ESTIMATING AND TESTING THE VALUE AT RISK MODELS: AN EMPIRICAL EVIDENCE FROM KHARTOUM STOCK EXCHANGE SUDAN

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ABSTRACT

This paper aims to estimate and test the Value at Risk (VaR) of portfolio i.e. Khartoum Stock Exchange (KSE) index via variance methods, historical simulation and quantile method for the period 2005-2011. The main results are: KAE index is stastionarity, not normally distributed, and 0.44 of the total returns are negative indicating losses. Only the empirical quantile have passed the back-testing procedure. Historical simulation, generalizes autoregressive heteroscedasticity (GRCH(1,1) and RiskMetrics underestimate the risk, while the generalized formula overestimates the risk.

Key Words: *losses, stastionarity, normality, mean reversion, VaR, risk*

Introduction

Value at risk (VaR) is the maximum loss that can occur over a given period, at a given confidence level, due to the exposure to market risk. It has been widely used for two reasons: an easily interpretable summary measure of risk, and allows its users to focus attention on normal market conditions in their routine operations (Basak &Shapiro 2001). Specifically, value at risk is a measure of losses due to “normal” market movements. Losses greater than the value at risk are suffered only with a specified small probability (Linsmeier and Pearson 1999). More formally, VaR measures the quantile of the projected distribution of gains and losses over a given time horizon (Fernandez 2003).

Value at Risk allows regulators and bank presidents to put a single number on their worst-case scenario and to plan for it accordingly. While Value at Risk can be used by any entity to measure its risk exposure, it is used most often by commercial and investment banks to capture the potential loss in value of their traded portfolios from adverse market movements over a specified period. Banks diversify their portfolios by investing in the minimum risk and returns assets that do not move together (Mishkin & Eakins,2006); distributing credit and deposits among wide range of clients (Rose & Hudgins, 2005); on the basis of weak correlations between risks (Bodie, et al,2005). Basle committee has launched a long term project of implementing VaR measures for various risk categories in the following order (Gourieroux and Jasiak 2001): VaR for market risk for portfolios of basic liquid assets such as stocks included in the market indexes, treasury bonds and foreign currencies; VaR for market risk for portfolios that contain basic liquid assets and derivatives such as options on interest rates, foreign currencies and market indexes; VaR on loan with default risk called credit risk (bonds for which market prices are available, and retails loans for which the bank has insider information about the individual credit histories of borrowers; back-testing procedure for assessing the goodness of fit of internal models and examining the model based predictors under extreme scenarios of price evolution (stress testing).

In 1993 the Bank of International Settlements (BIS) members met in Basle and amended the Basle Accord to require Banks and other financial institutions to hold in reserve enough capital to cover 10 days of potential losses based on the 95% 10-day VaR. In 1995 the governors of central banks gathered in Basle adopted mandatory measure, called the Value at Risk to be calculated by all the banks for each line of their balance sheet. Since then banks have been required to report the VaR to the regulators and update it daily, and hold sufficient amount of capital (required capital RC) as a hedge against extreme risks (Jackson, Maude, and Perraudin 1998).

Despite the wide use and common acceptance of VaR as a risk management tool, the method has frequently been criticized for being incapable to produce reliable risk estimates. When implementing VaR systems, there will always be numerous simplifications and assumptions involved. Moreover, every VaR model attempts to forecast future asset prices using historical market data which does not necessarily reflect the market environment in the future (Nieppola 2009).

Khartoum Stock Exchange established in 1994 is a body corporate with perpetual succession and a common seal. The purposes of Khartoum Stock Exchange are the following: the regulation and supervision of the issue and dealings in securities, for buying and selling; encouragement of savings, the development of investment awareness amongst citizen; widening and enhancement of the base of private ownership; development and promotion of the primary market securities; development and promotion of investment in securities and the preparation of the conducive investment; provision of all the factors that may assist in the facilitation of the liquidity of the invested money in securities; establishment and consolidation of the bases of the appropriate and fair dealings amongst the investors; collection of information ,statements, data, and statistics and their provision for all investors and those interested in the same; study of the legislation related to the stock exchange; coordination of the financial and monetary policies.

The purpose of this paper is to estimate and evaluate VaR for the Khartoum Exchange index via different methods. To the best of my knowledge no one has written about the estimation of VaR for Khartoum Stock Exchange.

Empirical Literature Review

Financial stability requires an accurate measurement and management of risk .The concept of Value at Risk (VaR), in particular, has received much attention and is now widely accepted as a useful measure of financial risk.

It has been presented by Baharul-Ulum (2011) and integrated with several volatility representations to estimate the market risk for the Malaysian non-financial sectors data. The models were used to obtain daily volatility forecasts and these volatilities are used to estimate the Value-at-Risk (VaR) for each sector based on the Monte Carlo Simulation (MCS) approach. The final results provided evidence that consideration of fat-tails and asymmetries are crucial issues when deciding to estimate VaR in managing financial risk.

Zedan (2011) examined the challenges faced by the Arab banking systems for the implementation of the new agreement, and focused on the focal points of the following: the historical development of the Convention, the objectives of the Convention and the scope of its applications, the three pillars of the Convention, to assess the new framework and the repercussions potential of Arab Banks, the reasons for joining the Arab Banks the new agreement and the necessary preparations that should be on the banks and monetary authorities have taken to implement the Arab new agreement. The risk of agricultural credit has been dealt with by Mustafa et al (2010). Two types of risks are encountered: the normal risks facing all banks offer advances, and the natural risks related to the agricultural process from the beginning to marketing of the production. The banks in the region adopted many policies and tools to encounter normal and natural risks. The agricultural Bank of Sudan ABS is one of the few banks adopt Basle II: i.e. minimum capital requirement, supervisory review, and market discipline. They found that all banks request real estate and financial guarantees, credit eligibility study. The ABS diversifies income and deductions, loans, geographical distribution; and agricultural insurance.

Abu Rahma (2009) studied the impact of liquidity of each bank on return and risk using the annual reports of the Palestinian commercial banks for the period 2002-2008. The extraction percentages are the indicators of liquidity and risk and return. Using correlation and regression analysis the main results of the study are: there is no correlation and impact between the bank liquidity and rate of return for all commercial banks, there is no correlation and impact between the bank liquidity and risk indicators, all the department of commercial banks apply liquidity ratios applicable to the Palestinian Monetary Authority. The accuracy of a VaR model has been examined by Nieppola (2009). The performance of the VaR model was measured by applying several different tests of unconditional coverage and conditional coverage. Three different portfolios (equities, bonds and equity options) with daily VaR estimates for one year time period were used in the backtesting process. The results of the backtest provided some indication of potential problems within the system. Severe underestimation of risk was discovered, especially for equities and equity options. However, the turbulent market environment caused problems in the evaluation of the back testing outcomes since VaR models were known to be accurate only under normal market conditions.

Using the techniques of credit risk mitigation on banks' value Othman (2008) aimed at analyzing the effect of principles of good lending, market segmentation, credit portfolio diversification, credit insurance, monitoring credit and bank strategy. He also explored the awareness of Jordanian banks of credit portfolio risk that leads ultimately to credit default in payment of obligations and its effect on the market value of the bank through returns to owners and stockholders. To assess the bank value, the researcher applied the measurement depending on the approximate equation of Tobin's Q. The study sample consisted of eleven Jordanian commercial banks during the years of 2001-2006. Using multiple linear regression the researcher showed the presence of a positive effect between the bank value and credit risk mitigation. He also studied the importance of maintaining the quality and components of the credit portfolio and containing its risks within accepted levels to establish the bank's value. In conclusion, the researcher asserts the necessity of using credit risk mitigation by Jordanian commercial banks to decrease portfolio credit risk and default risk in order to ensure acceptable returns for owners and stockholders.

Actuarial techniques combined with high volatility and extreme value cases appearing in insurance applications have been reviewed by Kisacik (2006). He compared two methods which are used for calculating Value-at-Risk measures. First one is traditional method and second one is an alternative method which uses extreme value theory. Traditional methods in VaR estimation assume normal distribution for the data. However, most of the financial data have heavy-tailed distribution. Extreme Value Theory is an appropriate way to study the tail behavior of the heavy-tailed distribution because extreme values refer to characteristics of tails. Moreover, many studies have shown that VaR calculated by using Extreme Value Theory gives more satisfactory results in measuring risk.

Fernandez (2003) stated that assets returns usually come from fat-tailed distributions. Therefore, computing VaR under the assumption of conditional normality can be an important source of error. She illustrated this point with Chilean and U.S. returns series by resorting to extreme value theory (EVT) and GARCH-type models. In addition, she showed that dynamic estimation of empirical quantiles can also give more accurate VaR estimates than quantiles of a standard normal. Berkowitz and O’Brien (2001) analyzed the distribution of historical trading profits and losses P&L and the daily performance of VaR estimates of 6 large U.S. banks and provided descriptive statistics on the trading revenues from such activities and on the associated Value-at-Risk forecasts internally estimated by the banks. To assess the performance of the banks’ structural models they compared their VaR forecasts with those from a standard GARCH model of the bank' P&L volatility.

Linsmeier and Pearson (1999) explained the concept of value at risk, and then described in detail the three methods for computing it: historical simulation; the variance-covariance method; and Monte Carlo or stochastic simulation. They then discussed the advantages and disadvantages of the three methods for computing value at risk. Finally, they described some alternative measures of market risk. The empirical performance of different VaR models using data on the actual fixed income, foreign exchange and equity security holdings of a large bank has been examined by Jackson, Maude, and Perraudin (1998). They examined how a bank applying the models would have fared in the past if the proposed rules had been in operation

Research Methodology

Daily returns of Khartoum Stock Exchange index are composed of different sectors. Tele communication and banking sector have the lion share. Data is available for the period 3/1/2005 to 31/12/2009 i.e. interim period followed the end of the civil war in the South. The main popular methods for calculating the VaR are: historical or empirical method, the parametric or analytical method, and simulation or Monte Carlo method. In this section data will be inspected by descriptive statistics, unit root test, and graphical representation and Lagrange Multiplier test LM. A number of techniques to estimate VaR will be discussed and back-testing procedure will be used for evaluation. The vast majority of variance methods which all relate the Value at Risk of a portfolio directly to the variance of standard deviation of portfolio returns as well as assuming the normal distribution (Goorbergh and Vlaar 1999).

Generalized Formula

The generalized formula for VaR requires daily profits and losses from trading activities: interest rate, foreign exchange, equity assets, liabilities, and derivatives contracts. The general form for calculating parametric VaR is:

$$Mean \times HPR + (Z - score \times Std\ Dev \times SQRT(HPR)) \quad (1)$$

Where: mean is the average expected return; Std Dev is the Standard Deviation; HPR is the Holding Period; Z-score is the Probability. It is fairly common to convert daily standard deviation into monthly or annual standard deviation by multiplying or diving by the square root of time as necessary.

Risk Metrics

RiskMetrics was originally an Internet-based service with the aim to promote VaR as a risk management method. The service provided free data for computing market risk. is special case of GARCH restricting both ω, μ *to* 0 and α *to* $1-\beta$. Furthermore the parameter β called the decay factor and renamed λ. Later, RiskMetrics became an independent consulting and software firm. (www.riskmetrics.com). The benchmark measure advocated in Morgan's (1996) RiskMetrics sets the conditional mean constant, and specifies the variance as an exponential filter

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

where $\lambda = 0.94$ and 0.97 for daily and monthly data respectively. The innovations are assumed to be Gaussian, thus the VaR measure is

$$F_{(t|t-1)}^{RM}(p) = \mu + \phi^{-1}(p)\sigma_t (3)$$

Obviously, for p=0.05, we would have $\phi^{-1}(p) = -1.64$ (Christoffersen etal 2011). Integrated general conditional heteroskedasticity IGARCH can best estimate the variance.

GARCH (m,s)

GARCH is the Generalized ARCH by Bollerslev (1986) models widely used in various branches of econometrics, especially in financial time series analysis.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \hat{\varepsilon}_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2; \varepsilon_t \sim N(0,1); \alpha_0 > 0; \alpha_i \geq 0; \beta_j \geq 0 (4)$$

The variance equation σ_t^2 is composed of three terms: the mean (long term average) α_0; news about volatility from the previous period (the ARCH term) a_{t-i}^2 and the GARCH term σ_{t-j}^2. It is a weighted average of the variance a (the constant), the ARCH term and the GARCH term. If there was unexpectedly large move in either the upward or the downward direction, then the forecaster will increase the estimate of the variance for the next period (Tsay 2002).

Historical Simulation

Historical simulation approaches use the actual percentiles of the observation period as value-at-risk measures. Historical simulation approaches do not make the assumptions of normality or serial independence. However, relaxing these assumptions also implies that historical simulation approaches do not easily accommodate translations between multiple percentiles and holding periods (Hendricks 1996). Each day in the time series carries the same weight, and history repeats itself (Cabedo & Moya 2003).

Empirical Quartile

Quantile estimation provides a nonparametric approach to VaR calculation. It makes no specific distributional assumption on the return of a portfolio except that the distribution continues to hold within the prediction period. There are two types of quantile methods. The first method is to use empirical quantile directly, and the second method uses quantile regression. It is defined as the fraction p use the linear interpolation between the two nearest p_i (Tsay 2005). If p lies a fraction f of the way p_i to p define the pth quantile to be:

$$Q(p) - (1-f)Q(p) - Q(p_{i+1})$$

The 0.99 quantile defines the value (let's call it x) for a random variable, such that the probability that a random observation of the variable is less than x is 0.99 (99% chance).

It is nonparametric methods, not assuming specific distribution calculated as follows:

$$\hat{x}_{0.01} = \frac{p_2 - p}{p_2 - p_1} r_{i_1} + \frac{p - p_1}{p_2 - p_1} r_{i_2}; p = 0.01; p_i = \frac{i_i}{n}$$

Empirical Results

Khartoum market efficiency was tested via variance-ratio test and found to be inefficient which indicates that successive return changes are not random and serially dependent.

Table 1: Empirical Results

Joint Tests		Value	df	Probability
Max |z| (at period 2)*		10.63022	341	0.0000
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.536455	0.043606	-10.63022	0.0000
4	0.320561	0.071513	-9.500936	0.0000
8	0.192720	0.099831	-8.086443	0.0000
16	0.110167	0.140603	-6.328704	0.0000

Throughout the analysis a holding period of one day will be used. Different levels of significances will be used ranging from very conservative 0.5% to 5%.

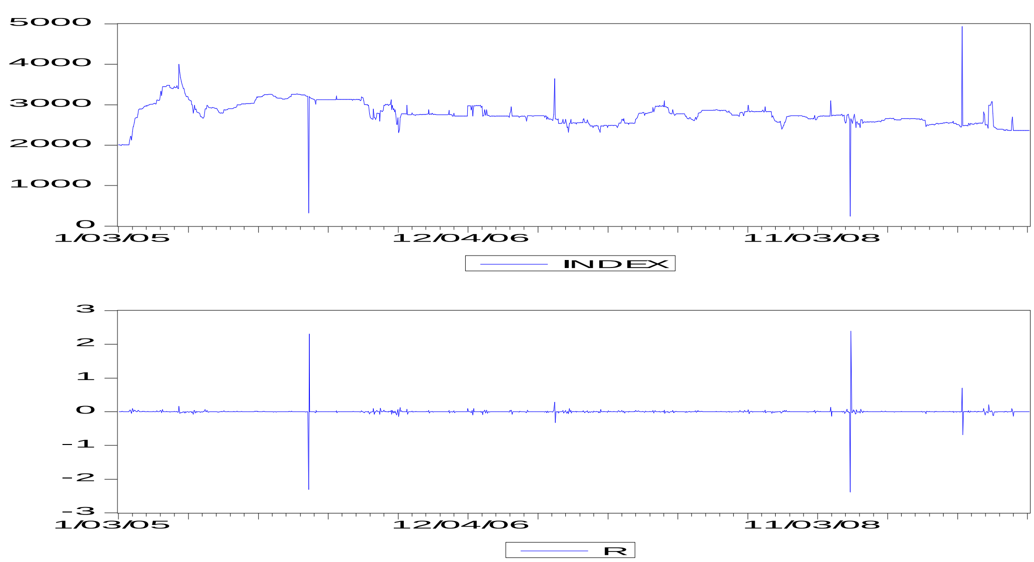
Table 2: Unit Root Test

ADF Test Statistic	-26.5879	1% Critical Value*	-3.4382
		5% Critical Value	-2.8642
		10% Critical Value	-2.5682

*MacKinnon critical values for rejection of hypothesis of a unit root.

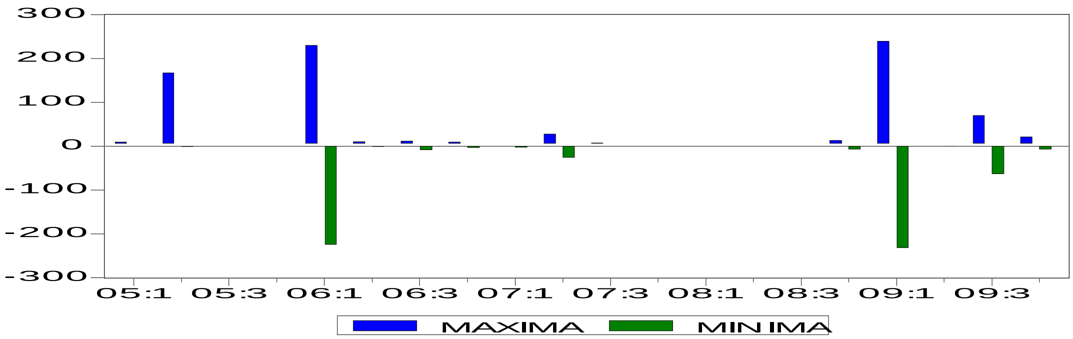
Augmented Dickey Fuller test rejects the existence of unit root in the return series at 0.99 confidence level as appears in the table (1). Descriptive statistics shown in annex (1) reveal that the index is negatively skewed indicating an existence of losses. The kurtosis estimates are highly sensitive to extremely large returns that are apparent in figure (1). The kurtosis of a normally distributed shock is 3 the index daily returns for the period 3/1/2005-31/12/2009 have an extremely high sample kurtosis of 281.95 indicating the rejection of normality assumption and confirmed by Jarque-Bera test of normality and W-test for Normality in figure (1). Applying LM test the F-statistic and Chi square-statistic were 428.28 and 322.46 respectively indicating the rejection of the null hypothesis of homoscadasticity. The Quantile-Quantile plot in figure (2) confirms the rejection of normality hypothesis.

Figure 1: Index and Returns



The number of negative returns is 576 out of 1302 i.e. 44%. Extreme negative values were in 18/1/2006 (-230.2618) and 20/8/2009 (-68.76901) and the positive were in 19/1/2006 (229.915) and 19/8/2009 (69.816). The sample has been divided into twenty blocks (quarters) and the maxima and minima of each block have been plotted below.

Figure 2: Maxima and Minima



GARCH (1,1) estimation results are presented in Annex(3). All estimated parameter are significantly different from zero. The null hypothesis of no ARCH term is accepted. The sum $\alpha + \beta < 1$ so the conditional variance exhibits mean reversion i.e. after a shock it will eventually return to its unconditional mean $w/(1 - \alpha - \beta) = 0.01684$. The computed VaR via GARCH (1,1) at different confidence levels, normal and t distribution are shown in table (2). RiskMetrics the estimation output of IGARCH (1,1) are presented in Annex (4). Historical Simulation for our observation period of 1303 days, the 99th percentile historical simulation value-at-risk measure is the thirty-sixth largest loss (-4.18893334) observed in the sample of 1303 outcomes (because the 1 percent of the sample that should exceed the risk measure equates to thirteen losses).

Empirical quantile

$$\hat{x}_{0.01} = \frac{p_2 - p}{p_2 - p_1} r_{13} + \frac{p - p_1}{p_2 - p_1} r_{14} = \frac{0.0007}{0.00077} * -8.849 + \frac{0.00002}{0.00077} * -8.28 = -8.832$$

Table 3: Value at Risk

Critical Value	Distributio n	Inverse CDF	Generalized Formula	GARCH(1,1)	IGARCH(1,1)
5%	Normal	-1.6446	-22.1638	-0.20091	-0.03175
	t-Student	-1.646	-22.1827	-0.2011	-0.03179
2.5%	Normal	-1.96	-26.4166	-0.24184	-0.04121
	t-Student	-1.9618	-26.4409	-0.24208	-0.04126
1%	Normal	-2.3263	-31.3558	-0.28938	-0.05219
	t-Student	-2.3292	-31.3949	-0.28975	-0.05228
0.5%	Normal	-2.5758	-34.7201	-0.32176	-0.05968
	t-Student	-2.5796	-34.7713	-0.32225	-0.05979

Back-testing Procedure

Unconditional Coverage: The most common test of a VaR model is to count the number of VaR exceptions, i.e. days (or holding periods of other length) when portfolio losses exceed VaR estimates. Denoting the number of exceptions as x and the total number of observations as T, we may define the failure rate as x/T . Results of the backtest at 0.99 confidence levels are shown on the table below:

Table 4: Back Test Results

Method	G. Formula	GARCH(1,1)	RiskMetrics	H. Simulation	E. Quantile
Failure	4	58	193	35	14
Rate %	0.3%	4.5%	15%	2.7%	1%

Thus empirical quantile is the only estimation method that passed the back test. The generalized formula overestimates the risk, while historical simulation, GARCH, and IGARCH underestimates the risk.

Discussion

Khartoum as many stock markets in developing countries is characterized by small size in terms of capitalization as percentage of GP , inefficiency and illiquidity The low level of deepening reflects the lack of small- and medium sized companies that are suitable for listing and trading. Despite the limitations Khartoum market has contributed a number of benefits to the investment climate in Sudan in particular auditing and security awareness. The inspection of the data resulted in the fact that the conditional returns are not normally distributed hence the computed VaR as expected underestimated the true VaR there are more outliers in the true series than in the normally distributed one. The violation of normality assumption led to the use of t-distribution as an alternative. As apparent from table (2) there are slight differences between the computed VaR based on normal and t distribution, no significant improvement has been achieved. The generalized formula which used the actual variance of the historical data overestimated the true VaR. It picked up only four outliers i.e. the extreme outliers. The focus of RiskMetrics on standardized returns implied that the focus should be on the size relative to the standard deviation. In other words, a large return (positive or negative) in a period of high volatility may result in a low standardized return, whereas the same return following a period of low volatility will yield an abnormally high standardized return. Since the focus of value at risk is on the downside risk and potential losses the empirical results of four out five methods used to calculate VaR either overestimate or underestimate the true VaR. This situation entails the use of extreme value theory to fit the distribution of the tail. Fortunately the empirical quantile fitted the true VaR at 99% confidence level. The inefficiency and illiquidity of the stock market can be overcome by encourage collaboration between regional stock exchanges that enable freely buy and sell of shares in these markets. It reduces the costs of international investors, improve liquidity and efficiency.

It is worth mentioning that the ordinary shares in KSE are a contract initiated between at least two partners with one providing all the capital and the other the management of the business. However where in the Western system the risk of asymmetric information is mitigated through extensive legal contracting between parties the premise in its Islamic counterpart is a common adherence to Islamic social values reinforced by shariaa compliance. As such the prohibition of speculation (gharrar) and any form of gambling (qimar), i.e. the manipulation of share prices for personal gain, together with the practices acting to informational disadvantage any party (jahalah) are part of the shariaa code regulating markets which is also reflected in common shared Islamic ethical values

Conclusions and Recommendations

The financial industry and regulatory authorities have clearly recognized that, in order to ensure financial stability, it is imperative to accurately measure financial risks and implement sound risk management. The concept of Value at Risk in particular has received much attention and is now widely accepted as a useful measure of financial risk. It has been examined via variance methods, conditional heteroscedasticity models, and nonparametric methods. Khartoum stock market experienced losses of 44% during the period 1/03/2005 – 12/31/009. From the variety of Value-at-Risk models that has been presented and empirically evaluated only the empirical quantile has passed the back-test.

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Appendix

Annex (1) Descriptive Statistics of Stock Return

	Return (R)	INDEX
Mean	0.000123	2774.64
Median	0.000004	2734.66
Maximum	2.39	4934.22
Minimum	-2.38	243.00
Std. Dev.	0.13	286.75
Skewness	0.05	-0.36
Kurtosis	281.95	13.98
Jarque-Bera	4224475	6575.804
Probability	0.000	0.000
Observations	1303	1303

Annex (2) ARCH Test

F-statistic	428.2843	Probability	0.000
Obs*R-squared	322.4636	Probability	0.000

Annex (3) GARCH(1,1) Output

Dependent Variable: R				
Method: ML – ARCH				
Date: 07/21/13 Time: 18:47				
Sample(adjusted): 1/04/2005 12/31/2009				
Included observations: 1303 after adjusting endpoints				
Convergence not achieved after 500 iterations				
	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	0.012504	7.09E-05	176.3633	0.0000
ARCH(1)	0.265559	0.09234	2.875891	0.0040
GARCH(1)	-0.0081	0.003194	-2.53542	0.0112
R-squared	-1E-06	Mean dependent variable		0.000123
Adjusted R-squared	-0.00154	S.D. dependent variable		0.134843
S.E. of regression	0.134947	Akaike info criterion		-1.76814
Sum squared resid	23.67382	Schwarz criterion		-1.75623
Log likelihood	1154.945	Durbin-Watson stat		2.986091

Annex (4) IGARCG(1,1)

Dependent Variable: LOG(INDEX/INDEX(-1))				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 07/23/13 Time: 01:09				
Sample (adjusted): 1/04/2005 12/31/2009				
Included observations: 1303 after adjustments				
Convergence achieved after 1 iteration				
Presample variance: backcast (parameter = 0.7)				
GED parameter fixed at 1.5				
GARCH = C(1)*RESID(-1)^2 + (1 - C(1))*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
RESID(-1)^2	0.012681	4.36E-07	29112.12	00000000
GARCH(-1)	0.987319	4.36E-07	2266609.6	00000000
R-squared	-0..00001	Mean dependent var		0.000123
Adjusted R-squared	0.000767	S.D. dependent var		0.134843
S.E. of regression	0.134791	Akaike info criterion		42.14553
Sum squared resid	23.67382	Schwarz criterion		42.14950
Log likelihood	-110.995	Hannan-Quinn criter.		42.14702
Durbin-Watson stat	2.986091			

Annex (5) Quarterly Maxima and Minima

Year	Quarter	Maxima	Minima
2005	Q1	9.523391	-4.615233
	Q2	16.2269	-7.292918
	Q3	2.697511	-1.189809
	Q4	2.067756	-0.967817
2006	Q1	229.9152	-230.2619
	Q2	9.829512	-7.549302
	Q3	11.91234	-14.681421
	Q4	8.97564	-9.16949
2007	Q1	5.035629	-8.848809
	Q2	27.9574	-32.03468
	Q3	6.671911	-4.269844
	Q4	3.852317	-4.269844

Annex (5) Quarterly Maxima and Minima (Continued)

2008	Q1	5.062961	-5.067035
	Q2	5.548635	-0.590755
	Q3	4.223577	-5.033596
	Q4	12.98418	-13.01249
2009	Q1	239.1014	-237.931
	Q2	1.26249	-6.104896
	Q3	69.87116	-68.76901
	Q4	21.12289	-13.1843

Annex (6) Annual Maxima and Minima

Year	2005	2006	2007	2008	2009
Maxima	16.22689	229.9152	27.9574	12.98418	239.1014

Null Hypothesis: Log R is a martingale
Date: 12/02/13 Time: 08:35
Sample: 1/03/2005 12/31/2009
Included observations: 341 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	10.63022	341	0.0000

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.536455	0.043606	-10.63022	0.0000
4	0.320561	0.071513	-9.500936	0.0000
8	0.192720	0.099831	-8.086443	0.0000
16	0.110167	0.140603	-6.328704	0.0000

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -0.0112928261439)

Period	Variance	Var. Ratio	Obs.
1	6.58028	--	341
2	3.53002	0.53645	363
4	2.10938	0.32056	351
8	1.26815	0.19272	346
16	0.72493	0.11017	350