INFORMATION CONTENT OF RISK REVERSAL IN ESTIMATING THE VALUE AT RISK OF CRUDE OIL FUTURES

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INFORMATION CONTENT OF RISK REVERSAL IN ESTIMATING THE VALUE AT RISK OF CRUDE OIL FUTURES

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Information Content of Risk Reversal in Estimating the

Value at Risk of Crude Oil Futures

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Thesis Abstract

Fatih Erkekoğlu, “Information Content of Risk Reversal in Estimating the Value at Risk of Crude Oil Futures”

This paper attempts to investigate the information content of risk reversal in estimating VaR of oil futures. Using CAViaR PlugIn models, we incorporated risk reversal into CAViaR models. We tested the performance of our model with daily returns of WTI crude oil futures. Our simulation results shows that CAViaR risk reversal PlugIn model significantly improves the performance of standard CAViaR models in terms of out sample hit percentage. We also tested the properties of VaR violation series. Coverage tests results indicate that our newly proposed model not only beats benchmark Riskmetrics and CAViaR models in out sample VaR forecast performance but also produce VaR violation series with properties of true coverage and randomness.

Tez Özeti

Fatih Erkekoğlu, “Ham Petrol Vadeli İşlemlerinde Tersine Riskin Bilgi İçeriği”

Bu makale tersine riskin riske maruz değer hesaplamadaki bilgi içeriğini incelemektedir. CAViaR PlugIn modelini kullanarak öncelikle tersine risk ölçeğini CAViaR modeliyle birleştirdik. Modelin performansını WTI ham petrol vadeli işlemler günlük değerleriyle test ettik. Simülasyon sonuçları CAViaR Tersine Risk Plugiın modellerinin standard CAViaR modellerinin performansını çok iyi derecede geliştirdiğini göstermiştir. Ayrıca riske maruz değer ihlal serisinin özelliklerini de modelin performansını anlamak amacıyla test ettik. Kapsama testi sonuçları yeni oluşturduğumuz modelin standart CAViaR modele ve Riskmetrics modeline göre çok daha iyi test sonuçları verdiğini göstermiştir.

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CONTENTS

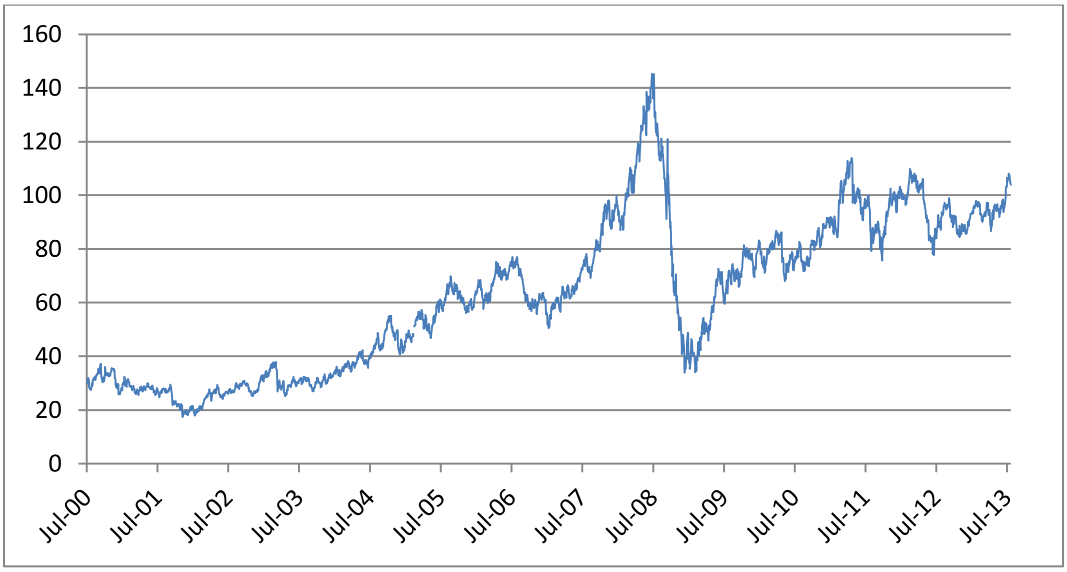
TABLES

FIGURES

CHAPTER 1

INTRODUCTION

Oil is the primary energy resource of globe. As oil holds this status for several decades, perhaps no other commodity has had such important role in economic and political history of twentieth century. Major shifts in the price of oil impacted global output levels and they are observed to be predecessors of recessions. Other than being global energy source, oil functions as primary income source for many countries. Most of Middle Eastern countries are highly dependent on revenue stream generated from oil operations, and shifts in price levels directly impact their budget balances.



Source: Bloomberg

Figure1 : Prices of WTI oil futures (first generic)

As the price of oil has far reaching consequences, determinants of oil prices are analyzed by many professionals. Most analysts believe that supply and demand factors are main determinant of oil prices. They also claim that price of 2000s were particularly related with changing growth expectations of emerging markets. Kilian and Hicks (2013) say that unexpected growth level of emerging countries explain the price movement in oil prices. Similarly, Hamilton (2009) argues economic growth explains sudden rise in oil prices. However, some recent research challenges this established analysis. This line of research argues positions of non-commercial traders, those who hold position in derivatives market but do not own the underlying asset, have direct impact on crude oil prices. Tang and Xiong (2009) showed that increasing trading volume of commodity futures lead to increase in correlation among different sets of commodities. Similarly, Singleton (2011) showed that futures price of crude oil are directly related with the number of open interest in the futures market.

Introduction of market based pricing in late 1980s, and oil based financial derivatives enabled investors to gain exposure to crude oil prices without having any contact with the physical product. Today trade volume of crude oil futures is more than ten times the production of crude oil, and most of these trades in the market are carried out by financial investors

As investors get exposure to oil price risk, oil price risk management becomes part of their agenda. However, the number of studies dealing with this particular area is relatively few. There are two sets of research in oil price risk management literature. First set of literature uses volatility models for estimating the oil price risk. Second set of research instead chooses Value-at-Risk (VaR), a broadly used measure of market risk.

Although these two streams of research use different tools for their analyses, their common characteristic is that they mostly use spot price data for their analyses. We observed that spot price data is not appropriate, particularly for analyzing oil price risk management. First of all, financial analysts are not actual traders of oil. They prefer not to have physical deliveries of contracts. Therefore, they are interested in futures and forwards prices. Second, market data shows that there may be discrepancies between the spot and futures prices because of the convenience yield, which is described as the benefit received by holding a physical product. One particular reason for this discrepancy is that crude oil is a non-perishable product. If the analysts expect crude oil prices to rise, rather than supplying it to the market, they choose to hold it for a certain amount of time. This decision limits the availability of storage and increase the price of oil futures. Third, local supply disruptions have immediate effect on spot price but their affect fades in futures prices.

To the best of our knowledge, literature on oil price risk management, do not incorporate market expectation for improving the performance of their models. However, financial analysts frequently use different sets of indicators to forecast future market behavior. For example, VIX, which is derived from implied volatilities of S&P 500 options, is used to gauge market stress for SP500 index. Similarly, risk reversals of FX options are closely watched by market makers.

The objective of this paper is to introduce a VaR model which utilizes the information content of risk measures and sets of models which give near-to-actual VaR estimates and iid VaR violation series. By using CAViaR PlugIn models, we incorporated market expectations to CAViaR type of VaR models. We tested the performance of these models for oil futures and compared the performance of newly introduced models with CAViaR models and the traditional Riskmetrics model. We found that our model produce near-to-actual VaR estimates. In addition, VaR violation series output of CAViaR with risk reversal models pass various tests and produce better test performance than standard CAViaR models.

The structure of the rest of the thesis is as follows. In chapter 2, we talked about VaR methodology. We described various VaR models and discussed some common characteristics of these models. Then, risk reversal is briefly explained. We then explained the CAViaR RR PlugIn model. In chapter 3, we presented our findings. We showed that our distribution series carries the characteristics of financial return distribution series.

CHAPTER 2

PRICE FORMATION OF OIL

History of Oil Pricing System

Before analyzing the current price system, it would be rather helpful to understand the historical perspective of crude oil pricing models. Instead of summarizing the entire history of crude oil, I will focus on post WW2 era. In this era, we observe different pricing mechanisms in different periods. Chronologically, these mechanisms are the concession system, OPEC based pricing system, reference pricing system, netback system of 1986, and finally the market based pricing.

Prior to 1960s, oil market was mostly controlled by large oil companies which are known as Seven Sisters. These companies were in control of almost 85% of annual production in 1960s. The role of governments in this era was granting concessions or licenses in return for tax and royalties. In this period, most of the trading was done through intercompany agreements. Companies who were long in production were entering into agreements with those who were short in supplies. Spot market transactions were almost nonexistent but they were posting a price, which is the price they were ready to accept. As most trading was done through intercompany deals, oil companies and host countries used this price for tax purposes.

To protect their interests, Saudi Arabia, Venezuela, Iraq, Kuwait, Iran formed the Organization of the Petroleum Exporting Countries (OPEC) cartel in 1960. Rising demand for oil in 1960s was mostly met by Middle Eastern OPEC members. In 1960s, the share of Middle Eastern countries in world oil production increased from 24% to 31% while OPEC as a whole controlled more than 50%. In this period, oil producing countries began to give up the concession system and demanded share in production. OPEC (Resolution No. XVI.90), called for participation of countries in their national companies. Partnership of host countries also brought in two new pricing terms: the official selling price (OSP), and the buyback price.

As the oil producing countries gained shares in their own national companies, they physically had access to crude oil extracted by national companies. Physical access necessitated the introduction of their shares of oil into the market. The introduction of government owned oil into the market brought the OSP, price of crude oil sold by participating country. Gradually, host countries abandoned obtaining oil physically; instead they began to sell their shares of production back to the company. They did this by using the buy-back price, which was the price paid by oil companies to host countries in return for their ownership. Three different pricing system for the same product (posted price, GSP, buyback price), and competition of oil companies against the discounted prices of host countries distorted the price formation mechanism of oil (Mabro, 2005).

OPEC introduced reference pricing system in 1974. In this system, GSP of member countries are determined by discounts or premiums to the benchmark Arabian Light 34^{o} API type of oil. Reference based pricing system faced with some difficulties. First, OPEC’s response to call for updating price differentials was slow. Instead of using OPEC imposed price differentials, member countries imposed their own price level. Second, increasing production of non-OPEC countries and slowing demand in 1980s weaken the price setting position of OPEC. As buyers found alternatives to OPEC oil, it became impossible to back reference based pricing system (Mabro, 2005). Oil price collapse of 1985 ended the era of reference based pricing system.

In response to decline in demand for Saudi oil, Saudi Arabia briefly introduced netback pricing system. In the netback pricing system, the price of crude oil is tied to the price of end products of refineries. Price of crude oil is determined as cost of production plus a share of profit obtained from the revenues of end products. Advantage of netback system to end product suppliers and refinery owners is that price risk of crude oil end products is shared by crude oil suppliers. The system was able also transfer price risk of end products to the suppliers. As refineries transferred some of their risk to the crude suppliers, they increased their production levels which eventually lead to oil glut and significant drop in prices which eventually led to collapse of 1986.

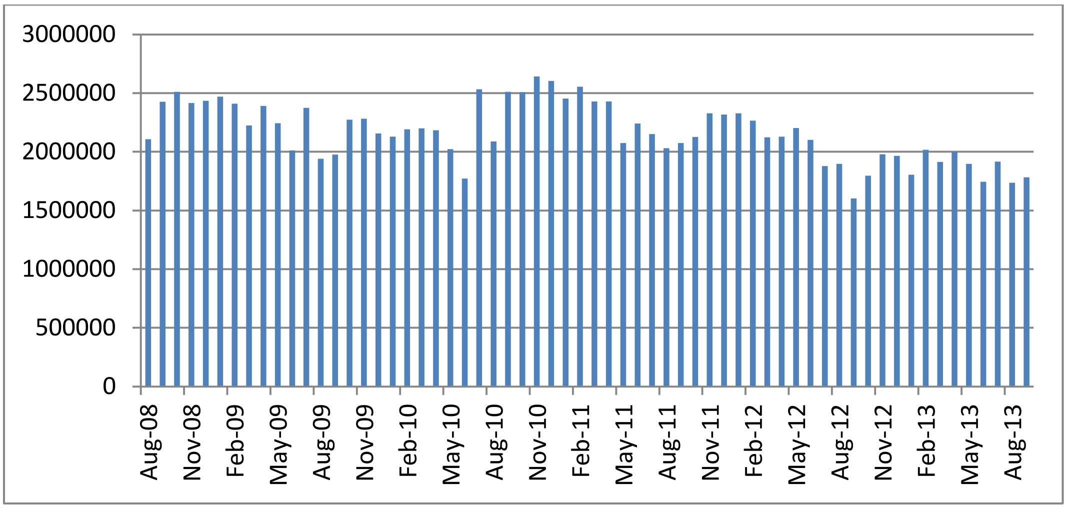
Lessons learned from reference based pricing system and netback pricing system, led PEMEX, Mexican national oil company, introduce market based pricing system in 1986. In this pricing system, prices of oil with different qualities are either derived from benchmark by a formula or price differential. Market based pricing enables different players to participate in the market and broadened the player base. Financial products offered by the market facilitate getting exposure to crude oil risk without having any contact with the base product.

Crude Oil Benchmarks

As the oil is not a uniform product, prices of different products are calculated as a combination of prices of benchmark crude oil. Different countries choose different formula and different pricing mechanisms. In these complex pricing systems, four benchmarks are mostly used by the market: Dubai/Oman, WTI, BFOE Brent, ASCI.

Price of Brent oil is derived from the oil extracted from Brent oilfield in North Sea. Proximity to European market and large physical base made it popular benchmark for European market and ensured its liquidity. (Fattouh, 2011). Today Brent is for pricing of two thirds of the global oil production.

The physical base of Brent was on the decline for the recent years and, price reporting agencies widened the baseline product by blending it with oil extracted from other North Sea bases. Today Brent is blend of four following fields: Brent, Forties, Oseberg, Ekofisk.



Source: Bloomberg

Figure 2: Daily Cargo Loading at North Sea

West Texas Intermediate (WTI) is a blend of crude oil produced in the fields of Oklahoma, Texas, Kansas and New Mexico. It is the physical base of most of light crude oil futures. However, as the price formation mechanism of WTI is significantly affected by supply disruptions, the use of WTI for oil cargo deliveries is on decline.

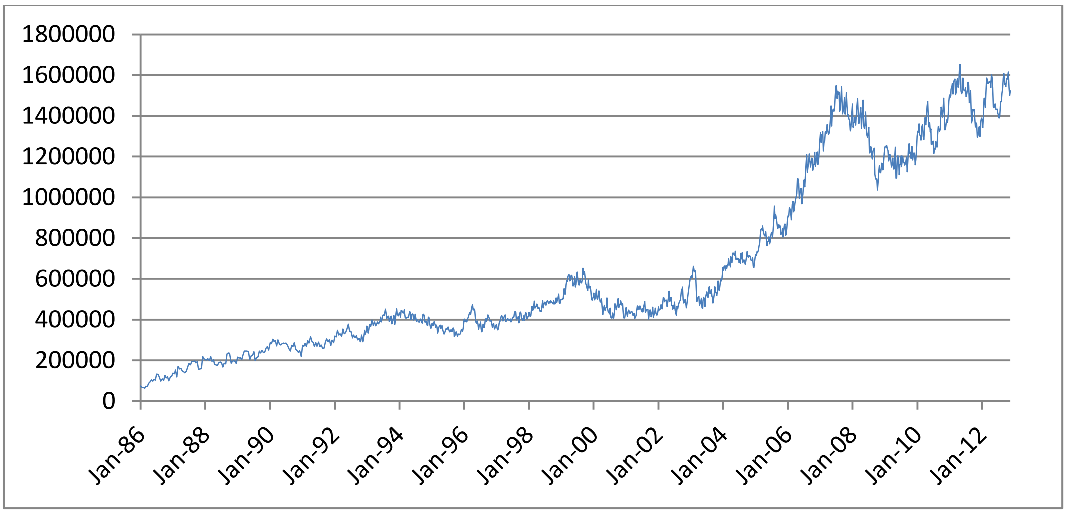
Price of Dubai oil is used as benchmark for deliveries to Asian market by Gulf countries. However, as the physical base of Dubai oil shrank, producers began to question its benchmark status and offering either to replace Dubai with Oman or blending two products.

Argus Sour Crude Oil index (ASCI) is price constructed from weighted averages of three oil grades from Gulf of Mexico: Mars, Poseidon, and Southern Green Canyon. As local factors created price differentials in WTI index, buyers looked for a benchmark with large physical base with little delivery disruptions for US market, and shifted from WTI to ASCI for cargo deliveries. Until now, Saudi Arabia and Iraq dropped using WTI over ASCI, and some Latin American countries are expected to use ASCI near future.

Futures Market of Crude Oil

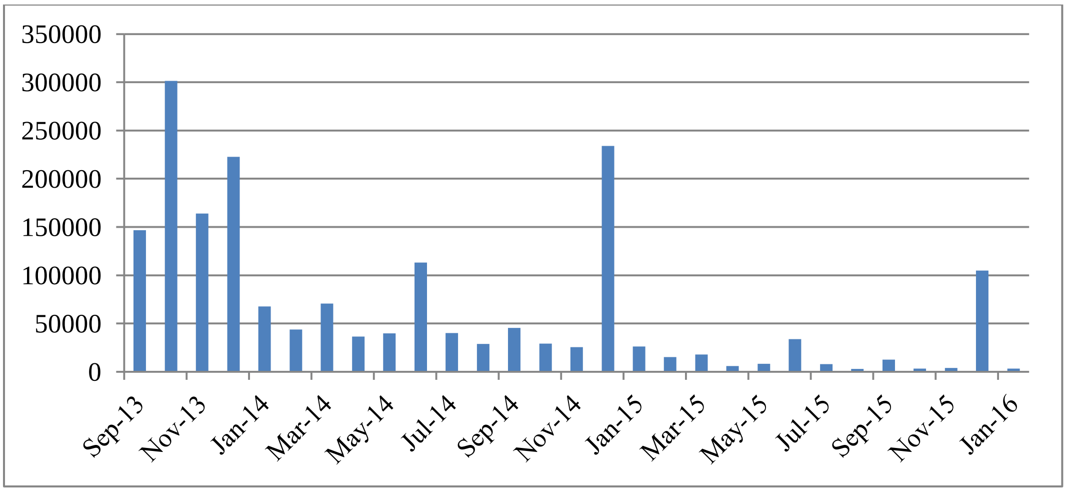
Futures are standardized contracts that obligate the seller to deliver an asset with specified characteristics on a certain date. Underlying asset may be financial asset (stock, bond) or physical asset (oil wheat etc.). Unlike forwards which are traded over the counter contracts, future contracts are traded on exchanges. Therefore futures traders do not bear the counterparty risk.

First futures contracts in oil were introduced by the New York Mercantile Exchange (NYMEX) in 1983. Today crude oil is the most liquid commodity futures market. Those who are exposed to oil price risk had the advantage of hedging their risk through futures. Second, those who wanted expose oil price risk were able to achieve their goal without dealing with physical product. Today two exchanges dominate oil futures market: New York Mercantile Exchange (NYMEX),and Intercontinental Exchange (ICE) with the former focusing on trade of WTI futures, and the latter focusing on Brent futures market. Their combined daily trade volume reaches to 1.2 million contracts, equivalent to 1.2 billion barrel. Considering the physical production of oil is 85 million barrel/day, trading volume in futures market reach to 13 times of baseline market.



Source: CFTC

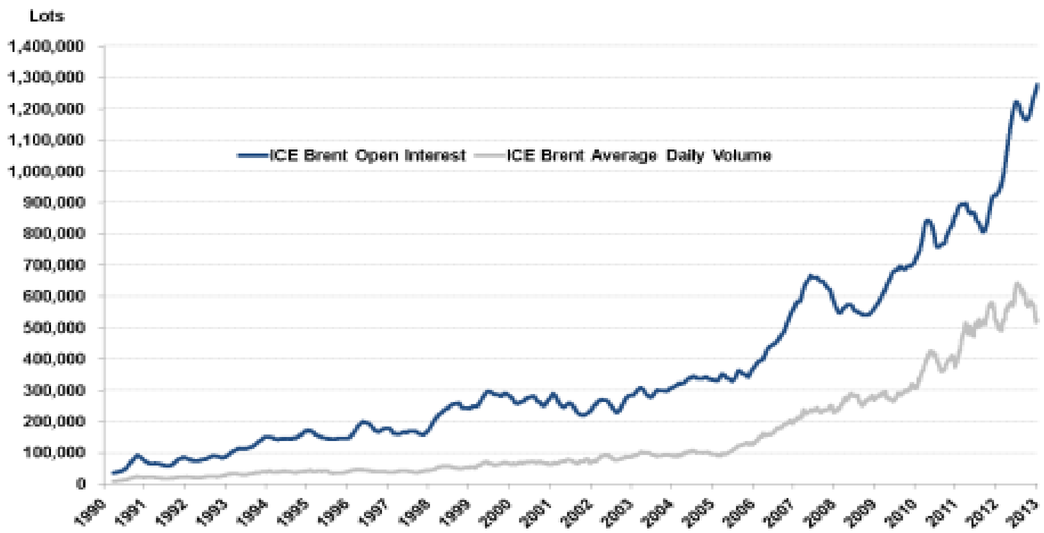
Figure 3: NYMEX open interest in crude oil futures



Source: CME group

Figure 4: Open interest in WTI futures

NYMEX is pioneer of WTI crude oil futures. Since it has launched its first crude oil futures in 1983, it is the primary market of crude oil derivatives. Most of futures are written for WTI light sweet crude oil. Specifications of these contracts are standardized with contract size of 1000 barrels. Contract period can be as long as 8 years. However, Contracts with more than one year to expiration are not very actively traded. Trading volume of contract with nearest to expiration are lower than succeeding month since most of traders close their position before entering the month. Trading of a future contract ends 22th day of the month proceeding the contract month. Any open position not closed until termination require physical delivery of oil on Cushing, Oklahoma.



Source: ICE

Figure 5: ICE Brent Futures Open Interest & Average Daily Volume

Brent futures are introduced by International Petroleum Exchange IPE (now ICE) in 1986. Although spot Brent is the primary benchmark of crude oil market, its derivates hasn't become popular as WTI derivates until recently. Unlike WTI futures traded on NYMEX, which requires physical delivery of product if the position is not closed before expiry date, Brent futures gives an option either settle in cash, with an option of physical delivery through Exchange for Physicals (EFP). EFP describes swap of physical product in return for futures asset. The party who is long in futures and needs the physical delivery of oil swaps his position in return for physicals. As these deals are privately settled, they are not reported by ICE.

CHAPTER 3

TECHNICAL CONCEPTS

Options

Options are contracts which give the owner the right to buy or sell an underlying asset at a specified price on or before expiry date. If an option gives the owner right to buy the underlying asset, it is called call option. An option which gives the owner right to sell the underlying asset at an agreed upon price is called put option.

An important concept about options is moneyness which tells the investors whether immediate exercise of the contract (if possible) generates income. Therefore, moneyness of an option is indicator of the option's ability generate cash flow. If immediate exercise of an option at the spot market price of the underlying asset generates income for option holder, the option is said to be in the money. If possible immediate exercise of the option does not generate cash flow for the investor, then; the option is called to be out of money. An option whose strike price is equal to current price of the underlying asset is said to be at the money.

A convenient way to describe an option is with its delta. Delta is the ratio of change in price of an option to the change in the price of underlying asset. Delta of a call option is typically shown to be between 0 and 100 for call options, and between 0 and -100 for put options. However, for practical purposes, the direction is not used. If an option is said to be 25-delta, it means that for one unit of change in the price of underlying asset, option value changes by 0.25 units.

Option delta also gives an idea about the moneyness of the option. If an option is 100-delta, then the option fully responds to changes in the price of underlying asset. It technically behaves like the underlying asset. If a call option is deep out of money, then response of the option price to underlying asset price is relatively small. As its ability to generate cash flows starts after exceeding the strike price, the option is relatively unresponsive to changes in spot price of the asset. Hence, out of money options have smaller delta.

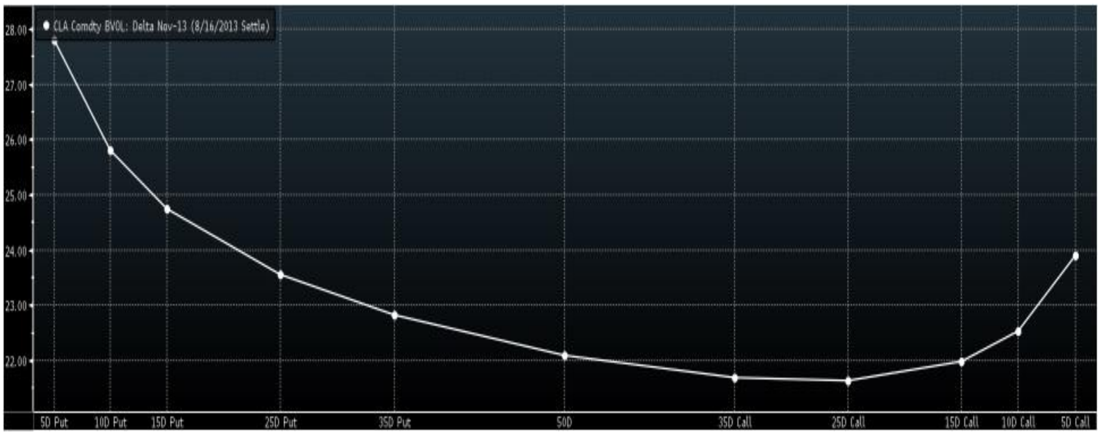
Implied Volatility

Black-Scholes is a mathematical formula used to price European options. Invention of the model enabled the calculation of theoretical price options and was pivotal in the growth of derivatives market. The formula assumes that return series follow lognormal distribution and volatility is constant across time.

Implied volatility is the market induced volatility estimate of an option derived from the empirical option price through Black Scholes formula. As different options have different characteristics (expiry date, interest rate, strike price), and implied volatility of an option is theoretically independent of these variables, implied volatility is convenient method to compare the relative prices of different options. Since it is derived from actual price of the option, it also represents market expectations about future volatility of underlying asset. Christensen and Prabhala (1998) compared the performance of historical volatility and implied volatility to forecast future volatility. They showed implied volatility outperforms historical volatility in predicting future volatility level. Giot (2005) measures the performance of implied volatility and historical volatility in estimating VaR of SP 500 and

NASDAQ. He reports that VaR models using implied volatility gave better performance. Jeon and Taylor (2013) showed that incorporating implied volatility through VIX index, an index derived from implied volatilities of out-of-money call options and out-of-money put options, into CAViaR models gave superior results than standard CAViaR models.

Volatility smile is the graphical representation of option volatilities with respect to their strike price. Theoretically, implied volatility of an option independent of its strike price- therefore implied volatility price graph should be a flat line. But empirical evidence shows that the implied volatility (IV) of options which are deep in the money or out of money are higher than IV of options whose strike price is close to spot price of underlying asset. This phenomenon can be explained by the difference in the volatilities of theoretical distribution and empirical distribution. Theoretically Black and Scholes model assume that return distribution of an underlying asset is lognormal. However, empirical evidence shows that return distribution of financial assets are leptokurtic, which implies fatter tails than lognormal distribution.



Source: Bloomberg

Figure 6: Volatility smile of November 2013 WTI options.

Figure X is the volatility smile of NXMEX WTI crude oil options with maturity of November 2013. As the figure shows, IVs of put options are higher than the IVs of options with same delta. Technically, even if difference exists between empirical distribution and theoretical distribution of the option, one should expect call and put options with same delta to be priced equally. The asymmetry in the volatility smile is called volatility skew. Two type of skew is observed in the data: reverse skew, and forward skew.

Empirically, reverse skew occurs if put options are priced higher than call options with same delta. In other words, option traders are biased toward in the money options. It is common phenomena particularly in currency market and stock market. Possible explanation of high demand for in-the-money options is the investors’ risk averseness against any market crash. As investors buy put options to protect themselves, demand for put options increase and so implied volatility of put options increase.

Another type of volatility skew is forward skew in which implied volatility of options with higher strike price are higher than the implied volatility of options with lower strike price. This forward skewness is generally observed in the commodity market. Commodity traders who do not want to be affected by sudden supply disruptions buy out of money call options to protect themselves any price spikes. Therefore, in commodity market, demand for out of money call options is higher than demand for in the money options.

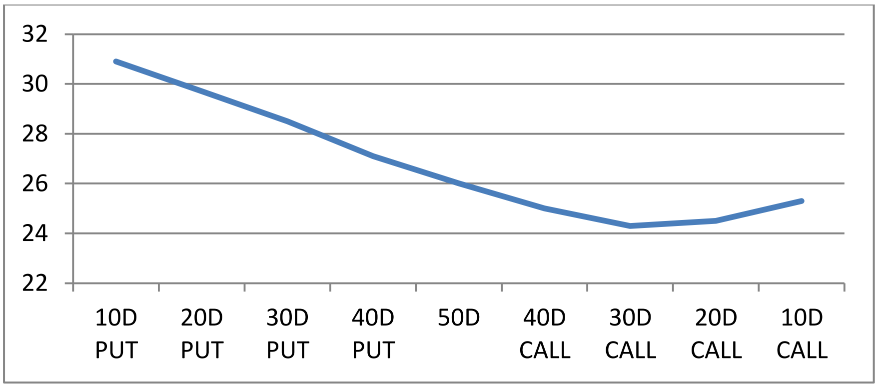


Figure 7: Volatility skew – reverse skew

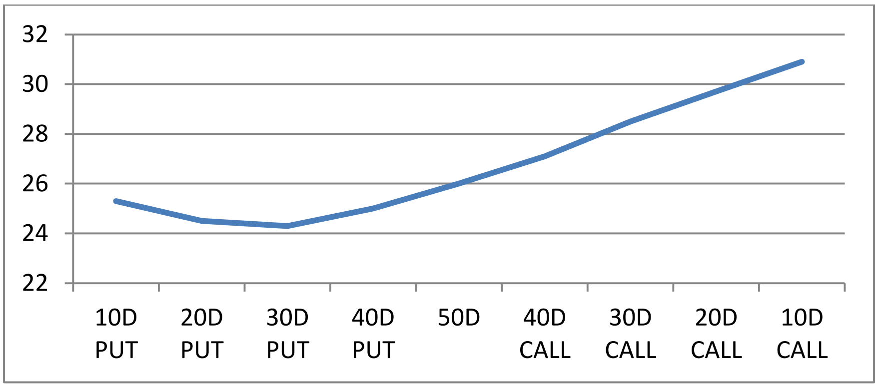
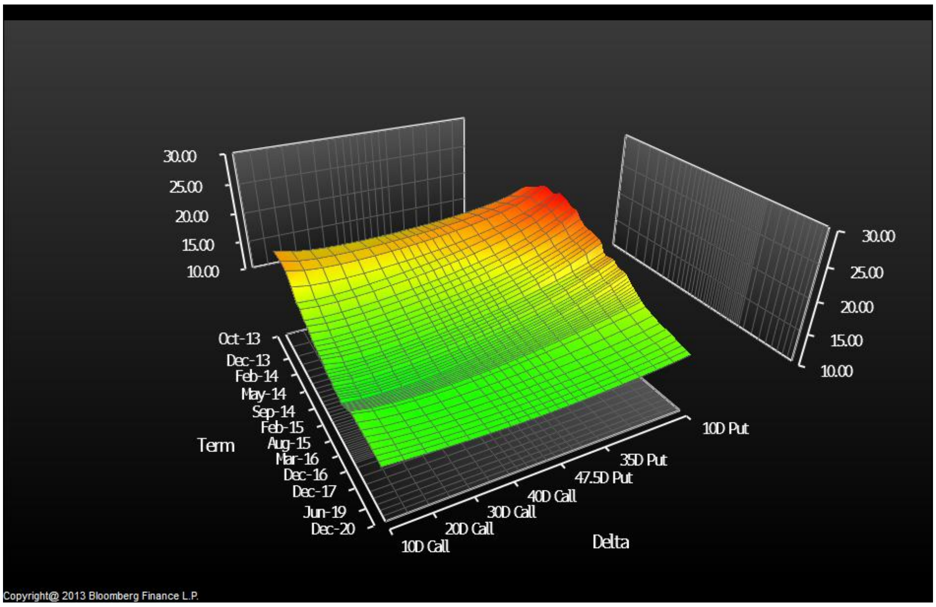


Figure 8: Volatility skew – forward skew

Volatility surface is the graphical representation of change in implied volatility with respect to strike price and maturity. As volatility component of BS model is independent of time and maturity we theoretically expect volatility surface to be flat. However, similar with figure X, this inference does not match with empirical observations. First, factors which lead to distortion in implied volatility-strike price graph also skews volatility surface as volatility surface is actually a collection of IW – strike price graphs with different maturity dates. Second, market expectation of investors and investor behavior affect term structure. Investors may demand premium for long term contracts as their risk perception for long periods is typically higher than short periods. Investors' expectation of market condition may be different for different time periods. In the case of bad market environment, investors pay premium for short maturity options and inverted term structure is observed.



Source: Bloomberg

Figure 9: Volatility surface of WTI crude oil options

To sum up, there are differences between theoretical assumptions and empirical observations. Such differences enable market participants to observe the behavior of other traders.

Risk Reversal

Risk reversal is a hedging strategy that involves buying an out of money (selling) call option and selling (buying) an out-of-money put option with same expiration date and same delta. It is also used to describe difference between implied volatilities of call and put options with same delta and maturity. As 25-delta options are most liquid options in the market, risk reversal is quoted for 25- delta options.

$$RR_{25} = \sigma_{call,25} - \sigma_{put,25}$$

Risk reversal is widely used measure in currency market as the market of FX futures and FX options are deep. A WSJ article written on July 10, 2012 states that:

"Risk reversal skews, used to gauge both investor sentiment towards a currency and underlying exposure, were trading with the least differential for euro puts over the equivalent calls since the start of April."

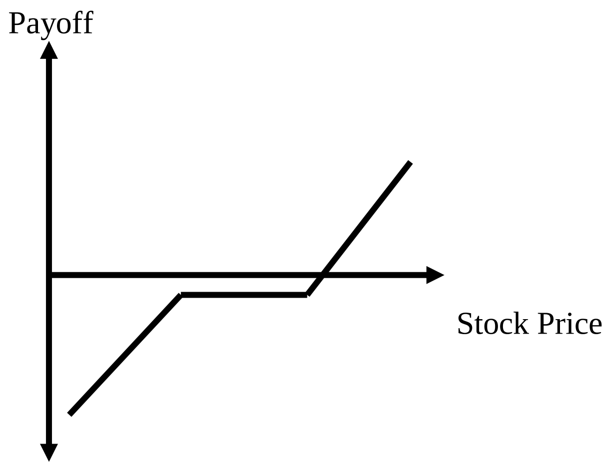


Figure 10: Payoff graph of risk reversal (buy OTM call + sell OTM put)

Risk reversal strategy is derived from the difference between real distribution of financial returns and theoretical assumption of Black and Scholes (BS) model. As IVs are derived from BS model and volatility of actual distribution higher than theoretical distribution, any skewness in volatility smile creates hedging advantage for investors. This can be used to gauge the market sentiment for future price movements. Positive risk reversal can be interpreted as the market is expecting rise in the prices, because it shows that market participants are willing to pay volatility premium for selling call option. Similarly, negative risk reversal can be interpreted as, investors are paying premium for put options.

Empirical studies on risk reversal are mostly done on currency market data. Brunnermeier et al. (2009) investigated the link between carry trades and currency crashes. He used risk reversal as a measure to track market sentiment. Malz (1997) estimates market induced probability distribution of Sterling using risk reversal and option prices. See Campa et al. (1998), Carr and Wu (2007) for other applications.

Value at Risk

Value-at-Risk (VaR) is a broadly used method for measuring market risk of a portfolio by finance professionals and academia. It measures the maximum potential loss incurred to portfolio as a results of market risk. Formally, we can define it as, for given information set Ω_t and confidence level of 1-θ, VaR of a return series $\{r_t\}$ is:

$$\Pr\,(r_t < -VaR_t |\, \Omega_t) = \theta$$

Different VaR models are proposed to estimate market risk. Engle and Manganelli (2001) investigate these methodologies in three categories: parametric methods, nonparametric methods and semiparametric methods. Although these methodologies address to the problem differently, they follow common three-step procedure. First, portfolio is marked to market daily. Second, return distribution of portfolio is estimated. Third, VaR of the portfolio is calculated.

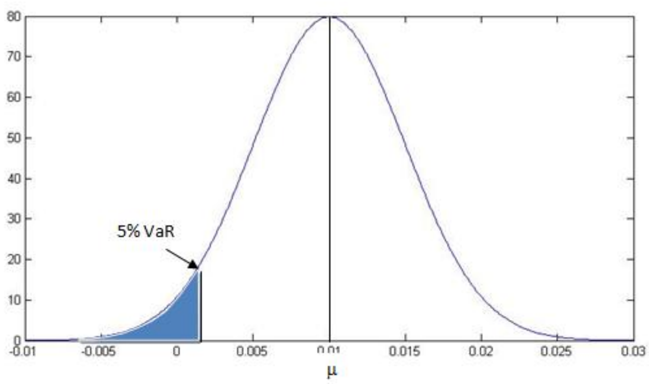


Figure 11: Calculation of VaR

Parametric methods impose certain assumptions about true data generating process of data. These methods include GARCH, EWMA models, skewed student t distribution. Clear benefit of parameterization is to define the return distribution.

However, choice of distribution may not actually represent the actual distribution. If there are any changes in volatility regime, then fitting whole distribution into one model may lead to misspecification. Lamoureux and Lastrapes (1990) show that structural shifts in volatility may lead to overestimation of volatility of stock returns. Wilson et al (1996) reports sudden changes in the volatility of oil futures. Findings of Fong and See (2002), and Vo (2009) confirms the existence of regime switching in oil prices.

Nonparametric methods are based on historical simulation and its variants. Simplicity of methodology and lower computational burden made it popular among finance professionals. To calculate VaR with historical simulation, time window is chosen and daily returns are ranked. Corresponding return level for quantile of VaR is acknowledged as empirical VaR level. Previous applications to oil market include Cabedo and Moya (2003), Sadeghi and Shavvalpour (2006). These studies found that historical simulation with ARMA forecast approach produce more favorable results than alternative methods. Similarly, Sadorsky (2006) compared the performance of performance of parametric models with non-parametric models for crude oil futures. His backtesting of models indicated that non-parametric models perform better than parametric models in term of number of VaR violations.

Historical simulation assumes that past performance of a portfolio is a good indicator for future performance. For relatively large significance levels, the asymptoticity assumption produce near to actual VaR estimates. However, nonparametric models may deliver poor performance for extreme or near to extreme VaR levels. Another problem we observed through our analysis is the importance of time window in calculations. Changes in the size of time window significantly altered VaR estimates. If the observations used to calculate VaR consists of crisis periods observations and the forecast period is tranquil period, then historical simulation produce very conservative (overestimate) VaR level.

Semiparametric models are combination of parametric methods and nonparametric methods. They usually fix a certain data generating process for some part of the distribution but they do not place restriction for other parts of the distribution. Semiparametric VaR methods include extreme value theory (EVT) models, quantile regression models, and other parametric methods combined with historical simulation such as filtered historical simulation, Hull White model.

EVT type models focuses on tail estimation. As they are designed to estimate tail events, they perform well for low VaR levels. Their applications to oil price risk estimation include Marimoutou et al (2009) and Krehbiel and Atkins (2005) which found, for seven of ten left tail events, conditional-EVT performed superior to benchmark parametric models. Downside of EVT models is that their performance is poor for more conventional VaR levels of 1% and 5%. Using, SP 500 data and some stock data, Danielsson and Vries (2000) compared the performance of their EVT type models with other common used models, and they found, for low VaR levels, performance EVT type model is higher than their benchmark models. However, performance of the model decreased as significance level increased. Bao et al. (2006) found that the performance of models in tranquil periods and crisis periods varies significantly

Quantile regression methodology which is used to estimate certain quantile level is also used for VaR estimation. These models do not impose restrictions on the whole distribution, instead econometrically estimate certain quantile level of the distribution. Important applications include CAViaR methodology developed by Engle and Mangenelli (2004), and Conditional VAR approach of Chernozhukov and Umantsev (2001). Apart from modeling advantages of CAViaR models, their performance superiority is also shown by previous studies. Bao et al. (2006) compared the performance of broad sets of VaR models for Asian stock market data. Results indicated that CAViaR class of VaR models worked better than other methods both in crisis periods and tranquil periods. Berkowitz et al. (2011) showed CAViaR models worked best for their desk level data. For application of CAViaR to oil price risk management, see Huang et al (2009).

Models

We compared the out of sample forecasting performance of three sets of VaR models in our analysis: CAViaR type models developed by Engle and Manganelli (2004), our CAViaR RR PlugIn models which are derived from CAViaR PlugIn models of Jeon and Taylor (2013) and benchmark Riskmetrics (1996) model.

CAViaR models are applications of quantile regression to risk management. The advantage of quantile regression models is that they do not impose any restriction on the shape of return distribution. Rather than fitting distribution into a model, they estimate certain quantile level. Estimation follows the method of Koenker and Bassett (1978):

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

Quantile regression differs from standard OLS model in terms of its objective function, minimizes least absolute deviation. LAD is empirically shown to produce more robust estimates than OLS for financial return series (see Koenker and Hallock, 2000)

Engle and Manganelli (2004) propose four CAViaR models to forecast VaR. These models are Adaptive model, Symmetric absolute value, asymmetric slope, indirect GARCH (1,1). Excluding adaptive model, we used rest of three models for our sample. The decision of exclusion is based on poor performance of adaptive models for our sample. It consistently produced so conservative VaR estimates that 0% or close to 0% out-of-sample hit percentage is observed for 1% VaR level. For same reason, we also excluded adaptive PlugIn model.

Symmetric absolute value:

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

Asymmetric slope:

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

Indirect GARCH (1,1):

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

Symmetric absolute value model assumes VaR of a portfolio responds symmetrically to returns with same magnitude but in different directions are identical. Asymmetric slope model assumes that VaR responds asymmetrically to daily returns. Indirect GARCH model formalizes the behavior of VaR as GARCH(1,1) process.

Jeon and Taylor (2013) extended CAViaR models to incorporate implied volatility into the models. We modified their CAViaR PlugIn models to augment CAViaR models with risk reversal. Among their five proposed models, we included augmented version of above CAViaR models:

Symmetric absolute value PlugIn model:

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

Asymmetric slope PlugIn model:

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

Indirect GARCH(1,1) model:

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

We also included Riskmetrics model as it is widely used VaR calculation method as it is widely used as benchmark VaR model. The model describes volatility sequence as exponentially weighted moving average (EWMA) process:

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda) r_{t-1}^2$$

For a given quantile level θ, VaR of the portfolio is:

$$VaR_t = \Phi(\Theta)\sigma_t$$

Critical point in the models is choice of lambda parameter. Different studies propose alternative lambda weight for EWMA models but they mostly report their

EWMA between 0.9 and 1. Consistent with Riskmetrics (1996), I used the decay parameter of 0.94.

CHAPTER 4

EMPIRICAL RESULTS

Data

Our dataset consists of daily return of West Texas Intermediate oil futures with less than two months to expiration date and implied volatility of 25 delta futures with same expiration. Data is provided from Bloomberg (Ticker: CL2 Comdty). For data availability reasons, we chose our analysis periods as from 31.10.2005 to 20.02.2013. The choice of WTI futures over Brent is the result of higher liquidity in WTI futures. Consistent with the literature, we reported daily return as 100 times the log of today's price over the price of previous day. Table 1 shows the summary statistics of WTI CL2 futures.

Table 1: Summary statistics of return Series of WTI CL2 futures.

Mean	0.010370
Median	0.000000
Maximum	5.550920
Minimum	-4.965311
Std. Dev.	0.972064
Skewness	-0.127466
Kurtosis	6.512936
Jarque-Bera	985.7367
Probability	0.000000
Sum	19.77631
Sum Sq. Dev.	1800.995
Observations	1907

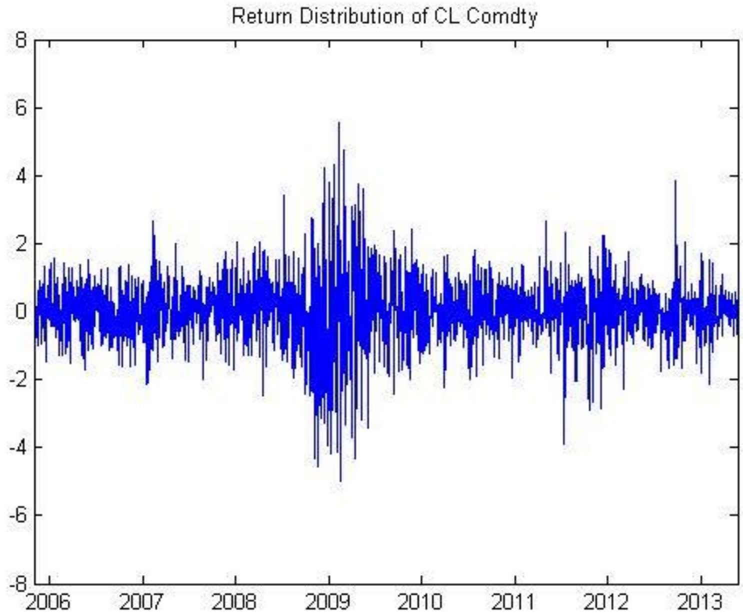


Figure 12: Return Distribution for the analysis period

Manganelli and Engle (2001) describe the behavior of financial return series as leptokurtic and negatively skewed. Looking at the summary statistics of the return distribution, characteristics of our return distribution corresponds with general characteristics of financial return series.

Simulation

We calculated one-day-ahead VaR forecasts of CAViaR models, CAViaR RR PlugIn models and Riskmetrics model for 1% and 5% levels. In sample period is set to span 1500 observations. First two sets of model use quantile regression methodology which requires nonlinear optimization. We therefore chose numerical method for calculation of VaR. Initial quantile levels are generated from first 300 observations. We initialized the simulation generating random 10,000 candidate vector of beta parameters. For each set of vector of parameters objective function value was calculated. We then chose vector of beta parameters that produces best 20 initial values. In the second step, we tried to improve the performance candidate parameters by neighborhood search. Neighborhood search is performed using Nelder Mead method and performed until the improvement is less than 10^{-10}.

We focused on 1% and 5%levels for VaR calculation as they are widely used significance levels for VaR calculations. We did not calculate for extreme values, such as 0.1% level, because our data set is not long enough for reality check.

Simulation Results

Table 2 and 3 report the simulation results of CAViaR models and CAViaR RR PlugIn models for 1% and 5% levels across with the results of benchmark Riskmetrics model. Looking at the out-of-sample hit percentages of CAViaR models, CAViaR model is able deliver hit percentage with close to actual level. Results of CAViaR RR PlugIn models are similar to CAViaR models. However, in terms 5% of out sample hit percentage, there is no clear superiority one model to the other model. For 1% out sample hit percentage, CAViaR models consistently understate VaR levels. Similarly CAViaR RR PlugIn models underreport VaR level but performance of second sets of models is superior to the first class. Our benchmark Riskmetrics model performed worse than and CAViaR PlugIn models. It significantly underreported VaR levels. This is the result of wrong Gaussian assumption of EWMA type models. For 5% VaR level, similar with 1% VaR results, Riskmetrics model delivered worse results than CAViaR and CAViaR PlugIn models.

Table 2: Simulation results of CAViaR Model

		SAV	AS	GARCH	Riskmetrics
1% VaR	In-sample Hit (%)	1	1	1	
	Out-of-sample Hit (%)	2.457	2.2113	2.2113	3.4398
5% VaR	In-sample Hit (%)	5	4.8667	4.9333	
	Out-of-sample Hit (%)	4.6683	4.4226	4.914	5.8968

Table 3: Simulation results of CAViaR RR PlugIn Model

		SAV	AS	GARCH	Riskmetrics
1% VaR	In-sample Hit (%)	0.9333	1.0667	0.8667	
	Out-of-sample Hit (%)	1.9656	1.9656	2.2113	3.4398
5% VaR	In-sample Hit (%)	4.9333	4.9333	4.9333	
	Out-of-sample Hit (%)	5.8968	4.6683	4.4226	5.8968

We also wanted to see if changing beta parameters daily would provide better forecasting output. As in the original simulation, initial in sample period covered 1500 observations. However, for each iteration, we expanded in-sample observations to cover the all the past observations. Results are reported in Table 4 and Table 5. Empirical results show daily updating of parameters improved the performance of both type of models. For the original simulation results, CAViaR models were not able to report less than 2% out of sample hit percentage for 1% level whereas all the rolling window out of sample VaR violation probabilities of 1% VaR is seen to be less than 2%. We observe similar improvement in CAViaR RR PlugIn models but improvement of result more modest than CAViaR type models. Considering our proposed model delivered better results for non-rolling window simulation, smaller magnitude of improvement is understandable.

Table 4: Rolling Simulation results of CAViaR Model

		SAV	AS	GARCH	Riskmetrics
1% VaR	In-sample Hit (%)	1.0000	1.0000	1.0000	
	Out-of-sample Hit (%)	1.9656	1.2285	1.7199	3.4398
5% VaR	In-sample Hit (%)	5.0000	4.8667	4.9333	
	Out-of-sample Hit (%)	4.9140	4.4226	4.9140	5.8968

Table 5: Simulation results of CAViaR RR PlugIn Model

		SAV	AS	GARCH	Riskmetrics
1% VaR	In-sample Hit (%)	0.9333	1.0667	0.8667	
	Out-of-sample Hit (%)	1.7199	1.4742	1.7199	3.4398
5% VaR	In-sample Hit (%)	4.9333	4.9333	4.9333	
	Out-of-sample Hit (%)	5.1597	4.914	4.1769	5.8968

Coverage Tests

We showed that our newly proposed models generated out of sample hit percentage closer to the coverage probability. However, closer to actual percentage does not necessarily imply that our models are correctly specified. It is essential to generate correctly specified VaR violation series which is iid and have a proability of VaR violation series statistically not different than theoretical value. To test the performance of VaR violation series we generated through simulations, we employed the method of Christoffersen (1998). Coverage and Independence tests of Christoffersen assess whether VaR violations generated by the models are iid distributed and statistically different from the hypothetical value.

Typical problem observed with VaR models is models are not able to generate close to actual VaR estimates. Unconditional coverage test measures if probability of VaR violation generated by the model is statistically different than the theoretical value. Formally, defining VaR violation sequence as follows:

$$I_t = \begin{cases} 1 \; if \; y_t > VaR_t \\ 0 \; if \; y_t < VaR_t \end{cases}$$

Given the sequence $\{I_t\}_{t=1}^{T}$ and information set Ω_t, unconditional coverage test tests the null hypothesis E[$I_t|\Omega_t$]=p against alternative $E[I_t \; |\Omega_t] \neq p$.

Test results for out-of-sample VaR violation series are documented in Table 10 and Table 11. 1% and 5% VaR results show only CAViaR and CAViaR RR PlugIn models pass unconditional coverage tests for 1% significance level. Riskmetrics model failed to provide true coverage. For 5% significance level, we reject the hypothesis of true coverage of all three CAViaR models in 1% VaR level whereas only one CAViaR RR PlugIn model, GARCH model, failed to pass the test for 1% VaR. The results suggest that VaR violation probabilities generated by CAViaR RR Plug In models are statistically indifferent to the theoretical value. Also they generate better performance than CAViaR models. 5% VaR results showed all models have the property of true coverage.

One requirement for correctly specified VaR model is to generate random VaR violation series because non-iid distributed VaR series carry information that is not exploited by the model. Independence test tests whether VaR violations for out-of sample forecasts are independently identically distributed. Test output show that model generated VaR violation series of CAViaR and CAViaR RR PlugIn models independently and identically distributed.

Conditional coverage test is a joint test for testing true coverage and randomness of VaR violation series. For 1% VaR level, all but Riskmetrics model passed the test of conditional coverage for 5% significance. All 5% VaR violation series passed the test of conditional coverage.

Table 6: Coverage Test results for CAViaR model (out-of-sample)

		LR_UC	LR_I	LR_CC	LR_UC_p	LR_I_p	LR_CC_p
1% VaR	SAV	6.2363	0.5051	6.7414	0.0125	0.4773	0.0344
	AS	4.5097	0.4081	4.9178	0.0337	0.5229	0.0855
	GARCH	4.5097	0.4081	4.9178	0.0337	0.5229	0.0855
	Rmetrics	15.0284	3.2700	18.2984	0.0001	0.0706	0.0001
5% VaR	SAV	0.0895	1.3025	1.3919	0.7649	0.2538	0.4986
	AS	0.2847	1.6057	1.8904	0.5936	0.2051	0.3886
	GARCH	0.0047	1.0368	1.0415	0.9454	0.3086	0.5941
	Rmetrics	0.6724	0.3016	0.9740	0.4122	0.5829	0.6145

Table 7: Coverage Test results for CAViaR model (in-sample)

		LR_UC	LR_I	LR_CC	LR_UC_p	LR_I_p	LR_CC_p
1% VaR	SAV	0	2.1928	2.1928	0.9979	0.1387	0.3341
	AS	0	2.1928	2.1928	0.9979	0.1387	0.3341
	GARCH	0	2.1928	2.1928	0.9979	0.1387	0.3341
5% VaR	SAV	0	1.2841	1.2841	0.9953	0.2571	0.5262
	AS	0.0538	2.952	3.0059	0.8165	0.0858	0.2225
	GARCH	0.0127	0.4981	0.5108	0.9102	0.4804	0.7746

Table 8: Coverage Test results for CAViaR RR PlugIn model (out-of-sample)

		LR_UC	LR_I	LR_CC	LR_UC_p	LR_I_p	LR_CC_p
1% VaR	SAV	3.0109	0.3216	3.3325	0.0827	0.5706	0.189
	AS	3.0109	0.3216	3.3325	0.0827	0.5706	0.189
	GARCH	4.5097	0.4081	4.9178	0.0337	0.5229	0.0855
	Rmetrics	15.0284	3.2700	18.2984	0.0001	0.0706	0.0001
5% VaR	SAV	0.6724	0.3016	0.974	0.4122	0.5829	0.6145
	AS	0.0895	1.3025	1.3919	0.7649	0.2538	0.4986
	GARCH	0.2847	1.447	1.7317	0.5936	0.229	0.4207
	Rmetrics	0.6724	0.3016	0.9740	0.4122	0.5829	0.6145

Table 9: Coverage Test results for CAViaR RR PlugIn model (in-sample)

		LR_UC	LR_I	LR_CC	LR_UC_p	LR_I_p	LR_CC_p
1% VaR	SAV	0.0675	2.4422	2.5097	0.795	0.1181	0.2851
	AS	0	2.1928	2.1928	0.9979	0.1387	0.3341
	GARCH	0.2794	2.7164	2.9958	0.5971	0.0993	0.2236
5% VaR	SAV	0.0127	1.4228	1.4356	0.9102	0.2329	0.4878
	AS	0	2.5423	2.5423	0.9953	0.1108	0.2805
	GARCH	0.0127	4.4106	4.4233	0.9102	0.0357	0.1095

Since I run the simulation with daily updating of parameters, I obtained VaR violation series for rolling models. I also tested the performance of these rolling simulation results. Test results obtained from rolling simulation models are superior to not rolled models. All models passed all three tests for 5% significance level which indicates the randomness and true coverage properties of rolling simulation output.

Table 10: Coverage Test Results for rolling CAViaR model (out-of-sample)

		LR_UC	LR_I	LR_CC	LR_UC_p	LR_I_p	LR_CC_p
1% VaR	SAV	3.0109	0.3216	3.3325	0.0827	0.5706	0.189
	AS	0.2047	0.1247	0.3294	0.6509	0.724	0.8481
	GARCH	1.7677	0.2456	2.0134	0.1837	0.6202	0.3654
	Rmetrics	15.0284	3.2700	18.2984	0.0001	0.0706	0.0001
5% VaR	SAV	0.0047	1.0368	1.0415	0.9454	0.3086	0.5941
	AS	0.2847	1.6057	1.8904	0.5936	0.2051	0.3886
	GARCH	0.0047	1.0368	1.0415	0.9454	0.3086	0.5941
	Rmetrics	0.6724	0.3016	0.9740	0.4122	0.5829	0.6145

Table 11: Coverage Test results for rolling CAViaR RR PlugIn model (out-of-sample)

		LR_UC	LR_I	LR_CC	LR_UC_p	LR_I_p	LR_CC_p
1% VaR	SAV	1.7677	0.2456	2.0134	0.1837	0.6202	0.3654
	AS	0.8163	0.18	0.9963	0.3663	0.6714	0.6077
	GARCH	1.7677	0.2456	2.0134	0.1837	0.6202	0.3654
	Rmetrics	15.0284	3.2700	18.2984	0.0001	0.0706	0.0001
5% VaR	SAV	0.0251	0.806	0.8311	0.874	0.3693	0.66
	AS	0.0047	1.0368	1.0415	0.9454	0.3086	0.5941
	GARCH	0.5963	1.7697	2.366	0.44	0.1834	0.3064
	Rmetrics	0.6724	0.3016	0.9740	0.4122	0.5829	0.6145

DQ Test

Coverage tests of Christoffersen (1998) tests the existence of first order dependence in the series. However, it is possible to observe higher order dependence between VaR series and return series. Engle and Manganelli (2004) propose DQ test which investigates the relation between VaR violation series and lags of VaR forecasts and return series.

We performed DQ test for CAViaR and CAViaR RR Plug In models. For 1% VaR violation series, p values of CAViaR and CAViaR RR PlugIn model shows all models pass the test for 5% level. None of VaR violation series pass the test for 1% but p values of CAViaR RR PlugIn models are more favorable than the results of CAViaR models.

Out of sample forecast performance of 1% VaR estimation sequence are poor for both series but better for CAViaR RR PlugIn type models. For 5% VaR sequence there is clear superiority of VAR sequence generated by CAViaR RR PlugIn type models. We can clearly state that DQ test performance of CAViaR RR PlugIn type models are superior to CAViaR models.

Table 12: DQ Test results for CAViaR Model

		SAV	AS	GARCH
1% VaR	DQ In-sample (p value)	0.1763	0.2108	0.2405
	DQ Out-of-sample (p value)	0.0288	0.0393	0.0432
5% VaR	DQ In-sample (p value)	0.7654	0.3792	0.8426
	DQ Out-of-sample (p value)	0.0844	0.0655	0.0582

Table 13: DQ Test results for CAViaR RR PlugIn Model

		SAV	AS	GARCH
1% VaR	DQ In-sample (p value)	0.1402	0.0726	0.1457
	DQ Out-of-sample (p value)	0.0396	0.0427	0.0433
5% VaR	DQ In-sample (p value)	0.7632	0.6642	0.2435
	DQ Out-of-sample (p value)	0.2751	0.1019	0.4826

CHAPTER 5

CONCLUSION

We proposed a new model which incorporates the expectation of market participants to CAViaR type models generated by Engle and Manganelli (2004). CAViaR models performed poorly for more extreme 1% level. Our CAViaR RR PlugIn models outperformed the corresponding CAViaR model for 1% level. Results show risk reversal carries information which is not covered by return series.

We applied various tests to analyze if our proposed models generate VaR violation series with true coverage, randomness and no higher order dependence. These tests ensured our out of sample hit percentage is statistically indifferent with nominal coverage probability and randomly distributed. Our proposed models passed these tests and performed better than CAViaR models.

APPENDIX A: SIMALTION OUTPUTS

Table A.1: Simulation Results of CAViaR Model for 1% VaR

	SAV	AS	GARCH
β_1	0.0161	0.0194	0.0674
Standard Error	0.0099	0.0095	0.0394
p-values	0.052	0.0208	0.0437
β_2	0.9561	0.9526	0.9358
Standard Error	0.017	0.0261	0.006
p-values	0	0	0
β_3	0.1167	0.0913	0.2971
Standard Error	0.057	0.0679	0.256
p-values	0.0204	0.0895	0.1229
β_4		0.1536	
Standard Error		0.1304	
p-values		0.1195	
RQ value	41.6031	41.4178	40.9026
In-sample Hit (%)	1	1	1
Out-of-sample Hit (%)	2.457	2.2113	2.2113

Table A.2: Simulation Results of CAViaR Model for 5% VaR

	SAV	AS	GARCH
β_1	0.0076	0.0102	0.0125
Standard Error	0.0099	0.0074	0.0237
p-values	0.223	0.0838	0.298
β_2	0.9505	0.9674	0.943
Standard Error	0.0192	0.0175	0.0114
p-values	0	0	0
β_3	0.0984	0.0125	0.155
Standard Error	0.0387	0.0338	0.398
p-values	0.0055	0.3559	0.3485
β_4	0	0.1047	0
Standard Error	0	0.041	0
p-values	0	0.0053	0
RQ value	153.899	152.7349	153.0282
In-sample Hit (%)	5	4.8667	4.9333
Out-of-sample Hit (%)	4.6683	4.4226	4.914

Table A.3: Simulation Results of CAViaR RR PlugIn Model for 1% VaR

	SAV	AS	GARCH
β_1	0.0278	0.0217	0.0505
Standard Error	0.0138	0.0137	0.0271
p-values	0.0222	0.0575	0.0312
β_2	0.9320	0.9425	0.9616
Standard Error	0.0161	0.0145	0.0041
p-values	0.0000	0.0000	0.0000
β_3	0.1671	0.1099	0.1506
Standard Error	0.0562	0.0578	0.2447
p-values	0.0015	0.0286	0.2691
β_4	-0.0545	0.1854	0.0281
Standard Error	0.0166	0.0938	0.0025
p-values	0.0005	0.0241	0.0000
β_5		-0.0388	
Standard Error		0.0348	
p-values		0.1325	
RQ value	41.2824	41.0526	40.0623
In-sample Hit (%)	0.9333	1.0667	0.8667
Out-of-sample Hit (%)	1.9656	1.9656	2.2113

Table A.4: Simulation Results of CAViaR RR PlugIn Model for 5% VaR

	SAV	AS	GARCH
β_1	0.0057	0.0076	0.027
Standard Error	0.0162	0.0079	0.0142
p-values	0.362	0.1668	0.0286
β_2	0.956	0.9705	0.9638
Standard Error	0.0185	0.0133	0.0055
p-values	0	0	0
β_3	0.0909	0.0227	0.0558
Standard Error	0.0262	0.0306	0.1879
p-values	0.0003	0.2297	0.3832
β_4	0.0127	0.0918	0.0454
Standard Error	0.0213	0.0252	0.0023
p-values	0.2749	0.0001	0
β_5		0.0117	
Standard Error		0.0115	
p-values		0.1558	
RQ value	153.8001	152.4324	151.2686
In-sample Hit (%)	4.9333	4.9333	4.9333
Out-of-sample Hit (%)	5.8968	4.6683	4.4226

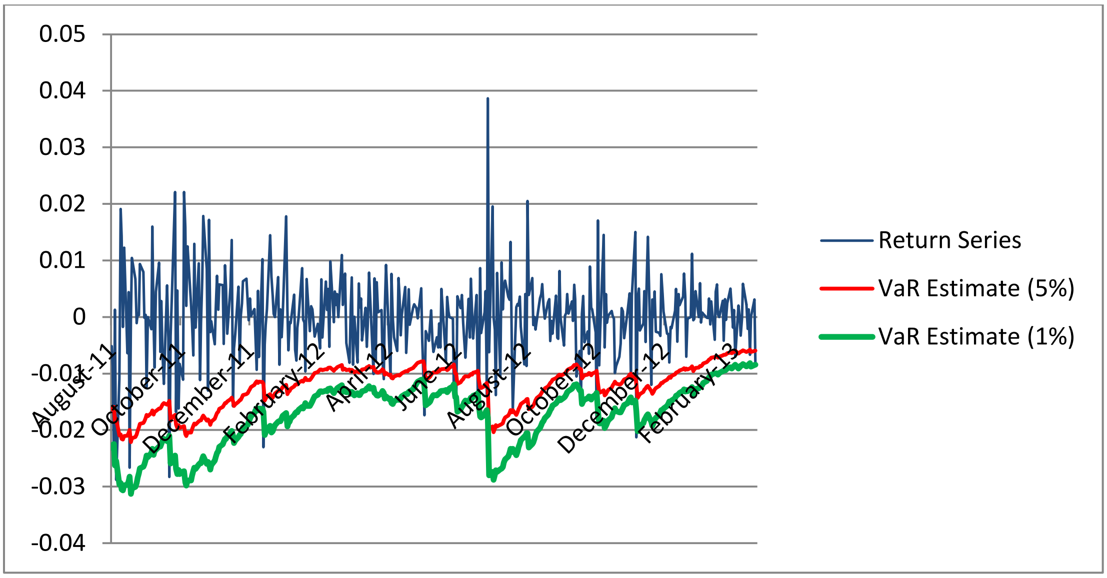


Figure A.1: VaR estimates of Riskmetrics model

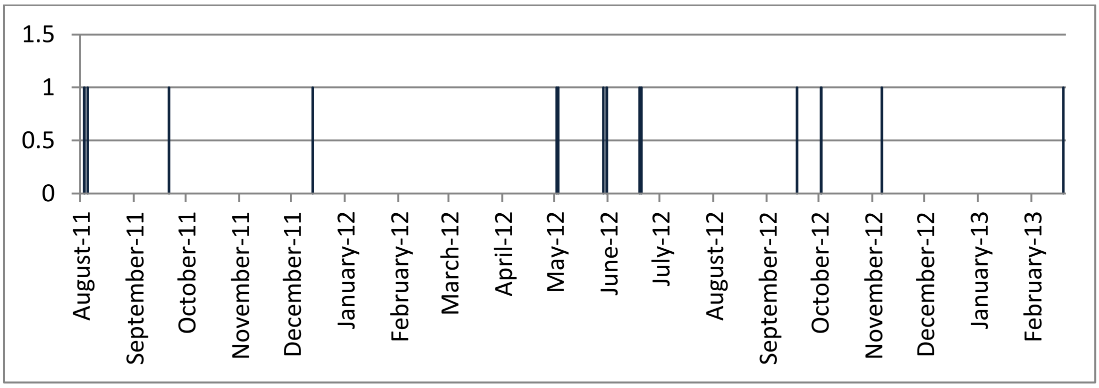


Figure A.2: Out of sample Hits of Riskmetrics model for 1% level.

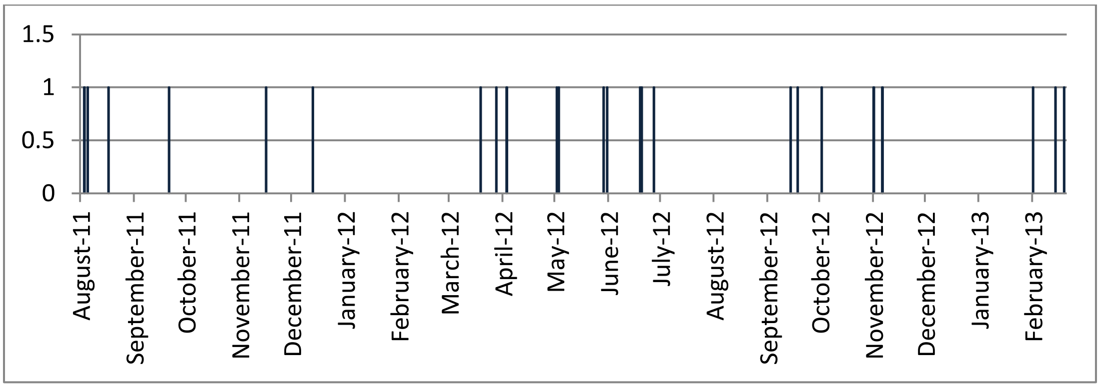


Figure A.3: Out of sample Hits of Riskmetrics model for 5% level.

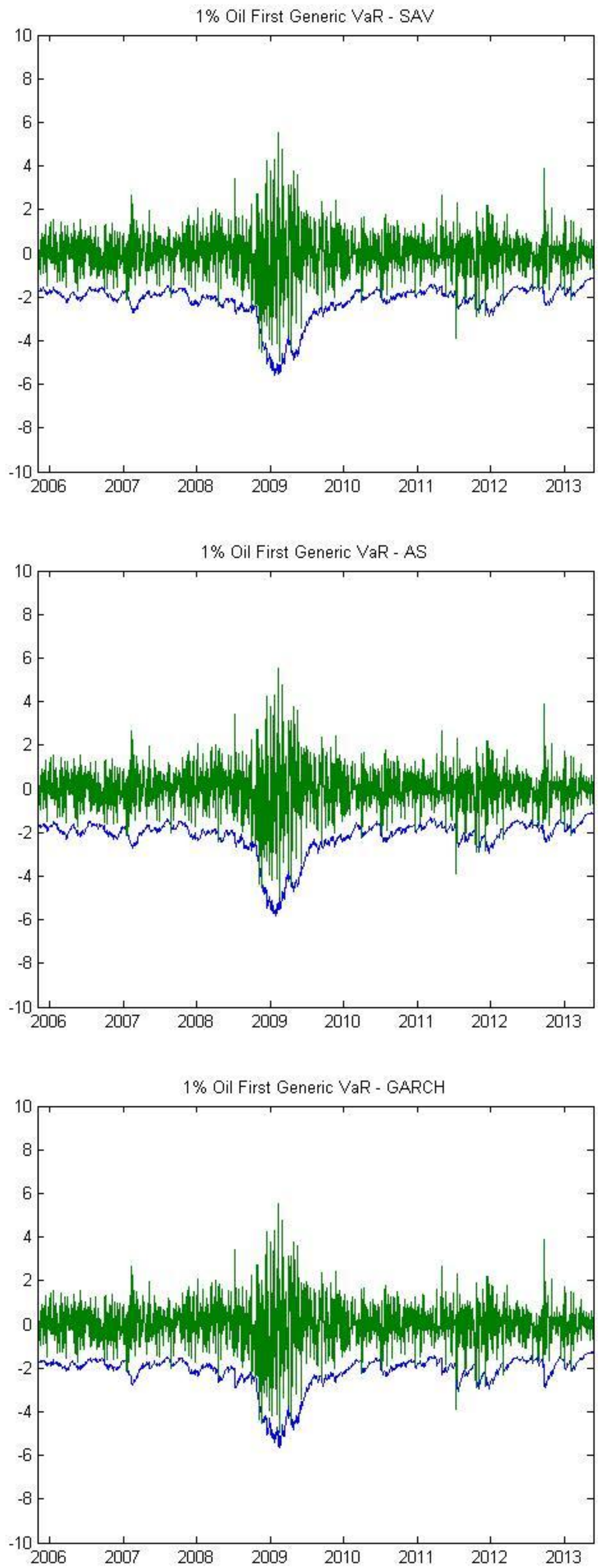


Figure A.4: VaR estimates of CAViaR models (1%)

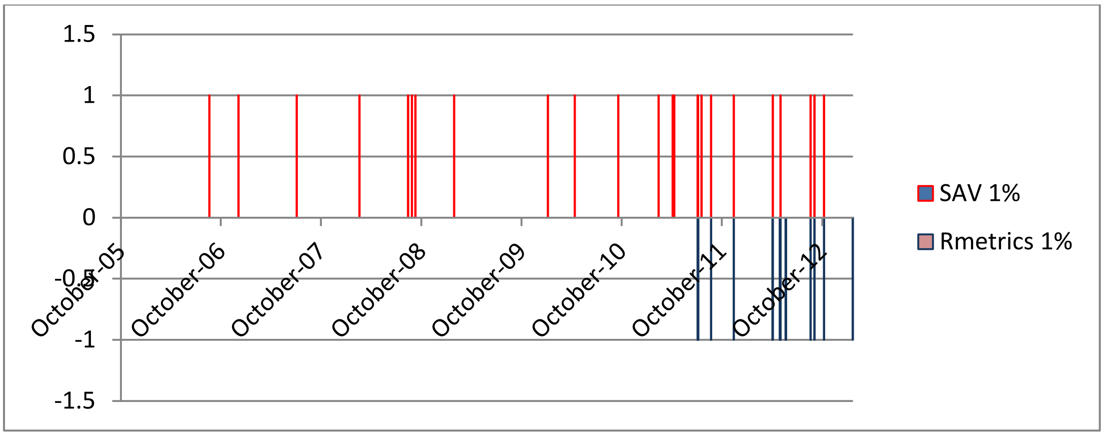


Figure A.5: In sample and out of sample hit estimtes of CAViaR SAV model (1%)

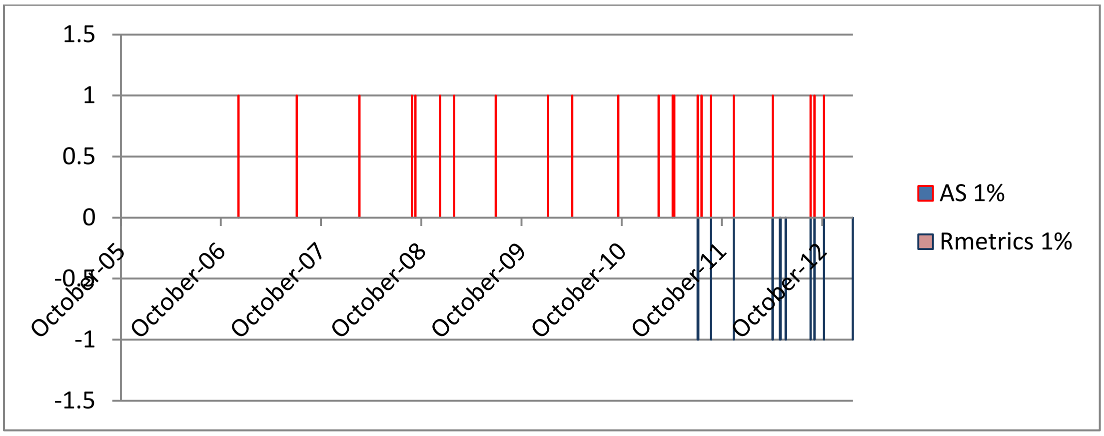


Figure A.6: In sample and out of sample hit estimtes of CAViaR AS model (1%)

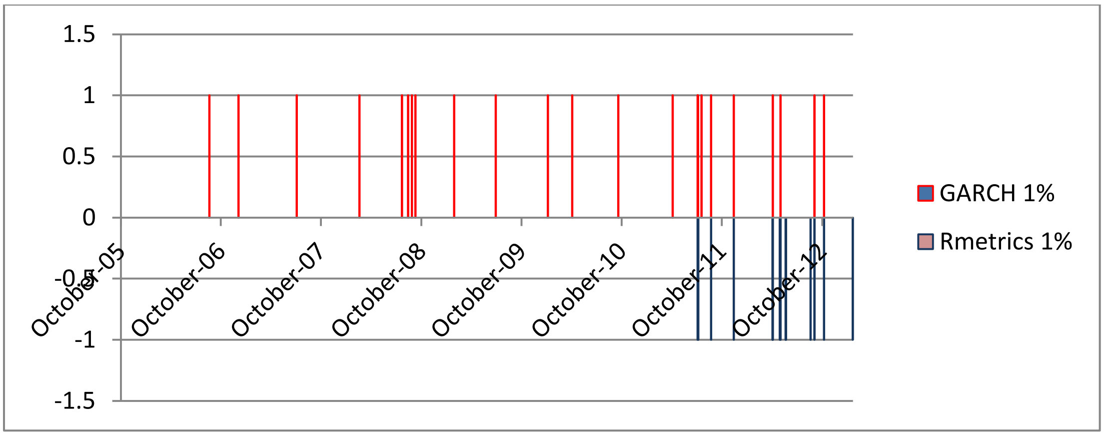


Figure A.7: In sample and out of sample hit estimtes of CAViaR GARCH model (1%)

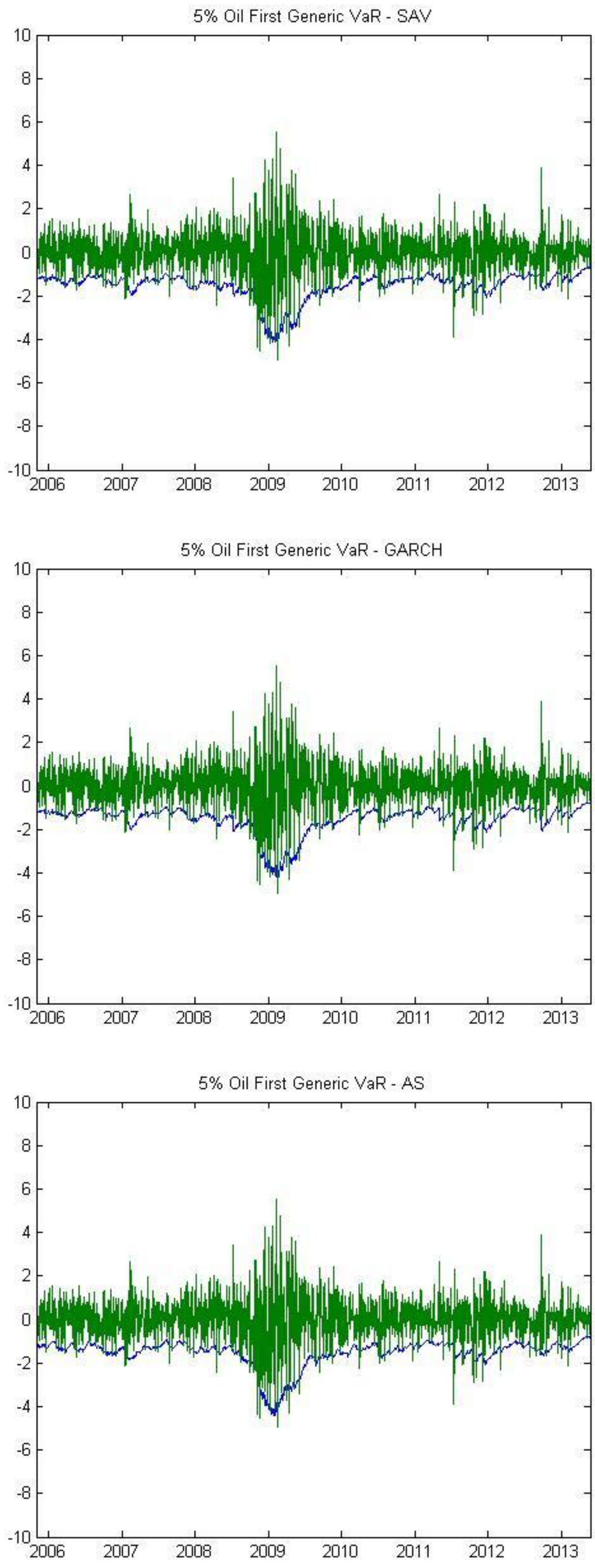


Figure A.8: VaR estimates of CAViaR models (5%)

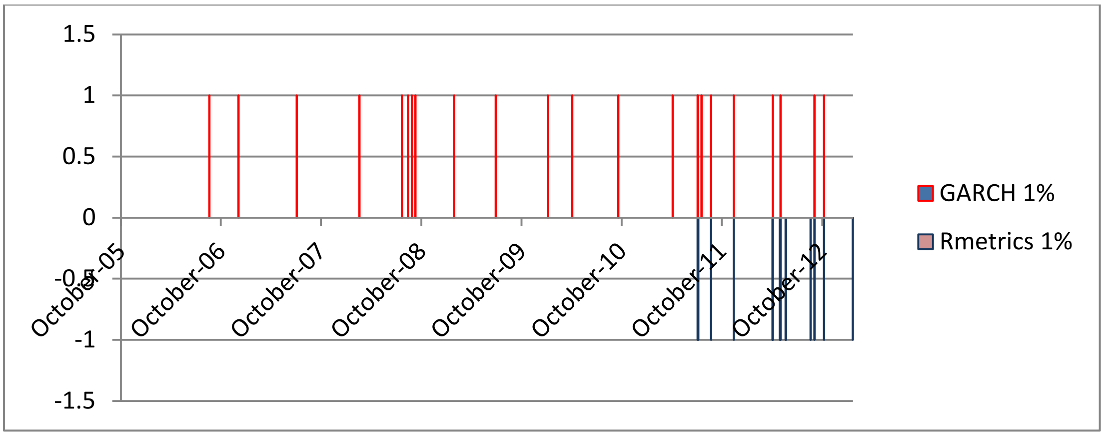


Figure A.9: In sample and out of sample hit estimtes of CAViaR AS model (5%)

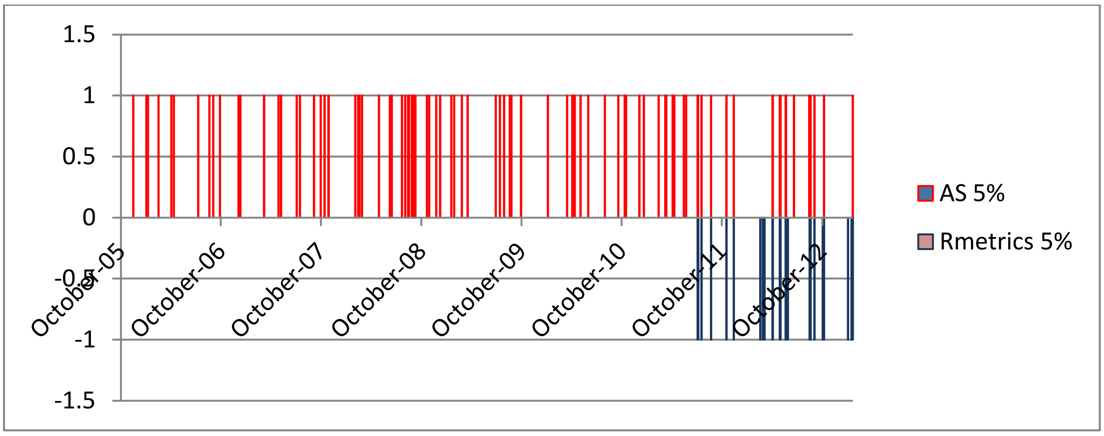


Figure A.10: In sample and out of sample hit estimtes of CAViaR SAV model (5%)

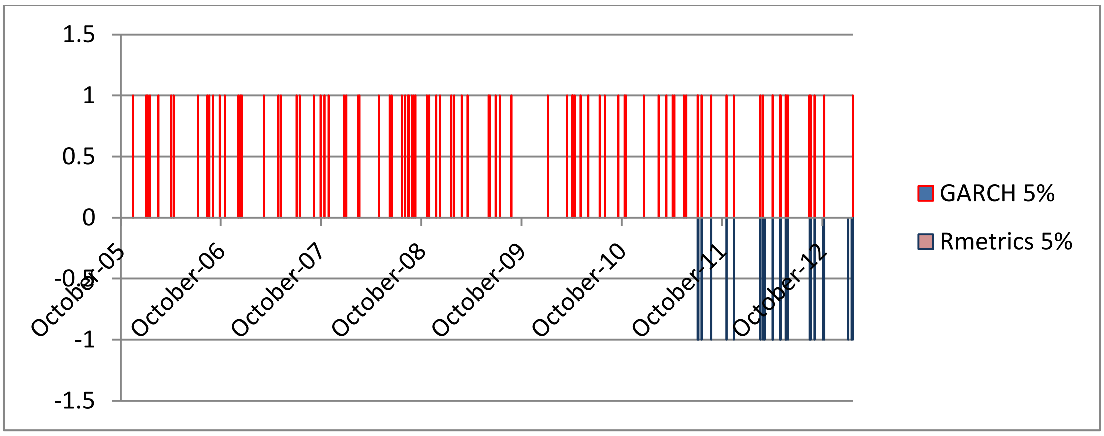


Figure A.11: In sample and out of sample hit estimtes of CAViaR GARCH model (5%)

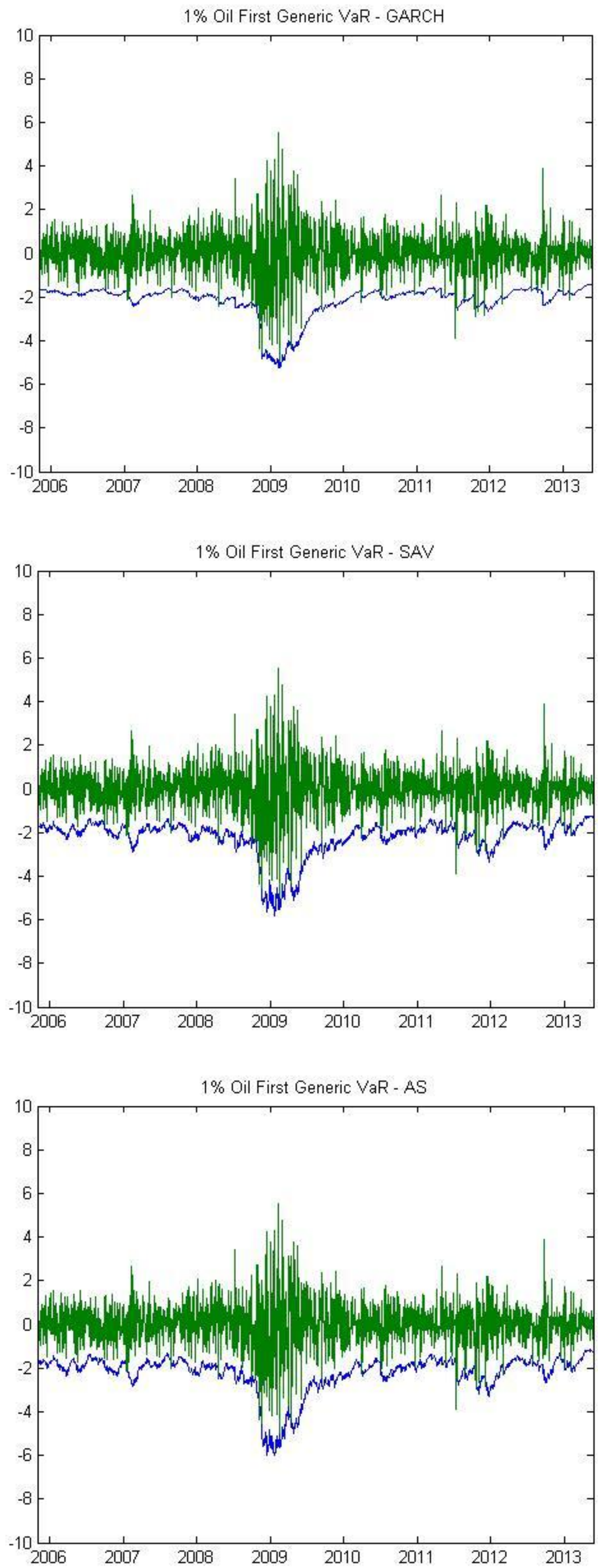


Figure A.12: VaR estimates of CAViaR RRPlugIn models (1%)

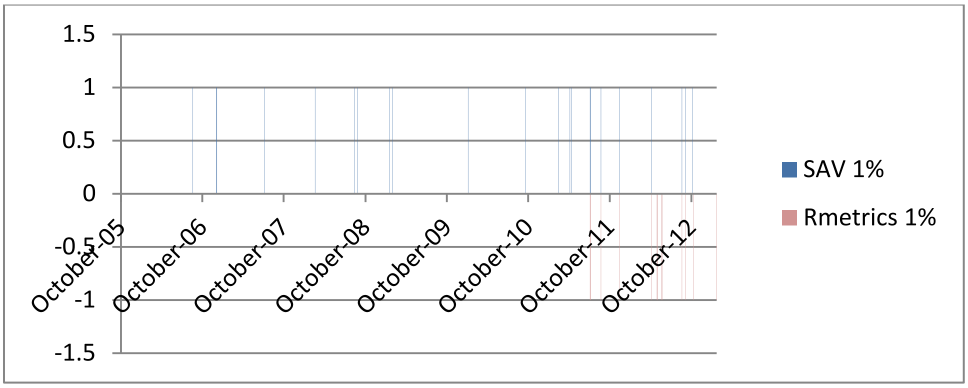


Figure A.13: In sample and out of sample hit estimtes of CAViaR RRPlugIn SAV (1%)

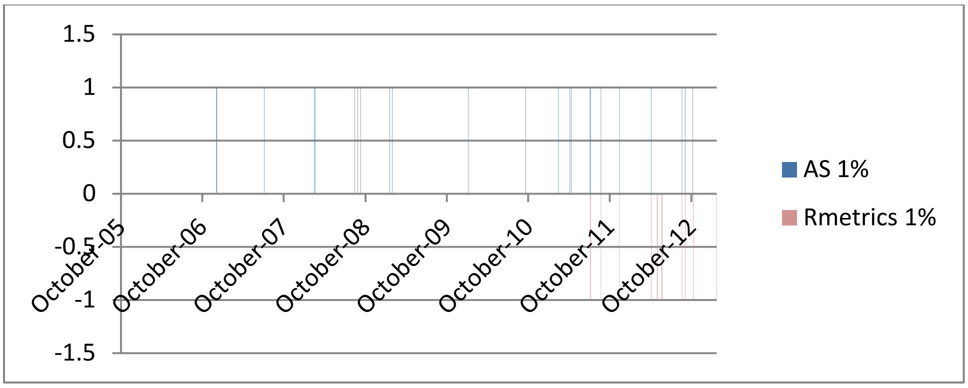


Figure A.14: In sample and out of sample hit estimtes of CAViaR RRPlugIn AS (1%)

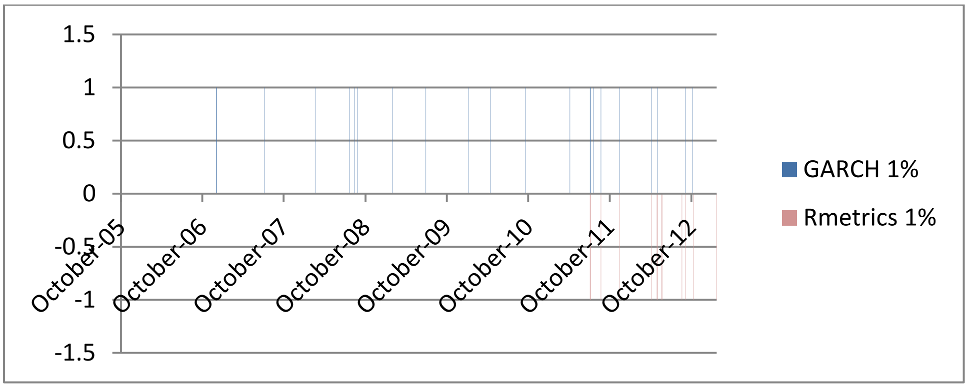


Figure A.15: In sample and out of sample hit estimtes of CAViaR RRPlugIn GARCH (1%)

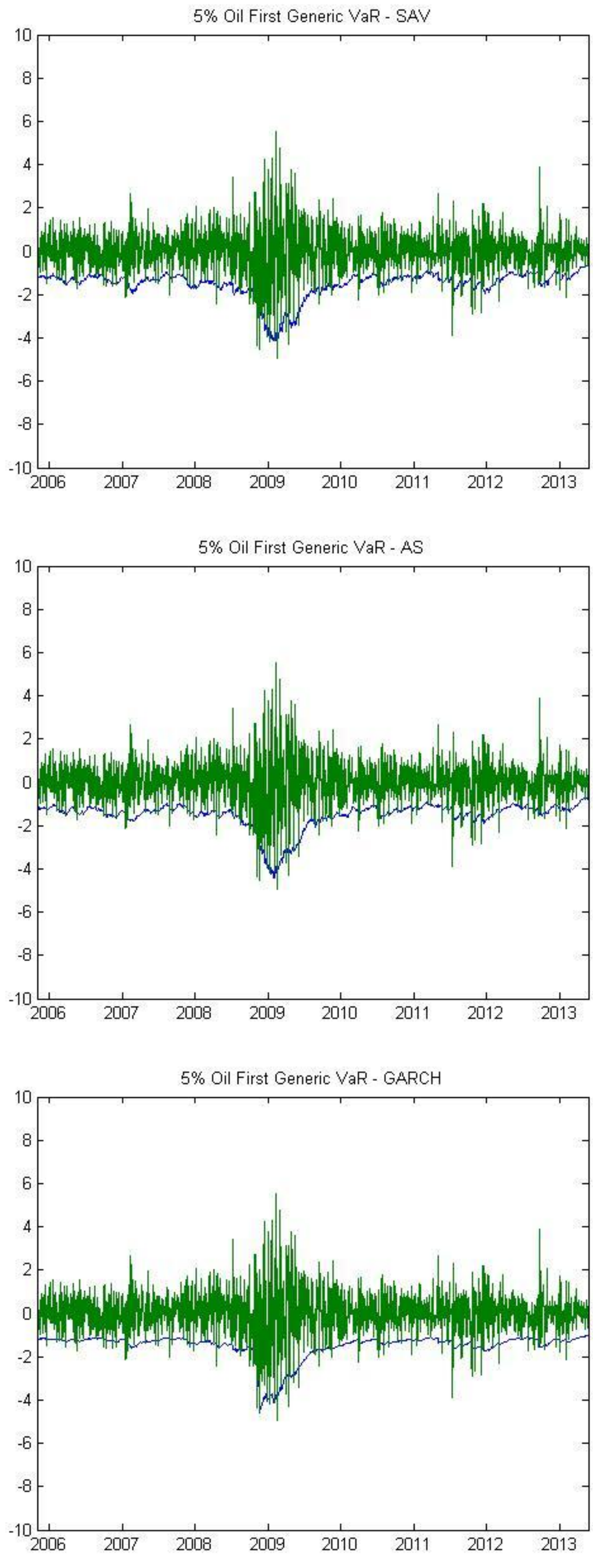


Figure A.16: VaR estimates of CAViaR RRPlugIn models (5%)

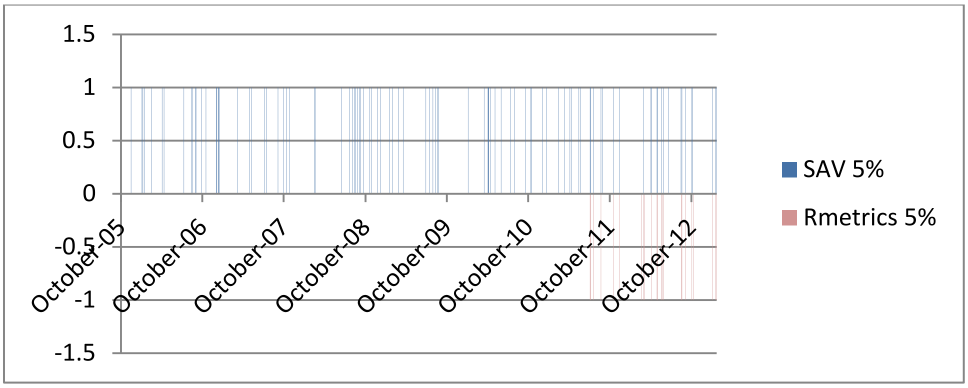


Figure A.17: In sample and out of sample hit estimtes of CAViaR RRPlugIn SAV (5%)

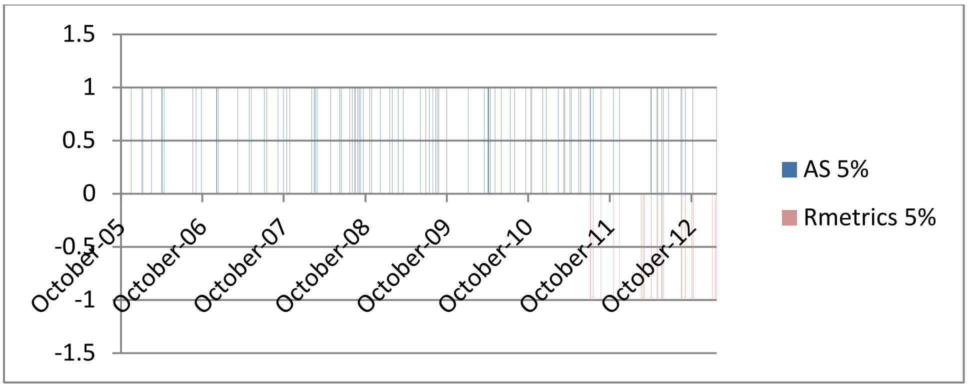


Figure A.18: In sample and out of sample hit estimtes of CAViaR RRPlugIn AS (5%)

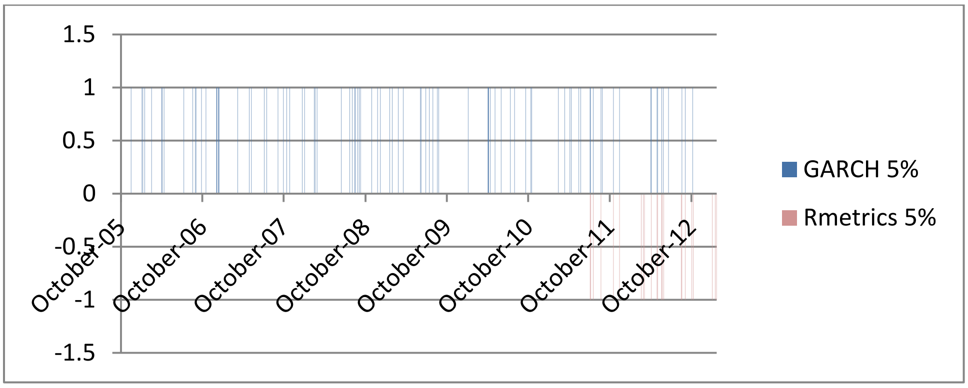


Figure A.19: In sample and out of sample hit estimtes of CAViaR RRPlugIn GARCH (5%)

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