CAViaR and the Empirical Study on China’s Stock Market

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Abstract. The patterns of China’s stock market during 2004 and 2020 are characterized by Value at Risks (VaR) of 3 important stock indexes: Shanghai Security Composite index (SSEC), Shanghai Stock Exchange B Share index (SHBSHR) and Shenzhen Security Component index (SZSC), applying conditional autoregressive value at risk (CAViaR) model. The estimation results fit the real situation well. The unique style of news impact curves illustrates the peculiarity of China’s stock market caused by imperfect market mechanism and the small traders’ psychology-overconfidence. By comparing the estimation results, we found that SAV was a proper model for calculating 1% VaR of both SSEC and SHBSHR, while it was better for SZSC to choose Indirect GARCH model for 1% VaR estimation.

1. Introduction
Since stock markets play an important role in modern economic growth, understanding its patterns and doing optimal decision based on such knowledge is necessary for both policy makers and traders in the markets. Value at Risk (VaR) is a simple and effective risk measure providing us with information of stock markets. Numerous methodologies are developed and applied in VaR calculation. As a classical method, conditional autoregressive value at risk (CAViaR) model is developed by Engle and Manganelli in 2004. Since then, numbers of researches based on CAViaR came out, and some of them were empirical studies based on china’s stock market. Huang and Lu (2004) proposed that the four typical CAViaR models are not suitable for China's stock market as expected from the aspect of model volatility. He (2005) studied the EGARCH effects of Shanghai and Shenzhen Stock Market return. He points out that, differences between the fluctuation characters of two markets make it desirable to choose CAViaR model as an estimation approach. The research of Lu (2004) on Shanghai and Shenzhen stock index return clarify that, to investigate the characters of China’s stock market, the Security Composite index (SSEC) and Shenzhen Security Component index (SZSC) are chosen to be the research objects. Besides, the Shanghai stock exchange B share index (SHBSHR) is also included. Since the SHBSHR is traded in dollars, it provides a better connection between domestic and foreign markets. Almost all of these empirical studies based on CAViaR models believe that CAViaR is not in line with China's reality. The huge differences in policy environment of stock market between China and the United States maybe the main reason.

Most of the studies mentioned above apply stock data before 2005, while a small number of studies in 2012 have concluded that CAViaR models are applicable to China’s stock market under certain situation. Since China's stock market has experienced several reforms and the mechanism has gradually become mature, we believe it is necessary to apply CAViaR model to have a new trial.
2. Research Framework

2.1 CAViaR Models
The empirical research process in this article follows the structure designed by Engle and Manganelli in 2004. The original CAViaR model is chosen to do VaR calculations based on empirical data of SSEC, SZSC, and SHBSHR daily returns. Quantile regression is engaged in estimating parameters of AS, SAV, Indirect GARCH (1,1) and Adaptive models.

Generic CAViaR specification might be the following:
\[
f_t(\beta) = \beta_0 + \sum_{i=1}^{q} \beta_i f_{t-i}(\beta) + \sum_{j=1}^{r} \beta_j (x_{t-j})
\]
(1)

Adaptive model:
\[
f_t(\beta) = f_{t-1}(\beta_1) + \beta_1 [1 + \exp(G[y_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \theta
\]
(2)

Symmetric absolute value:
\[
f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 |y_{t-1}|
\]
(3)

Asymmetric slope:
\[
f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 (y_{t-1})^+ + \beta_4 (y_{t-1})^-
\]
(4)

Indirect GARCH (1,1):
\[
f_t(\beta) = (\beta_1 + \beta_2 f_{t-1}^2(\beta) + \beta_3 y_{t-1}^2)^{1/2}
\]
(5)

2.2 Methodology and Data
3925 daily closing prices are taken as the daily return of three portfolios. These three indexes SSEC, SZSC, and SHBSHR are representative indicators of China's Stock Market and their movements and volatilities are strictly monitored and analyzed by market participants and regulators. All series run from 10 May 2004 to 30 June 2020. We choose one year prior to the starting point of Split-share structure reform, say May 10, 2004, as the initial time of our empirical study. The period is chosen in order to have relatively long enough time span which covers several remarkable reforms and shocks such as the 2008-2009 Global Financial Crises (GFC), stock depression during 2010-2012 and May 2015, system reform in 2014, the circuit breakers and new rules for reducing holdings issued in 2016, as well as Securities Law that formally implemented after the new revision in March 1, 2020. These data are collected from the Stock Star database. By 100 times the log returns' difference, 3924 daily return of the three assets' VaR are calculated following the equation:
\[
y_t = (log p_t - log (p_{t-1})) \times 100
\]
(6)

There are several reasons why we choose log return to estimate VaR. Firstly, the log return yields more significance econometric interpretation than that of arithmetic return. Secondly, it is easier for a log return to be extended from one period to multi-period. Besides, as the SHBSHR is traded with the dollar, the log return makes it possible to compare the three stocks' VaR without standardizing the measurement unit. Since the excess Kurtosis values of three assets are all larger than 3 demonstrating fat tail of return distribution, CAViaR models are proven to be a good choice (Liu and Huang, 2005). The sample is divided into two parts, the first 3424 observations as the in-sample test data which is used to estimate the CAViaR model consist of four models established by Engle and Manganelli (2004), and the last 500 observations of the sample are regarded as out of sample observations, and they used for model testing.

The performance of current method applied in evaluating VaR is assessed with previous data and situation, which is the process of back-testing. A good choice of testing model volatility is the Dynamic quantile test (DQ test) (Engle and Manganelli, 2004) that includes in-sample test and out-of-sample test. Calculating the values of Hits in-sample and out-of-sample is a way to test model precision. The closer the value is to the corresponding confidence level, the more accurate the model is. That is to say, when estimating 5% VaR, 4.98% Hits in-sample value indicates a desirable precision of the model.
News Impact Curves (NICs) is also combined in the empirical research framework. It is discussed by Pagan and Schwert (1990), and Engle and Ng (1991) show how do shocks influence conditional volatility.

All the calculations and figure plotting of this methodology are realized by Matlab 2014(b), and the original code is from Manganelli (2004). Modifications in original code are made to fit the empirical research in this article. The main changes are in some basic parameter and optimization path (for example the LineSearchType option is no longer valid in present Matlab version).

3. Empirical Results

Here we present results for 1%VaR and results in table 1, figure 1 and figure 2 (results for 5% and all graphs of the estimated 1% and 5% CaViaR specifications for the three assets are available from the author).

3.1 Model Specification and Estimates

The three assets' VaR series computed by four models with $\theta$th quantile are plotted and demonstrated. Taking the 1% SSEC VaR as an example in figure 1. It is clear that the 1% VaR figures show more significant fluctuation than that of 5% VaR (which is not provided in this paper), indicating a more accurate estimation for 1% VaR. As the 5% VaR tolerates higher risk, the figures with 1% VaR report more fluctuant trends. But generally speaking, the two different VaR levels figures show the same trends that reflect the actual situation of Chinese stock market fluctuation. We firstly focus on the figures' character. It is clear that the SAV, AS and Indirect GARCH model report more fluctuation pictures. In contrast, the Adaptive model draw a relatively smoother picture. This is due to the model assumptions. We could turn attention to discuss the specific stock's character VaR demonstrated, like figure 1, and it parallels actual situation of Chinese stock market fluctuation.

![Figure 1. 1% CAViaR plots for SSEC](image)

Here we applied the News Impact Curves (NICs) Engle and Ng (1993) developed to characterize and compare the diverse models' volatility quality. Taking the SSEC 1% VaR news impact curves as an example in Figure 2, comparisons are made of SAV, AS, Indirect GARCH and Adaptive models' NICs to demonstrate how the return news of assets influence the portfolio VaR under different model hypothesis. Generally speaking, past return show stronger influence on 1% VaR than 5% VaR for all models and portfolios. Which reflecting on the figures is the steeper slope of the polygonal line. While the NICs of SSEC forecasted by SAV and Indirect GARCH models appear to be symmetric, AS and
Adaptive ones become attractive to discuss. For Adaptive model, what we should focus on is the inflection points (break point/jump point) between horizontal lines. These points appear when the 'past return exceeded the previous' Engle (2004). For AS model, previous empirical study indicate that, if there are asymmetric influence, bad news always provide more information to model volatility than the good news do. Reflected on the figures are a steeper slope of lines on the left side zero point. However, our NICs of AS model draw a different picture regarding the three portfolios. As shown on the figure, an increase in price has higher impact on VaR than a decrease in price does. This phenomenon appears in all the AS NICs results of the 3 portfolios' both when considering 1% and 5% VaR. These results also deviate from the results Engle gave applying 1993 and 2004 American stock market data. This maybe because of the peculiarity of Chinese stock market which caused by the imperfect market mechanism, incomplete competitive structure and the small traders' psychology-overconfidence (Zhao and Zheng, 2002). This phenomenon was also corresponded with by the estimates of the $\beta_3$ and $\beta_4$ in the AS model formula presented in table 1, in which the absolute values of positive turns $\beta_3$ are larger than negative turn $\beta_4$.

Figure 2. 1% CAViaR News Impact Curves for SSEC

Table 1 gives the three assets' estimates for SAV, AS, Indirect GARCH and Adaptive models specifying 1% VaR. Corresponding standard errors, p-values and RQ function value are also provided. The model precision is evaluated by Hits in-sample (%) and out-of-sample (%) which show the possibility that VaR is exceeded. The $p$ values of DQ test for both in-sample and out-of-sample data are presented to estimated the volatility of forecast models, as stated in Engle and Manganelli (2004).

Observing the results provided in Table1, here are two interesting points for the estimated parameters. One striking result is that the one of autoregressive terms ($\beta_2$) is always significant, which suggests volatility clustering is important in the tails of distributions. Another one should be focused on is the parameters of the positive part of lagged terms in AS model, $\beta_3$. $p$-values of $\beta_3$ suggests strongly significant most of the time, whereas parameter of negative lagged terms $\beta_4$ are sometimes not significantly different from 0. This result indicates the presence of strong asymmetric impact on VaR of lagged returns. Also, the parameters of SAV model are all significant.

3.2 Model Precision and Volatility
Here we analyze the results of Hits in-sample and out-of-sample for different confident levels of VaR. For the 1% VaR results represented in table 1, SAV, AS and Indirect GARCH model work well in describing the left tail evolution for all portfolios, since all values are very close to 1 and even the lowest
one reaches 0.847%. These results indicate admirable model precision. The results for SHBSHR are appealing, generating a rather precise outcome for hits out-of-sample (remarkable precision 1.0% for SAV and 1% for Adaptive). However, the hits out-of-sample results for SSEC and SZSC are not that well which show the model precision diverse dramatically among models ranging from 0 to 1.

Here is another picture when focus on 5% VaR results that is not reported in this paper. The hits in-sample percentages show that SAV, AS, Indirect GARCH model all fit well with three portfolios. However, when considering out-of-sample percentages, only SSEC gets a decent value of 5.2% with SAV model.

| 1% VaR | Symmetric absolute value | Asymmetric slope | Indirect GARCH | Adaptive |
|--------|--------------------------|-----------------|----------------|----------|
|        | SSEC | SHBSHR | SZSC | SSEC | SHBSHR | SZSC | SSEC | SHBSHR | SZSC | SSEC | SHBSHR | SZSC |
| \( \beta_1 \) | 0.102 | 0.2836 | 0.1318 | 0.0474 | 0.0382 | 0.0657 | 0.0608 | 0.1773 | 0.1152 | 1.1226 | 1.0215 | 0.7204 |
| SEs    | 0.017 | 0.0696 | 0.0263 | 0.0424 | 0.0307 | 0.0599 | 0.0609 | 0.0707 | 0.0097 | 0.0659 | 0.0862 | 0.1133 |
| \( p \) value | 0 | 0 | 0.1322 | 0.1017 | 0.1361 | 0.1889 | 0.0487 | 0.0499 | 0 | 0 | 0 |
| \( \beta_2 \) | 0.9161 | 0.8049 | 0.9051 | 0.8687 | 0.8278 | 0.8634 | 0.8881 | 0.7436 | 0.8528 | 0 | 0 | 0 |
| SEs    | 0.0164 | 0.0444 | 0.0356 | 0.0735 | 0.0405 | 0.0719 | 0.0364 | 0.0471 | 0.0214 | 0 | 0 | 0 |
| \( p \) value | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| \( \beta_3 \) | 0.3237 | 0.7123 | 0.3364 | 0.5781 | 0.868 | 0.5777 | 0.8756 | 1.9386 | 0.9752 | 0 | 0 | 0 |
| SEs    | 0.0425 | 0.1338 | 0.0956 | 0.2315 | 0.276 | 0.2234 | 2.0343 | 2.0493 | 0.5107 | 0 | 0 | 0 |
| \( p \) value | 0 | 0 | 0.0002 | 0.0063 | 0.0008 | 0.0049 | 0.3335 | 0.1721 | 0.0281 | 0 | 0 | 0 |
| \( \beta_4 \) | 0 | 0 | 0 | 0.2541 | 0.3162 | 0.2289 | 0 | 0 | 0 | 0 | 0 | 0 |
| SEs    | 0 | 0 | 0 | 0.215 | 0.1107 | 0.1865 | 0 | 0 | 0 | 0 | 0 | 0 |
| \( p \) value | 0 | 0 | 0 | 0.1187 | 0.0021 | 0.1099 | 0 | 0 | 0 | 0 | 0 | 0 |
| RQ     | 81.609 | 3 | 92.4175 | 6 | 89.411 | 75.749 | 5 | 82.8831 | 86.812 | 78.915 | 87.6482 | 88.378 | 89.300 | 108.240 | 100.396 |
| Hits in-sample (%) | 1.0222 | 1.0222 | 0.9638 | 0.9638 | 1.0222 | 1.0222 | 1.0222 | 1.0222 | 1.0222 | 0.847 | 0.9638 | 1.0222 |
| Hits out-of-sample (%) | 0.4 | 1 | 0 | 0.4 | 1.6 | 0.2 | 0.4 | 1.8 | 0.6 | 0.4 | 1 | 0.6 |
| DQ in-sample \( p \) value | 0.7205 | 0.8473 | 0.7355 | 0.5146 | 0.7428 | 0.5636 | 0.8832 | 0.8709 | 0.8719 | 0.6373 | 0.3369 | 0.0593 |
| DQ out-of-sample \( p \) value | 0.8743 | 0.9996 | 1 | 0.9194 | 0.7576 | 0.766 | 0.8982 | 0.3735 | 0.9826 | 0.8061 | 0.4517 | 0.7769 |

RQ: the value of the regression quantile objective function
Hits in-sample/ out-of-sample: the percentage of times the VaR is exceeded
DQ: dynamic quantile test

No model is rejected by DQ test at 1% significant level both for in-sample and out-of-sample data. Increase the significant level to 5%, in-sample Indirect GARCH and Adaptive for SHBSHR are rejected.
The fact that SHBSHR is traded in dollars and closely connected to global stock market may cause this result. While out-of-sample AS for SHBSHR and SZSC are also rejected. Notice that the news of revision of Securities Law released a year prior which may influence the expectation and data is included in out-of-sample calculation.

3.3 Model Selection
The general results of back-testing indicated by DQ test and Hits percentage value are satisfied, indicating the validity of CAViaR model. In reality, criterions should be considered as the strategies of model selection (Wang, 2010). The insignificant models are excluded at first. In the second stage, DQ test provide evidence in choosing models. Among the survival models, the one with the lowest RQ value will be a desirable choice.

By employing these criterions in the empirical results, we can draw a conclusion in model selections when facing different stock market. Firstly we analyze the relevant statistics for the four CAViaR specifications of 1% VaR. Both SAV and Adaptive model provide significant parameter estimates for SSEC, SHBSHR and SZSC. However, Adaptive model didn’t perform well in DQ test. Considering the Hits percentage value and RQ value, SAV seems to be a good choice for SHBSHR. And it is also suitable for SSEC if remove the out-of-sample data. Indirect GARCH model also works well in parameter estimates for SZSC. With satisfied DQ test and Hits percentage value, it would be a desirable model for SZSC with the RQ value of 88.3786. Following the same steps, we can have the model selection results for 5% VaR estimation.

4. Conclusion
CAViaR models, even though not a new approach, is a classical method to estimate VaR. By incorporating a set of models, namely AS model, SAV model, Indirect GARCH model and Adaptive model, a back-test of China's stock market during the 10 May 2004 and 30 June 2020 is provided. The empirical results fit the real situation well in general. The results depict characters of the three portfolios, SSEC, SZSC and SHBSHR, by estimates and relevant statistics of 1% and 5% VaR for the four CAViaR Specifications. Hits in-sample and out-of-sample, DQ test are used to test model precision and volatility. While the VaR plots illustrate the fluctuations of portfolios, the NICs provide the information of how shocks affect market risks. It is noticeable that the AS NICs provide contradicting results to previous study. The reason for this interesting result may be the imperfect stock markets and small traders' psychology-overconfidence in China. Last, according to the model selection criterian, SAV is a proper model for calculating 1% VaR of SHBSHR and SSEC. It is better for SZSC to choose Indirect GARCH model for 1% VaR estimation.

5. Possible extension
Firstly, even though model selection criterion can be applied to assess model validity in calculation different VaR, uncertainty related to model selection in CAViaR model estimators causes some problems of identifying the better quantile predictor. Extensions can be created by solving the uncertainty problems, and a quasi-Bayesian model averaging model may provide such solution (Tsionnas, 2014). Secondly, by choosing the frequency of re-estimation cautiously (such as a year), the practical application effect of CAViaR model can be improved. Research results of CAViaR models can be extended to other risk managements in capital markets, such as exchange rate and interest rates, thus improve the market risk measurement level of financial institutions.

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