Modelling Risk on the Egyptian Stock Market: Evidence from a Markov-Regime Switching GARCH Process.

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This research aims at evaluating among market risk measures to equity exposures on the Egyptian stock market, while utilising a variety of parametric and non-parametric methods to estimating volatility dynamics. Historical Simulation, EWMA (RiskMetrics), GARCH, GJR-GARCH, and Markov-Regime switching GARCH models are empirically estimated. Value at Risk and Conditional Value at Risk measures are backtested in order to evaluate among the alternative models. Results indicate the superiority of asymmetric GARCH models when combined with a Markov-Regime switching process in quantifying market risk - as is evident from the results of the backtests - which have been performed in accordance with the current regulatory demands. Implications are important to regulators and practitioners.

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1. Introduction

Perhaps one of the oldest books ever attempting to describe risk in financial markets is "*Confusion of Confusions" (1688)*, written by Joseph de la Vega, who was an active trader on the stock exchange in Amsterdam by then (Dumez, 2015). Developing sound risk management policies in financial institutions is of current prominence to both industry practitioners and regulators. Different types of risk are distinguished in the finance literature; in specific, financial risk could take the form of credit risk (due to counterparty default probabilities), liquidity risk (due to capital losses on an asset arising from insufficient market activity), or market risk (due to changes in asset prices), among others (van den Goorbergh and Vlaar, 1999; Billinger and Eriksson, 2009).

This research focuses on the concept of market risk, and in specific, the concept of Value at Risk (VaR), which measures the maximum loss that might be realised on an investment; over the course of a given time period (van den Goorbergh and Vlaar, 1999). Conditional Value at Risk (CVaR) extends VaR by giving the conditional value of the loss, given that the VaR level is exceeded (McNeill et al, 2005 pp 44). The research will be focusing on VaR and CVaR as they have been the regulatory standards for quantifying market risk as is evident under the current Basel III framework, which requires banks and financial institutions to hold minimum capital requirements, in line with their market risk exposure on their trading books (BIS, 2019).

The analysis, therefore, aims at quantifying market risk on the books of banks and financial institutions trading on the Egyptian stock market. The EGX30 benchmark index, and the EGX70 index, which represent the top 100 performing stocks in terms of trading activity, will be used as proxies to the equity market in the analysis. In order to compute VaR and CVaR, several models to volatility will be estimated, and which will then be backtested by a variety of methodologies that are based on the current financial regulatory frameworks and industry practices.

2. Literature Review

In order to measure market risk, a suitable model for volatility needs to be estimated. The following literature review would therefore start by giving an overview on volatility, and on different models which could be used to estimate it. The following section would then give an overview on market risk and on VaR and CVaR estimation methodologies. Finally, the literature review would also briefly discuss the previous research findings, and the purpose of this research; before moving on to the methodology and empirical results.

2.1 Market Volatility

Historical models to volatility use available price data (P_t) in order to estimate returns (r_t). Given the assumption that changes in asset prices (ie returns) are i.i.d (ie strong white noise), volatility (σ) could be expressed in terms of sample variance (ie mean deviations of returns) this is also called the unconditional variance. (Alexander, 2008 pp132; Kempthorne et al, 2013)

with,
$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$$

where,
$$\sigma_t = \sqrt{var(r_t)} = \sqrt{E[(r_t - E[r_t])^2]}$$

A simple forecasting model where volatility is assumed to be a simple random walk with white noise centered around its lagged value (Poon, 2005 pp32);

$$\sigma_t = \sigma_{t-1} + \varepsilon_t$$

Therefore, a simple estimate for tomorrow's volatility ($\hat{\sigma}_{t+1}$) could be today's calculated volatility,

$$\hat{\sigma}_{t+1} = \sigma_t$$

Another method, the simple moving average, takes a prespecified rolling window forecast τ, where the estimate for tomorrow's volatility is the simple average of the past τ observations.

$$\hat{\sigma}_{t+1} = \frac{1}{\tau}(\sigma_t + \sigma_{t-1} + \cdots + \sigma_{t-\tau-1})$$

The exponential smoothing method is an extension of the moving average (Alexander, 2008 pp120, 129; Poon, 2005 pp33) which weights observations in favour of the most recent past. An exponentially weighted average (EWMA) method combines a moving average with exponential smoothing.

The RiskMetrics approach as has been developed by the US investment bank JP Morgan uses the EWMA in modelling volatility where lambda (λ) is a decay factor which shows the importance of volatility at time t (${\hat{\sigma}^2}_t$) relative to the squared returns at time t (R_t^2) which have the weights (1-λ). This is an empirical formula that is based on findings by RiskMetrics where λ normally takes a value of 0.94 for daily returns (RiskMetrics, 1996; van den Goorbergh and Vlaar, 1999; Billinger and Eriksson, 2009).

The formula[1] is recursive[2] which is described as follows:

$$\hat{\sigma}^2{}_{t+1} = \lambda\sigma_t^2 + (1-\lambda)r_t^2,$$

where, $$\hat{\sigma}_{t+1} = \sqrt{\hat{\sigma}^2{}_{t+1}}$$

2.1.1 GARCH Volatility Models

Volatility in financial markets exhibits clustering (Plot 3), a volatile period would tend to persist for a time period before returning to normal. Engle (1982) addresses this issue by proposing the Autoregressive Conditional Heteroscedasticity (ARCH) model in order to capture volatility clustering. Contrary to the historical volatility models, ARCH models do not use past standard deviations, but instead formulate a conditional variance (h_t) as a byproduct of the return equation via maximum likelihood procedures (we will be denoting ${\sigma^2}_t = h_t$ to follow the ARCH literature) (Poon, 2005 pp37).

The ARCH(q) model is described as follows:

$$r_t = \mu + \varepsilon_t,$$
$$\varepsilon_t = \sqrt{h_t}z_t$$
$$h_t = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2$$

Where the process z_t is is a white noise distribution and could take multiple forms and is scaled by the unconditional variance h_t, which is itself a function of past squared residuals. ω > 0 and α_j ≥ in order to ensure h_t is strictly positive. A more general model to volatility is the Generalised ARCH (p,q) of Bollerslev (1986) –

[1] More details on the assumptions of the formula could be found on the RiskMetrics Technical Document (1996).

[2] A more general representation is given by ${\hat{\sigma}^2}_t = \lambda^t\sigma_0^2 + (1-\lambda)\sum_{k=0}^{t-1}\lambda^k\, r_{t-k}^2$; the EWMA is considered a special case for the GARCH model as is described in the following section (van den Goorbergh and Vlaar, 1999; Alexander, 2008 pp120)

GARCH(p,q); where additional p lags of h_t are permitted as dependencies[3] in the model, and where $\beta_i \geq 0$:

$$h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2$$

Another phenomenon, which is also present in return series is the leverage effect. The leverage effect is where volatility tends to increase following negative returns than they do following similar-sized positive returns. One of the models within the GARCH family that allows for this effect is the GJR GARCH of (Glosten, Jagannathan and Runkle, 1993) where they add an extra leverage (δ) parameter, which would augment the volatility response only from negative shocks. This is where the indicator function D = 1, otherwise, if the past returns are positive, the normal GARCH estimation are used with D = 0 (Francq and Zakoian, 2019 pp42, 345; Poon, 2005 pp37; Alexander, 2008 pp131).

$$h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} (\alpha_j \varepsilon_{t-j}^2 + \delta_j D_{j,t-1} \varepsilon_{t-j}^2)$$

$$D_{t-1} = \begin{cases} 1 \text{ if } \varepsilon_{t-1} < 0 \\ 0 \text{ if } \varepsilon_{t-1} \geq 0 \end{cases}$$

2.1.2 Regimes in Volatility Models

When variants of the GARCH model are fitted empirically over sub-periods of longer time series, the estimated parameters would significantly differ, which indicates changing dynamics over time (Francq & Zakoian, 2019 pp353). One approach to modelling such changing volatility levels is to use a regime-switching framework whereby volatility persistence could take different values depending on whether it belongs to a high or low volatility regime; these classes of models are called normal and finite mixture GARCH (Alexander, 2008 pp163).

The basic idea is a *K* state volatility model, for example, a normal mixture GARCH (p,q) could be specified as follows for *i = {1, ..., K}* where *i* is a set of *K* different conditional variance specifications (ie normal mixture GARCH regimes) (Alexander and Lazar, 2004).

$$h_{it} = \omega_i + \sum_{k=1}^{K} \sum_{j=1}^{p} \beta_{ikj} h_{k,t-j} + \sum_{j=1}^{q} \alpha_{ij} \varepsilon_{t-j}^2$$

Where the probability of switching from one regime to the other does not vary over time[4]. Another way to model changes in regimes is to assume a Markov-Regime switching property where the probability of volatility switching from one regime to the other is allowed to vary over time by assuming a Markov Chain (Alexander, 2008 pp163; Haas, 2004).

The Markov Chain process Δ_t, where $t \geq 0$ with a discrete set of finite state space[5] non-negative integers $\mathbb{N}$ =

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[3] In this specification, the parameter omega (ω) corresponds to the long run (ie unconditional) variance, and the parameters alpha (α) and beta (β) give corresponding weights to the lagged squared residuals and the unconditional variance. It is evident from this specification that the EWMA takes the form of a GARCH model with no mean reversion (ie no omega coefficient), and with the parameters α and β replaced by $1-\lambda$ and λ respectively (van der Ghoorbergh and Vlaar, 1999; Alexander, 2008 pp120).

[4] The probabilities of the normal mixture GARCH models are computed at simultaneous points in time as being random draws on a Bernoulli variable with a constant probability of success; in other words, the probability that volatility is in state t is independent of the state of volatility in state t-1 (Alexander, 2008 pp63).

[5] The state space model (SSM) is an approach utilized to dynamic models of time series where unobserved (ie latent) components are modelled, and which has had many applications in financial economics (Bhar and Hamori, 2004).

{1, ..., D} (Francq and Zakoian, 2019).

Markov Chains are stochastic processes, alongside various other processes such as that of the random walk process which was outlined above (Bhar and Hamori, 2004). Considering a volatility process that transmits the binary digits 0 or 1 for low volatility and high volatility regimes respectively. Over time the probability that volatility will remain in the same regime at the consecutive observation is denoted by p (ie p_{00} and p_{11}), while the probability that volatility will switch regimes is denoted by 1-p (ie p_{01} and p_{10}) (Bhar and Hamori, 2004).

A two-state Markov-Chain, therefore, has the following transitional probability matrix:

$$P = \begin{bmatrix} p & 1-p \\ 1-p & p \end{bmatrix} = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}$$

The MS-GARCH(p,q) process, for k = *{1, ..., D}* regimes, is therefore given by:

$$h_t = \omega(\Delta_t) + \sum_{i=1}^{p} \beta_i(\Delta_t) h_{t-i} + \sum_{j=1}^{q} \alpha_j(\Delta_t) \varepsilon_{t-j}^2$$

where Δ_t is a latent (ie unobserved) Markov Chain on k = *{1, ..., D}* [6]where *k* is a set of *D* different Markov-Switching GARCH processes[7]. the resulting model would, therefore, have *d* different coefficients for ω, β and α (Francq & Zakoian, 2019).

2.2 Market Risk

As noted in the introduction, global regulatory authorities have endorsed VaR and ES as standards or best practices. Even without regulatory impositions, risk management practitioners are increasingly using such methods to reduce exposures as an internal risk management tool (Ming, 2014) Value at risk estimation - assuming the random variable Z is normally distributed with a mean of μ and a standard deviation of σ, and where q is the loss quantile of the distribution (McNeill et al, 2005 pp39) – is given by:

$$VaR_q(Z) = \mu + \sigma N^{-1}(q)$$

Where N is the cumulative distribution function of the variable Z. Other forms of N could be formulated, for example for a student's t distribution which allows for fat tails (which is a phenomenon observed in return series); the quantile would be calculated based on the student-t cumulative distribution function.

The same holds true for Conditional Value at Risk (CVaR or Expected Shortfall), which is defined as the average of the losses beyond a certain quantile of the distribution. Expected shortfall is closely related to VaR in that it gives a probability of loss, however, it would also inform on the magnitude of losses. In other words, CVaR is the conditional value of the loss, given that the VaR level is exceeded and given a density ϕ of the normal variable Z (McNeill et al, 2005 pp 44,45; Kjellson, 2013)

$$ES_q(Z) = \mu + \sigma \frac{\phi(N^{-1}(q))}{1-q}$$

2.3 Previous Research

In a seminal paper, Sourial and Mecagni (1999) analyse volatility on the Egyptian stock market by employing

[6] In the case of a Markov-Switching GARCH process, the $\mathbb{N}$ state space set is equal to the set *k* of Markov-Switching GARCH processes (Francq and Zakoian, 2019 pp346, 389).

[7] A theoretical framework to Markov Switching GARCH models is given in (Francq & Zakoian, 2019), and tractable algorithms are given by (Ardia et al. 2018) as per the formulations of Haas, 2004.

a GARCH process. Other research[8] also followed which have attempted to model and forecast volatility through alternative GARCH processes. It has come to our attention, however, that none of the previous research have contextualised volatility models in modelling market risk (as has been noted by Abdalla and Winker, 2012). Furthermore, all previous approaches to modelling volatility have not considered regime shifts, which have been shown in recent literature to outperform their single regime counterparts.

This research, therefore, explores the application of Value at Risk and Expected Shortfall methodologies, by estimating and backtesting several volatility models to a portfolio which closely resembles the equity trading book of a bank or financial institution with risk exposure on the Egyptian stock market. The study would explore historical volatility models, in addition to single state symmetric and asymmetric GARCH models. The study would also innovate by applying a Markov-Regime switching GARCH as is formulated by (Haas, 2004; Ardia et al, 2018).

3. Research Methodology

The research was written in R. The packages zoo (Zeileis and Grothendieck, 2005), xts (Ryan and Ulrich, 2018), readxl (Wickham and Bryan, 2019), writexl (Ooms, 2019), strucchange (Zeileis et al, 2003), FinTS (Graves, 2019), rugarch (Ghalanos, 2019), PerformanceAnalytics (Peterson et al, 2019), and MSGARCH (Ardia et al, 2019) were used. Microsoft Excel was also used throughout the process.

3.1 Empirical Tests and Results

The daily price data for the Egyptian Exchange (EGX) indexes® are publicly available on the website (www.egx.com.eg). We have chosen the top 100 performing equities in terms of trading activity. We have therefore gathered the daily data of the EGX30 benchmark Index for a period spanning more than 20 years from January 1998 until October 2019.

We have also gathered price information on the EGX70 Index in order to reperform our tests on medium to small capitalisation stocks on the market. We have also computed the returns and volatility in order to start estimating and modelling market risk.

In order to first perform an empirical analysis of the different models on hand, we will start by showing the descriptive statistics of returns on the two indexes (Table 1). In order to start modelling via Historical Simulation, we have selected a rolling window frame of 250 days which is based on regulatory frameworks (de Raaji and Raunig, 1998; Poon, 2005 pp132). Furthermore, we have also calculated the EWMA as pe the formulation of RiskMetrics.

Additionally, in order to also start modelling via GARCH methodologies, we have performed the ARCH test (Table 1) proposed by Engle (1982) which rejects the null hypothesis of no autocorrelation in the squared returns and concludes the necessity to model volatility via GARCH (Daróczi et al, 2013).

Thereby, we specify GARCH(1,1) and GJR-GARCH(1,1) specifications based on the assumption of normality in the residuals. Furthermore, we have also estimated a normal Markov switching GARCH specification (Haas, 2004; Ardia et el, 2018).

In order to allow for fat tails, which are evident from the skewness and kurtosis results (Table 1). We will also re-estimate the GARCH specifications based on a student-t distribution assumption for residuals. We will,

[8] See Tooma, 2003, Chkir et al, 2009, Abd el Aal, 2011, Abdalla and Winker, 2012, Ezzat, 2012, and Abdelhafez, 2018; among others.

therefore, be comparing Value at Risk and Expected Shortfall measures from the following models per index:

1. Historical Simulation – 250-day rolling window
2. EWMA - RiskMetrics
3. GARCH (1,1) – Normal
4. GARCH (1,1) – Student
5. GJR-GARCH(1,1) – Normal
6. GJR-GARCH(1,1) – Student
7. MS-GARCH(1,1) – Normal
8. MS-GARCH(1,1) – Student

In order to empirically test for regime changes in volatility, we have used the (Zielis et al, 2003) set of tests for multiple changes in time series data. We will first perform our test on the EGX30 and EGX70 price indices (Plot 3). The tests have identified several change points in the price series, and which would naturally reflect the existence of business cycles and exogenous shocks to the time series as is noted by (Francq & Zakoian, 2019 pp353). Our main test, however, is to test for the presence of regime shifts in volatility (Plot 3), which we have also performed based on the same tests. Results have also indicated the presence of multiple shifts in volatility regimes. For this reason, we have estimated Markov-Switching GARCH processes based on two different regimes (*ie* $k=\{1,2\}$).

The regression results of the GARCH models are presented in (Table 2) with the accompanying Akaike and Bayesian Information Criteria. The results are statistically significant[9]. We have computed VaR and ES for the different models above. A visual representation (Plot 1) for the VaR predictability of the models for the most recent year to date is presented (only normal GARCH models are plotted).

The Historical simulation appears to be the slowest in reacting, simply due to the averaged volatility which was used in the calculation. EWMA is evidently more reactive than HS due to the nature of the exponential smoothing as outlined in the literature review. GARCH and GJR-GARCH seem to be more conservative risk measures than EWMA possibly due to the non-restrictions in the parameters (ie the inclusion of mean reversion), with the effect of leverage somehow apparent (ie GJR-GARCH seems to be more conservative (ie reactive) than GARCH following negative returns.

The MS-GARCH measure for risk, however, appears to be the most conservative risk measure. Perhaps this could be more evident when daily returns on the EGX30 index over the most recent 250 days are added to the previous VaR plot (Plot 2); however, the following back-testing methodologies would essentially statistically evaluate from the different models on given confidence intervals.

3.2 Backtesting Methodology and Conclusion

As per the Basel regulations, banks and financial institutions are required to perform VaR backtesting procedures at least over a period of 12 months (250 days). This is primarily done by assessing the performance of the VaR measure and identifying if the proportion of actual losses greater than VaR is consistent with the 99% confidence level (Poon, 2005 pp132).

The unconditional coverage test developed by (Kupiec, 1995) will be used in order to begin our evaluation. If N is the number of times the portfolio loss is less than the predicted VaR with a size T, then ideally, the quantile

[9] We have checked for the significance of the coefficients and for the AIC and BIC criteria. However, this research is primarily focusing on the performance of VaR and ES backtesting methods as is shown in the proceeding section.

q should equate to *N/T*[10] which is subject to a likelihood ratio statistic[11].

An additional test would also be implemented which is the independence test as developed by (Christoffersen, 2003, pp186). The test evaluates whether VaR exceedances are independent of each other, where if exceedances are independent (ie do not cluster), then the VaR model is said to adopt sufficiently to large losses, while if exceedances are dependent, then the VaR model is said to insufficiently adapt to large losses[12] (Kjellson, 2013).

The conditional coverage test is finally given as the sum of the Likelihood ratios for the unconditional and the independence tests (ie $LR_{CC} = LR_{UC} + LR_{IND}$) (Christoffersen, 2003, pp 189).

Furthermore, we will be using the Christoferrsen and Pelettier, 2004) duration based VaR backtesting procedure which corrects for some drawbacks of the previous methodologies[13]. Finally, we will also be backtesting Expected Shortfall based on a test developed by (McNeill and Frey, 2000) which essentially tests if the exceedances of VaR are predictable by Expected Shortfall (ie the Conditional VaR estimate), through computing the exceedances between both estimates and analysing[14] if they are i.i.d (ie Expected Shortfall is a strong white noise and hence is systemically understated).

While the results (Tables 4 and 5) differ across both indices at the 99% confidence level, in general, results show the superiority of GJR-GARCH and MS-GARCH with student-t distributions based on the number of rejections to the null hypotheses (which correspond to model acceptance in all backtests and associated statistics).

It is also evident that the Historical Simulation and the EWMA are the worst performing. Results indicate that the fitted models on the EGX30 tend to be less reactive to rejections than models fitted on the EGX70 when switching from normal to student-t distributions for residuals. This could be due to the fact that the mid to low cap stocks exhibit more heavy tails (Table 1).

While we can distinguish between the two best performing models, we will be performing model which combines both asymmetric (ie GJR-GARCH) and regime shifting (ie MS-GARCH) processes to volatility dynamics. We have therefore added a Markov-Switching GJR-GARCH model with a student's-t distribution (Ardia et al, 2018) and have compared it to the alternatives per examined index. Results (Tables 4 and 5) indicate the superiority of the MS-GJR GARCH process to volatility when modelling market risk, as is seen for both the EGX30 and EGX70 indices.

Results therefore indicate that a combination of asymmetric and regime switching GARCH processes, with a student's t distribution for residuals, is more accurate at the 99% confidence level, in modelling market risk to an investment opportunity on the Egyptian stock exchange[15].

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[10] As an example, consider the 1% quantile (ie 99% VaR); over a 250-day observation frame. The breakeven is at the point where T/N is in the range of 1% (ie the range of 2 to 3 violations at the 99% confidence level)

[11] The likelihood ratio LR_{UC} is: $2\left[log\left(\left(\frac{N}{T}\right)^{N}\left(1-\frac{N}{T}\right)^{T-N}\right) - log\left(p^{N}(1-p)^{T-N}\right)\right]$ (van den Goorbergh and Vlaar, 1999)

[12] The likelihood ratio LR_{IND} is: $-2ln\left[\frac{L(\widehat{\pi})}{L(\widehat{\Pi})}\right]$, where $L(\widehat{\pi})$ is the likelihood under the alternative hypothesis of the Kupiec (1995) unconditional coverage test. $L(\widehat{\Pi})$ is a matrix of transitional probabilities for the sequence of VaR exceedances which is governed by a Markov Chain (Christoffersen, 2003 pp188).

[13] Christoffersen and Pelettier, 2004 present a procedure for backtesting VaR based on duration between exceedances. They show that for a correctly specified risk model, then the conditional expected duration from one VaR exceedance point until another should be constant in terms of days. The test is conducted based on the p value for the associated likelihood ratio. The authors also argue that the regulatory practice of 250-day observation is likely to be misleading; which is why we will be extending the VaR backtesting methodologies to cover the whole sample period.

[14] This test is against the alternative hypothesis (ie that the exceedances have a mean of greater than zero) with associated p values (McNeill and Frey, 2000).

[15] Implications to this research are relevant to Egyptian stock market regulators, and to risk management practitioners.

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5. Appendix

Table 1:

Index	Mean	Variance	Sigma	Skewness	Kurtosis	Engle ARCH-LM test
EGX30	0.000504	0.000275	0.016598	-0.336759	11.90831	Chi-squared = 565.7, p-value < 2.2e-16
EGX70	-0.000231	0.000269	0.016389	-1.316393	13.62057	Chi-squared = 355.4, p-value < 2.2e-16

Table 2:

	EGX30						EGX70					
Variables per Model	**GARCH-N**	**GARCH-T**	**GJR-GARCH-N**	**GJR-GARCH-T**	**MS-GARCH-N**	**MS-GARCH-T**	**GARCH-N**	**GARCH-T**	**GJR-GARCH-N**	**GJR-GARCH-T**	**MS-GARCH-N**	**MS-GARCH-T**
Omega ω	0.000009	0.00001	0.000009	0.000011	0.0000	0.0000	0.000009	0.000008	0.00001	0.000008	0.0000	0.0000
Alpha α	0.1468	0.1727	0.1473	0.1739	0.0643	0.0872	0.213453	0.214462	0.19736	0.208981	0.0375	0.017
Beta β	0.8315	0.8023	0.8284	0.7951	0.8912	0.9032	0.774238	0.784538	0.77364	0.781805	0.9094	0.982
Leverage δ*	-	-	0.0596	0.0902	-	-	-	-	0.18339	0.108549	-	-
Omega ω2**	-	-	-	-	0.0001	0.0001	-	-	-	-	0.0000	0.0002
Alpha α2**	-	-	-	-	0.1600	0.3117	-	-	-	-	0.1965	0.1492
Beta β2**	-	-	-	-	0.8334	0.4781	-	-	-	-	0.7893	0.5271
Leverage δ2**	-	-	-	-	-	-	-	-	-	-	-	-
Akaike IC	-5.593	-5.670	-5.594	-5.671	-30038	-30116	-5.727	-5.812	-5.740	-5.814	-16429	-16272
Bayesian IC	-5.588	-5.664	-5.588	-5.664	-29986	-30050	-5.718	-5.801	-5.729	-5.802	-16381	-16213

***Leverage δ for GJR GARCH specifications**

****Second set of α2, β2 and δ2 for MS GARCH specifications**

Table 3:

	EGX30		EGX70	
Probability Transition Matrix	**MS-GARCH-N**	**MS-GARCH-T**	**MS-GARCH-N**	**MS-GARCH-T**
p00	94.35%	97.15%	85.67%	96.15%
p01	5.65%	2.85%	14.33%	3.85%
p10	37.99%	3.28%	27.48%	6.16%
p11	62.01%	96.72%	72.52%	93.84%

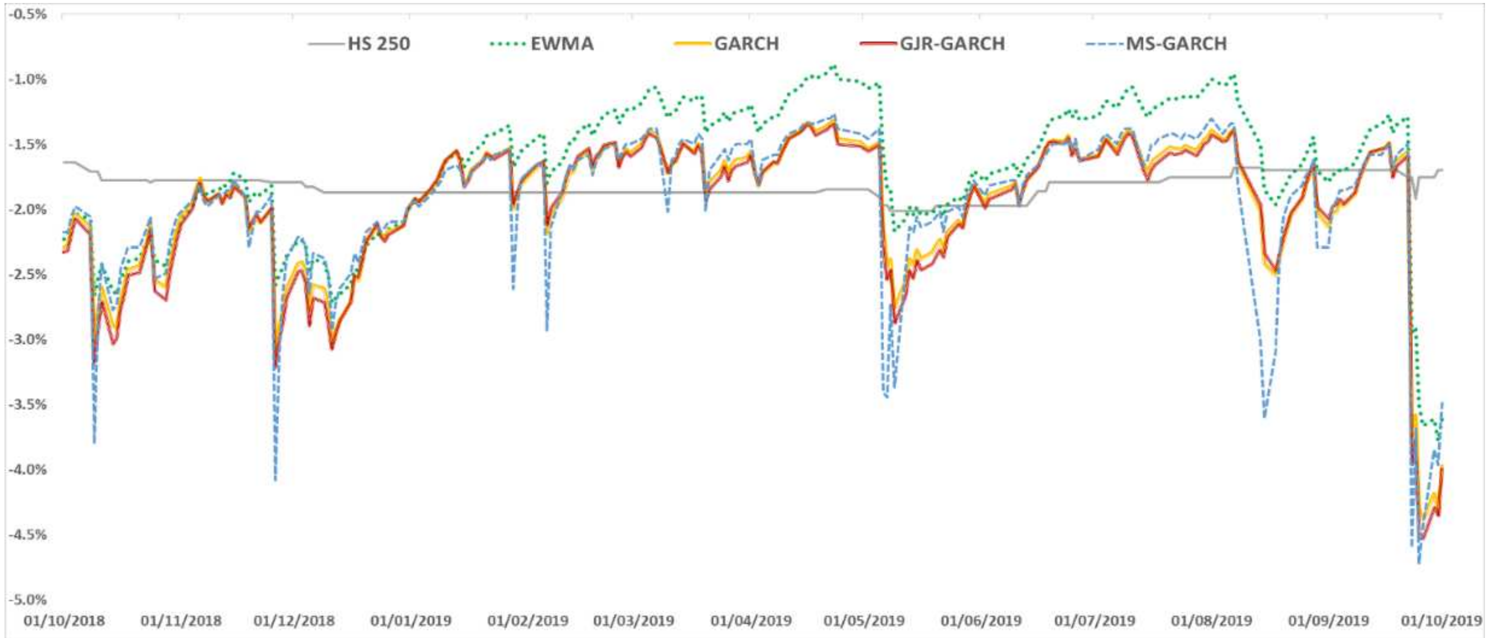
Table 4:

Backtesting Methodologies	Variable/ Statistic	HS 250	EWMA	GARCH-N	GARCH-T	GJR-GARCH-N	GJR-GARCH-T	MS-GARCH-N	MS-GARCH-T	MS-GJR-GARCH-T
		EGX30								
Expected Exceedances		50	53	53	53	53	53	53	53	53
Actual Exceedances		70	114	84	54	77	50	50	56	52
VaR - Kupiec (1995)	LRuc	6.7424	53.2218	15.4925	0.0171	9.5852	0.1806	0.1806	0.1627	0.0211
	Decision	"Reject H0"	"Reject H0"	"Reject H0"	"Fail to Reject H0"	"Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"
VaR - Chrostoffersen (2003)	LRcc	23.4530	89.6372	31.9726	0.3208	17.2085	0.6390	0.6390	0.4023	0.3976
	Decision	"Reject H0"	"Reject H0"	"Reject H0"	"Fail to Reject H0"	"Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"
VaR - Christoffersen and Pelettier (2004)	P-value	0.000003	0.002938	0.098460	0.916858	0.212698	0.630514	0.696003	0.651103	0.693934
	Decision	"Reject H0"	"Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"
ES (CVaR) - McNeill and Frey (2000)	P-value	0.581713	0.000001	0.000099	0.149217	0.000092	0.150153	0.090217	0.137335	0.125339
	Decision	"Fail to Reject H0"	"Reject H0"	"Reject H0"	"Fail to Reject H0"	"Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"

Table 5:

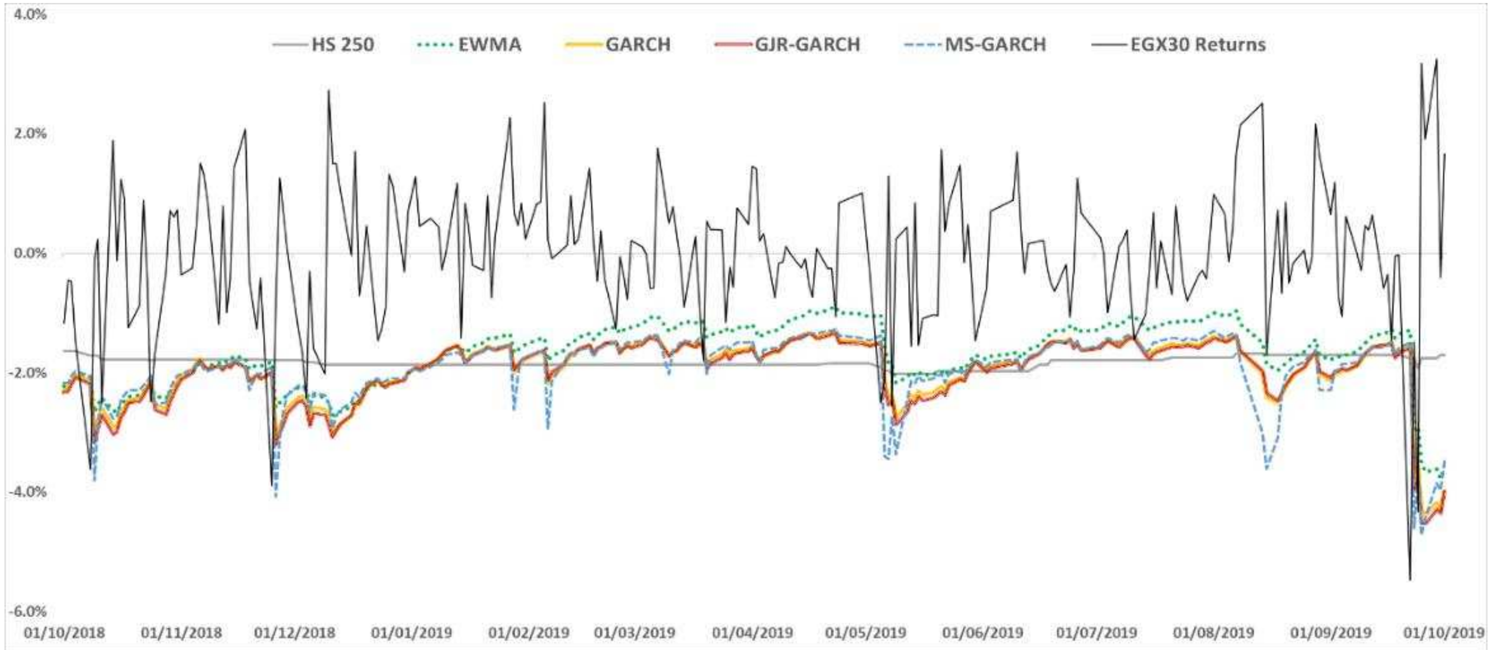
		HS 250	EWMA	GARCH-N	GARCH-T	GJR-GARCH-N	GJR-GARCH-T	MS-GARCH-N	MS-GARCH-T	MS-GJR-GARCH-T
		EGX70								
Expected Exceedances		25	28	28	28	28	28	28	28	28
Actual Exceedances		28	100	64	44	54	38	48	25	23
VaR - Kupiec (1995)	LRuc	0.1776	110.7570	33.4307	7.4913	18.5624	3.0119	11.4171	0.5211	1.0825
	Decision	"Fail to Reject H0"	"Reject H0"	"Reject H0"	"Reject H0"	"Reject H0"	"Fail to Reject H0"	"Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"
VaR - Chrostoffersen (2003)	LRcc	9.0759	134.1045	36.6753	9.2340	19.3136	5.6194	15.0815	1.9248	2.8705
	Decision	"Reject H0"	"Reject H0"	"Reject H0"	"Reject H0"	"Reject H0"	"Fail to Reject H0"	"Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"
VaR - Christoffersen and Pelettier (2004)	P-value	0.018429	0.002938	0.000048	0.561203	0.975068	0.442342	0.044069	0.073947	0.476107
	Decision	"Reject H0"	"Reject H0"	"Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"	"Reject H0"	"Fail to Reject H0"	"Fail to Reject H0"
ES (CVaR) - McNeill and Frey (2000)	P-value	0.124574	0.000000	0.000048	0.824156	0.000053	0.807592	0.042194	0.027641	0.137335
	Decision	"Fail to Reject H0"	"Reject H0"	"Reject H0"	"Fail to Reject H0"	"Reject H0"	"Fail to Reject H0"	"Reject H0"	"Reject H0"	"Fail to Reject H0"

Plot 1:



HS 250
EWMA
GARCH
GJR-GARCH
MS-GARCH
-0.5%
-1.0%
-1.5%
-2.0%
-2.5%
-3.0%
-3.5%
-4.0%
-4.5%
-5.0%
01/10/2018
01/11/2018
01/12/2018
01/01/2019
01/02/2019
01/03/2019
01/04/2019
01/05/2019
01/06/2019
01/07/2019
01/08/2019
01/09/2019
01/10/2019

Plot 2:



HS 250
EWMA
GARCH
GJR-GARCH
MS-GARCH
EGX30 Returns
4.0%
2.0%
0.0%
-2.0%
-4.0%
-6.0%
01/10/2018
01/11/2018
01/12/2018
01/01/2019
01/02/2019
01/03/2019
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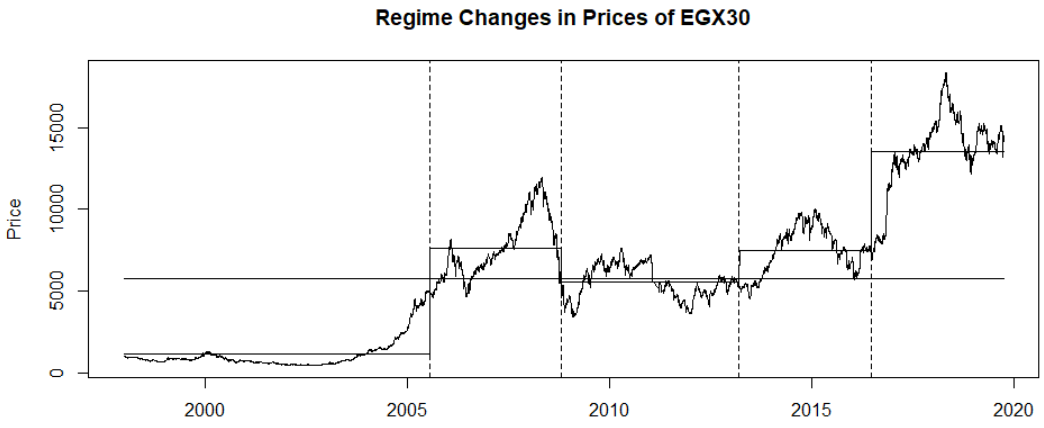
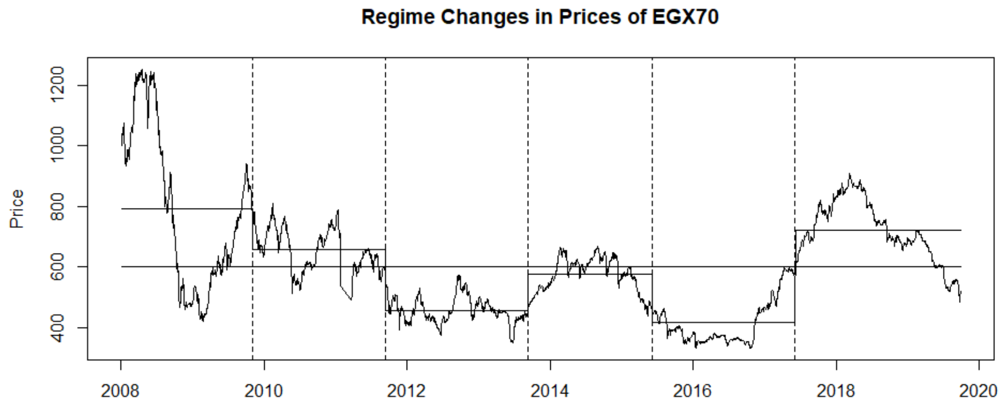
01/05/2019
01/06/2019
01/07/2019
01/08/2019
01/09/2019
01/10/2019

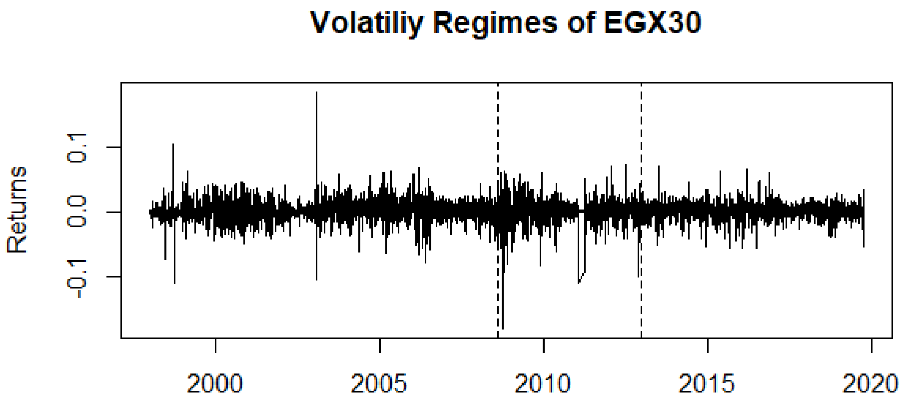
Plot 3:



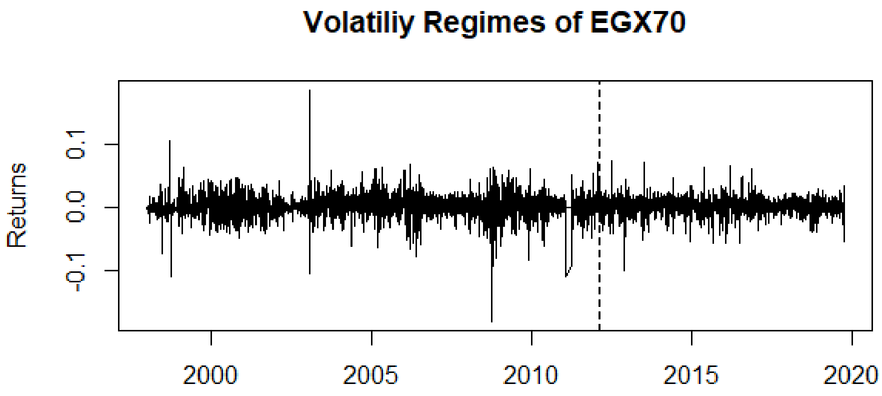
Regime Changes in Prices of EGX30
Price
0
5000
10000
15000
2000
2005
2010
2015
2020



Regime Changes in Prices of EGX70
Price
400
600
800
1000
1200
2008
2010
2012
2014
2016
2018
2020



Volatiliy Regimes of EGX30
Returns
-0.1
0.0
0.1
2000
2005
2010
2015
2020



Volatiliy Regimes of EGX70
Returns
-0.1
0.0
0.1
2000
2005
2010
2015
2020