Conditional Autoregressive Value at Risk by Regression Quantiles: Estimating market risk for major stock markets

by

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Abstract

This paper employs a new approach due to Engle and Manganelli (2004) in order to examine market risk in several major equity markets, as well as for major companies listed in New York Stock Exchange and Athens Stock Exchange. By interpreting the VaR as the quantile of future portfolio values conditional on current information, Engle and Manganelli (2004) propose a new approach to quantile estimation that does not require any of the extreme assumptions of the existing methodologies, mainly normality and i.i.d. returns. The CAViaR model shifts the focus of attention from the distribution of returns directly to the behaviour of the quantile. We provide a comparative evaluation of the predictive performance of four alternative CAViaR specifications, namely *Adaptive*, *Symmetric Absolute Value*, *Asymmetric Slope* and *Indirect GARCH(1,1)* models. The main findings of the present analysis is that we are able to confirm some stylized facts of financial data such as volatility clustering while the Dynamic Quantile criterion selects different models for different confidence intervals for the case of the five general indices, the US companies and the Greek companies respectively.

Keywords: Non-linear Regression Quantile, Value-at-Risk, Risk Management, Conditional Autoregressive

JEL classification: C53, G21; G28

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1. Introduction

During the 1990s we have observed a substantial increase in financial uncertainty as a result of the increased volatility that was observed in the stock returns of the mature markets but mainly of those of the emerging markets. This was the outcome of the increased flow of portfolio capital from the mature markets to the emerging markets of the South East Asia and the economies of transition of Central and Eastern European countries. Singh and Weisse (1998) report that during the period 1989-1995 the inflow of funds in emerging markets amounted to 107.6 billion US dollars as opposed to a mere 15.1 billion US dollars in the previous period 1983-1988. There are several reasons for these enormous inflow of portfolio funds to the emerging markets but certainly the most important was the fact that during the 1990s the mature markets has reached their limitations with respect to profit opportunities and made portfolio managers and institutional investors to look for new opportunities in these new markets.

However, the financial crisis of 1997-1998 as well as the bankruptcy of several financial institutions such as the BCCI and Barrings international banks have led to the increased price volatility and financial uncertainty. Such financial uncertainty have increased the likelihood of financial institutions to suffer substantial losses as a result of their exposure to unpredictable market changes. These events have made investors to become more cautious in their investment decisions while it has also led for the increased need for a more careful study of price volatility in stock markets. Indeed, recently we observe an intensive research from academics, financial institutions and regulators of the banking and financial sectors to better understanding the operation of capital markets and to develop sophisticated models to analyze market risk.

Market risk is one of the four types of risk that financial institutions can exposed themselves. It is considered as the most significant one since it represents the potential economic loss caused by the reduction in the market value of a portfolio. The existence of market risk and the recent financial disasters have raised the need for the development of practical risk management tools for financial institutions. This need has been reinforced by the Basel Committee of Banking Supervision (1996) has called for the use of internal market risk management to capital requirement by the financial institutions such as banks and investment firms.[1]

Value-at-Risk has become the standard tool used by financial analysts to measure market risk. VaR is defined as a certain amount lost on a portfolio of financial assets with a given probability over a fixed number of days. The confidence level represents 'extreme market conditions' with a probability that is usually taken to be 99% or 95%. This implies that in only 1% (5%) of the cases will lose more than the reported VaR of a specific portfolio. VaR has become a very popular tool among financial analysts which is widely used because of its simplicity. Essentially the VaR provides a single number that represents market risk and therefore it is easily understood.[2]

Although the VaR is conceptually a simple measure of market risk there exists a controversy with respect to the suitability of the alternative existing techniques employed to estimate the VaR. Indeed, the measurement of VaR is a very interesting statistical problem. Artzner *et al*. (1997, 1999) have derived a set of axioms that specify a *coherent risk* measure. Thus, a risk measure must poses the following characteristics. First. it should not exceed the maximum possible loss to occur

[1]For a detailed analysis see the Basle Committee on Banking Supervision's (1996), "*Amendment to the Capital Accord to Incorporate Market Risks*". Duffie and Pan (1997), Alexander (2005) and Drzik (2005) provide a comprehensive overview of value at risk measures.
[2] See also Bank for International Settlements (1988, 1999a,b,c, 2001).

Second, the proposed risk measure should be greater than the mean loss implying capital adequacy to cover losses. Third, in the event that there is a proportional change in the loss then we require that the risk measure changes proportionally as well. Finally, it must satisfy the property of superadditivity, implying that the risk measure calculated for two separate losses should be equal to the risk measure calculated on the sum of the two portfolios. As Boyle *et al*. (2005), Alexander *et al*. (2005) and Longin (2001) among others underline that the VaR methodology has certain limitations since it does not satisfy the properties of subadditivity and excess of the mean loss. Given these reservations regarding the use of the VaR as a measure for market risk several researchers have developed alternative risk measures.[3]

Calculating the VaR requires accurate knowledge of the distribution of extreme events. This is a difficult task since the distribution of portfolio returns is not constant over time and given that VaR is nothing more than a specific quantile of future portfolio values subject to current information we must find an appropriate model for time varying conditional quantiles. This crucial issue is coupled with the need for providing accurate estimates of the chosen distribution of portfolio returns. As Engle and Manganelli (2004) argue, if we do not correctly estimate the underlying market risk then this can lead to an allocation of capital below first-best and that can affect the profitability and/or the financial stability of the corresponding bank or an investment firm.

During the last decade several approaches in estimating the profit and losses distribution of portfolio returns have been developed and a substantial literature of empirical applications have emerged. These alternative methodologies have mainly focused on modeling the entire distribution of returns and there are based on the strict

[3] CVaR is an alternative risk measure that satisfies the coherency criteria by Artzner *et al*. (1997, 1999). It's advantage over VaR measures is that focuses on both the frequency and the size of extreme events.

assumptions of normality or i.i.d. returns. Engle and Manganelli (2004) have recently proposed an alternative approach that models not the entire distribution but focuses on the regression quantile which does require the above mentioned strict assumptions. This methodology which is called Conditional Autoregressive Value at Risk or CAViaR uses an autoregressive process in order to model the evolution of the regression quantile over time. The estimation of the unknown parameters is done with the use of the framework suggested by Koenker and Bassett (1978). Furthermore, Engle and Manganelli (2004) prove that these estimators are asymptotically efficient and consistent. Finally, they develop the Dynamic Quantile test which is used to examine the quality of the CAViaR results.[4]

In this paper we apply the CAViaR methodology in order to calculate VaR measures. We estimate and perform an evaluation of the predictive performance of four alternative CAViaR specifications, namely, *Adaptive*, *Symmetric Absolute Value*, *Asymmetric Slope* and *Indirect* GARCH(1,1). The data used consists of daily observations for the period January 3, 1990 to November 31, 2004. We focus our analysis to three groups of variables. The first group of data consists of the returns of six US companies traded in the NYSE. The second group of data refers to the stock returns of six major Greek firms. Finally, the third group of data includes the returns of five stock indices: The Standard and Poor's 500 (S&P500), the CAC40, the FTSE100, the NIKKEI225 and finally the FTSE20 for the Athens Stock Exchange. Our purpose is to compare the results obtained from the estimation of the four alternative CAViaR specification for a mature market, for an emerging market which is characterized by liquidity shortages and higher price volatility and finally across five equity markets of different characteristics.

[4] Chernozhukov (1999) has derived independently the same dynamic quantile test.

The remainder of the paper is organized as follows. Section 2 presents some of the most widely used VaR models. In section 3 we discuss the CAViaR methodology and its proposed alternative specifications. Section 4 we report our empirical results and finally section 5 provides our concluding remarks.

2. Review of the literature

During the 1990s several alternative modeling methodologies for the estimation of the VaR were advanced. The purpose of these models was to provide risk managers with a comprehensive and intuitively easily understood measure of the VaR. The motivation for the development of the VaR models relies on the stylized characteristics of financial data which have been firstly documented by Mandelbrot (1963) and Fama (1965). To recapitulate, these characteristics imply that the returns of financial assets have leptokurtic distributions, that their distributions are negatively skewed and finally they exhibit volatility clustering. As Engle and Manganelli (2001, 2004) point out these alternative methodologies adopted a common general structure: (a) We mark-to-market the portfolio on a daily basis; (b) Estimation of the distribution of returns and (c) Computation of the portfolio's VaR. The main difference among the alternative methodologies is linked to the estimation of the appropriate distribution of the portfolio returns. We can briefly discuss the advantages and disadvantages of the alternative VaR models using the following broad classification.[5]

The first class of models are fully parametric and includes applications such J.P. Morgan's Riskmetrics (1996) and GARCH models. These methodologies combine an econometric model with the assumption of conditional normality for the

[5] Jorion (2000) provides a complete analysis of the VaR methodology and alternative estimation methodologies

returns series. Specifically, these models rely on the specification of the variance equation of the portfolio returns and the assumption that the standardized errors are i.i.d. Additionally, when the GARCH methodology is applied we are also required to specify the distribution of the errors, which is usually taken to be the normal one, while it is assumed that the negative returns follow the same process like the rest of portfolio returns, (Bams *et al*. 2005; Burns, 2005; Angelidis *et al*. 2005; Alexander *et al*., 2005; Pojarlev and Polasek, 2000 and Polasek and Pojarlev, 2005 are among some of the many recent applications of GARCH methodology)

The application of the parametric methodologies has been criticized since they tend to give coefficients which underestimate the VaR mainly due to their failure to take into account the characteristic that the distribution of the portfolio returns have heavy tails. This underestimation of the VaR as well as possible misspecifications with respect to the variance equation along with the distribution of errors can be corrected by allowing alternative distributions of the errors such as the Gaussian, Student's t and Generalized Error Distribution. However, it is further shown that the GARCH-type models provide satisfactory estimates of the quantile only when a bad event has already occurred.

The second approach for the estimation of the distribution of profits and losses is the non-parametric historical simulation. This methodology makes no assumption about the distribution of the portfolio returns and is based on the concept of rolling windows. The idea is to select a window which is usually taken to be anywhere between 6 months to 2 years and assume that any portfolio return has the same likelihood to occur. Moreover, a return which falls outside the chosen window has probability equal to zero to occur. This methodology has several deficiencies. It is inappropriate to provide extreme quantiles since we cannot extrapolate beyond past observations. The proposed solution to this problem is the increase of the sample of observations but this will lead to estimates of the VaR which are biased downwards (or upwards) since we have a mixture of periods with low volatility with periods of high volatility.

Within this group of VaR models falls the hybrid approach developed by Boudoukh et al. (1998) which combines the historical simulation and Riskmetrics. This methodology applies weights to the portfolio returns that decline exponentially. Although this approach improves the previously discussed methodologies it also has problems since the selection of the parameters as well the calculation of the VaR do not depend on sound statistical theory but it is rather ad hoc.

The final group for the estimation of the VaR are the semiparametric models. The first approach in this category is the Extreme Value Theory proposed by Danielsson *et al*. (1998) and Danielsson and de Vries (2000). The advantage of this approach is that it is based on sound statistical theory which offers a parametric form for the tail of a distribution. This approach focuses on the asymptotic form of the tail, rather than modeling the complete distribution of portfolio returns and therefore we are able to obtain more efficient forecasts of the risk associated with a particular market position. Although this methodology is very appealing it does have two shortcomings. First, as Danielson and de Vries (2000) argue this approach performs well at very low quantiles but they fail to provide accurate estimations of the VaR at levels which are not considered very extreme. Second, this methodology is also based on the assumption of i.i.d. standardized errors which is as we have already discussed an important limitations. Despite its limitations this approach have found substantial applications recently, (Longin 2000; McNeil and Saladin, 2000; McNeil and Frey, 2000, Naftci 2000; Bekiros and Georgoutsos, 2005a,b; Brooks *et al*. 2005).

3. CAViaR

Recently, Engle and Manganelli (2004) proposed an alternative semiparametric method to estimate Value at Risk, namely Conditional Autoregressive Value at Risk (CAViaR). This approach is based on the simple intuition that it is better to model directly the quantile as it evolves through time instead of attempting to model and estimate the entire distribution of portfolio returns. Modelling the quantile instead of the entire distribution has the main advantage that we are not required to adopt the set of extreme assumptions which are invoked by alternative methodologies, among them normality or that returns are i.i.d.

As we know the basic motivation that relies behind the VaR methodologies is usually based on the characteristics of financial data as these have been firstly theorized by Mandelbrot (1963) and Fama (1965) and have been verified by numerous empirical works. Volatility clustering of portfolio returns is one of these stylized facts of financial data leads to the understanding that the corresponding distributions are autocorrelated. As a consequence the VaR must also follow a similar pattern since is directly linked with the standard deviation of the distribution. Therefore, Engle and Manganelli (2004) and Manganelli and Engle (2001) developed a conditional autoregressive quantile specification (CAViaR) in order to take account of the particular characteristic of the VaR.

Following Engle and Manganelli (2004) and Manganelli and Engle (2001) we consider a vector of portfolio returns that is observable defined as $\{y_t\}_{t=1}^{T}$. Let θ be the probability tied to VaR, x_t be a vector of observable variables at time t and β_θ to be a vector of unknown parameters. We also define $f_t(\beta) \equiv f(x_{t-1}, \beta_\theta)$ to be the θ-

quantile of the distribution of the portfolio returns at time t which has been formed at time $t-1$.[6] Therefore, a general formulation of CAViaR can be written as follows:

$$f_t(\beta) = \gamma_0 + \sum_{i=1}^{q} \gamma_i f_{t-i}(\beta) + \sum_{i=1}^{p} a_i l(x_{t-i}, \varphi) \tag{1}$$

where $\beta' = (a', \gamma', \varphi')$ and l is a function of a finite number of lagged values of observables. Moreover, in order for the quantile to have a smooth transition we use the autoregressive terms $\gamma_i f_{t-i}(\beta), i = 1,....q$. Finally, we use the term $l(x_{t-i}, \varphi)$ to provide a relationship between the θ-quantile $f_t(\beta)$ and the observable variables which are included in the information set. As Engle and Manganelli (2004) point out we can consider the lagged portfolio returns as the best choice for x_{t-1}. This implies that as y_{t-1} becomes negative then one should expect the VaR to increase while the VaR tends to decline in good days. Therefore, we expect that changes in y_{t-1} will affect symmetrically the VaR.

The purpose is to develop alternative specifications for the function l and then estimate the different models. Engle and Manganelli (2004) propose four alternative CAViaR specifications which we will estimate in our case. The first specification is called *Adaptive* which takes the following formulation:

$$f_t(\beta_1) = f_{t-1}(\beta_1) + \beta_1 \{[1 + \exp(G[y_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \theta\} \tag{2}$$

where G is some positive finite number and we underline that as $G \to \infty$, the last term of equation (1) converges to $\beta_1[I(y_{t-1} \leq f_{t-1}(\beta_1)) - \theta]$, where $I(.)$ is the

[6] For simplicity we have eliminated the subscript θ from the vector of unknown parameters

indicator function. The intuition behind the *adaptive* specification tells us that in those cases that the VaR has been exceeded then we should increase its value whereas in those cases that we do not exceed it then we should reduce its value by a small magnitude. Such a strategy will lead to a reduction of the probability to observe a sequence of hits while at the same time it is highly unlike that we will have zero number of hits. Engle and Manganelli (2004) also point out that this CAViaR specification has a unit coefficient on the lagged VaR.

A second specification is called *Symmetric Absolute Value* (SAV) and its mathematical formulation is given by:

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

This model responds symmetrically to past portfolio returns and it is mean reverting since the coefficient of the lagged VaR is not constrained to equal one. Furthermore, we could properly specify this quantile specification using a GARCH model with the standard deviation (and not the variance) is considered to follow a symmetric distribution with i.i.d. errors.[7]

The *Asymmetric Slope* (AS) is the third commonly used specification to estimate the l function. It is written as follows:

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 (y_{t-1})^+ + \beta_4 (y_{t-1})^- \tag{4}$$

The *Asymmetric Slope* model allows for an asymmetric response to positive and negative past portfolio returns.[8] Again this model is mean reverting. As with the

[7] See also Taylor (1986), Schwert (1988) and Engle (2002).

[8] $(x)^+ = \max(x,0), (x)^- = -\min(x,0)$.

SAV model we can correctly specify this specification by fitting a GARCH process with the standard deviation following this time an asymmetric distribution with i.i.d. errors.

The final specification is called *Indirect GARCH(1,1)* which is also mean reverting and as with the SAV specification it responds symmetrically to past returns. This specification can be correctly modeled under the assumption that the underlying data process follows a true GARCH(1,1) with an i.i.d. error distribution.[9] The algebraic expression of this specification as follows:

$$f_t(\beta) = (\beta_1 + \beta_2 f_{t-1}^2(\beta) + \beta_3 y_{t-1}^2)^{1/2} \tag{5}$$

The next to the analysis is the estimation of the parameters of the alternative CAViaR models. They are estimated using linear and non-linear quantile techniques. These techniques have been first introduced by Koenker and Basett (1978) who provide a thorough analysis how to apply the concept of sample quantile to a linear regression model. We consider the following model proposed by Engle and Manganelli (2004):

$$y_t = x_t'\beta^0 + \varepsilon_{\theta t} \qquad Quant_\theta(\varepsilon_{\theta t} \mid x_t) = 0 \tag{6}$$

where x_t is a p-vector of regressors and $Quant_\theta(\varepsilon_{\theta t} \mid x_t)$ is, as we have already defined, the θ-quantile of $\varepsilon_{\theta t}$ conditional, on x_t. White (1994) has shown that if we minimize the regression quantile objective function that was developed by Koenker

[9] It is worth to note that the CAViaR specifications are more general than the fitted GARCH models. They can allow for a wide range of assumptions the error distribution and they can also handle distributions with non-i.i.d. errors.

and Basett (1978) we can obtain consistent estimates under certain assumptions. This minimization can be consider as follows:

We define $f_t(\beta) \equiv x_t \beta$. Then any $\hat{\beta}$ that solves the following problem:

$$\min_{\beta} \frac{1}{T}[\theta - I(y_t < f_t(\beta))][y_t - f_t(\beta)] \tag{7}$$

Defines the θ^{th} regression quantile.

Within this framework Engle and Manganelli (2004) show that the only assumption required is the appropriate specification of the quantile process and more specifically we do not have to specify the entire distribution of the error terms. Furthermore, even if we erroneously specify the regression quantile process Engle and Manganelli (2004) argue that we can still obtain a minimization of equation (5) that satisfies the Kullback-Leibler Information Criterion (which measures the deviation between the true specification and the actual model).

Engle and Manganelli (2004) consider the case that $\hat{\beta}$ is a non-linear regression quantile estimator and they prove that this estimator is consistent and asymptotically normal. Furthermore, they show that there is a consistent estimator of the variance-covariance matrix. Engle and Manganelli (2004) then go on to derive the asymptotic distribution of the estimator. This allows us to conduct hypothesis tests of the quantile models.[10]

[10]Following the seminal paper by Koenker and Bassett (1978) a number of alternative regression quantile models have been developed over the last twenty years that takes into account alternative assumptions about the errors. Among others, Koenker and Bassett (1982) allow for the case of heteroskedastic errors, whereas Portnoy (1991) considers the case of non-stationary dependent errors. Furthermore, we have extensions that cover the cases of time series models, simultaneous equations and censored regression models and recently we have also extensions that deal with the case of autoregressive quantiles (Koenker and Zhao), (see Engle and Manganelli, 2004 for the relevant literature). All these models differ from Engle and Manganelli (2004) CAViaR models since they are linear in the parameters.

Engle and Manganelli (2004) also propose a new test for the evaluation of the alternative specifications which has better power properties than other existing tests. This test allows for the inclusion of a variety of alternative specifications. We define:

$$Hit_t(\beta^0) \equiv f(y_t < f_t(\beta^0)) - \theta \tag{8}$$

Where the function $Hit_t(\beta^0)$ is assumed to take a value $(1-\theta)$ every time y_t falls below the quantile, and it takes the value $-\theta$ in all other cases. Equation (8) implies that the expectation of $Hit_t(\beta^0)$ is zero. Furthermore, based on the definition of the quantile given in equation (1) we also assume that the conditional expectation of $Hit_t(\beta^0)$ given a set of information at period $t-1$ is zero. This implies that $Hit_t(\beta^0)$ must be uncorrelated with its own lagged values as well as with $f_t(\beta^0)$ and its expected value should equal zero. If these assumptions hold for $Hit_t(\beta^0)$ then we are certain that we have no misspecification error introduced, there is no autocorrelation in the *hits*, and we will obtain the correct fraction of exceptions. Based on definition (8) Engle and Manganelli (2004) derive two test statistics. First, they construct an *in-sample Dynamic Quantile test*. This test is a specification test which is used to select among alternative model specifications of a particular CAViaR process. Second, they construct an *out-of-sample Dynamic Quantile test*. This test is useful to the market regulators and/or the risk managers, since they can examine whether the VaR estimates that a particular financial institution satisfy certain properties such as that they are unbiased, they provide independent hits and they give quantile estimates which are independent. Moreover, it is argued that this second test has some nice features since it is simple in its application and it does not depend on the procedure used for the estimation. We obtain the results from this test simply by using a series of VaR values and the respective value of the portfolio.[11]

4. Empirical results

We apply the alternative conditional autoregressive Value at Risk model specifications on daily data for the period January 3, 1990 to November 30, 2004. The data was taken from Datastream. Our sample of 3261 observations is divided in three groups. The first refers to six stocks of US companies which are traded in the NYSE, namely ALCOA, McDONALDS, MERK, PEPSICO, COCA COLA and EXXON. The second one includes six blue chips of the Athens Stock Exchange, namely EMPORIKI BANK, NATIONAL BANK, PIREOS BANK, ALPHA BANK, COCA COLA and INTRACOM. The final group includes five general stock price indices namely, CAC40, FTSE100, NIKKEI225, NASDAQ and FTSE20 (of the ASE). We follow this strategy in order to investigate the performance of the CAViaR measures of market risk for the case of stocks trade in a mature market, in an emerging market and across different stock markets. In order to implement our analysis we construct historical series of portfolio for each case and we choose a specification of the functional form of the quantile. The daily returns are computed as 100 times the difference of the log of the prices.

Our analysis begins with estimation of the four CAViaR specifications described in section 3. For the estimation of the models we used the first 2761 observations and the last 500 for conducting the out-of-sample testing performance.

[11] The complete derivation of the two tests is given in Engle and Manganelli (2004, 370-371). Granger et al. (1989) and Cristoffersen (1998) are among other studies which have developed test statistics for the validity of the forecast model, but as Engle and Manganell (2004) point out they have low power against misspecification introduced by the presence of serial correlation in the conditional probabilities leading to a quantile measurement error.

We estimated 1% and 5% one day Value-at-Risk.[12] As Engle and Manganelli (2004) proved all the models are both continuous and continuously differentiable in β.[13] Our results are summarized in Tables 1-6 and Figures 1-17. The 5% VaR estimates for the returns of each individual equity and for each price index are plotted on the top of Figures 1-17.The bottom of Figures 1-17 reports a plot of the CAViaR new impact curve for the 1% VaR estimates for the returns of each equity and each price index. Looking into these plots we note that the Adaptive and the Asymmetric Slope new impact curves differ from the other two. That is, both the Indirect GARCH and Symmetric Absolute Slope models we observe that positive or negative returns have a symmetric impact on VaR. Furthermore, in the case of the Adaptive model it is clear that the most important news is whether past returns exceeded the previous VaR estimate or not.

We now turn to the results reported in Tables 1- 6 and we begin with an explanation of the relevant lines. Each table reports the value of the estimated parameters, the respective standard errors and the one-sided p-values. Furthermore, each table shows the value of the regression objective function given by equation 3 above. Finally, we report the percentage of times the VaR is exceeded and the in and out-of-sample p-value of the Dynamic Quantile test. The computation of the VaR series with the CAViaR models has been done with the initialization of $f_1(\beta)$ to the empirical θ-quantile of the first 300 observations. With respect to the computation of the DQ test we used a constant, the VaR forecast and the first four lagged hits as instrumental variables. In contrast, to avoid the presence of collinearity in the matrix of the first and higher order derivatives we did not include the constant and the VaR

[12] To estimate the Adaptive model we set $G = 10$, in all cases that G entered the definition of the Adaptive model in section 3.

[13] All assumptions which these models need to satisfy are given in Appendix A of Engle and Manganelli (2004) and they refer to asymptotic results but difficult to verify in finite samples.

forecast.[14] Following Engle and Manganelli (2004) we compute the standard errors and the variance covariance matrix of the in-sample DQ test and the calculation of the statistics $\hat{D}_T$ and $\hat{M}_T$ was done with the use of the k-nearest neighbour estimators, with $k = 40$ for the 1% VaR and $k = 60$ for the 5% VaR.[15]

The first important observation we make in all six tables is that the coefficient β_2 is very significant and this implies that volatility clustering is verified not only for the stock price returns of the five general indices but also in the returns of the companies' equity and more specifically this carries over to the tails of the distribution. Second, we note the accuracy of the alternative models. This is measured by the percentage of in-sample hits. Consider the results of the 1% VaR. We observe that for either the case of the mature market or the emerging market or even the case of the general stock indices the Symmetric Absolute Value, the Asymmetric Slope and the Indirect GARCH models provide estimates which are extremely close to the value of 1 and this is taken as evidence that they describe the evolution of the tail for most of the cases. Specifically, the results are particularly good for the stock returns of McDONALDS, MERK, COCA COLA and EXXON companies. In these cases we further observe that the out-of-sample hits are exactly equal to one or about 1.2%. For the stock returns of ALCOA and PEPSICO the accuracy of the in-sample hits is fairly good but the out-of sample hits are substantially below the value of 1. Furthermore, for most cases the Adaptive model provides inferior results either for in and out-of sample hits. Similar evidence is also obtained for the case of the companies listed in

[14] As Engle and Manganelli (2004) point out the lagged hit variables contain the indicator function. Given that the indicator function is Lipschitz continuous it satisfies condition DQ3 of theorem 4 (Engle and Manganelli, 2004).

[15] The calculation of the two statistics is described in Engle and Manganelli theorem 3 and 4. Furthermore, we for the optimization procedures we adopt the strategy explained in Engle and Manganelli (2004). The computations were made in Matlab 6.1 using the functions *fminsearch* and *fminunc* as the optimization algorithms while the loops to compute the recursive quantile functions were coded in C and they have been developed by Manganelli.

the Athens Stock Exchange. Again we see that the Symmetric Absolute Value, the Asymmetric Slope and the Indirect GARCH models provide accurate in-sample estimations whereas the Adaptive specification provides estimates well away from the 1% benchmark. The picture emerging for the comparison of the results for the five stock indices provides a similar pattern. The Symmetric Absolute Value, the Asymmetric Slope and the Indirect GARCH provide in-sample hits near the value of 1 but the out-of sample hits are in distance from this value. This is more evident for the FTSE20 which measures the performance of the 20 most important companies in the Athens Stock Exchange.

We then turn to the results for the 5% VaR. We first discuss the results for the U.S. companies which are traded in the NYSE. The in-sample hits range from 4.9% to 5.1% for the Symmetric Absolute Value, the Asymmetric Slope and the Indirect GARCH models while the Adaptive model misses the target in this case as well. The out-of sample forecasts are the cases of MERK when we apply any of these three models and also for the case of ALCOA when we apply the Indirect GARCH specification. When we turn to the case of the companies from the emerging markets we note that we obtain estimates which are extremely close to the value of 5% and this is taken as evidence that they describe the evolution of the tail for all cases under consideration. Looking into the out-of-sample forecasts the performance is similar to the one obtained in the developed market. Finally, a similar pattern emerges for all three specifications as well the adaptive model when we examine the five stock indices. A noticeable exemption is the FTSE20 index. The rejection of all specifications by the Dynamic Quantile-in-sample test may be attributed to the presence of a speculative bubble during the period 1998-2000.

A final comment we make is that in most cases the estimation of the Asymmetric Slope model give coefficient estimates for the negative lagged returns which are always negative while the estimates associated with the positive returns are not significantly different than zero.

The overall results from the present analysis show that the DQ test statistics select different CAViaR specifications for different confidence internals and this may lead to the argument that the process guiding the tail behaviour changes over time which contradicts the fundamental assumptions of the volatility parametric models that the tails of the distribution follow the same process like the rest of the portfolio returns.

5. Summary and concluding remarks

The present paper utilized a new framework for the estimation of the VaR for portfolio returns. The CAViaR modeling procedure has been recently proposed by Engle and Manganelli (2004) and it is a semiparametric method which shifts the analysis of developing a good measure of the VaR from the distribution of the portfolio returns directly to the behavior of the quantile.

We apply this methodology to estimate the VaR using daily observations for the period January 3, 1990 to November 30, 2004. We study the behaviour of four alternative CAViaR specifications for three sets of portfolio returns. We consider the equities of six U.S. companies, then the equities of six companies listed in the Athens Stock Exchange and finally five general indices.

The overall results show that this methodology provides very accurate measurement of the VaR for the US companies but provides less satisfactory results for the case of the companies whose stocks are traded at the ASE as well as for the five price indices.

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TABLE 1: Estimates and Relevant Statistics for the four Conditional Autoregressive Value at Risk Models

1%VaR	**Symmetric Absolute Value**			**Asymmetric slope**			**Indirect GARCH**			**Adaptive**		
	ALCOA	**MCD**	**MRK**	**ALCOA**	**MCD**	**MRK**	**ALCOA**	**MCD**	**MRK**	**ALCOA**	**MCD**	**MRK**
Beta 1	**0.0129**	**0.1085**	**0.1364**	0.0310	**0.1378**	**0.0554**	0.1538	0.2204	0.0706	**1.1023**	**0.4687**	**0.3404**
Standard Errors	*0.0053*	*0.0403*	*0.0516*	*0.0242*	*0.0665*	*0.0328*	*0.1029*	*0.1823*	*0.0753*	*0.0943*	*0.1188*	*0.1046*
p values	*0.0076*	*0.0035*	*0.0041*	*0.1004*	*0.0192*	*0.0455*	*0.0674*	*0.1133*	*0.1742*	*0.0000*	*0.0000*	*0.0006*
Beta 2	**0.9923**	**0.9419**	**0.9475**	**0.9653**	**0.8964**	**0.9711**	**0.9731**	**0.9432**	**0.9859**	0	0	0
Standard Errors	*0.0033*	*0.0295*	*0.0162*	*0.0170*	*0.0361*	*0.0161*	*0.0049*	*0.0144*	*0.0044*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.0223**	**0.1483**	**0.1059**	-0.0009	**0.1263**	0.0090	0.1081	0.2500	0.0633	0	0	0
Standard Errors	*0.0084*	*0.0729*	*0.0394*	*0.0312*	*0.0713*	*0.0432*	*0.3793*	*0.2190*	*0.3635*	*0*	*0*	*0*
p values	*0.0039*	*0.0209*	*0.0036*	*0.4885*	*0.0382*	*0.4172*	*0.3878*	*0.1268*	*0.4309*	*0*	*0*	*0*
Beta 4	0	0	0	**0.1823**	**0.3119**	**0.0936**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.0993*	*0.1485*	*0.0334*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0332*	*0.0178*	*0.0025*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	195.47	188.14	190.88	190.86	1.88.14	189.86	196.34	190.17	192.91	199.49	190.10	194.03
Hits in-sample(%)	0.9822	0.9822	0.9822	0.9515	0.9822	0.9822	1.0129	1.0129	0.9822	1.0436	1.0743	1.1050
Hits out-of-sample(%)	0.6000	1.0000	1.0000	1.2000	1.4000	1.0000	0.8000	1.0000	1.0000	0.8000	0.4000	1.0000
DQ in-sample (p values)	0.0433	0.0967	0.5054	0.7451	0.7436	0.7340	0.0262	0.0655	0.4657	0.5298	0.0702	0.5975
DQ out-of-sample (p values)	0.9912	0.9430	0.9996	0.8445	0.9044	0.9998	0.9966	0.9809	0.9980	0.8857	0.9133	0.0012

5%VaR	**Symmetric Absolute Value**			**Asymmetric slope**			**Indirect GARCH**			**Adaptive**		
	ALCOA	**MCD**	**MRK**	**ALCOA**	**MCD**	**MRK**	**ALCOA**	**MCD**	**MRK**	**ALCOA**	**MCD**	**MRK**
Beta 1	**0.0071**	**0.0387**	**0.0306**	**0.0069**	0.0038	**0.0414**	0.0573	0.0175	0.0043	**0.1501**	**0.2859**	**0.4779**
Standard Errors	*0.0029*	*0.0115*	*0.0167*	*0.0042*	*0.0138*	*0.0214*	*0.0448*	*0.0271*	*0.0241*	*0.0355*	*0.0602*	*0.0675*
p values	*0.0073*	*0.0004*	*0.0339*	*0.0497*	*0.3919*	*0.0267*	*0.1005*	*0.2588*	*0.4299*	*0.0000*	*0.0000*	*0.0000*
Beta 2	**0.9927**	**0.9595**	**0.9652**	**0.9858**	**0.9601**	**0.9512**	**0.9650**	**0.9695**	**0.9667**	0	0	0
Standard Errors	*0.0039*	*0.0068*	*0.0089*	*0.0036*	*0.0086*	*0.0119*	*0.0069*	*0.0045*	*0.0043*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.0146**	**0.0792**	**0.0703**	0.0071	**0.0757**	0.0190	0.0677	0.0655	0.0747	0	0	0
Standard Errors	*0.0065*	*0.0142*	*0.0154*	*0.0083*	*0.0232*	*0.0224*	*0.0816*	*0.1061*	*0.2297*	*0*	*0*	*0*
p values	*0.0118*	*0.0000*	*0.0000*	*0.1936*	*0.0006*	*0.1980*	*0.2032*	*0.2687*	*0.3726*	*0*	*0*	*0*
Beta 4	0	0	0	**0.0425**	**0.0785**	**0.1163**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.0079*	*0.0146*	*0.0278*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	677.75	592.47	627.77	674.74	592.88	620.30	677.95	594.59	630.23	681.04	605.12	622.69
Hits in-sample(%)	5.0031	5.0031	4.9724	5.0031	4.9724	4.9724	5.0645	4.9417	5.0645	5.4328	5.1565	4.8496
Hits out-of-sample(%)	4.4000	3.8000	5.4000	4.4000	4.4000	4.8000	5.2000	3.2000	5.0000	3.4000	3.2000	4.4000
DQ in-sample (p values)	0.0140	0.1404	0.0140	0.1782	0.1606	0.7128	0.0858	0.1879	0.0627	0.0528	0.0180	0.3899
DQ out-of-sample (p values)	0.9565	0.8789	0.0189	0.8185	0.8299	0.0001	0.8871	0.5762	0.0932	0.6494	0.2679	0.0001

TABLE 2: Estimates and Relevant Statistics for the four Conditional Autoregressive Value at Risk Models

1%VaR	Symmetric Absolute Value			Asymmetric slope			Indirect GARCH			Adaptive		
	PEPSI	COCA	EXXON	PEPSI	COCA	EXXON	PEPSI	COCA	EXXON	PEPSI	COCA	EXXON
Beta 1	**0.1531**	**1.4012**	**0.1670**	0.1893	**0.6336**	**0.0669**	1.0975	1.4216	0.1877	**0.3986**	**0.7651**	**0.5317**
Standard Errors	*0.0894*	*0.0463*	*0.0273*	*0.1461*	*0.1865*	*0.0416*	*1.1544*	*0.7568*	*0.1475*	*0.1512*	*0.1216*	*0.0703*
p values	*0.0434*	*0.0003*	*0.0000*	*0.0975*	*0.0002*	*0.0538*	*0.1709*	*0.0302*	*0.1016*	*0.0042*	*0.0000*	*0.0006*
Beta 2	**0.9335**	**0.5229**	**0.8988**	**0.8908**	**0.6457**	**0.8963**	**0.8907**	**0.7763**	**0.8978**	0	0	0
Standard Errors	*0.0341*	*0.1213*	*0.0159*	*0.0159*	*0.0847*	*0.0251*	*0.0622*	*0.0545*	*0.0186*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.1428**	**0.6255**	**0.2782**	**0.1347**	**0.3432**	**0.2328**	0.3138	0.8323	0.5366	0	0	0
Standard Errors	*0.0674*	*0.1288*	*0.0392*	*0.0567*	*0.2089*	*0.1054*	*0.2677*	*0.4695*	*0.1362*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0087*	*0.0502*	*0.0133*	*0.1206*	*0.0381*	*0.0000*	*0*	*0*	*0*
Beta 4	0	0	0	**0.2831**	**0.9444**	**0.2960**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.1890*	*0.4007*	*0.0602*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0671*	*0.0092*	*0.0000*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	189.41	177.50	135.52	187.63	173.17	136.14	191.72	176.32	135.89	193.89	185.87	140.26
Hits in-sample(%)	0.9813	1.0120	0.9813	0.9813	0.9813	0.9813	1.0120	1.0120	1.0120	1.0120	1.0426	1.1653
Hits out-of-sample(%)	0.6000	1.0000	1.2000	0.6000	1.2000	1.2000	0.2000	1.2000	1.2000	0	0.6000	0.2000
DQ in-sample (p values)	0.7362	0.5610	0.0429	0.7391	0.6177	0.5510	0.7484	0.5684	0.5809	0.4893	0.0032	0.0807
DQ out-of-sample (p values)	0.9833	0.9966	0.8638	0.9879	0.9860	0.9498	0.7805	0.9943	0.9552	0.9601	0.9073	0.7836

5%VaR	Symmetric Absolute Value			Asymmetric slope			Indirect GARCH			Adaptive		
	PEPSI	COCA	EXXON	PEPSI	COCA	EXXON	PEPSI	COCA	EXXON	PEPSI	COCA	EXXON
Beta 1	**0.0946**	**0.1934**	**0.0437**	**0.0662**	**0.1443**	0.0066	**0.1454**	**0.2656**	0.0202	**0.3468**	**0.3201**	**0.2053**
Standard Errors	*0.0214*	*0.0515*	*0.0107*	*0.0217*	*0.0323*	*0.0076*	*0.0560*	*0.1431*	*0.0233*	*0.0656*	*0.0366*	*0.0428*
p values	*0.0000*	*0.0001*	*0.0000*	*0.0011*	*0.0000*	*0.1948*	*0.0047*	*0.0317*	*0.1928*	*0.0000*	*0.0000*	*0.0000*
Beta 2	**0.9344**	**0.8660**	**0.9525**	**0.9319**	**0.8581**	**0.9525**	**0.9368**	**0.8652**	**0.9504**	0	0	0
Standard Errors	*0.0131*	*0.0390*	*0.0147*	*0.0151*	*0.0170*	*0.0099*	*0.0081*	*0.0281*	*0.0055*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.0893**	**0.1726**	**0.0953**	**0.0648**	**0.0653**	**0.1264**	0.0923	**0.2080**	0.1161	0	0	0
Standard Errors	*0.0192*	*0.0525*	*0.0249*	*0.0191*	*0.0306*	*0.0242*	*0.1177*	*0.0587*	*0.1135*	*0*	*0*	*0*
p values	*0.0000*	*0.0005*	*0.0001*	*0.0003*	*0.0163*	*0.0000*	*0.2165*	*0.0002*	*0.1532*	*0*	*0*	*0*
Beta 4	0	0	0	**0.1091**	**0.2681**	**0.0533**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.0389*	*0.0277*	*0.0219*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0025*	*0.0000*	*0.0074*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	623.46	579.55	484.60	622.10	568.39	480.85	623.65	579.41	483.60	630.41	579.35	494.31
Hits in-sample(%)	4.9678	4.9678	5.0291	4.9371	5.0291	5.0291	5.0291	5.0598	4.8758	4.9371	5.2131	48.496
Hits out-of-sample(%)	2.4000	3.4000	4.2000	2.4000	3.0000	3.2000	2.4000	3.4000	4.0000	3.6000	4.0000	3.2000
DQ in-sample (p values)	0.3575	0.0067	0.5124	0.8367	0.1924	0.3690	0.3200	0.0072	0.3057	0.0460	0.0000	0.0994
DQ out-of-sample (p values)	0.1050	0.4659	0.6450	0.1253	0.4333	0.4603	0.1385	0.7249	0.5205	0.3270	0.2391	0.2233

TABLE 3: Estimates and Relevant Statistics for the four Conditional Autoregressive Value at Risk Models

1%VaR	**Symmetric Absolute Value**			**Asymmetric slope**			**Indirect GARCH**			**Adaptive**		
	EMPOR	**NATL**	**PIREOS**	**EMPOR**	**NATL**	**PIREOS**	**EMPOR**	**NATL**	**PIREOS**	**EMPOR**	**NATL**	**PIREOS**
Beta 1	**0.4835**	**2,1290**	3.6870	**0.7331**	**1.4806**	2.5196	0.3568	**7.8829**	0.6931	**1.0399**	**0.7350**	**0.5332**
Standard Errors	*0.2192*	*0.5544*	*3.4230*	*0.3842*	*0.3142*	*2.5472*	*0.3222*	*3.1256*	*0.6514*	*0.1434*	*0.3740*	*0.2170*
p values	*0.0137*	*0.0000*	*0.1411*	*0.0282*	*0.0000*	*0.1613*	*0.1341*	*0.0058*	*0.1436*	*0.0000*	*0.0247*	*0.0070*
Beta 2	**0.8853**	**0.4313**	0.4382	**0.7995**	**0.4985**	**0.5521**	**0.9778**	**0.3071**	**0.9817**	0	0	0
Standard Errors	*0.0470*	*0.1379*	*0.4523*	*0.0752*	*0.0778*	*0.3197*	*0.0094*	*0.1169*	*0.0106*	*0*	*0*	*0*
p values	*0.0000*	*0.0009*	*0.1663*	*0.0000*	*0.0000*	*0.0421*	*0.0000*	*0.0043*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.1795**	**0.9970**	**0.3303**	**0.1861**	**0.3913**	**0.3072**	0.0881	3.4734	0.0426	0	0	0
Standard Errors	*0.0835*	*0.4031*	*0.1164*	*0.0887*	*0.0837*	*0.1491*	*0.4934*	*2.3526*	*0.1701*	*0*	*0*	*0*
p values	*0.0158*	*0.0067*	*0.0023*	*0.0179*	*0.0000*	*0.0197*	*0.4291*	*0.0699*	*0.4012*	*0*	*0*	*0*
Beta 4	0	0	0	**0.4316**	**1.0516**	**0.4577**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.1840*	*0.3405*	*0.2100*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0095*	*0.0010*	*0.0147*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	119.78	123.06	129.36	116.88	114.36	128.41	118.64	124.68	130.99	120.04	137.64	134.68
Hits in-sample(%)	1.0695	1.0695	1.0027	1.0695	1.0027	1.0027	1.0027	1.0027	1.0027	0.7353	0.6016	0.8690
Hits out-of-sample(%)	0.2000	0.4000	0.0000	0.2000	0.6000	0.0000	0.0000	0.4000	0.8000	0.2000	0.8000	0.6000
DQ in-sample (p values)	0.1813	0.0004	0.8680	0.9281	0.9770	0.9872	0.2268	0.2743	0.0482	0.0976	0.0284	0.0200
DQ out-of-sample (p values)	0.7675	0.8612	0.8512	0.7839	0.8290	0.9321	0.9189	0.9423	0.9319	0.9983	0.9877	0.7415

5%VaR	**Symmetric Absolute Value**			**Asymmetric slope**			**Indirect GARCH**			**Adaptive**		
	EMPOR	**NATL**	**PIREOS**	**EMPOR**	**NATL**	**PIREOS**	**EMPOR**	**NATL**	**PIREOS**	**EMPOR**	**NATL**	**PIREOS**
Beta 1	**0.7409**	**0.7495**	**1.0755**	**0.5382**	**0.4286**	**1.0766**	**2.9160**	**1.9948**	**1.5333**	**0.7912**	**0.4151**	**1.1619**
Standard Errors	*0.2864*	*0.1750*	*0.0107*	*0.1944*	*0.0891*	*0.3022*	*1.1063*	*0.3666*	*0.7489*	*0.0742*	*0.1340*	*0.1021*
p values	*0.0203*	*0.0000*	*0.0000*	*0.0028*	*0.0000*	*0.0002*	*0.0042*	*0.0000*	*0.0203*	*0.0000*	*0.0034*	*0.0000*
Beta 2	**0.7086**	**0.6478**	**0.5677**	**0.7162**	**0.6843**	**0.6843**	**0.4940**	**0.6392**	**0.6151**	0	0	0
Standard Errors	*0.1158*	*0.0825*	*0.1279*	*0.0704*	*0.0449*	*0.0449*	*0.0919*	*0.0867*	*0.0434*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.2653**	**0.4102**	**0.4386**	**0.1687**	**0.2814**	**0.2194**	0.4039	**0.5401**	**0.4878**	0	0	0
Standard Errors	*0.1298*	*0.0823*	*0.0827*	*0.0827*	*0.0479*	*0.0576*	*0.4735*	*0.2613*	*0.1974*	*0*	*0*	*0*
p values	*0.0067*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0001*	*0.1968*	*0.0194*	*0.0067*	*0*	*0*	*0*
Beta 4	0	0	0	**0.4274**	**0.5459**	**0.6461**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.1005*	*0.0784*	*0.0886*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	405.49	400.22	449.08	394.87	389.85	437.31	407.67	399.33	446.34	426.05	448.56	469.39
Hits in-sample(%)	5.0134	5.0134	4.9465	5.0134	5.0134	5.0134	5.0134	5.1471	5.0134	5.1471	4.6123	4.9465
Hits out-of-sample(%)	3.2000	2.8000	3.0000	3.6000	2.8000	3.6000	2.8000	3.2000	3.6000	2.8000	4.4000	4.8000
DQ in-sample (p values)	0.0107	0.0004	0.0461	0.9904	0.0937	0.8497	0.0069	0.0001	0.3057	0.3500	0.0068	0.0000
DQ out-of-sample (p values)	0.6045	0.2053	0.0182	0.4389	0.2606	0.4977	0.3923	0.3304	0.0628	0.4411	0.2778	0.4747

TABLE 4: Estimates and Relevant Statistics for the four Conditional Autoregressive Value at Risk Models

1%VaR	Symmetric Absolute Value			Asymmetric slope			Indirect GARCH			Adaptive		
	ALPHA	COCA	INTRAC	ALPHA	COCA	INTRAC	ALPHA	COCA	INTRAC	ALPHA	COCA	INTRAC
Beta 1	**1.4927**	**6.3413**	**1.2069**	**0.9554**	2.7066	**0.9683**	**1.7594**	**21.8432**	**4.8359**	**0.8267**	0.1781	**0.5916**
Standard Errors	*0.4021*	*4.4284*	*0.5123*	*0.4837*	*3.5445*	*0.5805*	*1.0322*	*48.1658*	*2.2902*	*0.4996*	*0.3611*	*0.2144*
p values	*0.0001*	*0.0761*	*0.0092*	*0.0242*	*0.2225*	*0.0477*	*0.0441*	*0.3251*	*0.0174*	*0.0490*	*0.3110*	*0.0029*
Beta 2	**0.5945**	0.1557	**0.6764**	**0.6189**	**0.6070**	**0.6625**	**0.8226**	**0.5943**	**0.6787**	0	0	0
Standard Errors	*0.0629*	*0.5282*	*0.0930*	*0.0706*	*0.4883*	*0.1071*	*0.0369*	*0.7880*	*0.0761*	*0*	*0*	*0*
p values	*0.0000*	*0.3841*	*0.0000*	*0.0000*	*0.1069*	*0.0000*	*0.0000*	*0.2254*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.7158**	0.1643	**0.5244**	**0.7033**	-0.0306	**0.4937**	**0.9738**	**0.2294**	**1.1203**	0	0	0
Standard Errors	*0.0778*	*0.1238*	*0.0948*	*0.0925*	*0.0918*	*0.1148*	*0.1285*	*0.1909*	*0.6541*	*0*	*0*	*0*
p values	*0.0000*	*0.0922*	*0.0000*	*0.0000*	*0.3695*	*0.0000*	*0.0000*	*0.1148*	*0.0434*	*0*	*0*	*0*
Beta 4	0	0	0	**0.8742**	0.1815	**0.6573**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.4414*	*0.1480*	*0.1511*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0238*	*0.1100*	*0.0000*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	88.73	115.07	88.03	89.55	114.47	87.22	89.05	114.36	86.67	102.28	117.31	97.58
Hits in-sample(%)	0.9959	1.0788	0.9959	0.9959	0.9959	0.9129	0.9959	1.0788	0.9959	0.6639	0.7469	0.4979
Hits out-of-sample(%)	0.8000	0.2000	0.6000	1.0000	0.2000	0.6000	0.8000	0.2000	0.8000	0.8000	0.2000	0.6000
DQ in-sample (p values)	0.9798	0.9851	0.9897	0.9793	0.9880	0.1261	0.9853	0.9882	0.1675	0.9995	0.9981	1.0000
DQ out-of-sample (p values)	0.8899	0.7594	0.9910	0.0010	0.7840	0.9907	0.9520	0.7839	0.9990	0.0002	0.7511	0.8849

5%VaR	Symmetric Absolute Value			Asymmetric slope			Indirect GARCH			Adaptive		
	ALPHA	COCA	INTRAC	ALPHA	COCA	INTRAC	ALPHA	COCA	INTRAC	ALPHA	COCA	INTRAC
Beta 1	**0.8476**	**1.0556**	**0.9945**	**1.8229**	**1.0786**	**0.8248**	**2.9534**	**3.9872**	**4.3256**	**0.4977**	**-0.0514**	**0.3803**
Standard Errors	*0.3176*	*0.4259*	*0.3019*	*0.2970*	*0.3862*	*0.3590*	*1.1873*	*1.8558*	*1.1824*	*0.1827*	*0.0651*	*0.1184*
p values	*0.0038*	*0.0066*	*0.0005*	*0.0000*	*0.0026*	*0.0108*	*0.0064*	*0.0158*	*0.0001*	*0.0032*	*0.2149*	*0.0007*
Beta 2	**0.6039**	**0.6370**	**0.5869**	**0.2173**	**0.6327**	**0.5948**	**0.5332**	**0.6309**	**0.4205**	0	0	0
Standard Errors	*0.1185*	*0.1206*	*0.1013*	*0.0909*	*0.0908*	*0.0994*	*0.0896*	*0.0856*	*0.0704*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0084*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.5401**	**0.3658**	**0.4347**	**0.5217**	**0.1671**	**0.2713**	**0.8778**	**0.4947**	**0.7805**	0	0	0
Standard Errors	*0.1415*	*0.1001*	*0.1537*	*0.2060*	*0.0692*	*0.0500*	*0.2100*	*0.1239*	*0.2309*	*0*	*0*	*0*
p values	*0.0004*	*0.0001*	*0.0023*	*0.0057*	*0.0079*	*0.0000*	*0.0000*	*0.0000*	*0.0004*	*0*	*0*	*0*
Beta 4	0	0	0	**0.8110**	**0.4052**	**0.5062**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.1003*	*0.1200*	*0.0743*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0000*	*0.0004*	*0.0000*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	328.17	396.05	316.52	325.50	391.16	311.99	324.59	395.25	311.33	357.88	409.43	329.83
Hits in-sample(%)	4.9793	4.9793	5.0622	4.8133	5.0622	5.0622	5.0622	4.9793	5.0622	4.6473	4.5643	4.7303
Hits out-of-sample(%)	3.2000	2.8000	2.8000	2.0000	3.2000	2.4000	2.2000	3.6000	2.4000	4.8000	1.0000	4.8000
DQ in-sample (p values)	0.4828	0.0377	0.0030	0.7456	0.5790	0.4113	0.4624	0.2472	0.0594	0.0000	0.0016	0.0000
DQ out-of-sample (p values)	0.0348	0.4221	0.2285	0.0396	0.5460	0.2457	0.0268	0.4080	0.2197	0.1837	0.0103	0.3573

TABLE 5: Estimates and Relevant Statistics for the four Conditional Autoregressive Value at Risk Models

1%VaR	Symmetric Absolute Value			Asymmetric Slope			Indirect GARCH			Adaptive		
	CAC40	FTSE20	NIKKEI	CAC40	FTSE20	NIKKEI	CAC40	FTSE20	NIKKEI	CAC40	FTSE20	NIKKEI
Beta 1	**0.1756**	**0.0196**	**0.1600**	**0.1359**	**0.5886**	**0.3751**	0.2344	0.0029	0.1611	**0.7361**	**1.0875**	**1.1999**
Standard Errors	*0.0829*	*0.0080*	*0.0473*	*0.0523*	*0.2954*	*0.1279*	*0.1597*	*0.0670*	*0.1464*	*0.1247*	*0.1570*	*0.1184*
p values	*0.0170*	*0.0072*	*0.0004*	*0.0047*	*0.0232*	*0.0017*	*0.0712*	*0.4826*	*0.1357*	*0.0000*	*0.0000*	*0.0000*
Beta 2	**0.9147**	**0.9820**	**0.9152**	**0.9102**	**0.6610**	**0.7371**	**0.9332**	**0.9374**	**0.8318**	0	0	0
Standard Errors	*0.0468*	*0.0059*	*0.0315*	*0.0265*	*0.0629*	*0.1028*	*0.0134*	*0.0105*	*0.0344*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.1859**	**0.0737**	**0.2026**	0.0529	0.4222	-0.0916	0.2912	0.4632	1.2497	0	0	0
Standard Errors	*0.0818*	*0.0228*	*0.0779*	*0.0608*	*0.4241*	*0.1092*	*0.2758*	*0.6007*	*0.9294*	*0*	*0*	*0*
p values	*0.0116*	*0.0006*	*0.0047*	*0.1923*	*0.1597*	*0.2009*	*0.1455*	*0.2203*	*0.0894*	*0*	*0*	*0*
Beta 4	0	0	0	**0.2552**	**1.0165**	**0.9297**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.0658*	*0.1658*	*0.3542*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0001*	*0.0000*	*0.0043*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	81.48	111.01	84.22	79.29	107.25	77.25	80.94	110.47	83.01	88.03	118.82	89.88
Hits in-sample(%)	1.0246	0.9734	1.0246	0.9734	1.0758	1.0246	1.0246	1.0758	1.0758	1.3320	1.0758	1.0758
Hits out-of-sample(%)	05988	0.5988	1.1976	0.9980	0.1996	1.5968	0.5988	0.7984	1.1976	0.1996	0.7984	0.7984
DQ in-sample (p values)	0.0004	0.1214	0.0000	0.0543	0.6991	0.2244	0.0005	0.0786	0.2540	0.0001*	0.0000*	0.0000*
DQ out-of-sample (p values)	0.9694	0.9903	0.9630	0.9841	0.7823	0.1204	0.9746	0.9632	0.7756	0.7750	0.7984	0.7984

5%VaR	Symmetric Absolute Value			Asymmetric slope			Indirect GARCH			Adaptive		
	CAC40	FTSE20	NIKKEI	CAC40	FTSE20	NIKKEI	CAC40	FTSE20	NIKKEI	CAC40	FTSE20	NIKKEI
Beta 1	**0.1311**	**0.1126**	**0.1588**	**0.0312**	**0.3842**	**0.1122**	**0.0799**	**0.4431**	**0.1262**	**0.6720**	**0.9906**	**0.8242**
Standard Errors	*0.0264*	*0.0283*	*0.0341*	*0.0140*	*0.1388*	*0.0324*	*0.0459*	*0.2502*	*0.0417*	*0.0739*	*0.1106*	*0.0650*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0130*	*0.0028*	*0.0003*	*0.0409*	*0.0383*	*0.0012*	*0.0000*	*0.0000*	*0.0000*
Beta 2	**0.8919**	**0.9075**	**0.8368**	**0.9221**	**0.6349**	**0.8300**	**0.8939**	**0.7553**	**0.7824**	0	0	0
Standard Errors	*0.0340*	*0.0190*	*0.0576*	*0.0289*	*0.0780*	*0.0392*	*0.0116*	*0.0508*	*0.0166*	*0*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*	*0*
Beta 3	**0.1903**	**0.1667**	**0.3014**	0.0598	**0.2100**	-0.0210	0.2791	0.5059	0.4751	0	0	0
Standard Errors	*0.0552*	*0.1001*	*0.0890*	*0.0531*	*0.1216*	*0.0392*	*0.2453*	*0.3811*	*0.3255*	*0*	*0*	*0*
p values	*0.0003*	*0.0001*	*0.0003*	*0.1300*	*0.0421*	*0.2959*	*0.1277*	*0.0922*	*0.0722*	*0*	*0*	*0*
Beta 4	0	0	0	**0.2137**	**0.7067**	**0.4391**	0	0	0	0	0	0
Standard Errors	*0*	*0*	*0*	*0.0668*	*0.0781*	*0.1505*	*0*	*0*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0*	*0.0007*	*0.0000*	*0.0018*	*0*	*0*	*0*	*0*	*0*	*0*
RQ	298.91	380.54	243.99	295.29	361.72	228.74	297.37	377.12	244.83	304.58	387.01	249.12
Hits in-sample(%)	5.0205	5.0205	5.0205	4.9693	5.0717	4.9693	5.0205	5.0717	5.1230	5.0205	4.9693	4.7643
Hits out-of-sample(%)	3.9920	3.7924	6.3872	4.3912	4.5908	8.3832	3.5928	3.1936	6.5868	3.3932	4.7904	4.9900
DQ in-sample (p values)	0.4757	0.0000*	0.0045*	0.8365	0.0090*	0.0676	0.9484	0.0001*	0.0141	0.8822	0.0575	0.1657
DQ out-of-sample (p values)	0.5708	0.6619	0.2786	0.8020	0.9689	0.0001	0.4439	0.4835	0.2790	0.2264	0.0937	0.3811

TABLE 6: Estimates and Relevant Statistics for the four Conditional Autoregressive Value at Risk Models

1%VaR	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	NASDAQ	FTSE100	NASDAQ	FTSE100	NASDA	FTSE100	NASDAQ	FTSE100
Beta 1	**0.5159**	0.0674	0.2461	0.0471	0.7020	0.0772	**0.9360**	0.0124
Standard Errors	*0.3314*	*0.0737*	*0.1741*	*0.0508*	*0.3597*	*0.1674*	*0.0903*	*0.1243*
p values	*0.0598*	*0.1802*	*0.0788*	*0.1769*	*0.0232*	*0.3223*	*0.0000*	*0.4602*
Beta 2	**0.7005**	**0.9527**	**0.6062**	**0.9593**	**0.5940**	**0.9454**	0	0
Standard Errors	*0.1718*	*0.0488*	*0.1295*	*0.0297*	*0.0710*	*0.0492*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*
Beta 3	0.9168	**0.1226**	**0.7504**	-0.0094	**2.2256**	0.2103	0	0
Standard Errors	*0.2230*	*0.0520*	*0.1677*	*0.0448*	*0.7681*	*0.4721*	*0*	*0*
p values	*0.2203*	*0.0092*	*0.0000*	*0.4171*	*0.0019*	*0.3279*	*0*	*0*
Beta 4	0	0	1.5136	**0.1087**	0	0	0	0
Standard Errors	*0*	*0*	*1.0013*	*0.0588*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0.0653*	*0.0323*	*0*	*0*	*0*	*0*
RQ	63.32	49.74	60.02	48.84	62.33	49.88	88.47	51.18
Hits in-sample(%)	0.9734	1.0246	0.9734	1.0246	1.0758	1.0246	0.9734	0.7684
Hits out-of-sample(%)	0.9980	0.7984	1.3972	0.7984	0.7984	0.7984	0.9980	0.3392
DQ in-sample (p values)	0.2292	0.4542	0.9610	0.9598	0.2292	0.9667	0.0000*	0.9944
DQ out-of-sample (p values)	0.8073	0.9968	0.5547	0.9962	0.9838	0.9994	0.6600	0.7911

5%VaR	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	NASDA	FTSE100	NASDAQ	FTSE100	NASDAQ	FTSE100	NASDAQ	FTSE100
Beta 1	**0.2797**	**0.1466**	**0.2068**	**0.0903**	**0.1615**	**0.1566**	**0.5404**	**0.1577**
Standard Errors	*0.0220*	*0.1526*	*0.0282*	*0.0493*	*0.0376*	*0.0954*	*0.0506*	*0.0519*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0335*	*0.0000*	*0.0504*	*0.0000*	*0.0012*
Beta 2	**0.7067**	**0.8719**	**0.6642**	**0.8965**	**0.6758**	**0.8731**	0	0
Standard Errors	*0.0143*	*0.1476*	*0.0434*	*0.0429*	*0.0162*	*0.0600*	*0*	*0*
p values	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0*	*0*
Beta 3	**0.5544**	0.0639	0.0238	-0.0094	0.8632	**0.0694**	0	0
Standard Errors	*0.0163*	*0.0636*	*0.0465*	*0.0337*	*0.5659*	*0.1216*	*0*	*0*
p values	*0.0000*	*0.1574*	*0.3048*	*0.3898*	*0.0636*	*0.0421*	*0*	*0*
Beta 4	0	0	**0.7806**	**0.1360**	0	0	0	0
Standard Errors	*0*	*0*	*0.1148*	*0.0628*	*0*	*0*	*0*	*0*
p values	*0*	*0*	*0.0000*	*0.0151*	*0*	*0*	*0*	*0*
RQ	199.44	169.08	184.03	166.15	198.56	169.08	213.93	169.43
Hits in-sample(%)	4.9693	4.9693	5.0205	4.9180	4.8668	4.9693	4.8156	4.1496
Hits out-of-sample(%)	5.5888	3.9920	5.5888	4.9900	5.3892	3.9920	4.7904	5.1896
DQ in-sample (p values)	0.9765	0.0000*	0.9392	0.8597	0.8079	0.0004	0.0745	0.9593
DQ out-of-sample (p values)	0.0956	0.1905	0.1762	0.0941	0.0272*	0.4143	0.2356	0.1716

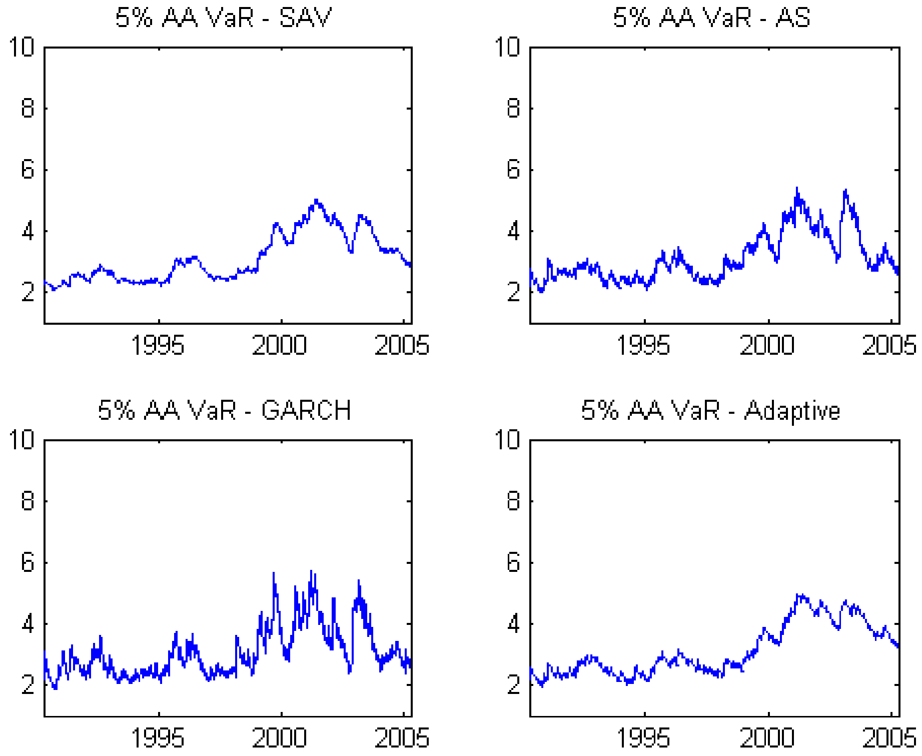

Figure 1(a): 5% Estimated Conditional Autoregressive VaR Plots for ALCOA: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

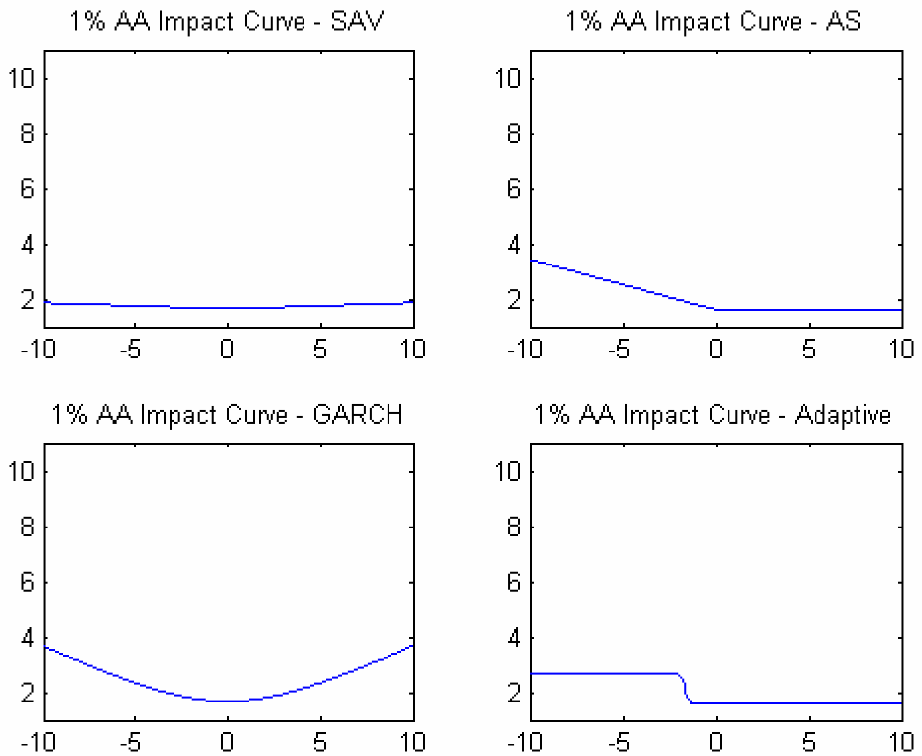

Figure 1(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for ALCOA: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

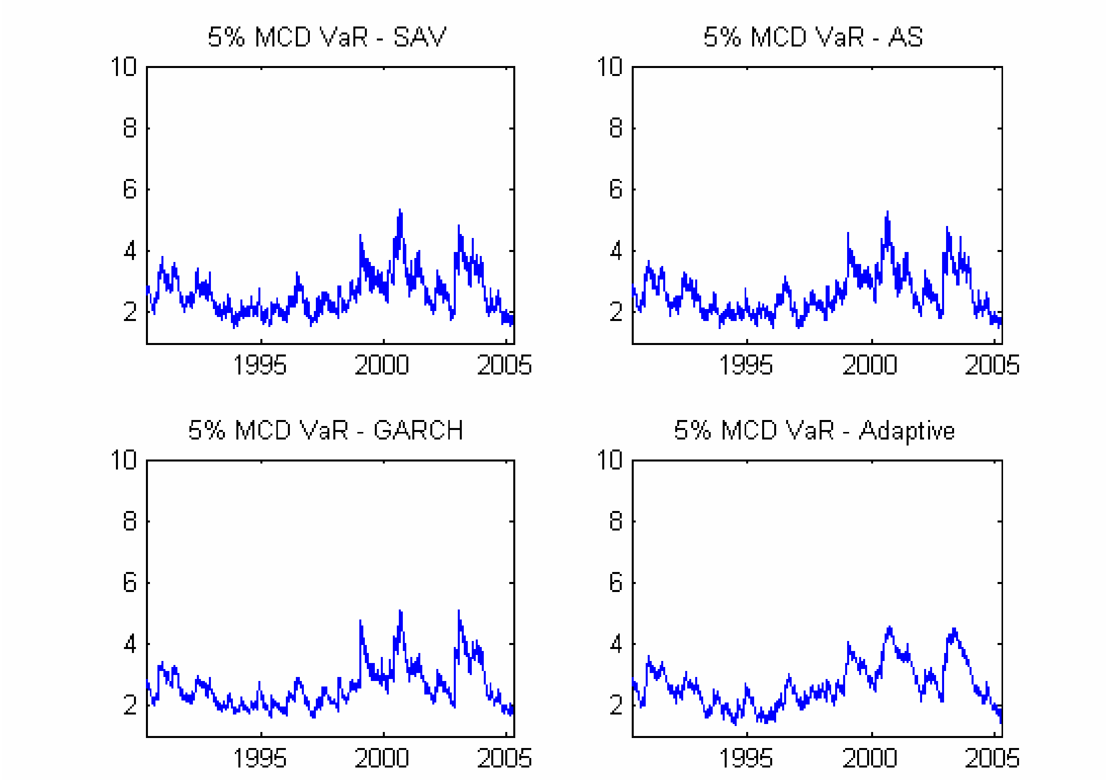

Figure 2(a): 5% Estimated Conditional Autoregressive VaR Plots for McDONALDS: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

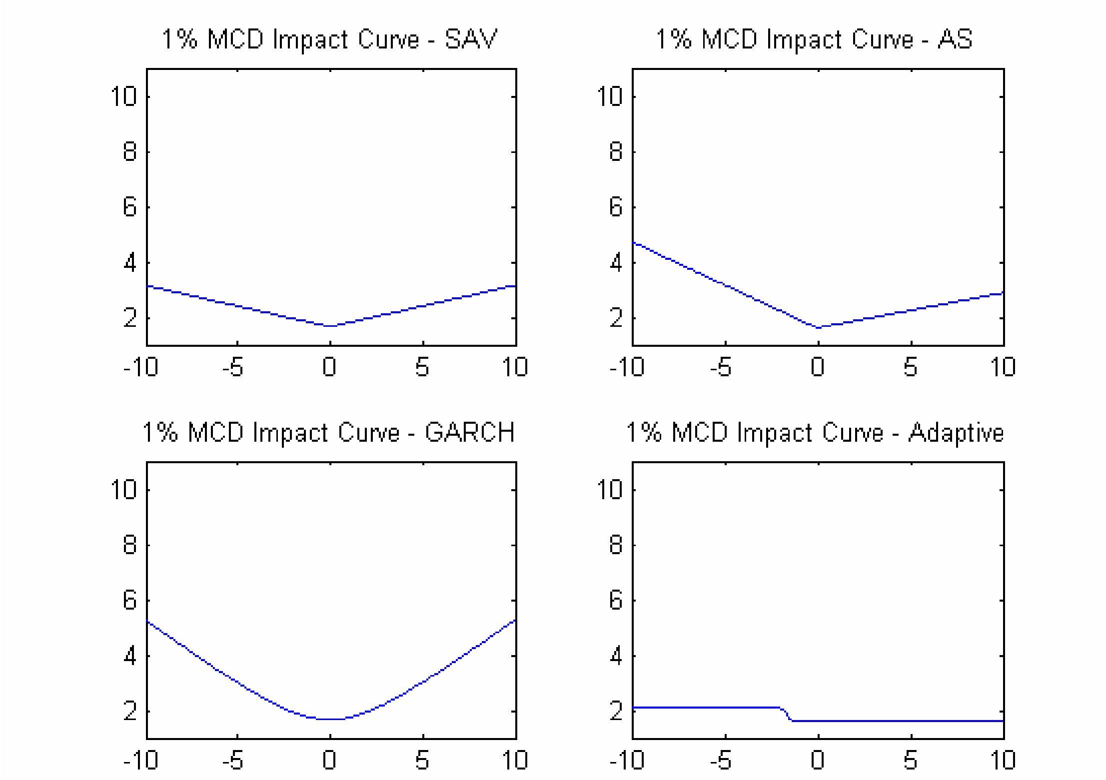

Figure 2(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for McDONALDS: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

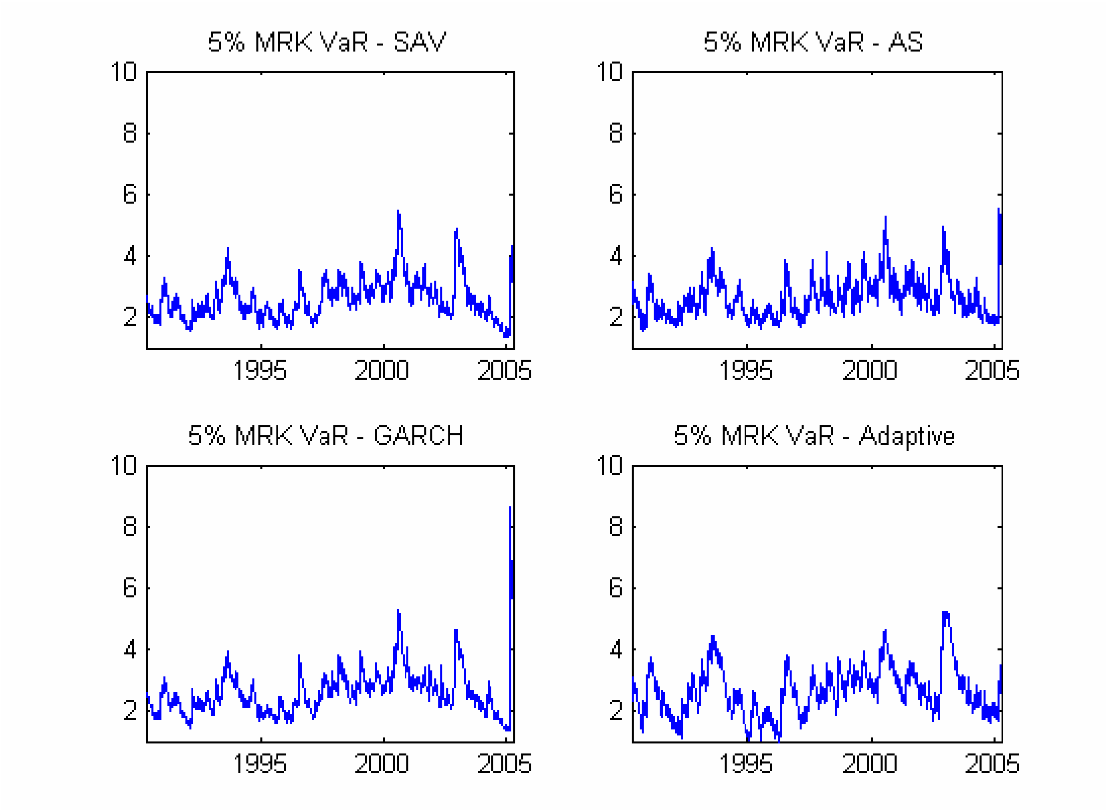

Figure 3(a): 5% Estimated Conditional Autoregressive VaR Plots for MERK: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

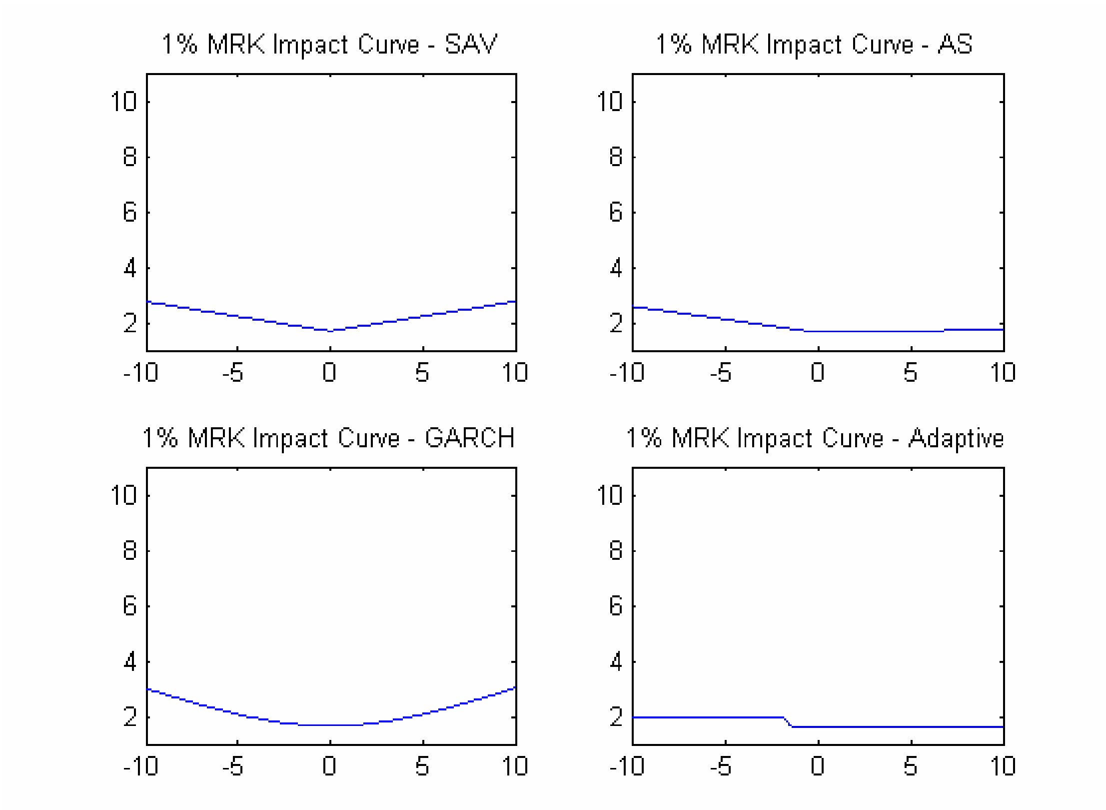

Figure 3(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for MERK: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

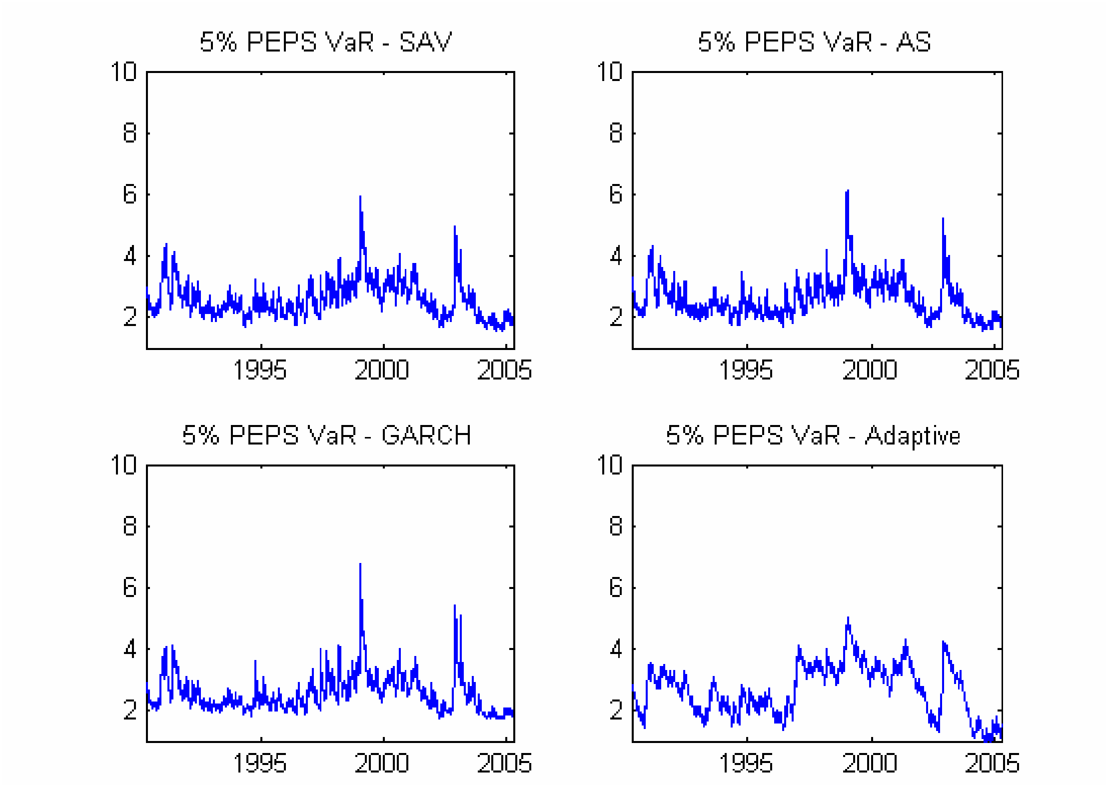

Figure 4(a): 5% Estimated Conditional Autoregressive VaR Plots for PEPSICO: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

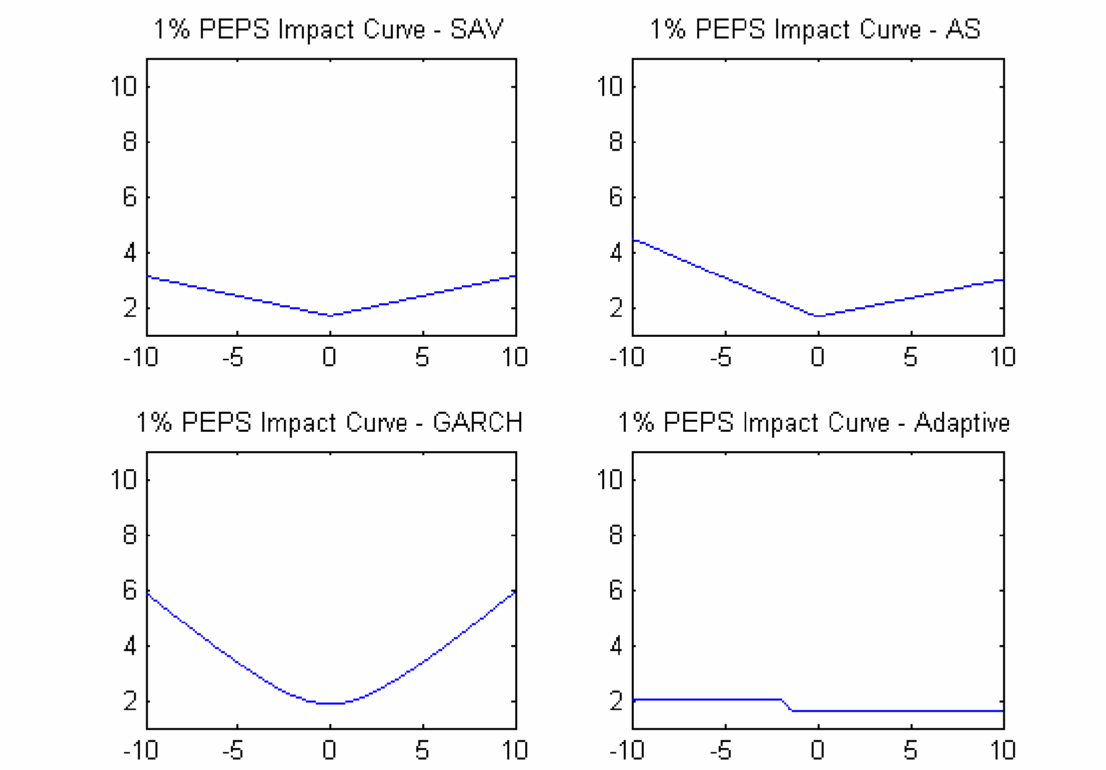

Figure 4(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for PEPSICO: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

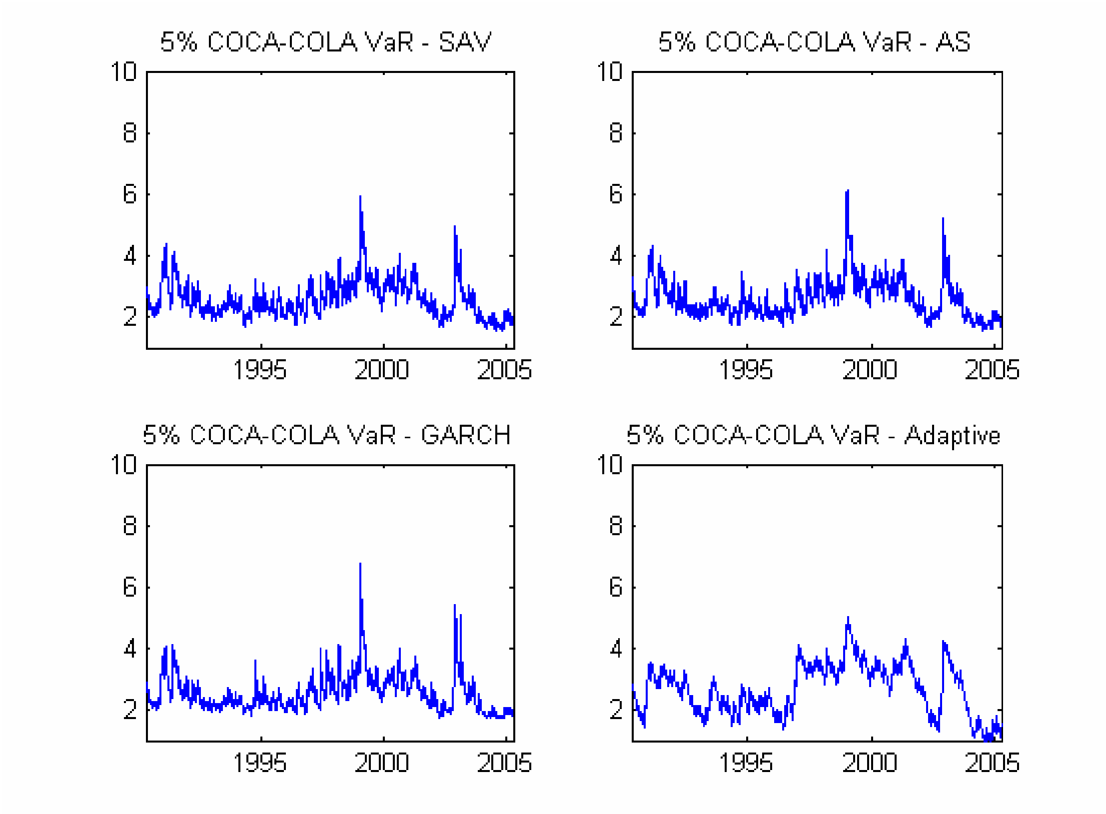

Figure 5(a): 5% Estimated Conditional Autoregressive VaR Plots for COCA COLA: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

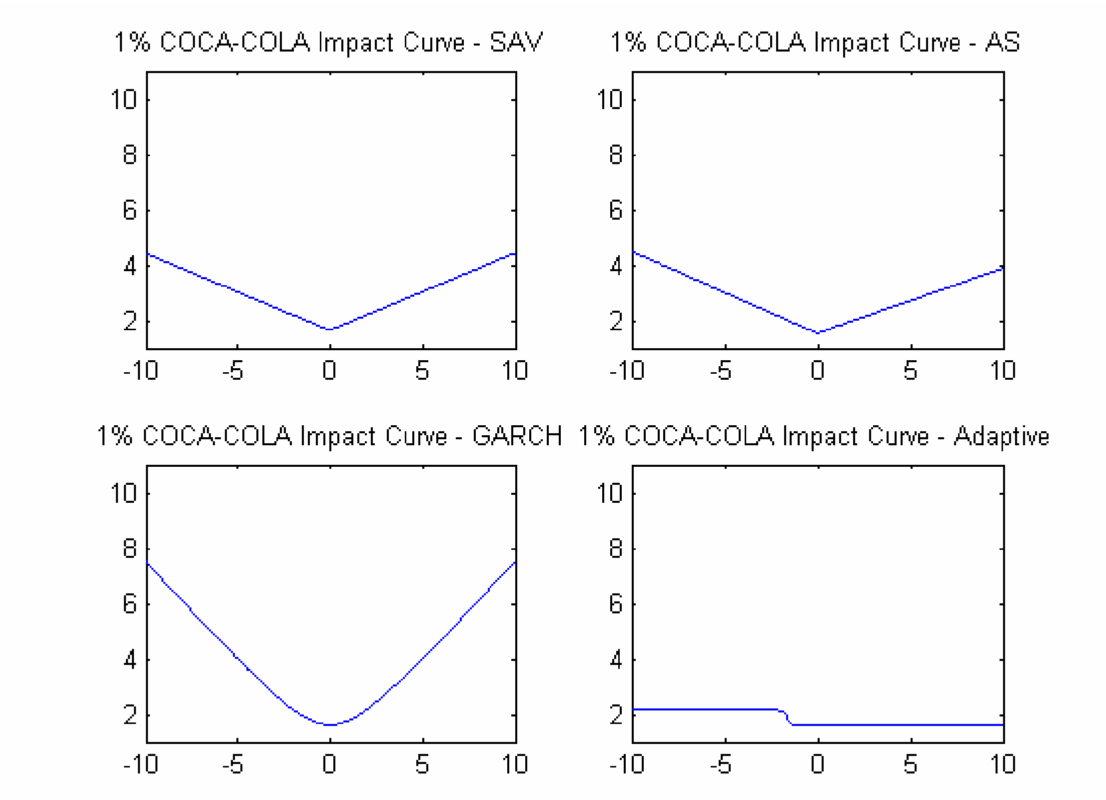

Figure 5(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for COCA COLA: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

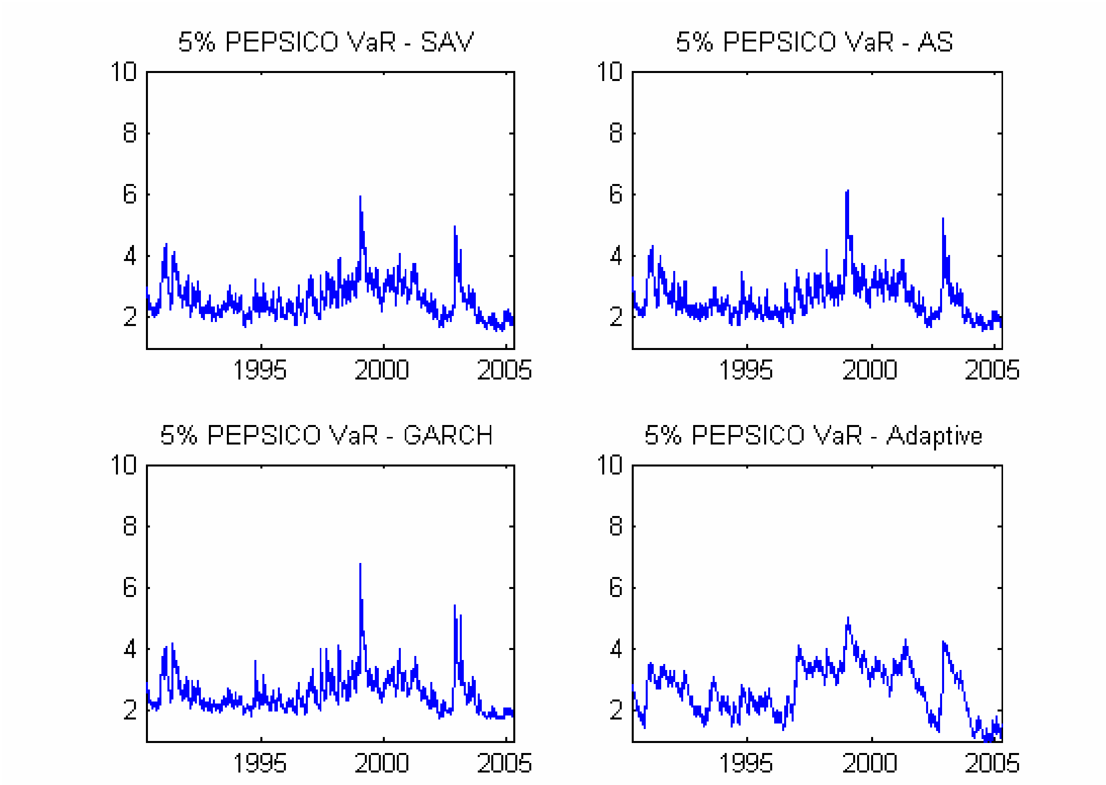

Figure 6(a): 5% Estimated Conditional Autoregressive VaR Plots for EXXON: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

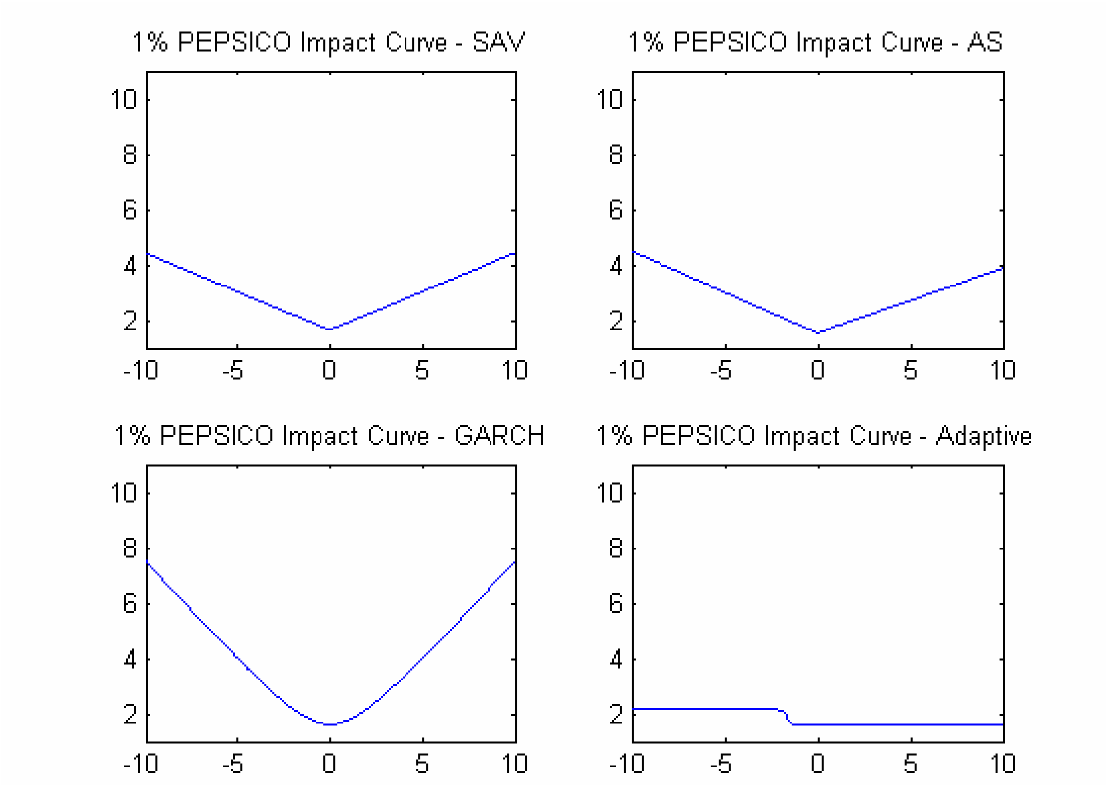

Figure 6(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for EXXON: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

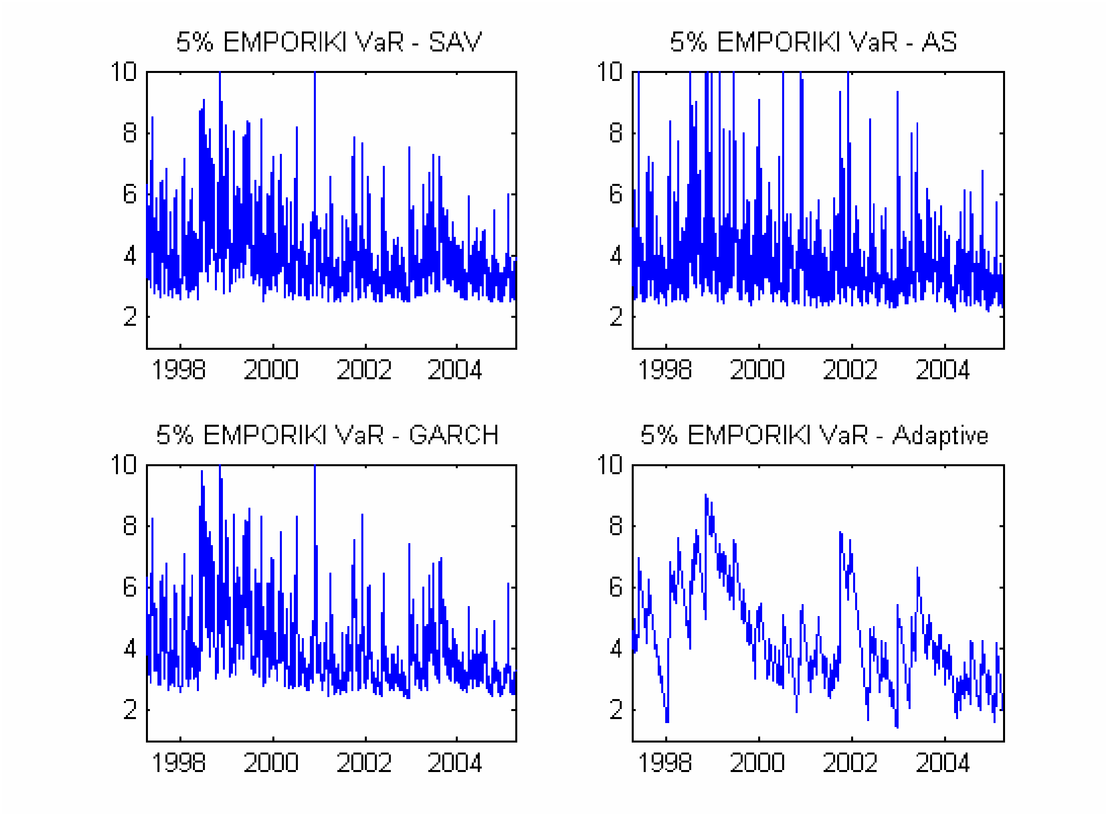

Figure 7(a): 5% Estimated Conditional Autoregressive VaR Plots for EMPORIKI: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

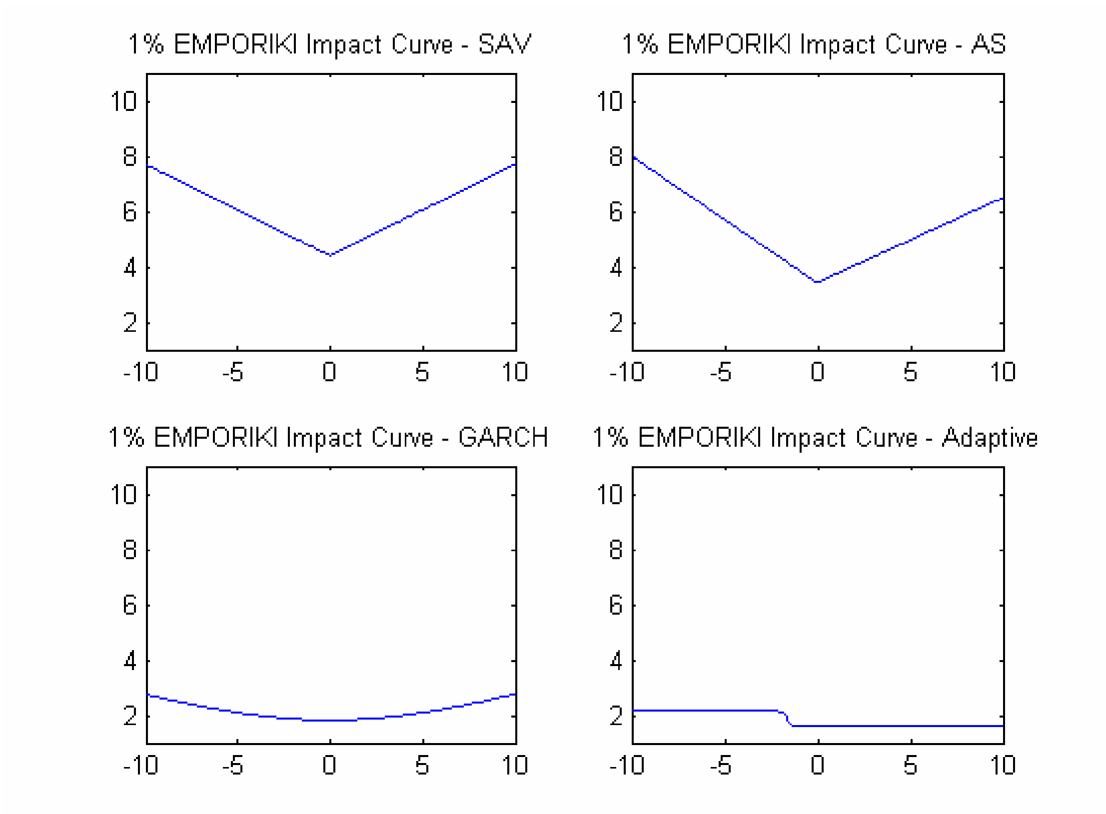

Figure 7(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for EMPORIKI: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

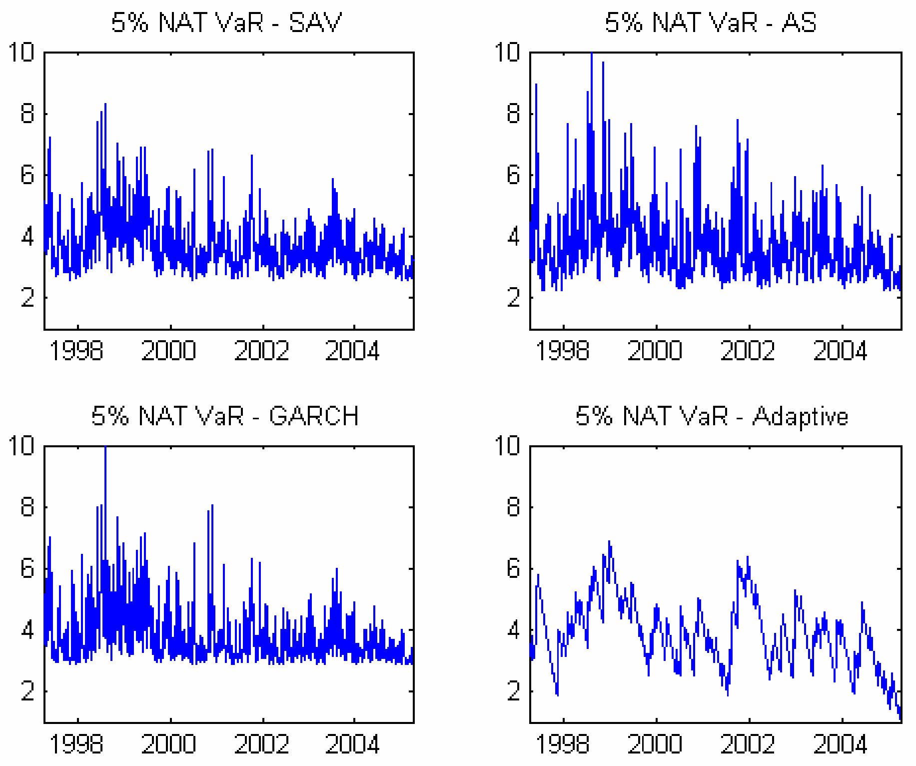

Figure 8(a): 5% Estimated Conditional Autoregressive VaR Plots for NATIONAL: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

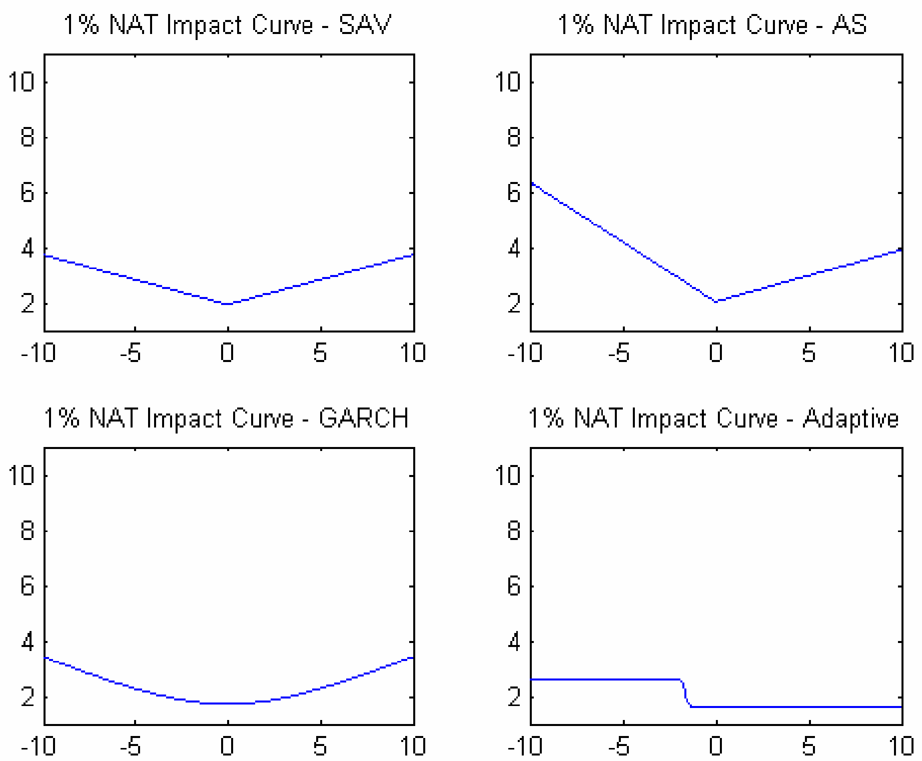

Figure 8(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for NATIONAL: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

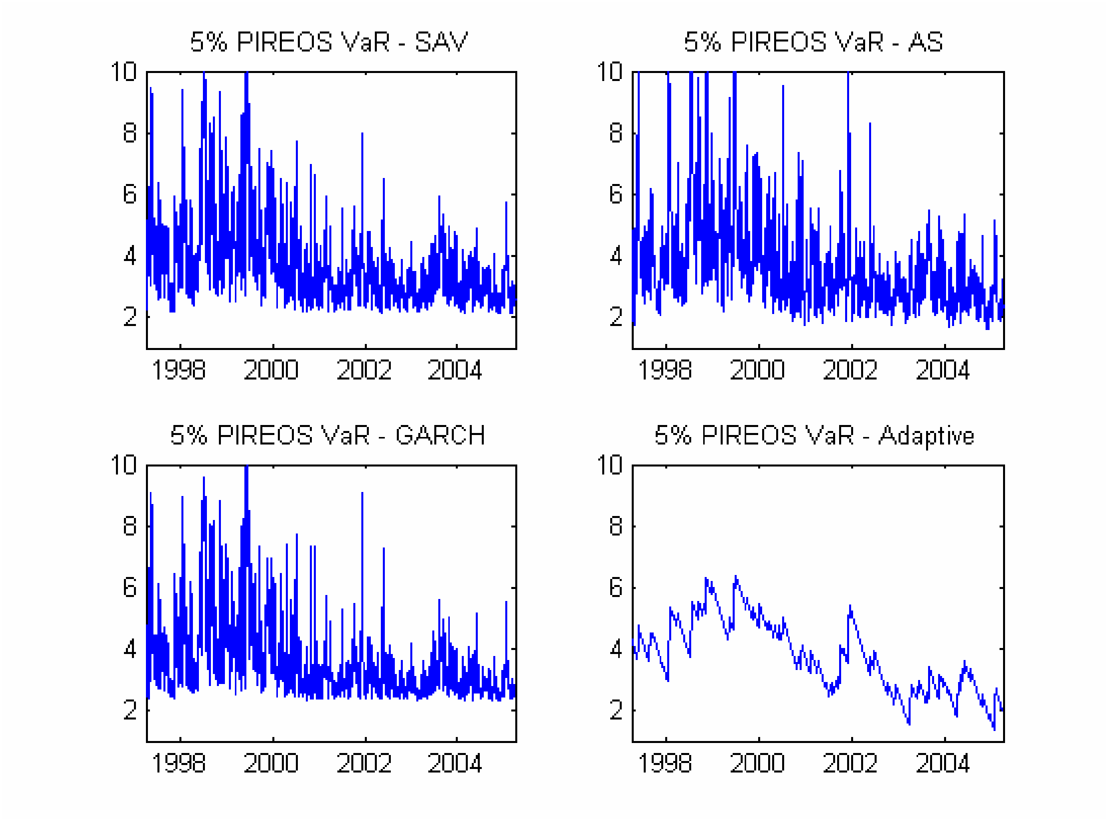

Figure 9(a): 5% Estimated Conditional Autoregressive VaR Plots for PIREOS: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

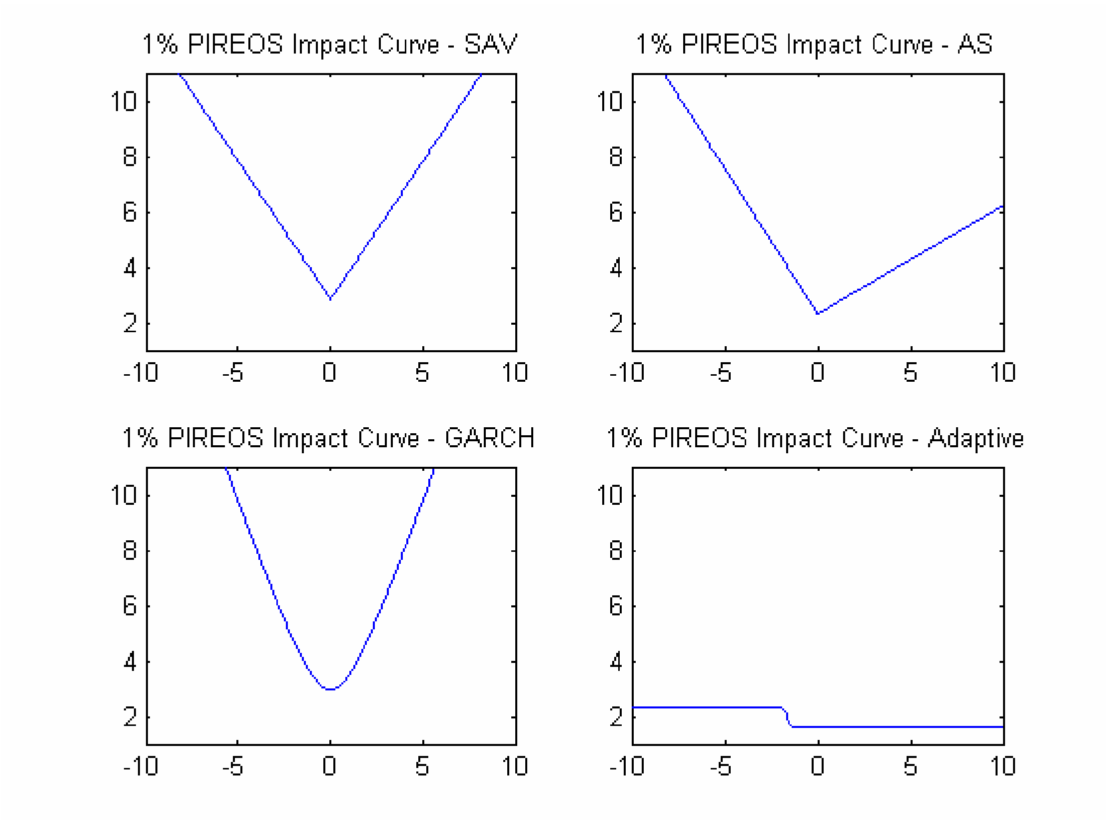

Figure 9(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for PIREOS: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

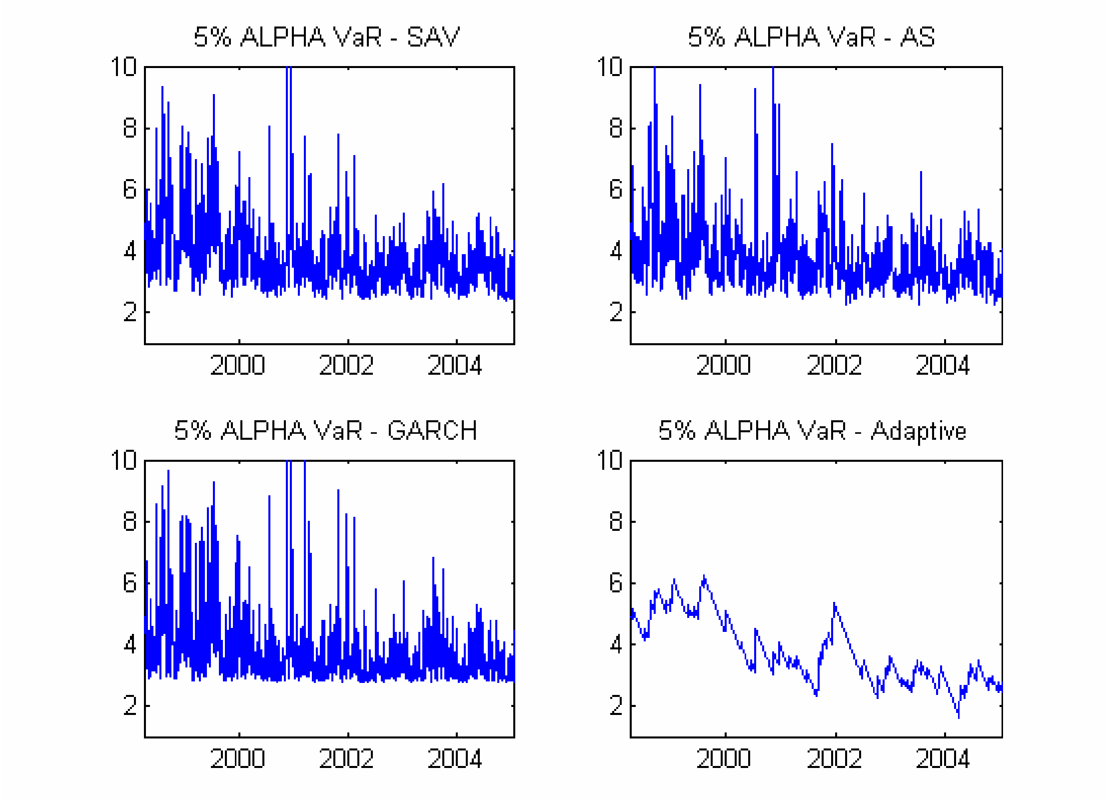

Figure 10(a): 5% Estimated Conditional Autoregressive VaR Plots for ALPHA: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

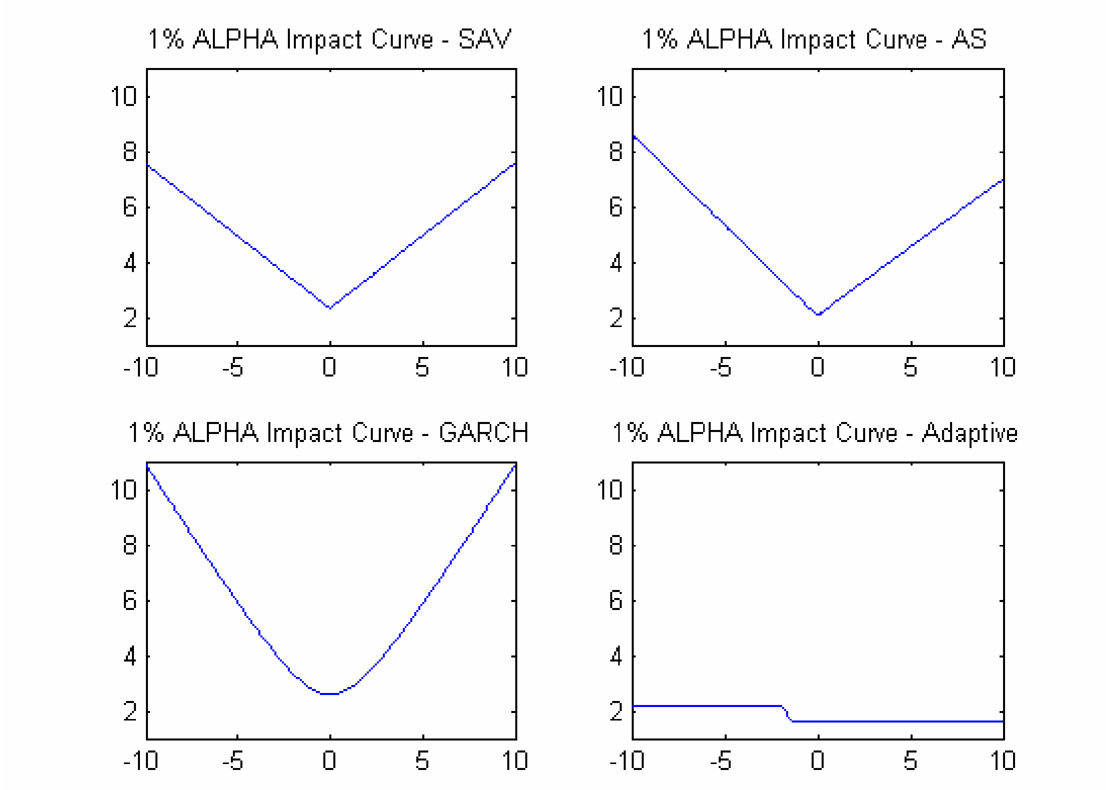

Figure 10(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for ALPHA: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

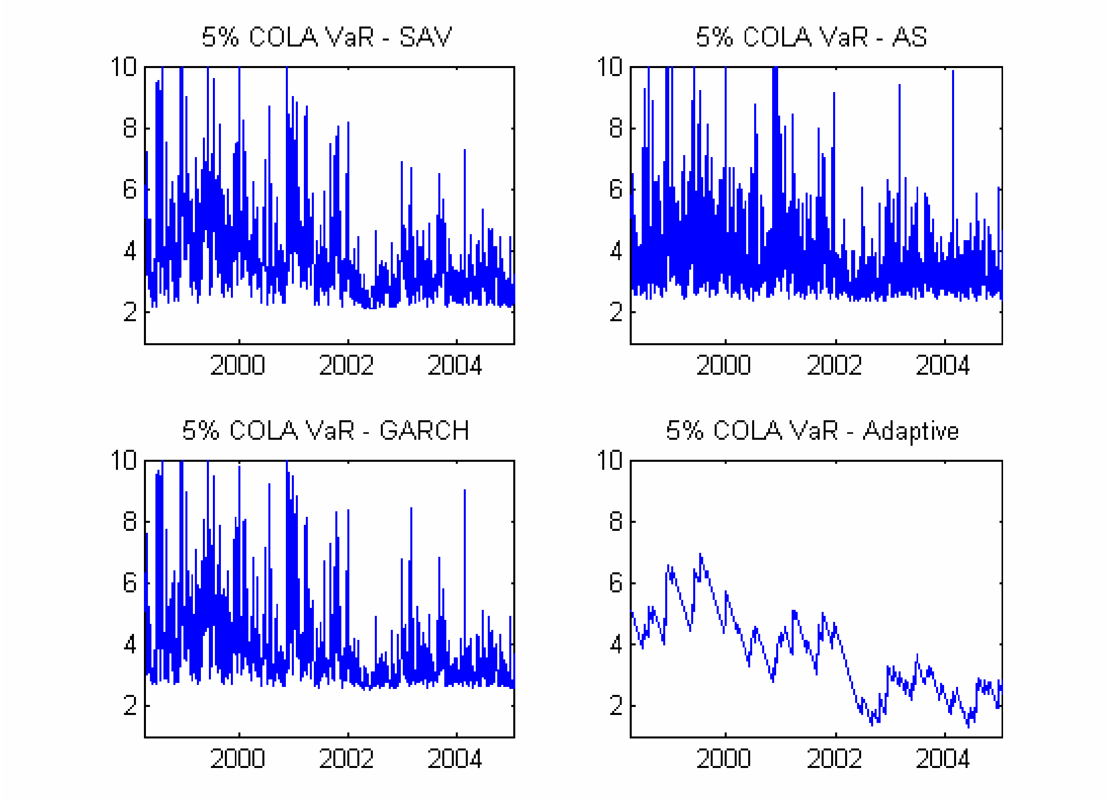

Figure 11(a): 5% Estimated Conditional Autoregressive VaR Plots for COLA(GR): (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

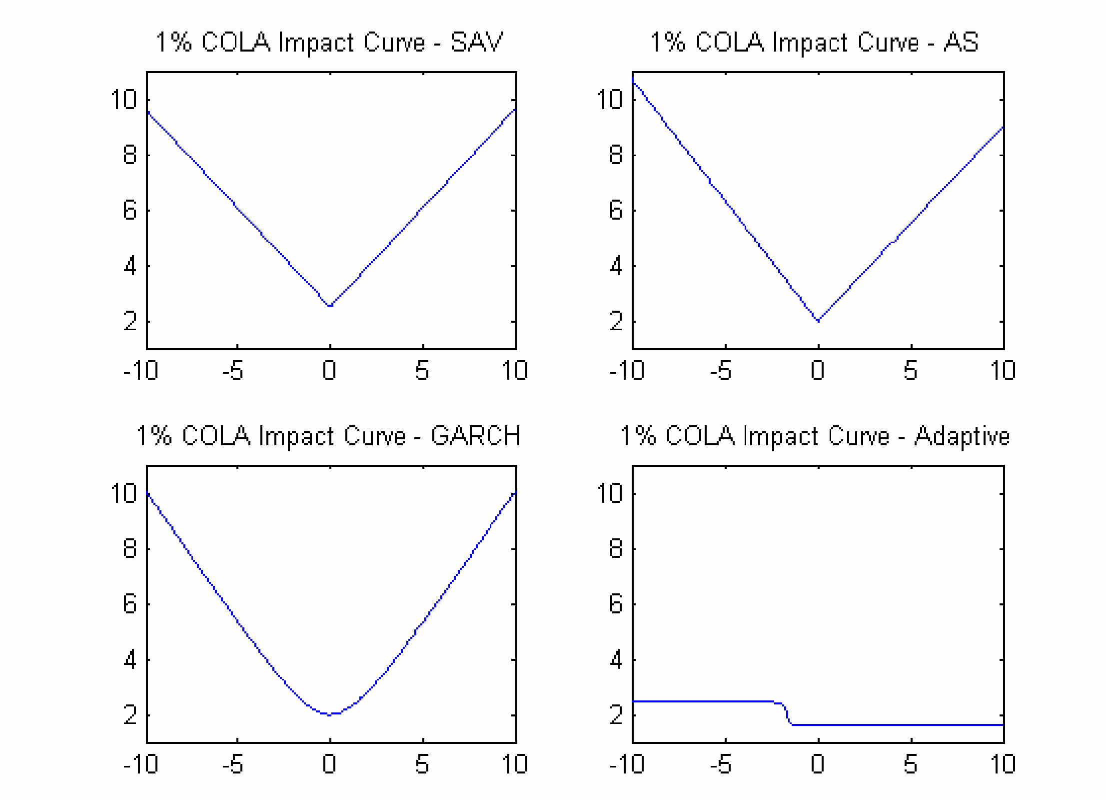

Figure 11(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for COLA(GR): (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

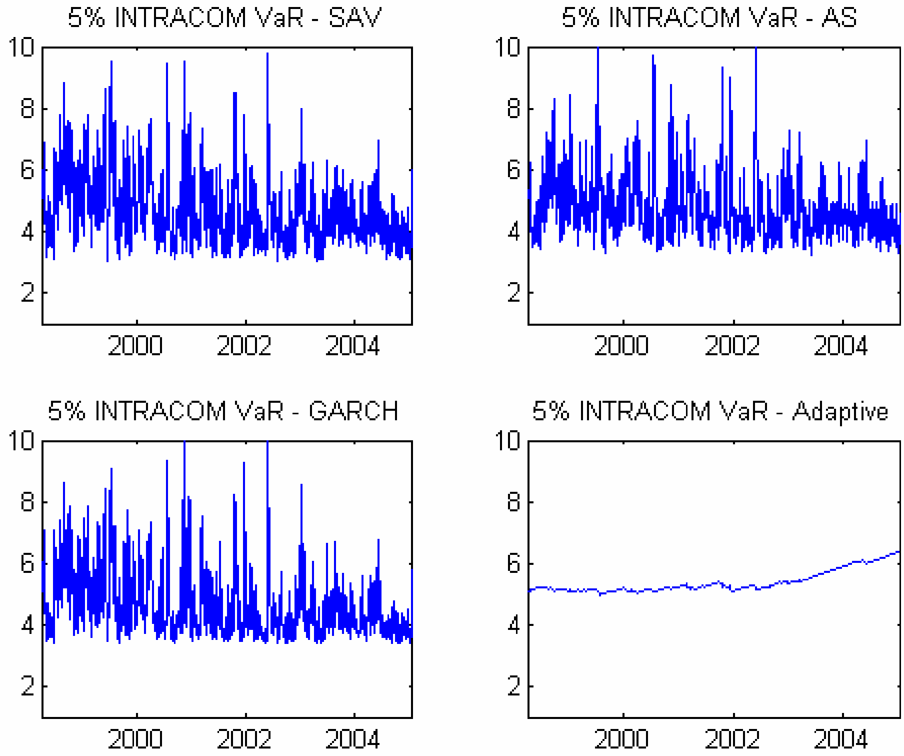

Figure 12(a): 5% Estimated Conditional Autoregressive VaR Plots for INTRAKOM: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

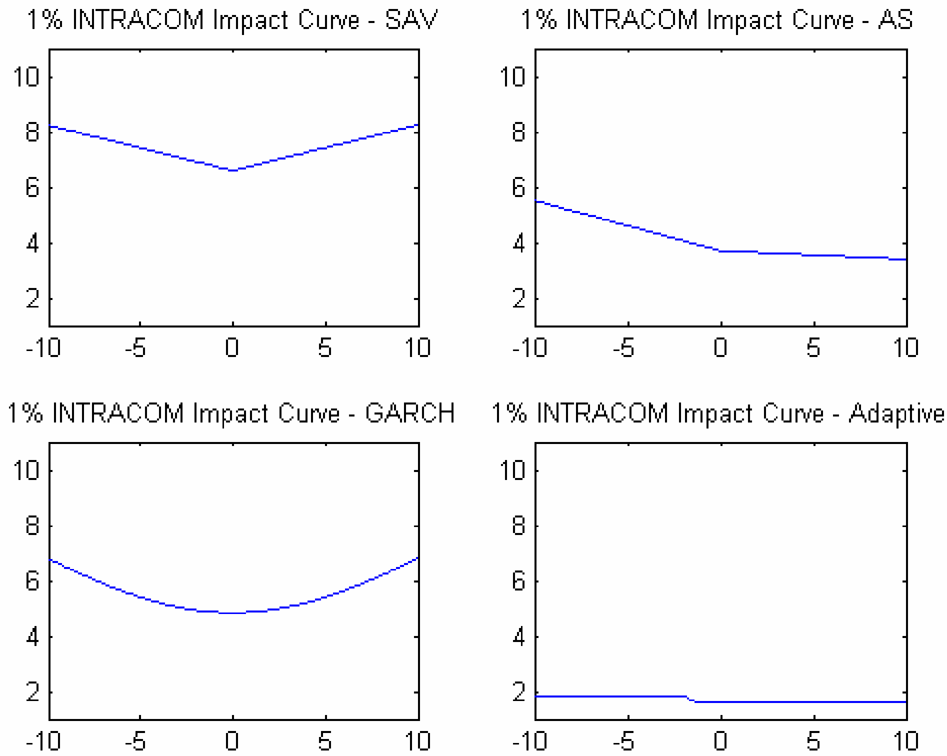

Figure 12(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for INTRAKOM: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

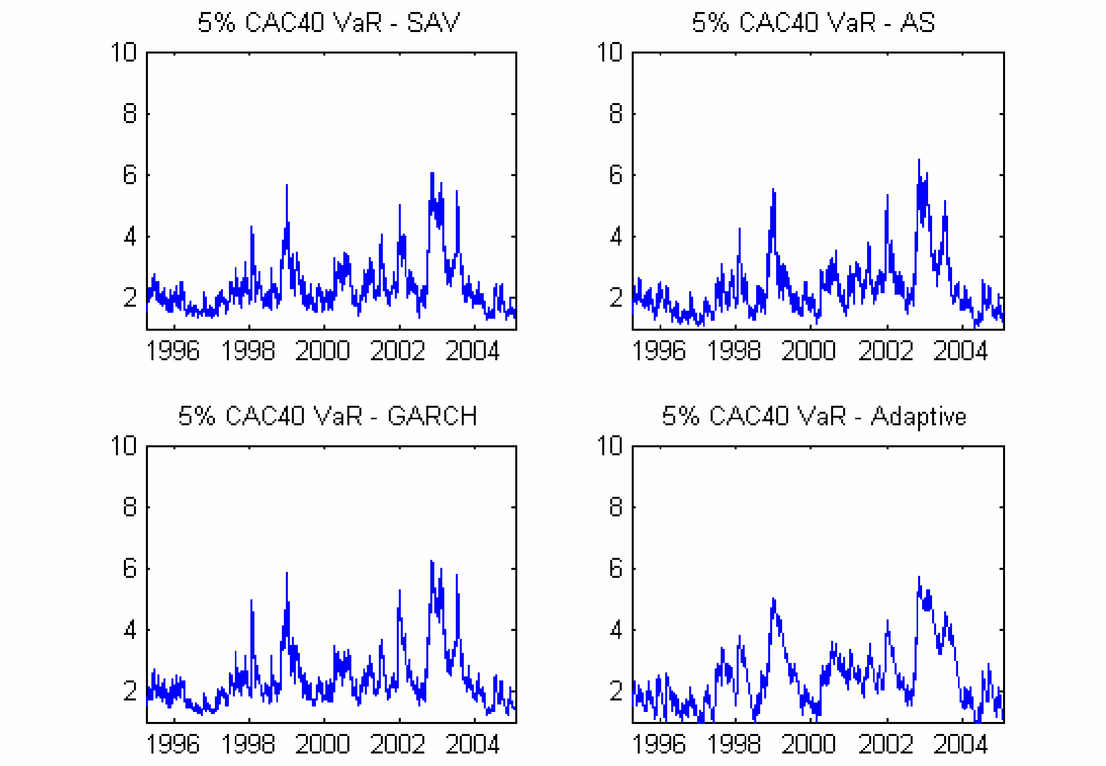

Figure 13(a): 5% Estimated Conditional Autoregressive VaR Plots for CAC40: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

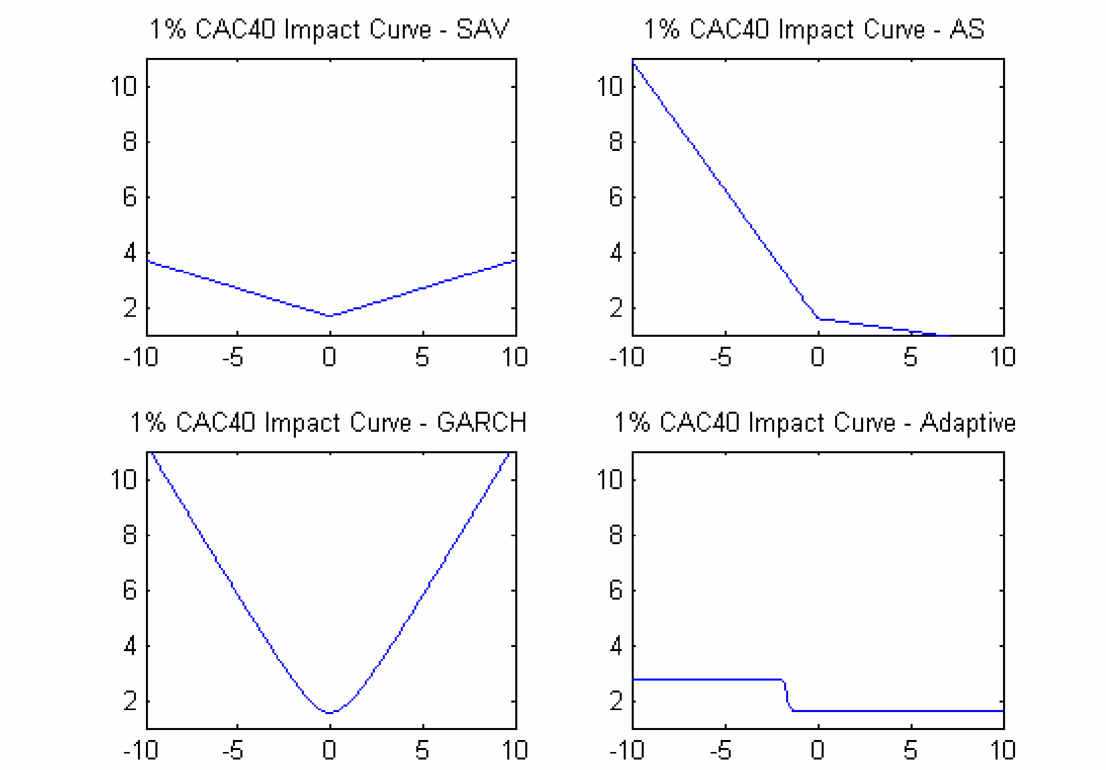

Figure 13(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for CAC40: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

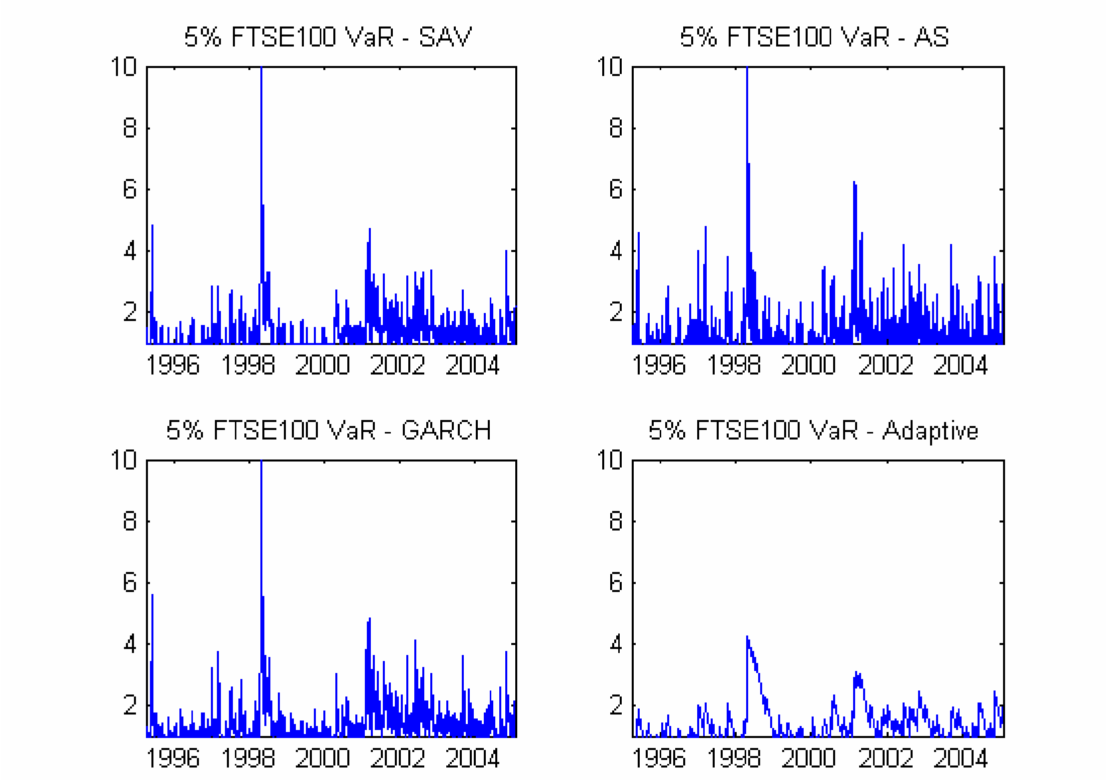

Figure 14(a): 5% Estimated Conditional Autoregressive VaR Plots for FTSE100: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

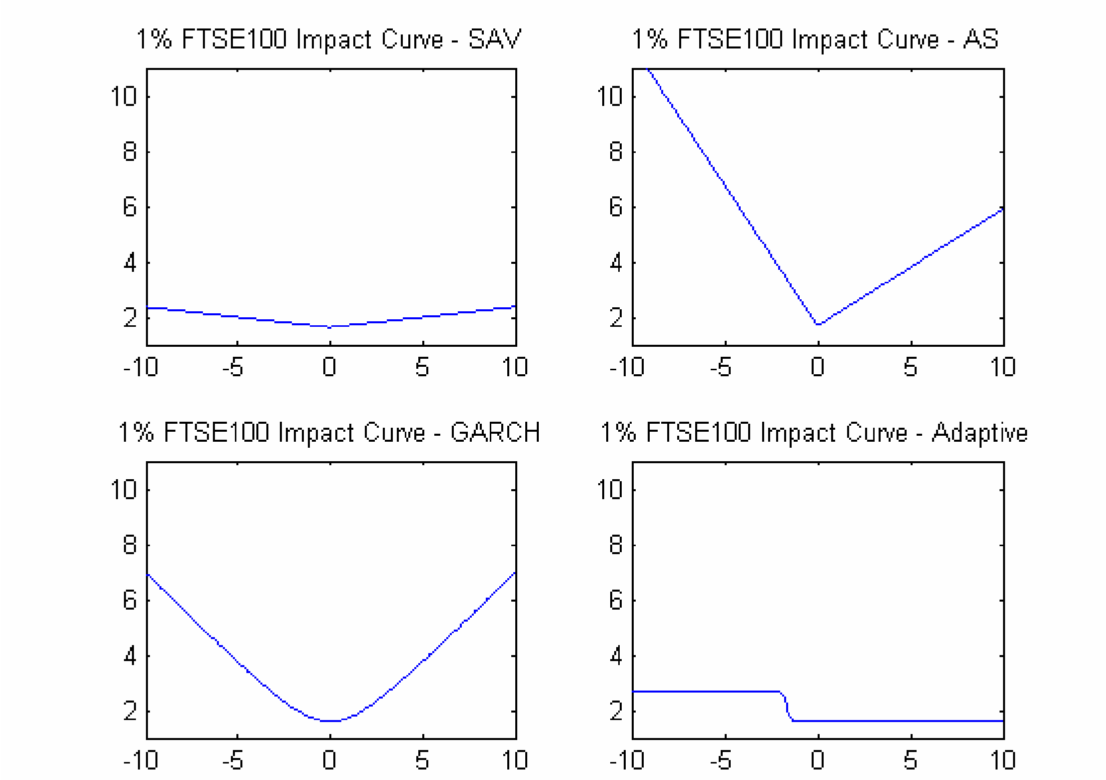

Figure 14(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for FTSE100: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

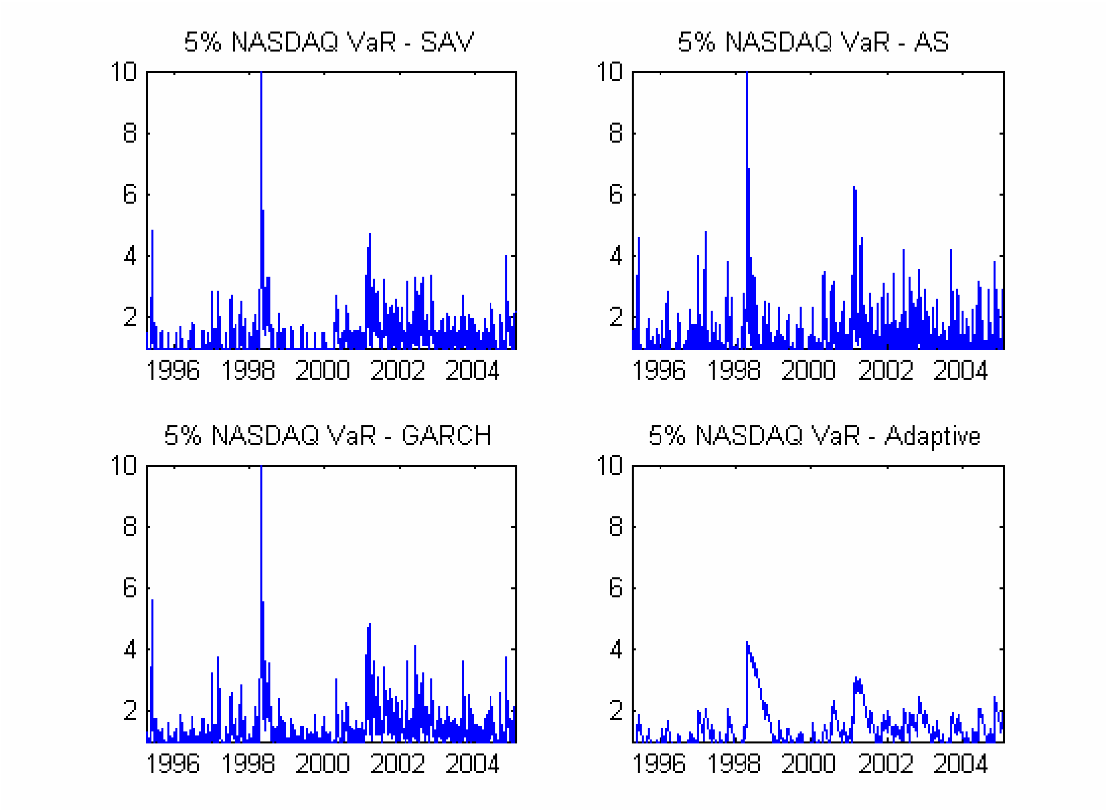

Figure 15(a): 5% Estimated Conditional Autoregressive VaR Plots for NASDAQ: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

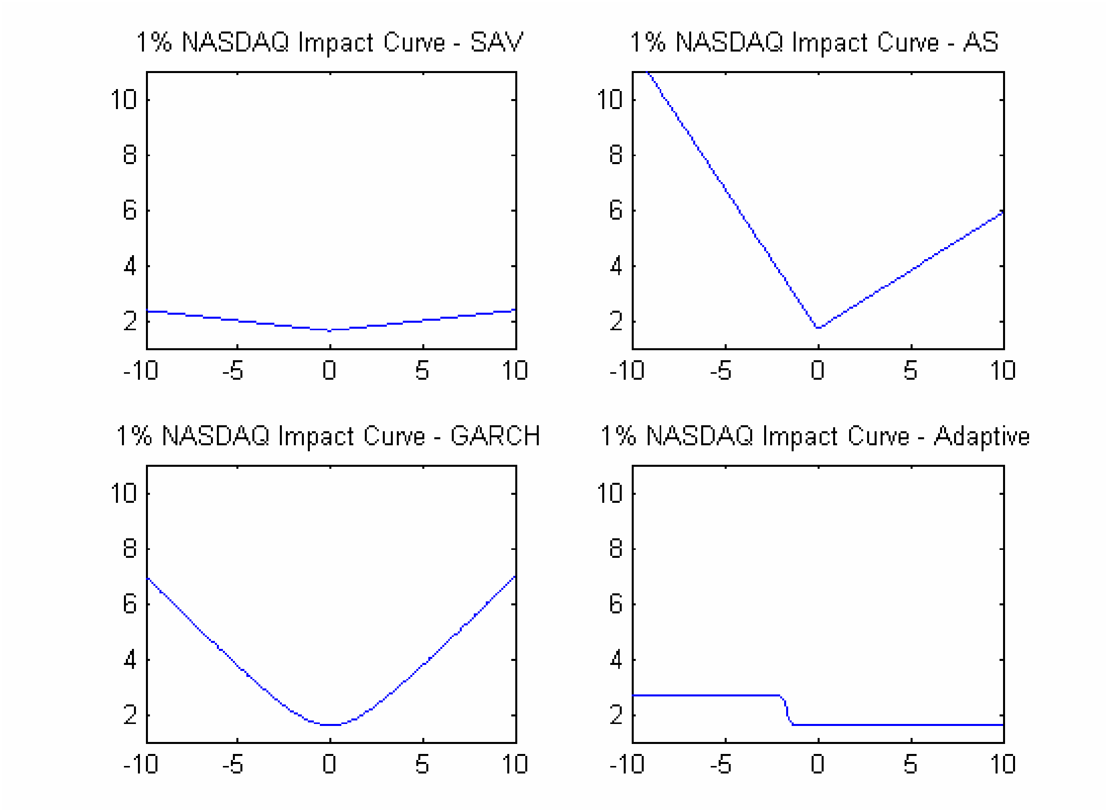

Figure 15(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for NASDAQ: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

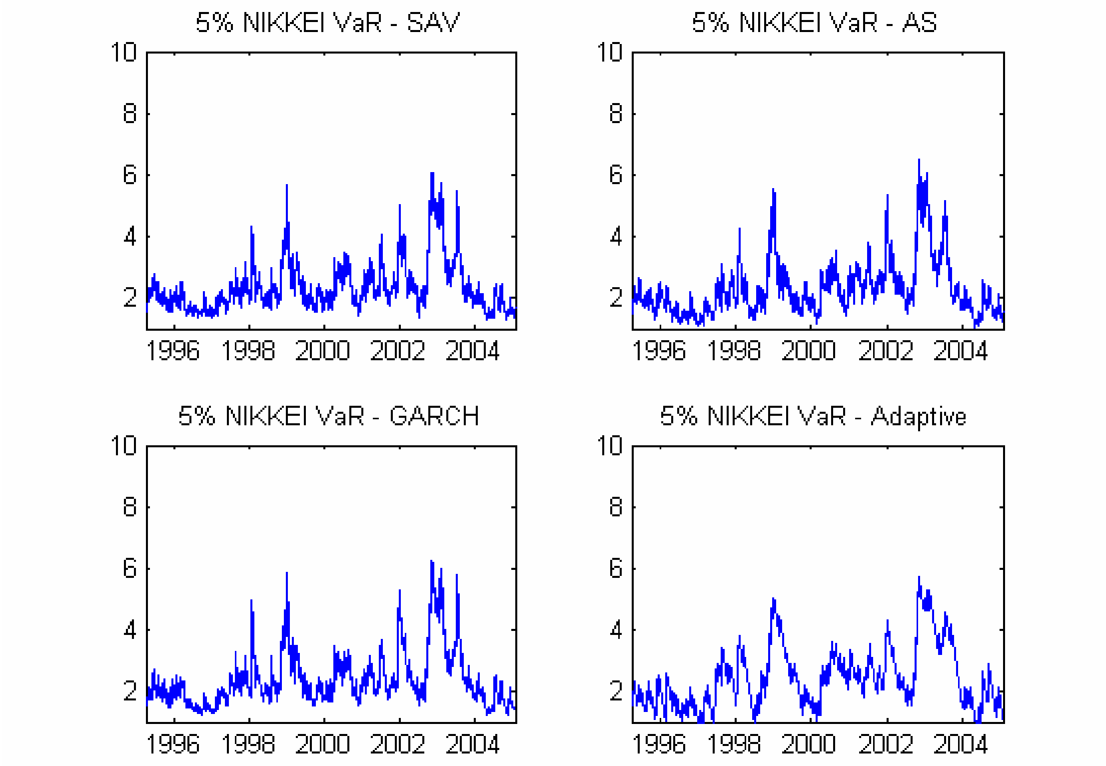

Figure 16(a): 5% Estimated Conditional Autoregressive VaR Plots for NIKKEI: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

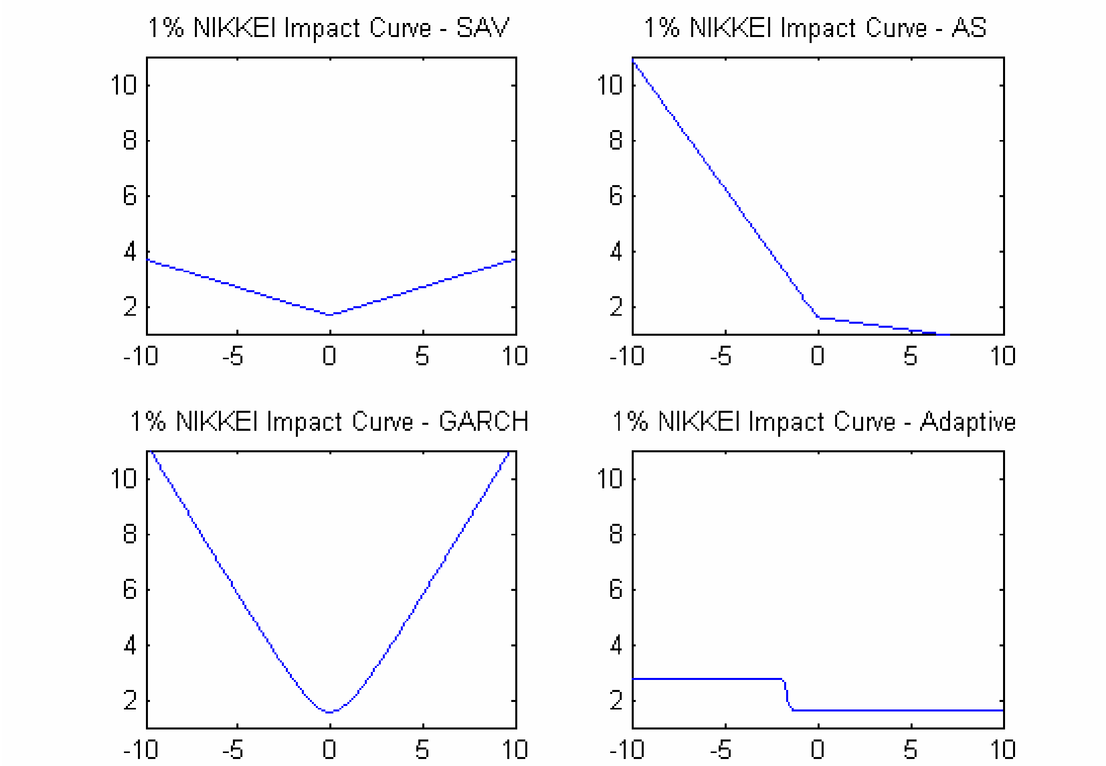

Figure 16(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for NIKKEI: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

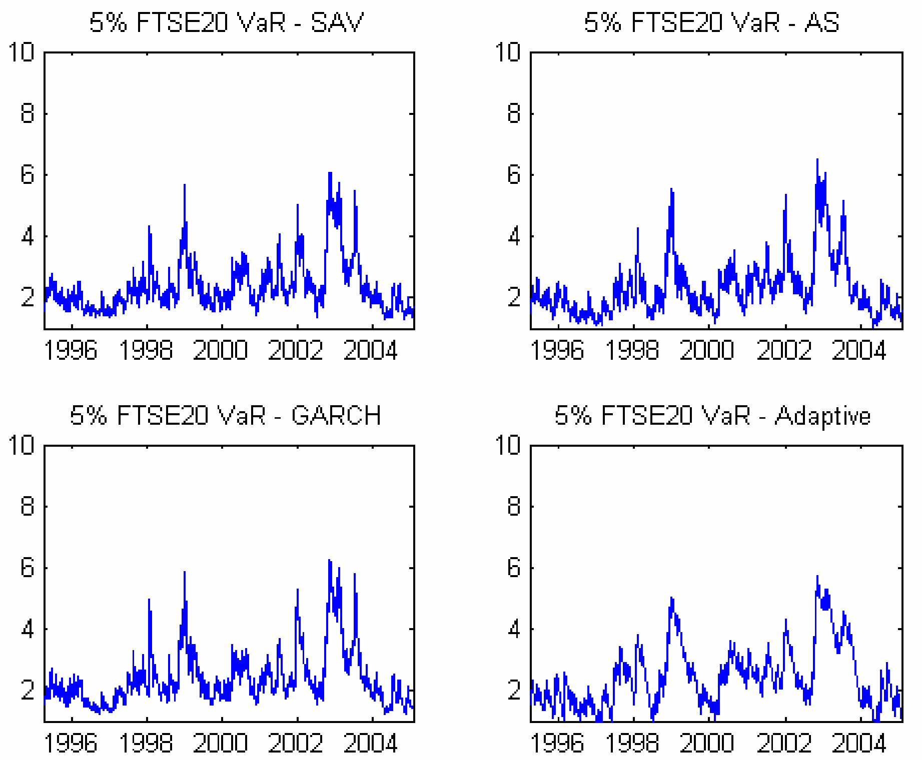

Figure 17(a): 5% Estimated Conditional Autoregressive VaR Plots for FTSE20: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.

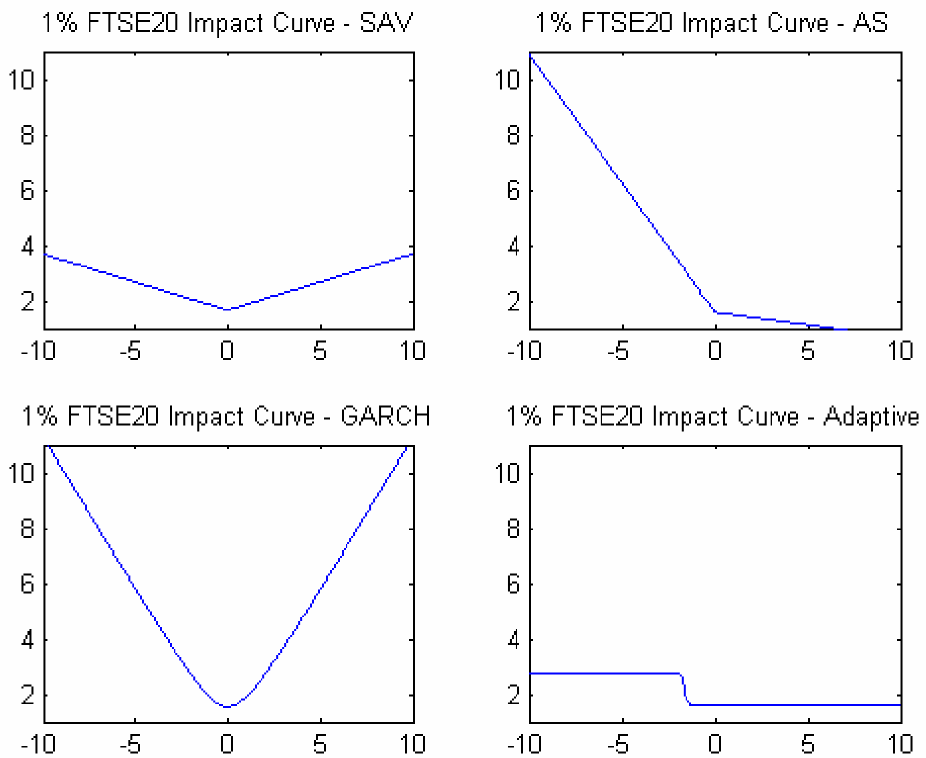

Figure 17(b): 1% Estimated Conditional Autoregressive VaR News Impact Curve for FTSE20: (a) Symmetric Absolute Value; (b) Asymmetric Slope ; (c) GARCH ; (d) Adaptive.