

# **The Risk-Return Tradeoff in Emerging Stock Markets: Evidence from China**

**CHEN MENGGEN**

*Email:* [cmg@gsm.pku.edu.cn](mailto:cmg@gsm.pku.edu.cn)

This Draft: June 2007

# **The Risk-Return Tradeoff in Emerging Stock Markets: Evidence from China**

**Abstract:** This paper investigates the risk-return tradeoff in Chinese emerging stock markets. The empirical results show that the dynamic risk-return relationship is quite different between Shanghai and Shenzhen stock markets. A positive and statistically significant risk-return relationship is only found for the daily returns in Shenzhen Stock Exchange, but this positive relation becomes insignificant for the lower frequency returns. On the contrary, the conditional mean of the stock return is negatively but insignificantly related to its conditional variance in Shanghai Stock Exchange in most cases, except for a positive and insignificant relationship in the CGARCH-M model for the daily returns. The variance of the stock returns has a significant persistent effect usually, regardless of the frequency of the data. The asymmetric effect is very significant for the daily returns in both markets, while it becomes weak or even disappears for the lower frequency data. In general, the CGARCH-M model seems to describe the dynamic behavior of the stock returns better than other GARCH-M type models.

**Key words:** Stock returns; Volatility; Asymmetric effect; GARCH-M type models

**JEL Codes:** G12, C22

## . Introduction

Theoretically, risk and return play important roles in the capital asset pricing model (CAPM). Asset pricing models always imply a positive relationship between risk and return under the assumption of investor risk aversion, as summarized in Baillie and DeGennaro (1990). In Sharpe-Lintner-Mossin mean-variance equilibrium of exchange, the expected excess return from holding an asset is proportional to the covariance of its return with the market portfolio (its " $\beta$ "), as a proxy of risk. Merton (1973) proposed an intertemporal capital asset pricing model (ICAPM) and suggested that the conditional expected excess return on the stock market should vary positively with the market's conditional variance, as the proxy of risk. This risk-return tradeoff is so fundamental in financial economics and usually is described as the "first fundamental law of finance" (Ghysels et al., 2005).

Accordingly, numerous empirical studies have been conducted to investigate the risk-return relation by using data from different countries or different stock markets. However, the results are ambiguous and the empirical studies available do not provide any conclusive evidence on this relationship over time. French et al. (1987), Baillie and DeGennaro (1990), Campbell and Hentschel (1992), and Goyal and Santa-Clara (2003) did find a positive albeit mostly insignificant relation between the conditional variance and the conditional expected return. Xuejing Xing and Howe (2003) documented a significant positive relationship between stock returns and the variance of returns in the UK stock markets with a bivariate GARCH-M model. Bali and Peng (2004) also found a positive and significant risk-return relation by using intraday data. On the contrary, Campbell (1987) and Nelson (1991) found a significantly negative relationship. There are also many studies which find a weak and negative relation between the stock return and conditional volatility<sup>1</sup>, e.g., Whitelaw (1994) and Brandt and Kang (2004). Turner et al. (1989), Glosten et al. (1993), and Harvey (2001) revealed both a positive and a negative relation depending on the method used.

Nelson (1991) and Glosten et al. (1993) argued that across time there is no theoretical agreement about the relationship between returns and volatility within a given period of time and that either a positive or a negative relationship between current stock returns and current volatility is possible.

---

<sup>1</sup> In fact, there is also a long tradition in finance that models stock return volatility as negatively correlated with stock returns (Black, 1976). Bekaert and Wu (2000) claimed that "it appears that volatility in equity markets is asymmetric: returns and conditional volatility are negatively correlated".

Paudyal et al. (1997) examined the intertemporal relationship between risk and return in a two regime market framework using data from five countries namely the UK, USA, Germany, Japan and Italy. They found the relationship between risk and return is not fixed across regimes and it varies in response to the environment under which the investors have to make decisions, so they insisted that when modeling this relationship the effect of macroeconomic variables should be taken into account. Bekaert and Wu (2000) which was critically motivated by findings of a negative risk-return relation also claimed that the empirical evidence for such a negative relationship between expected returns and volatility is mixed in the US stock markets. Qi Li et al. (2005) documented a positive but insignificant relationship for the majority of 12 largest international stock markets with a sample from January 1980 to December 2001, based on parametric EGARCH-M models. However, they found some evidence of a significant negative relationship between expected returns and volatility in 6 out of the 12 markets, using a flexible semiparametric specification of the conditional variance.

Notably, Ghysels et al. (2005) argued that the conflicting findings about the ICAPM in the above studies are mostly the result of differences in the approach to modeling the conditional variance. They studied the intertemporal relation between the conditional mean and the conditional variance of the aggregate stock market return by a mixed data sampling (MIDAS) approach and found a significantly positive relation between risk and return in the stock market. Lundblad (2005) argued that the mixed findings on risk-return tradeoff may be viewed as a statistical artifact of the small samples, rather than as evidence against the postulated relationship itself, and documented a significantly positive mean variance tradeoff using a longer historical record (1836-2003) of US and UK equity market data.

Although there is much literature on the dynamic relationship between risk and return of developed stock markets in industrialized countries (US, UK, Japan and Germany, etc.), there is a lack of similar studies for emerging stock markets, especially for Chinese stock markets. Harvey (1995) provided a comprehensive analysis of 20 new equity markets in emerging economies and found that the predictability of the stock returns has some important differences between the emerging and developed markets. Claessens et al. (1995) also showed some evidence of return predictability while studying the behavior of the stock return in emerging stock markets. Salomons and Grootveld (2003) found that the equity risk premium in emerging markets is significantly higher than that in developed markets. Kohers et al. (2006) argued that the risk associated with emerging markets, as measured by the standard deviation of returns, is higher than in developed markets and the return in emerging markets have been

higher than in developed markets for most periods. Therefore, the dynamic risk-return relationship in emerging stock markets needs be examined carefully.

With a sample of daily stock returns of Taiwan Stock Exchange over the period 1971-1993, Yensheng Huang (1997) found an inverse relationship between returns and systematic risk, idiosyncratic risk, and total risk respectively. Chui and Wei (1998) found a flat relationship between average stock return and beta in Hong Kong, Korea, Malaysia, Taiwan and Thailand. Under the framework of CAPM, Tang et al. (2006) showed beta is significantly and positively (negatively) related to realized returns when the market excess returns are positive (negative) in Hong Kong stock market. Chiang and Doong (2001) analyzed the relationship between stock returns and time-varying volatility by using TAR-GARCH(1,1)-in-mean specification, with the data for seven Asian stock markets including Hong Kong, Korea, Malaysia, Philippine, Singapore, Taiwan and Thailand, and found a significant positive risk-return relationship for daily data, while the size and the significance level of the GARCH effect become smaller or disappear for the weekly and monthly returns. They indicated that the null hypothesis of no asymmetric effect on the conditional volatility is rejected for the daily data, while it cannot be rejected for the monthly data. Tabak and Guerra (2002) suggested that contemporaneous returns and volatilities are significantly and positively correlated in Brazilian stock markets, and they also found an asymmetric effect, by using the EGARCH model. Salman (2002) found the stock return is positively associated with the estimate of the conditional standard deviation with a GARCH-M specification and the contemporaneous changes in volume have a positive effect on returns in Turkey stock market (ISE).

China launched two stock exchanges-Shanghai Stock Exchange in 1990 and Shenzhen Stock Exchange in 1991. As China became an increasingly market-oriented economy, the emerging stock markets have developed very quickly, along with fast economic growth. Su and Fleisher (1998) found that ARCH/GARCH models can be fitted to Chinese stock markets returns. Song et al. (1998) suggested that the daily return series may be best explained by the GARCH (1,1) specification among a class of GARCH models, using the sample from 21 May 1992 to 2 February 1996 of Shanghai and Shenzhen stock exchanges. They found a positive relationship between risk and return by GARCH-M (1,1), but failed to detect any leverage effect in Chinese stock markets. Lee et al. (2001) showed strong evidence of time-varying volatility and a fat-tailed conditional distribution with a sample of daily returns for Shanghai and Shenzhen A/B share indexes from 1990 or 1992 to 1997. They found that

volatility is highly persistent and predictable in China. However, they found no significant relation between expected returns and expected risk with GARCH-M model.

This paper extends the existing researches about Chinese stock markets in several ways. First, this study uses a longer sample to investigate the relationship between the stock return and the volatility in Chinese stock markets. The early research such as Song et al. (1998) and Lee et al. (2001), employed a rather short sample (before 1997), which maybe restricts the reliability of the conclusions. An extended and more recent sample (from the start of Chinese stock markets to March 2007) in this paper may come to a more reliable conclusion. Second, this study estimates the return and volatility relation with different frequency data (daily, weekly and monthly) together. Bali and Peng (2006) has argued that one is more likely to uncover a positive risk-return relation with higher frequency data. Both high-frequency and low-frequency data are used in the examination, which allows me to discriminate the performance with respect to different data frequencies and should come to some important implications. Third, a group of variant specifications of GARCH-M type models are used to test the risk-return tradeoff. In particular, I employ the CGARCH-M model which is relatively new in this line of research. Additionally, some diagnostic checks proposed by Engle and Ng (1993) are used in this paper, and this will help to assess the robustness of different models.

This paper investigates the risk-return tradeoff in Chinese emerging stock markets with a sample including daily, weekly and monthly market return series. I find that the dynamic risk-return relationship is quite different between Shanghai and Shenzhen stock markets, by using a group of four different specifications of GARCH-M type models. In Shenzhen stock market, a positive relationship between the stock return and its conditional volatility is found, but it is statistically significant only for the daily returns. On the contrary, a negative and insignificant risk return tradeoff is found in Shanghai stock market in most cases, except for the estimation for the daily return series in CGARCH-M model. In general, the CGARCH-M model seems to describe the dynamic behavior of the stock returns better than other GARCH-M type models, including standard GARCH-M, EGARCH-M and GJR-GARCH-M. Additionally, the daily returns for both Shanghai and Shenzhen stock markets exhibit a significant asymmetric effect, i.e., positive and negative innovations of the stock returns have different impact on the conditional volatility. However, the asymmetric effect becomes very weak or even disappears for the lower frequency data.

The remainder of this paper is organized as follows. Section discusses the econometric

methodology. Section introduces the data. Section reports the empirical results, and finally, section concludes the paper.

## • Methodology

### A. Theoretical Background

A considerable body of financial theory and empirical studies relates expected stock return to the notion of variance. For example, the theoretical asset pricing models of Sharpe (1964) and Black and Scholes (1974) directly relate the change in asset price to its own variance or to the covariance between its return and the return on the market portfolio. In Merton (1973) ICAPM, he derived that the conditional return on the wealth portfolio,  $E_t r_{M,t+1}$ , is a linear function of its conditional variance,  $\sigma_{M,t}^2$ , and the conditional covariance with the investment opportunity set,  $\sigma_{MF,t}$ :

$$E_t r_{M,t+1} - r_{f,t} = \left[ -\frac{J_{WW}W}{J_W} \right] \sigma_{M,t}^2 + \left[ -\frac{J_{WF}}{J_W} \right] \sigma_{MF,t} \quad (1)$$

where  $r_{f,t}$  is the risk-free return rate. The first term of the right hand side is called the risk component and the second term is called the hedge component.  $J(W(t), F(t), t)$  is the indirect utility function of the representative agent in wealth,  $W(t)$ , and any variables,  $F(t)$ , describing the evolution of the investment opportunity set over time, with subscripts denoting partial derivatives.  $\left[ -\frac{J_{WW}W}{J_W} \right]$  is the coefficient of relative risk aversion, which is typically assumed to be constant over time and positive for people who are risk averse. The second term is an adjustment to the conditional risk premium on the portfolio arising from innovations to the state variables about the variation in the investment opportunity set. And its sign depends on the relationship between the marginal utility of wealth and the state variables, i.e.,  $J_{MF}$ , and the conditional covariance between innovations in the wealth portfolio and the state variables, as  $J_W$  is positive.

Furthermore, Merton (1980) argued that under certain conditions, the second term in equation (1) can be negligible. Then, the risk-return tradeoff in the context of intertemporal equilibrium model can be reasonably approximated by

$$E_t r_{M,t+1} - r_{f,t} = \lambda_M \sigma_{M,t}^2 \quad (2)$$

where  $\lambda_M$  would be the coefficient of relative risk aversion for a representative investor. The general model reduces this restricted version if one assumes that the investment opportunity set is time invariant or if the representative investor has logarithmic utility. Since Merton's work, substantial empirical studies follow the above specification (e.g. Compbell,1987; Baillie and DeGennaro,1990; Nelson,1991; Poon and Taylor, 1992;Glosten et al.,1993; Engle and Ng,1993; Xuejing Xu and Howe,2003; Ghysels et al.,2005; Guo and Whitelaw,2006; etc.). Following most of literature, this paper investigates the risk-return relationship in Chinese emerging stock markets based on the framework of equation (2).

## B. Econometric Models

The main difficulty in testing is that the conditional variance of the market is not observable and must be filtered from past returns. The econometric model relating the market risk premium to conditional volatility naturally lends itself to GARCH-M technology. Stock return series have time-varying properties usually. ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH models could capture this effect and so are widely used in financial series. GARCH-M model introduced by Engle, Lilien and Robins (1987) and developed by Bollerslev, Engle and Wooldridge (1988) explicitly links the conditional variance to the conditional mean of returns and provides a framework to investigate the risk-return tradeoff in finance. Usually, the standard GARCH-M model can be specified as follows:

$$r_t = c + X' \theta + \lambda \sigma_t^2 + \varepsilon_t \quad (3)$$

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^p \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^q \beta_i \sigma_{t-i}^2 \quad (4)$$

$$E(\varepsilon_t) = 0, \text{Var}(\varepsilon_t) = \sigma_t^2$$

where  $r_t$  denotes the logarithmic stock return at time  $t$ , and  $\sigma_t^2$  is the conditional heteroskedastic term at time  $t$ .  $X$  represents the exogenous variables, while  $\varepsilon_t$  is the error term.

The standard GARCH-M model has got some limitations itself, which makes the results of GARCH-M model weak. First, the assumptions for parameters non-negativity are only sufficient and might be weakened in certain cases (Nelson, 1991). Second, it imposes parameter restrictions that are

often violated by estimated coefficients and that may unduly restrict the dynamics of the conditional variance process (Nelson,1991). Third, because of the choice of a quadratic form for the conditional variance, it fails to capture the asymmetric effect of volatility following good and bad news motivated by Black (1976). Usually, the volatility of stock return series show significant leverage effect and good news and bad news have different impact on the return, e.g. Nelson (1991), Glosten et al. (1993) and Bae et al. (2007) on US stock market, Poon and Taylor (1992) on UK stock market, and Koutmos (1992) on Canada, France and Japan stock markets.

The EGARCH or Exponential GARCH model proposed by Nelson (1991) overcomes the above limitations and implies that the leverage effect is exponential, rather than quadratic, and then forecasts of the conditional variance are guaranteed to be nonnegative. The EGARCH-M model specification is

$$r_t = c + X' \theta + \lambda \sigma_t^2 + \varepsilon_t \quad (5)$$

$$\log(\sigma_t^2) = \alpha_0 + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \quad (6)$$

$$E(\varepsilon_t) = 0, \text{ Var}(\varepsilon_t) = \sigma_t^2$$

In order to capture the leverage effect, Glosten, Jaganathan, and Runkle (1993) proposed another specification of the conditional variance, hereafter called GJR-GARCH or TGARCH (Threshold GARCH). The generalized specification for the conditional variance is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^k D_{t-k} \gamma_k \varepsilon_{t-k}^2 \quad (7)$$

$$D_{t-k} = \begin{cases} 1, & \text{if } \varepsilon_{t-k} < 0 \\ 0, & \text{if } \varepsilon_{t-k} \geq 0 \end{cases} \quad (8)$$

where  $D_{t-k}$  is an indicator function capturing the asymmetric effect. In this model, good news,  $\varepsilon_{t-i} > 0$ , and bad news,  $\varepsilon_{t-i} < 0$ , have differential effects on the conditional variance,  $\alpha_i$  and  $\alpha_i + \gamma_i$  respectively. If  $\gamma_i \neq 0$ , the news impact is asymmetric, and if  $\gamma_i > 0$ , bad news increases volatility, i.e., there is an asymmetric effect. With a sample of daily return series from the Japanese stock market, Engle and Ng (1993) found that GJR-GARCH is better than standard GARCH and EGARCH in capturing the risk-return relationship.

As Ghysels et al. (2005) stressed, better measures of conditional volatility might produce more

precise estimates of the risk-return relation. This paper also uses a relatively new variant: the asymmetric Component GARCH (or CGARCH) model proposed by Engle and Lee (1999) to explore the risk-return relation in Chinese stock markets. The CGARCH model permits both a long-run component of conditional variance,  $q_t$ , which is slowly mean reverting, and a short-run component,  $\sigma_t^2 - q_t$ , that is more volatile. The CGARCH(1,1)-M model specification is as follows:

$$\sigma_t^2 - q_t = \alpha_1(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma_1(\varepsilon_{t-1}^2 - q_{t-1})D_{t-1} + \beta_1(\sigma_{t-1}^2 - q_{t-1}) \quad (9)$$

$$q_t = c + \rho(q_{t-1} - c) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \quad (10)$$

where  $\sigma_t^2$  is still the volatility, while  $D_{t-1}$  is a dummy variable for asymmetric effects. If  $\gamma > 0$ , it indicates the presence of transitory leverage effects in the conditional variance. Christoffersen et al. (2004) showed that distinguishing short- and long-run components enables the CGARCH model to describe volatility dynamics better than the standard GARCH model. Guo and Neely (2006) pointed that the CGARCH model distinguishes the effects of the long-run and short-run volatility components on stock prices and will improve the understanding of the importance of various risks.

Following Nelson (1991), the return innovation is modeled as a generalized error distribution (GED)<sup>2</sup>. Because the non-normality in the emerging stock markets, such as China, is particularly severe, the choice of GED density is set by the inability of Gaussian GARCH processes to account for the leptokurtosis of the stock return series. The GED distribution can be written as follows:

$$\varepsilon_t | I_{t-1} \sim GED(0, \sigma_t^2, \nu)$$

$$f(\varepsilon_t) = \frac{\nu \exp[-0.5|\varepsilon_t/\sigma_t|/\psi]^\nu}{\psi 2^{[(\nu+1)/\nu]} \Gamma(1/\nu)}, \text{ where } \psi = \left[ \frac{2^{(2/\nu)} \Gamma(1/\nu)}{\Gamma(3/\nu)} \right]^{1/2} \quad (11)$$

In the equation above,  $\Gamma(\cdot)$  is the gamma function and  $\nu$  is a measure of tail thickness, which is equal to 2 for the normal density and less than 2 for the leptokurtic distribution.  $I_{t-1}$  is the set of information available at the beginning of time  $t$ .

---

<sup>2</sup> There are three assumptions commonly employed when working with ARCH models: normal (Gaussian) distribution, Student's t-distribution, and the Generalized Error Distribution (GED). The GED encompasses many different density functions depending on various values of the parameter  $\nu$  and is quite general. For example, when  $\nu = 2$  we have the standard normal distribute density, for  $\nu = 1$  we get double exponential distribution, and if  $\nu$  is infinite we obtain the uniform distribution.

## . Data

This paper evaluates the risk-return relationship associated with equity for the market as a whole. Therefore, the data used in this paper are the stock price indexes of Shanghai Stock Exchange and Shenzhen Stock Exchange. The sample ranges from 19 December, 1990, to 30 March, 2007, for Shanghai Composite Price Index and from 3 April, 1991, to 30 March, 2007, for Shenzhen Component Price Index. As Bali and Peng (2006) pointed out, the frequency of data have an important impact on the estimate of the risk-return relation, this paper investigates the risk-return tradeoff with daily, weekly and monthly return data simultaneously. The sample data are obtained from SINOFIN Database<sup>3</sup>. Additionally, the tests used the continuously compounded stock return rate directly, instead of the excess return rate (which is equal to the stock return rate minus the risk-free interest rate)<sup>4</sup>. Because there are no tradable short-term Treasury bill yields in Chinese capital markets and so the proper proxy of risk-free return rate isn't available. The continuously compounded return rate of stocks is calculated in natural logarithmic form:

$$r_t = \ln P_t - \ln P_{t-1} \quad (12)$$

where  $r_t$  is the stock market return and  $P_t$  is the stock index closing price at period  $t$ .

Table 1 reports the summary statistics for daily, weekly and monthly stock returns in both Shanghai and Shenzhen Stock Exchanges. During the sample period, the mean of daily returns is about 0.0009, the mean of weekly returns is 0.0043 and the mean of monthly returns is 0.0173, in Shanghai stock market. At the same time, the mean values of daily, weekly and monthly returns in Shenzhen stock market are 0.0006, 0.0028 and 0.0124 respectively. The statistics show that market returns are positively skewed in both markets, and what's more, the skewness values of the returns in Shanghai are much bigger than those in Shenzhen. The positive skewness implies the aggregate market return distributions of the shares traded in these two markets have a higher probability of earning positive returns. All the kurtosis values are much larger than 3. Jarque-Bera statistics are all very big and the corresponding probability-values are 0. This reveals that the distribution of all return series has a fat tail

---

<sup>3</sup> SINOFIN Database was built up by Peking University, which is very popular in China.

<sup>4</sup> The use of stock return instead of stock excess return is consistent with Baillie and DeGennaro (1990), Nelson (1991), Choudhry (1996), Lee et al. (2001) and Qi Li et al. (2005), etc. Many researchers argue that the practice of using stock returns produces little difference in estimation and inference in this line of study. Particularly, Baillie and DeGennaro (1990) compared two models based on stock return series and stock excess return series and found the results are quite similar.

and a leptokurtosis compared with the normal distribution. From Figure 1, we can find intuitively that large changes tend to be followed by large changes and small changes tend to be followed by small changes. Therefore, the volatilities in Chinese stock markets maybe exhibit a clustering phenomenon.

## . **Empirical Study**

### **A. Autocorrelation and Unit Root Test**

Autocorrelation coefficients for the return series are reported in Table 2. Autocorrelation reflects how quickly and completely stock prices adjust to new information. Whereas positive autocorrelation coefficients suggest a slow and partial price adjustment, negative autocorrelation coefficients suggest an overreaction effect. I calculate the autocorrelation coefficients for lags up to 36 and Table 2 only reports a part of the results. The results suggest a slowly decaying autoregressive effect in both Shanghai and Shenzhen stock exchanges. The autocorrelation coefficients of the daily return series for both Shanghai and Shenzhen are statistically significant at 1% level and the autocorrelations of the weekly and monthly returns is much weaker, while the monthly return is statistically insignificant for the first five order lags usually. However, the first-order autocorrelation coefficient of the monthly returns for Shenzhen is 0.215, statistically significant at 1% level. The first five order autocorrelation coefficients are all statistically positive for the daily returns in both markets. This partly show that stock price in Chinese stock markets usually under-react to new information. The signs of the autocorrelation coefficients for weekly and monthly data are mixed and seem to exhibit no obvious properties. Ljung-Box Q-statistics reveal that the independent and identically distributed hypothesis is rejected for all the stock return series and provide evidence of possible dependence in the first and higher moments of the return distribution in Chinese stock markets.

I employ the augmented Dickey-Fuller test and Phillips-Perron test to check the unit root of the sample series and the results are reported in Table 3. The values of  $t$ -statistic of ADF test and adj.  $t$ -statistic of Phillips-Perron test show that all variables reject the null hypothesis of unit root and all of the return series are stationary.

### **B. Estimates for the Risk-Return Tradeoff of Daily Stock Returns**

As reported in Table 1, the relatively large value of the kurtosis statistic suggests that the

underlying time series of Chinese stock markets are leptokurtic or far tailed and sharply peaked about the mean, as compared with the normal distribution. The advantage of GARCH type models just lie in capturing the time-varying volatility. I first apply the GARCH type models to the daily market return series of Shanghai and Shenzhen Stock Exchanges. As reported by Bollerslev et al. (1992), the GARCH(1,1) model appears to be sufficient to describe the volatility evolution of the stock return series, I only report the estimation for all models for  $p = 1$  and  $q = 1$ . The estimation is performed by the method of maximum likelihood. In the context of ICAPM of Merton (1973, 1980), the mean equation has no constants term, however the empirical studies usually include a constant term. The choice of the constant in the mean equations and the choice of the lags (in mean equations and variance equations) are determined by the criteria of AIC, SC and the values of Log likelihood.

Table 4 reports the estimation results, along with some diagnostic tests. In Panel A for the Shanghai stock market, the coefficient estimators that link the return and conditional volatility are negative and not statistically significant for GARCH-M, EGARCH-M and GJR-GARCH-M, while the coefficient estimate for CGARCH-M is positive and also not statistically significant. The outcome of mixed signs in the risk-return relation in Shanghai Stock Exchange is very consistent with Turner et al. (1989), Glosten et al. (1993), and Harvey (2001), whether there is a positive or a negative relation between return and volatility appears to depend on the method used. The insignificant coefficients also reveal that the relation between return and conditional volatility is weak and this is also found in Nelson (1991) and Qi Li et.al.(2005) for US stock markets. Furthermore, the negative results for GARCH-M, EGARCH-M and GJR-GARCH-M are very similar to those obtained by Lee et al. (2001), however that is contrary to those of Song et al. (1998). In the mean equations, the lagged orders for stock returns are up to 3 and this shows the past values have a significant impact on current returns. In the variance equations, the estimators for  $\gamma_1$  are statistically significant at different levels, respectively. This shows that the return series exhibit an asymmetric effect for positive and negative innovations. The stock market volatility tends to rise in response to a decrease in stock return (bad news) and to fall in response to an increase in stock return (good news).

The estimation results for Shenzhen daily Stock returns are in Panel B of Table 4. The coefficients linking stock return and its conditional volatility is positive and statistically significant. In contrast to

the Shanghai stock market, the outcomes of Shenzhen show a significantly positive risk-return tradeoff which is consistent with the asset pricing theory, and imply that investors will be compensated by higher return for bearing a higher level of risk. These results are inconsistent with Lee et al. (2001). The coefficient estimators for the AR components in the mean equations are positive and statistically significant. The past returns are able to predict future expected returns. In the variance equations, EGARCH and CGARCH models really capture an asymmetric volatility effect, but the reaction directions contradict each other. The GJR-GARCH model fails to capture any asymmetric effect.

Table 4 also reports the Ljung-Box statistics for 12<sup>th</sup>-order serial correlation in the level and squared residuals as well as the asymmetry test statistics (Sign bias, Negative size bias, Positive size bias, and Joint tests) developed by Engle and Ng (1993)<sup>5</sup>. The latter is included because the findings by Engle and Ng (1993) suggest the Ljung-Box test may not have much power in detecting misspecification related to asymmetric effects. In the diagnostic checks, the Ljung-Box statistics for 12<sup>th</sup>-order serial correlations in the residuals are significant for all models, in both the Shanghai and Shenzhen stock markets, and are all insignificant for the 12<sup>th</sup>-order squared residuals. On the other hand, all of the asymmetry test statistics indicate the estimated models fit the data well.

Consequently, the CGARCH model has the highest values of Log likelihood for both Shanghai and Shenzhen stock markets. This shows that CGARCH-M fits the data best among the four GARCH-M type models. However, empirical results reveal that GJR-GARCH-M model is not better than standard GARCH-M and EGARCH models for Chinese stock markets, though Glosten et al. (1993) and Engle and Ng (1993) found that it is the best parametric model for the data from US and Japan stock markets.

### C. Estimates for the Risk-Return Tradeoff of Weekly Stock Returns

Table 5 reports the estimation results for the weekly return series of Shanghai Stock Exchange in Panel A and Shenzhen Stock Exchange in Panel B. Shanghai stock market has a negative effect of stock risk on the mean return, however the coefficients are all statistically insignificant. The estimators of  $\gamma_1$  in the EGARCH, GJR-GARCH and CGARCH are statistically significant at the 5% or 10% levels,

---

<sup>5</sup> These tests examine whether squared standardized residuals from the estimated models,  $(\varepsilon_t / \sigma_{t-1})^2$ , are independent and identically distributed and are proposed by Engle and Ng (1993). The Sign bias test shows whether positive and negative innovations affect future volatility differently from the prediction of the model. The Negative size bias test shows whether larger negative innovations are correlated with larger biases in predicted volatility. The Positive size bias test shows whether larger positive innovations are correlated with larger biases in predicted volatility. Additionally, a Joint test of all three is usually used as well.

respectively. The asymmetric effect on the volatility for the positive and negative return innovations also exist in the Shanghai stock market. The positive size bias test among the diagnostic checks in EGARCH, GJR-GARCH and CGARCH are statistically significant at the 5% or 10% levels. The values of Log likelihood reveal that CGARCH model fits the weekly return behavior of Shanghai stock market better than other GARCH-M type models and GJR-GARCH-M better than standard GARCH-M and EGARCH-M models.

The estimation results for Shenzhen Stock Exchange exhibit a positive but insignificant linkage between the risk and mean return. At the same time, the estimators of the coefficients for the asymmetric effect on the volatility are all statistically insignificant. None of the Engle-Ng diagnostic checks show any evidence of misspecification in the four models, though the 12<sup>th</sup>-order Ljung-Box Q-statistics for the squared residues are statistically significant. A higher value of Log likelihood than those of other models supports that CGARCH-M might be a more reasonable model to use.

#### **D. Estimates for the Risk-Return Tradeoff of Monthly Stock Returns**

Table 6 reports the estimation results for the monthly return series of Shanghai Stock Exchange in Panel A and Shenzhen Stock Exchange in Panel B. The coefficient estimators of the conditional variance term in mean equations are all negative and statistically insignificant in Shanghai stock market. In the variance equations, only the CGARCH model exhibits a weak asymmetric effect on the conditional volatility of return innovations (with significance at the 10% level). Apart from the Ljung-Box Q(12) statistics in GARCH-M and GJR-GARCH models which are significant at the 10% level, the diagnostic checks show no more evidence for the misspecification of models. In Shenzhen stock market, the empirical relation between risk and return is negative; however it is statistically insignificant. The innovation of monthly returns provides no asymmetric effect on the conditional volatility. The diagnostic checks also show no evidence for the misspecification of models.

Although the diagnostic checks show that these models fit the monthly return data of Shanghai and Shenzhen stock markets well, too many insignificant or weakly significant coefficients in the mean and variance equations mean that we have not captured much of the variation in the mean returns in the regression.

Comparing the estimated results of the monthly return series (table 6) with those of the daily and weekly return series in table 4 and 5, I therefore come to the following conclusions from the

examination of the four different GARCH-M specifications<sup>6</sup>.

First, the market returns in both Shanghai and Shenzhen Stock Exchanges exhibit a significant variance persistent effect. The first-order autoregressive coefficients for  $\sigma_t^2$  in the variance equation are statistically significant for different GARCH-M type models, except for the estimation of the CGARCH-M model for the monthly returns of Shenzhen stock market.

Second, whether the GARCH-M type model is an appropriate specification to describe the conditional variance or not seems to depend on the frequency of the data. GARCH-M type models appear to fit the daily returns of Shanghai and Shenzhen stock markets well. While the GARCH-M specification is still valid for the weekly and monthly return, the significant level for the estimators become smaller and many coefficients of the regressors become statistically insignificant. Consequently, the explanatory power of the models decreases.

Third, the daily stock returns exhibit a significant volatility asymmetric effect, while the asymmetric effect of the return innovation on its conditional volatility becomes weak or disappears when the estimations are made on the low-frequency data.

Fourth, the past values of stock returns have an impact on the current returns; however the extent of the impact varies across the different-frequency returns. The significant coefficients of the AR components of the returns in the mean equation support the predictability of stock returns, and furthermore the daily return series appear to have longer lags than the weekly and monthly return series. This also shows that an over-reaction or under-reaction phenomenon to new information, depending on the sign of the coefficients, exists in Shanghai and Shenzhen Stock Exchanges. Obviously, the random-walk hypothesis can not be supported by the sample data in Chinese stock markets.

Fifth, regardless of the frequency of the data, the CGARCH-M model usually works better in fitting the dynamic behavior of the stock returns in Chinese stock markets than other GARCH-M type models, for the values of the Log likelihood in the CGARCH model dominate. However, the GJR-GARCH-M model doesn't work better than the standard GARCH-M and EGARCH-M models in Chinese stock markets, and this is inconsistent with the results of Glosten et al. (1993), Engle and Ng (1993) and some other studies for the data from different countries.

---

<sup>6</sup> I also estimate these models with the sample data under the assumptions of normal (Gaussian) distribution and Student's t-distribution for the error term  $\varepsilon_t$ . The results are similar to those of the Generalized Error Distribution (GED). For brevity, they are not reported while are available upon request.

## . **Conclusion**

This paper studied the risk-return relationship in Chinese emerging stock markets with a sample of daily, weekly and monthly market return series, using a class of variant GARCH-M models. The sample periods ranges from 19 December, 1990, to 30 March, 2007, for Shanghai Composite Price Index and from 3 April, 1991, to 30 March, 2007, for Shenzhen Component Price Index. In the context of ICAPM (Merton, 1973, 1980), the conditional mean is positively related to the conditional variance of stock market returns. Only the empirical results for the daily returns in Shenzhen Stock Exchange give support to the ICAPM, and show a positive and statistically significant risk-return relationship. The results for the weekly and monthly returns from Shenzhen Stock Exchange are consistently positive and statistically insignificant. However, this study finds a negative and insignificant relationship between the conditional mean of the stock return and its conditional variance in Shanghai Stock Exchange in most cases, except for the estimation for the daily return series in CGARCH-M model. Therefore, the dynamic risk-return relationship appears quite different between Shanghai and Shenzhen stock markets. The conclusion in this study is significantly inconsistent with those of Song et al. (1998) and Lee et al. (2001).

The empirical results also reveal that the autocorrelation of the return series in both Shanghai and Shenzhen stock markets are very significant, and furthermore, the higher frequency data appears to have longer lags. Obviously, the random walk hypothesis isn't supported by the sample data of Chinese stock markets. The variance of the stock returns has a significant persistent effect in general, regardless of the frequency of the data. The daily returns for both Shanghai and Shenzhen stock markets exhibit a significant asymmetric effect, i.e., positive and negative innovations of the stock returns have different impact on the conditional volatility. However, the asymmetric effect of the return innovation on its conditional volatility becomes weak or even disappears when the estimations are made on the low-frequency data.

The GARCH-M type models seem to fit the daily returns of Shanghai and Shenzhen stock markets well. While the GARCH-M specification is still valid for the weekly and monthly returns, the significance level for the estimators become smaller or the coefficients of the regressors become statistically insignificant. This point is quite consistent with the conclusion of Chiang and Doong (2001). Therefore, whether the GARCH-M type model is an appropriate specification to describe the

conditional variance or not seems to depend on the frequency of the data. Although the diagnostic checks give little evidence of the misspecification of the four GARCH-M type models used in this paper, I find the CGARCH-M model usually appear to work better in describing the dynamic behavior of the stock returns in Chinese stock markets than other GARCH-M type models, regardless of the frequency of the data. The GJR-GARCH-M model doesn't work better than the standard GARCH-M and EGARCH-M models in Chinese stock markets, and this is inconsistent with the result of Glosten et al. (1993), Engle and Ng (1993) and some other studies.

## References

- Bae, Jinho, Chang-Jin Kim and Charles R. Nelson, 2007, Why are Stock Returns and Volatility Negatively Correlated? *Journal of Empirical Finance*,14,pp.41-58.
- Baillie, R.T., DeGennarro, R.P., 1990, Stock Returns and Volatility. *Journal of Financial and Quantitative Analysis*,25, pp.203-214.
- Bali,Turan G. and Lin Peng,2006, Is there a Risk-Return Tradeoff? Evidence from High-Frequency Data. *Journal of Applied Econometrics*, Volume 21, Issue 8, pp.1169-1198.
- Bekaert, G., Wu, G., 2000. Asymmetric Volatility and Risk in Equity Markets. *Review of Financial Studies*,13, pp.1–42.
- Black, F. and M. Scholes,1974, The Valuation of Option Contracts and a Test of Market Efficiency. *Journal of Finance*,27, May, pp.399-418.
- Black, F.,1976, Studies of Stock Price Volatility Changes. *Proceedings of the Meetings of the American Statistical Association, Business and Economics Statistics Division*,pp.177–181.
- Bollerslev, Tim, Robert F. Engle, and J. M. Wooldridge,1988, A Capital Asset Pricing Model with Time-Varying Covariances. *Journal of Political Economy*,96, pp.116-131.
- Brandt, Michael W. and Qiang Kang, 2004, On the Relationship between the Conditional Mean and Volatility of Stock Returns: A Latent VAR Approach. *Journal of Financial Economics*,72, pp.217-257.
- Campbell, J., and Hentschel, L., 1992. No News is Good News: an Asymmetric Model of Changing Volatility in Stock Returns. *Journal of Financial Economics*,31, pp.281–318.
- Campbell, John Y.,1987, Stock Returns and the Term Structure, *Journal of Financial Economics*, 18, pp.373-399.
- Chiang Thomas C. and Shuh-chyi Doong,2001, Empirical Analysis of Stock Returns and Volatility: Evidence from Seven Asian Stock Markets Based on TAR-GARCH Model. *Review of Quantitative Finance and Accounting*,Vol.17, pp.301-318.
- Christoffersen, P., K. Jacobs, and Y. Wang, 2004, Option Valuation with Long-run and Short-run Volatility Components,Unpublished Working Paper, McGill University.
- Chui, A. and Wei, J.,1998, Book-to-market, Firm Size, and the Turn-of-the-year Effect: Evidence from Pacific-Basin Emerging Markets. *Pacific-Basin Finance Journal*, 6,pp.275-293.
- Claessens, Stijn, Susmita Dasgupta and Jack Glen,1995, Return Behavior in Emerging Stock Markets. *The World Bank Economics Review*, Vol.9,No.1, pp.131-151.
- Engle, R. and G. Lee,1999, A Long-Run and Short-Run Component Model of Stock Return Volatility, in *Cointegration, Causality and Forecasting*.Edited by R. Engle and H. White, Oxford University Press.
- Engle, R.F., Lilien, D.M., Robins, R.P.,1987, Estimating Time-varying Risk Premium in the Term Structure: ARCH-M Model. *Econometrica*,55, pp.391-407.

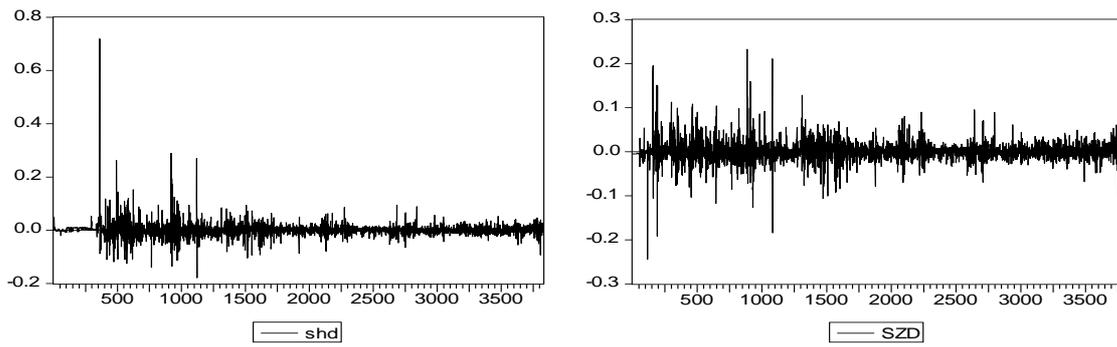
- Engle, R.F., Ng, V.K., 1993. Measuring and Testing the Impact of News on Volatility. *Journal of Finance*,48, pp.1749-1778.
- French, K.R., Schwert, G.W., Stambaugh, R.F., 1987,Expected Stock Returns and Volatility. *Journal of Financial Economics*,19, pp.3-30.
- Ghysels, E., P. Santa-Clara, and R. Valkanov, 2005, There Is a Risk-Return Tradeoff After All. *Journal of Financial Economics*, Vol.76,pp.509-548.
- Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993, On the Relation between the Expected Value and the Volatility of Nominal Excess Return on Stocks. *Journal of Finance*,48, pp.1779-1801.
- Goyal, A. and P. Santa-Clara,2003, Idiosyncratic Risk Matters! *Journal of Finance*,58, pp.975-1008.
- Guo Hui and Neely,2006, Investigating the Intertemporal Risk-Return Relation in International Stock Markets with the Component GARCH Model. Federal Reserve Bank of St.Louis working paper, <http://research.stlouisfed.org/wp/2006/2006-006.pdf>.
- Guo Hui and Robert F. Whitelaw,2006,Uncovering the Risk-Return Relation in the Stock Market. *Journal of Finance*, Vol.61(3), pp.1433-1463.
- Harvey, Campbell R, 1995, Predictable Risk and Returns in Emerging Markets. *The Review of Financial Studies*, Vol.8(3), pp.773-816.
- Harvey, Campbell R,2001, The Specification of Conditional Expectations. *Journal of Empirical Finance*, Vol.8(5), pp.573-638.
- Kohers,Gerald, Ninon Kohers and Theodor Kohers,2006, The Risk and Return Characteristics of Developed and Emerging Stock Markets: the Recent Evidence. *Applied Economics Letters*,Vol.13, Issue 11, pp.737-743.
- Koutmos, G,1992, Asymmetric Volatility and Risk Return Tradeoff in Foreign Stock Markets. *Journal of Multinational Financial Management*, 2, pp.27-43.
- Lee, C.F., Chen, G, Rui, O., 2001. Stock Returns and Volatility on China's Stock Markets. *Journal of Financial Research*,26, pp.523-543.
- Lundblad, Christian, 2005, The Risk Return Tradeoff in the Long-Run: 1836-2003. SSRN working paper.
- Merton, R.C., 1973, An Intertemporal Capital Asset Pricing Model. *Econometrica*,41, pp.867-887.
- Merton, R.C., 1980, On Estimating the Expected Return on the Market: an Exploratory Investigation. *Journal of Financial Economics*,8, pp.323-361.
- Nelson, D., 1991. Conditional Heteroscedasticity in Asset Returns: a New Approach. *Econometrica*,59, pp.347-370.
- Paudyal, Krishna and Liesl Saldanha,1997, Stock Returns and Volatility in Two Regime Markets: International Evidence. *International Review of Financial Analysis*,Vol.6, No.3, pp.209-228.
- Poon, S.H. and S.J.Taylor, 1992, Stock Returns and Volatility: an Empirical Study of the UK Stock Market. *Journal of Banking and Finance*,16,pp.37-59.

- Qi Li, Jian Yang, Cheng Hsiao and Young-Jae Chang, 2005, The Relationship between Stock Returns and Volatility in International Stock Markets. *Journal of Empirical Finance*, 12, pp. 650-665.
- Salman, Ferhan, 2002, Risk-Return-Volume Relationship in an Emerging Stock Market. *Applied Economics Letters*. vol.9, issue 8, pp.549-552.
- Salomons Roelof and Henk Grootveld, 2003, The Equity Risk Premium: Emerging vs. Developed Markets. *Emerging Markets Review*, Vol.4, No.2, June, pp.121-144.
- Sharpe, W.F., 1964. Capital Asset Prices: a Theory of Market Equilibrium under Conditions of Market Risk. *Journal of Finance*, 19, pp.425-442.
- Song, H. and Liu, X., 1998, Stock Returns and Volatility: An Empirical Study of Chinese Stock Markets. *International Review of Applied Economics*, 12, pp.129-140.
- Su, D.W. and Fleisher, B.M., 1998, Risk, Return and Regulation in Chinese Stock Markets. *Journal of Economics & Business*, Vol.50(3), pp.239-256.
- Tabak, Benjamin Miranda and Solange Maria Guerra, 2002, Stock Returns and Volatility. Central do Brasil, DEPEP working paper, <http://www.sbe.org.br/ebe24/060.pdf>.
- Tang, Gordon Y.N. and Wai Cheong Shum, 2006, Risk-Return Relationships in the Hong Kong Stock Market: Revisit. *Applied Financial Economics*, Vol.16, pp.1047-1058.
- Turner, Christopher M., Richard Startz, and Charles R. Nelson, 1989, A Markov Model of Heteroskedasticity, Risk, and Learning in the Stock Market. *Journal of Financial Economics*, 25, pp.3-22.
- Whitelaw, R., 1994, Time Variations and Covariations in the Expectation and Volatility of Stock Market Returns. *Journal of Finance*, 49, pp.515-541.
- Xuejing Xing and John S. Howe, 2003, The Empirical Relationship Between Risk and Return: Evidence from the U.K. Stock Market. *International Review of Financial Analysis*, 12, pp.329-346.
- Yensheng Huang, 1997, An Empirical Test of the Risk-Return Relationship on the Taiwan Stock Exchange. *Applied Financial Economics*, Vol.7, No.3, pp.229-239.

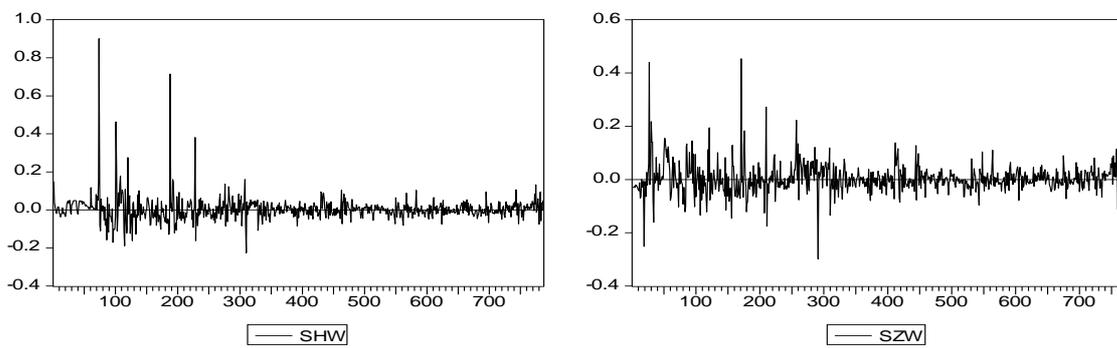
**Table 1**  
**Summary Statistics for the Sample Data**

Series	Shanghai			Shenzhen		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
Mean	0.000903	0.004286	0.017203	0.000570	0.002833	0.012418
Median	0.000660	0.001827	0.007781	-0.000466	-0.002190	0.000985
Maximum	0.719152	0.900825	1.019664	0.232669	0.453813	0.625077
Minimum	-0.179051	-0.226293	-0.373283	-0.244291	-0.298771	-0.289747
Std. Dev.	0.026960	0.065497	0.148925	0.023451	0.055273	0.122447
Skewness	5.924601	5.560782	2.522479	0.477693	1.503944	1.444828
Kurtosis	147.0672	68.79002	18.41997	18.53219	16.42102	7.653838
Jarque-Bera	3335488.	145989.0	2050.977	38221.17	6045.596	228.8135
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	3831	787	187	3788	767	183

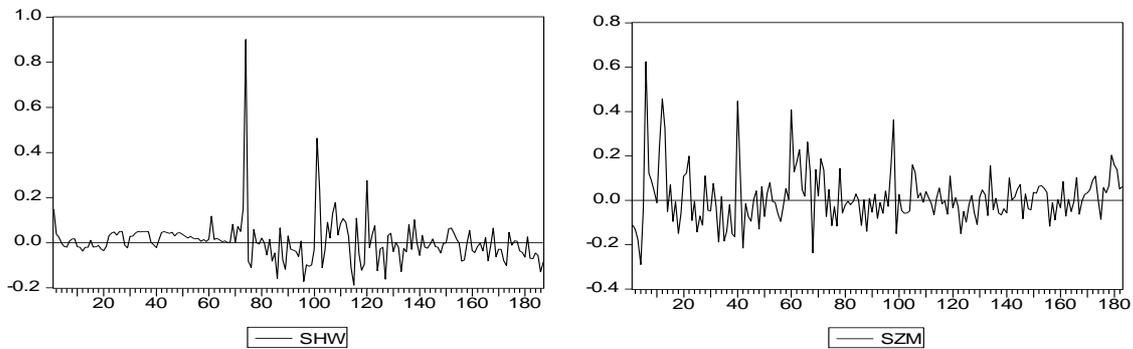
Note: Jarque-Bera statistics reveal the non-normality for all sample series.



Panel A. Distribution of Daily Return Series for Shanghai and Shenzhen Stock Exchange



Panel B. Distribution of Weekly Return Series for Shanghai and Shenzhen Stock Exchange



Panel C. Distribution of Monthly Return Series for Shanghai and Shenzhen Stock Exchange

**Figure 1. Distribution of Stock Return Series.** SHD, SHW and SHM are the daily, weekly and monthly continuously compounded return series for Shanghai Stock Exchange respectively. SZD, SZW and SZM are the daily, weekly and monthly continuously compounded return series for Shenzhen Stock Exchange respectively.

**Table 2****Autocorrelation Coefficients for Shanghai and Shenzhen Return Series for Various Lags**

Lag	Shanghai			Shenzhen		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
1	0.053*	0.085**	-0.069	0.048*	0.119*	0.215*
2	0.055*	-0.050**	0.052	0.035*	0.063*	0.052*
3	0.037*	0.059**	-0.016	0.037*	0.064*	0.041**
4	0.032*	0.015**	-0.142	0.068*	0.064*	-0.084**
5	0.033*	-0.019***	-0.076	0.038*	0.080*	-0.053**
10	-0.001*	-0.011	-0.114*	-0.013*	-0.008*	-0.075**
15	0.010*	-0.048	-0.137*	0.010*	-0.020**	-0.036
20	-0.028*	-0.019	0.048*	-0.018*	0.023**	0.053
25	-0.033*	-0.058	-0.046*	-0.009*	0.085**	-0.089***
30	0.018*	0.018*	0.004	0.039*	0.004	-0.144***
36	-0.010*	0.063*	0.121*	0.023*	0.012**	-0.098*
Q-statistics (36)	93.228	60.289	71.918	102.30	52.694	51.558

Note: This table reports the results of correlation coefficients for the sample series. We estimate the autocorrelation coefficients for various lags up to 36 and only report a part of the results in the table. Also, we only report the result of Ljung-Box Q-statistics for the 36<sup>th</sup>-order lag. The autocorrelation coefficients of the daily return series for both Shanghai and Shenzhen are statistically significant at 1% level and the autocorrelations of the weekly and monthly returns is much weaker, while the monthly return is statistically insignificant for the first five order lags usually.

\*, \*\*and \*\*\* represent significance at the 1, 5 and 10 percent levels, respectively.

**Table 3**  
**Unit Root Test for Shanghai and Shenzhen Return Series**

Variables	t-statistics	adj. t-statistics
SHD	-40.4232*	-59.0774*
SHW	-25.7909*	-25.7875*
SHM	-14.5246*	-14.5900*
SZD	-58.6126*	-59.5661*
SZW	-24.5325*	-25.0362*
SZM	-10.8053*	-10.7774*

Note: I employ the augmented Dickey-Fuller test and Phillips-Perron test to check the null hypothesis: the tested variable has a unit root. Lag Length are chose automatically based on SC, AIC and MAXLAG=29. The critical values for t-statistics with infinite observations are: -3.43 at 10%, -2.86 at 5% and -2.57 at 1%. The t-statistics of ADF test and adj. t-statistics of Phillips-Perron test show that all variables refuse the null hypothesis of unit root and the series are stationary.

\* represents significance at the 1 percent level.

**Table 4**

**Estimate for the risk-return tradeoff with daily return series**

	Panel A. Shanghai Daily Return -SHD				Panel B. Shenzhen Daily Return -SZD			
	GARCH-M	EGARCH-M	GJR-GARCH-M	CGARCH-M	GARCH-M	EGARCH-M	GJR-GARCH-M	CGARCH-M
<b>Mean Equation</b>								
C	0.000794* (4.48)	0.000643* (3.76)	0.000780* (4.35)	--	-0.001152* (-4.24)	-0.001654* (-5.30)	-0.001177* (-4.35)	-0.001440 (-5.67)
$\theta_1$	0.057386* (3.94)	0.050019* (3.63)	0.055778* (3.81)	0.052191* (4.16)	0.015678 (1.04)	0.010518 (0.76)	0.014337 (0.95)	0.014314 (0.90)
$\theta_2$	0.058056* (4.09)	0.054773* (3.99)	0.059471* (4.16)	0.058241 (3.99)*	0.007488 (0.51)	0.009823 (0.71)	--	0.010898 (0.71)
$\theta_3$	0.112196* (7.88)	0.112429* (8.20)	0.112384* (7.92)	0.105579* (7.32)	0.064944* (4.57)	0.069985* (5.10)	0.065655* (4.62)	0.069887* (4.71)
$\lambda$	-0.400986 (-0.91)	-0.163089 (-0.44)	-0.540127 (-1.18)	0.206371 (0.46)	1.734201** (2.56)	3.397108* (4.00)	1.796842* (2.66)	2.397147* (3.66)
<b>Variance Equation</b>								
$\alpha_0$	7.76E-06* (5.92)	-0.527377* (-12.04)	7.08E-06* (5.98)	0.132303 (0.34)	2.54E-05* (8.33)	-0.549564* (-8.80)	2.53E-05* (8.37)	0.000820* (3.98)
$\alpha_1$	0.265210* (11.92)	0.333874* (15.09)	0.212761* (10.23)	0.174821* (7.69)	0.227787* (9.51)	0.233638* (14.98)	0.222910* (7.98)	0.097784* (4.01)
$\beta_1$	0.772602* (54.29)	0.964280* (236.09)	0.782317* (57.52)	0.787879* (31.57)	0.744729* (38.01)	0.951660* (137.16)	0.744461* (38.18)	0.779763* (40.10)
$\gamma_1$	--	-0.043807* (-3.26)	0.084202** (2.53)	0.019900*** (1.85)	--	0.040050* (3.56)	0.011618 (0.33)	0.119186* (11.64)
Log likelihood	10289.95	10300.87	10292.82	10300.84	9888.48	9877.92	9888.44	9903.24
Ljung-Box Q(12)	32.491*** [0.091]	31.61* [0.002]	34.066* [0.001]	30.303* [0.003]	33.946* [0.001]	29.81* [0.001]	35.647* [0.000]	38.69* [0.000]
Ljung-Box Q <sup>2</sup> (12)	0.658 [1.000]	0.361 [1.000]	0.516 [1.000]	0.560 [1.000]	0.813 [1.000]	0.32 [1.000]	0.807 [1.000]	0.675 [1.000]
Sign bias	-1.19	-1.12	-1.28	-0.85	-1.30	-0.97	-1.32	-0.74
Negative size bias	0.97	0.94	1.08	0.76	0.63	0.03	0.66	-0.49
Positive size bias	-0.17	0.12	-0.02	-0.36	-0.46	-0.07	-0.40	-0.55
Joint test	0.517 [0.670]	0.466 [0.706]	0.636 [0.592]	0.398 [0.754]	0.831 [0.477]	0.447 [0.719]	0.814 [0.486]	0.422 [0.737]

Note: Table 4 reports the parameter estimates for GARCH-M, EGARCH-M, GJR-GARCH-M and CGARCH-M. In the ICAPM of Merton (1973, 1980), the mean equation has no constant term, however the empirical studies usually include a constant term. The choice of the constants in the mean equation is determined by the criterion of AIC, SC and the Log likelihood, as well as the choice of the lags. The results are estimated from the following specifications:

$$r_t = c + X' \theta + \lambda \sigma_t^2 + \varepsilon_t$$

$$\text{GARCH-M: } \sigma_t^2 = \alpha_0 + \sum_{j=1}^p \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^q \beta_i \sigma_{t-i}^2$$

$$\text{EGARCH-M: } \log(\sigma_t^2) = \alpha_0 + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}}$$

$$\text{GJR-GARCH-M: } \sigma_t^2 = \alpha_0 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^k D_{t-k} \gamma_k \varepsilon_{t-k}^2$$

$$\text{CGARCH-M: } \sigma_t^2 - q_t = \alpha_1 (\varepsilon_{t-1}^2 - q_{t-1}) + \gamma_1 (\varepsilon_{t-1}^2 - q_{t-1}) D_{t-1} + \beta_1 (\sigma_{t-1}^2 - q_{t-1})$$

$$q_t = c + \rho(q_{t-1} - c) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$$

Where  $r_t$  is the logarithmic stock return at time t, and  $\sigma_t^2$  is the conditional heteroskedastic term at time t. X represents the exogenous variables and  $D$  is a dummy variable indicating negative shocks.  $\varepsilon_t$  is the error term, where  $\varepsilon_t | I_{t-1} \sim GED(0, \sigma_t^2, \nu)$ .

This table reports the Ljung-Box statistics for 12th-order serial correlation in the level and squared standardized residuals as well as the asymmetry test statistics (Sign bias, Negative size bias, Positive size bias, and Joint tests) developed by Engle and Ng (1993). Sign bias test:  $z_t = a + bD_{t-1} + u_t$ ; Negative size bias test:  $z_t = a + bD_{t-1}\varepsilon_{t-1} + u_t$ ; Positive size bias test:  $z_t = a + b(1 - D_{t-1})\varepsilon_{t-1} + u_t$ , where  $z_t = (\varepsilon_t / \sigma_{t-1})^2$ . All corresponding tests statistics refer to the t-statistics of coefficient b in the above equation.

For brevity, a part of parameter estimators for the CGARCH-M model are not included in the table.

Additionally, (.) is the t-statistics and [.] is the p-values.

\*, \*\* and \*\*\* represent significance at the 1, 5 and 10 percent levels, respectively.

**Table 5**  
**Estimate for the risk-return tradeoff with weekly return series**

	Panel A. Shanghai Weekly Return –SHW				Panel B. Shenzhen Weekly Return –SZW			
	GARCH-M	EGARCH-M	GJR-GARCH-M	CGARCH-M	GARCH-M	EGARCH-M	GJR-GARCH-M	CGARCH-M
<b>Mean Equation</b>								
C	--	--	--	--	-0.003139** (-2.09)	-0.003761* (-2.25)	-0.003244** (-2.15)	-0.002354 (-1.46)
$\theta_1$	0.122568* (3.78)	0.114120* (3.69)	0.122592* (3.75)	0.118084* (3.52)	0.070080** (2.13)	0.061616*** (1.93)	0.067057** (2.03)	0.077585** (2.31)
$\theta_2$	0.053070*** (1.65)	0.059299*** (1.94)	0.053795*** (1.66)	0.057114*** (1.76)	0.062957*** (1.93)	0.058041*** (1.82)	0.060194*** (0.07)	0.083302** (2.55)
$\theta_3$	0.156853* (5.17)	0.160799* (5.59)	0.154699* (5.09)	0.157128* (5.32)	--	--	--	0.044452 (1.43)
$\lambda$	-0.209616 (-0.63)	-0.278686 (-0.82)	-0.270908 (-0.75)	-0.274693 (-0.68)	0.813206 (1.31)	0.933461 (1.28)	0.715528 (1.14)	0.404960 (0.56)
<b>Variance Equation</b>								
$\alpha_0$	0.000176* (3.40)	-0.953301* (-4.78)	0.000179* (3.36)	0.002637** (2.12)	0.000145* (2.86)	-0.632894* (-4.05)	0.000125* (2.76)	0.002472*** (1.94)
$\alpha_1$	0.376719* (5.64)	0.489246* (6.98)	0.295089* (5.36)	0.254036* (5.16)	0.242798* (4.38)	0.351442* (6.26)	0.198562* (3.86)	0.194536* (2.91)
$\beta_1$	0.642003* (13.76)	0.900654* (32.57)	0.635380* (11.94)	0.491346* (4.43)	0.744768* (17.20)	0.936747* (41.74)	0.757758* (18.66)	0.626890* (5.79)
$\gamma_1$	--	-0.073020*** (-1.87)	0.204346*** (1.93)	0.145527** (2.20)	--	-0.029095 (-0.88)	0.085720 (1.12)	0.024240 (0.49)
Log likelihood	1391.900	1390.103	1393.641	1401.291	1309.608	1309.459	1310.328	1312.783
Ljung-Box Q(12)	10.504 [0.572]	9.145 [0.691]	10.092 [0.608]	7.631 [0.813]	7.968 [0.788]	9.672 [0.645]	9.908 [0.624]	6.714 [0.876]
Ljung-Box Q <sup>2</sup> (12)	2.760 [0.997]	3.238 [0.994]	3.767 [0.987]	1.761 [1.000]	19.704*** [0.073]	20.479*** [0.059]	19.292*** [0.082]	25.760** [0.012]
Sign bias	-0.82	-1.20	-1.22	-0.29	0.90	0.52	0.73	0.36
Negative size bias	0.39	0.69	0.89	0.18	0.75	0.92	0.94	0.73
Positive size bias	1.08	2.29**	2.04**	1.66***	-0.09	0.45	0.26	0.37
Joint test	0.500 [0.682]	1.900 [0.128]	1.561 [0.197]	0.922 [0.430]	1.065 [0.363]	0.959 [0.412]	1.179 [0.317]	0.575 [0.632]

Note: See Table 4.

**Table 6**  
**Estimate for the risk-return tradeoff with monthly return series**

	Panel A. Shanghai Monthly Return –SHM				Panel B. Shenzhen Monthly Return –SZM			
	GARCH-M	EGARCH-M	GJR-GARCH-M	CGARCH-M	GARCH-M	EGARCH-M	GJR-GARCH-M	CGARCH-M
<b>Mean Equation</b>								
C	--	--	0.004079 (0.65)	0.007642 (1.13)	--	--	--	--
$\theta_1$	0.081432 (1.05)	0.075217 (1.17)	0.121070*** (1.66)	0.099750 (1.28)	0.117701** (1.97)	0.172938** (3.18)	0.119536** (2.06)	0.128618** (2.09)
$\theta_2$	0.140387** (2.08)	0.131197** (2.06)	0.160487** (2.51)	0.115079*** (1.69)	0.142089** (2.41)	0.163192** (2.90)	0.132134** (2.22)	0.157398* (2.67)
$\theta_3$	--	--	-0.084047 (-1.30)	--	--	--	--	--
$\lambda$	-0.206632 (-0.66)	-0.147086 (-0.36)	-0.330358 (-0.87)	-0.456308 (-0.83)	-0.194280 (-0.45)	-0.257080 (-0.49)	-0.185081 (-0.39)	-0.275519 (-0.53)
<b>Variance Equation</b>								
$\alpha_0$	0.002700 (1.57)	-0.256394 (-1.48)	0.001820 (1.37)	0.025385** (2.41)	0.001052 (0.96)	-0.086263 (-0.77)	0.000459 (0.81)	0.005922 (0.78)
$\alpha_1$	0.665610* (2.87)	0.217582*** (1.65)	0.462073** (1.98)	0.061645 (1.02)	0.123651 (1.53)	0.070538 (1.06)	0.058196 (1.21)	0.083618 (0.67)
$\beta_1$	0.366574** (2.18)	0.978711* (39.76)	0.523824* (3.25)	0.876027* (10.01)	0.795159* (5.77)	0.993829* (54.15)	0.879629* (12.29)	0.242903 (0.38)
$\gamma_1$	--	0.002412 (0.05)	0.094281 (0.30)	0.082074*** (1.65)	--	0.003343 (0.06)	0.058966 (0.64)	0.022160 (0.14)
Log likelihood	149.8174	153.0100	150.0106	154.2529	155.9092	157.1424	156.5303	157.6067
Ljung-Box Q(12)	19.076*** [0.087]	16.674 [0.162]	19.491*** [0.077]	18.101 [0.113]	12.634 [0.396]	12.969 [0.371]	11.517 [0.485]	12.751 [0.387]
Ljung-Box Q <sup>2</sup> (12)	1.915 [1.000]	0.706 [1.000]	1.026 [1.000]	1.138 [1.000]	3.351 [0.993]	7.582 [0.817]	5.110 [0.954]	6.024 [0.915]
Sign bias	-0.59	-0.52	-0.77	-0.55	-1.09	-1.48	-1.40	-1.36
Negative size bias	-0.31	-0.75	-0.25	-0.60	0.37	0.88	0.76	0.76
Positive size bias	0.87	0.83	-0.94	0.70	0.20	0.69	0.66	0.17
Joint test	0.538 [0.657]	0.967 [0.450]	0.663 [0.576]	0.728 [0.536]	0.461 [0.710]	0.733 [0.533]	0.665 [0.575]	0.660 [0.578]

Note: See Table 4.