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Robustness of Score-driven Location and Scale Models to Extreme Observations: An Application to the Chinese Stock Market

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ABSTRACT

Recently, the use of dynamic conditional score (DCS) time series models are suggested in the body of literature on time series econometrics. DCS models are robust to extreme observations because those observations are discounted by the score function that updates each dynamic equation. Examples of the DCS models are the quasi-autoregressive (QAR) model and the Beta-t-EGARCH (exponential generalized autoregressive conditional heteroscedasticity) model, which measure the dynamics of location and scale, respectively, of the dependent variable. Both QAR and Beta-t-EGARCH discount extreme observations according to a smooth form of trimming. Classical dynamic location and scale models (for example, the AR and the GARCH models) are sensitive to extreme observations. Thus, the AR and the GARCH models may provide imprecise estimates of location and scale dynamics. In the application presented in this paper, we use data from the Shanghai Stock Exchange A-Share Index and the Shenzhen Stock Exchange A-Share Index for the period of 5th January 1998 to 29th December 2017. For the corresponding stock index return time series, a relatively high number of extreme values are observed during the sample period. We find that the statistical performance of QAR plus Beta-t-EGARCH is superior to that of AR plus t-GARCH, due to the robustness of QAR plus Beta-t-EGARCH to extreme unexpected returns.

Keywords: Dynamic Conditional Score (DCS) Models; Quasi-autoregressive (QAR) Model; Beta-t-EGARCH (Exponential Generalized Autoregressive Conditional Heteroscedasticity) Model; Robustness to Extreme Observations; Shanghai Stock Exchange A-Share Index

JEL classification codes: C22; C52

1. Introduction

Creal, Koopman and Lucas (2013) and Harvey (2013) introduce a recent class of score-driven time series models, which are named as the generalized autoregressive score (GAS) models and the dynamic conditional score (DCS) models, respectively (we use the DCS notation in this paper). DCS models are characterized by the fact that every dynamic equation that drives a time-varying parameter is updated by the conditional score of the log-likelihood (LL) function with respect to the same time-varying parameter (hereinafter, we name the conditional score as the score function).

DCS models are observation-driven time series models. Classical observation-driven time series models from the body of literature are special cases of the DCS models. For example, the ARMA (autoregressive moving average) model (Box and Jenkins, 1970) is a classical observation-driven model of location, which is a special case of the QAR (quasi-AR) model (Harvey, 2013). Another classical observation-driven model is the GARCH (generalized autoregressive conditional heteroscedasticity) model (Engle, 1982; Bollerslev, 1986; Taylor, 1986), which is a special case of the Beta-t-GARCH model (Harvey and Chakravarty, 2008). From the literature on DCS models, for example, the following works compare the statistical performances of classical and DCS time series models: Blazsek and Villatoro (2015); Blazsek, Chavez and Mendez (2016); Blazsek and Mendoza (2016); Ayala, Blazsek and Escribano (2017); Blazsek, Escribano and Licht (2017, 2018); Blazsek and Hernandez (2018); Blazsek and Monteros (2017);

Blazsek, Carrizo, Eskildsen and Gonzalez (2018).

DCS models absorb the new information in a different way to the classical time series models. For example, for the classical ARMA and GARCH models, the new information is transformed according to linear and quadratic transformations, respectively. Those models do not discount the effects of extreme values in the noise, hence, they are not robust to extreme observations. It is noteworthy that GARCH actually accentuates the effects of extreme observations due to the quadratic transformation, which may lead to imprecise forecasts of conditional volatility (Blazsek, Carrizo, Eskildsen and Gonzalez, 2018). On the other hand, DCS models are robust to extreme observations, because those models discount the impact of the new information on location and scale by using the non-linear score function. For the QAR and Beta-t-EGARCH (exponential GARCH) models that are used in this paper, discounting of extreme observations is performed according to a smooth form of trimming. This is due to the properties of the Student's t distribution that is used as an error term in those models. Alternative examples of the error term from the body of literature on DCS models are the exponential generalized beta distribution of the second kind (EGB2) (Caivano and Harvey, 2014; Caivano, Harvey and Luati, 2016; Blazsek and Hernandez, 2018; Ayala, Blazsek and Escribano, 2017) and the normal-inverse Gaussian (NIG) distribution (Ayala, Blazsek and Escribano, 2017). The EGB2 and NIG distributions perform a smooth form of Winsorizing for the location equation (i.e. those models discount the extreme values less than DCS models with the Student's t distribution).

It is argued in the literature (Hussain, 2016; Carpenter, Lu and Whitelaw, 2018) that Chinese stock exchanges are more volatile than the United States (US) or European stock markets. This implies a relatively high number of extreme return observations for the Chinese stock market. In this paper, we apply a DCS model to analyze daily returns from the following two stock market indices: (i) Shanghai Stock Exchange A-Share Index; (ii) Shenzhen Stock Exchange A-Share Index. We compare the statistical performances of the AR plus t-GARCH (Bollerslev, 1987) and QAR plus Beta-t-EGARCH models. The error term in both models is the Student's t distribution, and the main difference between those models is with respect to how the new information is transformed in the dynamic equations. We find that QAR plus Beta-t-EGARCH is superior to AR plus t-GARCH, which is related to the fact that QAR plus Beta-t-EGARCH is robust to extreme values in the noise.

The remainder of this paper is organized as follows. Section 2 presents the stock market in China. Section 3 reviews the econometric models. Section 4 presents the statistical inferences. Section 5 describes the dataset. Section 6 summarizes the empirical results. Section 7 concludes.

2. The Stock market in China

The stock market in China has several special characteristics that make it a complex market. Since 1992, the shares traded on the Chinese stock market have been segmented into three categories according to stock exchange, listing currency and investment restrictions, as follows: (i) A-shares are traded on the Shanghai and Shenzhen Stock Exchanges in renminbi (RMB). Foreign investors have been trading those shares since 2002, but with several restrictions. (ii) B-shares are traded on the Shanghai Stock Exchange and on the Shenzhen Stock Exchange in US dollar (USD) and Hong Kong dollar (HKD), respectively. Those shares are available to foreign investors. (iii) H-shares are traded on the Hong Kong Stock Exchange in HKD, and those shares are the main investment channel for foreign investors.

In addition to the limitations of the share classification system, the access to the stock market of China is also restricted by the official prohibition of stock purchases that are financed with bank loans and also by the official prohibition of share purchases by financial institutions (including insurance companies, pension funds and listed companies) (Marszk, 2014). State-owned entities are not allowed to trade on the Shanghai and Shenzhen Stock Exchanges. A typical listed firm in China has two types of shares: The first type of shares are issued to state-owned entities; those shares are not traded in any stock exchange (Wong, 2006). The second type of shares are issued to private individual investors; those shares can be traded freely in a stock exchange (Wong, 2006).

The high volatility in the Chinese stock markets can be explained, in part, by way of the following reasons: Firstly, in accordance with the results of a study by Foucault, Sraerand Thesmar (2011), retail trading activity has a positive (increasing) effect on the volatility of stocker turns. Xinhua (2015) reports that, according to the research report of China International Capital Corporation (see Carpenter, Lu and Whitelaw, 2018), by mid-2015, the free-float market capitalization in the domestic A-Share market reached 4.76 trillion USD and 80% of that figure was held by retail investors. The China Securities Regulatory Commission (CSRC) reports that individual investors account for 80% or more of total trading volume on the Chinese stock markets (see Carpenter, Lu and Whitelaw, 2018).Thus, in contrast with the US or European equity markets, Chinese equity ownership and trading on the stock market are driven by individual investors and not by institutional investors. All of these facts have a positive (increasing) effect on the volatility of stock returns. Secondly, the Financial Times (2015a) reports that both the market capitalization and the number of retail investors have increased their presence heavily on the Chinese equity markets since 2008. This implies that many of the individual investors in China have no direct memory of the bubble and crash of the Chinese stock market in 2007 and 2008 and of the US stock market crisis in 2008. These individual investors are more eager to take more risk than institutional and more experienced investors. They invest in high volatility stocks, where some of these individual investors use margins to finance stock market transactions, and they tend to buy when the market goes up and sell when the market goes down. Due to the large trading volume, the trades undertaken by these individual investors significantly increase the volatility of stock returns (Financial Times, 2015b; Macquire Research, 2015).

The high volatility exhibited by the Chinese stock markets creates a significant number of extreme log-return observations on the Shanghai Stock Exchange A-Share Index and the Shenzhen Stock Exchange A-Share Index.

3. Econometric models

We model the daily log-return on the Shanghai Stock Exchange A-Share Index and the Shenzhen Stock Exchange A-Share Index. The daily log-return on these indices is $y_t = \ln(p_t/p_{t-1})$ for $t = 1,...,T$, where p_t is the daily closing value of each index (we use pre-sample data for p_0). Firstly, the AR(p) plus t-GARCH model is

$$y_t = \mu_t + v_t = \mu_t + \lambda_t^{1/2}\varepsilon_t \tag{1}$$

where the error term is $\varepsilon_t \sim t(\nu)$ independent and identically distributed (i.i.d.) with the Student's t distribution (ν denotes the degrees of freedom parameter); μ_t is the time-varying conditional location parameter of y_t that is the conditional expected return in our application; v_t denotes the unexpected return; $\lambda_t^{1/2}$ is the time-varying conditional scale parameter of y_t driving the conditional volatility of y_t. This conditional volatility is given by

$$\sigma_t = \left(\lambda_t \times \frac{\nu}{\nu-2}\right)^{1/2} \tag{2}$$

The conditional location of y_t is specified according to the following AR(p) model:

$$\mu_t = c + \sum_{j=1}^{p} \varphi_j y_{t-j} = c + \sum_{j=1}^{p} \varphi_j (\mu_{t-j} + \lambda_{t-j}^{1/2}\varepsilon_{t-j}) \tag{3}$$

where c is the constant parameter and φ_j with $j = 1,...,p$ are the dynamic parameters of the AR(p) model. The square of the conditional scale of y_t is specified according to the t-GARCH(1,1) model with leverage effects (Glosten, Jagannathan and Runkle, 1993), as follows:

$$\lambda_t = \omega + [\alpha + \alpha^* \mathbb{1}(v_{t-1} < 0)]v_{t-1}^2 + \beta\lambda_{t-1} = \omega + \{[\alpha + \alpha^* \mathbb{1}(\varepsilon_{t-1} < 0)]\varepsilon_{t-1}^2 + \beta\}\lambda_{t-1} \tag{4}$$

where α^* measures leverage effects, and $\mathbb{1}(\cdot)$ is the indicator function that takes the value one if the argument is true and zero otherwise; μ_t is initialized by using pre-sample data from y_t and λ_t is initialized by using the parameter λ_0. For the AR(p) model, the conditional location is updated by a linear transformation of the new information represented by ε_t (Equation 3). For the t-GARCH model, the conditional scale is updated by a quadratic transformation of the new information that is represented by ε_t (Equation 4). Thus, the new information that arrives to the market is not discounted in these models (as aforementioned, the updating term of the t-GARCH model accentuates the impact of the new information).

Secondly, the t-QAR(p) plus Beta-t-EGARCH model is given by

$$y_t = \mu_t + v_t = \mu_t + \exp(\lambda_t)\varepsilon_t \tag{5}$$

where $\varepsilon_t \sim t(\nu)$ denotes the i.i.d. error term. The interpretations of μ_t and v_t are the same as for the AR plus GARCH model; $\exp(\lambda_t)$ denotes the dynamic scale parameter, which drives the conditional volatility of y_t. This conditional volatility is given by

$$\sigma_t = \exp(\lambda_t)\left(\frac{\nu}{\nu-2}\right)^{1/2} \tag{6}$$

The conditional location of y_t is given by the following QAR(p) model:

$$\mu_t = c + \left(\sum_{j=1}^{p} \varphi_j \mu_{t-j}\right) + \theta u_{\mu,t-1} \tag{7}$$

where $u_{\mu,t}$ is proportional to the scorefunction with respect to μ_t (Harvey, 2013) and θ is the scaling parameter of the score function, which is formulated as:

$$u_{\mu,t} = \nu\exp(\lambda_t)\varepsilon_t/[\nu + \varepsilon_t^2] \tag{8}$$

The log of the conditional scale of y_t is the Beta-t-EGARCH model with leverage effects (Harvey, 2013):

$$\lambda_t = \omega + \alpha u_{\lambda,t-1} + \alpha^* \mathrm{sgn}(-v_{t-1})\left(u_{\lambda,t-1} + 1\right) + \beta\lambda_{t-1} \tag{9}$$

where $\mathrm{sgn}(\cdot)$ is the signum function; $u_{\lambda,t}$ is the score function with respect to λ_t, which is formulated as:

$$u_{\lambda,t} = (\nu + 1)\varepsilon_t^2/[\nu + \varepsilon_t^2] - 1 \tag{10}$$

μ_t is initialized by using pre-sample data for y_t and λ_t is initialized by using the parameter λ_0. An advantage of the use of the QAR(p) plus Beta-t-EGARCH(1,1) model is that the updating terms $u_{\mu,t}$ and $u_{\lambda,t}$ discount the impact of the new information ε_t on location and scale, respectively.

4. Statistical inference

Both models are estimated by using the maximum likelihood (ML) method. The ML estimate of parameters is given by:

$$\widehat{\Theta}_{ML} = \max_{\Theta} LL(y_1,\ldots,y_T;\Theta) = \max_{\Theta} \sum_{t=1}^{T} \ln f(y_t|y_1,\ldots,y_{t-1};\Theta) \tag{11}$$

where Θ is the vector of time-constant parameters; LL is the log-likelihood and $\ln f(\cdot)$ denotes the log of the conditional density function of the dependent variable. We obtain the ML estimates by numerical maximization at interior points of the parameter space. We use the gradient tolerance criterion of 10^{-5} for the numerical maximization. For several parameters, their transformed values are estimated. We compute the standard errors of those parameters by using the delta method (Davidson and MacKinnon, 2003).

In this paper, we assume that the asymptotic properties of ML for the dynamic location equations are satisfied for both AR plus t-GARCH and QAR plus Beta-t-EGARCH. Therefore, in the remainder of this section, we focus on the ML conditions corresponding to the dynamic scale equation. For t-GARCH(1,1) with leverage effects, covariance stationarity of y_t is supported if

$$C_{\lambda,1} = \alpha + \beta + \alpha^*/2 < 1 \tag{12}$$

For the same model, we also verify the following condition of consistency and asymptotic normality of ML that is demonstrated in the work of Jensen and Rahbek (2004):

$$C_{\lambda,2} = E\left[\frac{\beta}{(\alpha+\alpha^*/2)\varepsilon_t^2+\beta}\right] < 1 \tag{13}$$

For Beta-t-EGARCH(1,1), covariance stationarity of y_t is supported if

$$C_{\lambda,1} = |\beta| < 1 \tag{14}$$

For the same model, we also verify the following condition of consistency and asymptotic normality of ML that is demonstrated in the work of Harvey (2013):

$$C_{\lambda,2} = \beta^2 - \alpha\beta\frac{4\nu}{\nu+3} + [\alpha^2 + (\alpha^*)^2]\frac{12\nu(\nu+1)(\nu+2)}{(\nu+7)(\nu+5)(\nu+3)} < 1 \tag{15}$$

5. Data

We use data from the Shanghai A-Share Index (ticker: SHASHR Index) and from the Shenzhen A-Share Index (ticker: SZASHR Index) for the period of 5th January 1998 to 29th December 2017 (source of data: Bloomberg). Both indices are market capitalization weighted, tracking the daily price performance of all A-shares listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange, respectively. We use the log-return time series for both indices. We present the descriptive statistics of for both indices in **Table 1**. We present the evolution of level and log-return variables for the Shanghai Stock Exchange A-Share Index and the Shenzhen Stock Exchange A-Share Index in **Figure 1**.

	SHASHR Index	SZASHR Index
Start date	5th January 1998	5th January 1998
End date	29th December 2017	29th December 2017
Sample size (T)	4,837	4,837
Minimum	-0.0926	-0.0893
Maximum	0.0940	0.0924
Mean	0.0002	0.0003
Median	0.0006	0.0013
Standard deviation	0.0159	0.0176
Skewness	-0.3209	-0.5006
Excess kurtosis	4.8157	3.4555

Table1. Descriptive statistics

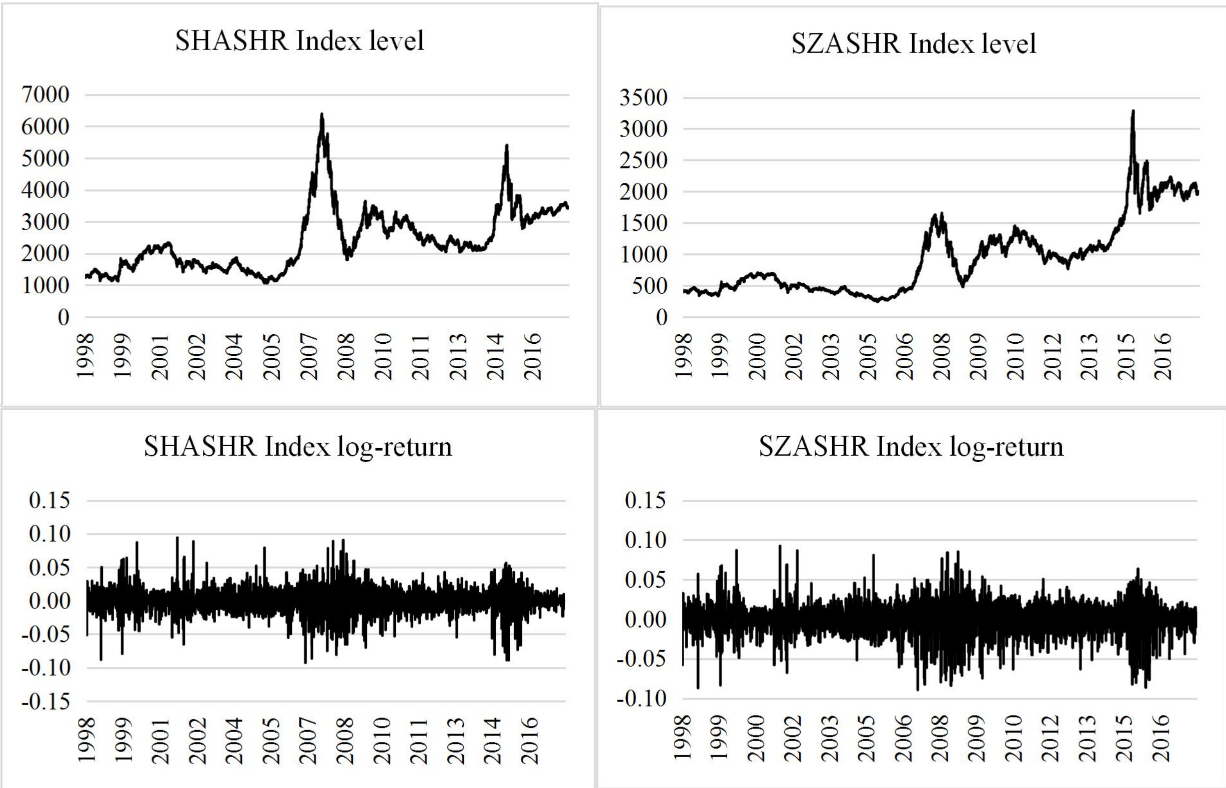

Figure 1; Evolution of SHASHR Index and SZASHR Index for the period 5th January 1998 to 29th December 2017**.**

6. Estimation results

We present the parameter estimates, the ML conditions and the statistical performances of both dynamic models in Tables 2 and 3 for SHASHR Index and SZASHR Index, respectively. For both models, we present the evolution of the conditional volatility σ_t in **Figure 2.**

As can be seen in Tables 2 and 3, the Ljung-Box (1978) (LB) test for 5 lags suggests that the residuals support the specifications for both models. The AR(10) and QAR(10) lag order selection is obtained by using the LB test (for lower lag orders of AR and QAR, the residuals are not independent according to the LB test). It can also be verified in Tables 2 and 3 that, for both t-GARCH(1,1) and Beta-t-EGARCH(1,1), the conditions for covariance stationarity and asymptotic normality of the ML estimator are supported.

The statistical performance of both models is evaluated by using the following likelihood-based performance criteria: (i) LL, (ii) Akaike Information Criterion (AIC), (iii) Bayesian Information Criterion (BIC) and (iv) Hannan-Quinn Criterion (HQC) (Davidson and MacKinnon,2003). We present these metrics in Tables 2 and 3. All likelihood-based metrics suggest that QAR plus Beta-t-EGARCH is superior to AR plus t-GARCH. We conclude that the QAR plus Beta-t-EGARCH model improves the AR plus t-GARCH model for the estimation of the expected return and volatility of both the Shanghai Stock Exchange A-share Index and the Shenzhen Stock Exchange A-share Index.

For the QAR plus Beta-t-EGARCH model, in **Figure 3** we present the treatment of extreme observations for location and scale that is undertaken by the updating terms of the dynamic equations. In **Figure 3**, we present the updating term of location as a function of the noise term for QAR(10). For the QAR(10) model, the new information is discounted according to the non-linear score function. In Figure 3, we also present the updating terms of log-scale as a function of the noise term for Beta-t-EGARCH(1,1). For the Beta-t-EGARCH(1,1) model, the new information is discounted according to the non-linear score function. As a consequence, the QAR plus Beta-t-EGARCH model is robust to extreme values in the unexpected return.

	AR plus t-GARCH			**QAR plus Beta-t-EGARCH**		
c	0.0003	*	(0.0002)	0.0000		(0.0000)
φ_1	0.0217		(0.0135)	0.1286		(0.2276)
φ_2	-0.0020		(0.0146)	1.4266	***	(0.1417)
φ_3	0.0505	***	(0.0144)	-0.0705		(0.3933)
φ_4	0.0124		(0.0140)	-1.0763	***	(0.1987)
φ_5	0.0008		(0.0142)	-0.5409	*	(0.2868)
φ_6	-0.0360	***	(0.0139)	1.1171	***	(0.2573)
φ_7	0.0179		(0.0138)	0.8931	***	(0.2731)
φ_8	0.0178		(0.0139)	-0.8134	**	(0.3862)
φ_9	0.0223	*	(0.0134)	-0.2712		(0.1796)
φ_{10}	0.0307	**	(0.0143)	0.1939		(0.2186)
θ	NA			0.0414	***	(0.0098)
ω	0.0000	***	(0.0000)	-0.0565	***	(0.0150)
α	0.0339	***	(0.0052)	0.0529	***	(0.0052)
α^*	0.0252	***	(0.0096)	0.0120	***	(0.0035)
β	0.9173	***	(0.0104)	0.9877	***	(0.0033)
λ_0	0.0002		(0.0001)	-4.3900	***	(0.3664)
ν	4.6666	***	(0.3164)	4.5876	***	(0.3023)
$C_{\lambda,1}$	0.9639			0.9877		
$C_{\lambda,2}$	0.9358			0.8562		
LB(5)	3.3817		(0.6414)	6.7041		(0.2436)
LL	2.9126			**2.9206**		
AIC	-5.8182			**-5.8338**		
BIC	-5.7954			**-5.8096**		
HQC	-5.8102			**-5.8253**		

Table 2. Parameter estimates and model diagnostics, SHASHR Index

Notes: Standard deviation (SD); not available (NA); log-likelihood (LL); Akaike information criterion (AIC); Bayesian information criterion (BIC), Hannan-Quinn criterion (HQC). Bold numbers indicate superior model performance. For the parameter estimates, standard errors are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	AR plus t-GARCH			QAR plus Beta-t-EGARCH		
c	0.0005	***	(0.0002)	0.0000		(0.0000)
φ_1	0.0568	***	(0.0147)	-0.2925	***	(0.1102)
φ_2	-0.0175		(0.0153)	0.6336	***	(0.1181)
φ_3	0.0654	***	(0.0151)	0.5879	***	(0.0593)
φ_4	0.0100		(0.0150)	0.0765		(0.1209)
φ_5	0.0026		(0.0143)	-0.6060	***	(0.1376)
φ_6	-0.0224		(0.0141)	-0.2393	**	(0.0988)
φ_7	0.0311	**	(0.0141)	0.2930	***	(0.0889)
φ_8	0.0280	*	(0.0147)	0.7854	***	(0.1078)
φ_9	0.0256	*	(0.0139)	0.2541	**	(0.1285)
φ_{10}	0.0281	**	(0.0141)	-0.5207	***	(0.1088)
θ	NA			0.0918	***	(0.0148)
ω	0.0000	***	(0.0000)	-0.0768	***	(0.0184)
α	0.0360	***	(0.0070)	0.0548	***	(0.0052)
α^*	0.0387	***	(0.0104)	0.0174	***	(0.0034)
β	0.9019	***	(0.0119)	0.9829	***	(0.0042)
λ_0	0.0002		(0.0002)	-4.2312	***	(0.4216)
ν	5.4742	***	(0.4291)	5.1447	***	(0.3673)
$C_{\lambda,1}$	0.9573			0.9829		
$C_{\lambda,2}$	0.9295			0.8390		
LB(5)	1.1739		(0.9474)	3.1622		(0.6750)
LL	2.7786			**2.7879**		
AIC	-5.5501			**-5.5684**		
BIC	-5.5273			**-5.5442**		
HQC	-5.5421			**-5.5599**		

Table 3. Parameter estimates and model diagnostics, SZASHR Index

Notes: Standard deviation (SD); not available (NA); log-likelihood (LL); Akaike information criterion (AIC); Bayesian information criterion (BIC), Hannan-Quinn criterion (HQC). Bold numbers indicate superior model performance. For the parameter estimates, standard errors are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

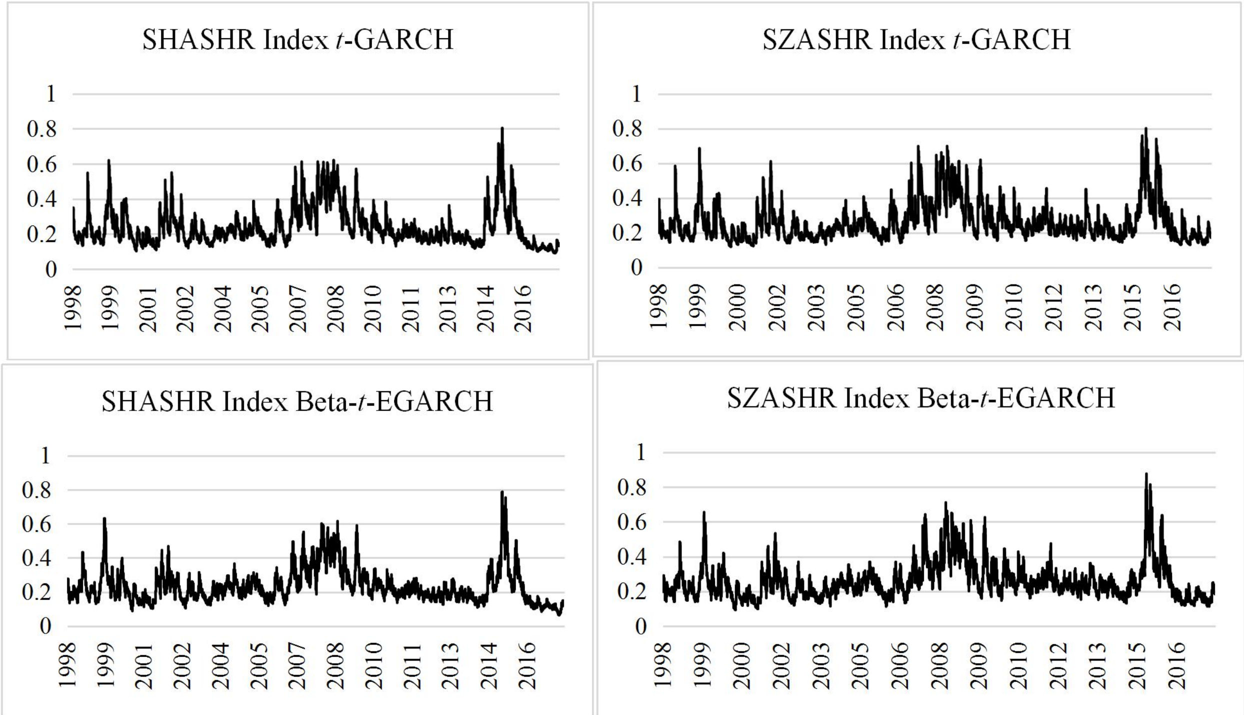

Figure 2; Evolution of annualized volatility for the period of 5th January 1998 to 29th December 2017.

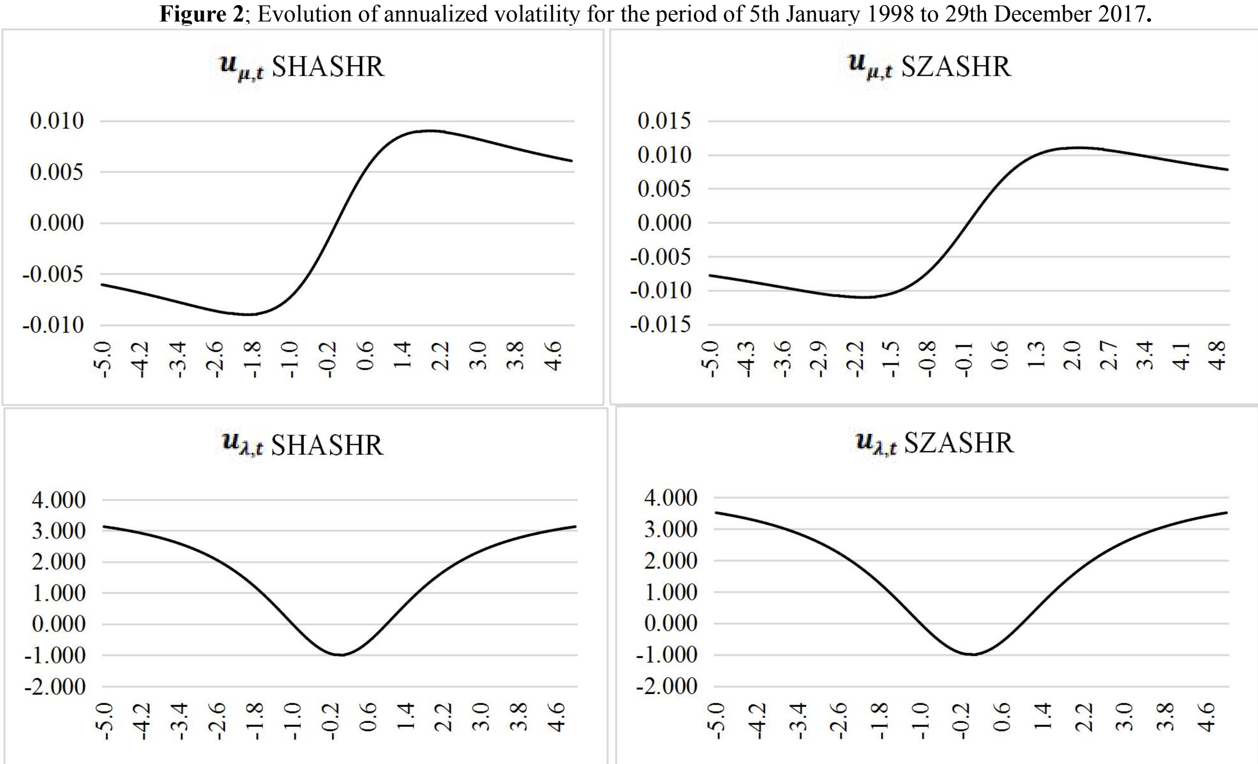

Figure 3; Score functions for location $u_{\mu,t}$ and scale $u_{\lambda,t}$.

7. Conclusions

In this work, we have presented an application of the DCS models for the Chinese stock market. DCS models are generalizations of classical time series models. Therefore, in many cases, DCS models provide a better fit to time series data than the classical time series models. The main difference between DCS and classical models is that DCS models are robust to extreme observations and, therefore, the ML conditions may be satisfied for DCS models, while the same conditions may not be satisfied for classical time series models that contain the same extreme observations. We have compared the statistical performance of the QAR plus Beta-t-EGARCH model with the AR plus t-GARCH model, in an application to data from the Shanghai Stock Exchange A-Share Index and the Shenzhen Stock Exchange A-Share Index. We have established that the statistical performance of the QAR(10) plus Beta-t-EGARCH(1,1) model is superior to that of the AR(10) plus t-GARCH(1,1) model. This is, in large part, due to the fact that DCS models are robust to extreme observations in the noise.

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