A gourmet's delight: caviar and the australian stock market

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Value-at-Risk (VaR) is the metric adopted by the Basel Accords for banking industry internal control and regulatory reporting. This has focused attention on the measuring, estimating and forecasting of lower tail risk. Engle and Manganelli (2004) developed the CAViaR model using Quantile Regression to calculate (VAR). In this paper we apply their model to Australian Stock Market indices and a sample of stocks, and test the efficacy of four different specifications of the model in a set of in and out of sample tests. We also contrast the results with those obtained from a GARCH(1,1) model, the RiskMetrics™ model and an APARCH model

I. Introduction

Value at risk (VaR) was adopted in the Basel Accords, beginning in 1988. Little research has been undertaken on the uses and applications of VaR or related metrics in Australia: Sy (2006), Engel and Gizycki (1999) and Gizycki and Hereford (1999) consider aspects of VaR, and Allen and Powell (2009) contrast VaR and CVaR (Conditional Value at Risk) as alternative risk metrics in an Australian context. This paper extends Australian empirical work by assessing the relative performance of the CAViaR model of Engle and Manganelli (2004).

There is an enormous body of work on volatility modelling, particularly the models nested in the ARCH/GARCH family. See surveys by Li, Ling and McAleer (2002); ARCH models by Bollerslev, Engle and Nelson (2003); and Jorion's (2006) review of VaR. Quantile regressions techniques were developed by Basset and Koenker (1978). (see Koenker's review (2005)). Davis and Dunsmuir (1997) and Koenker and Zhao (1996) extended applications in the time series domain. Taylor (2008) provided further extensions to the CAViaR model.

We apply Engle and Manganelli's (2004) CAViaR model to an Australian data set and compare the value at risk forecasts with one day ahead VaR forecasts obtained from GARCH(1,1), RiskMetrics^{TM} and Skewed student-t APARCH(1,1). The paper is divided into four sections; the following section two introduces quantile regressions, the CAViaR model, the data and the research design; section three presents the results and section four concludes.

II. The Research Design.

CAViaR

CAViaR, predicts VaR by modelling the lower quantiles, using a conditional autoregressive specification. Engle and Manganelli (2004) propose four different specification processes:: an Adaptive model, a Symmetric Absolute Value, an Asymmetric Slope and an Indirect GARCH model which we follow.

The Adaptive model is given by

$$f_t(\beta) = f_{t-1}(\beta_1) + \beta_1\{[1 + \exp(G[y_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \theta\}, \tag{1}$$

The symmetric absolute value model::

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3|y_{t-1}| \tag{2}$$

The asymmetric Slope model:

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3(y_{t-1})^+ + \beta_4(y_{t-1})^- \tag{3}$$

where, notation $(x)^+=max(x,0)$, $(x)^-=-min(x,0)$.

The indirect GARCH (1,1) model:

$$f_t(\beta) = (\beta_1 + \beta_2 f^2{}_{t-1}(\beta) + \beta_3 y^2{}_{t-1})^{1/2} \tag{4}$$

Other Var Models

We apply a standard Garch (1,1) model**,** the RiskMetrics^{TM} model, neither of which we will specify, plus the APARCH (1,1) model.

The APARCH(p,q) (Ding, Granger, and Engle (1993) model:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \tag{5}$$

where ω, α_i, γ_i, β_j and δ are the parameters to be estimated, also $\delta > 0$ and $-1 < \gamma_i < 1$ $(i = 1, \ldots, q)$.

Here δ gives the Box-Cox transformation of σ_t, while γ_i reflects the impact of negative and positive returns on volatility, or the leverage effect.

The VaR results from the four CAViaR methods and the other VaR models, viz., Gaussian Garch (1,1), RiskMetrics™ and Skewed student-t APARCH are tested using a dynamic quantile test, proposed by Engle and Manganelli (2004).

Data & Methodology

We apply the four CAViaR methods to the data: viz. two indices: the ASX-200, and the ASX-50 plus two stocks: NAB and ANZ, for a period of 15 years (September 1994-September 2009). This period includes the Global Financial Crisis. First, we include the GFC period, and then we exclude it (roughly the last two years of daily data, results not reported). A 500 day out of sample period is chosen here. We use percentage daily returns calculated in logarithms. Our data set amounts to 3869 observations (including the GFC period) and 3167 observations (excluding the GFC period).

We use 1000 returns with a 250 days forward moving window to forecast one day ahead 1% VaR (results for 5% are available from the authors), using Gaussian Garch(1,1), RiskMetrics™ and Skewed Student-t APARCH (1,1) VaR models, we estimate the models using the first 250 days and forecasting the one day ahead VaR, move the window a day ahead and re-estimate the model for forecasts. This is done to forecast 750 daily VaR values, for a period including the GFC, and then compare results with CaViAR using the DQ test. The R code from Lima and Neri (2007), is modified and used to calculate these three VaR models.

Backtest

The performance of the VaR models is assessed by computing their failure rates The failure rate can be defined as the number of times the return on a specific day exceeds (in absolute value) the forecasted VaR.. (See Kupiec (1995)).

A relevant VaR model should also feature a sequence of VaR violations which are not serially correlated. Engle and Manganelli (2004), suggest the Dynamic Quantile or DQ test. (We are thankful to Simone Manganelli for making available his MATLAB code for the exercise).

III. Results

We obtain our daily data series from Datastream and convert them into continuously compounded daily return series scaled by 100. We then estimate the 1% VaRs using the four models. The results for 1% VaRs are presented in Table 1 which includes the whole data set incorporating the financial crisis period. The table includes the values of the estimated parameters, and their associated standard errors and (one-sided) p values. It also shows the value of the regression quantile objective function, the percentage of times the VaR is exceeded, plus the p value of the DQ tests for both in and out of sample cases. In the out of sample DQ tests the instruments used were a constant, the VaR forecast and the first four lagged hits.

Table 1 shows that the autoregressive term (β_2) is always significant suggesting volatility clustering is important in the tails of the distributions. All the models appear to be highly precise, as measured by the in sample hits. In Table 1 for the 1% VaR all values are very close to 1, the weakest being the adaptive model, which has a value of 0.83 in the case of NAB.

In the out of sample tests none of the models work well .The DQ tests for the in-sample cases suggest no rejection of the asymmetric slope model. The results from the out of sample, DQ test shows that the technique loses its effectiveness at the time of financial distress (all values are lower than 1%). Figure 1 provides the graphs of the estimated 1% CAViaR specifications for the ASX-200. Fig. 3 shows the news impact curve, (calculated from the effects of one day lag data) for the ASX-200. The best-performing model, the asymmetric slope model, suggests that negative returns are likely to have a much stronger effect on the VaR estimate than positive returns. (This parallels findings in Allen, McAleer and Scharth (2009)).

Table 1. Estimates for four CAVIAR specifications (1% level)

INDIRECT GARCH		ASYMMETRIC SLOPE				SYMMETRIC ABSOLUTE VALUE			
ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200
0.668	0.750	0.595	0.329	0.199	0.182	0.548	0.204	0.349	0.582
0.313	0.346	0.696	0.462	0.088	0.081	0.321	0.185	0.152	0.130
0.016	0.015	0.196	0.238	0.012	0.013	0.044	0.135	0.011	0
0.699	0.614	0.656	0.851	0.784	0.791	0.759	0.923	0.793	0.642
0.070	0.078	0.348	0.201	0.069	0.068	0.143	0.080	0.093	0.099
0	0	0.030	0	0	0	0	0	0	0
0.989	1.507	0.477	0.228	0.138	0.081	0.567	0.131	0.323	0.745
1.079	1.377	0.511	0.394	0.057	0.059	0.297	0.122	0.117	0.214
0.180	0.137	0.175	0.282	0.008	0.085	0.028	0.143	0.003	0.000
0	0	0.895	0.217	0.660	0.671	0	0	0	0
0	0	0.960	0.248	0.226	0.267	0	0	0	0
0	0	0.176	0.191	0.002	0.006	0	0	0	0
93.399	89.119	215.791	236.830	90.965	86.625	216.454	238.387	94.755	90.393
0.980	0.980	1.009	1.009	1.009	1.009	0.980	0.980	0.980	0.980
3.800	4.000	3.200	3.400	3.600	4.000	2.400	3.200	4.200	3.800
0.000	0.000	0.733	0.923	0.075	0.073	0.752	0.485	0	0.000
0	0	0	0	0	0	0.002	0	0	0

	ADAPTIVE					
	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ
Beta1	0.168	0.358	0.339	0.294	2.210	2.047
Std Errors	0.102	0.110	0.110	0.072	1.161	2.563
p Values	0.050	0.001	0.001	0	0.029	0.212
Beta2	0	0	0	0	0.606	0.756
Std Errors	0	0	0	0	0.117	0.192
p Values	0	0	0	0	0	0
Beta3	0	0	0	0	1.900	0.693
Std Errors	0	0	0	0	1.898	1.201
p Values	0	0	0	0	0.158	0.282
Beta4	0	0	0	0	0	0
Std Errors	0	0	0	0	0	0
p Values	0	0	0	0	0	0
RQ	229.504	245.101	96.711	94.283	218.805	240.404
Hits in-sample(%)	0.831	1.039	1.069	1.039	0.980	0.980
Hits out-of-sample(%)	3.600	3.200	1.600	1.800	3.200	3.800
DQ In Sample (p value)	0	0.077	0	0	0.955	0.769
DQ Out of Sample (p value)	0	0	0.001	0.003	0	0

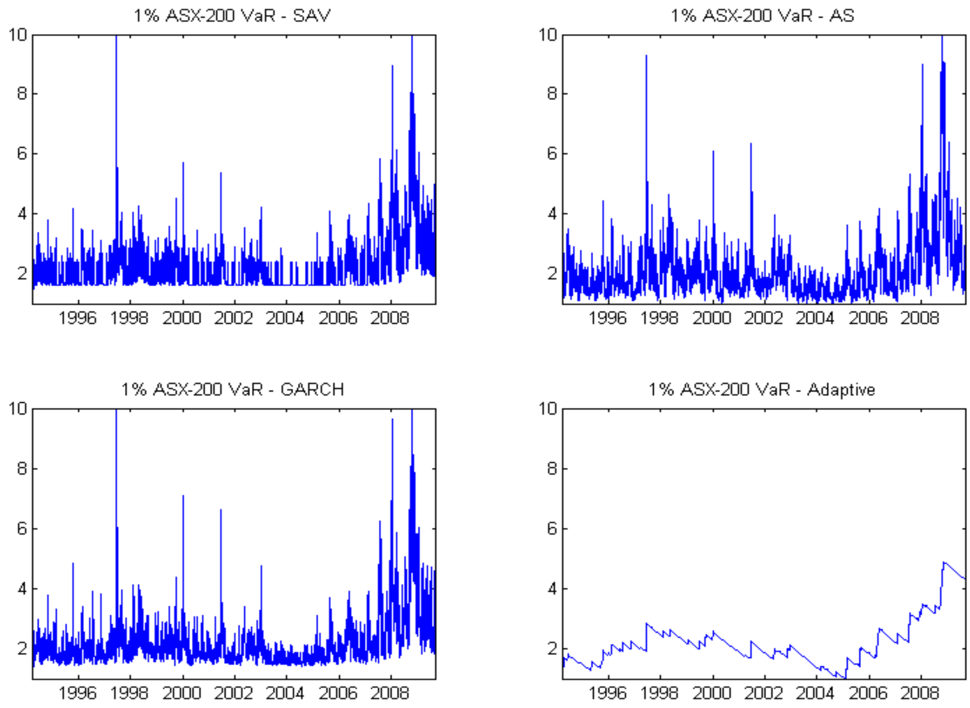

Figure 1. Estimated CAViaR graph 1%

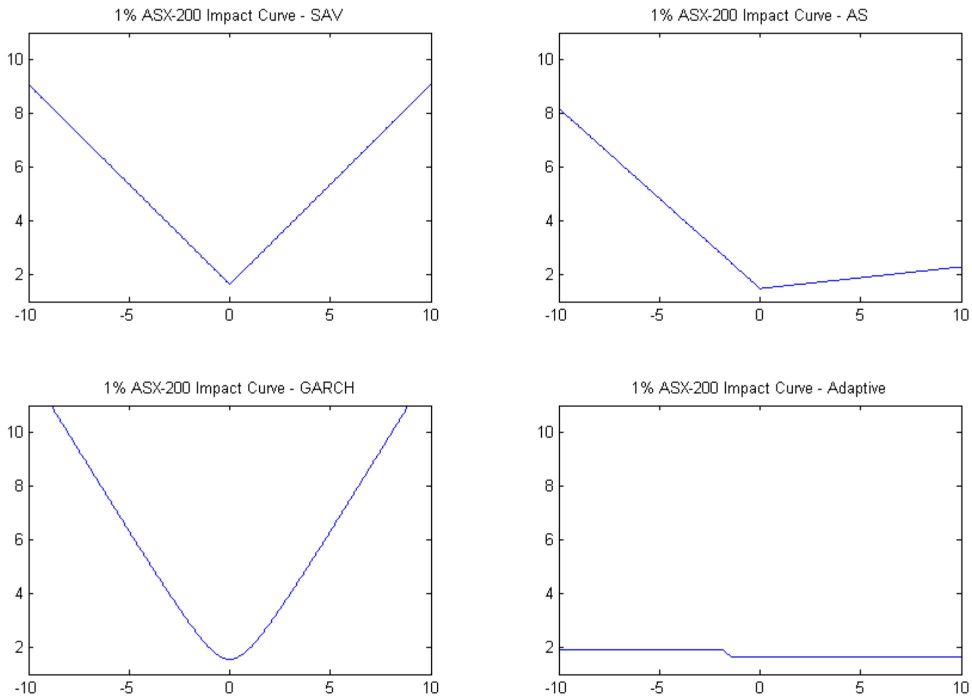

Figure 2. News impact curve for 1% CAVIAR specifications

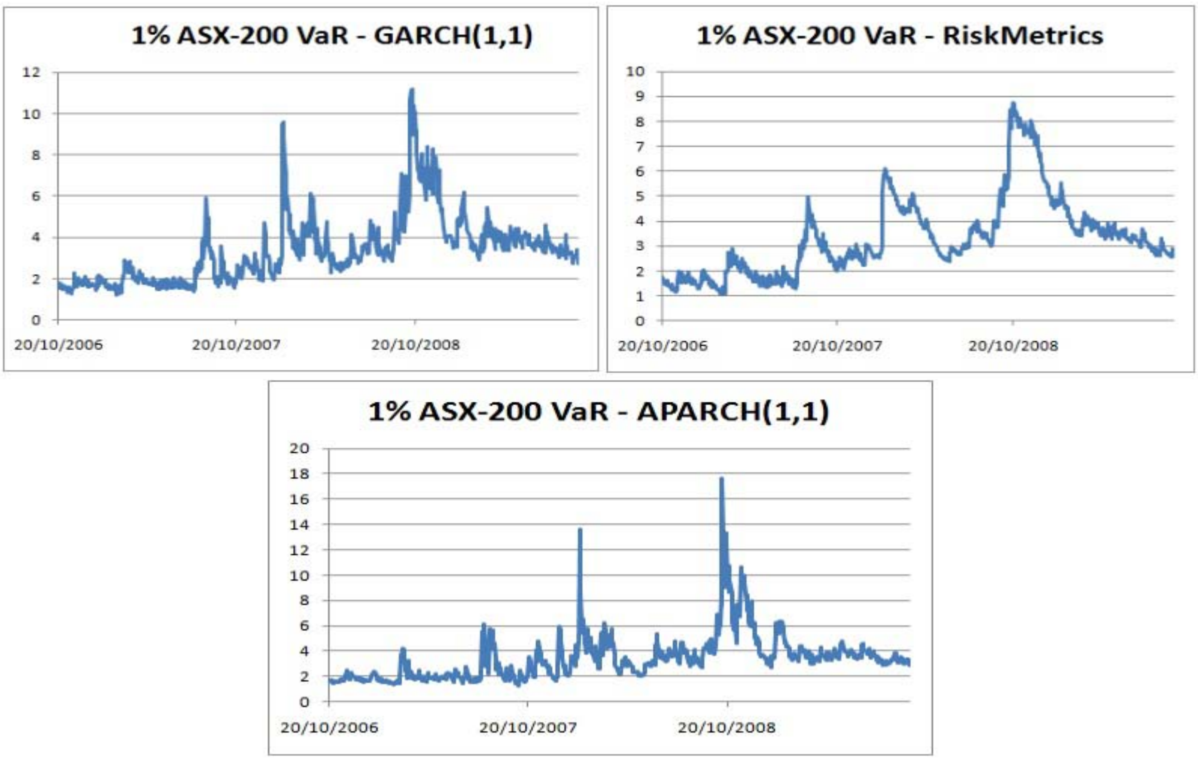

Figure 3. Normal GARCH(1,1), RiskMetrics and Skewed student-t APARCH(1,1) 1% VaR

Table 2. DQ Test Results for GARCH(1,1), riskmetrics and skewed student-t APARCH(1,1) 1% var

VaR (1%)	GARCH(1,1)				RiskMetrics				APARCH(1,1)			
	ASX-200	ASX-50	ANZ	NAB	ASX-200	ASX-50	ANZ	NAB	ASX-200	ASX-50	ANZ	NAB
DQ Hits	98.889	68.180	22.755	18.308	92.824	93.140	18.593	15.188	19.479	10.262	11.012	12.601
DQ (p Value)	0	0	0.001	0.006	0	0	0.005	0.019	0.003	0.114	0.088	0.050

One day ahead 1% VaR forecasts obtained from GARCH (1,1), RiskMetrics and Skewed student-t APARCH(1,1) are shown in (fig 3). Table 2, gives the DQ test results for 1% VaR, which shows that DQ test rejects the GARCH(1,1) and RiskMetrics model for the sample time series returns whilst APARCH(1,1) performs slightly better.

The significant DQ test results for the out of sample period, as indicated in Table 1 suggest rejection of all the models in this period. This was most likely due to the impact of the GFC. We tested this justification by excluding the period of the market turmoil from our sample data and then re-tested the specifications as proposed (these results are available from the authors on request). The results prove that this interpretation is correct and the out of sample estimates become significant when the period of turmoil is removed from the empirical investigation. In this case again the specification which works the best for the Australian market is the Asymmetric Slope Model. The GARCH based and similar models for VaR forecasting are not as efficient as CAViaR.

IV. Conclusion

We present a comparative analysis of CAViaR to GARCH(1,1), RiskMetrics and Skewed student-t APARCH(1,1) one day ahead VaR forecasts; and CAViaR appears to be superior. (Our out of sample results improve when the GFC is removed). All our models produce an excessive number of violations of the VaR in the period including the GFC and the DQ tests reject the models for this out of sample period.

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