of IPO initial return is 16% in the U.S. and 18% in Hong Kong. At the same time, the volatility of A-share markets is about 8 times as high as that of NYSE and is about three times as high as that of Hong Kong. Moreover, the average degree of IPO initial returns for 57 B shares is only 37.13%, while the volatility of B-share markets is less than one third as high as that of A-share markets. Therefore, we conjecture that China's high degree of IPO underpricing has led to herd-like behavior, speculative bubbles and contributed to the high volatility in stock markets.

7 Conclusions

In this paper, we analyze the dynamic behavior of risks and returns in Chinese stock markets. We find that the risk-adjusted mean stock returns are low and the volatility of stock-market returns is high in China relative to developed markets. Moreover, returns are positively auto-correlated to greater extent in Chinese stock markets than in developed markets. We find that the random walk hypothesis is rejected for Chinese stock markets using variance ratio tests while it can not be rejected for developed markets. A residual-based cointegration test shows that the daily A share market indices in Shanghai and Shenzhen tend to move together, but the daily B share market indices do not.

We establish an empirical model to capture the deterministic components of the variation in the stock-market returns and characterize the second order conditional moments using three error generation processes. We find that the variance of stock-market returns is time-varying, mildly persistent, leptokurtotic and is influenced by exogenous variables representing government market liberalization policies. We also find that the Shanghai B-share market is more integrated with the world equity markets than any other Chinese market, although even here the degree of integration appears to be weak. A share returns in Shanghai and Shenzhen tend to respond similarly to common news and economic factors, leading us to believe that there is potential for them to become a fully integrated national stock market. Encouraging cross-listing and eliminating the distinction between different classes of shares will improve stock-market liquidity and enhance capital mobilization.

Finally, we find that government's market liberalization policies have contributed to the high stock-market volatility in China. We also conjecture that market segmentation, both across different stock exchanges and across different share types, and extraordinary large IPO underpricing may have contributed to the high stock-market volatility as well.

The empirical model used in our paper is a univariate model. Therefore, some interesting questions are left unexplored. For example, what are the sources of differences in expected returns and volatility in A- and B-share markets? Has the degree of integration among Chinese stock markets and world markets improve over time? We are currently analyzing these questions using a multivariate factor asset pricing model with time-varying world market integration.

References

[1] Baillie, Richard T. and Tim Bollerslev, (1989), "The Message in Daily Exchange Rates: A Conditional Variance Tale". *Journal of Business and Economic Statistics* 7, 297-305.

[2] Bekaert, Geert and Campbell R. Harvey, (1995), "Emerging Equity Market Volatility". *working paper, Stanford University.*

[3] Bollerslev, Tim, (1986), "Generalized Autoregressive Conditional Heteroskedasticity". *Journal of Econometrics* 31, 307-327.

[4] Bollerslev, Tim, (1987), "A Conditional Heteroskedastic Time Series Model for Speculative Prices and Rates of Return". *The Review of Economics and Statistics* 69, 542-547.

[5] Bollerslev, Tim, Ray Y. Chou and Kenneth F. Kroner, (1992), "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence". *Journal of Econometrics* 52, 5-59.

[6] De Santis, Giorgio and Selahattin İmrohoroğlu, (1995), "Stock Returns and Volatility in Emerging Financial Markets". *working paper, University of Southern California.*

[7] Dickey, David A. and Wayne A. Fuller, (1979), "Distribution of the Estimators for Autoregressive Time Series with a Unit Root". *Journal of the American Statistical Association* 74, 427-431.

[8] Dickey, David A. and Wayne A. Fuller, (1981), "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root". *Econometrica* 49, 1057-1072.

[9] DuMouchel, W. H., (1975), "Stable Distributions in Statistical Inference: 2. Information from Stably Distributed Samples". *Journal of the American Statistical Association* 70, 386-393.

[10] Engle, Robert F., (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation". *Econometrica* 50, 987-1008.

[11] Fama, Eugene F., (1991), "Efficient Capital Markets: II". *The Journal of Finance* vol. XLVI, no. 5, 1575-1617.

[12] Fama, Eugene F. and Kenneth R. French, (1988), "Permanent and Temporary Components of Stock Prices". *Journal of Political Economy* 96, 246-273.

[13] Fama, Eugene F. and Richard Roll, (1971), "Parameter Estimates for Symmetric Stable Distributions". *Journal of The American Statistical Association* 66, 331-338.

[14] French, Kenneth R., G. William Schwert and Robert F. Stambaugh, (1987), "Expected Stock Returns and Volatility". *Journal of Financial Economics* 19, 3-30.

[15] Fuller, Wayne A., (1976), *Introduction to Statistical Time Series.* New York: John Wiley and Sons.

[16] Hsieh, David A., (1989a), "Modeling Heteroskedasticity in Daily Foreign Exchange Rates". *Journal of Business and Economic Statistics* 7, 307-317.

[17] Jorion, Phillipe, (1988), "On Jump Processes in the Foreign Exchange and Stock Markets". *Review of Financial Studies* 1, 427-445.

[18] Lo, Andrew W. and A. Craig MacKinlay, (1988), "Stock Market Prices Do Not Follow Random Walk: Evidence from a Simple Specification Test". *Review of Financial Studies* 1, 41-66.

[19] McCulloch, J. Huston, (1995), "Measuring Tail Thickness in Order to Estimate the Stable Index α: A Critique". *working paper, The Ohio State University.*

[20] MacKinnon, Ronald, (1991), "Critical Values for Cointegration Tests". Long-Run Economic Relationships, R.F. Engle and C.W.J. Granger, eds, London, Oxford, pp 267-276.

[21] Merton, R. C., (1980), "On Estimating the Expected Return on the Market: An Exploratory Investigation". *Journal of Financial Economics* 8, 323-361.

[22] Nelson, Daniel B., (1991), "Conditional Heteroskedasticity in Asset Returns: A New Approach". *Econometrica* 59, 347-370.

[23] Nelson, Daniel B. and Charles Q. Cao, (1992), "Inequality Constraints in the Univariate GARCH Model". *Journal of Business and Economic Statistics* 10, 229-235.

[24] Poterba, James and Lawrence Summers, (1988), "Mean Reversion in Stock Prices: Evidence and Implications". *Journal of Financial Economics* 22, 27-59.

[25] Perron, Pierre, (1988), "Trends and Random Walks in Macroeconomic Time Series: further Evidence from a New Approach". *Journal of Economic Dynamic and Control* 12, 297-332.

[26] Phillips, Peter C. B., (1987). "Time Series Regression with a Unit Root", *Econometrica* 55, 277-301.

[27] Phillips, Peter C. B. and Pierre Perron, (1988), "Testing for a Unit Root in Time Series Regression". *Biometrika* 75, 335-346.

[28] Su, Dongwei (1996), "Ownership Restrictions and Stock Prices: Evidence from Chinese Markets". *working paper, The Ohio State University.*

[29] Su, Dongwei and Belton M. Fleisher, (1997), "An Empirical Investigation of Underpricing in Chinese IPOs". *working paper, The Ohio State University.*

[30] World Bank Document, (1995), "China: The Emerging Capital Market". Volume I and II.

Table 1

Distributional Characteristics of Chinese Stock Markets and Other World Equity Markets Returns[a]

	Shanghai A share	Shanghai B share	Shenzhen A share	Shenzhen B share	MSCI world index	NYSE composite	Hong Kong Hang Seng
Daily return	0.13%	-0.09%	0.01%	-0.08%	0.03%	0.05%	0.09%
Standard deviation	4.17%	1.89%	3.37%	1.55%	0.8%	0.625%	1.61%
Sharpe ratio	3.12%	-4.76%	0.3%	-5.16%	3.75%	8%	5.59%
Minimum	-18.43%	-13.72%	-24.48%	-7.24%	-6.85%	-3.99%	-13.26%
Maximum	74.52%	13.82%	19.62%	13.87%	5.39%	5.47%	13.51%
Skewness[b]	5.351*	0.409*	0.895*	1.411*	-0.156*	0.263*	-0.609*
Kurtosis[c]	32.785*	8.569*	13.179*	23.831*	7.288*	7.646*	15.393*
Ljung-Box $Q(12)$[d]	25.374*	83.016*	31.17*	90.5*	21.41†	21.465†	19.408
Weekly return	0.62%	-0.42%	0.05%	-0.4%	0.14%	0.25%	0.46%
Standard deviation	10.52%	5.07%	8.18%	4.07%	1.71%	1.94%	3.3%
Shape ratio	5.89%	-8.28%	0.6%	-9.83%	8.19%	12.9%	13.94%
Minimum	-19.35%	-15.63%	-25.18%	-14.91%	-6.16%	-3.39%	-12.79%
Maximum	92.76%	25.7%	55.37%	25.59%	6.01%	1.5%	10.1%
Skewness	4.48*	1.42*	2.13*	1.46*	0.0868	-1.165*	-0.243
Kurtosis	32.785*	6.812*	11.25*	10.48*	0.971*	4.861*	1.361*
Ljung-Box $Q(12)$	6.1781	15.0529	13.78†	27.53*	13.728	16.098	18.732

*Statistically significant at the 5% level.

†Statistically significant at the 10% level.

[a]The sample periods are from the first-day of market trading to March 18, 1996 for Chinese stock markets and December 1990 to March 1996 for MSCI world index, NYSE composite index and Hong Kong Hang Seng index.

[b]Skewness (sk) $= \frac{T^2}{(T-1)(T-2)} \frac{\frac{1}{T}\sum_{t=1}^{T}(r_{j,t}-\bar{r}_j)^3}{\left[\frac{1}{T-1}\sum_{t=1}^{T}(r_{j,t}-\bar{r}_j)^2\right]^{3/2}}$

[c]Kurtosis (ku) $= \frac{T^2}{(T-1)(T-2)(T-3)} \frac{\frac{T+1}{T}\sum_{t=1}^{T}(r_{j,t}-\bar{r}_j)^4 - \frac{3(T-1)}{T^2}\left[\sum_{t=1}^{T}(r_{j,t}-\bar{r}_j)^2\right]^2}{\left[\frac{1}{T-1}\sum_{t=1}^{T}(r_{j,t}-\bar{r}_j)^2\right]^2}$

[d]Ljung-Box Portmanteau Statistics: $T(T+2)\left[\sum_{m=1}^{M}\frac{\varepsilon_{j,m}^2}{T-m}\right]$, where $\varepsilon_{j,m}$ is the m-th order autocorrelation of the residuals for the j-th time series. M is the number of autocorrelation used.

Table 2

Variance Ratio Tests for Random Walk Hypothesis for the Logarithm of Stock Market Indices[a]

	Number nq of base observations	Number q of base observations aggregated to form variance ratio			
		2	4	8	16
Daily stock market indices					
Shanghai A	1310	1.069*	1.167*	1.2696*	1.3277*
Shares		(2.4991)	(3.2257)	(3.278)	(2.6604)
Shanghai B	1015	1.2519*	1.3761*	1.4872*	1.6016*
Shares		(8.2841)	(6.3498)	(5.1205)	(4.1895)
Shenzhen A	1269	1.044	1.1207*	1.2375*	1.3523*
Shares		(1.5605)	(2.2811)	(2.8009)	(2.7775)
Shenzhen B	809	1.2083*	1.3827*	1.5626*	1.7282*
Shares		(6.0101)	(5.7386)	(5.24)	(4.4433)
MSCI World	1310	1.0929*	1.0893†	1.101	1.0941†
Index		(3.376)	(1.7217)	(1.2261)	(1.7649)
NYSE	1299	1.0166	1.0196	1.0453	1.0394
Composite		(0.1345)	(0.7047)	(0.8705)	(0.477)
Hong Kong	1356	0.9168*	0.8864*	0.8976	0.9549
Hang Seng		(-3.0686)	(-2.227)	(-1.2637)	(-0.371)
Weekly stock market indices					
Shanghai A	272	1.1009†	1.1227	1.1669	1.1671
Shares		(1.6689)	(1.0684)	(0.9001)	(0.5866)
Shanghai B	210	1.1486*	1.2921*	1.4022†	1.5735†
Shares		(2.1798)	(2.2277)	(1.8939)	(1.8273)
Shenzhen A	260	1.1185†	1.196†	1.323†	1.2702
Shares		(1.9181)	(1.6674)	(1.7095)	(0.9299)
Shenzhen B	172	1.2889*	1.4496*	1.6539*	1.8571*
Shares		(3.9365)	(3.0685)	(2.7414)	(2.3965)
MSCI World	271	1.0139	1.0397	1.0234	0.9978
Index		(0.2275)	(0.3478)	(0.1313)	(-0.0079)
NYSE	270	1.0134	1.1013	1.1256	1.2632
Composite		(0.2186)	(0.8865)	(0.6947)	(0.9278)
Hong Kong	275	0.9808	1.0755	1.0978	1.1388
Hang Seng		(-0.3259)	(0.6615)	(0.5365)	(0.492)

[a]The main rows display the variance ratios. Standardized heteroskedasticity-robust $\mathcal{Z}_j(q)$ statistics are reported in parentheses. Under the random walk hypothesis, the value of variance ratio is 1 and the $\mathcal{Z}_j(q)$ statistics have an asymptotic normal distribution. * and † denote statistically significant at the 5% and 10% level, respectively.

Table 3

Tests for Unit Roots for the Logarithm of Daily Stock Market Prices[a]

$$p_{j,t} = \hat{\rho}_j p_{j,t-1} + \hat{\epsilon}_{j,t}$$

$$p_{j,t} = \alpha_j^* + \rho_j^* p_{j,t-1} + \epsilon_{j,t}^*$$

$$p_{j,t} = \tilde{\alpha}_j + \tilde{\beta}_j(t - T/2) + \tilde{\rho}_j p_{j,t-1} + \tilde{\epsilon}_{j,t}$$

Null hypothesis tested	Test statistic[b]	Shanghai A shares	Shanghai B shares	Shenzhen A shares	Shenzhen B shares
$\hat{\rho}_j = 1$	$Z(t_{\hat{\rho}_j})$	-0.745	-1.3166	-0.036	-1.2064
$\rho_j^* = 1$	$Z(t_{\rho_j^*})$	-2.2641	-2.2262	-1.3089	-0.2084
$\rho_j^* = 1, \alpha_j^* = 0$	$Z(\Phi_1)$	3.0678	3.1914	0.8617	0.7357
$\tilde{\rho}_j = 1$	$Z(t_{\tilde{\rho}_j})$	-1.1316	-2.5849	-1.1377	-2.0043
$\tilde{\rho}_j = 1, \tilde{\alpha}_j = 0, \tilde{\beta}_j = 0$	$Z(\Phi_2)$	2.019	2.8259	0.7605	2.2132
$\tilde{\rho}_j = 1, \tilde{\beta}_j = 0$	$Z(\Phi_3)$	2.523	3.5279	1.1357	2.6017

[a]All the tests are based on Phillips-Perron Unit Root Tests, with size 4 Barlett Window. The Phillips-Perron test statistics share the same limiting distributions as those of Dickey-Fuller test statistics.

[b]Source for critical values: Fuller (1976, p. 373) and Dickey-Fuller (1981, p. 1063).

Critical values	$Z(t_{\hat{\rho}_j})$	$Z(t_{\rho_j^*})$	$Z(\Phi_1)$	$Z(t_{\tilde{\rho}_j})$	$Z(\Phi_2)$	$Z(\Phi_3)$
1%	-2.58	-3.43	6.43	-3.96	6.09	8.27
5%	-1.95	-3.12	4.59	-3.41	4.68	6.25
10%	n/a	-2.57	3.78	-3.12	4.03	5.34

Table 4

Tests for Cointegration

Figures in parentheses are t-statistics and figures in brackets are p-values.

Panel (I) OLS estimation for the cointegration regression $p^{sh}_{j,t} = \alpha_{j,0} + \alpha_{j,1} p^{sz}_{j,t} + \mu_{j,t}$			
	$\hat{\alpha}_{j,0}$	$\hat{\alpha}_{j,1}$	$\bar{R}^2$
A shares	0.0013	0.4476	0.1266
	(1.1081)	(13.3661)	
B shares	-0.0006	0.0185	0.0003
	(-1.0885)	(0.5002)	
Panel (II) Residual-based cointegration test (ADF test) for $\hat{\mu}_{j,t}$ [a] $\Delta\hat{\mu}_{j,t} = \gamma_{j,0} + \gamma_{j,1}\hat{\mu}_{j,t-1} + \sum_{k=1}^{K} \gamma_{j,k}\Delta\hat{\mu}_{j,t-k} + \nu_{j,t}$			
	ADF test statistic	Critical value [b]	$Q(K)$
A shares	-18.5712	-3.41	$Q(5) = 9.1594$
			[0.1029]
B shares	ADF test fails to find the value K in which $\nu_{j,t}$ is serially uncorrelated.		

[a] ADF test determines the appropriate number of lagged differences K by adding lags until a Lagrange Multiplier test fails to reject no serial correlation in $\nu_{j,t}$ at 5% level of significance.

[b] The critical values are computed by MacKinnon (1991, p. 267-276).

Table 5

Residual Diagnostic Tests

Figures inside the parentheses are heteroskedasticity-consistent standard errors and figures inside the brackets are p-values. $Q_8(\epsilon_j/\sigma_j)$ denotes the Ljung-Box Q statistic for serial correlation tests with 8 lags on standardized residuals. Bera-Jarque (1982) statistic is used to test for normality, and is calculated as: $\frac{T}{6}Skewness^2 + \frac{T}{24}(Kurtosis - 3)^3$, which is distributed as Chi-square with 2 degrees of freedom. The critical value for $\chi^2(2)$ at 1%, 5% and 10% levels are 9.21, 5.991 and 4.605.

	Shanghai A Shares	Shanghai B Shares	Shenzhen A Shares	Shenzhen B Shares
	Gaussian GARCH Model			
	with only local information variables			
$Q_8(\epsilon_j/\sigma_j)$	3.9437	7.1712	5.2187	6.9842
	[0.8522]	[0.5183]	[0.734]	[0.5383]
Skewness	2.3545	3.4975	6.6258	2.1448
	(0.825)	(1.3)	(2.0366)	(0.7225)
Kurtosis	8.6215	14.6961	54.6961	7.6324
	(2.1323)	(2.7522)	(10.3288)	(2.0119)
Bera-Jarque	2159.25	14084.7	1469785	868.83
	with both local and global information variables			
$Q_8(\epsilon_j/\sigma_j)$	4.0904	4.6341	3.5229	4.1608
	[0.8489]	[0.7959]	[0.8974]	[0.8423]
Skewness	2.4393	2.1461	1.7991	1.9583
	(0.8626)	(0.6984)	(0.3644)	(0.4487)
Kurtosis	9.0803	7.2489	4.661	6.799
	(4.1425)	(2.588)	(1.5642)	(2.1139)
Bera-Jarque	2754.83	812.56	186.25	486.98

(continue on next page)

Table 5

Residual Diagnostic Tests (continued)

	Shanghai A Shares	Shanghai B Shares	Shenzhen A Shares	Shenzhen B Shares
	TGARCH Model			
	with only local information variables			
$Q_8(\epsilon_j/\sigma_j)$	3.6026	2.7382	5.8249	5.4158
	[0.8911]	[0.9497]	[0.6663]	[0.7124]
Skewness	1.4621	1.4037	2.0193	1.4501
	(0.4852)	(0.4755)	(0.6331)	(0.4751)
Kurtosis	4.2055	20.2045	7.2603	4.4762
	(2.004)	(5.3781)	(2.1141)	(1.8775)
$LR_{1/\nu\to 0}$	73.43	33.78	57.6	39.14
	with both local and global information variables			
$Q_8(\epsilon_j/\sigma_j)$	2.4277	2.3334	4.6341	3.8026
	[0.965]	[0.969]	[0.7959]	[0.8745]
Skewness	1.054	1.2572	1.6154	1.46
	(0.3572)	(0.4083)	(0.4833)	(0.4755)
Kurtosis	1.6593	2.1504	4.623	3.7825
	(1.2108)	(1.3253)	(1.6774)	(1.621)
$LR_{1/\nu\to 0}$	65.93	39.14	54.78	35.11
	SGARCH Model			
	with only local information variables			
$Q_8(\epsilon_j/\sigma_j)$	3.436	1.8537	5.4158	1.4501
	[0.9041]	[0.9852]	[0.7124]	[0.9935]
Skewness	1.1663	1.4037	1.3532	1.5609
	(0.401)	(0.7359)	(0.4752)	(1.0622)
Kurtosis	2.5621	2.2952	3.1783	3.9651
	(0.9888)	(1.478)	(1.3528)	(1.6742)
$LR_{1/\nu=2}$	59.76	39.76	48.64	2.352
	with both local and global information variables			
$Q_8(\epsilon_j/\sigma_j)$	2.3438	0.8201	6.6658	2.361
	[0.9686]	[0.9991]	[0.5731]	[0.9679]
Skewness	0.5988	1.2258	1.4946	1.7991
	(0.3427)	(0.5107)	(0.5158)	(0.3667)
Kurtosis	0.4073	2.1443	3.8174	5.4245
	(0.4899)	(1.3888)	(1.4282)	(2.0366)
$LR_{1/\nu=2}$	53.33	44.08	50.43	2.352

Table 6

Maximum Likelihood Estimates of the SGARCH(1,1) Model

$$r_{j,t} = \delta_{\mathbf{j}}^{'}\mathbf{Z_{j,t-1}} + \epsilon_{j,t}$$

$$\epsilon_{j,t} = (\sigma_{j,t}^2)^{1/\nu} z_{j,t}$$

$$\log[E(e^{iXt})] = -|t|^{\nu}$$

$$\sigma_{j,t}^2 = \omega_j + \alpha_j \sigma_{j,t-1}^2 + \beta_j \epsilon_{j,t-1}^2$$

$\mathbf{Z_{j,t-1}}$ includes lagged one-week market return ($r_{j,t-1}$), lagged change in the exchange rate between Chinese yuan and U.S. dollar ($\Delta RMBUS_{t-1}$), lagged change in exchange rate between Hong Kong dollar and U.S. dollar ($\Delta HKUS_{t-1}$), lagged change in weekly turnover rate ($\Delta TO_{j,t-1}$), lagged MSCI world index return in excess of the 30-day U.S. Treasury Bill rate ($MSCI_{t-1}$), lagged Hong Kong Hang Seng index return in excess of the 30-day U.S. T-Bill rate (HS_{t-1}), lagged NYSE index return in excess of the 30-day U.S. T-Bill rate ($NYSE_{t-1}$), lagged change in term structure spread (TS_{t-1}) and lagged change in the 30-day U.S. T-Bill rate (ΔTB_{t-1}). * denotes 5% level of significance according to the Wald Confidence Limits.

	Shanghai A Shares	Shanghai B Shares	Shenzhen A Shares	Shenzhen B Shares	Shanghai A Shares	Shanghai B Shares	Shenzhen A Shares	Shenzhen B Shares
constant	-0.007	-0.005	-0.01	0.002	-0.004	-0.006	-0.007	-0.004
$r_{j,t-1}$	0.268*	0.191*	0.153*	0.242*	0.287*	0.202*	0.15*	0.291*
$\Delta RMBUS_{t-1}$	-0.012	-0.018	-0.036	-0.036	-0.013	-0.012	-0.037	-0.002
$\Delta HKUS_{t-1}$	0.342*	0.071	0.744*	0.32*	0.266	0.57	0.152	0.237
ΔTO_{t-1}	0.004	0.001	0.014	-0.001	0.006	-0.001	0.018	-0.002
$MSCI_{t-1}$	0.03	0.198	0.345*	-0.002				
HS_{t-1}	-0.06	-0.29*	0.094	0.087				
$NYSE_{t-1}$	-0.31*	-0.22	-0.35*	-0.074				
TS_{t-1}	0.433	-0.094	0.175	-0.239				
ΔTB_{t-1}	-5.937	0.03	-12.22	1.233				
$\hat{\omega}_j$	0.033*	0.004	0.011*	0.02*	0.018*	0.003	0.024*	0.017*
$\hat{\alpha}_j$	0.619*	0.552*	0.688*	0.732*	0.615*	0.318*	0.74*	0.743*
$\hat{\beta}_j$	0.121*	0.164*	0.169*	0.224*	0.107*	0.189*	0.214*	0.205*
ν	1.506*	1.493*	1.7666*	1.567*	1.551*	1.54*	1.676*	1.58*
Mean log likelihood	1.322	1.828	1.311	1.887	1.309	1.769	1.296	1.845

Table 7

Maximum Likelihood Estimates of the SGARCH(1,1) Model with Policy Dummy Variable

$$r_{j,t} = \delta_{\mathbf{j}}^{'}\mathbf{Z_{j,t-1}} + \epsilon_{j,t}$$

$$\epsilon_{j,t} = (\sigma_{j,t}^2)^{1/\nu} z_{j,t}$$

$$\log[E(e^{iXt})] = -|t|^{\nu}$$

$$\sigma_{j,t}^2 = \omega_j + \alpha_j \sigma_{j,t-1}^2 + \beta_j \epsilon_{j,t-1}^2$$

$$\delta_{\mathbf{j}}^{'}\mathbf{Z_{j,t-1}} = \delta_{j,0} + \delta_{j,1} r_{t-1} + \delta_{j,2}\Delta RMBUS_{t-1} + \delta_{j,3}\Delta HKUS_{t-1} + \delta_{j,4}\Delta TO_{t-1}$$

$$P_{j,t} = \begin{cases} 0 & : \text{ before the removal of the 5\% daily price change limit} \\ 1 & : \text{ after the removal of the 5\% daily price change limit.} \end{cases}$$

Figures inside the brackets are p-values and * denotes 5% level of significance according to the Wald Confidence Limits. $Q_8(\epsilon_j/\sigma_j)$ denotes the Ljung-Box Q statistic for serial correlation tests with 8 lags on standardized residuals. Likelihood ratio statistics is used to test the null hypothesis that $\hat{\eta}_j = 0$, and is asymptotically distributed as Chi-square with 1 degree of freedom. The critical value for $\chi^2(1)$ at 1%, 5% and 10% levels are 6.6349, 3.8415 and 2.7055, respectively.

	Shanghai A Shares	Shenzhen A Shares
constant	-0.011	-0.014
$r_{j,t-1}$	0.54*	0.63*
$\Delta RMBUS_{t-1}$	-0.027	-0.02
$\Delta HKUS_{t-1}$	0.013	0.282
ΔTO_{t-1}	0.022	-0.001
$\hat{\omega}_j$	0.008	0.06*
$\hat{\eta}_j$	0.061*	0.206*
$\hat{\alpha}_j$	0.499*	0.665*
$\hat{\beta}_j$	0.347*	0.179*
ν	1.57*	1.62*
Mean log likelihood	1.3879	1.3187
$LR_{\hat{\eta}_j=0}$	21.145	5.811
$Q_8(\epsilon_j/\sigma_j)$	3.1429	4.7865
	[0.9264]	[0.7803]

Table 8

Maximum Likelihood Estimates of the SGARCH(1,1) Model Using Sub-samples

$$r_{j,t} = \delta_{\mathbf{j}}^{'} \mathbf{Z_{j,t-1}} + \epsilon_{j,t}$$

$$\epsilon_{j,t} = (\sigma_{j,t}^2)^{1/\nu} z_{j,t}$$

$$\log[E(e^{iXt})] = -|t|^{\nu}$$

$$\sigma_{j,t}^2 = \omega_j + \alpha_j \sigma_{j,t-1}^2 + \beta_j \epsilon_{j,t-1}^2$$

$$\delta_{\mathbf{j}}^{'} \mathbf{Z_{j,t-1}} = \delta_{j,0} + \delta_{j,1} r_{t-1} + \delta_{j,2} \Delta RMBUS_{t-1} + \delta_{j,3} \Delta HKUS_{t-1} + \delta_{j,4} \Delta TO_{t-1}$$

* denotes 5% level of significance according to the Wald Confidence Limits. Likelihood ratio statistics is used to test the null hypothesis that $\frac{\omega_j^1}{1-\alpha_j^1-\beta_j^1} = \frac{\omega_j^2}{1-\alpha_j^2-\beta_j^2}$, and is asymptotically distributed as Chi-square with 3 degree of freedom. The critical value for $\chi^2(3)$ at 1%, 5% and 10% levels are 11.3449, 7.8147 and 4.6052, respectively.

	Shanghai A Shares		Shenzhen A Shares	
	First Subsample	Second Subsample	First Subsample	Second Subsample
constant	-0.006	-0.019	-0.019	-0.011
$r_{j,t-1}$	0.63*	0.352*	0.57*	0.294*
$\Delta RMBUS_{t-1}$	-0.02	-0.017	-0.02	-0.03
$\Delta HKUS_{t-1}$	0.105	0.171	0.268	0.015
ΔTO_{t-1}	0.034	0.011	0.054	-0.09
$\hat{\omega}_j$	0.018*	0.024*	0.03*	0.011*
$\hat{\alpha}_j$	0.464*	0.696*	0.599*	0.748*
$\hat{\beta}_j$	0.379*	0.218*	0.246*	0.223*
ν	1.537*	1.618*	1.449*	1.675*
Mean log likelihood	1.3687	1.3739	1.8604	1.2885
$\frac{\omega_j}{1-\alpha_j-\beta_j}$	0.1146	0.2791	0.1935	0.3793
LR	17.0837		31.7996	