An Empirical Analysis of Var Forcasting Techniques for Mena Countrieis

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ABSTRACT

The purpose of this paper is to do a comparative study of the different Value at Risk models' forecasting power using daily stock market indices of seven MENA countries. Historical simulation, variance-covariance method and Monte-Carlo simulation are compared to a benchmark RiskMetrics model and an EVT model. The models are compared for their out of sample predictive ability using White's (2000) reality check. The results show a better forecasting ability of the conventional VaR models on the EVT model for the MENA countries.

INTRODUCTION

All of life is the management of risk, not its elimination as Walter Wriston, former chairman of Citicorp once declared. Risk management for corporations is of utmost importance: the ones who are able to manage and overcome risks succeed and thrive, while those who let themselves expose to risk, are doomed. Risk management is the process by which various risk exposures are identified, measured and controlled. As simple as this definition sounds, there is no exact way to quantify risk. Risk can be defined as the volatility of the underlying asset's price or the degree of uncertainty about the asset's future value. Recent financial disasters in financial and non-financial firms and in governmental agencies increase the need for various forms of risk management. Financial misadventures are not new phenomenon, but the increase in their occurrence is a new phenomenon. The savings and loan (S&L) crisis in the United States was a major disaster. The manager of the Orange County Investment Pool (OCIP) took less than three years to increase that quasi-bank's potential one-month loss from a significant but perhaps manageable 1.8% to a disastrous 5% of its investors' deposit-like claims. Anyone who is aware of the leverage inherent in various interest rate derivatives knows he could have done this faster and even more ruinously had he set his mind to it. To their credit, most regulatory authorities appear to recognize that the core of the problem is not derivatives per se but inadequate risk management. Risk management is the process by which managers satisfy these needs by identifying key risks, obtaining consistent, understandable, operational risk measures, choosing which risks to reduce and which to increase and by what means, and establishing procedures to monitor the resulting risk position. Risk, in this context, may be defined as reductions in firm value due to changes in the business environment. Typically, the major sources of value loss are identified as: *Market risk* is the change in net asset value due to changes in underlying economic factors such as interest rates, exchange rates, and equity and commodity prices. *Credit risk* is the change in net asset value due to changes the perceived ability of counter-parties to meet their contractual obligations. *Operational risk* results from costs incurred through mistakes made in carrying out transactions such as settlement failures, failures to meet regulatory requirements, and untimely collections. *Performance risk* encompasses losses resulting from the failure to properly monitor employees or to use appropriate methods including model risk.

Market risk is the most important of the four risks because it has the most dramatic loss effect on the firm. One method to measure market risk is the Value at Risk (VaR) value. VaR is a measure of the maximum loss during a given number of days with a certain probability. In simpler words, it is a number that indicates how much a financial institution can lose with probability q over a given time horizon. The popularity of VaR comes from the fact that it reduces the market risk associated with any portfolio to just one number that is the loss associated with a given probability.

There is a vast literature on VaR and risk modeling. One of the earliest studies on VaR by Allen (1994) compares the performance of historical simulation using Monte-Carlo technique to variance covariance approach. Beder (1995) compares eight different VaR methodologies and classifies them with respect to their performance. Jamshidian and Zhu (1997) compares the efficiency of Monte-Carlo simulations to variance-covariance approach for options and other derivatives. A major disadvantage of VaR models is its inability to capture extreme price movements during financial turmoil. This fact arises from the normality assumption used in the VaR models. Zangari (1996) investigates VaR models under non-normality assumption. The normality assumption of VaR models makes the forecasts done during times of stress and turmoil inaccurate. Danielsson (2000) argues on the same idea saying that the analysis done during times of stability cannot provide guidance in times of crisis. He argues that using historical prices to forecast the future does not have any accurate results during crisis periods.

To correct for this inaccuracy in VaR estimates, recent research has been directed towards using Extreme Value Theory (EVT) in VaR models. Danielsson (2000) compares GARCH models to an EVT method and concludes that both GARCH and EVT do not have good performance criteria. He suggests not using those methods by regulators. Danielsson and Morimoto (2000) use a VaR model based on EVT to forecast the Japanese market risk, without getting significant results. Despite the recent questions about VaR based models to capture the market risk and its adequacy as a measure for risk. VaR remains a very useful tool to give a simple measure of risk.

IMPORTANCE OF THE STUDY ON MENA COUNTRIES

The VaR analysis on MENA countries have important implications on the investment strategy for any fund manager or corporate company who want to invest in the region. The VaR analysis on the stock market indices indicate the maximum loss an investor can expect at a given confidence level. The globalization of the world economy and the investment opportunities present in the region incites many investors to consider the MENA region as a lucrative opportunity to invest. For this global investor, VaR presents a simple, convenient and accurate measure of the worse case expected loss that he can suffer with a certain probability.

The last 10 years have witnessed major liberalization processes in the MENA region. The major findings about the liberalization in the MENA region can be found in the working paper of Bekaert, Geert, Harvey and Lundblad (2004). After the liberalization takes place, the MENA countries are open to foreign investors. One major issue raised in the Bekaert, Geert, Harvey and Lundblad paper is the high market volatility of the liberalized countries. This high volatility can affect negatively an investor who wants to invest in one of the MENA countries. Here comes VaR measure’s importance. VaR is a very convenient measure to measure in one number the market volatility. Thus a good forecast of any MENA country would be an excellent indicator for any investor about the risk he’s facing when investing in this particular country.

DATA AND METHODOLOGY

The purpose of this paper is to compare the relative predictive performance of various VaR models for a sample of Middle East and North African (MENA) countries. Several traditional VaR models are used along with an EVT based model. I use three standard VaR models namely the variance-covariance method, historical simulation and Monte-Carlo Simulation. Those methods are widely referred in the literature and academic books. A complete review of those methods can be found in the books of Jorion (2000) and Hull (2003). I use both ARCH and GARCH tools for the three models mentioned above. For the EVT model, I use the generalized extreme value (GEV) distribution. Longin (1996, 2000) uses this approach to forecast risk. Overall I do a comparison of four different VaR models’ performance and their out-of-sample predictive ability.

The daily stock market indices of the following countries Bahrain, Egypt, Israel, Jordan, Morocco, Saudi Arabia and Turkey from 1996 to 2002 are used in this paper. I compare the VaR forecasts generated by the four models for 1999-2000 and 2001-20002 out of sample periods.

The main finding in the paper is surprisingly in favor of the traditional standard models. The EVT model did not perform better than the 3 standard models. In fact, the EVT method was the worse among the 4 methods used.

The paper is organized as follows. In section 2 I present the four VaR models used and the forecasting techniques used. Section 3 presents the empirical results. Section 4 presents the policy implications of the results. Section 5 concludes.

Forecasting Variability

The number of models that exist estimating volatility are is getting bigger and bigger every day. Also the level of complexity of those models is getting higher. The different volatility models are the following: The most influential models were the first: the GARCH model of Bollerslev(1986), and the EGARCH of Nelson(1991). Asymmetric models of Glosten, Jaganathan Runkle(1993) Rabemananjara and Zakoian(1993), Engle and Ng(1993) and power models such as Higgins and Bera(1992), Engle and Bollerslev(1986), and Ding Granger and Engle(1993) joined models such as SWARCH, STARCH, QARCH and many more. All those models try to estimate very accurate volatility measures. However the level of their complexity is very high, sometimes this complexity level makes it hard to grasp for the average person. The average investor needs to know about the volatility of a particular asset or portfolio in a simple and accurate manner. From here stems the important of the VaR model. VaR measures the volatility in one figure which is very easy to understand and interpret.

Var Models

The Value at Risk of a financial asset is defined as $VaR_t(\alpha)$ can be defined as the conditional quantile:

$\Pr(y_t \leq VaR_t(\alpha) | F_{t-1}) = \alpha$

If $\{yt\}_{t=1}$ follows a stochastic process such as yt=μt+εt, where E(εt|Ft−1)=0 and $E(\varepsilon_t^2|Ft-1)=\sigma^2$ given the information set Ft−1(σ-field) at time t− 1.Let zt =εt/σt have the conditional distribution Φt with zero conditional mean and unit conditional variance, i.e., zt|Ft−1 − Φt(0,1).

The three standard methods that I used to estimate the VaR are explained in the following.

Christoffersen and White Testing Methodology

Christoffersen (1998) and White (2000) developed tests to evaluate the out-of sample forecast accuracy. The evaluation of out of sample forecasts is done as follows. There are n predictions in each of the five models used. The first prediction is based on the model with parameters 1 to R, the next prediction is based on 2 to R+1 etc. When we compare those estimates with the benchmark model in our case RM (0.97) we want to find the likelihood of the coverage of those models against the benchmark model. This is the Christoffersen test. It is a likelihood ratio of the maximum coverage. The reality test on the other hand is a test to predict the forecasting ability of the different models with the correcting done to prevent any dependence among models. This test is developed by White (2000).

Variance-covariance approach

The variance/covariance approach is based on the assumption that the underlying market factors have a multivariate normal distribution. Using this assumption, it is possible to determine the distribution of market portfolio profits and losses, which is also normal. Once the distribution of possible portfolio profits and losses has been obtained, standard mathematical properties of the normal distribution are used to determine the loss that will be equaled or exceeded *x* percent of the time, i.e. the value at risk.

For example, suppose a portfolio consisting of a single instrument, the 3-month FX forward contract, and also assume that the holding period is one day and the probability is 5%. The distribution of possible profits and losses on this simple portfolio can be represented by the normal probability density function. This distribution has a mean of zero, which is reasonable because the expected change in portfolio value over a short holding period is almost always close to zero. The standard deviation, which is a measure of the spread or dispersion of the distribution, is approximately $52,500. A standard property of the Normal distribution is that outcomes less than or equal to 1.65 standard deviations below the mean occur only 5 percent of the time. That is, if a probability of 5 percent is used in determining the value at risk, then the value at risk is equal to 1.65 times the standard deviation of changes in portfolio value. Using this fact,

From this, it should be clear that the computation of the standard deviation of changes in portfolio value is the focus of the approach. While the approach may seem rather like a "black box" because it is based on just a handful of formulas from statistics textbooks, it captures the determinants of value at risk mentioned above. It identifies the intuitive notions of variability and co-movement with the statistical concepts of standard deviation (or variance) and correlation. These determine the variance-covariance matrix of the assumed normal distribution of changes in the market factors.

Historical simulation

Historical simulation is a simple approach that requires relatively few assumptions about the statistical distributions of the underlying market factors. To illustrate the procedure with a simple portfolio consisting of a single instrument, the 3-month FX forward for which the distribution of hypothetical market profits and losses is assumed to be normal. In essence, the approach involves using historical changes in market rates and prices to construct a distribution of potential future portfolio profits and losses, and then reading off the value at risk as the loss that is exceeded only 5% of the time.

The distribution of profits and losses is constructed by taking the *current* portfolio, and subjecting it to the *actual* changes in the market factors experienced during each of the last N periods, here days. That is, N sets of hypothetical market factors are constructed using their current values and the changes experienced during the last N periods. Using these hypothetical values of the market factors, N hypothetical mark-to-market portfolio values are computed. Doing this allows one to compute N hypothetical mark-to-market profits and losses on the portfolio, when compared to the current mark-to-market portfolio value. Even though the actual changes in rates and prices are used, the mark-to-market profits and losses are hypothetical because the current portfolio was not held on each of the last N periods. The use of the actual historical changes in rates and prices to compute the hypothetical profits and losses is the distinguishing feature of historical simulation, and the source of the name.

Monte Carlo Simulation

The Monte Carlo simulation methodology has a number of similarities to historical simulation. The main difference is that rather than carrying out the simulation using the observed changes in the market factors over the last N periods to generate N hypothetical portfolio profits or losses, one chooses a statistical distribution that is believed to adequately capture or approximate the possible changes in the market factors. Then, a pseudo-random number generator is used to generate thousands or perhaps tens of thousands of hypothetical changes in the market factors. These are then used to construct thousands of hypothetical portfolio profits and losses on the current portfolio, and the distribution of possible portfolio profit or loss. Finally, the value at risk is then determined from this distribution.

Extreme Value Theory

The major critique against the traditional VaR methods is the fact that those methods ignore the extreme values and directly focus on the whole distribution for risk measurements. The extreme values are located at the tails of the return distributions. The focus of the EVT is to model the tails rather than the entire return distribution. There are numerous theoretical and empirical papers on EVT, for a good overview the paper by Embrehcts et al (1997) is a good choice. The EVT method used in this paper is GEV as described in Longin (1996, 2000) papers.

Empirical Results

Stock market indices are obtained from The EMBD database for Bahrain, Egypt, Jordan, Israel, Morocco, Saudi Arabia, and Turkey. The results are presented in alphabetical order. The sample period of the data is from 1996 to 2002. I compare the VaR forecasts generated by the four models for 1999-2000 and 2001-20002 out of sample periods.

The models are estimated using R=937 observations. The out-of-sample forecast evaluation is conducted over two sub-periods, Period 1 (1999–2000, P= 127), Period 2 (2001–2002 P=127). Summary statistics of the return distributions are not reported in this paper. The data used in this paper is slightly shorter than most of the similar studies done for other markets. This is due to the fact that I only gathered my data from one source. For a longer period of data on similar markets, there’s the study done by Ho et al (2000).

The empirical analysis conducted in this paper have a number of implications for predictive performance of various VaR models – for 7 countries, for 2 out-of-sample periods, for two-tail probabilities (α=0.01, 0.05).

In tables 1-7, the results of Christoffersen’s (1998) tests for coverage probabilities corresponding to various VaR models presented. The most important finding is that the risk forecasting performance of the ARCH family, GARCH with normal distribution GarchN, is much better than the EVT model. GarchN model produces the best conditional and unconditional probabilities for Bahrain and Egypt, the EVT model does not produce any satisfactory probability coverage for these two countries. The performance of the EVT model is more satisfactory for the remaining countries in the sample. Another point to mention is that the

GarchN model and the MC model are less sensitive to the choice of the confidence level α than the EVT model.

The reality check presented in tables 8 to 14 is done using White (2000) procedure. The results obtained show that the predictive power of many VaR models perform better than the benchmark model RM(0.97). The majority of p-values are small, and they're smaller for period 2. Again, this shows that many models perform better than the benchmark model by generating better forecasts. The forecasting ability of the EVT model seems weak for all the countries studied in this paper except for Bahrain and Egypt. In the latter two cases also the forecasts results of the EVT model are not significantly different from the traditional models like the historical simulation and the Monte Carlo method.

CONCLUSION

In this paper a comprehensive predictive assessment of VaR models is studied. I assess 6 different VaR models using 2 different reality checks. The Riskmetrics RM(097) is used as benchmark model for comparison. The interval forecasting test of Christoffersen (1998) is also used. According to Christoffersen tests the traditional models, ARCH family, produce much better results than the EVT model. The reality check test shows that again traditional models produce better forecasts than the EVT model. This conclusion is consistent with Danielsson (2000). As far as comparing EVT with Monte-Carlo method, the results show that Monte-Carlo method produce better forecasts than the EVT model.

APPENDIX

			Period1						Period2			
Model	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2
RM(0.97)	0.043	0.31	9.54	0.019	3.5	12.68	0.073	5.08	11.17	0.025	3.84	10.25
MA(200)	0.048	0.06	21.18	0.017	1.3	2.64	0.079	7.75	15.02	0.041	4.39	8.31
GarchN	0.047	0.04	16.25	0.012	0.11	0.17	0.071	4.31	3.87	0.019	0.76	10.25
HS	0.071	3.61	29.63	0.005	2.61	0.02	0.203	152.4	12.09	0.073	0.24	19.37
MC	0.008	30.08	0.06	0.004	2.61	0.01	0.111	31.06	9.04	0.057	1.82	3.5
Longin	0.151	70.12	15.36	0.012	0.11	3.79	0.301	347.02	17.94	0.143	0.76	10.25
			Period1						Period2			
Model	B0.05k	RC1	RC2	B0.01k	RC1	RC2	B0.05k	RC1	RC2	B0.01k	RC1	RC2
RM(0.97)	5.41	0.127	0.255	7.38	0.177	0.322	5.67	0.196	0.358	7.7	0.277	0.559
MA(200)	6.76	0.88	0.396	9.04	0.678	0.539	5.98	0.537	0.519	7.97	0.444	0.738
GarchN	6.52	0.891	0.434	7.9	0.465	0.583	6.17	0.789	0.577	8.39	0.609	0.776
HS	6.47	0.846	0.461	7.9	0.485	0.583	6.22	0.808	0.596	8.12	0.475	0.819
MC	6.47	0.823	0.461	8.1	0.612	0.672	6.17	0.787	0.596	8.39	0.58	0.819
Longin	7.25	0.914	0.547	9.65	0.709	0.767	6.78	0.907	0.66	10.97	0.766	0.885

Table 1: Christoffersen Tests and Reality check tests: Bahrain

			Period1						Period2			
Model	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2
RM(0.97)	0.06	0.94	3.92	0.012	0.11	0.14	0.084	10.88	6.87	0.017	2.29	0.32
MA(200)	0.061	1.39	4.19	0.01	0	0.1	0.081	8.74	10.94	0.017	2.29	7.36
GarchN	0.065	2.34	0.94	0.015	1.29	0.25	0.075	5.92	5.08	0.017	2.29	0.32
HS	0.077	6.8	2.68	0.012	0.11	0.14	0.081	8.74	14.05	0.023	6.53	5
MC	0.061	1.34	0.54	0.01	0	0.1	0.083	9.79	3.26	0.017	2.29	0.32
Longin	0.058	0.6	0.05	0.01	0	0.1	0.081	8.74	3.67	0.017	2.29	0.32
			Period1						Period2			
Model	B0.05k	RC1	RC2	B0.01k	RC1	RC2	B0.05k	RC1	RC2	B0.01k	RC1	RC2
RM(0.97)	6.68	0.851	0.567	9.37	0.73	0.784	6.69	0.894	0.662	10.33	0.771	0.893
MA(200)	7.47	0.908	0.614	10.36	0.705	0.811	6.97	0.921	0.69	10.97	0.759	0.893
GarchN	6.58	0.918	0.617	8.28	0.584	0.817	6.16	0.783	0.695	8.17	0.517	0.897
HS	6.21	0.728	0.621	8.1	0.631	0.817	6.16	0.747	0.695	8.17	0.52	0.897
MC	6.47	0.838	0.621	8.1	0.612	0.817	6.17	0.78	0.695	8.54	0.586	0.9
Longin	9.04	0.869	0.715	13.36	0.716	0.86	8.83	0.861	0.792	13.04	0.703	0.916

Table 2: Christoffersen Tests and Reality Check Tests: Egypt

			Period1					Period2			
Model	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2
RM(0.97)	0.065	2.34	0.02	0.013	0.56	0.19	0.083	9.79	0.11	0.012	0.11	0.14
MA(200)	0.065	2.34	1.36	0.013	0.56	0.19	0.086	12.03	0.36	0.012	0.11	0.14
GarchN	0.046	0.17	5.28	0.004	2.61	0.01	0.171	101.16	0.6	0.017	2.29	0.32
HS	0.274	283.22	5.43	0.192	419.93	10.15	0.426	649.94	4.17	0.359	588.11	2.24
MC	0.027	7	3.84	0.008	0.31	0.06	0.146	68.07	1.76	0.054	49.61	0.17
Longin	0.077	6.81	0.3	0.012	0.11	0.14	0.19	129.77	0.38	0.06	60.3	0.51
			Period1						Period2			
Model	B0.05k	RC1	RC2	B0.01k	RC1	RC2	B0.05k	RC1	RC2	B0.01k	RC1	RC2
RM(0.97)	4.77	0.804	0.836	8.56	0.811	0.787	8.22	0.816	0.818	11.46	0.692	0.689
MA(200)	4.48	0.409	0.66	7.14	0.184	0.531	7.4	0.236	0.5	8.71	0.244	0.523
GarchN	5.05	0.875	0.76	8.21	0.713	0.697	8.9	0.854	0.627	13.73	0.72	0.589
HS	4.55	0.536	0.856	7.83	0.576	0.728	7.41	0.31	0.69	8.35	0.257	0.586
MC	4.62	0.594	0.859	7.83	0.565	0.728	7.37	0.29	0.688	8.28	0.269	0.613
Longin	4.49	0.46	0.874	7.59	0	0.728	7.42	0.283	0.699	8.35	0.244	0.613

Table 3: Christoffersen Tests and Reality Check tests: Israel

			Period1						Period2			
Model	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2
RM(0.97)	0.043	0.31	9.54	0.019	3.5	12.68	0.073	5.08	11.17	0.025	3.84	10.25
MA(200)	0.048	0.06	21.18	0.017	1.3	2.64	0.079	7.75	15.02	0.041	4.39	8.31
GarchN	0.047	0.04	16.25	0.012	0.11	0.17	0.071	4.31	3.87	0.019	0.76	10.25
HS	0.071	3.61	29.63	0.005	2.61	0.02	0.203	152.4	12.09	0.073	0.24	19.37
MC	0.008	30.08	0.06	0.004	2.61	0.01	0.111	31.06	9.04	0.057	1.82	3.5
Longin	0.151	70.12	15.36	0.012	0.11	3.79	0.301	347.02	17.94	0.143	0.76	10.25
			Period1						Period2			
Model	B0.05k	RC1	RC2	B0.01k	RC1	RC2	B0.05k	RC1	RC2	B0.01k	RC1	RC2
RM(0.97)	4.69	0.691	0.858	7.5	0.449	0.829	7.44	0.336	0.103	8.35	0.235	0.607
MA(200)	4.58	0.558	0.859	7.83	0.56	0.829	7.41	0.319	0.103	8.35	0.257	0.607
GarchN	4.53	0.525	0.862	7.84	0.577	0.839	7.38	0.28	0.103	8.35	0.264	0.607
HS	5.61	0.933	0.888	11.68	0.757	0.875	6.61	0.108	0.104	12.27	0.733	0.617
MC	2.89	0.009	0.021	3.44	0.061	0.345	4.28	0.004	0.005	4.76	0.127	0.307
Longin	2.83	0.01	0.015	3.34	0.069	0.335	4.25	0.003	0.004	4.64	0.12	0.297

Table 4: Christoffersen Tests and Reality Check tests: Jordan

			Period1						Period2			
Model	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2
RM(0.97)	0.069	3.59	2.36	0.015	1.3	0.25	0.073	5.08	3.44	0.01	0.01	0.1
MA(200)	0.065	2.34	1.36	0.012	0.11	0.14	0.061	1.34	3.92	0.015	1.3	0.25
GarchN	0.071	4.31	2.04	0.017	2.29	0.32	0.084	10.87	6.87	0.01	0.01	0.1
HS	0.061	1.34	9.56	0.013	0.56	0.19	0.048	0.04	0.5	0.01	0.01	0.1
MC	0.063	1.81	0	0.013	0.56	0.19	0.083	9.79	0.11	0.012	0.11	0.14
Longin	0.061	1.34	0	0.013	0.56	0.19	0.084	10.87	0.49	0.013	0.56	0.19
			Period1						Period2			
Model	B0.05k	RC1	RC2	B0.01k	RC1	RC2	B0.05k	RC1	RC2	B0.01k	RC1	RC2
RM(0.97)	3.9	0.811	0.807	4.43	0.543	0.526	9.03	0.85	0.825	11.39	0.678	0.689
MA(200)	3.34	0.085	0.129	4.29	0.448	0.699	8.83	0.54	0.72	10.13	0.247	0.368
GarchN	3.89	0.678	0.235	5.29	0.757	0.792	8.55	0.427	0.567	11.26	0.584	0.56
HS	3.82	0.677	0.26	5.09	0.696	0.882	8.64	0.396	0.678	9.66	0.258	0.526
MC	2.91	0.035	0.036	4.16	0.408	0.874	7.93	0.134	0.282	9.21	0.172	0.426
Longin	3.37	0.112	0.036	4.34	0.52	0.881	8.57	0.331	0.292	10.03	0.274	0.459

Table 5: Christoffersen Tests and Reality Check tests: Morocco

			Period1						Period2			
Model	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2
RM(0.97)	0.052	0.04	3.76	0.013	0.56	0.19	0.073	5.09	1.74	0.019	3.5	0.39
MA(200)	0.042	0.7	1.04	0.01	0	0.1	0.065	2.34	0	0.023	6.53	0.56
GarchN	0.06	0.93	4.39	0.013	0.56	0.19	0.081	8.74	0.12	0.021	4.92	0.47
HS	0.025	8.36	0.97	0.01	0	0.1	0.094	17.1	6.14	0.036	21.96	1.82
MC	0.031	4.7	1.01	0.008	0.31	0.06	0.084	10.88	0.17	0.013	0.56	0.19
Longin	0.042	0.7	1.94	0.01	0	0.1	0.079	7.75	0.01	0.019	3.5	0.39
			Period1						Period2			
Model	B0.05k	RC1	RC2	B0.01k	RC1	RC2	B0.05k	RC1	RC2	B0.01k	RC1	RC2
RM(0.97)	2.55	0.031	0.022	3.38	0.134	0.611	5.38	0.006	0.007	6.55	0.06	0.142
MA(200)	3.29	0.168	0.022	4.61	0.632	0.62	6.47	0.02	0.007	8.23	0.149	0.142
GarchN	3.81	0.623	0.022	4.7	0.635	0.635	8.99	0.643	0.007	10.15	0.337	0.144
HS	3.01	0.046	0.022	4.01	0.316	0.637	8.15	0.159	0.007	9.07	0.139	0.144
MC	3.37	0.126	0.022	4.39	0.5	0.646	8.35	0.245	0.007	9.68	0.203	0.144
Longin	3.49	0.301	0.023	7.63	0.767	0.698	6.43	0.022	0.007	10.31	0.362	0.147

Table 6: Christoffersen Tests and Reality check tests: Saudi Arabia

			Period1						Period2			
Model	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2	ˆp0.05k	LR1	LR2	ˆp0.01k	LR1	LR2
RM(0.97)	0.05	0	0.08	0.017	2.29	0.32	0.075	5.92	1.47	0.023	6.53	5.01
MA(200)	0.056	0.34	0.1	0.015	1.3	0.25	0.063	1.81	3.49	0.019	3.5	1.82
GarchN	0.058	0.6	0.05	0.021	4.93	0.47	0.084	10.87	1.46	0.021	4.92	5.7
HS	0.042	0.7	0	0.013	0.56	0.19	0.073	5.09	5.61	0.023	6.53	1.21
MC	0.042	0.7	1.94	0.019	3.5	0.39	0.065	2.34	3.08	0.015	1.3	0.25
Longin	0.04	1.1	0.03	0.019	3.5	0.39	0.063	1.81	1.62	0.015	1.3	0.25
			Period1						Period2			
Model	B0.05k	RC1	RC2	B0.01k	RC1	RC2	B0.05k	RC1	RC2	B0.01k	RC1	RC2
RM(0.97)	2.13	0.013	0.013	3.01	0.102	0.58	4.36	0	0	5.34	0.041	0.056
MA(200)	2.06	0.013	0.01	2.76	0.069	0.532	4.4	0.003	0	5.13	0.033	0.048
GarchN	6.16	0.811	0.319	7.63	0.772	0.532	8.78	0.502	0	10.75	0.449	0.05
HS	5.85	0.828	0.344	7.63	0.777	0.532	8.78	0.507	0	10.62	0.403	0.05
MC	3.74	0.582	0.344	4.22	0.434	0.532	8.85	0.509	0	9.7	0.197	0.05
Longin	3.25	0.177	0.344	4.38	0.529	0.532	6.39	0.014	0	7.5	0.111	0.05

Table 7: Christoffersen Tests and Reality check tests: Turkey

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