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A Comparison of CAViaR Estimates Through Regression Quantiles

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Abstract

This paper builds on the study by Engle and Manganelli (2004), titled "CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles," published in the Journal of Business and Economic Statistics. It investigates the application of Conditional Autoregressive Value at Risk (CAViaR) within the stock markets of Iraq, Jordan, Oman, Saudi Arabia, Kuwait, and Egypt. The study analyzes daily time-series data of stock market indices from early 2011 to the end of 2023. CAViaR estimates for two risk levels (1% and 5%) are presented across four different models: Adaptive, Indirect GARCH, Asymmetric Slope, and Symmetric Absolute Value. Overall, the results indicate that the Adaptive model performs effectively at both risk levels, highlighting the positive impact of the variable. Additionally, the findings reveal performance differences among the various VaR models, underscoring the importance of selecting the appropriate model for risk analysis.

Keywords: Valu at Risk, CAViaR, Stock Market, Regression Quantiles

Introduction

The term “Value at Risk” (VaR) was not introduced into the financial literature until the early 1990s; however, the fundamental concept began receiving attention much earlier. In approximately 1922, the New York Stock Exchange informally tested the capital reserves of its member firms for the first time (Schwarz, 1998).

The formal suggestion of the VaR concept can be traced back to Bamoul (1963), who examined a model known as the "Expected-Gain Confidence Limit Criterion," three decades before VaR became widely adopted in financial risk management. Additionally, early "Safety Models" proposed by financial theorists such as Roy (1952) and Telser (1955) laid the groundwork for the development of VaR models, contributing to the evolution of risk measurement techniques (Roy, 1952; Telser, 1955).

VaR was further popularized as a criterion to measure the maximum potential loss of a portfolio in 1994 by Weatherstone (1994). This metric quantitatively assesses risk and has become one of the key tools for risk management in finance. VaR is defined as the maximum loss that a portfolio could incur, such that the reduction in portfolio value does not exceed a specified amount over a defined time period with a certain confidence level. In essence, VaR gauges the worst expected loss under normal market conditions over a specified time horizon at a predetermined confidence level (Jorion, 2001; Dowd, 2005).

The Value at Risk (VaR) measure has gained significant popularity and acceptance among investors and financial sector participants in recent years. Its appeal stems largely from its ability to provide a concise statistic summarizing potential losses over a specified time horizon (Mohamed, 2005).

Although the fluctuations in a portfolio’s value can be influenced by a multitude of risk factors, VaR specifically aims to estimate declines in portfolio value attributed to market risk. Market risk encompasses uncertainties in future returns arising from changes in market conditions, such as fluctuations in prices or interest rates (Kormas, 1998; Jorion, 2007).

VaR was designed to furnish analysts with a single value that encapsulates information regarding portfolio risk. The VaR model consists of three primary components: the time horizon, the confidence level, and the amount of capital at risk (Dowd et al., 2003; McNeil & Frey, 2000).

The structure of this paper is organized as follows: the second section reviews empirical research concerning VaR estimation, the third section summarizes the estimation methods, the fourth section presents the results of these estimates, and the fifth section concludes the discussion.

Review of Empirical Studies

Guldimann is recognized as the pioneer of the term Value at Risk (VaR) (Guldimann, 2000). In the late 1980s, he served as the manager of the research department at J.P. Morgan. During this period, the risk management group faced a critical decision regarding whether to pursue risk-free investments in long-term bonds to generate a stable income or to maintain the bank's stock market value through investments in foreign exchange and equities.

Ultimately, the bank concluded that the value risk posed a greater concern than the earning risk, prompting the research group to explore a more comprehensive study of risk management.

At that time, effective risk management for derivatives became increasingly crucial. The Group of Thirty (G-30), which included representatives from J.P. Morgan, initiated efforts to establish best practices for risk management. The term “Value at Risk” was introduced in the G-30 report published in July 1993, marking the first instance of the widespread use of the term VaR. Other terms synonymous with VaR, such as "Capital at Risk" and "Dollars at Risk," were also utilized to describe similar concepts (Bergstrom, 1999). Given this context, the prevailing view in financial literature is that VaR represents an innovative approach to risk management and control.

In recent years, VaR has achieved considerable popularity and acceptance among investors and financial sector professionals. This method's appeal largely derives from its simplicity in providing a summary statistic that estimates potential losses over a defined time horizon (Mohamed, 2005; Jorion, 2007). This paper reviews empirical studies related to the estimation of VaR utilizing various models.

De Jesús and Ortiz (2011) use the c-quantile of fat-tailed distribution to analyze VaR. An innovation in their work is in the application of Extreme Value Theory (EVT) not only in the left tail of the return distribution but also in its right tail, while evaluating long and short positions. A Generalized Extreme Value Distribution (GEVD) is used to analyze the two large stock markets of Latin America, Brazil, and Mexico. A Conditional VaR (CVaR) is employed to determine the risk resulting from investment in those markets with daily index data for the period 1970-2004. The results confirm the presence of fat tails in both markets as a result of excessive kurtosis. The empirical evidence indicates that VaR and CvaR based on the EVT would provide more accurate and robust information about the financial risk compared to the conventional parametric estimations. In summary, VaR and CvaR based on EVT can be converted into highly precious tools for the risk management of portfolio assets. In addition, the EVT-based risk analysis also provides valuable information for the banking industry and its regulatory authorities to determine the most effective capital needs. Like any other model, EVT also has some shortcomings. The most important point is seen in individual and constant estimation of risk. It does not consider the stochastic volatilities in most financial series.

Mabrouk and Saadi (2012) evaluated the performance of several volatility models in estimating the one-day VaRof seven stock market indices (Dow Jones, Nasdaq100, S&P 500, DAX30, CAC40, FTSE100, and Nikkei 225) using some distributive assumptions. Because a return series shows volatility clustering and long memory, they examined GARCH-type models, including fractionally integrated models under normal, Student-t, and Swed Student-t. Matched with this idea, that the accuracy of VaR estimates is sensitive to the used volatility model adequacy, they found that the AR (1)-FIAPARCH(1,1) model under a Swed Student-t distribution outperforms all other models. The considered models include widely used models such as GARCH (1,1) or HYGARCH (1,1). The superior performance of the Swed Student-t FIAPARCH model exists for all stock market indices and for both long and short trading positions. Their findings can be explained based on the fact that Student-t FIAPARCH can jointly explain the outstanding features of financial time series: fat tail, asymmetry, volatility clustering, and long memory. In this lieu, since the RiskMetrics model cannot explain most of these stylized facts, it provides a more accurate VaR estimation.

Fathi Vajargah and Shoghi (2015) examined the simulation of the stochastic differential equation of geometric Brownian motion by the quasi-Monte Carlo method and its application in the prediction of the total index of stock market and value at risk. There are some parameters in the prediction of the total stock index that are uncertain in the future and may be changed, and this uncertainty has few risks. The calculations should be performed under the risk conditions for a true analysis. One of the evaluation methods under the risk and uncertainty is the use of geometric Brownian motion random differential equation and simulation by Monte Carlo and quasi-Monte Carlo methods. The pseudo-random tails are used in the Monte Carlo method to generate pseudo-random numbers, but in the quasi-Monte Carlo method, quasi-random sequences are used with better uniformity and faster convergence compared to pseudo-random sequences. Prediction of total stock index and VaR through this method is better and more precise than the Monte Carlo method. They first evaluated the random differential equation of geometric Brownian motion and its simulation, by using the quasi-Monte Carlo method, and then its application in predicting the total stock index and VaR. For this purpose, the total stock values of TES for 5 years from November 2009 to November 2014 and Monte Carlo and quasi-Monte Carlo methods are used to simulate and measure the total index of TSE and VaR. It was indicated that the quasi-Monte Carlo method and Sobol sequence were better than the Monte Carlo method with less error and with a confidence interval of 99%, one can invest in TSE because the TSE total index is lower than the predicted VaR for one percent of probability.

Gong and Weng (2016) generalized a recently suggested spatial autoregressive model and introduced a spatiotemporal model for stock return forecasts. They supported this idea that stock return is affected not only by absolute values of factors like firm size and book-to-market ratio but also by the relative values of factors such as trade volume and market value ranking in each period. This paper has studied a new method for constructing stock reference groups. This method is called a quartile. They compared the daily volatilities forecast performance with the out-of-sample forecast performance of VaR estimated with different methods by using the empirical method for 50 indices in the Shanghai Stock Exchange. The empirical results indicate that the spatial-temporal model provides surprisingly great performance in terms of considering spatial dependencies among individual stocks, and creates more precise VaR forecasts compared to the other three models introduced in the previous literature. Moreover, findings show that both allowing series correlation in the disturbance and using time-varying spatial weight matrices can highly improve the prediction accuracy of a spatial autoregressive model.

Slim et al. (2017) reassessed the evidence on the forecast ability of the GARCH-type models in estimating the VaR of global stock market indices with improved return distribution. The performance of 21 VaR models generated by a combination of conditional volatilities, including GARCH, GJR, and FIGARCH, and seven distributed assumptions for return innovations are examined. They implemented stringent backtesting during crises and post-crisis periods for the developed, emerging, and frontier markets. The results show that skewed-t along with fat-tailed Lévy distributions would considerably improve the one-day forecast of VaR for long and short trading positions during the crisis period without considering the volatility model. However, they found no evidence that the feature of given volatilities is better than others in the markets. The relevant models indicate evidence of long memory in the developed markets and conditional asymmetry in the frontier markets. On the contrary, the standard GARCH is the best feature for estimating VaR forecasts in emerging markets. The inclusion of high volatilities in the estimation sample depicts the predictability of VaR during a post-crisis period where even the normal distribution competes with more complicated samples in terms of statistical accuracy and regulatory capital allocation.

Riedle (2018) has used the stock market bubbles to increase VaR and achieve a countercyclical risk measure. The inflation of VaR generates an expected loss between the minimum loss and maximum loss, covering an extreme return that exceeds VaR models. This paper shows that bubbles considerably affect the probability of a stock market crash. When two years are assumed, the effect loses its significance, indicating that bubbles lead to a higher probability of crisis within the short run. According to the results, the relationship between bubbles and realized volatilities is modeled, and realized volatilities leave a considerable effect on the bubbles, which rises with the length of the realized volatility. Therefore, it is argued that longer periods of realized volatility have a significant effect on the formation of bubbles, which in turn increases the risk of a stock market crash.

Zhang et al. (2018) suggest a dynamic spatial panel with the generalized autoregressive conditional heteroscedastic model (DSP-GJR-GARCH) to provide accurate VaR forecasts. The proposed model considers spatial-temporal dependence as well as asymmetric return volatilities based on spatial econometric theories. They shape an economic spatial weight matrix and set a part of initial estimated values as unknown parameters to achieve more precise parameter estimations. In the next step, they compare the proposed model with three closely related models, including GARCH, spatial-temporal AR, and dynamic spatial panel GARCH models, concerning the performance of daily volatility and VaR forecasting. The comparative empirical data consists of six composite indicators of major countries, which are the USA (DJI), Germany (DAX), France (FCHI), Britain (ISEQ), Japan (N225), and China (SSE). The comparative computational results indicate that because the proposed model takes into account spatial dependence and time series correlation simultaneously, it can present a more accurate prediction of VaR than the three models. Moreover, the findings suggest that the prediction accuracy of a spatial regression model can be improved by considering asymmetric volatilities in the disturbances. Therefore, it is concluded that DSP-GJR-GARCH outperforms the other three compared models.

Jongadsayakul (2021) uses SET50 daily returns from July 3, 2015, to December 27, 2019, to estimate VaR for evaluating risk exposure in the Stock Exchange of Thailand and Thailand Futures Exchange by using three following models: non-parametric method with the historical simulation approach, parametric method with GARCH family models, and semi-parametric method with historical simulation of volatility wight of the GARCH family models. The accuracy of the estimated models is evaluated by doing the VaR tests of unconditional coverage, independent, and conditional coverage. To estimate the return volatilities for spot and futures SET50 index, this paper uses GRACH (1,1), TARCH (1,1), and EGARCH (1,1) models with normal distribution assumptions. In predicting VaR with a confidence level of 95%, historical simulation, and asymmetric GARCH models (TARCH and EGARCH models) provide solid results and have higher volatility weight historical simulation. In addition, a comparison between stock investments with correlation to the SET50 index performance and futures investment of the SET50 index indicates that SET50 index futures investment has higher risk. Therefore, decisions made on investment in Futures trades of the SET50 index must be more careful because this market is more volatile rather than the underlying spot market. However, a combination of historical simulation and asymmetric GARCH models never guarantees the success of the VaR model.

Simlai (2021) investigates the extent to which the cost-effective measure of maximum likely loss that encompasses the tail risk of return as VaR- explains the relationship between accruals and cross-sectional dispersion of expected stock return. The portfolios are constructed based on the measurement of total accruals (TA) and VaR at the level of individual assets that reflect the dynamic behavior of the asset distribution. The author documents that VaR is matched with accruals at the portfolio level, and there is a positive significant relationship between VaR and the cross-section of portfolio return. Allowing a double-sort consisting of VaR and TA further indicates that the spread between portfolios with low and high TA is significantly reduced after controlling VaR. They also conduct a cross-sectional regression analysis at the firm level and show that TA- and VaR-based characteristics – but not factor-mimicking portfolios– are compensated with the higher expected return, and VaR neither becomes a subset of nor becomes a subset of TA. Ultimately, cross-sectional decomposition analysis shows that firm-level VaR takes at least 7% of the accrual premium even in the presence of size and book-to-market price. These findings support improper pricing for an explanation of accrual anomaly.

Shaik and Padmakumari (2022) examined the VaR estimation models and their prediction performance, by using a series of back-testing methods on BRICS (Brazil, Russia, India, China, South Africa) indices and the US stock market indices. This study employs three different VaR estimation models, namely normal (N), historical (HS), exponential weighted moving average (EMWA) procedures, and eight back-testing models. The empirical analysis has been done during three different periods: the overall period (2006-2021), the global financial crisis (GFC) (2008-2009), and the COVID-19 period (2020-2021). Simulation methods of this study indicate that during severe periods such as GFC and COVID-19, both N and HS models underestimate the risks when the recession moment appears and overestimate the risk whenever the market is restabilized. Also, the results show that the EMWA model outperforms the estimation N and HS models for all size stock market indices during overall and crisis periods. The results suggest that VaR models provide weak performance during crisis periods such as GFC and COVID-19 compared to the overall sample period. In general. This model ranks the VaR models based on their predictive performances as EWMA, Historical, and Normal, respectively. Dynamic VaR models such as EWMA would outperform static methods such as historical and conventional simulation approaches. However, the predictive performance of VaR models during a crisis fails catastrophically. This causes a crucial concern about the usefulness of VaR models during extreme events.

The future performance of stock markets is the most vital factor in portfolio creation. As machine learning techniques are progressing, new facilities have been opened to incorporate prediction concepts into portfolio selection. A composite approach that forms machine learning algorithms for stock return prediction and a mean-VaR model for portfolio selection is shown in the paper written by Behera et al. (2023) as a unique portfolio construction technique. Machine learning regression models such as Random Forest, Extreme Gradient Boosting (XGBoost), Adaptive Boosting (AdaBoost), Support Vector Machine Regression (SVR), k-nearest Neighbors (KNN), and Artificial Neural Network (ANN) are used to predict stock. Values of the next period of stock with greater return are chosen in the first stage of this construction. Furthermore, the optimization model of the Mean-VaR portfolio is used to select the portfolio in the second stage. The monthly dataset of the Bombay Stock Exchange (BSE), India, Tokyo Stock Exchange, Japan, and Shanghai Stock Exchange, China have been used as the research sample, and findings indicate that the mean-VaR model with AdaBoot prediction outperforms other models.

In their study, Peng et al. (2023) introduce another VaR predictor, G-VaR, which follows a new method. G-VaR is created based on the concept of model uncertainty inspired by the recent mathematical theory of sublinear expectations. In the present case, this model suggests that the inherent volatility of financial returns cannot be determined by one distribution, but rather by the infinite statistical distributions. The G-VaR predictor is precisely identified by considering the worst scenario among these potential distributions. Many tests on both the NASDAQ Composite Index and the S&P500 Index indicate the perfect performance of the G-VaR predictor, which is superior to most existing benchmark VaR predictors. It is difficult to provide a fully clear explanation for the surprising success of G-VaR. Most likely, the concept of model uncertainty carries a certain power when considering return volatilities. Such volatilities are time-varying with a sophisticated nature. Therefore, the worst scenario approach that is adopted by G-VaR in all potential volatility distributions confirms that it is well-matched with the analyzed data. Judgment on the empirical data presented herein indicates that this model uncertainty approach seems stronger than many available approaches with model certainty in which, a unique statistical distribution is assumed for the volatility process.

Estimation Method

For a series of portfolio returns (*rt*), the CAViaR model is written as follows:

$$f_t(\boldsymbol{\beta}) = \beta_0 + \sum_{i=1}^{q} \beta_i f_{t-i}(\boldsymbol{\beta}) + \sum_{j=1}^{r} \beta_j l(\mathbf{x}_{t-j}),$$

where:

(βt) is a function that models VaR conditionally.

$\beta 0$ is a constant value

βi includes coefficients related to past returns

F_{t-i} includes variables depending on volatilities

p and q include several lags in returns and volatilities

The role of $l(x_{t\_j})$ is to link $f_t(\beta)$ to observable variables belonging to the information set. Therefore, this term plays a role that is highly similar to the curve of influence of news in GARCH models has been introduced by Engle and Ng (1993).

CavaR processes that are estimated in this research inspired by Engle and Manganelli (2004) as shown below:

Adaptive:

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

Symmetric absolute value:

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

Asymmetric slope:

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

Indirect GARCH(1, 1):

$$f_t(\boldsymbol{\beta}) = \left(\beta_1 + \beta_2 f_{t-1}^2(\boldsymbol{\beta}) + \beta_3 y_{t-1}^2 \right)^{1/2}.$$

Regression quantiles are introduced as a specific method for estimating values at risk. The estimation process in this case is presented as follows:

$$\min_{\boldsymbol{\beta}} \frac{1}{T} \sum_{t=1}^{T} \left[\theta - I\left(y_t < f_t(\boldsymbol{\beta}) \right) \right] [y_t - f_t(\boldsymbol{\beta})].$$

This formula tends to find optimum values of β parameters to compare $f(\beta)$ with the real data of y_t. In this formula:

B is the vector of parameters that must be optimized.

T indicates many observations in data.

it shows real data during time t

ft(β) is a prediction model during time t based on the parameters *β*

[yt-ft(ƒt(β))] indicates the difference between actual and forecasted values. The purpose is to minimize this error.

The whole formula tends to minimize weighted mean error, which depends on two factors:

θ is the objective quantile (a percentage of distribution, for example)

The pointer function indicates the effect of predictions higher or lower than VaR.

Empirical Results

This study comprises daily data on return on the total stock market index in Jordan, Iraq, Saudi Arabia, Oman, Qatar, Egypt, and Kuwait. Four types of CAViaR models have been used for 1% and 5% estimates. The results of the VaR estimate are reported in the tables below. This table includes estimate parameters, standard errors, and p values. Moreover, the following terms exist in these tables:

Beta: coefficients estimated for the model. These values indicate the effect of independent variables on the VaR.

RQ: the amount of objective function of quantile regression. This value shows the model fit quality. The lower this value, the better the model will be.

Hits in-sample (%): percentage of cases that exceed the VaR estimated in the real sample. This shows how much a model can provide accurate estimates for training data.

Hits out-of-sample (%): percentage of cases that exceed the VaR estimated in the out-of-sample data. This measure indicates the model's potential for forecast under the new conditions.

DQ in-sample (p values): the p-value of the DQ test for training data. The p-value less than 0.05 indicates that the model has significantly violated the basic hypotheses.

DQ out-of-sample (p values): the p-value of the DQ test for out-of-sample data. Similar to the DQ in-sample, the lower p-value indicates that the model has failed in forecasting new data.

Table 1. Results of CAViaR estimation in four different models for the stock markets of Iraq and Jordan

	Symmetric absolute value		Asymmetric slope		Indirect GARCH		Adaptive	
VaR 1%	Jordan	Iraq	Jordan	Iraq	Jordan	Iraq	Jordan	Iraq
B1	0.151	0.8438	0.151	0.8438	0.151	0.8438	0.2532	0.876
Prob	0.0053	0	0.035	0.4556	0.0073		0.0039	0
B2	0.7184	-0.0049	0.7183	-0.0049	0.7184	-0.0049		
Prob	0	0	0	0.4763	0			
B3	0.5494	9.243	0.5495	9.243	0.5494	9.243		
Prob	0.0007	0	0.0698	0	0.0642			

B4			0.6467	4.2135				
Prob			0.0002	0.4893				
RQ	49.2896	277.8985	49.2896	277.8985	49.2896	277.8985	52.8877	988.8615
HitInSample	1.0179	0.9724	0.987	0.9724	1.0179	0.9724	0.802	0.8188
HitOutOfSample(p values)	0.8913	0.8876	0.8913	0.8876	0.8913	0.8876	0.5348	0.2959
DQinSample	0.0594	0.9625	0.0602	0.9627	0.0594		0	0.2754
DQoutOfSample(p values)	0.9677	0	0.9677	0	0.9677	0	0.9629	0.9414
VaR 5%								
B1	0.0377	0.3587	0.0377	0.3588	0.0377	0.3587	0.2641	0.365
Prob	0.0013	0.3993	0.002	0.4467	0		0	0
B2	0.8406	-0.0045	0.8406	-0.0045	0.8406	-0.0045		
Prob	0	0	0	0.4463	0			
B3	0.2291	2.484	0.2291	2.4839	0.2291	2.484		
Prob	0	0.3463	0.1492	0.1401	0.0001			
B4			0.3114	0.2563				
Prob			0	0.4948				
RQ	160.9593	1018.422	160.9593	1018.422	160.9593	1018.422	166.3442	1096.6167
HitInSample	4.9969	4.9642	4.9969	5.0154	4.9969	4.9642	3.578	4.4012
HitOutOfSample(p values)	5.7041	6.5089	5.7041	6.5089	5.7041	6.5089	4.0998	4.4379
DQinSample	0.0124	0.3413	0.0129	0.7529	0.0094		0.3572	0.2564
DQoutOfSample(p values)	0.1392	0.2902	0.1392	0.2902	0.1392	0.2902	0.1686	0.2719

In Table 1, CAViaR estimates related to the stock markets of Jordan and Iraq have been proposed for two risk levels (1% and 5%) within four different models: Adaptive, Indirect GARCH, Asymmetric Slope, and Symmetric Absolute Value.

At risk level 1%, the Adaptive model reported beta values of 0.253 and 0.876 for the stock markets of Jordan and Iraq, respectively. The obtained values imply the positive effect of variables on the risk estimation although this effect is higher in Iraq. According to the probability rate, this coefficient is significant in both markets.

The RQ value of the Adaptive model equaled 52.888 for Jordan, while equaled 49.290 in other models. These values respectively equaled 988.86 and 277.89 for the stock market of Iraq. These values imply the high quality of fit in the Adaptive model.

In the Hits in-sample case, around 80% in both markets indicates the good power of the Adaptive model in predicting training data. The Indirect GARCH model also has about 90% in both markets, indicating the high forecast accuracy of this model. In the case of Hits out-of-sample, the p-value of the DQ test on training data (DQ in-sample) equaled 0.000 for the Adaptive model and 0.059 for Indirect GARCH, which signifies the significance of these models' results.

For a risk level of 5%, the Beta of the Jordan market equals 0.264 in the Adaptive model, which implies a higher positive effect compared to the level of 1%. On the contrary, this value equals 0.365 for the Iraq market which indicates less positive effect than the level of 1%. These estimates have been statistically significant in both markets. In the Indirect GARCH model, Beta values equaled 0.038 and 0.358 for Jordan and Iraq respectively, which shows the accuracy of this model.

The RQ value of this risk level in the Adaptive model equaled 166.344 for the Jordan market, while equaled 160.959 for other models. This value was estimated to be greater than 1000 for the Iraq market, which implies the good quality of these models.

In general, the Adaptive model performs well at both risk levels and indicates the positive effect of variables explicitly. Other models also provide acceptable performance. However, different values in Hits and RQ imply differences in forecast accuracy and fit quality of models.

Table 2. Results of CAViaR estimation in four different models for the stock markets of Saudi Arabia and Oman

	Symmetric absolute value		Asymmetric slope		Indirect GARCH		Adaptive	
VaR 1%	Saudi Arabia	Oman	Saudi Arabia	Oman	Saudi Arabia	Oman	Saudi Arabia	Oman
B1	0.0812	0.0876	0.0812	0.0876	0.0812	0.0876	0.9334	0.6737
Prob	0.1294	0.3025	0.1267	0.3207	0.1448	0.2207	0	0
B2	0.8038	0.7749	0.8038	0.7749	0.8038	0.7749		
Prob	0	0	0	0.0001	0	0		
B3	0.7578	0.7192	0.7578	0.7192	0.7578	0.7192		
Prob	0	0	0.2899	0.1734	0.0739	0.1008		
B4			1.038	1.5951				
Prob			0.0032	0				
RQ	128.7329	65.2612	128.7329	65.2612	128.7329	65.2612	153.9074	80.3418
HitInSample	1.0179	1.0182	0.987	1.0182	1.0179	1.0182	1.0487	0.8639
HitOutOfSample(p values)	0.8913	0.5357	0.8913	0.5357	0.8913	0.5357	0.713	0.8929
DQinSample	0.618	0.734	0.4946	0.7451	0.6448	0.7329	0	0.0031
DQoutOfSample(p values)	0.0024	0.9411	0.0024	0.9411	0.0024	0.9411	0.9526	0.6669
VaR 5%								
B1	0.1692	0.071	0.1692	0.071	0.1692	0.071	0.9684	0.4032
Prob	0	0.0009	0	0.001	0	0	0	0
B2	0.6344	0.7621	0.6344	0.7621	0.6344	0.7621		
Prob	0	0	0	0	0	0		
B3	0.5907	0.3804	0.5907	0.3804	0.5907	0.3804		

Prob	0	0	0.1779	0	0	0		
B4			0.2277	0.4665				
Prob			0	0				
RQ	387.1706	202.6435	387.1706	202.6435	387.1706	202.6435	398.622	213.0123
HitInSample	4.9969	4.9985	5.0278	5.0293	4.9969	4.9985	4.781	4.1654
HitOutOfSample(p values)	5.3476	3.3929	5.3476	3.3929	5.3476	3.3929	4.4563	4.2857
DQinSample	0	0.0002	0	0.0002	0	0.0002	0.0014	0.0895
DQoutOfSample(p values)	0.1967	0.0674	0.1967	0.0674	0.1967	0.0674	0.0021	0.2795

Table 3. Results of CAViaR estimation in four different models for the stock markets of Qatar and Kuwait

	Symmetric absolute value		Asymmetric slope		Indirect GARCH		Adaptive	
1%VaR	Qatar	Kuwait	Qatar	Kuwait	Qatar	Kuwait	Qatar	Kuwait
B1	0.0687	-0.0072	0.0687	-0.0072	0.0687	-0.0072	0.8942	0.4549
Prob	0.2483	0.486	0.2761	0.4869	0.3002	0.4821	0	0
B2	0.8284	0.8118	0.8284	0.8118	0.8284	0.8118		
Prob	0	0	0	0	0	0		
B3	0.6191	0.8801	0.6191	0.8801	0.6191	0.8801		
Prob	0.0003	0.002	0.0878	0.0473	0.0104	0.2282		
B4			0.732	0.8865				
Prob			0.0001	0.002				
RQ	116.3371	27.1586	116.3371	27.1586	116.3371	27.1586	126.2227	34.5529
HitInSample	1.0179	1.0274	0.987	1.0274	1.0179	1.0274	0.8945	0.7991
HitOutOfSample(p values)	0.8913	1.9868	0.8913	1.9868	0.8913	1.9868	1.2478	1.3245
DQinSample	0.073	0.9813	0.0662	0.9776	0.0998	0.9775	0.0049	0
DQoutOfSample(p values)	0.5382	0	0.5382	0	0.5382	0	0.2759	0.9507
VaR 5%								
B1	0.0903	0.1278	0.0903	0.1278	0.0903	0.1278	0.6209	0.3683
Prob	0	0.0812	0	0.0811	0.0003	0.0586	0	0
B2	0.8304	0.6351	0.8304	0.6351	0.8304	0.6351		
Prob	0	0	0	0.0001	0	0.0001		
B3	0.2114	0.5418	0.2114	0.5418	0.2114	0.5418		

Prob	0	0.0133	0.0004	0.0072	0	0.1301		
B4			1.2648	0.6629				
Prob			0	0.1056				
RQ	335.18 31	76.624 7	335.18 31	76.624 7	335.18 31	76.624 7	340.05 73	80.363
HitInSample	4.9969	5.0228	5.0278	5.0228	4.9969	5.0228	4.5342	4.5662
HitOutOfSampl e(p values)	8.7344	7.2848	8.7344	7.2848	8.7344	7.2848	4.8128	5.298
DQinSample	0.0008	0.6336	0.0008	0.6063	0.0006	0.6429	0.5671	0.5886
DQoutOfSampl e(p values)	0.0001	0.7267	0.0001	0.7267	0.0001	0.7267	0.0365	0.1788

Table 4. Results of CAViaR estimation in four different models for the stock market of Egypt

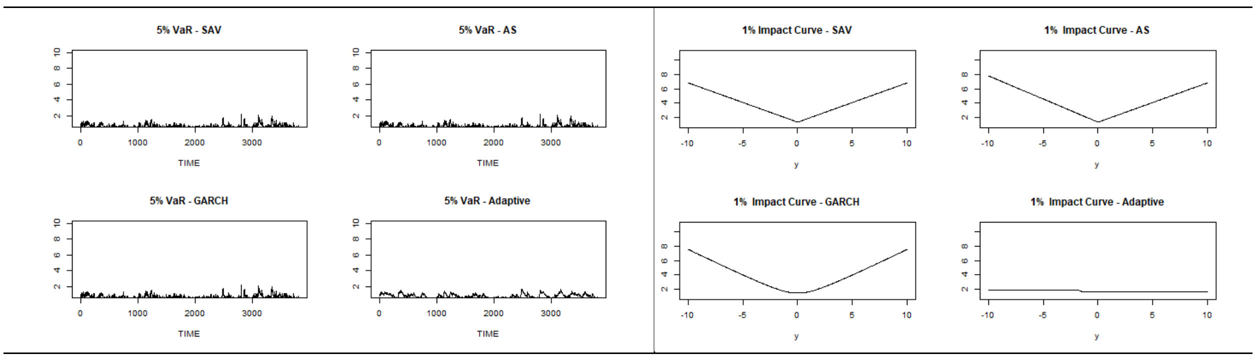
Egypt	Symmetric absolute value	Asymmetric slope	Indirect GARCH	Adaptive
VaR 1%				
B1	0.6810	0.6817	0.6810	0.2359
Prob	0.0297	0.0509	0.2418	0.0674
B2	0.6458	0.6455	0.6458	
Prob	0.0000	0.0001	0.0000	
B3	0.6261	0.6262	0.6261	
Prob	0.0075	0.1026	0.1783	
B4		0.1831		
Prob		0.2337		
RQ	149.6866	149.6866	149.6866	177.6766
HitInSample	0.9870	1.0179	0.9870	1.0796
HitOutOfSample(p values)	0.5348	0.5348	0.5348	0.7130
DQinSample	0.5578	0.4593	0.5326	0.0000
DQoutOfSample(p values)	0.8985	0.8985	0.8985	0.5151
var 5 %				
B1	0.3711	0.3711	0.3711	0.1945
Prob	0.0003	0.0003	0.0046	0.0001
B2	0.5586	0.5586	0.5586	
Prob	0.0000	0.0000	0.0000	
B3	0.5877	0.5877	0.5877	
Prob	0.0000	0.0239	0.0000	
B4		0.7110		

Prob		0.0000		
RQ	484.9535	484.9535	484.9535	517.3725
HitInSample	4.9969	4.9661	4.9969	4.6885
HitOutOfSample(p values)	4.9911	4.9911	4.9911	5.7041
DQinSample	0.0382	0.0152	0.0318	0.0000
DQoutOfSample(p values)	0.7461	0.7461	0.7461	0.0011

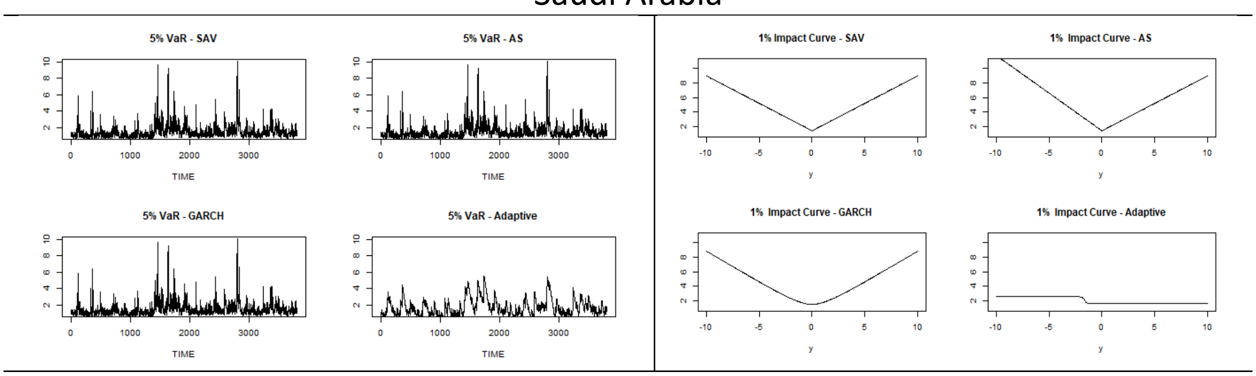
In general, the tables above indicate that the Adaptive model performs well at both risk levels and explicitly shows the positive effect of variables. Other models also provide acceptable performance, but different values in Hits and RQ show the difference between forecast accuracy and fit quality of models.

Eight graphs are estimated herein for each country, which consists of four curves of impact for VaR 1% and four graphs of VaR 5% from four different models. In these graphs, the Symmetric Absolute Value (SAV) diagram indicates the impact of variations in positive and negative returns on the VaR estimate. The Asymmetric Slope (AS) model indicates the presence or absence of symmetry in the market. For instance, negative returns leave a greater impact on the VaR in some cases. The GARCH diagram describes the volatilities model thoroughly, and finally, the Adaptive diagram shows the effect of negative and positive returns and past news on the VaR.

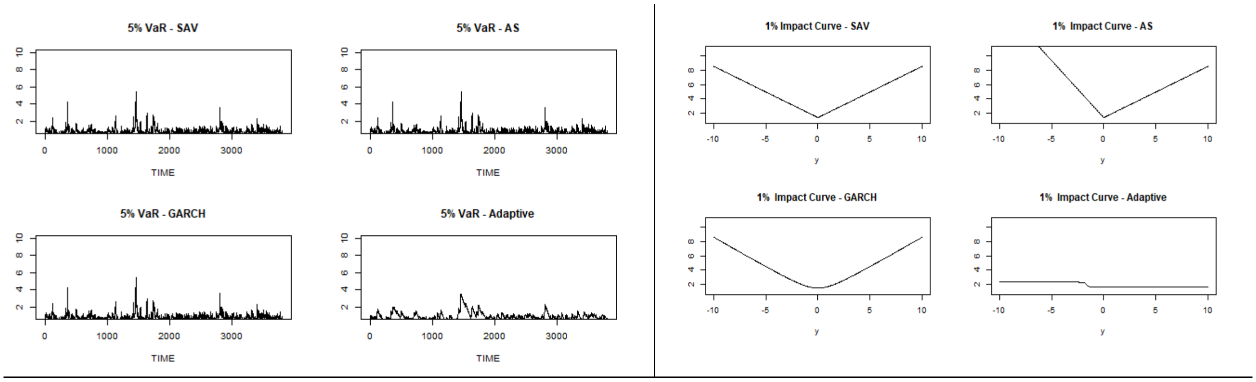
Jordan



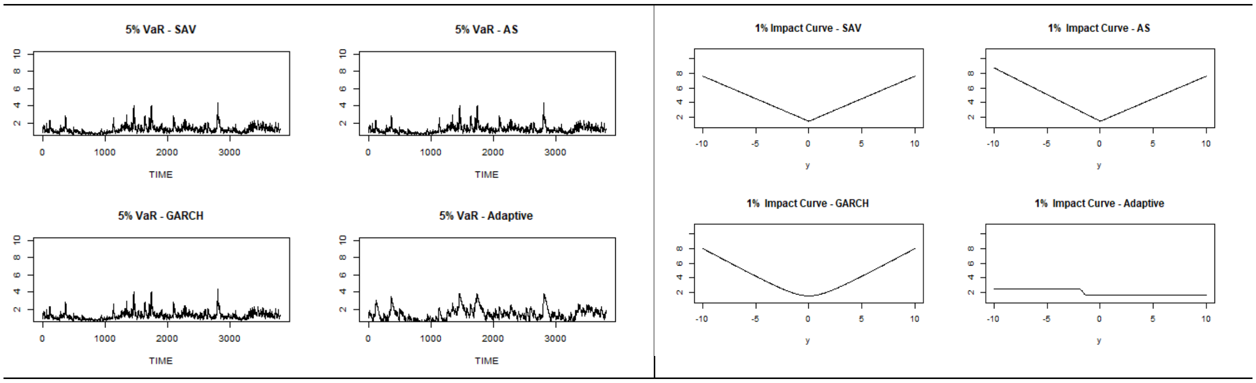
Saudi Arabia



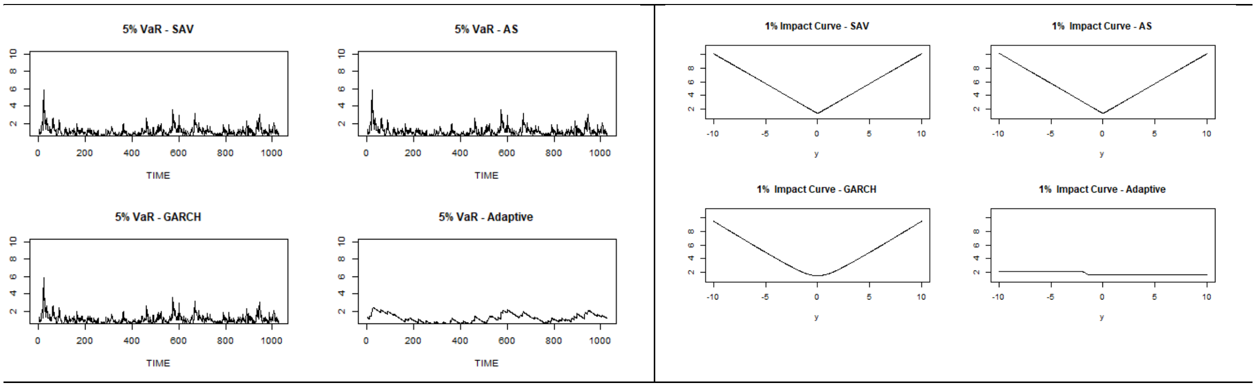
Oman



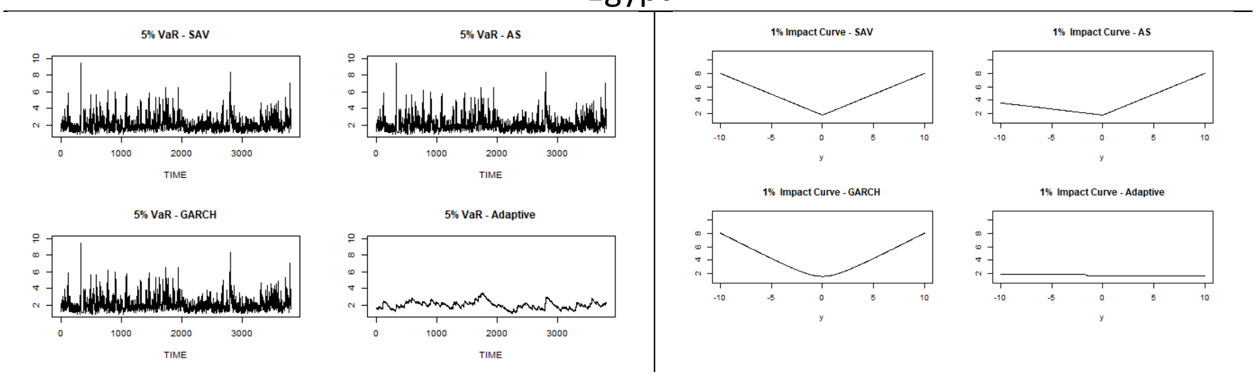
Qatar



Kuwait



Egypt



According to the diagrams shown above:

- The SAV diagram depicts the symmetric impact of positive and negative returns so that the estimated VaR has been uniformly distributed on both sides of the axis.
- AS diagram shows the asymmetric impact, particularly in negative returns. This indicates a higher sensitivity of the market to negative volatilities.
- The GARCG diagram describes volatilities thoroughly and depicts the symmetric variations. Specific characteristics of the market volatilities are observable in this model.
- The Adaptive diagram indicates a stronger impact of past news on the VaR. The behavior of volatilities is not monotone, referring to asymmetric impacts.

These diagrams explicitly depict the difference between the performances of various VaR models, emphasizing the importance of selecting the proper model for risk analysis. The obtained results can contribute to a better understanding of volatile behaviors and risks in the market and help analysts choose proper models.

Conclusion

This paper utilizes the CAViaR model developed by Manganelli and Engle (2004) to analyze the stock markets of Iraq, Jordan, Oman, Saudi Arabia, Kuwait, and Egypt at two risk levels, 1% and 5%. The study employs four different models: Adaptive, Indirect GARCH, Asymmetric Slope, and Symmetric Absolute Value. This approach leverages auxiliary regressions to enhance the accuracy of Value at Risk (VaR) estimates and facilitates improved modeling of temporal dependencies and volatilities. Daily time-series data from the stock markets of the selected countries, covering the period from early 2011 to the end of 2023, were utilized for this analysis. CAViaR estimates pertinent to these stock markets are presented in the study. The findings reveal that the Adaptive model demonstrates strong performance at both risk levels. However, the analysis also highlights variations in Hit rates and RQ values, pointing to differences in forecast accuracy and the overall quality of model fits. Additionally, the results underscore the performance disparities among the various VaR models, reinforcing the need for careful selection of an appropriate model for effective risk analysis.

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