The efficacy of Value at Risk models in Caribbean Equity Markets

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Within recent years, the global financial crisis and the European Sovereign debt crisis have underscored the necessity for more robust and dynamic financial risk management metrics and tools. One such tool, which continues to gain prominence and is at the forefront of market risk management, is the Value at Risk (VaR) model. VaR models, which estimate the loss from a fixed set of trading positions over a fixed time horizon that would be equaled or exceeded with a specified probability, have performed relatively well in the developed financial markets of the world. This paper evaluates the efficacy and applicability of the commonly used VaR models in the emerging equity markets of the Caribbean. It also makes recommendations on how existing VaR models may be enhanced to increase their usefulness within the Caribbean context.

Keywords: Value at Risk, Caribbean, Equity Markets

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1. Introduction

The rules of the Basel Committee on Banking Supervision (1996) require banks to use Value at Risk (VaR) models to determine market risk capital requirements. Consequently, VaR models are widely used by banks and other non-bank financial institutions in the G7 countries to quantify and manage the market risk in their trading portfolios.Empirical studies, such as Lunde*et al.* (2005) and Engle (2001), have established the efficacy of VaR models in the more developed financial markets of the world.Lima *et al.* (2006) and Varma (1999) demonstrate the usefulness of VaR in the context of the larger and more actively traded emerging equity markets of Brazil and India, respectively. There are, however, no known studies which address the subject of VaR modeling in the Caribbean context

The major stock exchanges of the Caribbean, namely the Barbados Stock Exchange (BSE), the Eastern Caribbean Stock Exchange (ECSE), the Jamaica Stock Exchange (JSE) and the Trinidad and Tobago Stock Exchange (TTSE), are not very comparable, in many aspects,either to the developed equity markets (such as the stock exchanges of the G7 countries) or to the larger and more actively traded emerging equity markets (such as the stock exchanges of Brazil and India). The liquidity, trade frequency, availability, number of market participants and market capitalization of most of the stocks traded on the BSE, ECSE, JSE and TTSE are much smaller than that of stocks listed on the aforementioned developed and emerging equity markets.

Several studies, such as Sargeant(1995), Craigwell *et al.* (1999), Craigwell *et al.* (2007) and Watson (2009), have characterized the BSE, JSE and TTSE as inefficient, in an underdeveloped state and having disappointing performance. Various capital market innovations such as liquidity enhancing services, equity generating services and price risk covering services, amongst others, have been recommended by Sergeant (1995). The Caribbean equity markets currently lack developed futures and options exchanges which mayhelp to enhance market liquidity and efficiency.

Notwithstanding these identified weaknesses in the regional stock exchanges, some institutional investors such as pension funds, insurance companies and credit unions are required by the regulatory bodies to invest a certain percentage of their portfolio in domestic and/or regional equities. In addition, there are many individual investors across the Caribbean who rely on the regional equity markets for investment returns and wealth generation.

It is against this background thatthis study was undertaken. Its objective is to evaluate the effectiveness and applicability of the simple and commonly used VaR models in the emerging equity markets of the Caribbean. It also makes recommendations on how these VaR models may be enhanced to increase their usefulness within the Caribbean context.

The results obtained from, and the recommendations given in, this study canbe used by Caribbean financial institutions to assist in evaluating the market risk capital requirement for its regional equity portfolios. This would in turn facilitate the allocation of the optimum amount of capital to support equity trading activities.The individual investor can use the VaR models presented in this paper to set appropriate stop loss limits which are commensurate with their return objectives and risk tolerance. This would help to minimize the investors' equity price risk and facilitate the preservation of capital.

The rest of the paper is made up as follows: a brief review of the literature on available VaR models and the Caribbean equity markets is available in the following section. Next, the data and methodology used in the paper are laid out and discussed. Following this, the results are presented and analyzed. The paper then concludes with some recommendations.

2. Literature Review

There is a significant amount of published work on VaRmodels and the theoretical concepts upon which they are based. A comprehensive and in-depth technical presentation of the VaRmodel is given by Jorion (2007). An intuitive and less technical presentation of VaR models is given in Choudhry (2006) and a state-of-the-art presentation is given in Dowd (2005). Shorter treatises, but with sufficient practical illustrations and applications, are presented in PRMIA (2005).

There also exist several publications on the applicability and usefulness of VaR modelsin various financial markets around the world. Engle (2001) uses Auto Regressive Conditional Heteroskedasticity (ARCH) and GeneralizedAuto Regressive Conditional Heteroskedasticity (GARCH) models to estimate VaR, with a great degree of success, in the US stock markets (using the NASDAQ and DJIA indices) and the US Treasury bond markets.Using intra-day returns of the International Business Machines (IBM) US listed stock, Lunde*et al.* (2005) demonstrated that the GARCH(1,1) VaR model is rarely outperformed.

Turning to the emerging stock markets, Lima et al. (2006) have found that VaR methods which utilize the quantile regression with ARCH effects have performed well in the Sao Paulo (Brazil) stock exchange during periods of market turmoil. Varma (1999) concludes that “GARCH with generalized error distribution kernels performs exceedingly well at all common risk levels (from 0.25% to 10%)" in the Indian stock market. In addition, the Exponentially Weighted Moving Average (EWMA) model has also performed well at the 10% and 5% risk levels within the context of the aforementioned market.

In the emerging Arab stock markets of Egypt, Jordan and Morocco; Guermat*et al.* (2003) established that using VaR models based on extreme value theory and volatility updating produced more accurate forecasts of volatility.Andjelic*et al.* (2010) uses the stock indices of the Slovenian, Croatian, Serbian and Hungarian markets to demonstrate the delta normal and historical simulation VaR models are successful at the 95% and 99% confidence levels, respectively, in those markets. The results of this paper indicate that "methods shown to afford accurate VaR estimates in developed markets do not necessarily have application on the emerging markets".

With respect to the equity markets in the Caribbean, several studies suggest that they are inefficient and under-developed when compared to other prominent emerging markets around the world. Watson (2009) uses Wright's rank and sign statistics to conclude that the BSE, JSE and TTSE, in all their aspects, are all inefficient according to the Fama Efficient Market Hypothesis.Craigwell *et al.* (1999) and Craigwell *et al.* (2007) use the unit root test with co-integration procedures and the Phillips-Perron unit root tests, respectively, to conclude that the BSE is inefficient.Koot*et al.*(1989) conclude that the JSE is inefficient using non-parametric runs test. Sergeant (1995) and Bourne (1998)use simple Ordinary Least Squares and standard significance tests to show that the TTSE is inefficient. Robinson (2001) demonstrates that the BSE, JSE and TTSE market capitalization is not large even by emerging market standards. Robinson (2001) largely attributes the non-rejection of the efficiency hypothesis for the BSE to the "thinness" of that market and it was strongly suggested that the conclusion of market efficiency in the BSE may be inaccurate.

The brief literature review reveals that there is a significant amount of published work on VaR models. In addition, there are several papers on the Caribbean equity markets. However, it was difficult to find published research, in the public domain, on the topic of VaR in the context of the Caribbean equity markets. This shortage was one of the primary motivating factors for undertaking this study.

3. Data and Methodology

This study uses the daily price and returns data of the stock indices of the four major stock exchanges in the Caribbean region: the BSE, the ECSE, the JSE and the TTSE. The specific indices used to test the efficacy or effectiveness of the selected VaRmodels are the Local Index on the BSE, the EC-Share Index on the ECSE, the Market Index on the JSEIndexand the Composite Indexon the TTSE. The datasets were collected from the respective websites of the various stock exchanges in the case of the BSE[3], JSE[4] and TTSE[5]. ECSE dataset was obtained from the Caribbean Centre for Money and Finance website[6] and Bloomberg.

The stock indices' daily price and return data for the period January 2005 to July 2008 (the sample period) are used to construct the VaR models. The period August 2008 to July 2009 (the test period) was selected as the "out-of-sample" period to test the efficacy of the models constructed. This period, considered by many as the height of the recent global financial crisis, saw the collapse of Lehman Brothers, Government bail out of AIG and Glitniras well as the seizure of Washington Mutual by the Federal Deposit Insurance Corporation. This was a time of increased volatility in equity markets throughout the world. During the week of October 6th to October 10th 2011, the Dow Jones Industrial Average lost 22.1 percent, its worst week in 75 years, while the S&P 500 dropped 18.2 percent, its worst week since 1933.This period was selected to test how well the VaR model performs in times of market turmoil.During the sample and test periods, the assumption of a five (5) business day week was used. On public holidays and in instances of a three (3) day trade week (such as on the TTSE), it was assumed that the price remained the same as the previous day's closing price.

[3] http://www.bse.com.bb
[4] http://www.jamstockex.com
[5] http://stockex.co.tt
[6] http://www.ccmf-uwi.org/files/data/tables/Stock_Exchange_Index.xls

Table 4.1
Summary Descriptive Statistics for Caribbean Stock Indices
Based on Daily Returns Data for the period Jan. 2005 to July 2008

	BSE	ECSE	JSE	TTSE
Mean	0.000146	0.000688	6.82E-05	9.29E-05
Median	0.000000	0.000000	0.000000	0.000000
Maximum	0.030671	0.202823	0.101255	0.017005
Minimum	-0.085346	-0.092893	-0.063889	-0.017081
Std. Dev.	0.004037	0.012363	0.008622	0.003246
Skewness	-9.765543	5.720587	1.368244	0.454588
Kurtosis	229.6778	104.0896	30.45063	9.275622
Jarque-Bera	2010180.	401925.5	29553.16	1561.490
Probability	0.000000	0.000000	0.000000	0.000000
Sum	0.136050	0.640938	0.063598	0.086614
Sum Sq. Dev.	0.015170	0.142306	0.069205	0.009811
Observations	932	932	932	932

Table 4.2
Summary Descriptive Statistics for Caribbean Stock Indices
Based on Daily Returns Data for the period Aug. 2008 to July 2009

	BSE	ECSE	JSE	TTSE
Mean	-0.000863	-0.001192	-0.001237	-0.001528
Median	0.000000	0.000000	-0.000409	-0.000633
Maximum	0.015448	0.135933	0.032102	0.013584
Minimum	-0.054464	-0.402409	-0.044921	-0.034713
Std. Dev.	0.005448	0.026861	0.007524	0.003896
Skewness	-7.161237	-12.32609	-1.353491	-3.016279
Kurtosis	67.24148	194.8556	13.34436	24.75556
Jarque-Bera	47111.60	406902.2	1243.378	5542.947
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-0.225368	-0.311098	-0.322968	-0.398730
Sum Sq. Dev.	0.007717	0.187587	0.014720	0.003947
Observations	261	261	261	261

Table 4.1 and Table 4.2 present some simple summary descriptive statistics for the sample period and test period, respectively. Both tables illustrate that the hypothesis of normally distributed daily returns on all exchanges, in the sample and test periods, is resoundingly rejected using the Jarque-Bera test. From Table 4.1, it can be seen that for the sample period, the average daily returns for all selected indices are positive. In the same period, the daily returns on all indices, except on the BSE, are positively skewed. Table 4.2 shows an almost complete reversal of these trends during the test period (August 2008 to July 2009): the average daily returns on all the

indices are negative. In addition, the daily returns on all the indices are negatively skewed. Table 4.2 also shows that all the indices, with the exception of the JSE, experienced significant increases in volatility as measured by the standard deviation of the daily returns. This can also be seen in Charts4.1 to 4.4. These indicators suggest a downturn in the Caribbean equity markets during the test period in which returns were negative and there were significant increases in the volatility of returns.

Chart 4.1

BLI Daily Returns - Jan 2005 to July 2009

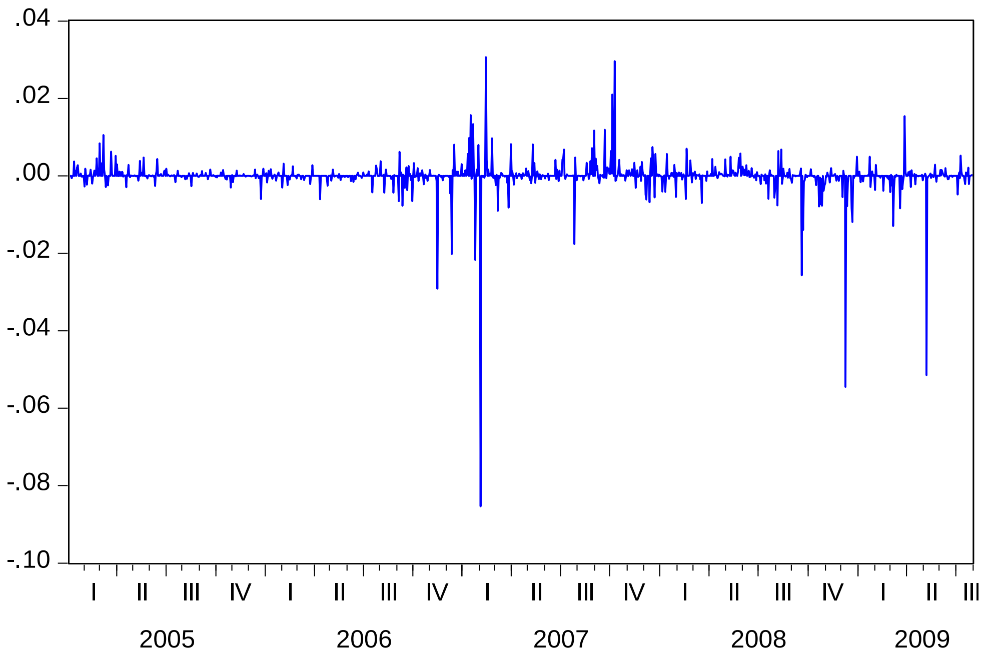


Chart 4.2

ECSECI Daily Returns - Jan 2005 to July 2009

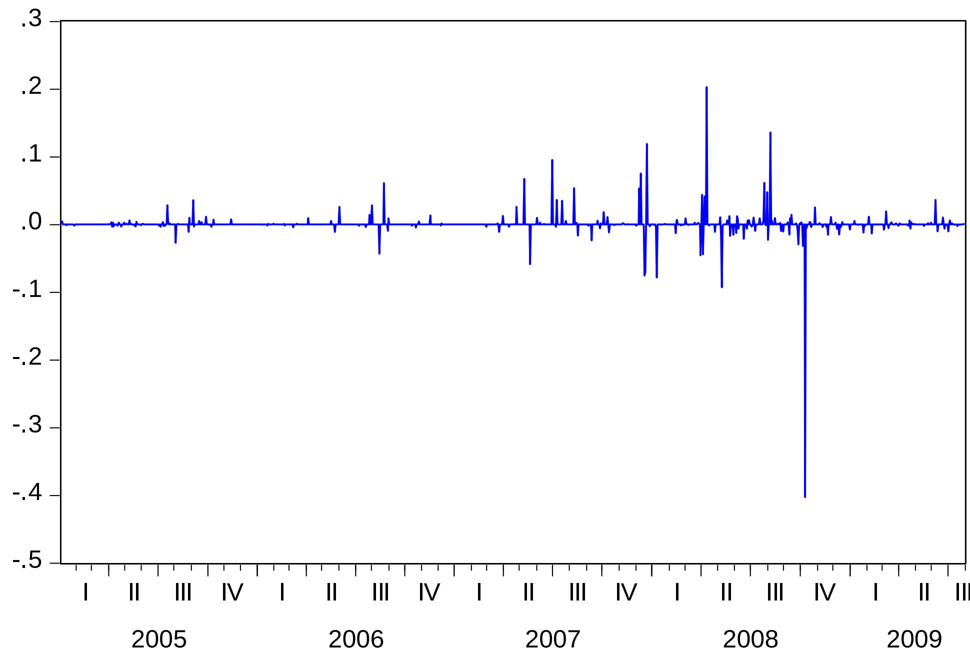


Chart 4.3

JMI Daily Returns - Jan 2005 to July 2009

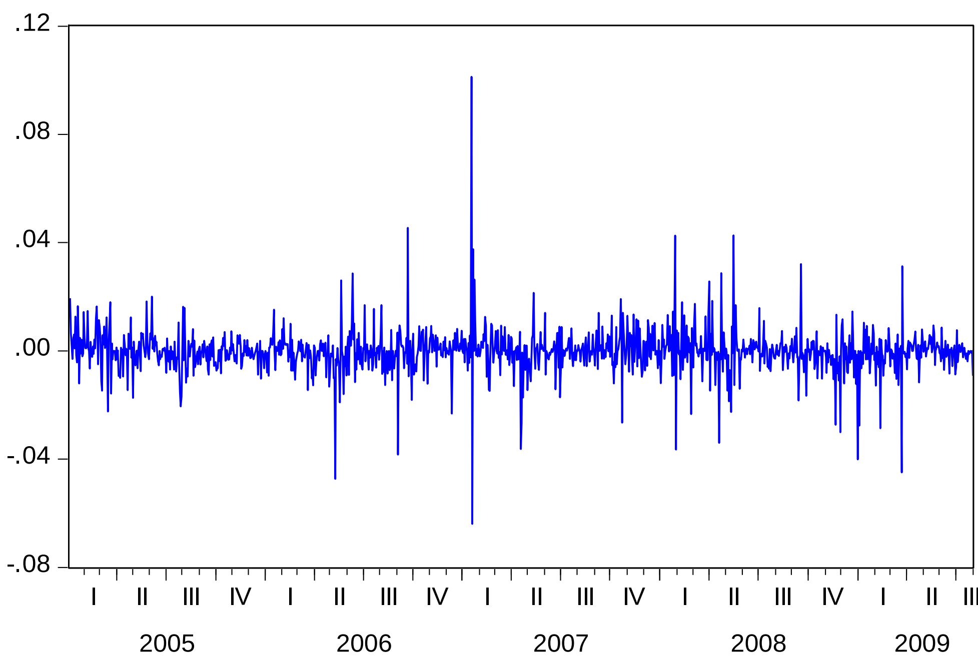
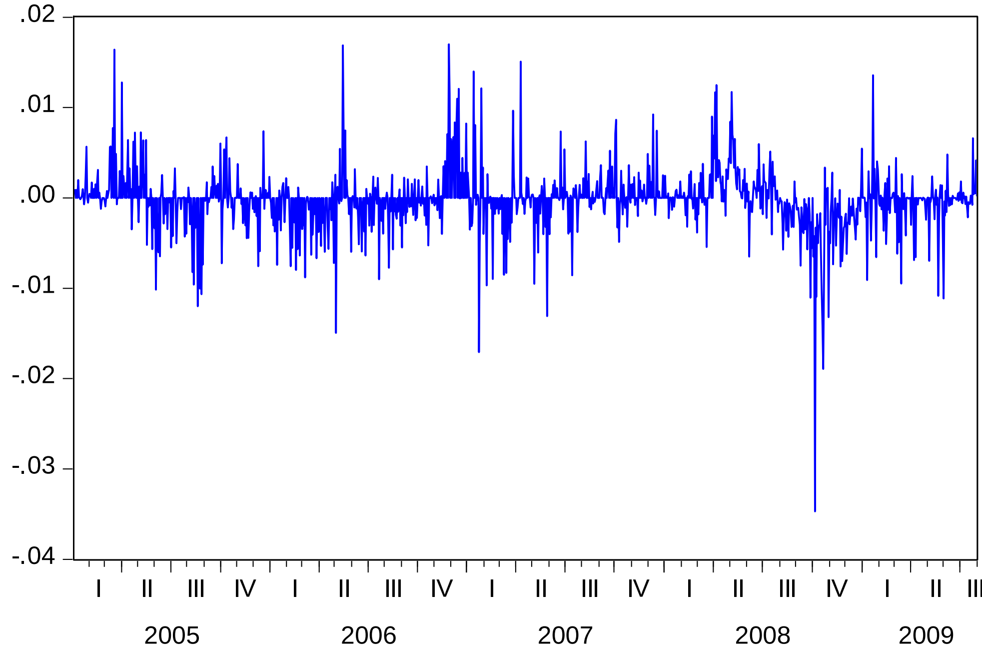


Chart 4.4

TTCI Daily Returns - Jan 2005 to July 2009



Using the data in the sample period and the test period, simple VaR models, under the assumption of constant and unconditional volatility, are constructed using the historical and the parametric methodologies. The 95% and 99% confidence limits are used in this paper. The efficacy of these models was tested within the sample and the test periods. VaR models, using the assumption of conditional or "time-varying" volatility, were also constructed and tested for the test and sample periods. The models were compared against one another and the most effective VaR model for each stock market was identified and recommended.

The efficacy of the VaR models constructed is evaluated through"backtesting", using a number of different criteria. Firstly, the actual exception rate (also called failure rate) is tested to ensure that it is less than or equal to the expected exception rate using a fully non-parametric approach called Bernoulli trials – see Jorion (2007). The null hypothesis of this test, which is the model is correctly calibrated, is tested using a binomial probability distribution or the normal approximation to the binomial distribution. Secondly, in order to verify the results of the first test, a powerful test[7]recommended by Kupiec (1995) was utilized. This test uses the tail points of the log-likelihood ratio to develop acceptance regions for the null hypothesis that actual exception rate is equal to the expected exception rate. Thirdly, the models' ability to make

[7] A powerful test minimizes the probability of type 1 and type 2 errors.

accurate forecasts of the realized volatilityis tested using the approach advocated by Engle *et al.* (2000) and used by Lunde*et al.* (2005). This test usesR^2in the following regression, in which $r^2$is the squared returns and $h^2$is the forecasted volatility from the constructed VaR model:

$$\log(r^2_t) = a + b\log(h^2_t) + u_t \qquad (3)$$

The higher the R^2,the more effective the model is at forecasting actual volatility. The fourth test used is the Root Mean Square Error (RMSE) criterion.The lower the RMSE, the more effective is the VaR model. The first and the fourth criteria were used to the test the VaR models in the sample period, whilst all four criteria were used to test the VaR models in the test period. The sufficiently effective VaR models in the test period, which have passed the first two test criteria, were ranked using a simple efficacy ratio. This ratio, which is calculated as the R^2 divided by the RMSE, quantifies the volatility predictive power per $ of RMSE. The most effective VaR models, therefore, have an actual exception rate that is less than or equal to the expected exception rate and demonstrates the ability to maximize the accuracy of its forecasts of realized volatility (R^2) whilst simultaneously minimize the error of its forecasts (RMSE)

The paper tests the efficacy of VaR models in the less efficient equity markets of the Caribbean. It primarily focuses on whether or not the presence of time varying volatility affects the effectiveness of some of the commonly used VaR models in the Caribbean equity markets.

4. Results

5(a) Barbados Stock Exchange

(i) HistoricalVaR Models with Constant Volatility Assumption

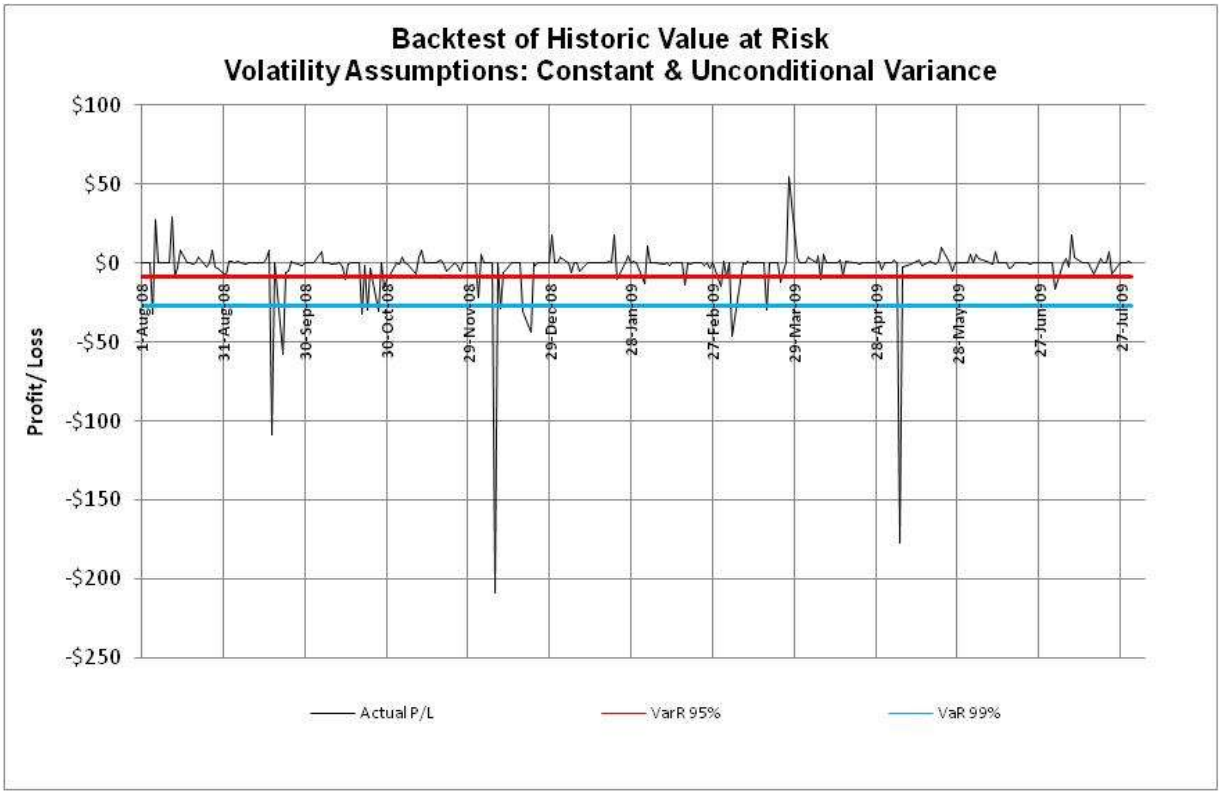
Table 5.1shows that the Historical VaR was sufficiently effective in the sample period of January 2005 to July 2008 both at the 95% and 99% confidence levels. However, these models were not sufficiently effective in the test period. The actual exception rate was double the expected exception rate in the case of the 95% HS VaR and almost five times the expected exception rate for the 99% HS VaR. The null hypothesis that actual exception rate is equal to the expected exception rate is rejected for the 95% and 99% HS VaR models using the non-parametric Bernoulli trials. This result is also confirmed using the Kupiec(1995) log-likelihood parametric test. Chart 5.1 shows that the number and magnitude of actual exceptions were greater those forecasted by the models. These results are largely attributable to the fact that the frequency and quantum of losses in the test period was greater than the sample period (Chart 4.1).

Table 5.1

Summary of Back Testing Results for the Historical VaR on the BSE
Constant Volatility and Unconditional Variance

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Static Unconditional	99% Static Unconditional
<u>IN SAMPLE VaR BACKTESTING</u>		
No. of observation	932	932
Expected Exception Rate	5.00%	1.00%
Actual Exception Rate	5.04%	1.07%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	0.0601	0.2239
Conclusion	Unbiased VaR	Unbiased VaR
(2) Root Mean Square Error	17.40	31.37
<u>OUT OF SAMPLE VaR BACKTESTING</u>		
No. of observation	261	261
Expected breach/failure rate	5.00%	1.00%
Actual breach/failure rate	10.34%	4.98%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	3.9619	6.4636
Conclusion	Biased VaR	Biased VaR
(2) Parametric testing: Kupiec(1995) LLR		
Confidence Level for Test	95%	99%
Null: actual exception rate = expected ex. rate		
Alt: actual exception rate ≠ expected ex rate		
Applicable Critical Value	3.8415	6.6349
Test Statistic (LRuc)	12.1606	21.3891
Conclusion	Biased VaR	Biased VaR
(3) R^2 from OLSR lg(return^2) vslg(VaR^2)	0.0000	0.0000
(4) Root Mean Square Error (RMSE)	20.87	31.19
Efficacy Ratio: (R^2 / RMSE)	0.00000	0.00000

Chart 5.1 – BSE



5(a)(ii) Parametric VaR Models with Constant Volatility Assumption - BSE

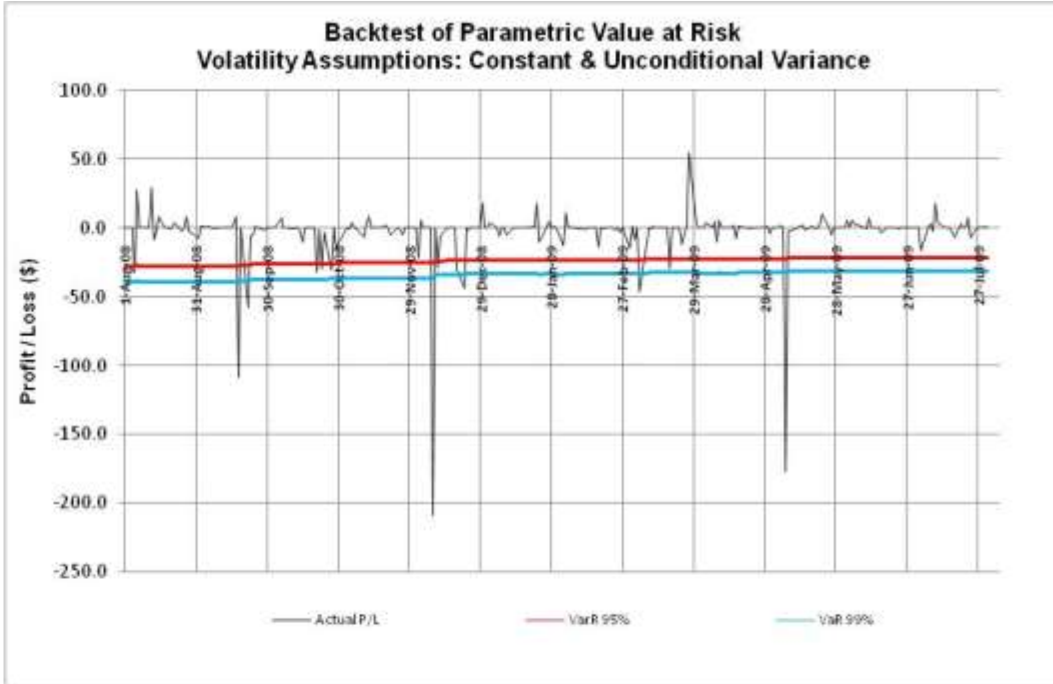
Table 5.2 shows that the P VaRwas sufficiently effective in the sample period at the 99% confidence level. However, the P VaR model was not sufficiently effective at the 95% level. It is interesting to note that if the 99% P VaR was tested using the non-parametric Bernoulli trial at the 95% confidence level, instead of 99% confidence level, the null hypothesis that the actual exception rate is less than or equal to the expected exception rate would have been rejected. This would have led to conclusion that, for the sample period, the 99% P VaR model was biased.

Conversely, both the 95% and 99% P VaR were sufficiently effective in the test period. This was confirmed by both the Bernoulli trials and Kupiec (1995) tests. The actual exception rate was not statistically different from the expected exception rate. A visual presentation of this is given in Chart 5.2. The predictive power of the models to forecast actual volatility is 1.11% for both the 95% and 99% P VaR models. The parametric VaR model is based on the underlying assumption that the returns follow a normal distribution. In the case of BSE, its daily returns in the test period were more normally distributed than the daily returns in the sample period. This is evidenced by the significantly smaller Jarque-Bera test statistic in the test period (47,111.6) compared to the corresponding statistic in the sample period (2,010,180.2). The summary descriptive statistics from Tables 4.1 and 4.2 also support this conclusion. The BSE is more negatively skewed and has more positive excess kurtosis (compared to the normal distribution) in the sample period than in the test period.

Table 5.2
Summary of Back Testing Results for the Parametric VaR on the BSE
Volatility Assumption: Constant & Based on Unconditional Variance

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Static Unconditional	99% Static Unconditional
IN SAMPLE VaR BACKTESTING		
No. of observation	933	932
Expected Exception Rate	5.00%	1.00%
Actual Exception Rate	1.29%	0.54%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	-5.2049	-1.4222
Conclusion	Biased VaR	Unbiased VaR
(2) Root Mean Square Error (RMSE)	29.91	39.55
OUT OF SAMPLE VaR BACKTESTING		
No. of observation	261	261
Expected breach/failure rate	5.00%	1.00%
Actual breach/failure rate	4.98%	2.30%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	-0.0142	2.1089
Conclusion	Unbiased VaR	Unbiased VaR
(2) Parametric testing: Kupiec(1995) LLR		
Confidence Level for Test	95%	99%
Applicable Critical Value	3.8415	6.6349
Test Statistic (LRuc)	0.0002	3.2536
Conclusion	Unbiased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0111	0.0111
(4) Root Mean Square Error (RMSE)	29.10	37.17
Efficacy Ratio: (R^2 / RMSE)	0.00038	0.00030

Chart 5.2 – BSE



5(a)(iii) HS VaR Models with Non-Constant Volatility Assumption - BSE

The use of the 260-day rolling standard deviation metric produces unbiased HS VaR models at the 95% and 99% confidence levels in the sample period. However, the ability of the 99% HS VaR model using the 260-day rolling standard deviation to forecast the realized volatility is significantly reduced compared to the 99% HS VaR using the assumption of unconditional variance. The former has a significantly higher Root Mean Square Error (RMSE) of 44.96 compared to 31.37 of the latter. In the sample period, the two VaR models computed using the 22 day rolling standard deviation (22-day rolling standard deviation) measure of volatility seems to be biased as they have actual exception rates that are higher than expected and relatively high RMSEs.

In the test period, only the 95% HS VaR using the 260-day rolling standard deviation volatility measure appears to be sufficiently effective. All the other models (95% HS VaR using 22-day rolling standard deviation, 99% HS VaR using 260-day rolling standard deviation and the 99% HS VaR using 22-day rolling standard deviation) are not sufficiently effective given their high actual exception rates, high RMSEs and lower predictive power to forecast realized volatility. Charts 5.3 and 5.4 offers a possible explanation for the high RMSEs observed. After days with large losses on the BSE, the HS VaR is significantly higher until that particular data point drops out of the sample. If after the large loss, the next day yields a gain or a significantly smaller loss, the rolling standard deviation HS VaR overestimates the value at risk.

Chart 5.3 – BSE

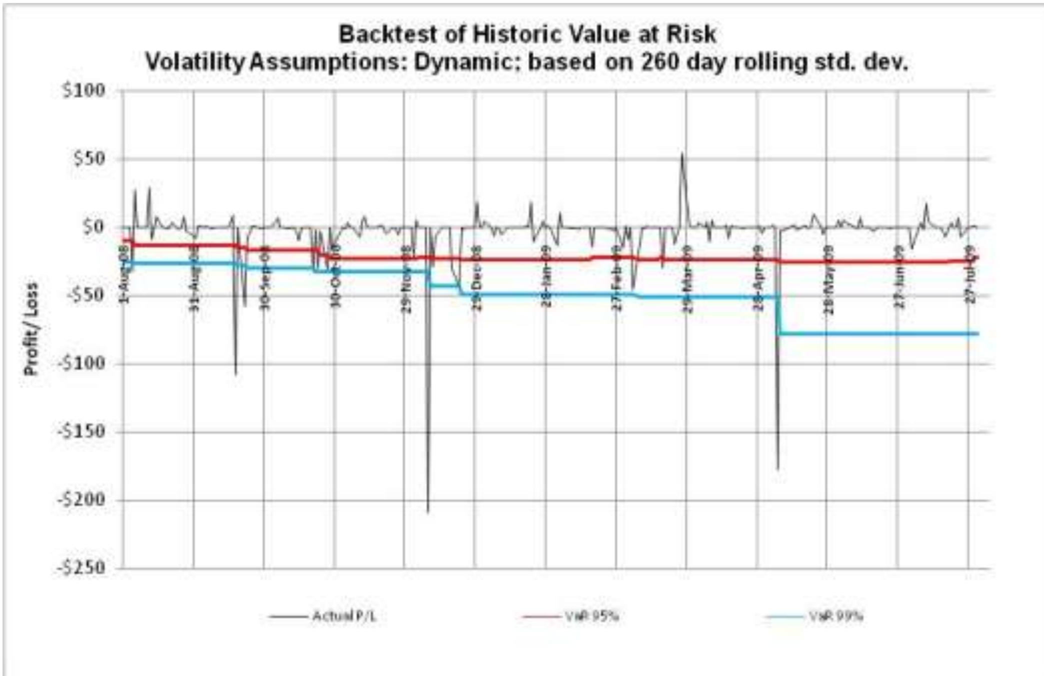


Chart 5.4 – BSE

Table 5.3
Summary of Back Testing Results for the Historical VaR on the BSE
Volatility Assumption: Non-constant

VaR Confidence Level	95%	95%	99%	99%
Volatility Assumption #1	Dynamic	Dynamic	Dynamic	Dynamic
Volatility Assumption #2	260 day rsd	22 day rsd	260 day rsd	22 day rsd
IN SAMPLE VaR BACKTESTING				
No. of observation	932	932	932	932
Expected Exception Rate	5.00%	5.00%	1.00%	1.00%
Actual Exception Rate	5.69%	8.80%	1.72%	5.15%
(1) Non-parametric Bernoulli Trials				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	1.9600	1.9600	2.5758	2.5758
Test Statistic	0.9619	5.3205	2.1991	12.7339
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(2) Root Mean Square Error	17.19	21.39	44.96	48.80
OUT OF SAMPLE VaR BACKTESTING				
No. of observation	261	261	261	261
Expected breach/failure rate	5.00%	5.00%	1.00%	1.00%
Actual breach/failure rate	4.98%	9.20%	2.68%	4.60%
(1) Non-parametric Bernoulli Trials				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	1.9600	1.9600	2.5758	2.5758
Test Statistic	-0.0142	3.1099	2.7310	5.8415
Conclusion	Unbiased VaR	Biased VaR	Biased VaR	Biased VaR
(2) Parametric testing: Kupiec(1995) LLR				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	3.8415	3.8415	6.6349	6.6349
Test Statistic (LRuc)	0.0002	7.8356	5.1069	18.1788
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(3) R^2 from OLSR lg(return ^{2}) vs lg(VaR ^{2})	0.0059	0.0007	0.0165	0.0001
(4) Root Mean Square Error (RMSE)	27.92	30.69	54.12	75.09
Efficacy Ratio: (R^2 / RMSE)	0.00021	0.00002	0.00030	0.00000

5(a)(iv) P VaR Models with Non-Constant Volatility Assumption - BSE

Table 5.4 shows that in the sample period, the 95% P VaR using 22-day rolling standard deviation, the 95% P VaR using GARCH(1,1) and the 99% P VaR using 260-day rolling standard deviation were sufficiently effective. In addition, P VaR using 22-day rolling standard deviation and the 95% P VaR using EWMA were not effective at the 95% and 99% confidence levels. The P VaR using GARCH(1,1) breaks down at the 99% confidence level.

In the test period, all the models with the exception of the P VaR using 260-day rolling standard deviation and 22-day rolling standard deviation at the 99% confidence level, were sufficiently effective. Whilst these models were effective, it was observed that they possessed relatively high RMSEs and relatively low R^2 values. Visual representations of backtesting in the test period are provided in Charts 5.5 to 5.8.

Table 5.4
Summary of Back Testing Results for the Parametric VaR on the BSE
Volatility Assumption: Non-constant

VaR Confidence Level	95%	95%	95%	95%	99%	99%	99%	99%
Volatility Assumption #1	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic
Volatility Assumption #2	260 day rsd	22 day rsd	EWMA	GARCH(1,1)	260 day rsd	22 day rsd	EWMA	GARCH(1,1)
IN SAMPLE VaR BACKTESTING								
No. of observation	932	932	932	932	932	932	932	932
Expected Exception Rate	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%
Actual Exception Rate	3.54%	4.94%	6.65%	6.22%	1.72%	3.54%	4.18%	4.18%
(1) Non-parametric Bernoulli Trials								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	1.9600	1.9600	1.9600	1.9600	2.5758	2.5758	2.5758	2.5758
Test Statistic	-2.0440	-0.0902	2.3145	1.7134	2.1991	7.7957	9.7710	9.7710
Conclusion	Biased VaR	Unbiased VaR	Biased VaR	Unbiased VaR	Unbiased VaR	Biased VaR	Biased VaR	Biased VaR
(2) Root Mean Square Error (RMSE)	29.57	29.57	28.93	29.04	38.87	38.61	35.16	35.16
OUT OF SAMPLE VaR BACKTESTING								
No. of observation	261	261	261	261	261	261	261	261
Expected breach/failure rate	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%
Actual breach/failure rate	5.36%	6.13%	4.60%	4.60%	3.83%	5.36%	1.92%	1.92%
(1) Non-parametric Bernoulli Trials								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	1.9600	1.9600	1.9600	1.9600	2.5758	2.5758	2.5758	2.5758
Test Statistic	0.2698	0.8378	-0.2982	-0.2982	4.5973	7.0858	1.4868	1.4868
Conclusion	Unbiased VaR	Unbiased VaR	Unbiased VaR	Unbiased VaR	Biased VaR	Biased VaR	Unbiased VaR	Unbiased VaR
(2) Parametric testing: Kupiec(1995) LLR								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	3.8415	3.8415	3.8415	3.8415	6.6349	6.6349	6.6349	6.6349
Test Statistic (LRuc)	0.0712	0.6569	0.0913	0.0913	12.2981	24.7614	1.7431	1.7431
Conclusion	Unbiased VaR	Unbiased VaR	Unbiased VaR	Unbiased VaR	Biased VaR	Biased VaR	Unbiased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0053	0.0005	0.0020	0.0025	0.0052	0.0008	0.0045	0.0045
(4) Root Mean Square Error (RMSE)	31.12	41.31	38.62	38.59	39.70	53.40	46.69	46.69
Efficacy Ratio: (R^2 / RMSE)	0.00017	0.00001	0.00005	0.00006	0.00013	0.00001	0.00010	0.00010

Chart 5.5 – BSE

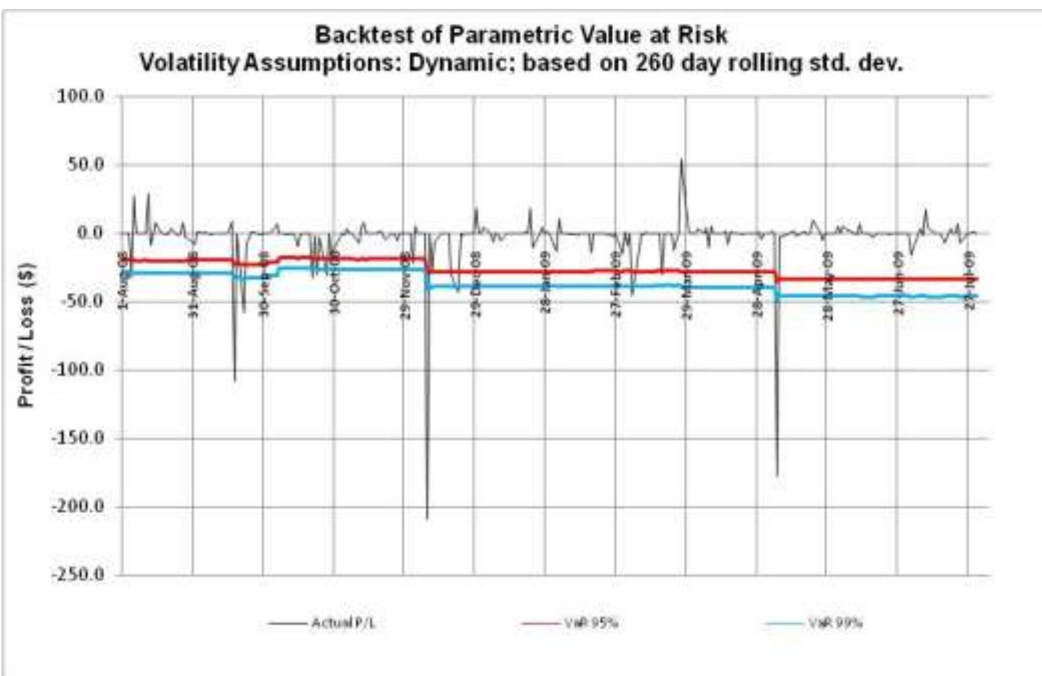


Chart 5.6 – BSE

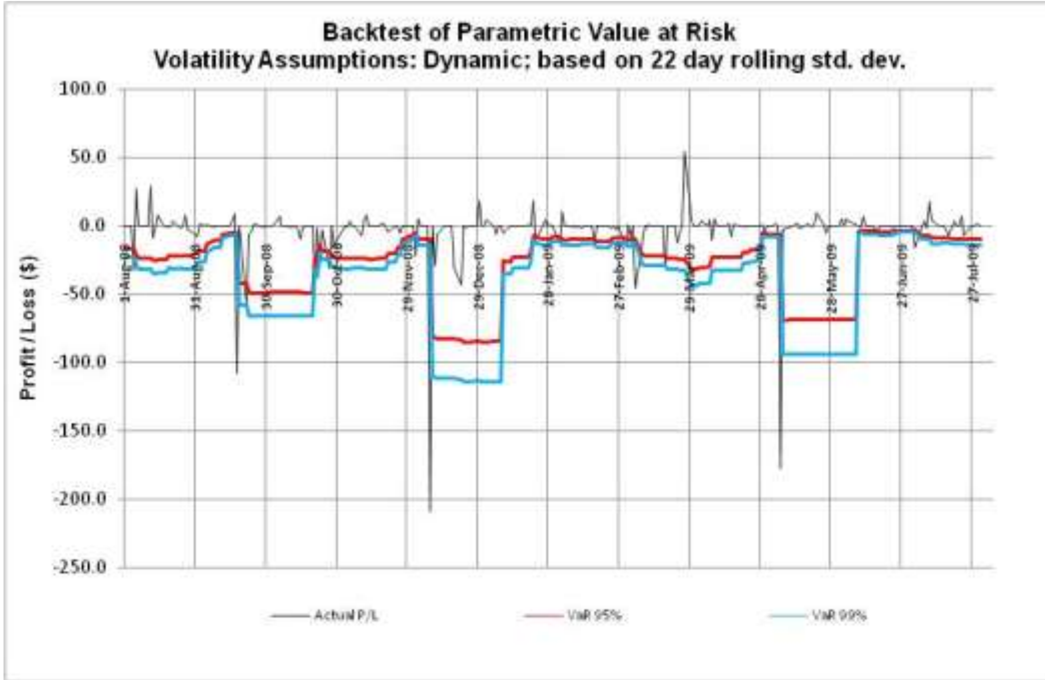

Backtest of Parametric Value at Risk
Volatility Assumptions: Dynamic; based on 22 day rolling std. dev.
100.0
50.0
0.0
-50.0
-100.0
-150.0
-200.0
-250.0
Profit / Loss ($)
1-Aug-08
31-Aug-08
30-Sep-08
30-Oct-08
29-Nov-08
29-Dec-08
28-Jan-09
27-Feb-09
29-Mar-09
28-Apr-09
28-May-09
27-Jun-09
27-Jul-09
Actual P/L
VaR 95%
VaR 99%

Chart 5.7 – BSE

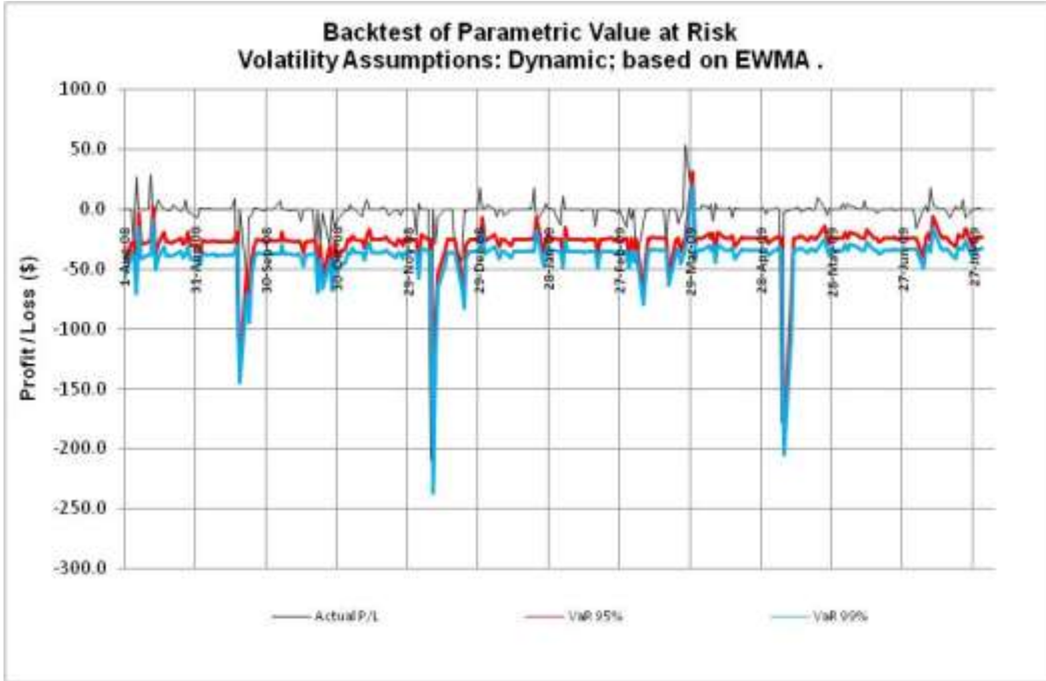
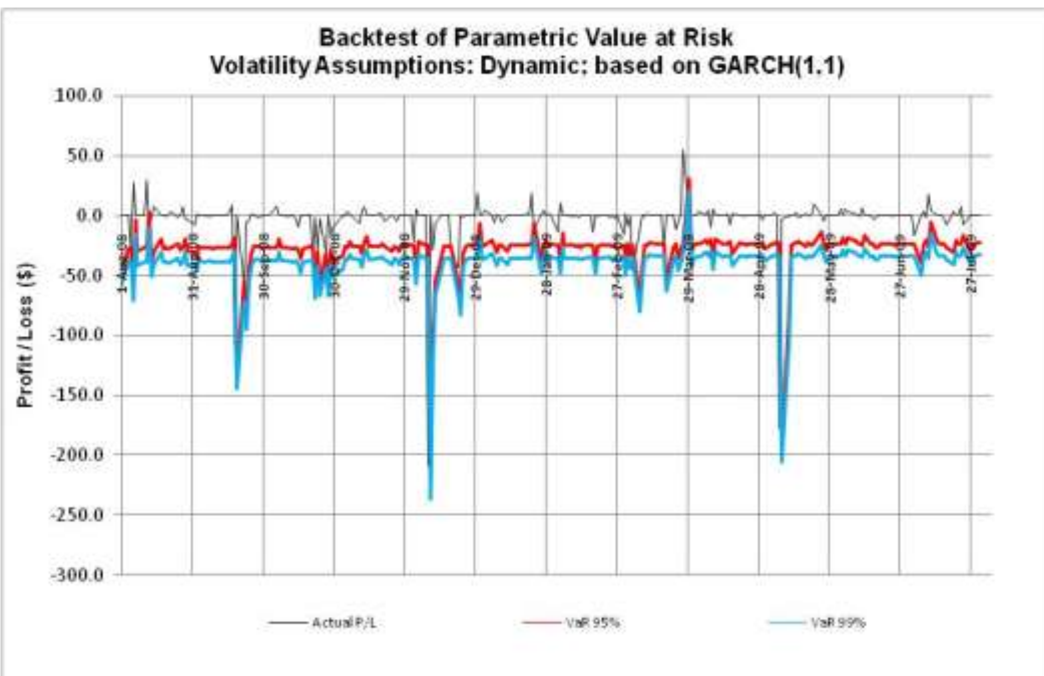


Chart 5.8 – BSE



(5)(b) Eastern Caribbean Stock Exchange ECSE

(i) HS VaR Models with Constant Volatility Assumption - ECSE

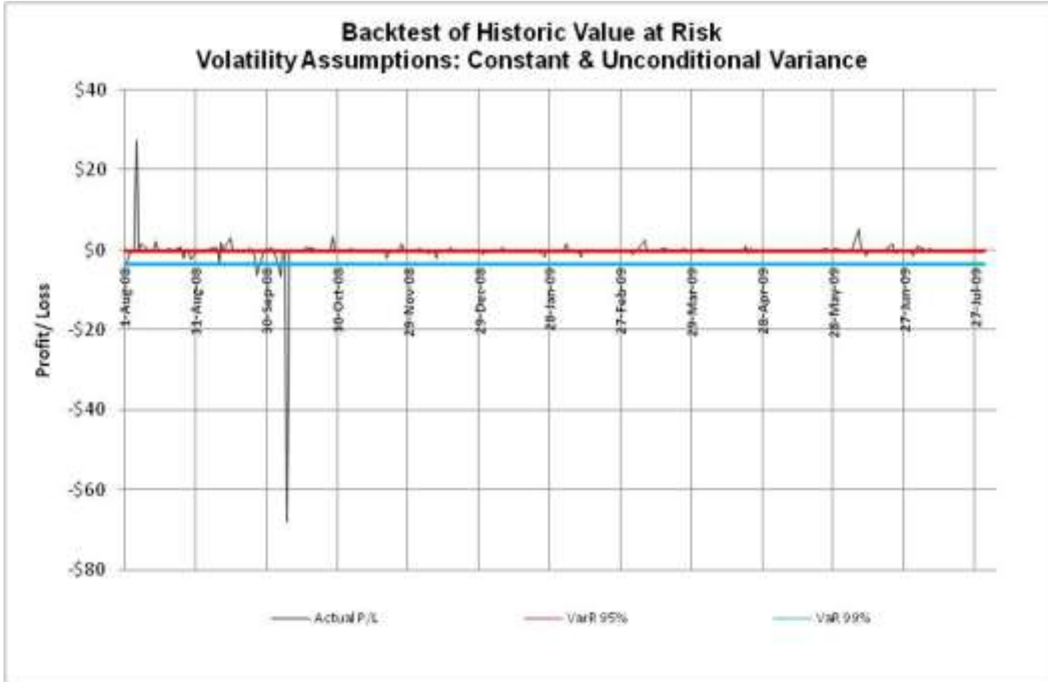
Table 5.5 shows that the HS VaR was sufficiently effective in the sample period both at the 95% and 99% confidence levels. However, only the 99% HS VaR was sufficiently effective in the test period. Similar to the backtesting of the parametric VaR for the BSE, it is observed that if the 99% HSVaR was tested using the non-parametric Bernoulli trial at the 95% confidence level, instead of 99% confidence level, the null hypothesis that the actual exception rate is less than or equal to the expected exception rate would have been rejected. This would have led to conclusion that, for the test period, the 99% HS VaR model was biased.In the test period, the HS VaRmodels has low volatility predictive power but has very low RMSEs. Please refer to Chart 5.9 for the backtesting of these models in the test period.

Table 5.5

Summary of Back Testing Results for the Historical VaR on the ECSE
Volatility Assumptions: Constant & Based on Unconditional Variance

VaR Confidence Level	95%	99%
Volatility Assumption #1	Static	Static
Volatility Assumption #2	Unconditional	Unconditional
IN SAMPLE VaR BACKTESTING		
No. of observation	932	932
Expected Exception Rate	5.00%	1.00%
Actual Exception Rate	5.04%	1.07%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	0.0601	0.2239
Conclusion	Unbiased VaR	Unbiased VaR
(2) Root Mean Square Error	2.03	4.13
OUT OF SAMPLE VaR BACKTESTING		
No. of observation	261	261
Expected breach/failure rate	5.00%	1.00%
Actual breach/failure rate	10.73%	1.53%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	4.2459	0.8647
Conclusion	Biased VaR	Unbiased VaR
(2) Parametric testing: Kupiec(1995) LLR		
Confidence Level for Test	95%	99%
Null: actual exception rate = expected ex. rate		
Alt: actual exception rate ≠ expected ex rate		
Applicable Critical Value	3.8415	6.6349
Test Statistic (LRuc)	13.7714	0.6430
Conclusion	Biased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0000	0.0000
(4) Root Mean Square Error (RMSE)	4.62	5.69
Efficacy Ratio: (R^2 / RMSE)	0.00000	0.00000

Chart 5.9 – ECSE



5(b)(ii) P VaR Models with Constant Volatility Assumption - ECSE

Table 5.6 shows that the P VaR was sufficiently effective in the sample period only at the 99% confidence level. There was a similar trend in the test period where only the 99% P VaR was sufficiently effective in the test period. Please refer to Chart 5.10 for the backtesting done.

Chart 5.10 – ECSE

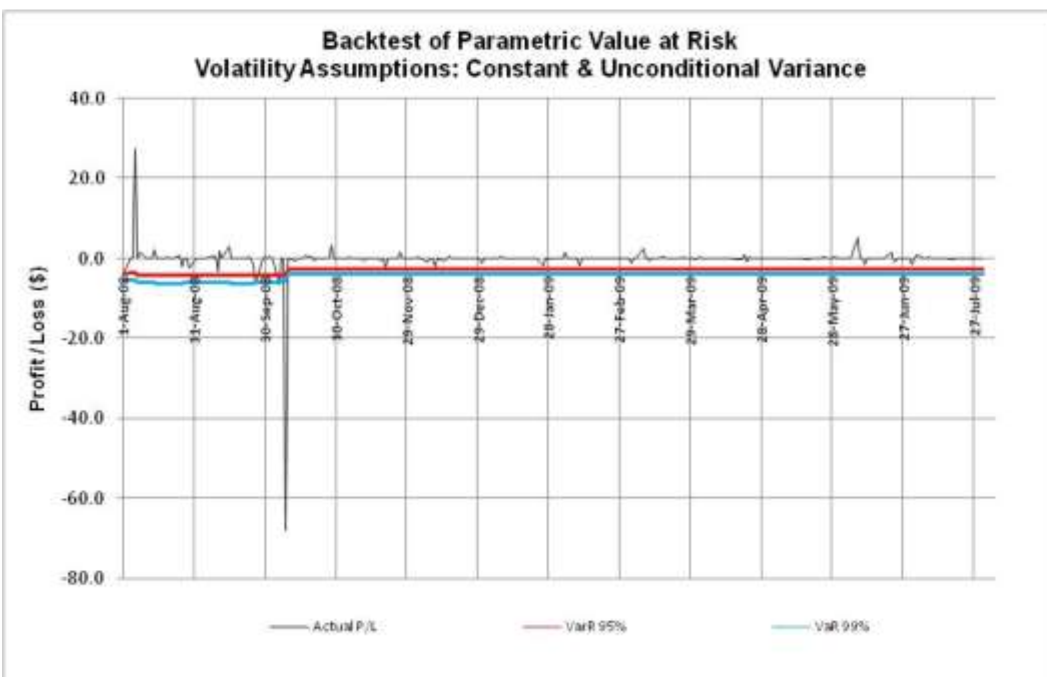


Table 5.6
Summary of Back Testing Results for the Parametric VaR on the ECSE
Volatility Assumption: Constant & Based on Unconditional Variance

VaR Confidence Level	95%	99%
Volatility Assumption #1	Static	Static
Volatility Assumption #2	Unconditional	Unconditional
IN SAMPLE VaR BACKTESTING		
No. of observation	933	932
Expected Exception Rate	5.00%	1.00%
Actual Exception Rate	1.18%	0.86%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	-5.3552	-0.4346
Conclusion	Biased VaR	Unbiased VaR
(2) Root Mean Square Error (RMSE)	3.31	4.24
OUT OF SAMPLE VaR BACKTESTING		
No. of observation	261	261
Expected breach/failure rate	5.00%	1.00%
Actual breach/failure rate	1.53%	1.15%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	-2.5703	0.2426
Conclusion	Biased VaR	Unbiased VaR
(2) Parametric testing: Kupiec(1995) LLR		
Confidence Level for Test	95%	99%
Applicable Critical Value	3.8415	6.6349
Test Statistic (LRuc)	8.9664	0.0562
Conclusion	Biased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0361	0.0361
(4) Root Mean Square Error (RMSE)	5.38	6.16
Efficacy Ratio: (R^2 / RMSE)	0.00671	0.00586

5(b)(iii) HS VaR Models with Non-Constant Volatility Assumption - ECSE

Table 5.7 shows that the HS VaR using 260-day rolling standard deviation produces sufficiently effective VaR models in the sample period, at the 95% and 99% confidence levels. In the sample period the 22-day rolling standard deviation is sufficiently effective only at the 95% confidence level.

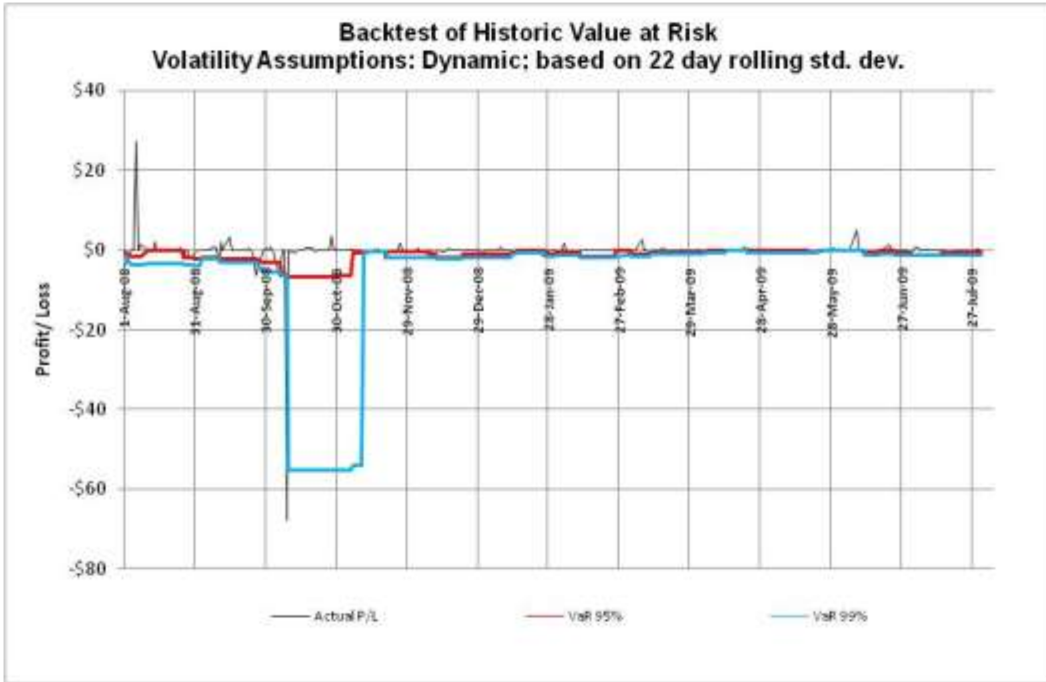
In the test period, only the HS VaR using the 260-day rolling standard deviation is effective both at the 95% and 99% confidence levels. The HS VaR using the 22-day rolling standard deviation breaks down in the test period both at the 95% and 99% confidence levels. Please refer to Charts 5.11 and 5.12.

Table 5.7
Summary of Back Testing Results for the Historical VaR on the ECSE
Volatility Assumption: Non-Constant

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Dynamic 260 day rsd	95% Dynamic 22 day rsd	99% Dynamic 260 day rsd	99% Dynamic 22 day rsd
IN SAMPLE VaR BACKTESTING				
No. of observation	932	932	932	932
Expected Exception Rate	5.00%	5.00%	1.00%	1.00%
Actual Exception Rate	5.58%	5.58%	1.72%	4.08%
(1) Non-parametric Bernoulli Trials				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	1.9600	1.9600	2.5758	2.5758
Test Statistic	0.8116	0.8116	2.1991	9.4418
Conclusion	Unbiased VaR	Unbiased VaR	Unbiased VaR	Biased VaR
(2) Root Mean Square Error	2.08	3.00	4.75	4.27
OUT OF SAMPLE VaR BACKTESTING				
No. of observation	261	261	261	261
Expected breach/failure rate	5.00%	5.00%	1.00%	1.00%
Actual breach/failure rate	2.68%	8.43%	0.38%	4.98%
(1) Non-parametric Bernoulli Trials				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	1.9600	1.9600	2.5758	2.5758
Test Statistic	-1.7183	2.5419	-1.0016	6.4636
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(2) Parametric testing: Kupiec(1995) LLR				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	3.8415	3.8415	6.6349	6.6349
Test Statistic (LRuc)	3.5261	5.4062	1.3113	21.3891
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0010	0.0072	0.0110	0.0125
(4) Root Mean Square Error (RMSE)	5.02	4.81	10.03	16.67
Efficacy Ratio: (R^2 / RMSE)	0.00020	0.00150	0.00110	0.00075

Chart 5.11 – ECSE

Chart 5.12 – ECSE



5(b)(iv) P VaR Models with Non-Constant Volatility Assumption - ECSE

Table 5.8 shows that the 99% P VaR using 260-day rolling standard deviation as well the 95% P VaR using EWMA and GARCH(1,1) produces unbiased VaR estimates in the sample period. The EWMA and GARCH(1,1) P VaR models break down at the 99% confidence level.

In the test period, the EWMA and GARCH(1,1) models are sufficiently effective at the 99% confidence level but not at the 95% level. The other P VaR models that are sufficiently effective are the 22-day rolling standard deviation at the 95% confidence level and the 260-day rolling standard deviation at the 99% confidence level.Whilst these models are effective, it can be observed that their RMSEs are higher than that of the HS VaR models using non-constant volatility assumptions. Notwithstanding it can also be seen that the P VaR models have better volatility forecasting power given their higher R^2 values compared to that of the HS VaR models. this Please refer to Charts 5.13 to 5.16.

Chart 5.13 – ECSE

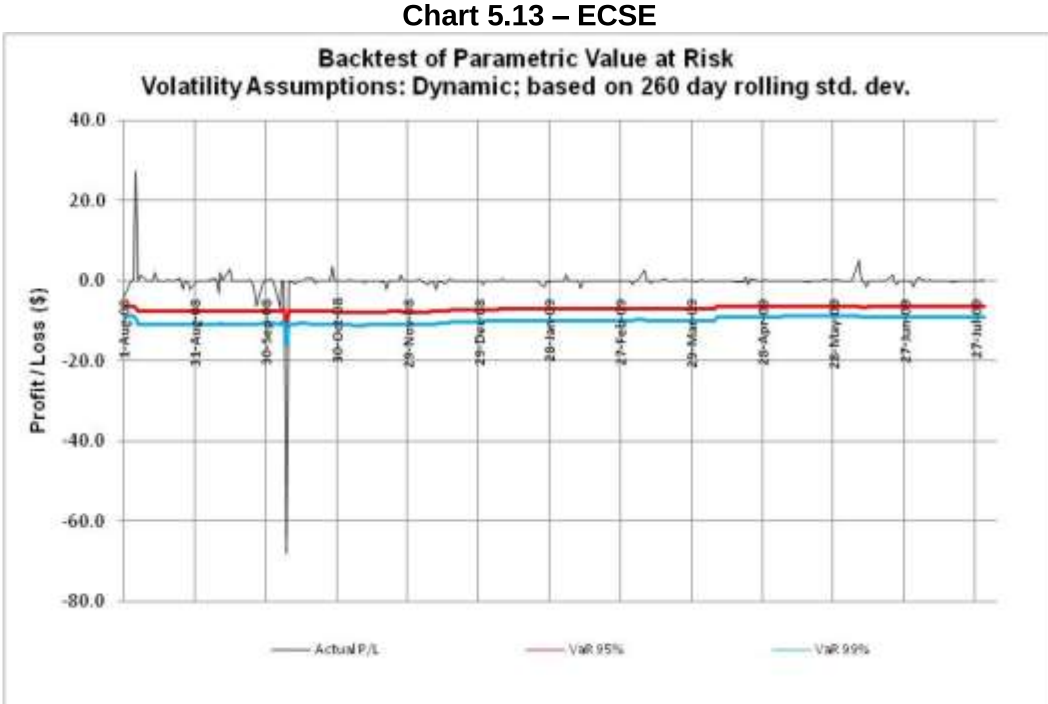


Table 5.8
Summary of Back Testing Results for the Parametric VaR on the ECSE
Volatility Assumption: Non-Constant

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Dynamic 260 day rsd	95% Dynamic 22 day rsd	95% Dynamic EWMA	95% Dynamic GARCH(1,1)	99% Dynamic 260 day rsd	99% Dynamic 22 day rsd	99% Dynamic EWMA	99% Dynamic GARCH(1,1)
IN SAMPLE VaR BACKTESTING								
No. of observation	932	932	932	932	932	932	932	932
Expected Exception Rate	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%
Actual Exception Rate	1.50%	3.54%	6.33%	6.12%	1.29%	2.90%	5.26%	5.26%
(1) Non-parametric Bernoulli Trials								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	1.9600	1.9600	1.9600	1.9600	2.5758	2.5758	2.5758	2.5758
Test Statistic	-4.8996	-2.0440	1.8637	1.5631	0.8823	5.8205	13.0631	13.0631
Conclusion	Biased VaR	Biased VaR	Unbiased VaR	Unbiased VaR	Unbiased VaR	Biased VaR	Biased VaR	Biased VaR
(2) Root Mean Square Error (RMSE)	3.17	3.73	3.34	3.36	4.02	4.96	3.77	3.77
OUT OF SAMPLE VaR BACKTESTING								
No. of observation	261	261	261	261	261	261	261	261
Expected breach/failure rate	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%
Actual breach/failure rate	0.38%	5.36%	2.30%	2.30%	0.38%	3.45%	1.53%	1.53%
(1) Non-parametric Bernoulli Trials								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	1.9600	1.9600	1.9600	1.9600	2.5758	2.5758	2.5758	2.5758
Test Statistic	-3.4223	0.2698	-2.0023	-2.0023	-1.0016	3.9752	0.8647	0.8647
Conclusion	Biased VaR	Unbiased VaR	Biased VaR	Biased VaR	Unbiased VaR	Biased VaR	Unbiased VaR	Unbiased VaR
(2) Parametric testing: Kupiec(1995) LLR								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	3.8415	3.8415	3.8415	3.8415	6.6349	6.6349	6.6349	6.6349
Test Statistic (LRuc)	19.5388	0.0712	4.9742	4.9742	1.3113	9.6611	0.6430	0.6430
Conclusion	Biased VaR	Unbiased VaR	Biased VaR	Biased VaR	Unbiased VaR	Biased VaR	Unbiased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0219	0.0154	0.0032	0.0032	0.0242	0.0156	0.0013	0.0013
(4) Root Mean Square Error (RMSE)	8.15	8.45	7.38	7.38	10.69	10.87	8.49	8.49
Efficacy Ratio: (R^2 / RMSE)	0.00269	0.00182	0.00043	0.00043	0.00226	0.00144	0.00015	0.00015

Chart 5.14 – ECSE

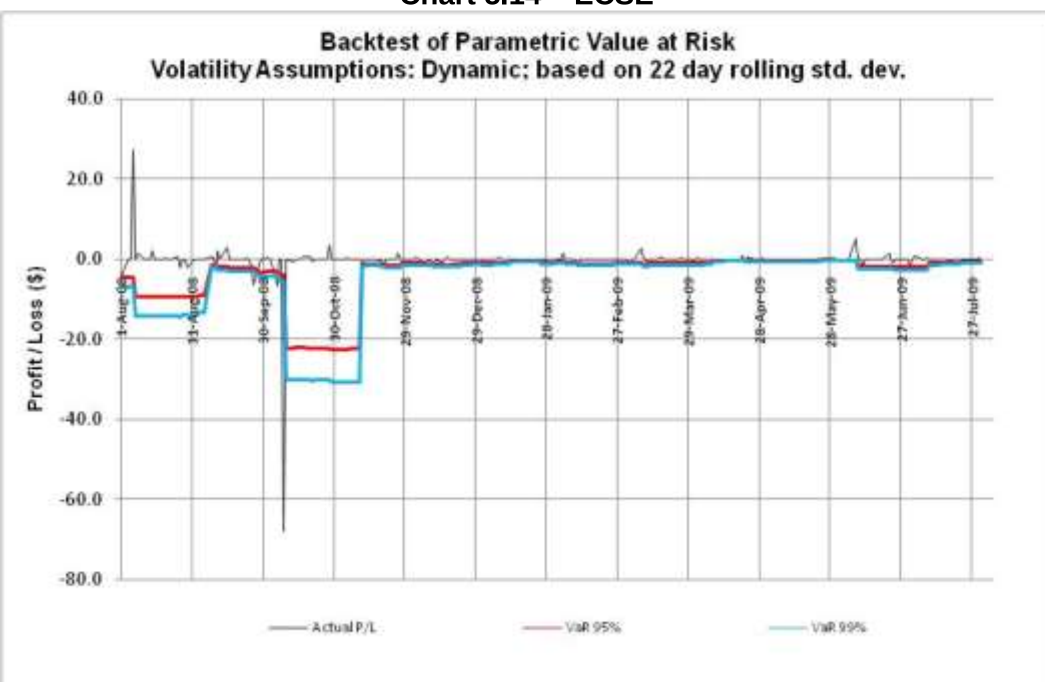


Chart 5.15 – ECSE

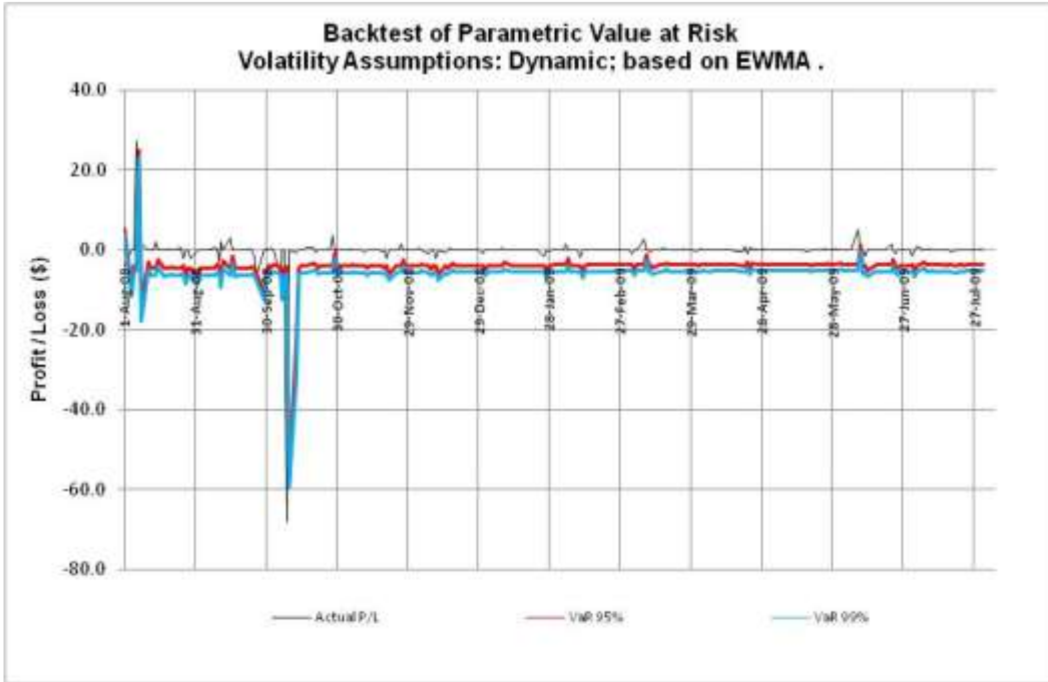
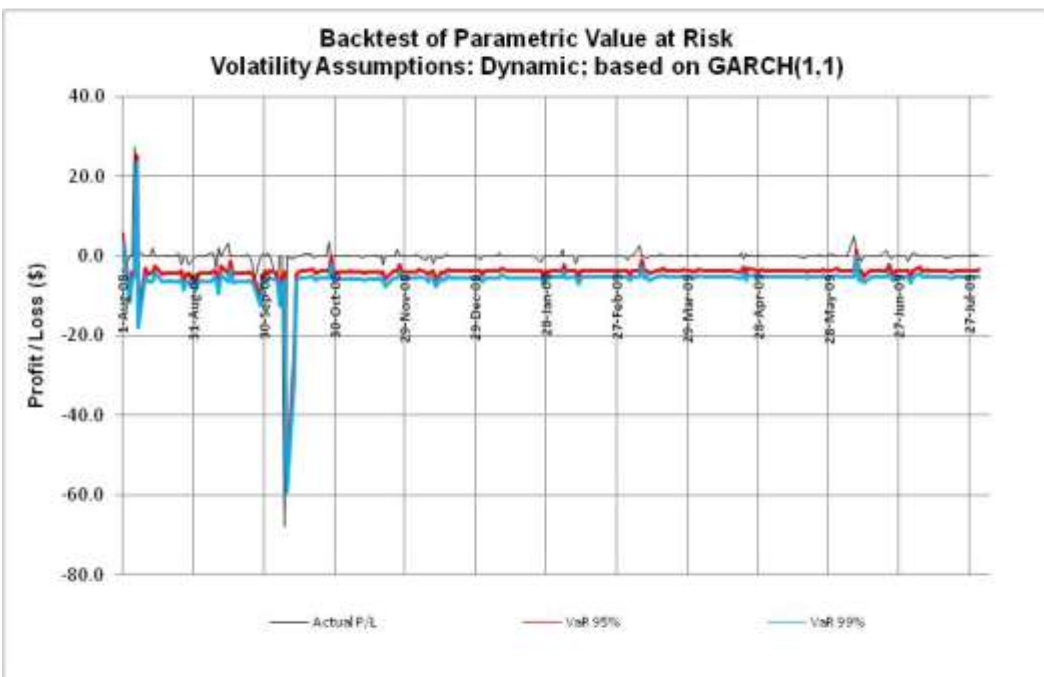


Chart 5.16 – ECSE



(5)(c) Trinidad & Tobago Stock Exchange TTSE

(i) HS VaR Models with Constant Volatility Assumption - TTSE

Table 5.9 shows that the HS VaR was sufficiently effective in the sample period both at the 95% and 99% confidence levels. However, none of the models presented in the table were effective in the test period. In the case of the 99% HS VaR in the test period, the non-parametric Bernoulli trial test and the Kupiec(1995) test giving conflicting results. The Bernoulli trial test indicates that the VaR model is biased whilst the Kupiec (1995) test indicates that the model is unbiased. The results of the Bernoulli trial test is considered more accurate in this instance as Table 5.9 illustrates the actual exception rate of the HS 99% VaR is more than twice the expected exception rate in the test period. This may also been seen in Chart 5.17.

Chart 5.17 – TTSE

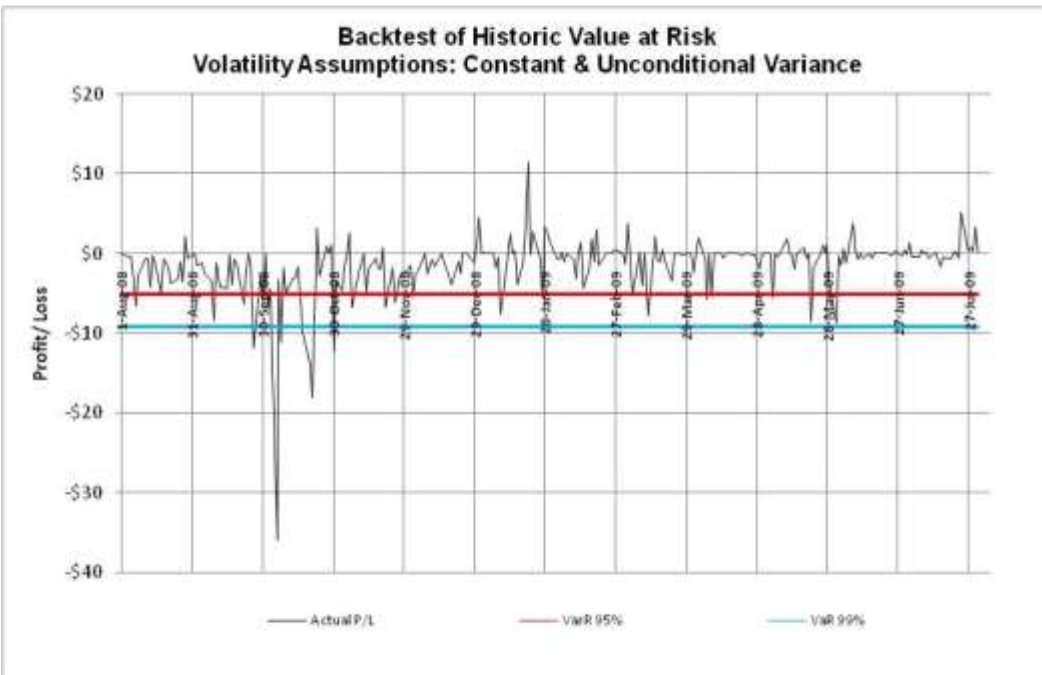


Table 5.9
Summary of Back Testing Results for the Historical VaR on the TTSE
Volatility Assumptions: Constant & Based on Unconditional Variance

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Static Unconditional	99% Static Unconditional
IN SAMPLE VaR BACKTESTING		
No. of observation	932	932
Expected Exception Rate	5.00%	1.00%
Actual Exception Rate	5.04%	1.07%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	0.0601	0.2239
Conclusion	Unbiased VaR	Unbiased VaR
(2) Root Mean Square Error	6.13	9.88
OUT OF SAMPLE VaR BACKTESTING		
No. of observation	261	261
Expected breach/failure rate	5.00%	1.00%
Actual breach/failure rate	10.34%	2.68%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	3.9619	2.7310
Conclusion	Biased VaR	Biased VaR
(2) Parametric testing: Kupiec(1995) LLR		
Confidence Level for Test	95%	99%
Null: actual exception rate = expected ex. rate		
Alt: actual exception rate ≠ expected ex rate		
Applicable Critical Value	3.8415	6.6349
Test Statistic (LRuc)	12.1606	5.1069
Conclusion	Biased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0000	0.0000
(4) Root Mean Square Error (RMSE)	5.16	8.58
Efficacy Ratio: (R^2 / RMSE)	0.00000	0.00000

5(c)(ii) P VaR Models with Constant Volatility Assumption - TTSE

Table 12 shows that the P VaR was sufficiently effective in the sample period only at the 95% confidence level. In the test period, none of the P VaR(with constant volatility assumptions) was effective neither at the 95% nor at the 99% confidence levels. Please refer to Chart 5.18.

Chart 5.18 – TTSE

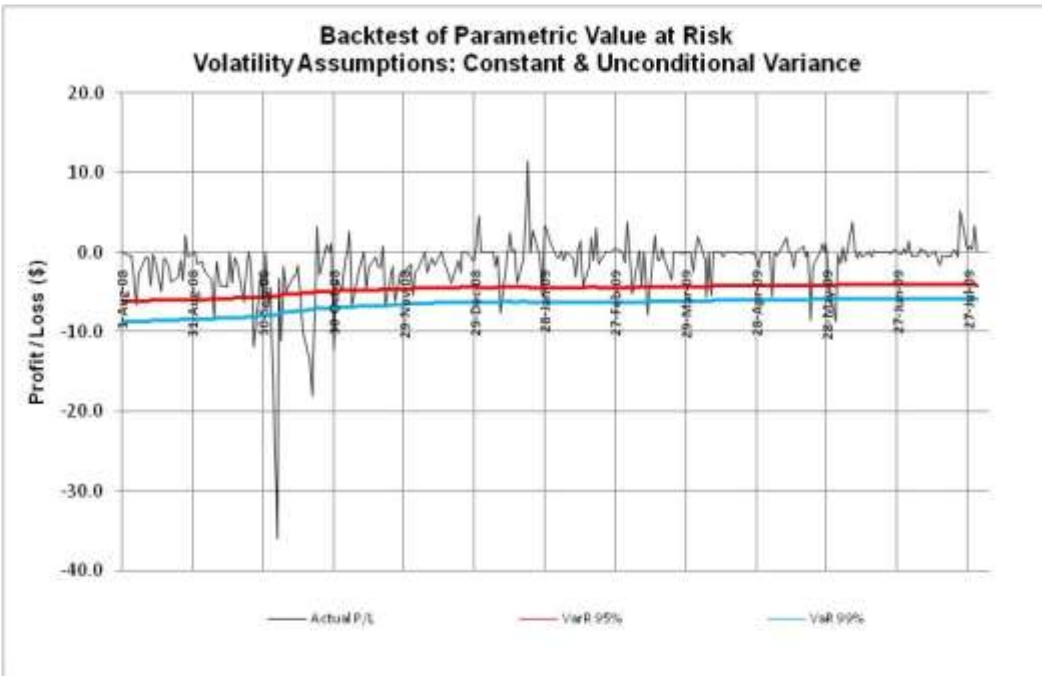


Table 5.10
Summary of Back Testing Results for the Parametric VaR on the TTSE
Volatility Assumptions: Constant & Based on Unconditional Variance

VaR Confidence Level	95%	99%
Volatility Assumption #1	Static	Static
Volatility Assumption #2	Unconditional	Unconditional
IN SAMPLE VaR BACKTESTING		
No. of observation	933	932
Expected Exception Rate	5.00%	1.00%
Actual Exception Rate	5.04%	2.25%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	0.0526	3.8452
Conclusion	Unbiased VaR	Biased VaR
(2) Root Mean Square Error (RMSE)	6.34	8.33
OUT OF SAMPLE VaR BACKTESTING		
No. of observation	261	261
Expected breach/failure rate	5.00%	1.00%
Actual breach/failure rate	11.11%	5.36%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	4.5300	7.0858
Conclusion	Biased VaR	Biased VaR
(2) Parametric testing: Kupiec(1995) LLR		
Confidence Level for Test	95%	99%
Applicable Critical Value	3.8415	6.6349
Test Statistic (LRuc)	15.4622	24.7614
Conclusion	Biased VaR	Biased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.1138	0.1138
(4) Root Mean Square Error (RMSE)	4.78	6.25
Efficacy Ratio: (R^2 / RMSE)	0.02380	0.01820

5(c)(iii) HS VaR Models with Non-Constant Volatility Assumption - TTSE

Table 5.11 shows that the HS VaR using 260-day rolling standard deviation produces sufficiently effective VaR models in the sample period, at the 95% and 99% confidence levels. In the sample period the 22-day rolling standard deviation is sufficiently effective only at the 95% confidence level.

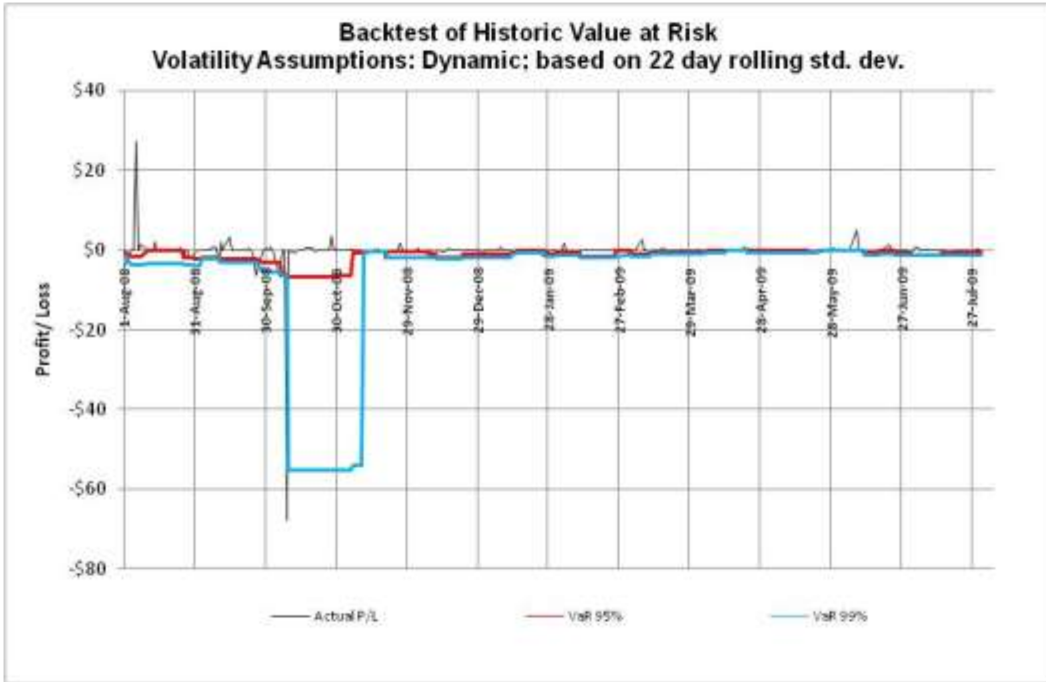
In the test period, only the HS VaR using the 260-day rolling standard deviation is effective both at the 95% and 99% confidence levels. The HS VaR using the 22-day rolling standard deviation breaks down in the test period both at the 95% and 99% confidence levels. Please see Charts 5.19 and 5.20.

Table 5.11
Summary of Back Testing Results for the Historical VaR on the TTSE
Volatility Assumption: Non-Constant

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Dynamic 260 day rsd	95% Dynamic 22 day rsd	99% Dynamic 260 day rsd	99% Dynamic 22 day rsd
IN SAMPLE VaR BACKTESTING				
No. of observation	932	932	932	932
Expected Exception Rate	5.00%	5.00%	1.00%	1.00%
Actual Exception Rate	5.58%	5.58%	1.72%	4.08%
(1) Non-parametric Bernoulli Trials				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	1.9600	1.9600	2.5758	2.5758
Test Statistic	0.8116	0.8116	2.1991	9.4418
Conclusion	Unbiased VaR	Unbiased VaR	Unbiased VaR	Biased VaR
(2) Root Mean Square Error	2.08	3.00	4.75	4.27
OUT OF SAMPLE VaR BACKTESTING				
No. of observation	261	261	261	261
Expected breach/failure rate	5.00%	5.00%	1.00%	1.00%
Actual breach/failure rate	2.68%	8.43%	0.38%	4.98%
(1) Non-parametric Bernoulli Trials				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	1.9600	1.9600	2.5758	2.5758
Test Statistic	-1.7183	2.5419	-1.0016	6.4636
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(2) Parametric testing: Kupiec(1995) LLR				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	3.8415	3.8415	6.6349	6.6349
Test Statistic (LRuc)	3.5261	5.4062	1.3113	21.3891
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0010	0.0072	0.0110	0.0125
(4) Root Mean Square Error (RMSE)	5.02	4.81	10.03	16.67
Efficacy Ratio: (R^2 / RMSE)	0.00020	0.00150	0.00110	0.00075

Chart 5.19 – TTSE

Chart 5.20 – TTSE



5(c)(iv) P VaR Models with Non-Constant Volatility Assumption - TTSE

Table 5.12 shows that the P VaR using the 260-day rolling standard deviationis effective both at the 95% and 99% confidence levels in the sample period. The only other model that is sufficiently effective in the sample period is the P VaR using the 22-day rolling standard deviation at the 95% confidence level. In the test period,the 95% P VaR using EWMA and GARCH(1,1) produces unbiased VaR estimates. The EWMA and the GARCH(1,1) P VaR models break down at the 99% confidence level. The P VaR based on the rsdare not effective in the test period neither at the 95% nor at the 99% confidence levels. Please refer to Charts 5.21 to 5.24 for a pictorial representation of the backtesting done in the test period.

Chart 5.21 – TTSE

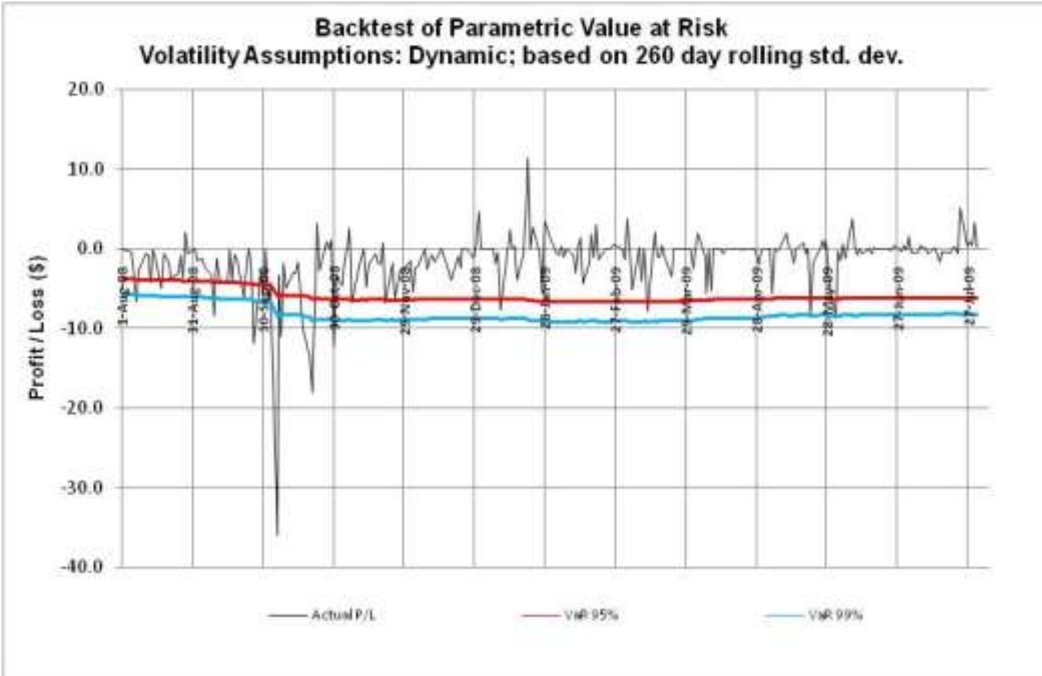


Chart 5.22 – TTSE

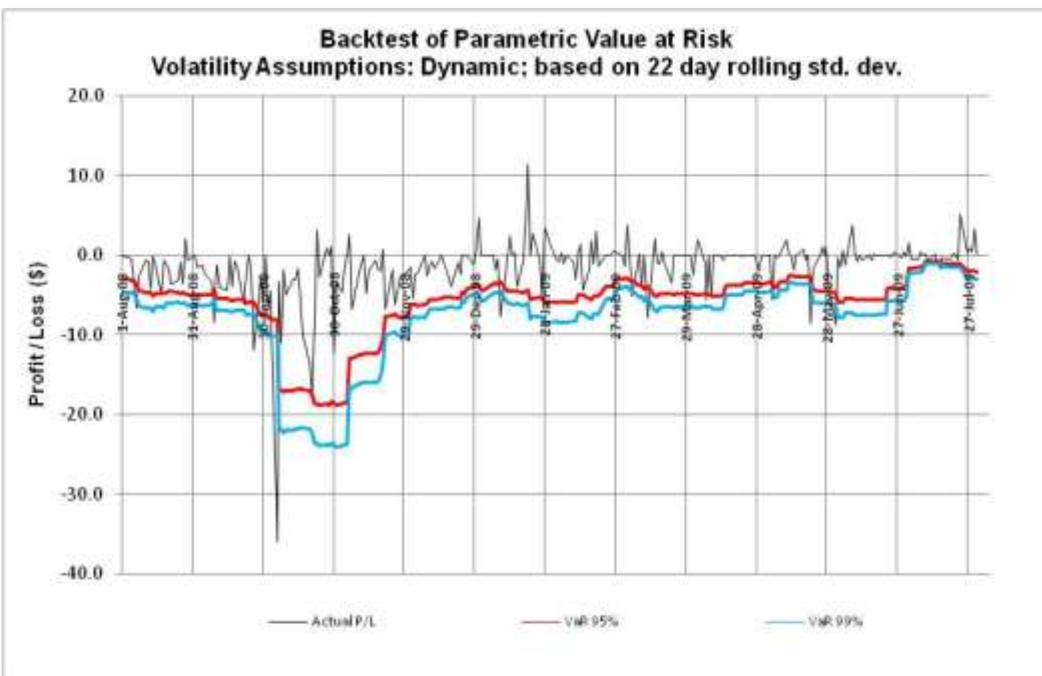


Table 5.12
Summary of Back Testing Results for the Parametric VaR on the TTSE
Volatility Assumption: Non-Constant

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Dynamic 260 day rsd	95% Dynamic 22 day rsd	95% Dynamic EWMA	95% Dynamic GARCH(1,1)	99% Dynamic 260 day rsd	99% Dynamic 22 day rsd	99% Dynamic EWMA	99% Dynamic GARCH(1,1)
<u>IN SAMPLE VaR BACKTESTING</u>								
No. of observation	932	932	932	932	932	932	932	932
Expected Exception Rate	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%
Actual Exception Rate	4.18%	6.12%	8.91%	8.91%	1.82%	3.11%	4.72%	4.72%
(1) Non-parametric Bernoulli Trials								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	1.9600	1.9600	1.9600	1.9600	2.5758	2.5758	2.5758	2.5758
Test Statistic	-1.1422	1.5631	5.4707	5.4707	2.5283	6.4789	11.4170	11.4170
Conclusion	Unbiased VaR	Unbiased VaR	Biased VaR	Biased VaR	Unbiased VaR	Biased VaR	Biased VaR	Biased VaR
(2) Root Mean Square Error (RMSE)	6.38	5.80	6.80	6.82	8.37	7.60	8.63	8.63
<u>OUT OF SAMPLE VaR BACKTESTING</u>								
No. of observation	261	261	261	261	261	261	261	261
Expected breach/failure rate	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%
Actual breach/failure rate	8.43%	7.66%	6.51%	6.51%	4.60%	4.21%	3.07%	3.07%
(1) Non-parametric Bernoulli Trials								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	1.9600	1.9600	1.9600	1.9600	2.5758	2.5758	2.5758	2.5758
Test Statistic	2.5419	1.9739	1.1218	1.1218	5.8415	5.2194	3.3531	3.3531
Conclusion	Biased VaR	Biased VaR	Unbiased VaR	Unbiased VaR	Biased VaR	Biased VaR	Biased VaR	Biased VaR
(2) Parametric testing: Kupiec(1995) LLR								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	3.8415	3.8415	3.8415	3.8415	6.6349	6.6349	6.6349	6.6349
Test Statistic (LRuc)	5.4062	3.3744	1.1537	1.1537	18.1788	15.1434	7.2547	7.2547
Conclusion	Biased VaR	Unbiased VaR	Unbiased VaR	Unbiased VaR	Biased VaR	Biased VaR	Biased VaR	Biased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0318	0.1079	0.0710	0.0717	0.0177	0.1042	0.1035	0.1035
(4) Root Mean Square Error (RMSE)	5.96	6.45	6.83	6.84	7.85	8.38	8.56	8.56
Efficacy Ratio: (R^2 / RMSE)	0.00534	0.01674	0.01040	0.01048	0.00226	0.01243	0.01209	0.01209

Chart 5.23 – TTSE

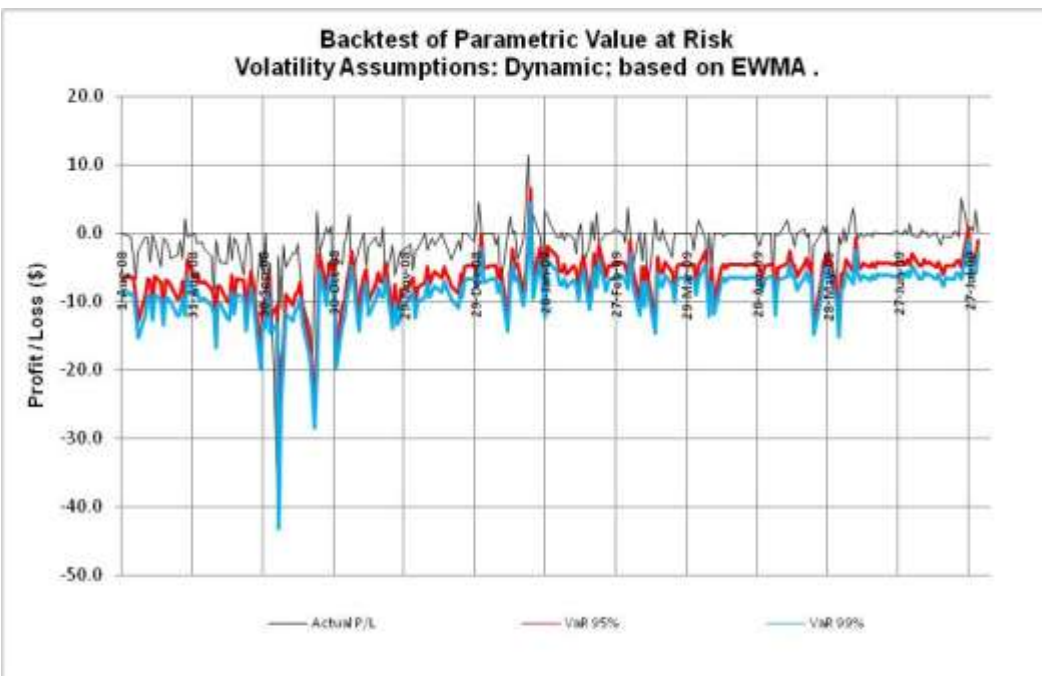
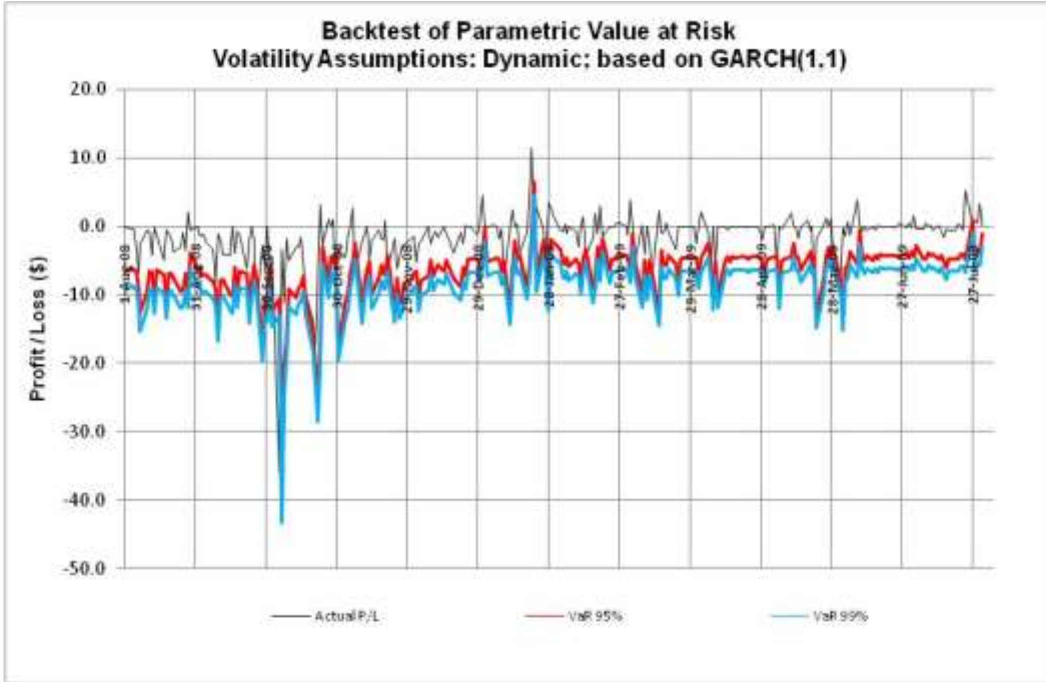


Chart 5.24 – TTSE



(5)(d) Jamaica Stock Exchange JMI

(i) HS VaR Models with Constant Volatility Assumption - JMI

Table 5.13 shows that the HS VaR was sufficiently effective in both the sample period and the test period at the 95% and 99% confidence levels. Please see Chart 5.25.

Chart 5.25 – JMI

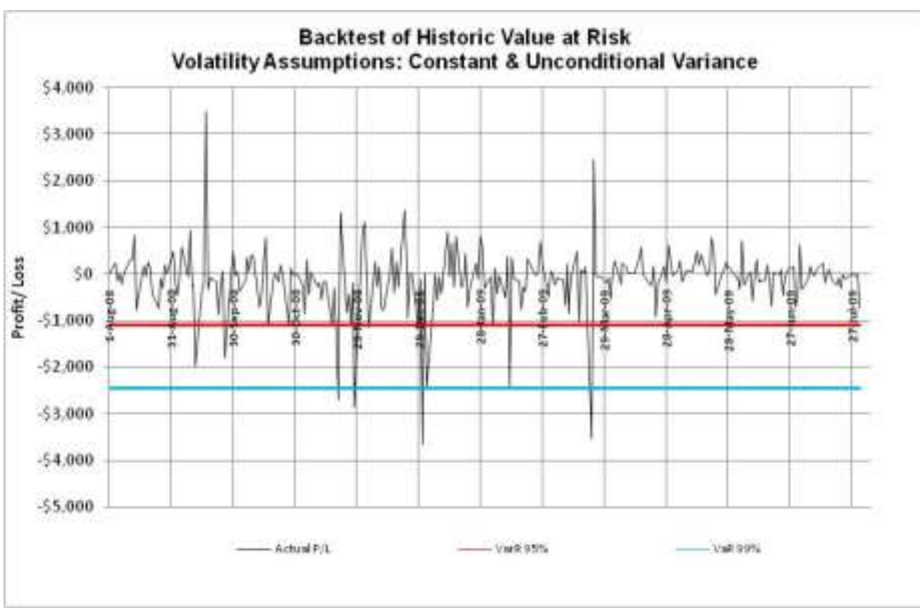


Table 5.13
Summary of Back Testing Results for the Historical VaR on the JMI
Volatility Assumptions: Constant & Based on Unconditional Variance

VaR Confidence Level	95%	99%
Volatility Assumption #1	Static	Static
Volatility Assumption #2	Unconditional	Unconditional
IN SAMPLE VaR BACKTESTING		
No. of observation	932	932
Expected Exception Rate	5.00%	1.00%
Actual Exception Rate	5.04%	1.07%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	0.0601	0.2239
Conclusion	Unbiased VaR	Unbiased VaR
(2) Root Mean Square Error	1,393.62	2,593.86
OUT OF SAMPLE VaR BACKTESTING		
No. of observation	261	261
Expected breach/failure rate	5.00%	1.00%
Actual breach/failure rate	4.60%	1.53%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	-0.2982	0.8647
Conclusion	Unbiased VaR	Unbiased VaR
(2) Parametric testing: Kupiec(1995) LLR		
Confidence Level for Test	95%	99%
Null: actual exception rate = expected ex. rate		
Alt: actual exception rate ≠ expected ex rate		
Applicable Critical Value	3.8415	6.6349
Test Statistic (LRuc)	0.0913	0.6430
Conclusion	Unbiased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0000	0.0000
(4) Root Mean Square Error (RMSE)	1,196.90	2,426.32
Efficacy Ratio: (R^2 / RMSE)	0.00000	0.00000

5(d)(ii) P VaR Models with Constant Volatility Assumption - JMI

Table 5.14 shows that the P VaR was sufficiently effective in the sample period only at the 99% confidence level. In the test period, both the 95% and 99% P VaR (with constant volatility assumptions) models were effective. Please refer to Chart 5.26 for graph of the backtesting done in the test period.

Chart 5.26 – JMI

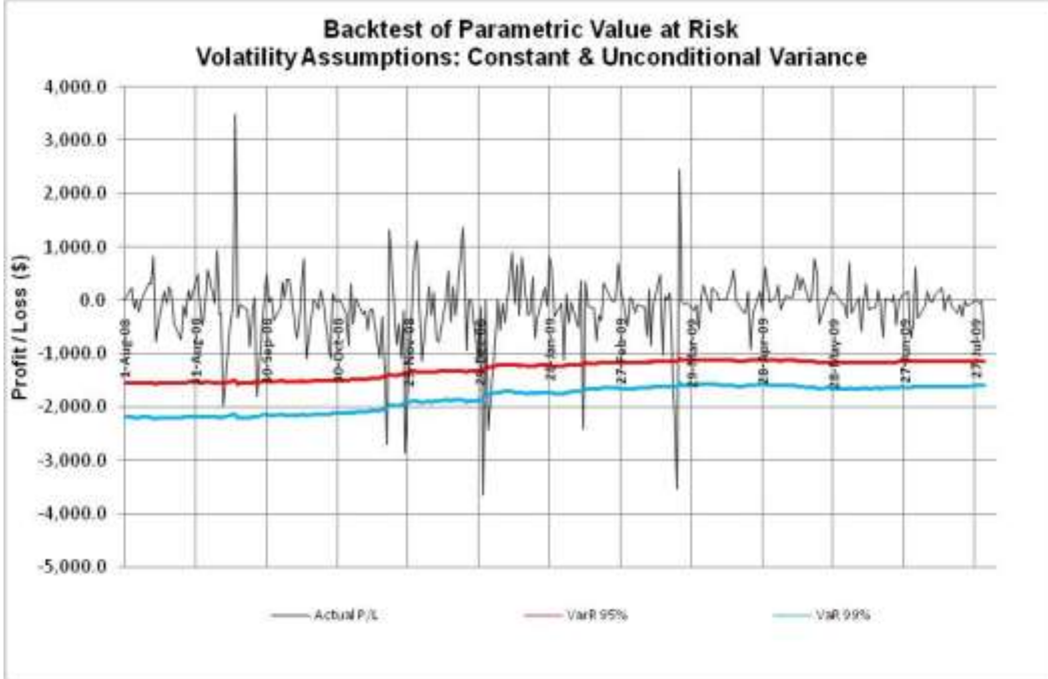


Table 5.14
Summary of Back Testing Results for the Parametric VaR on the JMI
Volatility Assumptions: Constant & Based on Unconditional Variance

VaR Confidence Level	95%	99%
Volatility Assumption #1	Static	Static
Volatility Assumption #2	Unconditional	Unconditional
IN SAMPLE VaR BACKTESTING		
No. of observation	933	932
Expected Exception Rate	5.00%	1.00%
Actual Exception Rate	3.32%	1.39%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	-2.3509	1.2115
Conclusion	Biased VaR	Unbiased VaR
(2) Root Mean Square Error (RMSE)	1,656.96	2,184.61
OUT OF SAMPLE VaR BACKTESTING		
No. of observation	261	261
Expected breach/failure rate	5.00%	1.00%
Actual breach/failure rate	3.07%	2.30%
(1) Non-parametric Bernoulli Trials		
Confidence Level for Test	95%	99%
Applicable Critical Value	1.9600	2.5758
Test Statistic	-1.4342	2.1089
Conclusion	Unbiased VaR	Unbiased VaR
(2) Parametric testing: Kupiec(1995) LLR		
Confidence Level for Test	95%	99%
Applicable Critical Value	3.8415	6.6349
Test Statistic (LRuc)	2.3726	3.2536
Conclusion	Unbiased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0074	0.0074
(4) Root Mean Square Error (RMSE)	1,363.21	1,851.18
Efficacy Ratio: (R^2 / RMSE)	0.00001	0.00000

5(d)(iii) HS VaR Models with Non-Constant Volatility Assumption - JMI

Table 5.15 shows that the HS VaR using 260-day rolling standard deviation produces sufficiently effective VaR models in the sample period, at the 95% and 99% confidence levels. In the sample period the 22-day rolling standard deviation is not sufficiently effective at the 95% and 99% confidence levels.

Similar to the sample period, in the test period, only the HS VaR using the 260-day rolling standard deviation is effective both at the 95% and 99% confidence levels. The HS VaR using the 22-day rolling standard deviation breaks down in the test period both at the 95% and 99% confidence levels. Please see Charts 5.27 and 5.28.

Table 5.15
Summary of Back Testing Results for the Historical VaR on the JMI
Volatility Assumptions: Non Constant

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Dynamic 260 day rsd	95% Dynamic 22 day rsd	99% Dynamic 260 day rsd	99% Dynamic 22 day rsd
IN SAMPLE VaR BACKTESTING				
No. of observation	932	932	932	932
Expected Exception Rate	5.00%	5.00%	1.00%	1.00%
Actual Exception Rate	5.58%	9.98%	1.29%	4.40%
(1) Non-parametric Bernoulli Trials				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	1.9600	1.9600	2.5758	2.5758
Test Statistic	0.8116	6.9737	0.8823	10.4294
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(2) Root Mean Square Error	1,355.80	1,355.83	2,339.04	2,029.74
OUT OF SAMPLE VaR BACKTESTING				
No. of observation	261	261	261	261
Expected breach/failure rate	5.00%	5.00%	1.00%	1.00%
Actual breach/failure rate	3.45%	9.58%	1.53%	5.75%
(1) Non-parametric Bernoulli Trials				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	1.9600	1.9600	2.5758	2.5758
Test Statistic	-1.1502	3.3939	0.8647	7.7079
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(2) Parametric testing: Kupiec(1995) LLR				
Confidence Level for Test	95%	95%	99%	99%
Applicable Critical Value	3.8415	3.8415	6.6349	6.6349
Test Statistic (LRuc)	1.4777	9.1898	0.6430	28.2848
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Biased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0082	0.0091	0.0023	0.0060
(4) Root Mean Square Error (RMSE)	1,352.04	1,341.33	2,721.16	1,944.58
Efficacy Ratio: (R^2 / RMSE)	0.00001	0.00001	0.00000	0.00000

Chart 5.27 – JMI

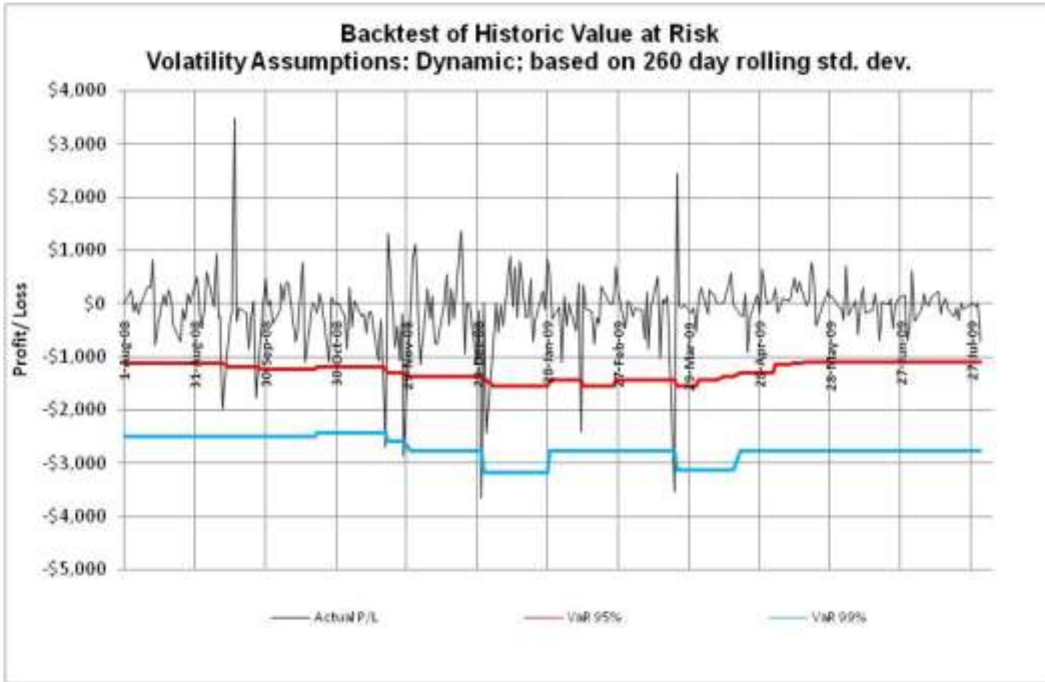
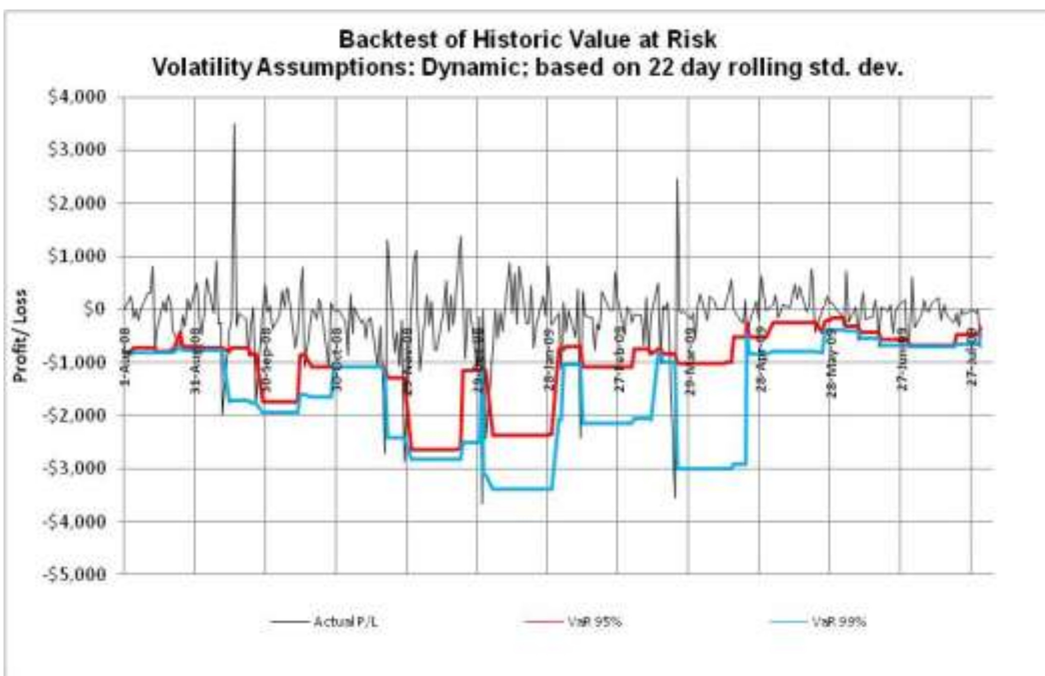


Chart 5.28 – JMI



5(d)(iv) P VaR Models with Non-Constant Volatility Assumption - JMI

Table 5.16 shows that the P VaR using both the 260-day rolling standard deviationand 22-day rolling standard deviationis effective only at the 95% confidence levels in the sample period. All the other P VaR models are ineffective in the sample period. In the test period, all P VaR models, except the one using the 22-day rolling standard deviation, are sufficiently effective at the 95% and 99% confidence levels. Please refer to Charts 5.29 to 5.32.

Chart 5.29 – JMI

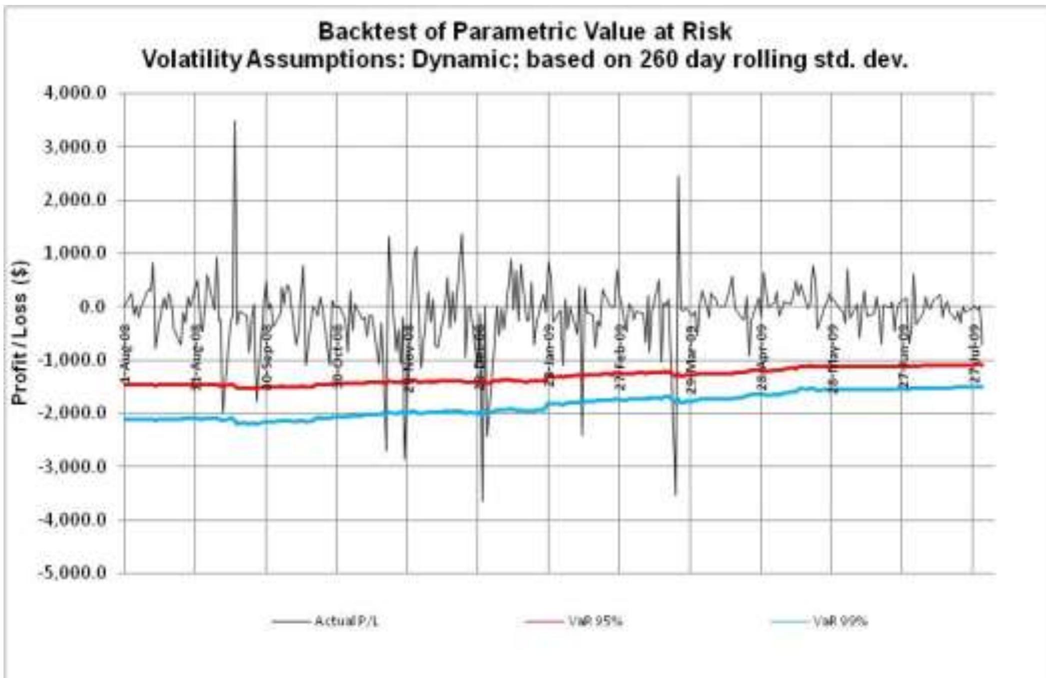


Table 5.16
Summary of Back Testing Results for the Parametric VaR on the JMI
Volatility Assumptions: Non Constant

VaR Confidence Level Volatility Assumption #1 Volatility Assumption #2	95% Dynamic 260 day rsd	95% Dynamic 22 day rsd	95% Dynamic EWMA	95% Dynamic GARCH(1,1)	99% Dynamic 260 day rsd	99% Dynamic 22 day rsd	99% Dynamic EWMA	99% Dynamic GARCH(1,1)
IN SAMPLE VaR BACKTESTING								
No. of observation	932	932	932	932	932	932	932	932
Expected Exception Rate	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%
Actual Exception Rate	4.08%	6.01%	8.91%	9.23%	2.15%	2.90%	4.18%	4.18%
(1) Non-parametric Bernoulli Trials								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	1.9600	1.9600	1.9600	1.9600	2.5758	2.5758	2.5758	2.5758
Test Statistic	-1.2925	1.4128	5.4707	5.9216	3.5160	5.8205	9.7710	9.7710
Conclusion	Unbiased VaR	Unbiased VaR	Biased VaR	Biased VaR	Biased VaR	Biased VaR	Biased VaR	Biased VaR
(2) Root Mean Square Error (RMSE)	1,587.62	1,626.96	1,839.43	1,833.99	2,074.03	2,145.63	2,260.48	2,260.48
OUT OF SAMPLE VaR BACKTESTING								
No. of observation	261	261	261	261	261	261	261	261
Expected breach/failure rate	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%
Actual breach/failure rate	3.07%	8.05%	5.36%	5.75%	2.30%	3.83%	1.92%	1.92%
(1) Non-parametric Bernoulli Trials								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	1.9600	1.9600	1.9600	1.9600	2.5758	2.5758	2.5758	2.5758
Test Statistic	-1.4342	2.2579	0.2698	0.5538	2.1089	4.5973	1.4868	1.4868
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Unbiased VaR	Unbiased VaR	Biased VaR	Unbiased VaR	Unbiased VaR
(2) Parametric testing: Kupiec(1995) LLR								
Confidence Level for Test	95%	95%	95%	95%	99%	99%	99%	99%
Applicable Critical Value	3.8415	3.8415	3.8415	3.8415	6.6349	6.6349	6.6349	6.6349
Test Statistic (LRuc)	2.3726	4.3385	0.0712	0.2932	3.2536	12.2981	1.7431	1.7431
Conclusion	Unbiased VaR	Biased VaR	Unbiased VaR	Unbiased VaR	Unbiased VaR	Biased VaR	Unbiased VaR	Unbiased VaR
(3) R^2 from OLSR lg(return^2) vs lg(VaR^2)	0.0210	0.0085	0.0051	0.0048	0.0192	0.0085	0.0006	0.0006
(4) Root Mean Square Error (RMSE)	1,380.94	1,348.12	1,622.37	1,608.59	1,866.91	1,759.41	2,065.28	2,065.28
Efficacy Ratio: (R^2 / RMSE)	0.00002	0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000

Chart 5.30 – JMI

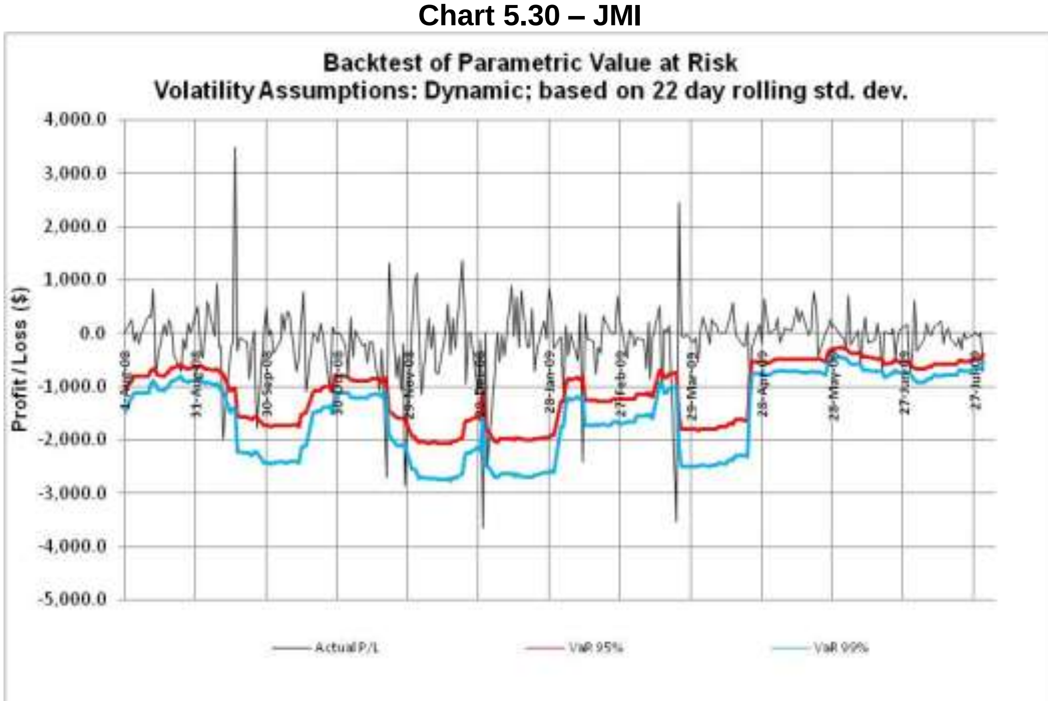


Chart 5.31 – JMI

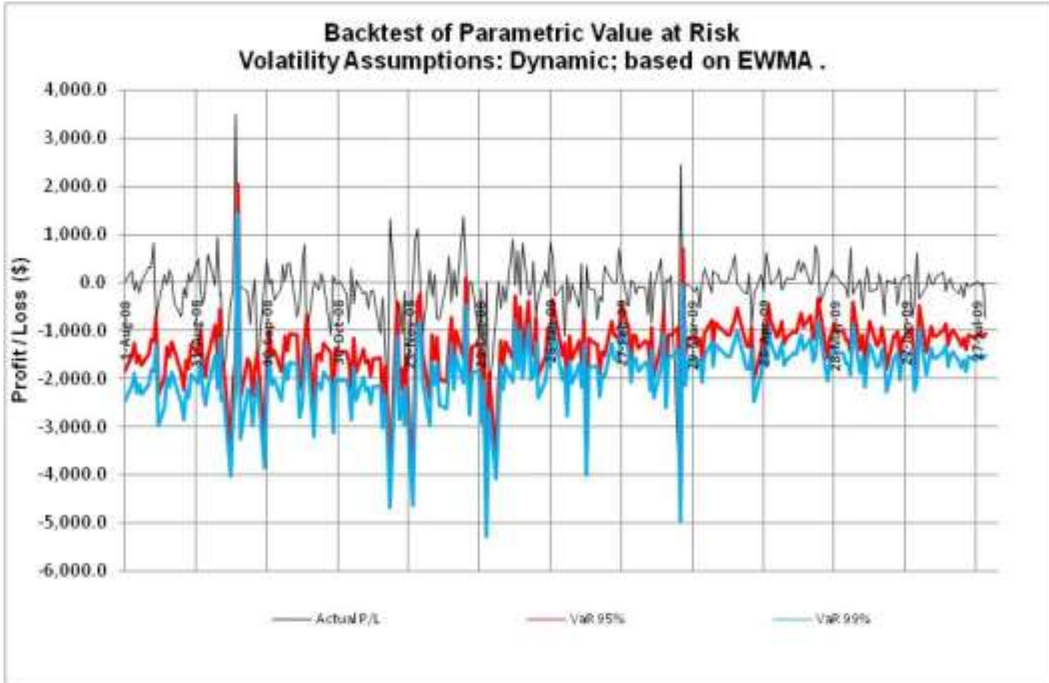
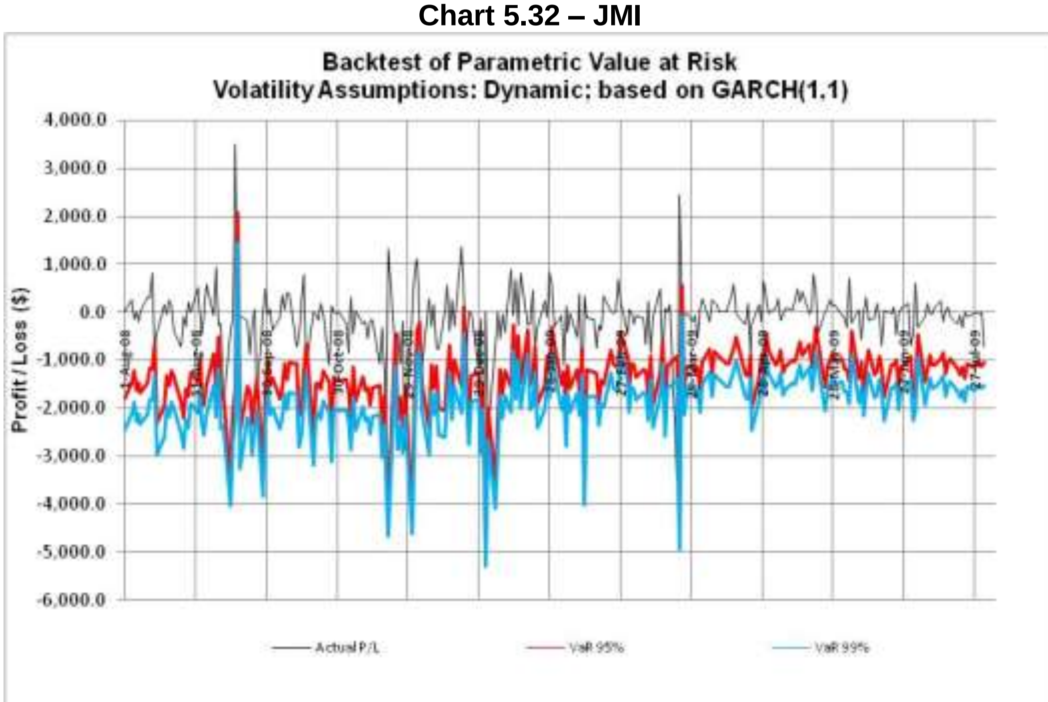


Chart 5.32 – JMI



Summary of Results

Table 5.17
Summary of Results for VaR Models used for the BSE

VaR Model	Volatility	Effective	Efficacy Ratio	Rank
HS VaR 95%	Constant	No	NA	NA
HS VaR 99%	Constant	No	NA	NA
P VaR 95%	Constant	Yes	0.000381	1
P VaR 99%	Constant	Yes	0.000299	2
HS VaR 95%	260d rsd	Yes	0.000211	3
HS VaR 95%	22d rsd	No	NA	NA
HS VaR 99%	260d rsd	No	NA	NA
HS VaR 99%	22d rsd	No	NA	NA
P VaR 95%	260d rsd	Yes	0.000170	4
P VaR 95%	22d rsd	Yes	0.000012	9
P VaR 95%	EWMA	Yes	0.000052	8
P VaR 95%	GARCH(1,1)	Yes	0.000065	7
P VaR 99%	260d rsd	No	NA	NA
P VaR 99%	22d rsd	No	NA	NA
P VaR 99%	EWMA	Yes	0.000096	5
P VaR 99%	GARCH(1,1)	Yes	0.000096	5

Table 5.18
Summary of Results for VaR Models used for the ECSE

VaR Model	Volatility	Effective	Efficacy Ratio	Rank
HS VaR 95%	Constant	No	NA	NA
HS VaR 99%	Constant	Yes	0.000000	8
P VaR 95%	Constant	No	NA	NA
P VaR 99%	Constant	Yes	0.005864	1
HS VaR 95%	260d rsd	Yes	0.000199	5
HS VaR 95%	22d rsd	No	NA	NA
HS VaR 99%	260d rsd	Yes	0.001097	4
HS VaR 99%	22d rsd	No	NA	NA
P VaR 95%	260d rsd	No	NA	NA
P VaR 95%	22d rsd	Yes	0.001823	3
P VaR 95%	EWMA	No	NA	NA
P VaR 95%	GARCH(1,1)	No	NA	NA
P VaR 99%	260d rsd	Yes	0.002265	2
P VaR 99%	22d rsd	No	NA	NA
P VaR 99%	EWMA	Yes	0.000153	6
P VaR 99%	GARCH(1,1)	Yes	0.000153	6

Table 5.19

Summary of Results for VaR Models used for the TTSE

VaR Model	Volatility	Effective	Efficacy Ratio	Rank
HS VaR 95%	Constant	No	NA	NA
HS VaR 99%	Constant	No	NA	NA
P VaR 95%	Constant	No	NA	NA
P VaR 99%	Constant	No	NA	NA
HS VaR 95%	260d rsd	No	NA	NA
HS VaR 95%	22d rsd	No	NA	NA
HS VaR 99%	260d rsd	No	NA	NA
HS VaR 99%	22d rsd	No	NA	NA
P VaR 95%	260d rsd	No	NA	NA
P VaR 95%	22d rsd	No	NA	NA
P VaR 95%	EWMA	Yes	0.010401	2
P VaR 95%	GARCH(1,1)	Yes	0.010477	1
P VaR 99%	260d rsd	No	NA	NA
P VaR 99%	22d rsd	No	NA	NA
P VaR 99%	EWMA	No	NA	NA
P VaR 99%	GARCH(1,1)	No	NA	NA

Table 5.20

Summary of Results for VaR Models used for the JMI

VaR Model	Volatility	Effective	Efficacy Ratio	Rank
HS VaR 95%	Constant	Yes	0.000000	11
HS VaR 99%	Constant	Yes	0.000000	11
P VaR 95%	Constant	Yes	0.000005	4
P VaR 99%	Constant	Yes	0.000004	5
HS VaR 95%	260d rsd	Yes	0.000006	3
HS VaR 95%	22d rsd	No	NA	NA
HS VaR 99%	260d rsd	Yes	0.000001	8
HS VaR 99%	22d rsd	No	NA	NA
P VaR 95%	260d rsd	Yes	0.000015	1
P VaR 95%	22d rsd	No	NA	NA
P VaR 95%	EWMA	Yes	0.000003	6
P VaR 95%	GARCH(1,1)	Yes	0.000003	7
P VaR 99%	260d rsd	Yes	0.000010	2
P VaR 99%	22d rsd	No	NA	NA
P VaR 99%	EWMA	Yes	0.000000	9
P VaR 99%	GARCH(1,1)	Yes	0.000000	9

Using the BSE on the Barbados Stock Exchange, Table 5.17 shows that the most effective VaR model in the test period in the 95% P VaR based on the constant volatility assumption. This model significantly outperforms its counterpart at the 99% confidence level as well as all other HS VaR and P VaR models based on the assumption of time varying volatility such as those models with utilize the concepts of rolling standard deviation, EWMA and the GARCH(1,1).

Table 5.18 shows that the most effective VaR model for the ECSE in the test period is the 99% P VaR based on the constant volatility assumption. Interestingly, this model's counterpart at 95% confidence level is not effective on the ECSE. Similar to the case of the BSE, the most effective VaR model significantly outperforms theVaR models which are based on the assumption of time carrying volatility. Of interest is that the P VaR based on the 360-day rolling standard deviation outperforms VaR models using EWMA and GARCH(1,1).

Table 5.20 shows that the most effective VaR model for the JMI, in the test period, is the 95% P VaR based on the 260-day rolling standard deviation volatility assumption. In second place is that model's counterpart at the 99% confidence level. In third place is the 95% HS VaRwith the 260-day rolling standard deviation volatility assumption, which outperforms the VaR models based on EWMA and GARCH(1,1). In the case of Jamaica, models with the 260-day rolling standard deviation volatility assumption outperformed models with assumed constant volatility – which were the most effective on the BSE and the ECSE.

Table 5.19 shows that the only two effective VaR models for the TTSE, in the test period, were the 95% P VaR based on the EWMA and GARCH(1,1) volatility assumptions. All other VaR models were ineffective. This is primarily due to the assumption of a five day trading week. The assumption of a five (5) business day week was used, to construct the VaR models, during the sample and test periods for all the indices in this paper. On puBSEc holidays and in instances of a three (3) day trade week, it was assumed that the price remained the same as the previous day's closing price. The TTSE changed to five-day trade week from a three-day trade week effective 1 April, 2008 – that is, close to the end of the sample period. Thus, the volatility computed in the sample period and subsequently used to construct VaR models for the test period, was underestimated. The volatility (standard deviation) of the TTSE calculated on the five-day trade week assumption and subsequently used to construct the VaRmodels, was 0.3246% (correct to 4 significant figures). The actual volatility of the TTSE in the sample period was 0.4753% (correct to 4 significant figures).

Table 4.2 clearly shows the distribution of the daily returns on the BSE, ECSE, JSE and TTSE, in the test period, is not normally distributed. Notwithstanding this, the P VaR models, which are based on the assumption that returns are normally distributed, are the most effective VaR models in all the markets in this study. This finding is supported by the work of Andjelic*et al.* (2010), which shows that the delta normal and historical simulation VaR models are successful at the 95% and 99% confidence levels in the emerging equity markets of selected Central and Eastern European countries.

In the case of the BSE and the ECSE VaR models based on the assumption of time varying volatility did not have a significant advantage over those models that used the constant volatility assumption. However, in the case of the JSE and the TTSE, VaR models based on the assumption of time varying volatility were more effective then those models that used the constant volatility assumption. On the TTSE, VaR models with the assumption of constant volatility were not sufficiently effective in the test period.

5. Conclusion

This paper illustrates a very first attempt to evaluate the effectiveness and applicability of the simple and commonly used VaR models in the emerging equity markets of the Caribbean. The data provides evidence that the most effective VaR models are: the parametric VaR (assuming constant volatility) in the Barbados and Eastern Caribbean equity markets, the parametric VaR (assuming non-constant volatility using the 260-day rolling standard deviation) in the Jamaica equity market and the parametric VaR (assuming non-constant volatility using both the Exponentially Weighted Moving Average and a simple GARCH(1,1) model) in the Trinidad & Tobago equity markets. The parametric VaR was very effective in all markets. VaR models utilizing the assumption of time varying volatility were more effective in the Jamaica and Trinidad & Tobago equity markets than in the Barbados and Eastern Caribbean equity markets.

Further research is required to corroborate these results and, in particular, to examine theefficacy on VaR model using Monte Carlo simulation.

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