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Modeling Volatility for the Chinese Equity Markets

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A series of GARCH models are investigated for the volatility of the Chinese equity data from the Shenzhen and Shanghai markets. There has been empirical evidence of volatility clustering, contrary to findings in previous studies. Each market contains different GARCH models which fit well. The models are used to test for a spill-over effect between the two Chinese markets, an example of volatility transmission within one country and between two equity exchanges. Our testing suggests that there is no volatility transmission between the two markets.

Key Words: Emerging markets; Volatility clustering; GARCH-M; IGARCH; TAGARCH; Spill-over effect.
JEL Classification Numbers: C51, G14.

1. INTRODUCTION

The relatively new Chinese stock markets show encouraging trends, with the number of Chinese people buying shares estimated to be about 60 million at the end of 2000.[1] Furthermore, after being accepted as a member of the World Trade Organization in November 2001, China should be opening

[1] www.stockstar.com/statistics

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its domestic stock market to international capital in a few years time and, as a result, is likely to become an important player in the future global financial market.

No doubt that there will be a variety of studies of various aspects of the Chinese stock market by the global investment community and academia. In this paper we take a look at two important aspects of this market. First, because return volatility (simply volatility hereafter) is a key input for pricing financial products and asset allocation decisions, we look at this parameter for the Chinese equity market. In many studies such as those by French, Schwert, and Stambaugh (1987), Chou (1988), Akgiray (1989), Baillie and DeGennaro (1990), Kim and Kon (1994), there is evidence that GARCH models are able to model stock returns displaying volatility clustering in some international stock markets.[2] In this paper we use GARCH modeling for estimating volatility since it can take into account various characteristics of the data.

Secondly, we investigate whether there is any transmission process of volatility between China's two equity exchanges, Shenzhen and Shanghai. This transmission process of volatility is referred to in literature as the *volatility spill-over effect* and it has been studied in literature between different countries. If real, this phenomenon can have a major impact on asset pricing and may lead to arbitrage opportunities. There is no investigation, as far as we are aware, into volatility transmission between different stock exchanges within the same country.

In addition, it is worth mentioning the comparative time series analysis of the Shanghai and the New York stock exchange composite price indices, weekly rates of return, and volatilities over the period of 1992-2002 as described by Chow and Lawler (2003). They show that the volatilities are significantly negatively correlated, with each market's volatility Granger causing volatility on the other market. International investors can therefore diversify better their portfolios by including such emerging markets. The benefits of diversification on emerging markets is also extensively discussed by Bekaert and Harvey (1997).

Even more fundamental is the question of how to model the volatility on each exchange and what type of GARCH model is more suitable for each market. Will the same type of model or different model(s) emerge? These questions have a profound implication for investment decisions and risk management.

This paper deals mainly with the volatility data on the two Chinese stock exchanges and is organized as follows. In Section 2 we provide a series of GARCH models that are investigated for the two markets. Section 3 contains empirical evidence for the Shenzen and Shanghai exchanges while

[2]Bollerslev et al. (1992) provide a detailed survey of GARCH modeling.

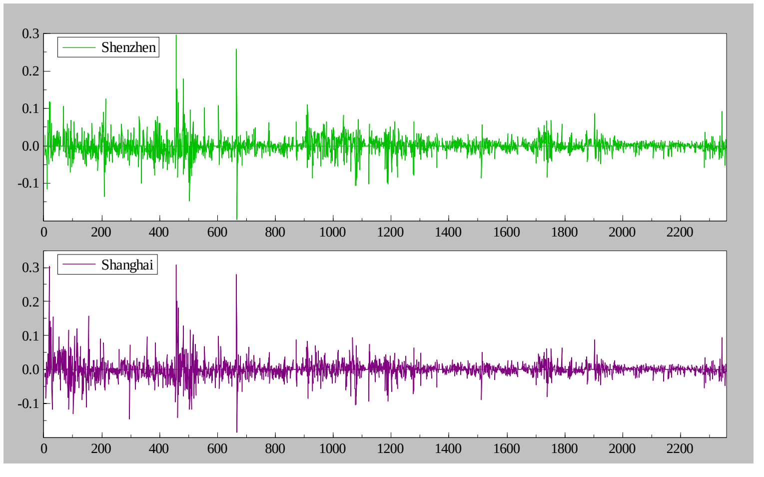
Section 4 tests whether there is a spill-over effect between the Shanghai and Shenzhen markets. The last section summarizes our conclusions.

2. MODELING VOLATILITY FOR CHINESE EQUITY MARKETS

The analysis is done using the econometric package PcGive10.0 for GARCH modeling.[3] The data used for estimation of GARCH models are the time series of daily closing prices of the index on the Shanghai and Shenzhen Stock Exchanges obtained from Datastream. The sample period is from November 1, 1992 to November 1, 2001, with a total of 2,349 observations for each of the two markets. The daily returns were calculated as the change in the logarithm of closing prices of successive days: $R_t = \ln(S_t) - \ln(S_{t-1})$.

Akgiray (1989) notes that if a return series represented by $R_t = \ln\left(\frac{S_t}{S_{t-1}}\right)$ can be regarded as a white noise process (with the implication that the share price is a pure random walk), the series should be identically and independently distributed with a zero mean and constant variance. Moreover, the series of absolute and squared values of R_t are also supposed to show a lack of autocorrelation. Although Song, and Romilly (1997) found that the two Chinese market returns series followed a random walk process, the results of our analysis presented here indicate that the series of returns on indices of both Chinese markets are not pure white noise.

FIG. 1. Time series of daily returns for two markets

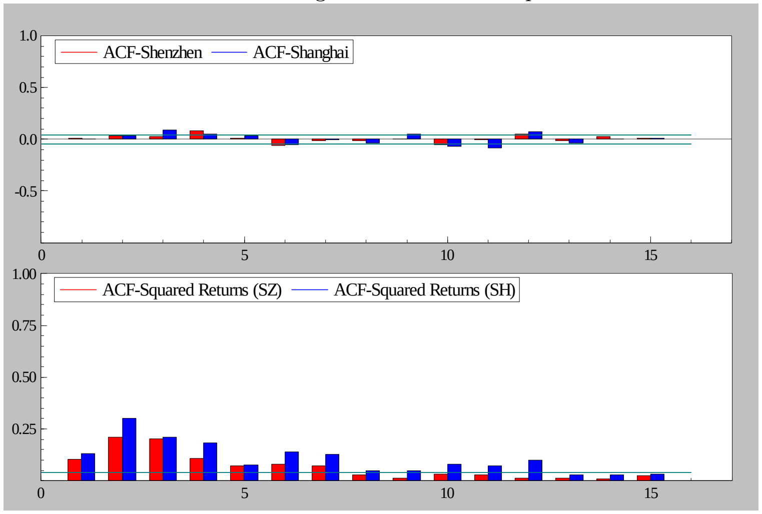


The spikes in Figure 1 suggest that the daily return series are not random walk processes, and that there exists significant volatility clustering. The

[3]See Doornik and Hendry (2001) and Hendry and Doornik (2001).

presence of serial correlation is implicit from the correlogram of actual and squared returns in Figure 2.

FIG. 2. The correlogram of actual and squared returns



Whereas the autocorrelations of the daily returns are close to zero (see the upper part of Figure 2), the correlogram of the squared returns shows quite a different picture (see the lower part of Figure 2), with clear signs of serial correlation; this is especially true for the Shenzhen Exchange. There also appears to be some seasonality since at 6 and 11 periods the autocorrelation is higher; this may correspond to the 5-day working week cycle. This suggests that the Shanghai and Shenzhen price index time series can at most be regarded as a martingale process and the corresponding return series as martingale differences. For a martingale difference process, even if past observations contain no information for prediction, it may be possible to construct a non-linear model such that the non-linearity is captured in higher order moments?variance in this case. Thus, volatility models such as $GARCH(1,1)$ may be successfully used for assessing the return volatilities of share prices in a financial market.

Some earlier studies on daily stock returns, such as Mandelbrot (1963, 1967) and Fama (1965), emphasized that the distribution of stock returns often exhibit leptokurtosis, skewness, and volatility clustering, all in contrast to the properties of an independent and identical Gaussian distribution. The statistical evidence presented in Table 1 shows that Chinese stock returns are also not normally distributed.

The descriptive statistics for the two price index returns are the (1) mean, (2) standard deviation, (3) first to twelfth order autocorrelation coefficients,

TABLE 1.

Descriptive statistics for the market price indices, R_1 and R_2 are the log returns of the Shenzhen and Shanghai exchanges respectively

Statistics	R_1	R_2	$\|R_1\|$	$\|R_2\|$	R_1^2	R_2^2
Mean	0.00032601	0.00054054	0.016221	0.016487	0.00067895	0.00081688
SD	0.026055	0.028576	0.020392	0.023346	0.0029376	0.0039704
ρ_1	0.0019213	−0.0028246	0.30978	0.32575	0.10241	0.13135
ρ_2	0.038010	0.036613	0.35209	0.37611	0.20869	0.30395
ρ_3	0.023184	0.091858	0.30652	0.31720	0.20186	0.21159
ρ_4	0.082076	0.045480	0.26711	0.28463	0.10744	0.18528
ρ_5	0.010766	0.031429	0.23742	0.21929	0.074198	0.076805
ρ_6	−0.060190	−0.054203	0.24060	0.25331	0.079906	0.14046
ρ_7	−0.016232	−0.0080156	0.19206	0.22885	0.074836	0.12720
ρ_8	−0.017404	−0.039664	0.17101	0.18699	0.030532	0.048750
ρ_9	0.0053153	0.046499	0.14335	0.18429	0.014831	0.050689
ρ_{10}	−0.048561	−0.068903	0.15646	0.21785	0.032720	0.080166
ρ_{11}	−0.0055714	−0.088106	0.15832	0.21581	0.028623	0.072727
ρ_{12}	0.048554	0.076931	0.12154	0.21125	0.012129	0.099236
Skewness	1.0716	1.8471				
Kurtosis	16.989	21.764				
$Q(12)$	36.89	40.23	379.85	332.14	158.45	96.13
Jarque-Bera	4985.2	6981.3				

(4) skewness, (5) excess kurtosis, (6) the Ljung-Box $Q(12)$ statistic for testing the hypothesis that all autocorrelations up to lag 12 are jointly equal to zero, and (6) the Jarque-Bera normality test statistic. For the absolute and squared returns series, the skewness, kurtosis and normality statistics are not applicable. The kurtosis, skewness and Jarque-Bera normality statistics reported in the first two columns of Table 1 indicate that the null hypothesis of a normal distribution can be rejected for both series.

The independence assumption in each of the series is tested by calculating the first to twelfth order autocorrelation coefficients. The Ljung-Box $Q(12)$ statistics for the cumulative autocorrelation up to twelfth-order autocorrelation in the two return series are both greater than 21.02 (the 5% critical value from a distribution with 12 degrees of freedom), suggesting that the hypothesis of independence in daily returns should be rejected. Furthermore, the autocorrelation coefficients and Ljung-Box $Q(12)$ statistic for the absolute and squared return series also indicate a very strong autocorrelation. Overall, these results clearly support the rejection of the hypothesis that the two Chinese time series of daily stock returns are time series with independent daily values. Moreover, the statistics justify the use of the GARCH specification in modeling the volatility of the Chinese stock markets.

3. GARCH MODELS FOR SHENZEN AND SHANGHAI EXCHANGES

More formally the model we propose is given by

$$R_t = \eta + \sum_{i=1}^{r} \theta_i R_{t-i} + \varepsilon_t + \sum_{j=1}^{s} \phi_j \mu_{t-j} \tag{1}$$

where R_t is the daily returns of a market index $R_t = \ln\left(\frac{S_t}{S_{t-1}}\right)$ and $\mu_\tau \Omega_{t-1} \sim N(0, h_t)$.

Equation (1) represents the $ARMA(r,s)$ process, and the conditional variance of returns, h_t, is then specified as:

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \mu_{t-j}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{2}$$

where the parameters in equation (2) should satisfy: $\alpha_0 > 0, \alpha_i, \beta_i > 0, \;\; i = 1, \ldots, p, \;\;\; j = 1, \ldots, q.$

As suggested by Akgiray (1989), allowing the conditional variances to depend on past-realized variances is consistent with the actual volatility pattern of markets where there are both stable and unstable periods.

Engle, Lilien, and Robins (1987) found that an increase in risk (variance) tends to result in higher expected returns in share prices. Therefore, the GARCH in mean or GARCH-M model is a natural extension of the GARCH model, since it introduces a conditional variance (or standard deviation) term in equation (1):

$$R_t = \eta + \lambda h_t + \sum_{i=1}^{r} \theta_i R_{t-i} + \varepsilon_t + \sum_{j=1}^{s} \phi_j \mu_{t-j}. \tag{3}$$

The relationship between stock return volatility and the sign of stock returns is also one of interest. It is argued by Engle and Ng (1993) that the relationship has a negative sign; that is, when stock returns decrease the volatility increases, and vice versa. This phenomenon is termed the "leverage effect." It may be modelled by the asymmetric volatility model or threshold ARCH (or TAGARCH) model in which a multiplicative "indicator" dummy variable is introduced to capture the influence of the sign of stock returns on the conditional variance:

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j (\mu_{t-j}^{-} \kappa_1)^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \kappa_2 \mu_{t-1}^2 I(\mu_{t-1} < \kappa_1) \qquad (4)$$

where $I(\bullet)$ is the indicator function; κ_1 is the asymmetry parameter and κ_2 is threshold parameter. This specification allows the impact of the squared errors on conditional volatility to be different according to the sign of the lagged error terms.

The process of fitting the GARCH type models can start with the mean equation (1) and the variance equation (2). The orders of the AR and MA process in the mean equation (1) are determined by the partial autocorrelation function (PACF) and the autocorrelation function (ACF) of the return series of the Shanghai and Shenzhen exchanges, respectively. The final GARCH specification is selected by looking at the properties of standardized residuals, which are the conventional residuals divided by their fitted conditional standard deviation. In order to retain the model, the residuals should be independent and identically distributed with mean zero and variance one.

For the data investigated here, the models $TAGARCH(1,1)$ for the Shanghai exchange and $GARCH(1,1)$ for the Shenzhen exchange, with the mean equations of $ARMA(10,10)$ for Shanghai and $ARMA(8,8)$ for Shenzhen, fit the data well. Other models such as $GARCH(p,q)$ with parameters $p = 1, 2, \ldots, 6$ and $q = 1, 2, \ldots, 6$ were also analyzed, but there were no significant improvements in goodness-of-fit based on likelihood-ratio tests and other statistics such as the standard deviation of the regression, the Akaike Information Criterion (AIC), and the Schwarz Criterion (SC).

Now the effect of risk on returns can be analyzed using the $GARCH(1,l)$-M model in which returns are assumed to be related to the conditional standard deviation which is the square root of h_t , as well as to the ARMA terms. Table 2 presents the estimation results of various GARCH specifications, where I to III correspond to $GARCH(1,1)$, GARCH-M(1,1), TAGARCH models, respectively. In the table the t-statistics are indicated in parentheses; the ARCH of residuals is tested with the F-statistic and the normality test of residuals is tested with a χ^2 test.

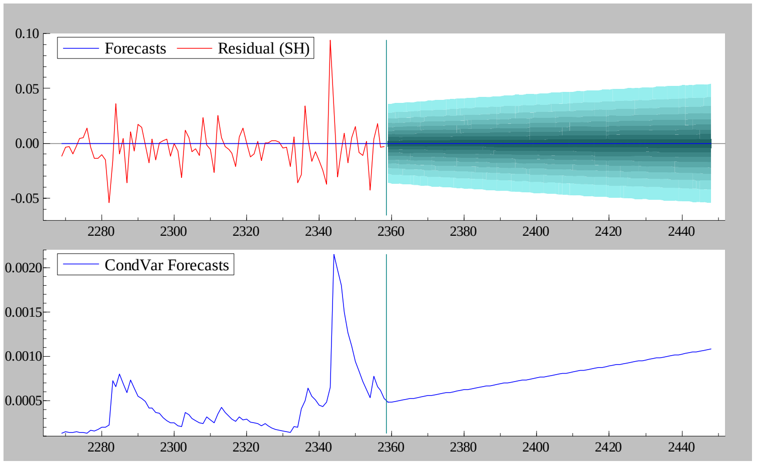
The estimates of the $GARCH(1,1)$ model for Shenzhen exchange show that, except for the constant mean model, all parameters in the mean and variance models are statistically significant and the values of the estimated parameters α_0, α_1 and β_1 satisfy the constraints for GARCH stability. This suggests that for the Shenzhen exchange, the main feature of the GARCH model, the mean reversion of the variance rate is satisfied. For the Shanghai exchange, the sum of α_1 and β_1 is equal to unity in the first three

GARCH models. Therefore, the two exchanges are integrated and a more appropriate model would be an $IGARCH(1,1)$ model given by the equation:

$$E[h_{t+H}] = h_t + \alpha_0 \times H \tag{5}$$

This means that the expected conditional variance grows linearly with the forecast horizon H. This point is illustrated in Figure 3 by estimating a $GARCH(1,1)$ model and then forecasting 90 days into the future. The results provide evidence that there is an exact linear relationship between the expected conditional variance and our forecast horizon. Moreover, the residuals become larger and larger with time, indicating that the return time series will be more volatile because of the growing variance of the future returns.

FIG. 3. Volatility Forecasts given by the fitted IGARCH (1,1) model



The results of the ARCH test reported in Table 2 are used as a stepping stone to show how well the GARCH models have eliminated the autoregressive conditional heteroscedasticity. The null hypothesis is that the coefficients of the autoregressive model for the residuals are jointly equal to zero and an F-test can be used. The information provided in Table 2 and Figures 4 and 5 indicates that the GARCH models employed, $GARCH(1,1)$ for the Shenzhen exchange and $TAGARCH(1,1)$ for the Shanghai exchange, are reliable in capturing the volatility dynamics on the Chinese markets. The upper graphs in Figures 4 and 5 show the scaled residuals while the lower two graphs show the correlograms indicating that the autocorrelations in the squared residuals have indeed disappeared.

Another noticeable feature in Table 2 is that the normality test of residuals of all the GARCH models failed. In this case, the distribution of

TABLE 2.

Parameter estimates for GARCH of models

	Shenzhen				Shanghai			
Parameter	I	II	III	IV	I	II	III	IV
ARMA								
η	0.00049	−0.00092	0.00062	0.00090	0.00032	−0.00052	0.00032	0.00068
	(0.902)	(−0.791)	(1.22)	(1.83)	(0.82)	(−0.577)	(0.777)	(1.36)
θ_3					0.072	0.081	0.085	0.080
					(0.461)	(0.468)	(0.564)	(0.513)
θ_5	−0.215	−0.006	−0.280	−0.407				
	(−2.18)	(−0.276)	(−0.928)	(−1.47)				
θ_6	−0.653	−0.554	−0.124	−0.158	−0.287	−0.334	−0.326	−0.335
	(−6.07)	(−21.7)	(−0.378)	(−0.51)	(−2.26)	(−2.66)	(−3.12)	(−3.51)
θ_8	−0.211	−0.516	−0.487	−0.469	−0.247	−0.236	−0.213	−0.229
	(−3.23)	(−19.1)	(−1.21)	(−1.16)	(−2.19)	(−2)	(−1.95)	(−2.1)
θ_{10}					0.0730	0.0698	0.0710	0.0721
					(0.751)	(0.583)	(0.657)	(0.733)
ζ_3					−0.033	−0.031	−0.031	−0.030
					(−0.225)	(−0.187)	(−0.212)	(−0.206)
ζ_5	0.243	0.015	0.322	0.462				
	(2.3)	(0.549)	(1.08)	(1.58)				
ζ_6	0.603	0.516	0.028	0.068	0.293	0.293	0.284	0.295
	(5.24)	(15.6)	(0.487)	(0.204)	(3.16)	(2.3)	(2.76)	(3.19)
ζ_8	0.203	0.520	0.487	0.465	0.195	0.196	0.175	0.190
	(2.6)	(15.3)	(1.16)	(1.11)	(1.84)	(1.71)	(1.65)	(1.82)
ζ_{10}					−0.070	−0.067	−0.066	−0.069
					(−0.822)	(−0.607)	(−0.657)	(−0.813)
λ		0.059				0.079		
		(1.37)				(1.22)		
GARCH								
α_0	4.4E-05	4.4E-05	3.9E-05	4.4E-05	4.5E-06	4.6E-06	2.2E-06	4.5E-06
	(3.54)	(1.87)	(1.91)	(3.27)	(2.8)	0.877	0.771	(2.81)
α_1	0.203	0.203	0.126	0.219	0.080	0.081	0.066	0.080
	(3.56)	(2.66)	(2.44)	(4.09)			2.17	
β_1	0.747	0.747	0.745	0.733	0.920	0.919	0.926	0.920
	(14.6)	(7.33)	(7.69)	(15.1)	(36.2)	(17.5)	33	(36)
δ_1				0.061				0.015
				(1.55)				(0.474)
κ_1			−0.007				0.002	
			(−1.98)				0.506	
κ_2			0.265				0.032	
			(1.15)				0.741	
ARCH-Test	0.088	0.091	0.131	0.108	0.104	0.220	0.301	0.213
$\chi^2(2)$	3832.2	3843.4	3468.2	3726.9	4072	3655	3363.6	3646.9
Log-like	5464.13	5464.30	5471.53	5468.95	5663.56	5664.55	5674.95	5663.24

FIG. 4. Analytical Graphs for GARCH (1,1) in Shenzhen Exchange

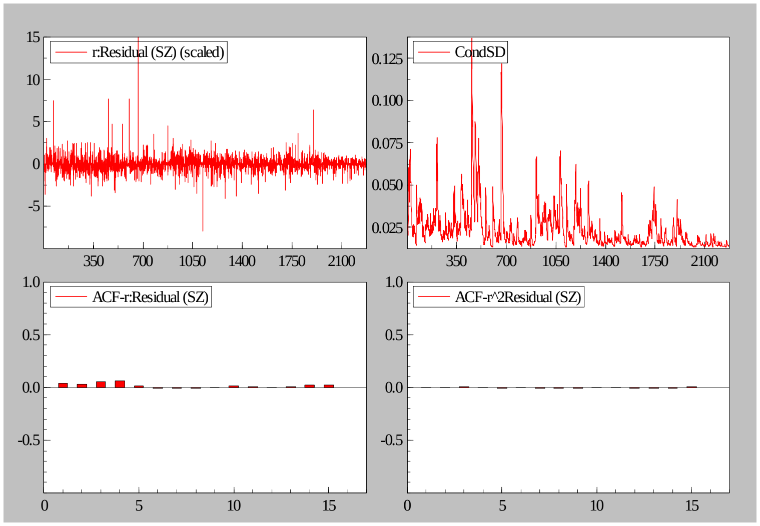
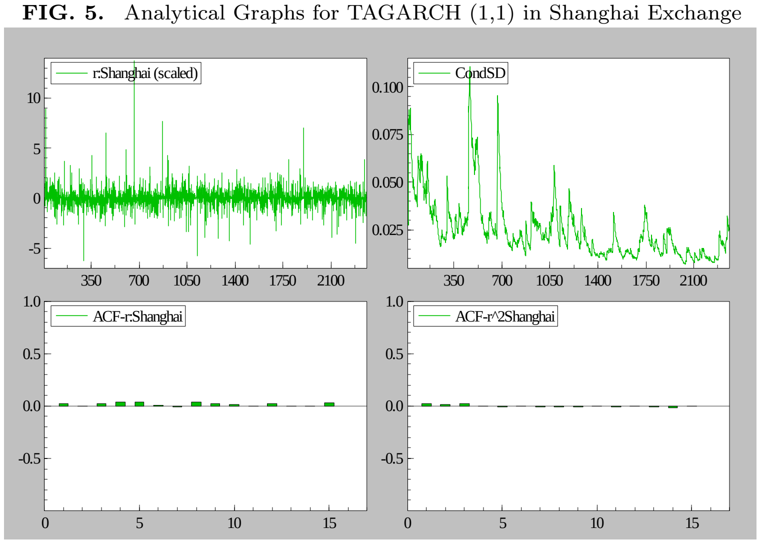


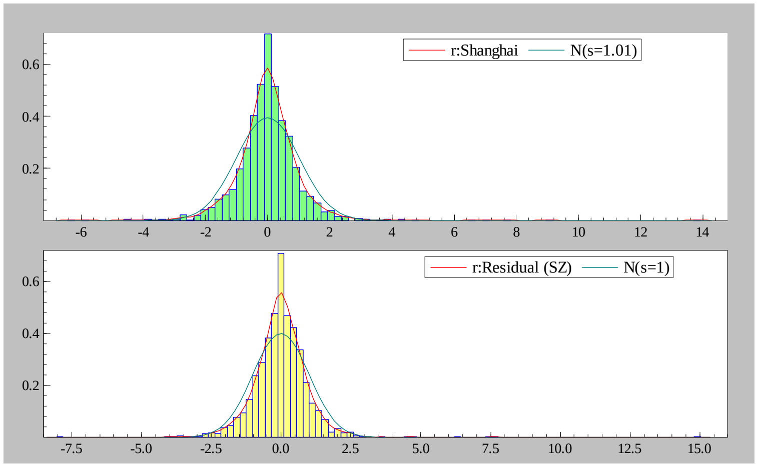
FIG. 5. Analytical Graphs for TAGARCH (1,1) in Shanghai Exchange



residuals seems to be well approximated by a χ^2 distribution and Figure 6 shows the estimated density of scaled residuals of $GARCH(1,1)$ for the Shenzhen exchange and of $TAGARCH(1,1)$ for the Shanghai exchange.

Note that the scaled residuals $\{\hat{\varepsilon}_t\}$ do not have a zero mean and there is excess kurtosis clearly visible in the residual density plot. For comparison, a normal distribution with the same mean and variance has much fatter tails.

FIG. 6. The estimated density of scaled residuals of GARCH(1,1) in Shenzhen and of TAGARCH(1,1) in Shanghai.



Thus, we can conclude that for the Chinese stock market the returns are more clustered around the mean, but at the same time are characterized by more extreme values compared with the corresponding normal distribution. This empirical finding contradicts the common view that stock market returns have a distribution with thinner tails than the normal distribution.

Consider now the $TAGARCH(1,1)$ family of models. Arguably, these models are more appropriate for equities than $GARCH(1,1)$ because the volatility of an equity's price tends to be inversely related to the price so that a negative μ_{t-1} has a bigger effect on h_t than the same positive μ_{t-1} In fact, the estimates of $TAGARCH(1,1)$ support this position because it provides the highest log-likelihood among the different model specifications in both markets. The $TAGARCH(1,1)$ seems to be suitable for the Shanghai exchange in that it makes the mean-reverting process possible.

4. VOLATILITY TRANSMISSION: THE SPILL-OVER EFFECT

The idea of volatility spill-over was first proposed by Hamao, Masulis, and Ng (1990) to examine the short-run interdependence of price volatility across the New York, Tokyo, and London stock markets. Subsequently several researchers have investigated this phenomenon. For example, Kim and Rogers (1995) considered the effects on the Korean market of volatility in both the U.S. and Japanese financial markets. Chelley-Steekey and Steeley (1996) examined the transmission of volatility between and within capitalization-ranked portfolios in the United Kingdom and confirmed the existence of a spill-over effect. In contrast to these other studies that have investigated the volatility spill-over across two or more markets in other countries, such as Booth et al. (1997) or Karolyi (1995), our focus is on two Chinese stock markets. The case of the two Chinese markets is particularly interesting because it is possible that the dynamics of prices on the two markets are different.

In their study of the Chinese stock markets, Liu Song, and Romilly (1996) found that the Shanghai and Shenzhen share prices are cointegrated. Here we use GARCH models to examine the possibility of volatility transmission between the Shanghai and Shenzhen markets in order to determine whether volatility in one market will influence the other and vice versa.

To model the spill-over effect of volatility in market B on market A, a lagged squared error term from the mean equation of the GARCH model for market B may be introduced into the GARCH model for market A as an explanatory variable in the conditional variance equation. The estimate of the coefficient of the lagged squared error term is then examined; a statistically significant estimate would suggest a spill-over effect. The spill-over effect from market B to market A may be captured by the following specification:

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \mu_{t-j}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{k=1}^{w} \delta_k \varepsilon(B)_{t-k}^2 \tag{6}$$

where the $\varepsilon(B)_{t-k}^2$ denotes previous shocks to market B. Equations (3) and (6) together constitute the GARCH-spill-over model. The coefficients (i.e., the δs) measure the impact of past shocks to the returns of market B on the conditional volatility of market A.

The estimation results for the $GARCH(1,1)$ spill-over model are provided in Table 2 as model IV, along the other GARCH models investigated above. The information in Table 2 reveals that the GARCH-M(1,1) estimates for the two markets show that the risk of stocks, as measured by the standard deviation, is positively related to the level of returns. This evidence is consistent with a positive risk premium on stock indexes; that is, higher risks result in higher returns. Although the coefficients are not statistically significant, the signs of the coefficients can serve to determine whether we have a correct model specification. The estimates of the δs in both markets are not significant, suggesting that shocks to the stock returns in one market do not transmit to the other; in other words, there appears to be no spill-over effect between the two Chinese stock markets.

5. CONCLUSIONS

Volatility is a key parameter in financial modeling and GARCH modeling is probably the best platform for estimating it since it can take into account various characteristic of the data. The two Chinese equity markets gain an important position on the international finance arena and investors are more and more attracted by the benefits of diversification and strong growth over the past decade.

Our analysis reveals that there is significant evidence of volatility clustering, a result that is different from the previous literature. There is a strong presence of serial correlation and in estimating the volatility parameter a series of GARCH models have been investigated.

The daily data on the Shenzhen exchange is fitted well by a $GARCH(1,1)$ model while the data on the Shanghai exchange by a $TAGARCH(1,1)$ model. These two models capture well the dynamics of the volatility, an important feature for risk management purposes.

Since there are two exchanges operating in the same market, there is a possibility for a spill-over effect between the two. We found no empirical evidence for this. However, the forecasts presented show that the rates of change for the two market variances are different, an important conclusion that should not be overlooked when pricing financial products.

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