Asymmetry Effects in Chinese Stock Markets Volatility: A Generalized Additive Nonparametric Approach

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2007

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Abstract

The unique characteristics of the Chinese stock markets make it difficult to assume a particular distribution for innovations in returns and the specification form of the volatility process when modelling return volatility with the parametric GARCH family models. This paper therefore applies a generalized additive nonparametric smoothing technique to examine the volatility of the Chinese stock markets. The empirical results indicate that an asymmetric effect of negative news exists in the Chinese stock markets. Furthermore, compared with other parametric and nonparametric models, the generalized additive nonparametric model demonstrates a better performance for return volatility forecasts, particularly for the out-of-sample forecast. The generalized additive nonparametric technique has the potential to be widely applied to other emerging stock markets that have similar characteristics to the Chinese stock markets.

Keywords: Asymmetry effect; Nonparametric GARCH model; Chinese stock market; News Impact Curve; Additive Approach

JEL classification : G15, C14

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1 Introduction

Chinese stock markets have grown rapidly since establishment of the Shanghai Stock Exchange (SHSE) in December 1989 and the Shenzhen Stock Exchange (SZSE) in April 1991. Specially, with the recent boom in China's economy, the China's stock markets have been attracting an enormous amount of attention from policy makers, investors, and academics.[1] These Chinese stock markets are interesting and deserve attention also because they exemplify many unique characteristics that differ from the western well-developed western financial markets. One of the unique characteristics is that the Chinese stock markets are the only equity markets covered by the International Finance Corporation that have completely segmented trading between domestic and foreign investors (see Chui and Kwok, 1998; Yang, 2003). The A- shares market is only open to Chinese domestic investors while the B-shares market was only open to foreign investors before February 2001.[2] Many studies (see Chui and Kwok, 1998; Yang, 2003) address also the fact that the Chinese stock markets are tightly controlled by the government and the markets are at most a partially privatized one in which the state maintains state shares in varying amounts. The presence of market segmentation and heavy government regulations give rise to mispricing, information asymmetry, and make the market clearly imperfect and incomplete (Chan et al., 2007). Further, the stock trading is still new to most domestic participants. The A-shares are dominated by domestic individual investors who typically lack sufficient knowledge and experience in investments (China Securities and Futures Statistical Yearbook, 2004).

Given the unique characteristics of the markets and that the typical Chinese investor is more prone to speculation and less sophisticated than those from more mature markets (Tan et al., 2008), the Chinese stock volatility behaves also differently from other markets. Therefore, the conventional volatility models, such as GARCH family approaches, that heavily rely on volatility specification and known distributions of the returns, might be insufficient to characterize the volatility of the Chinese market. Bülman and McNeil (2002) propose a nonparametric GARCH model (NP model hereafter), in which the hidden volatility process is a function of lagged volatility and lagged value of the innovations from returns and will be estimated by an iterative nonparametric algorithm. What makes this model more attractive comparing to the parametric GARCH family models is that it requires neither the specification of the

[1] Two papers give a comprehensive review of the studies on the Chinese stock markets, i.e., Wang et al. (2004) and Chan et al. (2007).

[2] In order to increase mobility of B-share and to strengthen the foreign fund investment on capital market, with a view of paving the way towards China accession to WTO, the Chinese government lifted the restriction of people in the territory of China investing in B-shares on February 19, 2001. Even after the rule changes, B-shares cannot exceed 25% of the total shares of a company so that Chinese stock markets will not be over-influenced by foreign investment, and the domestic investor can trade and own B shares only if they have foreign currency.

functional form of the hidden volatility process nor that of the distribution of the innovations .

In this paper, we investigate the Chinese stock return volatility and the asymmetric effect [3] of shocks on returns volatility by applying the NP model. Moreover, we contribute methodologically to the literature by suggesting a Generalized Additive Model with the Nonparametric approach (GAM NP model hereafter) that applies the iterative estimation algorithm of the NP model to the Generalized Additive Model of Hastie and Tibshirani (1990). The motivation for such an adjustment is that our proposed GAM NP model becomes computationally more efficient. Further, as will be shown in the Monte Carlo simulation and the empirical investigation of this paper, this newly proposed GAM NP model can deliver a more accurate volatility estimate and forecast than the NP model and parametric GARCH family models . Also novel in our approach is that we extend the news impact curve from Engle and Ng (1993) to the nonparametric context, and use it to measure and examine the asymmetric effect of shocks.

Currently, the GARCH family models are the most used ones in the investigation of the Chinese stock return volatility and the asymmetric effect of market news on the volatility. For example, Yeh and Lee (2000) use the GJR model proposed by Glosten et al. (1993) to examine the Chinese stock markets volatility from May $22, 1992$ to August 27, 1996. They find that investors in China chase after good news indicating that the impact of good news (positive unexpected returns) on future volatility is greater than that of bad news (negative unexpected returns). By estimating both the GJR and the EGARCH model, Friedmann and Sanddorf-Köhle (2002) report that bad news increases volatility more than good news in A-share indices and Composite indices, whereas good news increases volatility more than bad news in B-share indices based on a sample beginning on May 22, 1992 and ending on September $16, 1999$. The good news chasing investor phenomenon in China makes the Shanghai and Shenzhen stock markets relatively unique and different from many other stock markets in the world. Lee et al. (2001) provide the same result as Friedmann and Sanddorf-Köhle (2002) with the EGARCH model and daily returns data from December 12, 1990 to December 31, 1992. Zhang and Li (2008) investigates the asymmetry effect of bad news on the Chinese stock volatility with a partial adjustment process. They find that the leverage effect begins to appear beginning in May 1996. Dividing the total sample into two periods, Huang and Zhu (2004) produce results from the EGARCH and the GJR model showing that the leverage effect only exists in the period between February 2001 and September 2003.

In view of the different findings from past research regarding the leverage effect of the Chinese stock return volatility, we examine the Chinese stock markets volatility by using recent data from January 2,

[3] The leverage effect refers to that volatility increases more after a negative than after a positive shock of the same magnitude (see Black, 1976; Christie, 1982).

1997 to August 31, 2007. Several questions will be addressed in the investigations: Do Chinese stock markets volatilities asymmetrically react to shocks as in most mature stock markets in the world? Are investors in the Chinese stock markets still chasing after good news? Do volatilities in the Shanghai and in the Shenzhen stock market react similarly to the market news ? The answers to these questions have important implications for market practitioners forecasting stock returns and volatility, and for risk managers formulating optimal strategies for portfolio selection and risk management.

The results from this paper suggest that the leverage effect exists in the Chinese stock markets, i.e., bad news affects the return volatility more than good news. However, implied by the News Impact Curve (NIC) from the NP GAM model, a limited amount of good news is needed to keep the market calm. Further, compared with the superior performance of the NP GAM model in the in-sample volatility estimation and out-of-sample forecast, the GJR and EGARCH models tend to overestimate the volatility process in turbulent periods and yield larger estimation errors. Our results suggest that the GAM NP model is a more appropriate tool to use in estimating the Chinese stock return volatility than the parametric GARCH models, i.e., the GJR and EGARCH models.

The rest of the paper is organized as follows. In section 2, we present the GAM NP model and the model estimation algorithm. Section 3 performs the Monte Carlo simulation to evaluate the performance of the GAM NP model. Section 4 examines the asymmetric effects on the volatility with the proposed GAM NP model and compares the performance of the GAM NP model with the NP model and various GARCH family models. Section 5 concludes.

2 Modelling time-varying volatility

In this section, we introduce the Generalized Additive Nonparametric (GAM NP) model and the model estimation algorithm used for the Chinese stock markets volatility estimation. As we will evaluate and compare the performance of the GAM NP model with the parametric models, we first introduce the parametric GARCH family models.

2.1 Parametric GARCH family models

The GARCH model of Bollerslev (1986) is the most widely used model for the volatility estimation since it was first proposed in 1986. As pointed out by Bera and Higgins (1993), most of the applied financial works show that GARCH (1,1) provides a flexible and parsimonious approximation to the conditional variance dynamics and is capable of representing the majority of financial series. The GARCH (1,1)

model is written as,

$$R_t = \mu + X_t, \quad X_t = \sigma_t z_t, \quad z_t \sim N(0,1),$$
$$\sigma_t^2 = \omega + \alpha_1 X_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{1}$$

where $\omega > 0,\ \alpha_1,\ \beta_1 \geq 0,\ (\alpha_1 + \beta_1) < 1$, and X_{t-1} may be treated as a collective measure of news about equity returns arriving to the market over the previous periods.

In the simple GARCH (1,1) approach good news and bad news, i.e. positive and negative shocks, have the same impact on the conditional variance. Many studies have found evidence of asymmetry in stock price behavior, i.e., negative surprises seem to increase volatility more than positive surprises.[4] To allow asymmetric effects in the volatility, Glosten et al. (1993) add an additional term in the conditional variance and formulate the so called GJR model. The GJR (1,1) is specified as follows,

$$R_t = \mu + X_t, \quad X_t = \sigma_t z_t, \quad z_t \sim N(0,1),$$
$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + (\alpha_1 + \gamma_1 N_{t-1}) X_{t-1}^2, \tag{2}$$

where $\omega > 0, \alpha_1 \geq 0, (\alpha_1 + \gamma_1) \geq 0, \beta_1 \geq 0$, $(\alpha_1 + 0.5\gamma_1 + \beta_1) < 1$. N_{t-1} is an indicator for negative X_{t-1}, that is, $N_{t-1} = 1$ for $X_{t-j} < 0, N_{t-1} = 0$ for $X_{t-1} \geq 0$. The structure of this model indicates that a positive X_{t-1} contributes $\alpha_1 X_{t-1}^2$ to σ_i, whereas a negative X_{t-1} has a larger impact of $(\alpha_j + \gamma_1) X_{t-1}^2$ with $\gamma_1 > 0$. Therefore, if parameters γ_1 is significantly positive, then negative innovations generate more volatility than positive innovations of equal magnitude.

Another volatility model that accounts for the asymmetric impacts on the conditional variance is the Exponential GARCH model (EGARCH) proposed by Nelson (1991). In contrast to the previous model, the EGARCH(1,1) is specified as,

$$R_t = \mu + X_t, \quad X_t = \sigma_t z_t, \quad z_t \sim N(0,1),$$
$$log\sigma_t^2 = \omega + \beta_1 log\sigma_{t-1}^2 + \alpha_1 \{ \frac{|X_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - E[\frac{|X_{t-1}|}{\sqrt{\sigma_{t-1}^2}}] \} + \gamma_{t-1} \frac{X_{t-1}}{\sqrt{\sigma_{t-1}^2}}. \tag{3}$$

Here the coefficient γ signifies the leverage effect of shocks on the volatility. The key advantage of the EGARCH model is that the positive restrictions are not needed to be imposed on the variance coefficients. The coefficients γ need to be negative for evidence of asymmetric effects.

[4] This is the so called leverage effect

In this paper, we will leave the functional form of the variance process as unspecified and attempt to estimate it as an additive nonparametric mean. We show that the nonparametric model can capture the leverage effect from the negative news and outperform two of the parametric GARCH family models most commonly considered.

2.2 The Generalized Additive nonparametric model

Compared with the parametric models, a nonparametric model enjoys advantages of relaxing the specification of the variance process and the assumption of innovations. One example is the NP model from Bülman and McNeil (2002), which is written as follows,

$$\begin{aligned} R_t &= \mu + X_t, \quad X_t = \sigma_t z_t, \\ \sigma_t^2 &= f(X_{t-1}, ..., X_{t-p}, \sigma_{t-1}^2, ..., \sigma_{t-q}^2), \end{aligned} \tag{4}$$

where the stationary stochastic process $\{X_t;\ \ t \in \mathbb{Z}\}$ is adapted to the filtration $\{F_t;\ t \in \mathbb{Z}\}$ with $F_t = \sigma(\{X_s;\ \ s < t\})$ (a s-field filtration), and $\{z_t;\ t \in \mathbb{Z}\}$ is an i.i.d. innovation with zero mean and unit variance and a finite fourth moment, and z_t is assumed to be independent of $\{X_s;\ \ s < t\}$, and $f : \mathbb{R} \times \mathbb{R}_+ \longmapsto \mathbb{R}_+$ is a strictly positive valued function. σ_t is the time varying volatility and σ_t^2 is the conditional variance of $Var\,[X_t \mid F_{t-k}]$, where $\{1 \leq k \leq max(p, q)\}$. Bülman and McNeil (2002) have shown that the nonparametric function f can be estimated by regressing X_t^2 on the lagged variables X_{t-1} and σ_{t-1}^2 using a nonparametric smoothing technique.

However, the proposed model cannot avoid the common problem of a multidimensional nonparametric smoothing, i.e., the "curse of dimensionality".[5] In order to overcome this difficulty, Hastie and Tibshirani (1990) propose the generalized additive model, which enables the dependent variable to depend on an additive predictor through a nonlinear function. We apply the generalized additive procedure from Hastie and Tibshirani (1990) to the NP model which gives rise to the GAM NP model as follows,

$$\begin{aligned} R_t &= \mu + X_t, \quad X_t = \sigma_t z_t, \\ \sigma_t^2 &= \mu + f(X_{t-1}) + g(\sigma_{t-1}^2), \end{aligned} \tag{5}$$

where $f : \mathbb{R} \longmapsto \mathbb{R}_+$ are the positive valued functions and satisfying $f(x) = f(-x)$, e.g., $f(x) =$

[5]The curse of dimensionality is a common problem for nonparametric estimation of a multidimensional regression, i.e., the optimal rate of convergence decreases with dimensionality (Linton and Mammen, 2005). For the multidimensional smoothing, efforts must be made in order to alleviate the problem (Härdle et al., 2004).

$\alpha|x|, 0 < \alpha < 1$, $g : \mathbb{R}_+ \longmapsto \mathbb{R}_+$ are the positive non-decreasing functions and satisfying $g(\sigma^2) = \beta\sigma, 0 < \beta < 1$.

We observe that the model in equation (5) can be written with the following transformation:

$$\begin{aligned} X_t^2 &= \mu + f(X_{t-1}) + g(\sigma_{t-1}^2) + V_t, \\ V_t &= (\mu + f(X_{t-1}) + g(\sigma_{t-1}^2))(z_t^2 - 1), \end{aligned} \tag{6}$$

It is obvious that V_t is a martingale difference series with $E[V_t] = E[V_t|F_{t-1}] = 0$ and $Cov[V_s, V_t] = Cov[V_s, V_t|F_{t-1}] = 0$, for $s < t$.

From equation (6), it follows that,

$$\begin{aligned} E[X_t^2|F_{t-1}] &= \mu + f(X_{t-1}) + g(\sigma_{t-1}^2) + V_t, \\ Var[V_t^2|F_{t-1}] &= Var[V_t|F_{t-1}] = (\mu + f(X_{t-1}) + g(\sigma_{t-1}^2))^2(E[z_t^4] - 1), \end{aligned} \tag{7}$$

This suggests that we can estimate the conditional variance by a nonparametric regression procedure of a generalized additive model. The regression procedure is performed according to the additive structure of σ^2 by using the back-fitting algorithm, which was first introduced by Friedman and Stuetzle (1981) and generalized by Hastie and Tibshirani (1990). It is now a widely used tool for iterative procedures for nonparametric estimation. We estimate the conditional variance by the generalized additive model according to the following formula:

$$\hat{\sigma}_t^2 = \hat{\mu} + \hat{f}(X_{t-1}) + \hat{g}(\hat{\sigma}_{t-1}^2). \tag{8}$$

2.3 Estimation Algorithm

Assume we have a data sample $\{X_t^2;\ 1 \le t \le n\}$ satisfying the process of (5),[6]

1. In the first step, we calculate a first estimate of volatility $\sigma_{t,0}^2;\ 1 \le t \le n$ as the initial estimation by fitting the data with the GARCH (1,1) model by a maximum likelihood.

2. We regress $\{X_t^2;\ 2 \le t \le n\}$ on the lagged returns $\{X_{t-1};\ 2 \le t \le n\}$ through a nonparametric smoothing procedure with the back-fitting algorithm to obtain estimates of $\hat{f}_m$ of f, and $\hat{g}_m$ of g. m is the current iteration.

[6]Readers who are interested in the justifications and proofs of this algorithm are referred to Bülman and McNeil (2002)

3. In the third step , we calculate $\{\hat{\sigma}^2_{t,m} = \hat{\mu}_m + \hat{f}_m(X_{t-1,m-1}) + \hat{g}_m(\hat{\sigma}^2_{t-1,m-1});\ 2 \leq t \leq n\}$ as specified in (8).

4. We proceed to increment the iteration *m* and return to the second step until $m = M$ where M is the pre-specified total number of iterations.

5. Finally, we average the last k of such estimates to obtain the final smoothed volatility, $\hat{\sigma}_{t,final}$, and perform the final nonparametric regression with the back-fitting algorithm by regressing $\{X^2_t;\ 2 \leq t \leq n\}$ against $\{X_{t-1};\ 2 \leq t \leq n\}$ and $\hat{\sigma}^2_{t-1,final}$ to get the final estimates $\hat{f}_m\ of\ f$ and $\hat{g}_m\ of\ g$.

3 Monte Carlo simulation

In the Monte Carlo simulation, a GARCH model with a leverage effect and a standard GARCH model are simulated and estimated in order to show that with an asymmetric effect, the GAM NP model can offer better estimates of the unobserved volatility than the NP model and parametric GARCH family models. We generate $n = 1000$ observations and 50 realizations for each random process. For the nonparametric models, the number of iterations is set to be $M = 8$, and a final smoothing is performed by averaging the last four ($K = 5$) iterations according to the algorithm presented in the previous section. The performance of each model is evaluated by using the mean of the Mean Squared Error (MSE) and the Mean of the Absolute Error (MAE) from each iteration. The MSE and the MAE are calculated according to the formulas,

$$
\begin{aligned}
MSE(\hat{\sigma}_{s,m}) &= \frac{1}{n-20}\sum_{t=21}^{n}(\hat{\sigma}_{t,m} - \sigma_t)^2, \\
MAE(\hat{\sigma}_{s,m}) &= \frac{1}{n-20}\sum_{t=21}^{n}|\hat{\sigma}_{t,m} - \sigma_t|,
\end{aligned}
\tag{9}
$$

where $\hat{\sigma}_{t,m}$ is the estimated volatility at time t from each iteration and σ_t is the true volatility at time t. The first twenty values are excluded from the calculation because the estimates of the volatility at the first few points may be unreliable.

3.1 The simulation results

The data are simulated from the variance process which follows a GARCH and a Threshold GARCH (TGARCH) model specified as follows,

$$\sigma_t^2 = 7 \; + \; 0.1 \; \sigma_{t-1}^2 \; + \; 0.66 \; X_{t-1}^2, \tag{10}$$

$$\sigma_t^2 = 7 \; + \; 0.1 \; \sigma_{t-1}^2 \; + \; (0.66 \; I_{\{X>0\}} + 0.2 I_{\{X \leq 0\}}) X_{t-1}^2, \tag{11}$$

In the variance process of equation (11), the asymmetry effect of the positive and negative shocks from returns have been built into the ARCH effect, along the lines of models suggested by Glosten et al. (1993) and Fornari and Mele (1997). We simulate the process given by equation (11) with t distributed residuals and estimate it with both Gaussian and t distributed errors. Figure 1 plots the true volatility surfaces of process specified in equation (10) and equation (11), respectively. It can be easily seen that if the true volatility is under the GARCH specification of process given by equation (10) (the left plot), the volatility surface is very smooth. However, with the asymmetry effect of process given by equation (11), there is a significant broken segment on the volatility surface. In this case, we show that the GAM NP model can smooth the segmented volatility surface quite well and therefore outperforms the parametric models. For purpose of comparison, we fit the simulated process given by equation (11) with the EGARCH , GJR and NP models, and compare their goodness-of-fit with the GAM NP model.

- Figure 1 about here -

In Figure 2 we plot the estimated volatility surfaces of the eight iterations and the final smoothing of the GAM NP model from one randomly chosen iteration. We can clearly observe that the smoothing has been well performed already after the first iteration and the surface has been perfectly smoothed at the final stage of smoothing. This indicates that the estimation algorithm is recovering the essential features of the volatility surface, and reassures that the smoothing method is converging.

- Figure 2 about here -

Table 1 reports the model performance comparison from the GARCH, EGARCH, GJR , GAM NP, and NP models. Table 2 presents simulation results of the goodness-of-fit from the nonparametric models. It is evident from the tables that the MSE and the MAE of the nonparametric models are much

lower than the ones from the parametric GARCH models. For example, it can be seen from Table 2 that the MSE and the MAE are 0.555 and 0.615 for the GARCH model with Gaussian errors before smoothing. The MAE and the MAE start to decrease in each iteration and reach 0.221 (0.261) and 0.339 (0.405) at the final stage of smoothing for the GAM NP (NP) model. Although the EGARCH and GJR (TGARCH) models have partly captured the asymmetric effects, they cannot match the goodness-of-fit of the nonparametric models. For example, it can be seen from Table 1 that the MSE and MAE of the EGARCH model with Gaussian errors are 0.3 and 0.43, respectively, while that of the GJR model are 0.39 and 0.507, respectively. More interestingly, the goodness-of-fit of the GAM NP model indicates that the GAM NP model performs even better than the NP model, e.g. the MSE (MAE) of the GAM NP model is 4 % (1%) lower than that of the NP model. We also notice that the choice of the distribution for the parametric GARCH models clearly matters. There is evidence that the EGARCH and GJR models with t distributed innovations perform better than the ones with Gaussian innovations, but this is not the case for nonparametric estimations. The NP and GAM NP models provide nearly identical results with both Gaussian and t errors. Figure 3 plots the estimated volatility process compared with the true volatility, which is an arbitrary selection of 100 observations from a simulated realization of process given by equation (11). The left hand plot shows the true volatility (solid line) compared with parametric GARCH (1,1) estimates with t innovations (dotted line) and the right hand plot shows the true volatility (solid line) with the GAM NP estimate obtained after a final smooth (dotted line). It is clearly shown in the figure that the GAM NP model yields volatility estimates which better match the true volatility movements than the GARCH model. In particular, the sharp spikes observed at the fortieth and ninetieth observations of the true volatility can be well captured by the GAM NP model but not by the GARCH model.

- Tables 1,2 and Figure 3 about here -

From the Monte Carlo simulation, we conclude that the GAM NP model provides more accurate volatility estimation and captures more asymmetric effect of shocks compared with parametric GARCH models and the NP model.

4 The Chinese stock markets volatility

4.1 The data

The data used in this paper includes the daily closing prices of the two Chinese primary indices, namely the Shanghai Stock Exchange Composite Index (SHCI) and the Shenzhen Stock Exchange Component Index (SZCI) from January 2, 1997 to August 31, 2007. The SHCI is published since 1991 and includes all Shanghai listed companies weighted by capital stocks. The SZCI is published since 1995 and is a value-weighted index of 40 stocks listed on the Shenzhen Stock Exchange. As key market regulations such as the raising/down limit, was not well established until the end of 1996, we chose to analyze the data starting from January 2, 1997. The daily prices are downloaded from http:www.sohu.com.

In order to assess and compare the predictive performance of the GAM NP model with various parametric models, the data is further divided into an in-sample group (from January 2, 1997 to August $31, 2006$) and an out-of-sample group (from September 1, 2006 to August 31, 2007). The whole sample has 2622 observations and the last 243 are used for out-of-sample forecasts. All data are converted to their daily log returns, and multiplied by 100 as follows,

$$r_t = 100(log(P_t) - log(P_{t-1})). \tag{12}$$

In order to give some sensible comparisons, we calculate the realized volatility as the proxy of the true volatility for the out of the sample forecast. The realized volatility is extracted from high frequency data (5 minutes). This method has been extensively used in the literature.[7] The high frequency data are obtained from the http://www.wstock.net.

Table 3 provides the statistic summary of the returns of both indexes. It can be seen that both series have their mean close to zero, exhibit high kurtosis and are negatively skewed. In particular, the skewness in the Shanghai stock market is much higher than the Shenzhen stock market. The Jarque-Bera test further confirms that the return distributions are non-normal. The Dicky-Fuller test suggests that they are stationary time series.

Figure 4 plots the index price and returns of the SHCI and the SZCI. The returns largely mirror each other and look very volatile. Both series also display strong volatility clustering. These are typical characteristics of financial time series. Further, there are several peaks and troughs in the return series. The first peak occurred on May $12, 1997$, where the SHCI/SZCI hit a record high $6103.62/1500$ points.

[7] See e.g., French et al. (1987), Day and Lewis (1992), Pagan and Schwert (1990), and Andersen et al. (2001a,b)

After going through a stable two-year period, it experienced a sharp decline before rising and reaching its second peak on July $1, 1999$. Thereafter the stock indices began to increase in a relatively stable fashion, reaching its third peak in $2000 - 2001$. It then declined again until the first half of 2005. However, after that the stock market began to rise rapidly and it continued to accelerate upwards until it reached another historical high on August $31, 2007$. It can be seen, therefore, that the period 2005 to 2007 is the most volatile period in the SHCI and SZCI.

- Table 3 and Figure 4 about here -

4.2 The in sample estimation results from various models

We first fit the series from January 02, 1997 to August 31, 2006 with the standard GARCH(1,1) model. Considering the existence of the asymmetry effects in the Chinese stock markets, we also fit the data with the EGARCH and GJR models. For all these models, the innovations are assumed to be both Gaussian and student-t distributed. The estimated parameters and Ljung-Box Q-statistics tests of the standardized residuals are presented in Table 4. Note that all parameters of the conditional volatility are significant at the 5% significance level. The coefficient of lagged variance β shows very high volatility persistence. The sum of α and β from the GARCH model are close to 1, which supports the evidence of volatility clustering. The P-values of Ljung-Box Q-statistic test at the lag 20 of standardized residual series from all models fail to suggest the autocorrelation at a 5% significance level. Thus all models appear to be adequate in describing the linear dependence in the return and volatility series.

In the Shanghai stock market, the estimated value of the leverage parameters γ of the EGARCH and GJR models with Gaussian/t distributed innovations is: -0.036 /-0.063 and 0.06 / 0.095, respectively. In the Shenzhen stock market, the value of γ for these two models of Gaussian/t innovation is: 0.028 /-0.035 and 0.036 /0.055. All these parameters are significant at the 5% level with the exception of the γ from the EGARCH model with Gaussian errors in the Shenzhen market. The significance of the parameters indicates the existence of asymmetry effect in the Chinese stock markets, i.e., bad news (negative shock) has a larger impact on return volatility than good news (positive shock). In particular, the asymmetric effect is higher in the SHCI than in the SZCI. It is also worth noting that the leverage effect estimated from models fitted with t distributed innovation is higher than the ones with normal distributed innovations. The existence of the asymmetry effect as in other mature stock markets in the world may be a positive sign for market efficiency and completeness, and it may also show that the

Chinese stock market is integrating with other world stock markets.

- Table 4 about here -

Next we use the proposed GAM NP technique to smooth the Chinese stock volatility surface based on the volatility and innovations obtained from the GARCH(1,1) model. We evaluate its performance by calculating various loss functions and compare the results from the GAM NP model with the parametric models. For reference, we also estimate the NP model from Bülman and McNeil (2002) and compare its result with the newly proposed GAM NP model. We use three goodness-of-fit measures.

1. The MSE1: the Mean Squared Error between the squared innovation X_t^2 and the squared estimated volatility σ_t^2 . As $X_t^2 = \sigma_t^2 + V_t$, where V_t is the martingale series with zero mean, the mean squared error between both can be a good indicator to illustrate the goodness of fit. However, since this assumption is the theoretical foundation underpinning our empirical study, this indicator alone is not sufficient as a measure of goodness-of-fit.

2. The MSE2: the Mean Squared Error between estimated volatility and the true volatility proxy, $\hat{\sigma}_t = \sqrt{(y_t - \bar{y})^2}$, where y_t is the daily return at time t and $\bar{y}$ is the mean of y_t.

3. The MAE: the Mean Absolute Error between estimated volatility and the true volatility proxy, $\hat{\sigma}_t = |(y_t - \bar{y})^2|$, where y_t is the daily return at time t and $\bar{y}$ is the mean of y_t.

The goodness of fit results of various models are presented in Table 5. It is clear that the GARCH model performs the worst according to all goodness-of-fit measures. Compared with the GARCH model, the EGARCH model improves the volatility estimation by capturing the leverage effects. For the GJR model, it slightly improves the result from the GARCH estimation in the Shanghai Stock Exchange (SHSE), while in the Shenzhen Stock exchange (SZSE), it is even worse off than the GARCH model. This is perhaps not surprising because the asymmetric effect in the Shenzhen stock market is not as strong as in the Shanghai stock market. However, this may indicate that in the Chinese stock markets, the EGARCH model can capture more leverage effect than the GJR model. When looking at the GAM NP model, we observe a significant improvement of the GAM NP model compared with the EGARCH model with Gaussian errors with the improvement measured by the MSE1 about 1% in the SHCI and 3% in the SZCI. In addition, all loss functions from the GAM NP model with t distributions do not differ from the ones with Gaussian distributions.

Figure 5 plots the volatility for the in-sample period. The light gray lines are the volatility proxy of $\hat{\sigma}_t = \sqrt{(y_t - \bar{y})^2}$, while the blue lines are the estimated volatility. The three volatility plots on the left-hand side are for the GAM NP, EGARCH, and GJR models in the Shanghai stock market. The right plots are for the Shenzhen stock market. Again, it can be seen from these plots that the GAM NP model performs better than the EGARCH and the GJR models in capturing the rise and fall movements of return volatility.

- Table 5 and Figure 5 about here -

As argued previously, due to the high degree of regulations in the Chinese stock markets, the GAM NP can provide a more appropriate tool for measuring the asymmetry effect in return volatility without having to assume the functional form of the volatility process and the distribution of innovations. There are many emerging stock markets which attract investors from all over the world. These markets may be as imperfect and incomplete as in the Chinese stock markets. We believe that the GAM NP model can be an effective technique of capturing the leverage effect in these markets as well.

4.3 Analyzing asymmetry via News Impact Curve

We have shown in the previous section that leverage effect exists in the Chinese stock markets when analyzed through the EGARCH and GJR models. We now further examine the asymmetry effects from the GAM NP model perspective. We use the News Impact Curve proposed by Engle and Ng (1993) to demonstrate the asymmetry of shocks estimated from the GAM NP model. The news impact curve (NIC) relates today's returns to tomorrow's volatility and works as a major tool for measuring how new information is incorporated in volatility estimates. Holding constant the information dated $t-2$ and earlier, it displays the implied impact of the functional relationship between conditional variance at time t and the shock term (error term) at time $t-1$. Engle and Ng (1993) define the NIC as the expected conditional variance of the next period conditional on the current shocks ϵ_t.

$$E(\sigma_{t+1}^2|\epsilon_t) \tag{13}$$

For the NIC of the GAM NP model, we extend the original news impact curve to the nonparametric

context as follows,

$$\sigma_t^2 = f(X_{t-1}) + g(\sigma), \tag{14}$$

where X_{t-1} are the shocks from news, f and g are the estimated nonparametric functions from the GAM NP model. The relationship between the shocks and the conditional volatility is therefore described in the nonparametric functions of f.

- Figure 6 about here -

The News Impact Curves of the EGARCH, GJR, and GAM NP models in the Shanghai and Shenzhen markets are plotted in Figure 6. The parameter values used for constructing the NIC of the EGARCH and GJR models are from Table 4, the nonparametric functions f and g are the estimated nonparametric functions given by equation (5). It is obvious that all models suggest the existence of asymmetric effects in stock returns because the NICs of all models are not symmetric but skewed. Typically, negative news drives volatility up more than good news. In these models, any news today drives up volatility tomorrow. For example, in the SHCI, the asymmetric effect is clearly shown with all curves displaying a proximate 20 degree slope for "good news" and a 40 degree slope for "bad news". We observe less asymmetric effect of bad news relative to good news in the Shenzhen stock market.

The NIC of the EGARCH and the GJR model have their minimum shocks at $X_t = 0$, which means that no news is good news. In contrast to the parametric models, the NIC of the GAM NP model has its minimum larger than zero, i.e. 0.5 in the SHSE and 1.5 in the SZSE. In this model, the NIC is a right-shifted asymmetric parabola. This phenomenon is consistent with the TGARCH model NIC from Engle and Ng (1993) and Christian (2007). This potentially suggests that, in the Chinese stock markets, the minimum amount of good news is required for the markets to remain as calm as possible. In this case, no news implies a higher volatility than in the tranquil market period. This further suggests that although the model implies the existence of a leverage effect, the typical good news chasing behavior of the Chinese stock investors found by Yeh and Lee (2000), has not changed. One of the reasons of Chinese investors' good news chasing behavior explained by Yeh and Lee (2000) is that due to the lack of institutional investors, the trading values of the Shanghai and Shenzhen stock markets are completely generated by individual investors who have no access to inside information and irrationally act on noise as if it were information that would give them an edge. In fact, due to the fact that the Chinese stock markets are still dominated by the local investors and lack institutional practitioners, the Chinese investors are still

potentially chasing good news. This typically reflects the investors behavior in Shenzhen.[8] The fast growing stock market and its development produce more noises, making the investors more likely to speculatively and impetuously chase "good news".

Given the fact that GAM NP better explains the volatility of the Chinese stock markets, we can see from the NIC that both the EAGRCH and the GJR model underestimate the volatility reaction to the extreme shocks (the GAM NP has the highest variance in both directions when news is larger than 2 and smaller than -2), and overestimate the volatility reaction to normal shocks (the news is between 2 and -2). Further, the GAM NP model has the best performance to capture the asymmetric effect of shocks because the slopes of the two sides of the NIC of the GAM NP model are both steeper than the EGARCH and the GJR models.

As a result, compared with the EGARCH and the GJR model, the GAM NP model can provide us with superior volatility estimates which capture the asymmetric effects of market news. The GAM NP model is more flexible in reflecting the actual market's conditions as implied by the news impact curve. The findings from this paper have important implications for portfolio selection, asset pricing, and risk management. For instance, as implied by the news impact curves, there are significant differences in the predicted volatility incorporated with asymmetric effects of market news in the GAM NP model and other models. This may lead to a significant difference in current option price, portfolio selection, and dynamic hedging strategies. Only the most appropriate model can provide us with the best estimate of return volatility.

4.4 Out-of-Sample forecast performances

To demonstrate the importance of our results and the application of the GAM NP model in practice, we calculate the 90% forecasted return intervals which are based on one day ahead out-of-sample forecasts. The out-of-sample period is from September $1, 2006$ to August $31, 2007$. In addition to the previous session used volatility proxy, the realized volatility, which is calculated from the 5-minute high frequency data, is also used. The realized volatility is calculated as $\hat{\sigma}_t = \sqrt{\sum_{i=1}^{n} r_{i,t}^2}$, where $r_{i,t}$ are the log return at time i and day t. The return intervals are calculated according to $\hat{r_t} = \hat{\mu} \ \pm q_k \sqrt{\hat{\sigma}}$, where q_k is the percentage of the quantile of t distributed errors, $\hat{\mu}, \hat{\sigma}$ are the forecasted conditional mean and volatility.

The performance of the out-of-sample volatility forecasts of various models are summarized in Table

[8]Within the last 20 years, owing to China's economic liberalization under the policies of reformist leader Deng Xiaoping, Shenzhen became China's first, and arguably one of the most successful Special Economic Zones, moving from a small village to a major financial center and China's second busiest port.

6. It is clear from this table that among different models, the GAM NP model performs the best in delivering the lowest forecast error. The reduction of the volatility forecast error from the GAM NP model is more significant compared to the one from the in- sample forecast in Table 5. For example, in the SHSE, the MSE (MAE) of the GAM NP model are 10% (7%) for the $\sqrt{(y_t - \hat{y})^2}$ proxy and 11% (9%) for the implied volatility proxy, which is lower than the one from the GARCH model. Similarly, in the SZSE, there are about 5% reduction in the MSE and MAE for both volatility proxies. Compared with the GJR model, the EGARCH model appears to be a better parametric model in capturing market news asymmetric effect in the out-of-sample forecast. We notice that the GJR model in many cases performs even worse than the GARCH model. The poor performance of the GJR model in the out-of-sample volatility forecast has also been reported by Wei (2002). The author shows that the GJR model has the highest forecast errors compared with a random walk model when examining the Chinese stock markets return volatility.

- Table 6 and Figure 7 about here -

The superior performance of the GAM NP model can be also seen from Figure 7 where we plot the estimated volatility against the realized volatility. The grey line in the background is the realized volatility, the blue line is the estimated volatility from the EGARCH and GJR models (with t distributed errors). By comparing the plots of the volatility between the fitted and proxy of the volatility, we can see that the estimated volatility series from the GAM NP model is more capable of capturing movements of the volatility in the SHSE and the SZSE. The spikes in the volatility movements in both markets are better captured by the GAM NP model. For example, the spike on March 03, 2007 is better captured by the GAM NP model, while the EGARCH model underestimates and the GJR model overestimates this spike.

Figure 8 plots the 90% intervals of the forecasted returns based on the forecasted conditional mean and the volatility from various models in the SHCI and the SZCI. Interestingly, the intervals built upon the forecasted conditional mean and variance from various models do not differ that much when the market is relatively stable. When extreme events occur in the market, however, both of the EGARCH and GJR models provide a much wider return interval than the GAM NP model does. The most obvious example is the sudden drop in the SHCI and SZCI index on February 27, 2007 [9] where the return from the EGARCH and GJR models is overestimated in the upper bound and underestimated in the lower bound.

[9] In the absence of any sign of circumstances, the "Black Tuesday" came and dumped the SHSE and the SZSE. The SHCI and the SZCI declined by 8,84% and 9,29%, and hit the record of the biggest daily drop within the last ten years.

It is worth noting that the lower bound of the interval is the 5% daily Value-at-Risk (VaR) measure when the initial value of the investment is 1 Yuan. Hence, when the market becomes extremely volatile, the VaR based on the parametric model is overestimated in both Shanghai and Shenzhen stock markets.

- Figure 8 about here -

This result is generally in line with the studies of Engle and Ng (1993), Yeh and Lee (2000), and Friedmann and Sanddorf-Köhle (2002). In particular, Engle and Ng (1993) provide evidence that the predicted volatility by the EGARCH model is much higher than those predicted by other models. Yeh and Lee (2000) argue that the application of the GJR model to daily Chinese returns leads to the overshooting of estimated conditional variance in the periods of high volatility. Friedmann and Sanddorf-Köhle (2002) examine the asymmetry by extending the news impact curve of Engle and Ng (1993) to the Conditional News Impact Curve. The authors argue that the overshooting of the volatility predictions from the GJR model is due to an acceleration of the news impact in the periods of high volatility. They also found that the EGARCH can overestimate volatility in a manner similar to the GJR model.

In summary, the GAM NP model performs much better than the parametric model in describing the volatility characteristics and capturing the rise and fall of the volatility in the Chinese stock markets. The forecasted returns generated by the GAM NP model are more accurate when compared with the EGARCH and the GJR model, especially when the market is very volatile. Because the EGARCH and GJR models tend to overestimate the volatility in turbulent periods and therefore yield larger estimation errors in general, they are not appropriate tools that can be used in estimating the Chinese stock volatility compared with the GAM NP model.

5 Conclusion

By using more recent data, this paper updates previous studies on Chinese stock return volatility by examining the return volatility and the asymmetric effect of market news on the volatility in the Chinese stock markets using a Generalized Additive Model with a Nonparametric approach. The back-fitting algorithm from the Generalized Additive model of Hastie and Tibshirani (1990) is applied to the nonparametric smoothing technique from Bülman and McNeil (2002). Compared with the parametric GARCH models which are commonly used for capturing volatility asymmetry, the GAM NP performs much better in capturing the asymmetry effect and in describing the characteristics of the Chinese stock return

volatility.

With respect to the asymmetric reaction of the predicted return volatility to good news and bad news, we find that the return volatility strongly responses more to bad news in the Chinese stock markets in our sample period. We extend the news impact curve to the nonparametric setting to further examine the asymmetry effect implied by the GAM NP model. Interestingly, the evidence based on the news impact curve of the GAM NP model suggests that good news chasing behavior of the Chinese domestic investor continues to exist. The markets behave in a manner that they expect a certain amount of good news in order to keep them as calm as possible.

When all the models are employed to obtain the overnight out-of-sample forecast, the GAM NP model yields the lowest forecast errors and outperforms the parametric models by capturing the observed spikes in the volatility of returns. On the other hand, the EGARCH and the GJR models tend to overestimate the volatility and returns in the high volatility periods. The forecasted returns are therefore more accurate from the GAM NP model especially when the market is very volatile. We recommend the use of the GAM NP model in estimating and investigating the return volatility in the Chinese stock markets and other emerging stock markets which have similar features of the Chinese stock markets.

References

T. G. Andersen, T. Bollerslev, F. X. Diebold, and H. Ebens. The distribution of realized stock return volatility. *Journal of Financial Economics*, 61:43–76, 2001a.

T. G. Andersen, T. Bollerslev, F. X. Diebold, and P. Labys. Great realizations. *Risk*, 13:105–108, 2001b.

A. K. Bera and M. L. Higgins. Properties, estimation and testing. *Journal of Economic Surveys*, 7: 305–362, 1993.

F. Black. Studies of Stock Price Volatility Changes. *Proceeding of the meetings of the American Statistics Association*, Business and Economics Section:177–181, 1976.

T. Bollerslev. Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Economics*, 31: 307–327, 1986.

P. Bülman and A. J. McNeil. An algorithm for nonparametric GARCH modelling. *Computational and Data Analysis*, 40:665–683, 2002.

K. C. Chan, H. G. Fung, and S. Thapa. China financial research: A review and synthesis. *International review of Economics and Finance*, 16:416–428, 2007.

B. Christian. A Better Asymmetric Model of Changing Volatility in Stock and Exchange Rate Returns: Trend-GARCH. *The European Journal of Finance*, 13:65Ű87, 2007.

A. A. Christie. The Stochastic Behavior of Common Stock Variancies:Value, Leverage and Interest Rate Effects. *Journal of Financial Economics*, 10:407–432, 1982.

A. Chui and C. Kwok. Cross-autocorrelation between A shares and B shares in the Chinese stock market. *Journal of financial research*, 21:333–353, 1998.

T. Day and C. Lewis. Stock market volatility and the information content of stock index option. *Journal of Econometrics*, 52:267–87, 1992.

R. Engle and V. K. Ng. Measuring and Testing the Impact of News on Volatility. *The Journal of Finance*, 48.5:1749–1778, 1993.

F. Fornari and A. Mele. Sign- and Volatility-Switching ARCH models: Theory and Applications to International Stock Markets . *Journal of Applied Econometrics*, 12:49–65, 1997.

K. R. French, G. W. Schwert, and R. E. Stambaugh. Expected Stock Returns and Volatility. *Journal of Financial Economics*, 19:3–29, 1987.

J. H. Friedman and W. Stuetzle. Projection Pursuit Regression. *Journal of American Statistical Association*, 76:817, 1981.

R. Friedmann and W. G. Sanddorf-Köhle. Volatility clustering and nontrading day in Chinese stock markets. *Journal of Economics and Business*, 54:193–217, 2002.

L. R. Glosten, R. Jagannathan, and D. E. Runkle. On the relationship between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, 48:1779–1801, 1993.

W. Härdle, M. Müller, S. Sperlich, and A. Werwatz. *Nonparametric and Semiparametric Models* . Springer Series in Statistics, Berlin, 2004.

L. Hastie, T. and R. Tibshirani. *Generalized Additive models* . Chapman and Hall, New York, 1990.

W. C. Huang and Y. Zhu. Are Shocks Asymmetric to Volatility in Chinese Stock Markets. *Review of Pacific Basin Financial Marekts and Policies*, 7:379–395, 2004.

C. F. Lee, G. Chen, and O. M. Rui. Stock returns and volatility on China's stock markets. *The journal of financial research*, XXIV4:523–543, 2001.

O. Linton and E. Mammen. Estimating semiparametric ARCH models by kernel smoothing methods. *Econometrica*, 73:771–836, 2005.

D. B. Nelson. Conditional heteroskedasticity in asset pricing, a new approach. *Econometrica*, 59:347–40, 1991.

A. R. Pagan and G. W. Schwert. Alternative models for conditional stock market volatility. *Journal of Econometrics*, 45:267–90, 1990.

L. Tan, T. C. Chiang, J. R. Mason, and E. Nelling. Herding behaviour in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal*, 16:61–77, 2008.

P. Wang, A. Liu, and P. Wang. Return and risk interactions in Chinese stock markets. *Journal of international financial markets, Institutions & Money*, 14:367–384, 2004.

W. Wei. Forecasting stock market volatility with non-linear GARCH models: a case for China. *Applied Economics Letters*, 9:163–166, 2002.

J. Yang. Market Segmentation and Information Asymmetry in Chinese Stock Markets: A VAR Analysis. *The Financial Review*, 38:591–609, 2003.

Y. Yeh and T. Lee. The interaction and volatility asymmetry of unexpected returns in the Greater China stock markets. *Global Finance Journal*, 11:129–149, 2000.

B. Zhang and X. Li. The asymmetric behaviour of stock returns and volatilities: evidence from Chinese stock market. *Applied Economics Letter*, 15:959–962, 2008.

6 Tables

Table 1: Model performance comparison from simulation results

	Normal		Student-t	
	MSE	MAE	MSE	MAE
GARCH	0.5554(0.0466)	0.6155(0.0201)	0.5553(0.0464)	0.6155(0.0201)
GJR	0.3901(0.0424)	0.5070(0.0272)	0.3896(0.0420)	0.5066(0.0270)
EGARCH	0.3004(0.0445)	0.4295(0.0296)	0.2976(0.0378)	0.4273(0.0230)
NP	0.2614(0.0477)	0.4051(0.0373)	0.2614(0.0477)	0.4051(0.0373)
GAM NP	0.2215(0.0581)	0.3387(0.0459)	0.2215(0.0582)	0.3387(0.0459)

Note: the Standard Errors of the MSE and MAE are in parentheses.

Table 2: Simulation results from the GAM NP and the NP models

	Normal				Student-t			
Models	NP Regression		GAM NP Regression		NP Regression		GAM NP Regression	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
GARCH	0.555 (0.047)	0.615 (0.020)	0.555 (0.047)	0.615 (0.020)	0.555 (0.046)	0.616 (0.020)	0.555 (0.046)	0.616 (0.020)
Iteration 1	0.347 (0.043)	0.460 (0.027)	0.286 (0.048)	0.393 (0.031)	0.347 (0.043)	0.460 (0.027)	0.286 (0.048)	0.393 (0.031)
Iteration 2	0.281 (0.045)	0.414 (0.032)	0.237 (0.053)	0.349 (0.041)	0.281 (0.045)	0.414 (0.032)	0.237 (0.053)	0.349 (0.041)
Iteration 3	0.267 (0.045)	0.406 (0.034)	0.225 (0.056)	0.339 (0.044)	0.267 (0.045)	0.406 (0.034)	0.225 (0.056)	0.339 (0.043)
Iteration 4	0.262 (0.044)	0.405 (0.033)	0.221 (0.055)	0.338 (0.044)	0.262 (0.044)	0.405 (0.033)	0.221 (0.055)	0.338 (0.044)
Iteration 5	0.264 (0.046)	0.406 (0.035)	0.221 (0.058)	0.337 (0.045)	0.264 (0.046)	0.406 (0.035)	0.221 (0.057)	0.337 (0.045)
Iteration 6	0.263 (0.047)	0.406 (0.037)	0.222 (0.058)	0.339 (0.045)	0.263 (0.047)	0.406 (0.037)	0.222 (0.058)	0.339 (0.045)
Iteration 7	0.262 (0.048)	0.405 (0.037)	0.224 (0.061)	0.341 (0.049)	0.262 (0.048)	0.405 (0.037)	0.224 (0.061)	0.341 (0.049)
Iteration 8	0.263 (0.048)	0.406 (0.037)	0.224 (0.060)	0.340 (0.047)	0.263 (0.048)	0.406 (0.037)	0.224 (0.060)	0.340 (0.047)
Final	0.261 (0.048)	0.405 (0.037)	0.221 (0.058)	0.339 (0.046)	0.261 (0.048)	0.405 (0.037)	0.221 (0.058)	0.339 (0.046)

Note: the Standard Errors are in parentheses.

Table 3: Data description

	Shanghai Composite Index (SHIC)	**Shenzhen Component Index (SZCI)**
Size	2573	2573
Mean	0.068	0.067
Median	0.070	0.048
Min	-9.334	-9.935
Max	9.401	9.530
Std.	1.576	1.738
Skewness	-0.203	-0.090
Kurtosis	8.331	7.524
Jarque-Bera Test	3064.2(0.001)	2198.0(0.001)
Dickey-Fuller Test	-50.972(0.001)	-49.107(0.001)

Note: the P values are reported for the Jarque-Bera and Dickey-Fuller Tests in parentheses.

Table 4: In-sample estimations of the GARCH, EGARCH, and GJR models

	Shanghai Composite Index						Shenzhen Component Index					
	GARCH		EGARCH		GJR		GARCH		EGARCH		GJR	
	Normal	Student-t	Normal	Student-t	Normal	Student-t	Normal	Student-t	Normal	Student-t	Normal	Student-t
μ	0,000	0,014	-0,011	0,009	-0,018	0,004	-0,021	-0,029	0,040	-0,034	-0,034	-0,037
	(0,021)	(0,023)	(0,024)	(0,023)	(0,025)	(0,023)	(0,026)	(0,026)	(0,029)	(0,025)	(0,028)	(0,026)
ω	0,095	0,093	0,038	0,027	0,082	0,090	0,067	0,097	0,080	0,027	0,062	0,093
	(0,013)	(0,023)	(0,005)	(0,009)	(0,012)	(0,022)	(0,010)	(0,024)	(0,010)	(0,009)	(0,010)	(0,024)
α	0,139	0,117	0,242	0,239	0,098	0,077	0,100	0,102	0,276	0,216	0,082	0,080
	(0,011)	(0,018)	(0,018)	(0,029)	(0,011)	(0,018)	(0,007)	(0,016)	(0,018)	(0,027)	(0,008)	(0,016)
β	0,829	0,848	0,964	0,957	0,845	0,844	0,879	0,865	0,932	0,967	0,882	0,863
	(0,013)	(0,021)	(0,006)	(0,010)	(0,012)	(0,021)	(0,007)	(0,019)	(0,009)	(0,009)	(0,007)	(0,019)
γ			-0,036	-0,063	0,060	0,095			0,028)	-0,035	0,036	0,055
			(0,008)	(0,016)	(0,014)	(0,028)			(0,010)	(0,014)	(0,011)	(0,024)
DoF		4,638		4,87		4,725		4,848		4,952		4,882
		(0,455)		(0,486)		(0,458)		(0,517)		(0,539)		(0,518)
Q(20)	24,32	24,43	24,91	25,48	25,12	25,53	27,29	27,17	26,10	27,55	28,28	28,97

Note: the Standard Errors are in parentheses.

Table 5: Goodness-of-fit for in-sample forecasts

Model	Distribution	SHCI			SZCI		
		MSE1	MSE2	MAE	MSE1	MSE2	MAE
GARCH	Normal	39.123	1.312	0.880	48.509	1.472	0.934
	Student-t	38.908	1.299	0.879	48.380	1.461	0.935
EGARCH	Normal	38.037	1.248	0.860	48.232	1.462	0.944
	Student-t	37.883	1.242	0.858	47.956	1.431	0.926
GJR	Normal	38.884	1.301	0.875	48.564	1.471	0.933
	Student-t	38.787	1.295	0.874	48.457	1.462	0.934
NP	Normal	37.846	1.263	0.871	47.631	1.439	0.930
	Student-t	37.851	1.263	0.871	47.817	1.438	0.929
GAM NP	Normal	37.700	1.238	0.859	47.858	1.429	0.924
	Student-t	37.708	1.238	0.859	47.874	1.430	0.924

Table 6: Goodness-of-fit for out-of-sample forecasts

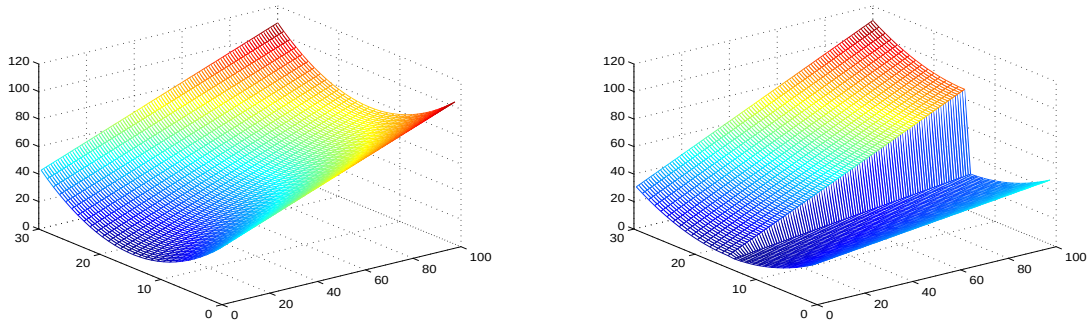
Model	Distribution	Shanghai Composite Index				Shenzhen Component Index			
		Benchmark I*		Benchmark II**		Benchmark I*		Benchmark II**	
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
GARCH	Normal	2.13	1.129	0.596	0.58	2.602	1.257	0.731	0.653
	Stduent-t	2.088	1.114	0.587	0.58	2.559	1.241	0.709	0.642
EGARCH	Normal	2.026	1.087	0.573	0.55	2.531	1.228	0.696	0.644
	Stduent-t	1.983	1.064	0.577	0.55	2.49	1.218	0.683	0.62
JGR	Normal	2.138	1.123	0.639	0.59	2.607	1.256	0.724	0.643
	Stduent-t	2.12	1.109	0.625	0.59	2.563	1.238	0.744	0.655
NP	Normal	1.905	1.047	0.515	0.53	2.411	1.195	0.626	0.604
	Stduent-t	1.903	1.045	0.517	0.53	2.403	1.192	0.628	0.604
GAM	Normal	1.93	1.056	0.526	0.53	2.468	1.205	0.69	0.62
	Stduent-t	1.928	1.055	0.528	0.53	2.472	1.207	0.692	0.619

Note: Benchmark I: use $\hat{\sigma}_t = \sqrt{(y_t - \hat{y}_t)^2}$ as the true volatility proxy

Benchmark II: use realized volatility:$\hat{\sigma}_t = \sqrt{\sum_{i=1}^{n} r_{i,t}^2}$ as the true volatility proxy.

7 Figures

Figure 1: Volatility surfaces from simulated processes



(a) Symmetric: process (10)

(b) Asymmetric: process (11)

Figure 2: Smoothed volatility surface from each iteration

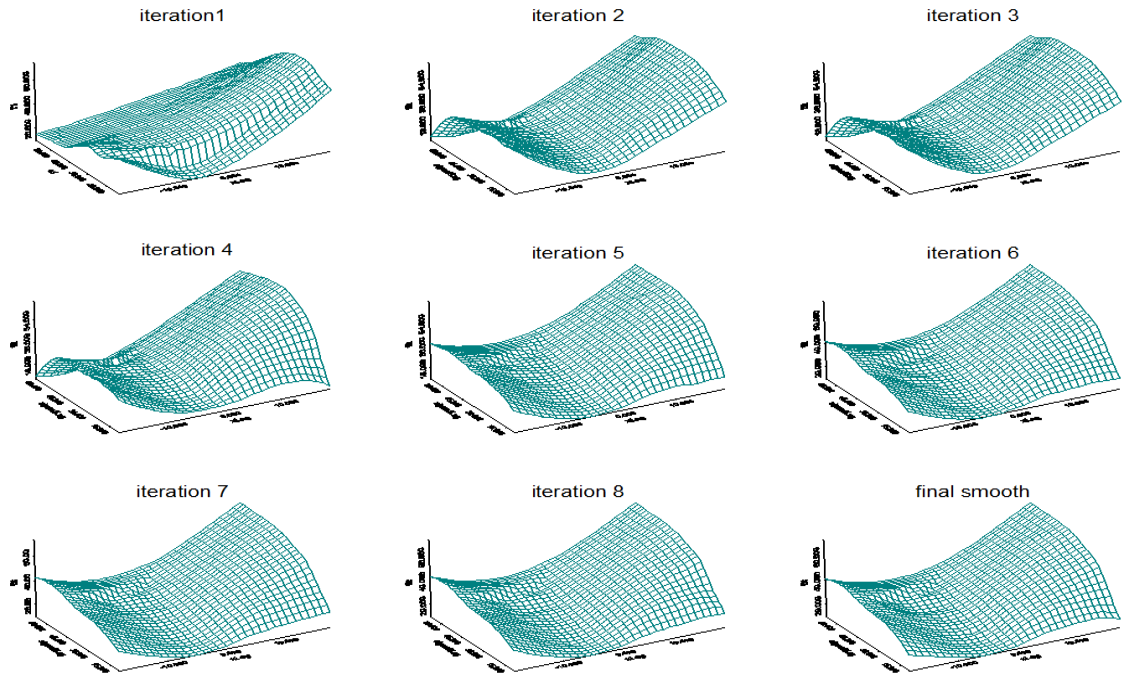
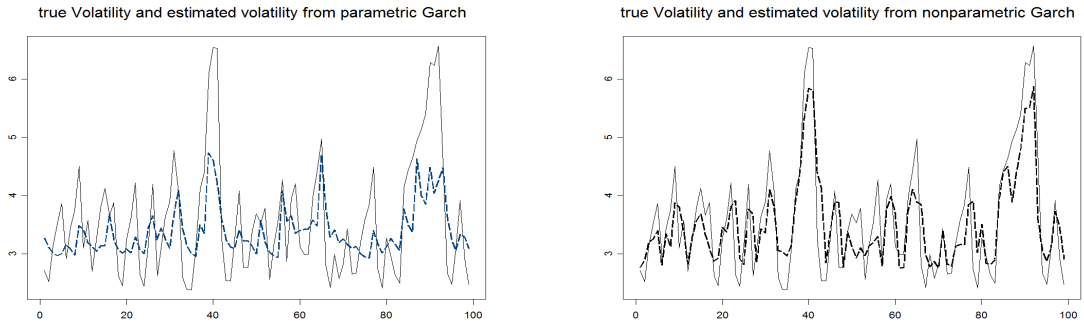


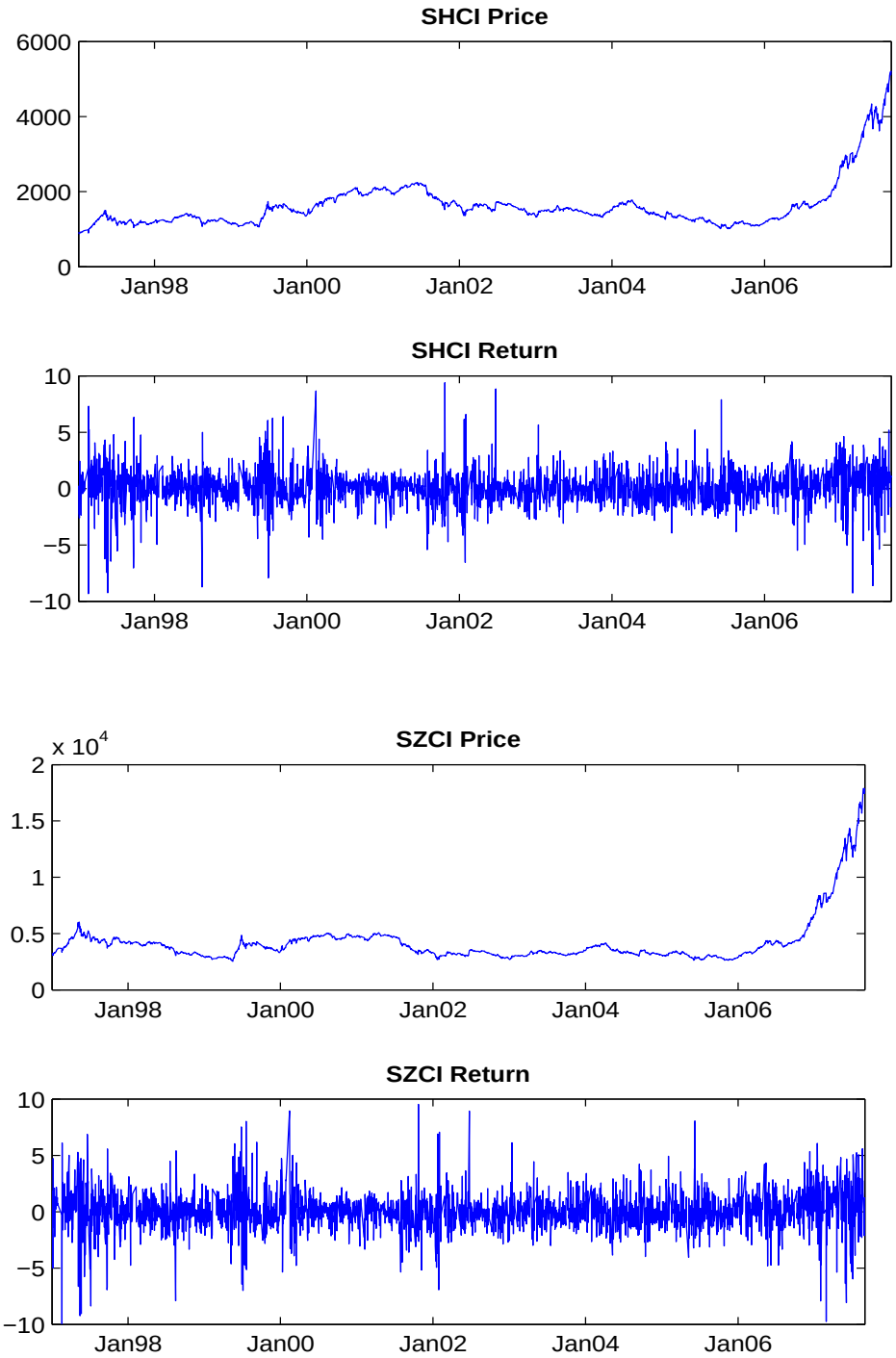
Figure 3: Simulated volatility and true volatility



(a) Parametric GARCH model

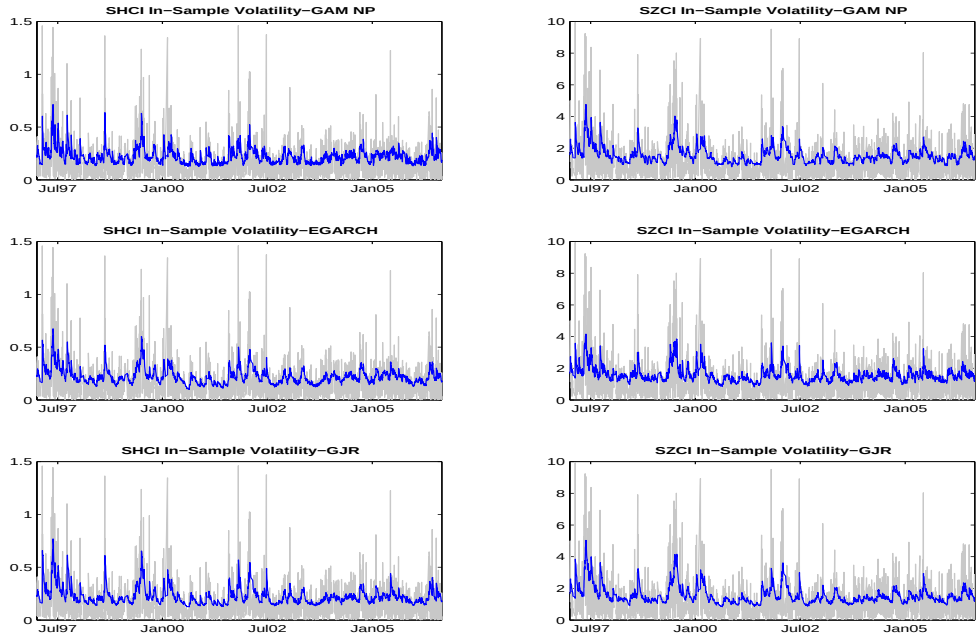
(b) GAM NP model

Figure 4: Price and return for SHCI and SZCI



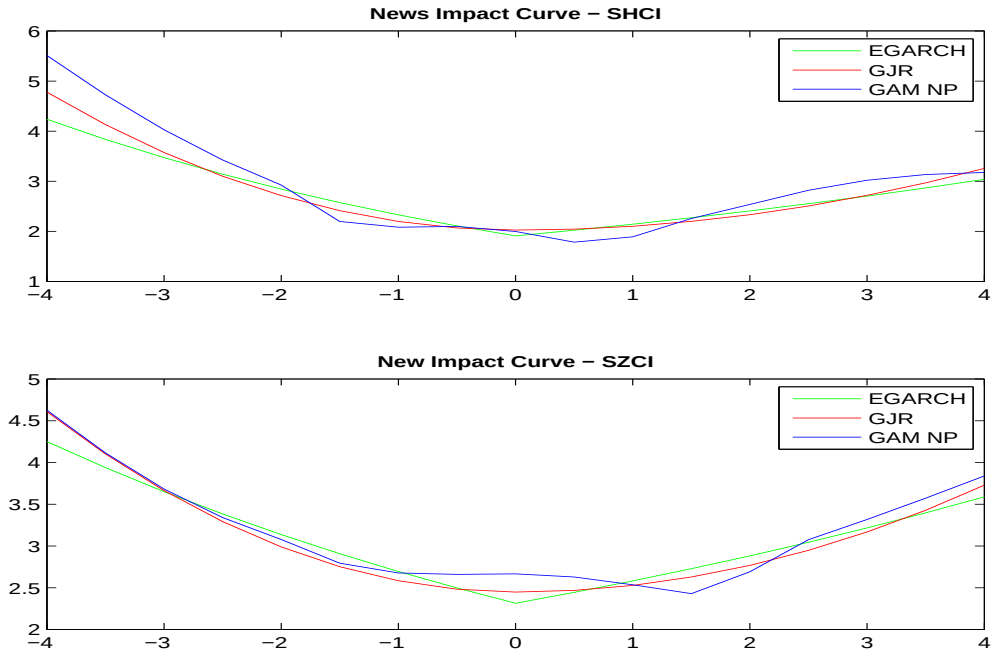
SHCI: Shanghai Composite Index, SZCI: Shenzhen Component Index

Figure 5: The estimated volatility from in-sample volatility estimation and the true volatility



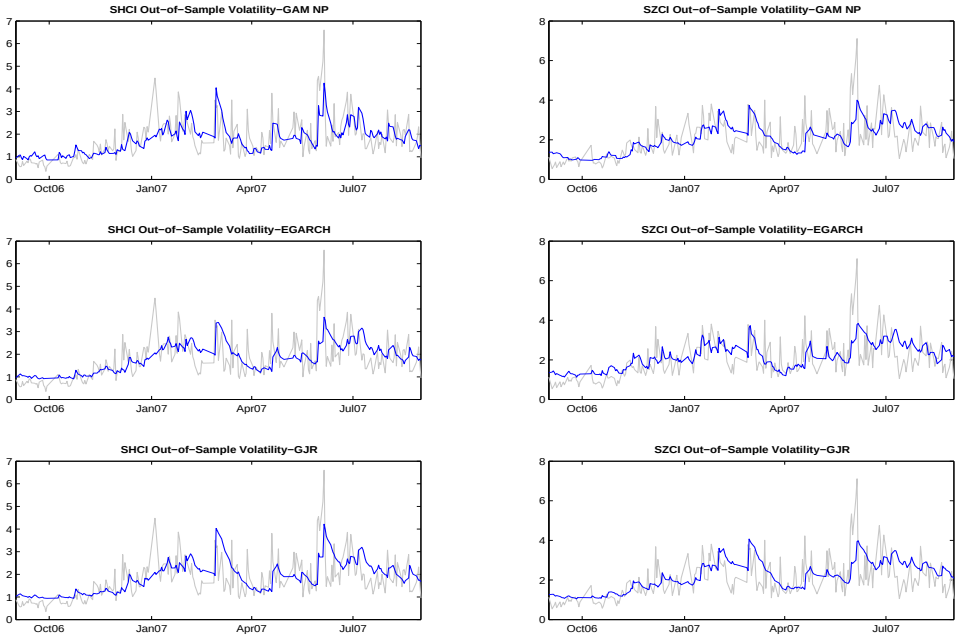
The gray lines are volatility proxies, the blue lines are estimated volatilities.

Figure 6: News impact curves



The X-axis represents the lagged market news, the Y-axis represents the volatility estimated by the models

Figure 7: Out-of-Sample volatility forecast



The light-gray lines are volatility proxies and the blue lines are realized volatilities.

Figure 8: The 90 % conditional prediction interval