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ABSTRACT

Value-at-Risk (VaR) has become the universally accepted metric adopted internationally under the Basel Accords for banking industry internal control and for regulatory reporting. This has focused attention on methods of measuring, estimating and forecasting lower tail risk. One promising technique is Quantile Regression which holds the promise of efficiently calculating (VAR). To this end, Engle and Manganelli in (2004) developed their CAViaR model (Conditional Autoregressive Value at Risk). 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

Keywords: VaR; Quantile regressions; Autoregressive; CAViaR

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1. Introduction

Value at risk (VaR) remains the standard measure of market risk used by financial institutions and their regulators since it was first promoted by J.P. Morgan and RiskMetrics and subsequently adopted in the Basel Accords, beginning in 1988. VaR is used globally by financial institutions and their regulators and Australia has also adopted the Basel Accords. In June 2003, APRA announced its decision to implement Basel II in its totality. The International Monetary Fund (2009) under-took an analysis of Basel 11 implementation in Australia and was largely complementary, but noted that: "It will be important for APRA to continue to undertake increasingly complex work (drill down reviews for advanced banks, stress testing, assessment of Pillar 2 risks, and economic capital models, etc.) to assure itself that banks remain well capitalized relative to their risks".

Despite the importance of this topic, very little research has been undertaken on the uses and applications of VaR or related metrics at all in Australia. A search of the Australian Prudential Regulatory Authority's (APRA) website revealed Sy (2006), Engel and Gizycki (1999) and Gizycki and Hereford (1999) as being the only papers considering aspects of VaR. More recently Allen and Powell (2009) have contrasted VaR and CVaR (Conditional Value at Risk) as alternative risk metrics in an Australian context. This paper seeks to further address this gap in Australian empirical work by assessing the relative performance of the recently developed CAViaR model (Conditional Autoregressive Value at Risk by regression quantiles model of Engle and Manganelli (2004) with more customary approaches.

VaR is a measure of how much a certain portfolio can lose within a given time period, for a given confidence level. Despite its apparent simplicity in summarizing the downside risk of a portfolio it is not an easy number to calculate. To summarise: Value-at-Risk (VaR) is probably the most used measure of risk since the 1996 amendment to the Basel Capital Accord which proposed that commercial banks with significant trade activity could use their own VaR measure to define how much capital they should set aside to cover their market risk exposure, and typically bank regulatory agencies audit the VaR methodology employed by the banks. (See the APRA website; http://www.apra.gov.au/ADI/Prudential-Standards-and-Guidance-Notes-for-ADIs.cfm).

Its application has also been fostered by the enormous body of work on volatility modelling, such as the time series models nested in the ARCH/GARCH family. For surveys of the latter see Li, Ling and McAleer (2002), the survey of ARCH models by Bollerslev, Engle and

Nelson (2003), whilst Jorion (2006) reviews the concept and applications of VaR. (See Holton (2003) also). Subsequently, there have been parallel developments in the stochastic volatility and realised volatility literature.

The empirical literature on modelling VaR contains three different categories of methods: parametric, nonparametric and semi-parametric.

1. Parametric approaches involve a parameterisation of the behaviour of prices. Quantiles are estimated using a volatility forecast with an assumption about the type of the distribution utilised; e.g. Gaussian. Typically, exponential smoothing or a GARCH model is used to forecast the volatility.
2. The most widely used nonparametric method is historical simulation, which requires no distributional assumptions and estimates the VaR as the quantile of the empirical distribution of historical returns from a moving window drawn from recent periods.
3. An alternative approach is to use a quantile regression based methods as in Engle and Manganelli (2004) who consider an autoregression of the estimated VaRs. Thus, whilst statistical volatility models rely on the assumption that the shape of the conditional distribution is fixed over time and that it is only the volatility that varies. The recently proposed Conditional Autoregressive Value at Risk (CAViaR) model requires no such assumption, and allows quantiles to be modelled directly in an autoregressive framework.

The development of quantile regressions techniques was by Basset and Koenker (1978). (For a comprehensive account of these recent developments see Koenker (2005)). Koekner (2005) notes that: "Quantile regression is gradually emerging as a unified statistical methodology for estimating models of conditional quantile functions. By complementing the exclusive focus of classical least-squares regression on the conditional mean, quantile regression offers a systematic strategy for examining how covariates influence the location, scale, and shape of the entire response distribution". This approach had been directly foreshadowed by Boscovitch and Laplace in the 18th Century and in the next by Edgeworth (1888). Applications of quantile regressions in the time series domain have been slowly developing. Davis and Dunsmuir (1997) were some of the first with a very general treatment of the asymptotics of the median regression estimator for regression models with autoregressive moving average (ARMA) errors, obtaining an asymptotically normal theory under quite general conditions. Koenker and Zhao (1996) began work on developing a type of ARCH framework for applications of quantile regressions. Recently, Engle and Manganelli (2004) have developed the CAViaR model. Taylor (2008) has extended the model to include double kernel quantile regressions in the context of an exponentially weighted framework. Taylor (2008) points out that estimating the VaR amounts to forecasting, conditional on current information, the tail quantiles of the distribution of a series of financial returns. Although a variety of approaches have been proposed for forecasting conditional tail quantiles, there is no established method. Quantile regression is very promising technique because of its strength in exploring relationships with covariates through the quantiles.

In this article we apply Engle and Manganelli's (2004) CAViaR model to an Australian index and a sample of Australian stocks and compare the value at risk forecasts with one day ahead Var forecasts obtained by means of Gaussian GARCH(1,1) VaR, 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 with the other VaR models used for the study and the data and research design implemented in the paper, section three presents the results and a short conclusion follows in section four.

2. Quantile Regression ,the CAViaR model and the Research Design.

2.1 QUANTILE REGRESSION

CAViaR uses quantile regression for estimation of its parameters; first introduced by Koenker and Bassett (1978), as an extension of classical ordinary least squares (OLS) estimation of conditional mean models to the estimation of a group of models for conditional quantile functions for a data distribution. The central special case is the median regression estimator that minimizes a sum of absolute errors. The remaining conditional quantile functions are predicted by minimizing an asymmetrically weighted sum of absolute errors, weights being the function of quantile of interest. This makes quantile regression a robust technique even in presence of outliers. Taken together the group of estimated conditional quantile functions offer a more complete view of the effect of covariates on the location, scale and shape of the distribution of the response variable.

Quantiles refer to the generalized case of dividing an unconditional distribution into parts. The technique of quantile regression extends this idea to build models which express the quantile of conditional distribution of the response variable as function of observed covariates. Linear regression coefficient represents the change in the response variable produced by a one unit change in the predictor variable associated with that coefficient. Quantile regression coefficients gives the change in a specified quantile of the response variable produced by a one unit change in the predictor variable.

Consider a series of observations on random variables generated by the following model

$$y_t = x'_t\beta_\theta + \varepsilon_{\theta t}, \qquad Quant_\theta(y_t|x_t) = x_t{}'\beta_\theta \tag{1}$$

Where x_t is a p-vector of regressors and $Quant_\theta(y_t|x_t) = x_t{}'\beta_\theta$ is the θ quantile of y_t conditional on x_t.

Koenker and Bassett (1978) show that θ^{th} regression quantile is defined as any $\hat{\beta}_\theta$ that solves the following generalized objective function

$$\min_\beta \frac{1}{T}\left\{\sum_{t:y_t\geq x_t'\beta} \theta|y_t - x_t'\beta| + \sum_{t:y_t<x_t'\beta}(1-\theta)|y_t - x_t'\beta|\right\} \tag{2}$$

Let $f_t(\beta) \equiv x_t\beta$, rewriting the above expression in terms of indicator function ($I()$) gives the equivalent objective function

$$min_\beta \frac{1}{T}\sum_{t=1}^{T}[\theta - I(y_t < f_t(\beta))][y_t - f_t(\beta)] \tag{3}$$

To simplify, Quantiles as proposed by Koenkar and Bassett (1978) can be defined through an optimization problem. Similar to the problem of defining sample mean as the solution of the problem of minimizing the sum of squared residuals (as done in OLS regression), the median quantile (0.5) is defined through the minimization of sum of absolute residuals. The symmetrical piecewise linear absolute value function assures same number of observations above and below the median of the distribution.

We will not discuss further the mathematical details of the regression technique, please refer to Koenker's (2005) monograph for a comprehensive discussion.

2.2 CAViaR

The problem in estimating VaR is that it is a particular quantile of potential future portfolio values, conditioned on current available information. However, portfolio returns and risk change over time, so a time-varying forecasting procedure is required. Essentially this involves forecasting a value each period that will be exceeded with a probability of *(1-θ)* by the current portfolio value. In this case $\theta \in (0,1)$ are representative of the confidence level attached to the VaR.

CAViaR, uses quantile regressions and instead of modelling the whole return distribution for calculation of VaR, it models the required quantiles of the return distribution directly. To predict the value at risk by modelling the lower quantiles, the model uses a conditional autoregressive specification, inspired by the fact that the distribution of volatilities over time is auto-correlated, hence the model. Engle and Manganelli (2004) propose four different specification processes for the calculation of value at risk viz: an Adaptive model, a Symmetric Absolute Value, an Asymmetric Slope and an Indirect GARCH model. We follow suit and test the relative suitability of all the four models on our Australian sample data set in the calculation of VaR and contrast the results with those of more standard approaches.

The first model; an Adaptive model, is a smoothed version of a step function (for finite G), is given by

$$f_t(\beta) = f_{t-1}(\beta_1) + \beta_1\{[1 + \exp(G[y_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \theta\}, \tag{4}$$

Adaptive model as the name suggests changes itself depending on whether VaR is exceeded or not, it takes a higher value when VaR is exceeded but decreases slightly otherwise. Engle and Manganelli (2004) note that the structure of the Adaptive CAViaR model is such that the estimator increases the VaR uniformly regardless of the extent the returns exceed the VaR.

A second model which features symmetric absolute values is set out below:

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3|y_{t-1}| \tag{5}$$

A third has an asymmetric Slope:

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3(y_{t-1})^+ + \beta_4(y_{t-1})^- \tag{6}$$

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

Whilst the fourth is an indirect GARCH (1,1):

$$f_t(\beta) = (\beta_1 + \beta_2 f^2{}_{t-1}(\beta) + \beta_3 y^2{}_{t-1})^{1/2} \tag{7}$$

These last three models are similar to GARCH models in structure, the second and the fourth model are symmetrical and hence responds symmetrically to past returns. The third model responds asymmetrically to returns and captures the asymmetric leverage effect. The fourth model is same as GARCH(1,1) model in form but with a difference of estimation technique used, this model estimated by directly using quantile regressions against the maximum likelihood in usual GARCH.

Taylor (1986) and Schwert (1988), first introduced VaR models based on symmetric and asymmetric quantile specification, and it was subsequently analysed by Engle (2002). A merit of the CAViaR specification, as suggested by Engle and Manganelli (2004), is that it is more general than these GARCH models.

2.3 OTHER VAR MODELS

2.3.1 Garch (1,1)

A very widely used method of VaR forecast is using Gaussian or normal Garch(1,1) forecasts, which is given by

$$\sigma^2{}_t = \omega + \alpha_1 \varepsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} \tag{8}$$

This model assume normality of the return distribution and uses maximum likelihood for estimation of the model as opposed to the proposed indirect GARCH(1,1) which used quantile regressions to model the specific quantile of interest directly.

2.3.2 RiskMetrics^{TM}

In simplest of its forms the basic RiskMetrics (Morgan, 1996) is equivalent to a normal Integrated GARCH model (IGARCH), where the autoregressive and decay parameters are predefined to 0.94 and 0.06 respectively. RiskMetrics is the most simple and still the most used VaR model available. The model is given by:

$$\sigma^2{}_t = \omega + (1-\lambda)\varepsilon^2{}_{t-1} + \lambda\sigma^2{}_{t-1} \tag{9}$$

Where $\omega = 0$ and λ is usually set to 0.94 for daily data and 0.97 for weekly data. There are many extensions to this basic RiskMetrics model which are freely available at RiskMetrics Group website.

2.3.3 APARCH (1,1) with Skewed Student-t

Ding, Granger, and Engle (1993), introduced the Asymmetric power ARCH, or APARCH model as an extension to GARCH model. The APARCH(p,q) model can be described as

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^{\delta} \tag{10}$$

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

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.

Fernández and Steel (1998), proposed to extend the Student distribution by adding a skewness parameter to account for the excess skewness and kurtosis in the return series. The main drawback with this procedure is that it is modelled in terms of mode and the dispersion of the distribution, which is checked by Lambert and Laurent (2001) who re-expressed the skewed student density in terms of the mean and the variance. This innovation process has zero mean and unit variance.

The innovation process z is said to be (standardized) skewed-Student distributed if:

$$f(z|\xi, \upsilon) = f(x) = \begin{cases} \frac{2}{\xi + \frac{1}{\xi}} sg[\xi(sz + m)|\upsilon], \ if \ z < -\frac{m}{s} \\ \frac{2}{\xi + \frac{1}{\xi}} sg[(sz + m)/\xi|\upsilon], \ z \geq -\frac{m}{s} \end{cases} \tag{11}$$

where $g(.|\upsilon)$ is the symmetric or unit variance Student density and ξ is the asymmetry coefficient. m and s^2 are respectively the mean and the variance of the non-standardized skewed-Student.

To summarize, ξ models the asymmetry, while υ expresses the tail thickness. See Lambert and Laurent (2000, 2001) for detailed explanation.

The VaR results from the four CAViaR methods and the other VaR models, viz., Gaussian Garch (1,1), RiskMetrics^{TM} and Skewed student-t APARCH are tested using a dynamic quantile test, as proposed by Engle and Manganelli (2004). We will omit further details of the methods for the sake of brevity, as further insights can be obtained from their original paper.

2.4 Data and Methodology

We apply the four CAViaR methods to Australian stock market data, viz. Two indices: the ASX-200, and the ASX-50 plus two stocks: NAB and ANZ, from ASX-200 for a period of 15 years (September 1994-September 2009). As this period includes the period of Global Financial Crisis, we do the empirical investigation in two steps. First, we include the GFC period, and then we exclude it (roughly last two years daily data). A 500 day out of sample period is chosen here which amounts to approximately two years of daily returns. We make use of percentage daily returns calculated in logarithms. Our total data set amounts to 3869 observations (including the GFC period) and 3167 observations (excluding the GFC period).

We will use 1000 returns with a 250 days forward moving window to forecast one day ahead 1% and 5% VaR using Gaussian (normal) Garch(1,1), RiskMetrics™ and Skewed Student-t APARCH (1,1) VaR models, we start with estimating the models with first 250 days and forecasting the one day ahead VaR, then moving the window a day ahead and re-estimating the model for forecast. This is done to forecast 750 daily VaR values, for a period including the GFC and excluding it and then compare it with CaViAR model based on the Dynamic Quantile test. The R code from Lima and Neri (2007), is modified and used to calculate these three VaR models.

2.5 Backtest

The performance of the VaR models is assessed by computing their failure rate for the return series. Failure rate can be defined number of times the return on a specific day exceeds (in absolute value) the forecasted VaR for that day. As the computation of failure rate follows a binomial distribution (a sequence of yes and no observations), it is possible to test $H_0: f = \alpha$ against $H_1: f \neq \alpha$, where f is the failure rate.

Kupiec (1995) proposed this test as the unconditional coverage test, in which the hypothesis is tested using a likelihood ratio test. The likelihood ratio test is given as

$$LR = -2\ln\left(\frac{\alpha^N(1-\alpha)^{T-N}}{\hat{\alpha}^N(1-\hat{\alpha})^{T-N}}\right) \tag{12}$$

where N is the number of VaR violations, T is the total number of observations and α is the theoretical failure rate. $\hat{\alpha}$ is defined as $\hat{\alpha} = \frac{N}{T}$. $LR \sim \chi^2_{(1)}$ under the null hypothesis that $\alpha = \hat{\alpha}$.

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 with new *Hit* variable; $Hit_t(\alpha) = I\big(y_t < -VaR_t(\alpha)\big) - \alpha$. DQ test suggest testing jointly the hypothesis that $E\big(Hit_t(\alpha)\big) = 0$ and $Hit_t(\alpha)$ is uncorrelated with the variables included in the information set.

Engle and Manganelli (2004), suggests that both tests can be done using the following artificial regression

$$Hit_t = X\lambda + \epsilon_t, \qquad \epsilon_t = \begin{cases} -\alpha, & prob(1-\alpha) \\ (1-\alpha), & prob(\alpha) \end{cases} \tag{13}$$

Where X is a Txk matrix whose first column is a column of ones the next p columns are $Hit_{t-1},\ldots,Hit_{t-p}$ and the k - p - 1 remaining columns are additional independent variables (including the VaR itself).

The DQ test statistics is given by

$$\frac{\hat{\lambda}' X' X \hat{\lambda}}{\alpha(1-\alpha)} \sim \chi^2(k) \tag{14}$$

Where $\hat{\lambda}$ is the OLS estimate of λ.

Engle and Manganelli (2004) explain that the in-sample test, or DQ test is a specification test for the particular CAViaR process under study and it can be very useful for model selection purposes. They suggest the parallel DQ out of sample tests could be used by regulators to check that the VaR estimates submitted by a financial institution satisfy some basic model specification requirements such as unbiasedness, independent hits and independence of the quantile estimates. We utilise their tests and Matlab code in this paper. (We are thankful to Simone Manganelli for making available his MATLAB code for the exercise).

3. RESULTS

To apply the models we first had to extract our daily index and stock price series from Datastream and convert the series into continuously compounded daily return series which are scaled by 100. We then estimate the 1% and 5% VaRs using the four models previously introduced. In the case of the first adaptive model, we follow Engle and Manganelli (2004) and set G equal to 10. This permits a direct comparison with their sets of results.

The results for 1% and 5% VaRs for the four models are presented in Table 1 and Table 2 which presents the results as obtained for the whole data which includes the financial crisis period. The tables include 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 (equation-3), the percentage of times the VaR is exceeded, plus the p value of the DQ tests for both in and out of sample cases.We follow Engle and Manganelli (2004) and compute the VaR series for CAViaR models by initialising $f_1(\beta)$ to the sample θ quantile using the first 300 observations. In the out of sample DQ tests the instruments used were a constant, the VaR forecast and the first four lagged hits. The algorithm for computing in the in-sample DQ test is explained in Engle and Manganelli (2004).

The results for 1% and 5% VaRs presented in Tables 1 and 2 for this Australian data set share many common characteristics with those presented by Engle and Manganelli (2004) for their US data set which featured General Motors, IBM and the S&P 500 index. One notable result is that the autoregressive term (β_2) is always very significant. This matches their results and implies that volatility clustering is also important in the tails of the distributions, in these cases, in these extreme quantiles. 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. A similar picture emerges for the 5% VaR presented in Table 2. The weakest case is again the adaptive model which has a value of 4.42 for the ASX200 but all its percentage hits are less accurate than the other three models. This finding, which exactly parallels Engle and Manganelli (2004) adds weight to their observation that a focus on the number of exceptions, or breaches of the VaR, as suggested by the Basle Committee on Banking Supervision (1996) is likely to be a sub-optimal way of evaluating a VaR model. This finding, which exactly parallels Engle and Manganelli (2004) adds weight to their observation that a focus on the number of exceptions, or breaches of the VaR, as suggested by the Basle Committee on Banking Supervision (1996) is likely to be a sub-optimal way of evaluating a VaR model.

In the out of sample tests none of the models work well for either 1% or 5% VaRs. They all show excessive breaches of VaR, sometimes double the number targeted. The DQ tests for the in-sample cases suggest no rejection of the asymmetric slope model which appears to have the optimum performance. Once again, the adaptive model is the weakest and it is rejected at the 5% level for 3 of the 4 series with the exception being ANZ.

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%). Also the in sample statistics show that only the Asymmetric Slope specification is efficient for all the sample data for both 1% and 5% VAR. Figure 1 and Figure 2 provide the graphs of the estimated 1% and 5% CAViaR specifications for the ASX-200. The spike at the end indicates the increasing volatility due to the effects of global financial crisis. Figure 3 shows the news impact curve, (calculated from the effects of one day lag data) for ASX-200, which shows the effect on VaR from the previous day's portfolio return when considered as the effect of news or changes in fundamentals. It is notable that 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 is a finding supported by Allen, McAleer and Scharth (2009) in their work on modelling volatility.

As a comparison test, when compared to the one day ahead 1% and 5% VaR forecasts obtained from Gaussian GARCH (1,1), RiskMetrics and Skewed student-t APARCH(1,1) (figure 4, figure 5). Table 3, gives the DQ test results for 1% VaR, which shows that DQ test rejects the GARCH(1,1) and RiskMetrics for all the sample time series returns while it slightly improves in case of APARCH(1,1) but it still doesn't give significant p-values for all the time series. Table 4, gives the DQ test results for 5% VaR, the p-values in this case are significant for few cases, while RiskMetrics is the best performing model in this case GARCH(1,1) and APARCH (1,1) improves slightly. These results shows that according to DQ test none of the model is able to give highly significant VaR results for all the four time series.

Table 1: Estimates for Four CAVIAR Specifications (1% Level)

	ADAPTIVE				INDIRECT GARCH				ASYMMETRIC SLOPE				SYMMETRIC ABSOLUTE VALUE			
	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200
Beta1	0.168	0.358	0.339	0.294	2.210	2.047	0.668	0.750	0.595	0.329	0.199	0.182	0.548	0.204	0.349	0.582
Std Errors	0.102	0.110	0.110	0.072	1.161	2.563	0.313	0.346	0.696	0.462	0.088	0.081	0.321	0.185	0.152	0.130
p Values	0.050	0.001	0.001	0	0.029	0.212	0.016	0.015	0.196	0.238	0.012	0.013	0.044	0.135	0.011	0
Beta2	0	0	0	0	0.606	0.756	0.699	0.614	0.656	0.851	0.784	0.791	0.759	0.923	0.793	0.642
Std Errors	0	0	0	0	0.117	0.192	0.070	0.078	0.348	0.201	0.069	0.068	0.143	0.080	0.093	0.099
p Values	0	0	0	0	0	0	0	0	0.030	0	0	0	0	0	0	0
Beta3	0	0	0	0	1.900	0.693	0.989	1.507	0.477	0.228	0.138	0.081	0.567	0.131	0.323	0.745
Std Errors	0	0	0	0	1.898	1.201	1.079	1.377	0.511	0.394	0.057	0.059	0.297	0.122	0.117	0.214
p Values	0	0	0	0	0.158	0.282	0.180	0.137	0.175	0.282	0.008	0.085	0.028	0.143	0.003	0.000
Beta4	0	0	0	0	0	0	0	0	0.895	0.217	0.660	0.671	0	0	0	0
Std Errors	0	0	0	0	0	0	0	0	0.960	0.248	0.226	0.267	0	0	0	0
p Values	0	0	0	0	0	0	0	0	0.176	0.191	0.002	0.006	0	0	0	0
RQ	229.504	245.101	96.711	94.283	218.805	240.404	93.399	89.119	215.791	236.830	90.965	86.625	216.454	238.387	94.755	90.393
Hits in-sample(%)	0.831	1.039	1.069	1.039	0.980	0.980	0.980	0.980	1.009	1.009	1.009	1.009	0.980	0.980	0.980	0.980
Hits out-of-sample(%)	3.600	3.200	1.600	1.800	3.200	3.800	3.800	4.000	3.200	3.400	3.600	4.000	2.400	3.200	4.200	3.800
DQ In Sample (p value)	0	0.077	0	0	0.955	0.769	0.000	0.000	0.733	0.923	0.075	0.073	0.752	0.485	0	0.000
DQ Out of Sample (p value)	0	0	0.001	0.003	0	0	0	0	0	0	0	0	0.002	0	0	0

Table 2 : Estimates for Four CAVIAR Specifications (5% Level)

	ADAPTIVE				INDIRECT GARCH				ASYMMETRIC SLOPE				SYMMETRIC ABSOLUTE VALUE			
	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200
Beta1	0.297	0.235	0.085	0.123	0.125	0.235	0.156	0.121	0.081	0.060	0.069	0.074	0.213	0.127	0.119	0.165
Std Errors	0.052	0.039	0.032	0.041	0.039	0.109	0.070	0.047	0.039	0.028	0.022	0.035	0.084	0.031	0.044	0.038
p Values	0	0	0.004	0.002	0.001	0.016	0.013	0.005	0.019	0.015	0.001	0.016	0.005	0	0.003	0
Beta2	0	0	0	0	0.938	0.881	0.801	0.789	0.904	0.908	0.880	0.857	0.850	0.898	0.879	0.830
Std Errors	0	0	0	0	0.007	0.021	0.041	0.034	0.030	0.021	0.038	0.047	0.056	0.023	0.043	0.037
p Values	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Beta3	0	0	0	0	0.068	0.160	0.281	0.347	0.114	0.123	0.042	0.041	0.167	0.148	0.147	0.218
Std Errors	0	0	0	0	0.267	0.176	0.092	0.151	0.043	0.039	0.055	0.040	0.050	0.033	0.029	0.043
p Values	0	0	0	0	0.400	0.181	0.001	0.011	0.004	0.001	0.224	0.149	0.001	0	0	0
Beta4	0	0	0	0	0	0	0	0	0.124	0.143	0.247	0.317	0	0	0	0
Std Errors	0	0	0	0	0	0	0	0	0.048	0.026	0.079	0.109	0	0	0	0
p Values	0	0	0	0	0	0	0	0	0.005	0	0.001	0.002	0	0	0	0
RQ	568.528	602.671	315.075	298.806	562.865	607.282	310.937	295.440	558.334	597.072	305.697	289.118	560.724	598.899	312.262	297.835
Hits in-sample(%)	4.512	4.868	4.571	4.423	5.016	5.076	5.016	4.987	5.016	5.046	5.016	5.016	4.987	4.987	4.957	5.016
Hits out-of-sample(%)	6.200	6.600	8.200	6.800	11.200	9.200	11.200	11.000	11.000	8.400	9.800	9.800	12.000	8.600	11.200	10.800
DQ In Sample (p value)	0.119	0.281	0.009	0.020	0.002	0.251	0.011	0.011	0.991	0.069	0.432	0.921	0.874	0.411	0.019	0.003
DQ Out of Sample (p value)	0.014	0.117	0	0.000	0	0.000	0	0	0	0.005	0	0	0	0.003	0	0

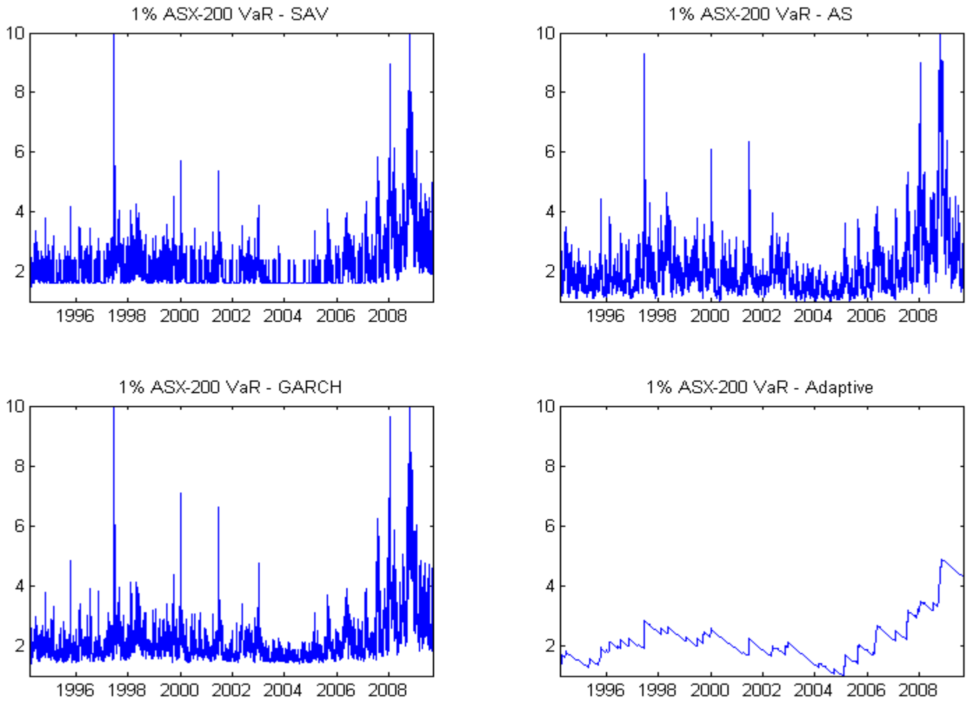


Figure 1: Estimated CAViaR Graph 1%

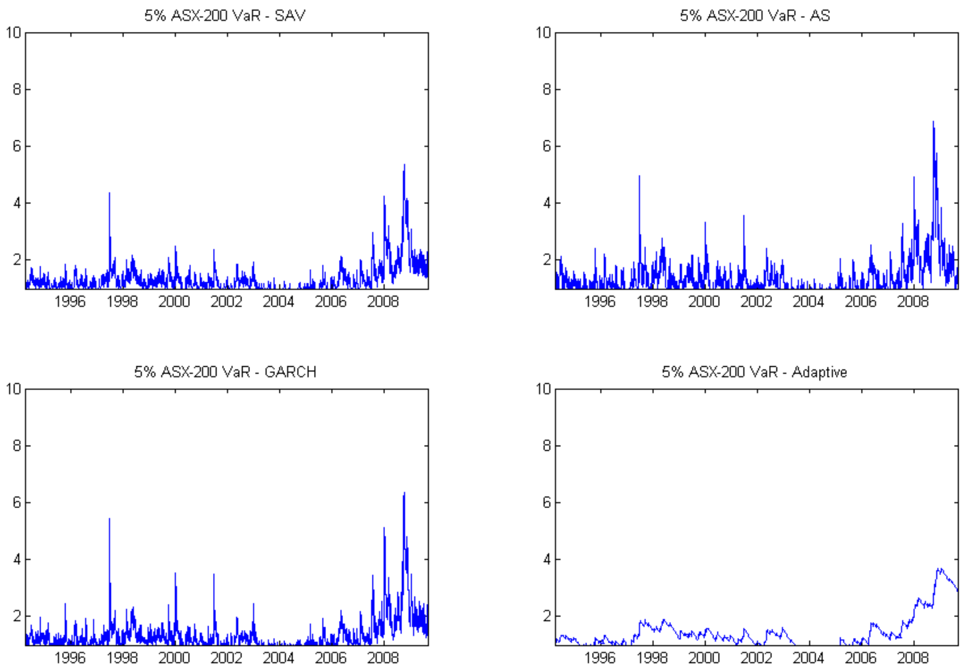


Figure 2: Estimated CAViaR Graph 5%

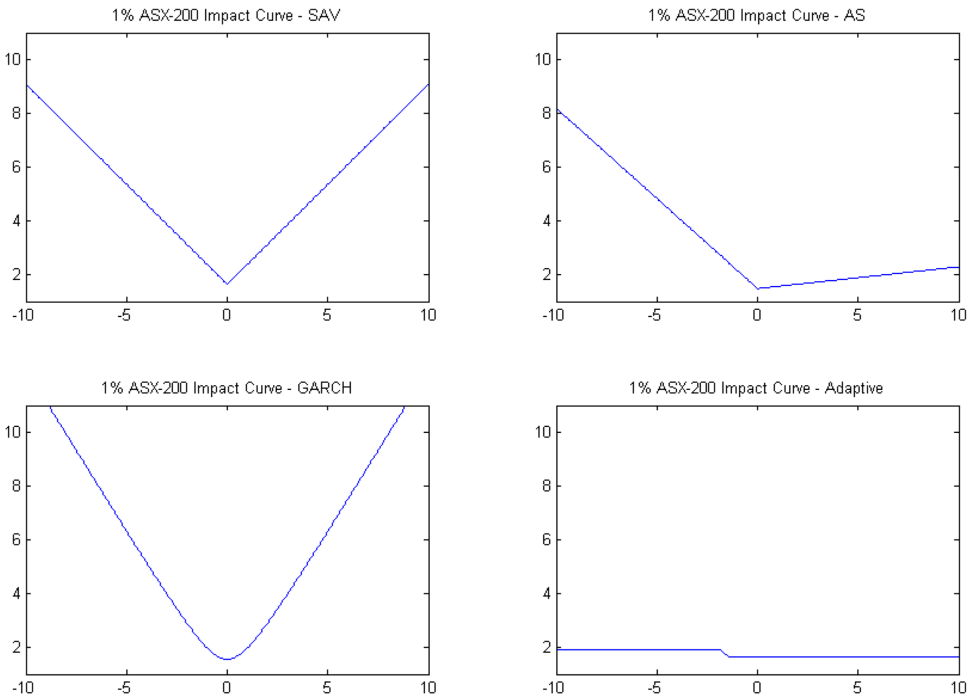


Figure 3: News Impact Curve for 1% CAVIAR specifications

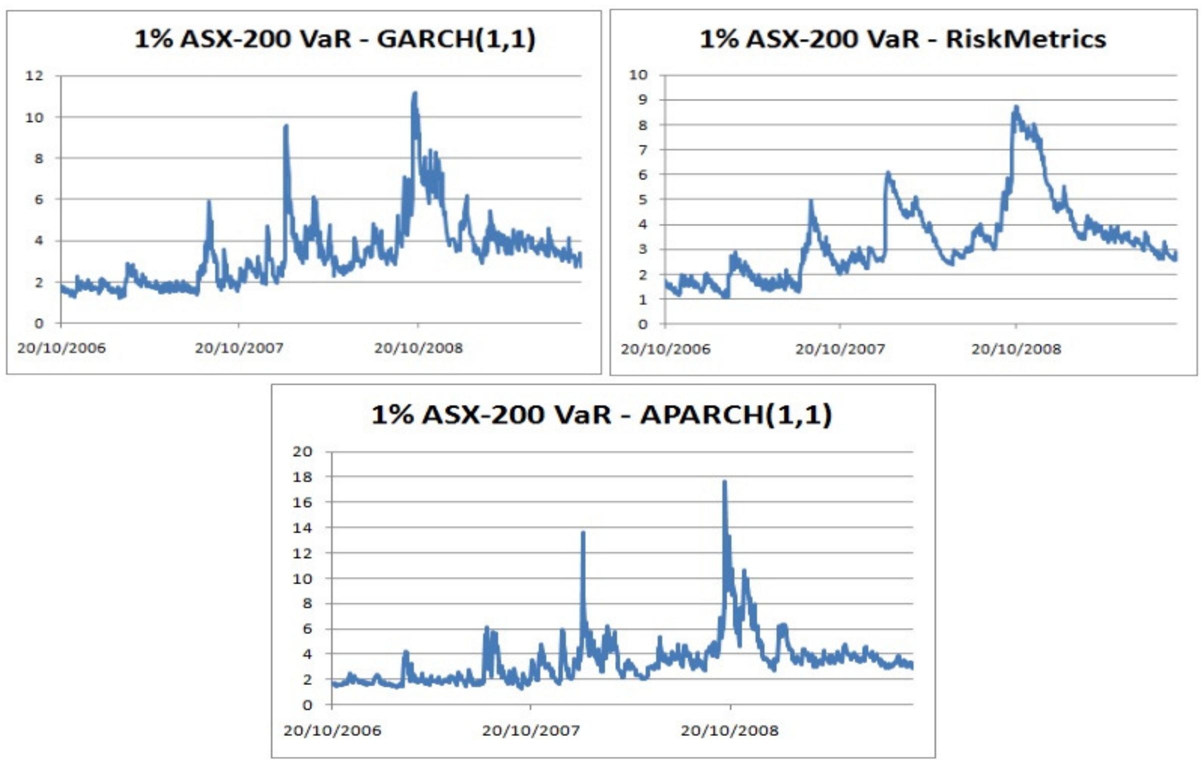
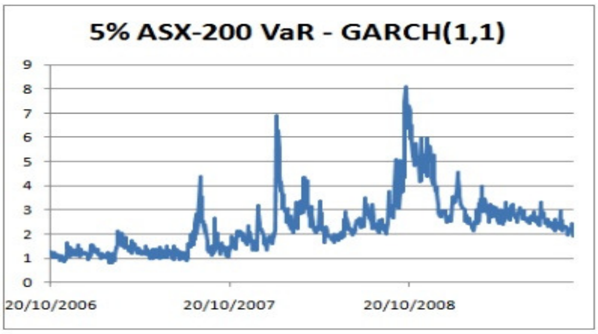


Figure 4: Normal GARCH(1,1), RiskMetrics and Skewed student-t APARCH(1,1) 1% VaR



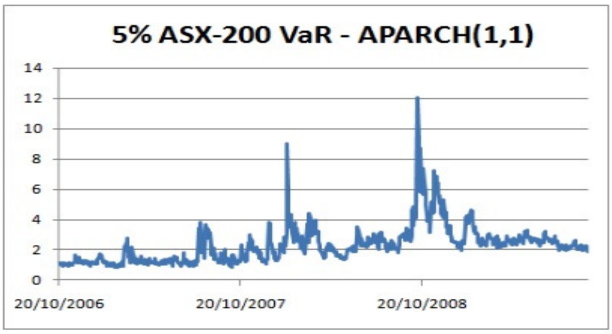


Figure 5: Normal GARCH(1,1), RiskMetrics and Skewed student-t APARCH(1,1) 5% VaR

Table 3: 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

Table 4: DQ Test Results for GARCH(1,1), RiskMetrics and Skewed student-t APARCH(1,1) 5% VaR

VaR (5%)	**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	15.263	20.917	8.826	5.602	16.277	11.575	8.750	5.955	12.293	12.334	16.728	16.444
DQ (p Value)	0.018	0.002	0.184	0.469	0.012	0.072	0.188	0.428	0.056	0.055	0.010	0.012

Table 5: Estimates for Four CAVIAR Specifications (1% Level) with excluding the GFC period

	ADAPTIVE				INDIRECT GARCH				ASSYMETRIC SLOPE				SYMMETRIC ABSOLUTE VALUE			
	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200	NAB	ANZ	ASX-50	ASX-200
Beta1	0.067	0.453	0.329	0.258	3.088	2.112	0.941	0.788	0.920	0.290	0.228	0.237	0.798	0.303	0.551	0.647
Std Errors	0.194	0.191	0.127	0.071	1.223	1.268	0.746	0.737	0.313	0.550	0.069	0.052	0.532	0.353	0.145	0.480
p Values	0.365	0.009	0.005	0.000	0.006	0.048	0.104	0.143	0.002	0.299	0.001	0	0.067	0.196	0.000	0.089
Beta2	0	0	0	0	0.538	0.749	0.641	0.611	0.572	0.867	0.748	0.723	0.718	0.891	0.679	0.605
Std Errors	0	0	0	0	0.115	0.086	0.186	0.219	0.117	0.236	0.088	0.094	0.249	0.142	0.098	0.327
p Values	0	0	0	0	0	0	0.000	0.003	0	0.000	0	0	0.002	0	0	0.032
Beta3	0	0	0	0	2.391	0.713	0.847	1.330	0.518	0.202	0.157	0.115	0.468	0.175	0.360	0.560
Std Errors	0	0	0	0	2.398	1.100	0.705	1.778	0.299	0.486	0.078	0.065	0.456	0.201	0.127	0.313
p Values	0	0	0	0	0.159	0.259	0.115	0.227	0.042	0.339	0.021	0.039	0.152	0.192	0.002	0.037
Beta4	0	0	0	0	0	0	0	0	1.053	0.206	0.768	0.889	0	0	0	0
Std Errors	0	0	0	0	0	0	0	0	0.400	0.267	0.479	0.719	0	0	0	0
p Values	0	0	0	0	0	0	0	0	0.004	0.221	0.054	0.108	0	0	0	0
RQ	192.739	192.151	76.308	73.806	184.313	187.902	74.122	70.044	180.438	185.318	72.384	67.731	183.031	186.838	75.162	70.940
Hits in-sample(%)	0.787	0.937	0.862	0.825	1.050	1.012	0.975	0.975	0.975	1.012	1.050	0.975	0.975	0.975	0.975	1.050
Hits out-of-sample(%)	0.200	1.400	1.800	1.800	0.200	0.800	1.400	1.200	0.200	0.800	1.200	1.400	0.200	0.800	1.600	2.000
DQ In Sample (p value)	0.460	0.564	0.001	0.000	0.939	0.930	0.015	0.015	0.641	0.941	0.025	0.014	0.935	0.822	0.004	0.030
DQ Out of Sample (p value)	0.718	0.013	0	0	0.784	1.000	0.040	0.979	0.779	0.999	0.963	0.824	0.783	1.000	0.054	0

Table 6 DQ test results for pre GFC period 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	46.882	50.637	38.336	20.868	55.025	77.312	2.113	11.147	42.756	39.599	17.375	8.735
DQ (p Value)	0	0	0	0.002	0	0	0.909	0.084	0	0	0.008	0.189

The significant DQ test results for the out of sample period, as indicated in Table 1 and Table 2 suggest rejection of all the models in this period. This was most likely due to the impact of the GFC. We test this justification by excluding the period of the market turmoil from our sample data and then testing the specifications as proposed with other settings kept the same. Table -5 presents the results of the 1% CAViaR specifications with the period of the GFC removed. 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. Here again it is interesting to see how the other models performs in normal market conditions. DQ test results as shown in Table 6 suggest that these methods don't improve after removing the GFC period either. The analysis shows the usual regression modelling of GARCH based and similar models for Value at Risk forecast is not efficient enough when compared to CAViaR.

4. Conclusion

In this paper we have applied the robust method of quantile regression to predict VaR using Engle and Manganelli's (2004) CAViaR model applied to a sample of company and index returns from the Australian Market. As a primary objective we have done a comparative analysis of CAViaR with normal GARCH (1,1), GARCH(1,1), RiskMetrics and Skewed student-t APARCH(1,1) one day ahead forecast, which clearly shows the efficiency of CAViaR over the later methods. modelling. Our findings closely parallel those of Engle and Manganelli (2004) from their original paper featuring US data sets. Their new class of CAViaR models, which specify the evolution of quantiles over time using a special type of autoregressive process appear to work well on this Australian data set apart from during the period coloured by the GFC. The findings also suggest that behaviour in the tails may well be different from the rest of the distribution. The GFC produced more extreme returns and all our models produce an excessive number of violations of the VaR in this period and the DQ tests reject the models for this out of sample period. This suggests we still have a long way to travel before we can achieve satisfactory VaR models for periods of extreme stress

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