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Comparative Study of Modelling and Forecasting Volatility: The Case of Egypt, and Japan

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Abstract

The purpose of this paper is to evaluate the forecasting performance of linear and non-linear (GARCH) models in terms of their in-sample and out-of-sample forecasting accuracy for EGX30 and Nikkei225 indices as an example of an emerging and developed markets respectively.

We employ GARCH, GARCH-IN-MEAN, EGARCH, GJR-GARCH, Multivariate GARCH, and Nelson's EGARCH for forecasting using daily price data of the indices for the period of 2001 to 2019. We find that the volatility shocks on the indices returns are quite persistent. Furthermore, our findings show that the indices have leverage effect, and the impact of shocks is asymmetric, and consequently it can be stated that the impact of negative shocks on volatility are higher than positive shocks.

The results suggest that the Nelson's EGARCH model is the most accurate model in the GARCH class for forecasting, as this model outperforms the other models. Additionally, we find that emerging stock markets have higher volatilities than those in developed markets. Further, these results imply that the EGARCH model might be more useful than other models when implementing risk management strategies and developing stock pricing model.

This paper contributes to the literature by comparing two significant global markets; one of the largest developed economies in the world, Japan, and one of Africa's largest developing economies, Egypt.

Keywords: GARCH Models, Leverage Effect, EGX30 & Nikkei225, Volatility, Out-of-Sample Forecast.

JEL classification:C5; C32; G15; G17

1. Introduction

Modelling and forecasting the volatility of stock market returns has been an important area of research in recent years. The reason being that investors want to understand the level of risk they will be exposed to as part of their decision-making process. Assets with higher volatility are viewed by investors as riskier because volatility can result in large variations of returns.

Pilbeam and Langeland (2015) define volatility as the standard deviation or variance of the returns of an asset during a given time-period. They also state that volatility is a key parameter in the pricing of financial derivatives and that all modern option-pricing techniques rely heavily on volatility parameters for price evaluation.

Alexander (1999) suggests that high volatility within a market may act as a deterrent to potential investors as they are concerned by the impact that the variability in speculative market prices may have on their returns.

Engle and Patton (2007) state that volatility models used widely can be split into two general classes: the first class formulates the conditional variance directly as a function of observables; the second formulates models of volatility that are not functions purely of observables. The simplest examples of the first class are the autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models. Both models are widely used in finance.

The aim of this paper is to evaluate the forecasting performance of linear and non-linear (GARCH) models in terms of their in-sample and out-of-sample forecasting accuracy for EGX30 and Nikkei225 indices as an example of an emerging and developed market respectively. GARCH, GARCH-IN-MEAN, EGARCH, GJR-GARCH, Multivariate GARCH, and Nelson's EGARCH are employed for forecasting, using daily price data of the indices for the period of 2001 to 2019.

Research in the area relating to GARCH modelling of stock return volatility is extremely limited for emerging/developing markets (Adesina, 2013; Bekaert and Wu, 2000) and there do not appear to be studies examining return volatility with symmetric and asymmetric GARCH models of the Egyptian and Japanese stock markets, over a substantial time frame. This paper uses data from 3rd January 2001 to 31st December 2019 for two popular world-wide stock exchange indices namely EGX-30 and Nikkei 225. The EGX-30 index includes the top 30 companies in terms of liquidity and activity listed on the Egyptian Stock Exchange and the Nikkei 225 (Nikkei) index includes 225 Japanese companies listed on the Tokyo Stock Exchange (Al Rahahleh and Kao, 2018), giving a total of 3,580 observations.

Previous research has suggested that developing markets have higher sample average returns, returns that are more predictable, have higher volatility and a low correlation with developed market returns (Bekaert and Wu, 2000). The differences identified between developed and developing markets could have implications for potential investors. This paper attempts to close the gap in the literature by comparing volatility forecasts of one of the largest developed economies in the world, Japan, and one of Africa’s largest developing economies, Egypt.

Previous research has also suggested that volatility can vary depending upon whether return shocks are present. Mwita and Nassiuma (2015) examine the nature and characteristics of volatility of Kenyan stock markets using a symmetric volatility GARCH model to estimate the volatility of stock returns during the time frame, 1985-2011. Their results find that there is evidence of time varying stock return volatility during this period. In addition, following a financial crisis, negative returns shocks have higher volatility than positive returns shocks. Therefore, analyzing a substantial timeframe will allow for the investigation of whether positive or negative shocks would influence volatility.

The main results show that the volatility of shocks on the indices returns are quite persistent, the indices have leverage effect, and the impact of shocks is asymmetric. Asymmetric shocks suggest that the impact of negative shocks on volatility are higher than positive shocks and the shocks are of the same size for both EGX30 and Nikkei225 indices. The results also suggest that the Nelson's

EGARCH model is the most accurate model in the GARCH class for forecasting, as this model outperforms the other models. In addition, the results show that emerging stock markets have higher volatilities than those in developed markets, due to the weaker economic fundamentals often present in emerging markets.

The rest of this paper is organized as follows: section 2 reviews the previous literature, section 3 discusses the methodology, section 4 analyses the data and results and section 5 concludes the paper.

2. Literature Review

ARCH (Autoregressive Conditional Heteroskedasticity) and Generalized ARCH (GARCH) models have become a research focus over the last few decades as they have emerged as prominent tools in estimating volatility (Gabriel, 2012). Mwita and Nassiuma (2015) state that volatility plays a substantial role in many financial decisions as the ability to accurately measure and predict stock market volatility has widespread implications, particularly with regards to estimated returns.

2.1. ARCH vs GARCH

Over time there have been many models that attempt to estimate stock market volatility; these include both ARCH and generalized ARCH (GARCH). ARCH was proposed by Engle (1982) and generalized ARCH proposed by Bollerslev (1986). Lim and Sek (2013) state that many extensions of the models have been proposed over time with the aim of improving volatility estimations, namely, GARCH-M, IGARCH, EGARCH (Nelson, 1991), Threshold GARCH (Glosten *et al*, 1993), Asymmetric GARCH model AGARCH (Engle, 1990) and Fractionally Integrated FIGARCH (Baillie *et al*, 1996).

There has been much research with regards to which model performs better in estimating volatility and the results of these seem to be mixed. According to Lim and Sek (2013) some studies show that using a simple GARCH (p,q) model produces more preferable results and some show extensions of GARCH models perform better, with performance of these models varying across markets and time frame.

Bollerslev (1986) results show that the GARCH model outperformed the ARCH model. Whereas, Baillie and Bollerslev (1991) found that the GARCH model was relatively poor when estimating patterns of volatility within the US foreign exchange (FOREX) market. Pilbeam and Langeland (2015) state that the latest study of option valuation showed that the GARCH model for the S&P index is more appropriate than another volatility method.

There are various findings when it comes to analyzing the reliability of GARCH extensions models. Hansen and Lunde (2005) find that none of the models in the GARCH family outperforms the simple GARCH (1,1) which seems to be unexpected as it does not rely upon a leverage effect (Pilbeam and Langeland, 2015).

Forte and Manera (2002) investigate the forecasting performance of three popular nonlinear GARCH models, VS-GARCH, GJR-GARCH and Q-GARCH, with the symmetric GARCH (1,1) model as a benchmark. They use data from ten European stock price indices. With regards to the standard GARCH specification, they find that the non-linear models in general lead to better forecasts in terms of both smaller forecast errors and lower biases.

Hamadu and Ibiwoye (2010) show that the EGARCH model outperforms other models when testing in model-estimating evaluation and out-of-sample volatility forecasting suggesting that EGARCH is more reliable than other GARCH models for modelling stock price returns.

There seems to be mixed findings with regards to Nelson's EGARCH model, Pilbeam and Langeland (2015) state that it has several advantages over linear GARCH models, however this may be limited to certain studies because although Brownlees and Gallo (2010) find that while EGARCH frequently produces the most accurate forecast, it is sometimes outperformed by the linear GARCH model.

Donaldson and Kamstra (2005) find that the GJR-GARCH (1,1) model was a better predictor at forecasting international stock return volatility than GARCH(1,1) and EGARCH(1,1). Whereas, Balaban (2004) believe that the standard GARCH model is the most accurate at forecasting U.S. dollar-Deutschemark exchange rate volatility. Ng and McAleer (2004) use a simple GARCH (1,1) and threshold ARCH (TARCH(1,1)) models to estimate forecasting volatility of daily returns for the USA using the Standard and Poor (S&P) 500 Composite Index and Japan using the Nikkei 225 Index. Their results suggest that the TARCH (1,1) model is more accurate for the S&P 500 dataset than GARCH, whereas the opposite is the case for the Nikkei 225 Index.

Pilbeam and Langeland (2015) argue that although there is a rich body of literature on volatility forecasting, the question as to which model is optimal is still yet to be answered.

2.2. Intra-day Data in GARCH Models

Abounoori and Zabol (2020) state that conventional GARCH models generally use only daily stock returns to calculate variances which leads to the information set of conventional GARCH models being limited. They suggest that 'information obtained from daily returns is lower than the different criteria derived from intraday data' (p.300). Andersen *et al* (2003) also suggests that GARCH models can be slow to react to volatility changes as the models are based on moving averages with decreasing weight. Abounoori and Zabol (2020) state that due to these limitations there was a need to introduce intra-day data into the GARCH model framework. Engel (2002) suggested including a realized variance as an exogenous variable in GARCH models. However, Abounoori and Zabol (2020) state that there is a disadvantage to this as only one-day ahead conditional variance prediction is possible.

Abounoori and Zabol (2020) use the Gold five-minute intra-day data for seven years from 2012 to 2018, to compare the realized GARCH model with some conventional GARCH models such as GARCH, EGARCH, and GJR-GARCH.

Abounoori and Zabol (2020) suggest that a good model not only should fit data well but also it should have accurate performance in predicting out-of-sample volatility. Therefore, in their paper they compare the models in two ways, by firstly considering how well data has been fitted to the models and, secondly, the accuracy of the prediction of the conditional variance of the sample. They do this by using 'the rolling window approach and using a loss function to select the most accurate model' (p.300). Their results show that the RGARCH method for GOLD outperforms the other methods in terms of data fit and accuracy. Kayahan *et al* (2002) tend to support this conclusion as their assessment of the relative performance of realised volatility (RV) using intra-day returns from an emerging market is considered to be a more successful estimate than that of a conventional GARCH model.

Therefore, Abounoori and Zabol (2020) conclude that the using RGARCH models instead of conventional GARCH models provide a more accurate estimation for the conditional variance as a proxy of volatility. Which they believe is a key factor in risk management and portfolio management.

2.3. Developed vs Emerging Markets

Adesina (2013) suggests that the study on GARCH modelling is more heavily focused on developed markets than emerging markets. Cheteni (2016) is one of the few papers to analyse the relationship between stock returns and volatility of stock markets within a developed country, South Africa, and a developing country, China. They use a GARCH model to estimate volatility of the stock returns from the Johannesburg Stock Exchange FTSE/JSE Albi index and the Shanghai Stock Exchange Composite Index. They use data from 1998 to 2014 and their empirical results show that both markets exhibit high volatility and display similar features in terms of volatility clustering. Cheteni (2016) suggest that the most plausible explanation for this similarity may be that there is more trading between the two economic systems. However, they state that the paper did not try to identify all the possible causes for the unexpected similarity in clustering between the two stock exchanges because the model used is unable to fully capture the aspects of leverage and asymmetry in the stock returns. They suggest that a model measuring those two aspects may contribute a better understanding between the two stock markets (Cheteni, 2016).

Abdalla and Winker (2012) estimate the volatility of two African stock exchanges, the Cairo and Alexandria Stock Exchange (CASE), in Egypt, and Khartoum Stock Exchange (KSE), in Sudan. They examine the period from 2006 to 2010 using symmetric and asymmetric GARCH models and their results show that volatility 'is an explosive process for the KSE index returns series, while it is quite persistent for the CASE index returns series' (p.10). In addition, the asymmetric GARCH models find evidence of asymmetry in stock returns within the two markets, which confirms the presence of leverage effect within the return series.

Lee *et al* (2017) examine a mixture of developed and developing markets by using index return series for Malaysia (FTSE KLCI), Indonesia (JKSE), Hong Kong (Hang Seng), and Japan (Nikkei) to investigate the robustness of three volatility forecasting models: Exponential Weighted Moving Average (EWMA), Autoregressive Integrated Moving Average (ARIMA) and Generalized Auto-Regressive Conditional Heteroscedastic (GARCH).

The results suggest that none of the chosen forecasting models appears be robust for all four stock markets. However, they find the GARCH (1, 1) model to be the best forecasting model for stock markets in Malaysia, Indonesia, and Japan, while EWMA model is found to be the best forecasting model for Hong Kong stock market. Furthermore, their results indicate that the Hong Kong stock market exhibits higher volatility than the Malaysian market which could suggest that developed stock markets can have higher volatilities than those in developing markets. These results are somewhat supported by Cheteni (2016) who find that both the South African and Chinese stock markets exhibit high volatility. Overall, Lee *et al* (2017) state that GARCH (1, 1) appears to be the better forecasting model for the majority of the markets in the sample, but as the sample is limited to just two developed and two developing markets which are all based in Asia, they suggest that further studies examining different markets could display very different results.

Abdelhafez (2018) focus their analysis on one country, Egypt, to investigate which model is more reliable when forecasting volatility. Different Symmetric and Asymmetric GARCH models are used to determine which model is most appropriate to analyze the data. The symmetric models used are GARCH (1, 1), GARCH (1, 2), GARCH (2, 1), GARCH (2, 2) and GARCH-IN-MEAN (1, 1) and the asymmetric models are TARCH (1, 1) and EGARCH (1, 1). The results show that the most appropriate models to analyze data from the Egyptian Stock Market are GARCH (1, 2), GARCH (2, 1), TARCH (1, 1) and EGARCH (1, 1). In addition, they find the best model in estimating volatility and forecasting in the Egyptian stock market is the TARCH (1, 1) model as well as it being the more appropriate model in capturing the leverage effect.

This paper contributes to the literature by comparing two significant global markets; one of the largest developed economies in the world, Japan, and one of Africa's largest developing economies, Egypt. Daily indices return from the Nikkei-225 and EGX-30 are used along with symmetric and asymmetric GARCH models. In addition, the timeframe examined is substantial, 2001 to 2019, and covers one of the most significant financial crises in recent years, the global financial crisis 2007-2009.

3. Methodology

Six Symmetric and Asymmetric GARCH models were used to describe and forecast the volatility of the EGX-30 and Nikkei-225 daily indices return.

3.1. Multivariate GARCH (MGARCH) Model

MGARCH stands for multivariate GARCH. MGARCH allows the conditional-on-past-history covariance matrix of the dependent variables to follow a flexible dynamic structure (Pilbeam and Langeland, 2015).

3.2. Forecasting using Nelson EGARCH

This paper attempts to model and forecast the volatility of the EGX-30 and Nikkei-225 daily indices return during 2001–2019, using the Nelson's EGARCH model. The analysis covers from 3rd January 2001 to 31st December 2017 and from January 2017 to 31st December 2019, as in-sample and out-of-sample sets, respectively. The results have been estimated with AIC and BIC as the measures of performance. It has been shown that Nelson's EGARCH for forecasting is the best-fitted model to capture the leverage effect (Brownlees and Gallo, 2010; Poon and Granger, 2003; Dury and Xiao, 2018).

4. Data and Empirical Results

4.1. Data

Two countries are analysed within this paper, one developed, Japan, and one emerging, Egypt. Daily closing prices in USD for all stock indices from the two countries are collected from the Egyptian and Japan Stock markets for a period of 2001-2019, which consists of an in-the-sample period of 2001-2017 and the forecast commences in 2018-2019. The daily data runs from 3rd January 2001 to 31st December 2019, giving a total number of 3,580 observations.

Figure 1 and Figure 2 show that daily log of returns during the time frame used and there are clear periods of volatility clustering. In Figure 1 and Figure 2 it can be seen that that the series are stationary with most of the returns being located around zero. However these show spikes in the first order difference in periods with high volatility.

It is clearly observed that stock index returns of the emerging market (Egypt) exhibit higher patterns as compared to the other developed market (Japan) over the sample period of 2001-2019. In addition, a more fluctuating trend is found for the other developed stock market. Therefore, the results obtained confirm that volatility in emerging markets is higher than the volatility in developed markets.

Figure1: Log of Daily Stock Returns for EGX30 from (2001-2019)

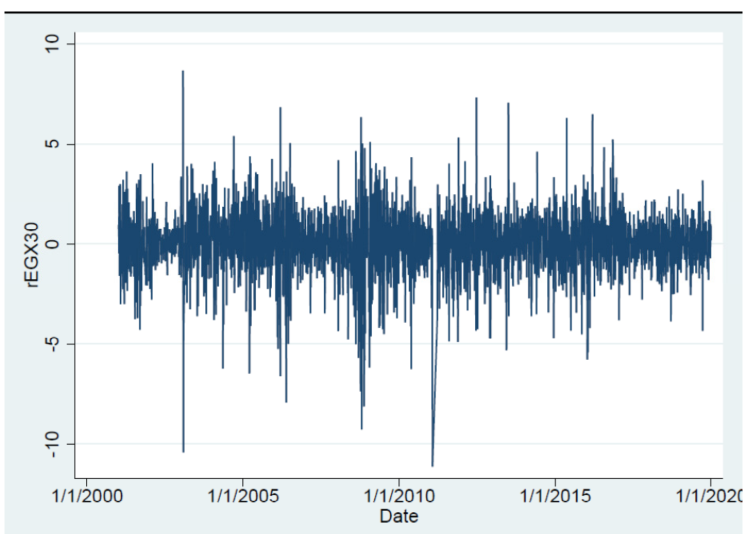


Figure 2: Log of Daily Stock Returns for Nikkei225 from (2001-2019)

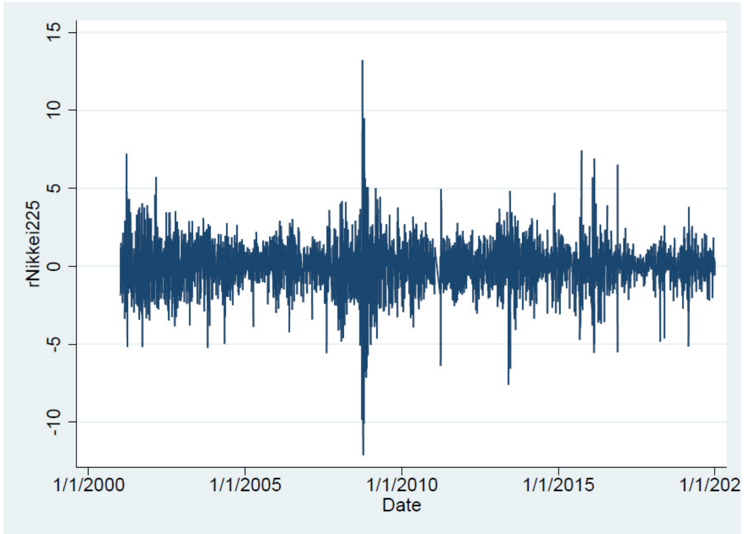


Figure 3 and figure 4 show the empirical distribution of returns, a histogram is used to illustrate the density of returns and a curve from normal distribution is overlaid. Figure 3 and figure 4 show that the distribution of returns remarkably differs from normality given the excess kurtosis and light left skewness implying some asymmetry.

Figure 3: The Distribution of Daily Stock Returns for EGX30 from (2001-2019)

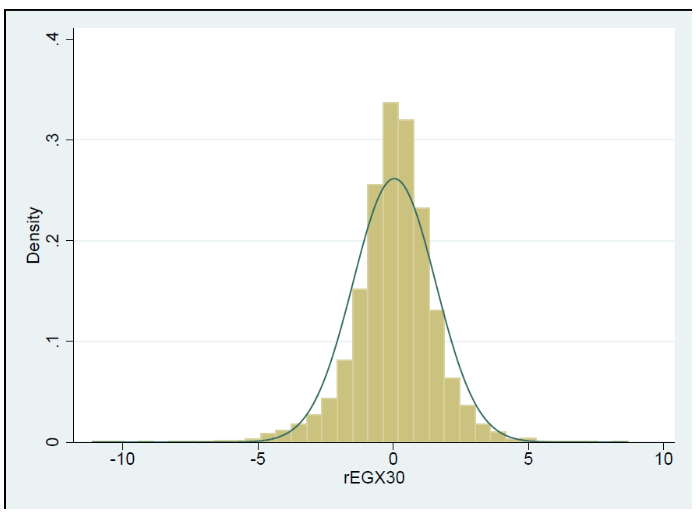


Figure 4: The Distribution of Daily Stock Returns for Nikkei225 from (2001-2019)

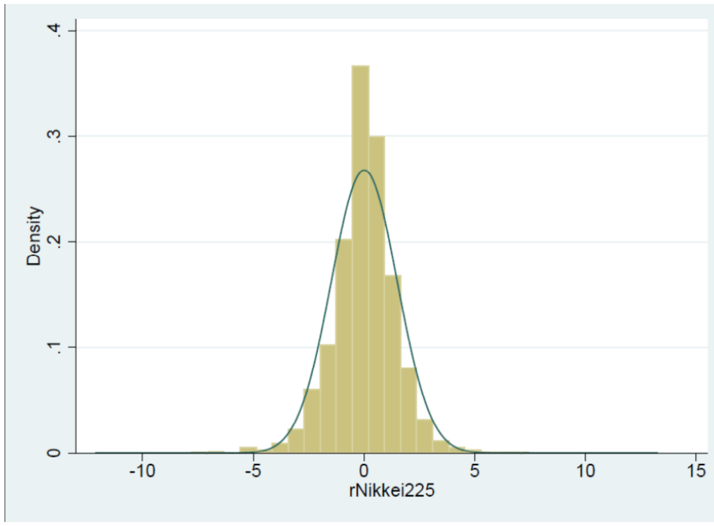


Table 1 and Table 2 present descriptive statistics for all stock indices. Throughout the sample period, all stock indices of Egypt and Japan exhibit positive values during the sample period, from which a higher mean value of 0.04 is found for Egypt, compared to a lower mean value of 0.01 is found for Japan.

As shown in Table 1 and Table 2, statistics for skewness and kurtosis, all confirm that price distributions for all the two stock indices are not normally distributed. The distribution of returns remarkably differs from normality given the excess kurtosis and light left skewness implying some asymmetry. Heavy tailed leptokurtic distribution implies the index has higher risk and return in the sample space. Leptokurtic distributions can also show a higher value at risk in the left tail due to the larger amount of value under the curve in the worst-case scenarios. Overall, a greater probability for negative returns further from the mean on the left side of the distribution leads to a higher value at risk. Values of the standard deviations obtained for Egypt stock market is the highest, i.e., 1.52, implying that this market is more volatile than the Japanese stock market.

Table 1: Descriptive Statistics of the Stock Returns for EGX30

	Percentiles	**Smallest**		
1%	-4.499185	-11.11695		
5%	-2.400029	-10.43237		
10%	-1.637448	-9.271788	Obs	3580
25%	-0.7115662	-8.104535	Sum of Wgt.	3580
50%	0.1011361		**Mean**	**0.042608**
		Largest	**Std.Dev.**	**1.525093**
75%	0.8736477	6.833863		
90%	1.703329	7.056956	Variance	2.325908
95%	2.343112	7.314331	**Skewness**	**-0.52923**
99%	3.783681	8.676474	**Kurtosis**	**7.296516**

Table 2: Descriptive Statistics of the Stock Returns for Nikkei225

	Percentiles	**Smallest**		
1%	-4.109823	-12.111		
5%	-2.341594	-10.088		
10%	-1.680566	-9.84905	Obs	3580
25%	-0.6882214	-7.59736	Sum of Wgt.	3580
50%	0.0516572		**Mean**	**0.01315**
		Largest	**Std.Dev.**	**1.48921**
75%	0.7846138	7.42617		
90%	1.641034	7.455602	Variance	2.21776
95%	2.169084	9.494146	**Skewness**	**-0.2101**
99%	3.765568	13.23458	**Kurtosis**	**9.61806**

4.2. Models Tests

4.2.1. Testing for Serial Correlation

The Durbin's alternative test strongly rejects the null of no first-order serial correlation, so the model was refitted with three lags of rEGX30 included as regressors and then rerun.

Although L2.rEGX30 is not statistically different from zero, the output indicates that including the three lags of rEGX30 has removed any serial correlation from the errors as shown in Table 3, and the test strongly accepts the null of no first-order serial correlation. Additionally, for rNikkei225 table 4 indicates that the test strongly accepts the null of no first-order serial correlation.

Table 3: Durbin's Alternative Test for Autocorrelation for Stock Returns for EGX30

lags(p)	**chi2**	**df**	**Prob>chi2**
1	1.61	1	0.2045
2	1.61	1	0.2045
3	1.61	1	0.2045

H0: no serial correlation

Table 4: Durbin's AlternativeT for Autocorrelation for Stock Returns for Nikkei225

lags(p)	**chi2**	**df**	**Prob>chi2**
1	1.657	1	0.1980

H0: no serial correlation

4.2.2. Testing for Autoregressive Conditional Heteroskedasticity

Engle (1982) suggests a Lagrange Multiplier Test (LM) for checking for autoregressive conditional heteroskedasticity (ARCH) in the errors. The null hypothesis is tested and there are no ARCH effects in the residuals. The results of this ARCH-LM test for EGX30 series and Nikkei225 series are reported in Table 5 and Table 6, respectively. Additionally, the volatility clustering pattern observed on return series graph depicted on Figure 1 and Figure 2 above suggests ARCH type model, as well.

Table 5 shows the results for tests of ARCH(1), ARCH(2), and ARCH(3) effects for EGX30 series, respectively. At the 1% significance level, all three tests reject the null hypothesis that the errors are not autoregressive conditional heteroskedastic. Table 6 shows the results for tests of ARCH(1), ARCH(2), and ARCH(3) effects for Nikkei225 series, respectively. At the 1% significance level, all three tests reject the null hypothesis that the errors are not autoregressive conditional heteroskedastic.

Table 5: LM Test for Autoregressive Conditional Heteroskedasticity (ARCH) for Stock Returns for EGX30

lags(p)	chi2	df	Prob>chi2
1	211.443	1	0.0000
2	155.369	2	0.0000
3	106.714	3	0.0000

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Table 6: LM Test for Autoregressive Conditional Heteroskedasticity (ARCH) for Stock Returns for Nikkei225

lags(p)	chi2	df	Prob>chi2
1	133.731	1	0.0000
2	258.871	2	0.0000
3	186.939	3	0.0000

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Therefore, these results reject *H0* and show that the series has ARCH effect on the residuals, implying that variance of returns of EGX30 series and Nikkei225 series are non-constant.

4.3. Empirical Results

Since the residuals have ARCH effects GARCH is employed process to model this conditional heteroscedasticity. Considering that the data is not normally distributed GARCH parameters are estimated and the ARMA(1,1) mean equation is estimated.

4.3.1 Parameter Estimation of Symmetric GARCH Models

4.3.1.1. The GARCH (1, 1) Model

The reported α_1 (ARCH term) measures the extent to which a volatility shock today feeds through into next period's volatility (Campbell et al. 1997). The coefficient for EGX30 is 0.2580729 which shows the presence of volatility clustering in the series over the period. The volatility changes over time and its degree shows a tendency to persist, i.e., there are periods of low volatility and periods where volatility is high. The estimate of β_1 (GARCH term) coefficient is 0.8161335 indicates a long memory in the variance. This means that changes in the current volatility will affect future volatilities for a long period or the impact of old news on volatility is long lasting. The sum of ARCH and GARCH terms $\alpha_1 + \beta_1$ is 1.0742064 indicating volatility shocks are quite persistent. The financial implication of these coefficients for investors is that EGX30 index returns' volatility exhibits clustering, and this permits investors to establish future positions in expectation of this characteristic**.** The same occurs for the series, Nikkei225, the estimate of α_1 coefficient is 0.2425265 and this shows the presence of volatility clustering in the series over the period. The volatility changes over time and its degree shows a tendency to persist, i.e., there are periods of low volatility and periods where volatility is high. The estimate of β1 (GARCH term) coefficient is 0.9464579 indicates a long memory in the variance. The sum of ARCH and GARCH terms $\alpha_1 + \beta_1$is 1.1889844 indicate that the random error series is non-stationary, and this is the main difference between the estimation results of EGX30 and Nikkei225 indices. Estimation results are reported on Table 7 and Table 8.

It is clear that the parameters of the model are significant. The variance intercept term cons in the `ARCH' panel is very small, and the `ARCH'-parameter **`L1.arch'** is around 0.25, 0.24 while the coefficient on the lagged conditional variance **`L1.garch'** is larger at 0.81., 0.94 for EGX30 and Nikkei225.

Table 7: Estimation Results of GARCH Model for Stock Returns for EGX30

Number of obs = 3580
Distribution: Gaussian
Log likelihood = -6397.824

	--						
	|		OPG				
	rEGX30	Coef.	Std.Err.	z	P>|z|	[95% Conf. Interval]	
	-------------+--						
rEGX30	|						
	_cons	0.0837	0.022839	3.66	0.000	0.038936	0.1284632
	-------------+--						
ARCH	|						
	arch						
	L1.	**0.258073**	0.018825	13.71	**0.000**	0.221176	0.2949697
	|						
	garch						
	L1.	**0.816134**	0.075506	10.81	**0.000**	0.668144	0.964123
	|						
	_cons	-0.16971	0.148546	-1.14	0.253	-0.46085	0.121436
	--						

Table 8: Estimation Results of GARCH Model for Stock Returns for Nikkei225

Number of obs = 3580
Distribution: Gaussian
Log likelihood = -6311.482

	--						
	|		OPG				
	rNikkei225	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
	-------------+--						
rNikkei225	|						
	_cons	0.035104	0.020528	1.71	0.087	-0.0051289	0.075338
	-------------+--						
ARCH	|						
	Arch						
	L1.	**0.242527**	0.021698	11.18	**0.000**	0.1999997	0.285053
	|						
	Garch						
	L1.	**0.946458**	0.083928	11.28	**0.000**	0.7819616	1.110954
	|						
	_cons	-0.40289	0.15175	-2.65	0.008	-0.7003128	-0.10546
	--						

4.3.1.2. GARCH-in-MEAN (1, 1) Model

It is clear that the parameters of the model are significant. The header describes the estimation sample and reports a Wald test against the null hypothesis that all the coefficients on the independent variables in the mean equations are zero. Here the null hypothesis is rejected for EGX 30 index, but the null hypothesis is accepted for Nikkei225 index.

For EGX 30 index, the estimated parameter on the mean equation (**sigma2** in the ARCHM panel) has a negative sign but is statistically significant. It could be concluded that for these returns, there is a negative feedback from the conditional variance to the conditional mean. This means that the greater the holding of the stock, the greater the risk and the lower the return. Here, it would be advised that the investor exits quickly from this financial portfolio. On the contrary, for Nikkri225 index, the estimated parameter on the mean equation has a positive sign but is statistically not significant. It could be concluded that for these returns, there is no feedback from the conditional variance to the conditional mean. The results are reported on Table 9 and 10.

Table 9: Estimation Results of GARCH-in-MEAN Model for Stock Returns for EGX30

Number of obs = 3580
Distribution: Gaussian Wald chi2(1) = 4.50
Log likelihood = -6395.396 Prob > chi2 = 0.0340

	|		OPG					
	rEGX30	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]		
rEGX30	|							
	_cons	0.199307	0.056059	3.56	0	0.089433	0.309181	
ARCHM	|							
	sigma2	**-0.05761**	0.027172	-2.12	**0.034**	-0.11087	-0.00435	
ARCH	|							
	arch							
	L1.	0.255324	0.018388	13.89	0.000	0.219284	0.291364	
	|							
	garch							
	L1.	0.828698	0.074719	11.09	0.000	0.682251	0.975145	
	|							
	_cons	-0.19552	0.147081	-1.33	0.184	-0.48379	0.092754	

Table 10: Estimation Results of GARCH-in-MEAN Model for Stock Returns for Nikkei225

Number of obs = 3580
Distribution: Gaussian Wald chi2(1) = 2.82
Log likelihood = -6309.878 Prob > chi2 = 0.0928

	|		OPG					
	rNikkei225	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]		
rNikkei225	|							
	_cons	-0.05378	0.05712	-0.94	0.346	-0.16573	0.058175	
ARCHM	|							
	sigma2	**0.048268**	0.028718	1.68	**0.093**	-0.00802	0.104554	
ARCH	|							
	Arch							
	L1.	0.243199	0.0216	11.26	0.000	0.200863	0.285535	
	|							
	Garch							
	L1.	0.940985	0.084374	11.15	0.000	0.775614	1.106355	
	|							
	_cons	-0.39407	0.153076	-2.57	0.010	-0.6941	-0.09405	

4.3.2. Parameter Estimation of Asymmetric GARCH Models

4.3.2.1. EGARCH (1, 1) Model

The exponential GARCH (EGARCH) model extends the classical GARCH by correcting the non-negativity constraint and by allowing for asymmetries.

It is clear that the parameters of the model are significant for EGX 30 and Nikkei225 indices and this indicates the model is appropriate to analyze the stock market data in Egypt. The negative estimate on the **`L1.earch'** (leverage asymmetric effect) for EGX 30 and Nikkei225 indices is significant and this means that the volatility is asymmetry, and the negative "L1.earch" coefficient implies that negative returns have a greater impact on future volatility than positive returns. It indicates that negative shocks imply higher conditional variance than positive shocks. In the real world, investors are more responsive to negative news compared to positive news and imply that the volatility spillover mechanism is asymmetric.

Since asymmetry coefficient, **"L1.earch_a"** coefficient for EGX 30 and Nikkei225 indices is significant and positive, it is expected that the relationship between the past variance and the current variance is positive in absolute value. This indicates that the existence of leverage effect is observed in returns of the Egyptian and Japan stock markets. Estimation results are reported on Table 11 and Table 12.

Table 11: Estimation Results of EGARCH Model for Stock Returns for EGX30

Number of obs = 3580
Distribution: Gaussian
Log likelihood = -6399.144

	--						
	|		OPG				
	rEGX30	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
	-------------+--						
rEGX30	|						
	_cons	0.072755	0.02207	3.3	0.001	0.029497	0.116012
	-------------+--						
ARCH	|						
	Earch						
	L1.	**-0.04998**	0.015702	-3.18	**0.001**	-0.08076	-0.01921
	|						
	earch_a						
	L1.	0.465918	0.022496	20.71	0.000	0.421827	0.510008
	|						
	Egarch						
	L1.	1.003404	0.06344	15.82	0.000	0.879064	1.127745
	|						
	_cons	-0.0368	0.050345	-0.73	0.465	-0.13548	0.061873
	--						

Table 12: Estimation Results of EGARCH Model for Stock Returns for Nikkei225

Number of obs = 3580
Distribution: Gaussian
Log likelihood = -6294.772

			OPG				
	rNikkei225	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
rNikkei225	|						
	_cons	0.010308	0.021565	0.48	0.633	-0.03196	0.052574
ARCH	|						
	earch						
	L1.	**-0.08616**	0.015265	-5.64	**0.000**	-0.11608	-0.05624
	|						
	earch_a						
	L1.	0.437894	0.028376	15.43	0.000	0.382278	0.493509
	|						
	egarch						
	L1.	1.205213	0.064303	18.74	0.000	1.079183	1.331244
	|						
	_cons	-0.18547	0.049191	-3.77	0.000	-0.28189	-0.08906

5. The GJR-GARCH (1, 1) Model

The GJR model is a simple extension of the GARCH model with an additional term added to account for possible asymmetries. It is clear that the parameters of the model are significant for EGX 30 and Nikkei225 indices and this indicates that the model is appropriate. Similar to the EGARCH model; it is found that all ARCH, TARCH and GARCH terms are statistically significant for EGX 30 and Nikkei225 indices.

A negative coefficient estimate is found on the "**L1.tarch**" term (leverage asymmetric effect) for EGX 30 and Nikkei225 indices. This is significant and this means that the volatility is asymmetry. The negative L1.tarch coefficient implies that negative effects lead in the coming period to greater conditional variance than positive effects, leading to further price declines. This indicates that the existence of leverage effect is observed in returns of the Egyptian and Japan stock markets. Estimation results are reported on Table 13 and Table 14.

Table 13: Estimation Results of GJR-GARCH Model for Stock Returns for EGX30

Number of obs = 3580
Distribution: Gaussian
Log likelihood = -6395.487

--							
	|		OPG				
	rEGX30	Coef.	Std.Err.	Z	P>|z|	[95% Conf.Interval]	
-------------+--							
rEGX30	|						
	_cons	0.074131	0.023579	3.14	0.002	0.027917	0.120344
-------------+--							
ARCH	|						
	arch						
	L1.	0.295315	0.023882	12.37	0.000	0.248508	0.342123
	|						
	tarch						
	L1.	**-0.08367**	0.028027	-2.99	**0.003**	-0.1386	-0.02874
	|						
	garch						
	L1.	0.822745	0.078364	10.5	0.000	0.669155	0.976336
	|						
	_cons	-0.15163	0.15126	-1	0.316	-0.4481	0.14483
--							

Table 14: Estimation Results of GJR-GARCH Model for Stock Returns for Nikkei225

Number of obs = 3580
Distribution: Gaussian
Log likelihood = -6302.986

--							
	|	OPG					
	rNikkei225	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
-------------+--							
rNikkei225	|						
	_cons	0.012722	0.021756	0.58	0.559	-0.02992	0.055363
-------------+--							
ARCH	|						
	arch						
	L1.	0.327724	0.033079	9.91	0.000	0.262891	0.392558
	|						
	tarch						
	L1.	**-0.15957**	0.030222	-5.28	**0.000**	-0.2188	-0.10033
	|						
	garch						
	L1.	0.998586	0.081333	12.28	0.000	0.839176	1.157995
	|						
	_cons	-0.46177	0.146329	-3.16	0.002	-0.74857	-0.17497
--							

4.3.3. Parameter Estimation of Multivariate GARCH Models

For each dependent variable, the estimates for the conditional mean equation are found first, followed by the conditional variance estimates in a separate panel. It is evident that the parameter estimates are all statistically significant. In the final panels Stata reports results for the conditional correlation parameters. For example, the conditional correlation between the standardized residuals for ` rEGX30, and rNikkei225 estimated to be 0083034 and not statistically significant, indicates no relationship at all between rEGX30, and rNikkei225.

Table 15: Estimation Results of Multivariate GARCH Models for EGX30 and Nikkei225

Number of obs = 3580
Distribution: Gaussian
Log likelihood = -12709.18

		Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
rEGX30	|						
	_cons	0.08388	0.02306	3.6	0.000	0.0386	0.12910
ARCH_rEGX30	|						
	Arch						
	L1.	0.25805	0.02748	9.3	0.000	0.2041	0.31191
	|						
	Garch						
	L1.	0.81629	0.09574	8.5	0.000	0.6286	1.00394
	|						
	_cons	-0.17001	0.18233	-0.99	0.350	-0.527	0.18736
rNikkei225	|						
	_cons	0.03516	0.02168	1.6	0.100	-0.007	0.07766
ARCH_rNikkei225	|						
	Arch						
	L1.	0.24282	0.03138	7.7	0.000	0.1813	0.30433
	|						
	Garch						
	L1.	0.94588	0.11192	8.4	0.000	0.7265	1.16525
	|						
	_cons	-0.40207	0.19957	-2.0	0.040	-0.793	-0.0109
corr(rEGX30,rNikkei225)		**0.008303**	0.016704	0.5	**0.619**	-0.024	0.04104

4.3.4. Forecasting using Nelson EGARCH

This sub-section is focused on generating forecasts based on the Nelson's EGARCH model estimated earlier for the forecast period 31Dec2017 to 31Dec2019. The conditional variance forecasts are examined graphically by creating Plot 1 and Plot 2 which contain the static and dynamic forecasts respectively. For the dynamic forecasts (red line) for EGX30 index and Nikkei 225 indices, the value of the conditional variance starts from a historically low level at the end of the estimation period, relative to its unconditional average. Therefore, the forecasts converge upon their long-term mean value from below as the forecast horizon increases.

Turning to the static forecasts (blue line) for EGX30 index, it is evident that the variance forecasts have one large spike in mid-2018 and another large spike in late 2018. After a period of relatively low conditional variances in the first half of 2019, the variances stabilize and enter a phase of historically quite high variance in the second half of 2019. It is evident that the variance forecasts have one large spike in mid-2019 and another large spike in late 2019. Turning to the static forecasts (blue line) for Nikkei 225 index, it is evident that the variance forecasts have one large spike in first 2018 and another large spike in mid-2018. After a period of relatively high conditional variances in the first half of 2018, the variances stabilize and enter a phase of historically quite low variance in the second half of 2018. It is evident that the variance forecasts have one spike in first 2019 and another large spike in late 2019.

2020 sees a large decrease in conditional variances and they remain at a relatively low level for the rest of the sample period for EGX30 index and Nikkei 225 indices. Since in the case of the static forecasts a series of rolling one-step ahead forecasts for the conditional variance are investigated, the values show much more volatility than those for the dynamic forecasts as shown in Figure 5 and Figure 6. Similar to previous studies, it is concluded that stock markets in developed countries like Japan are less volatile as compared to those in emerging countries.

Figure 5: Static and Dynamic Forecasts of the Conditional Variance for EGX30

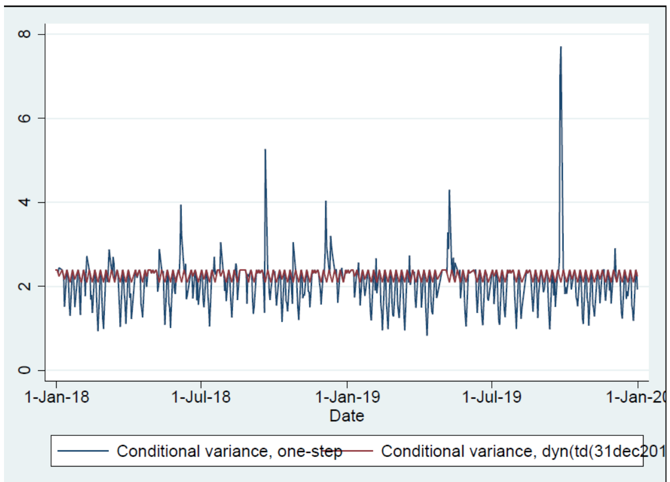
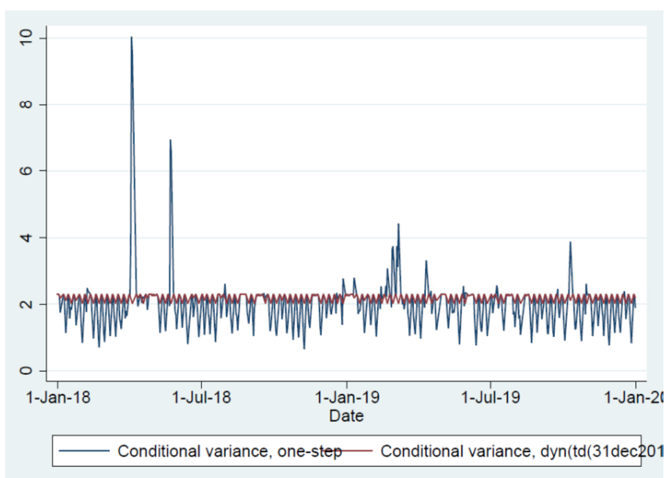


Figure 6: Static and Dynamic Forecasts of the Conditional Variance for Nikkei225



4.3.5. Choosing the Best Fitting Model

To evaluate the performance of the GARCH models used to analyze the Egyptian and Japan stock markets data, the following selection criteria is used:

1. Akaike Information Criterion (AIC).
2. Bayesian information criterion (BIC).

Table 16: Results of Different GARCH Models Tests for EGX30

Model	AIC	BIC
GARCH	12803.65	12828.38
GARCH-In-MEAN	12800.79	12831.71
EGARCH	12808.29	12839.2
GJR-GARCH	12800.97	12831.89
Multivariate GARCH	25436.37	25492.01
Forecasting using EGARCH	**11677.3**	**11707.67**

Table 17: Results of Different GARCH Models Tests for Nikkei225

Model	AIC	BIC
GARCH	12630.96	12655.7
GARCH-In-MEAN	12629.76	12660.67
EGARCH	12599.54	12630.46
GJR-GARCH	12615.97	12646.89
Multivariate GARCH	25436.37	25492.01
Forecasting using EGARCH	**11503.25**	**11533.62**

From Table (16, 17) above, it can be seen that the Forecasting using Nelson EGARCH model has the lowest AIC and BIC values (11677.3, -11707.67, 11503.25, 11533.62) for EGX30 and Nikkei225 indices respectively. Thus, it can be concluded that **Nelson EGARCH model** is the best model for the Egyptian and Japan stock markets.

5. Conclusion

This paper uses standard GARCH, asymmetric EGARCH and GJR-GARCH models to analyze volatility in EGX30 and Nikkei225 returns for the period of 3rd January 2001 to 31st December 2019. In addition, considering that Japan is one of the world largest economies, any slowdown or changes in its stock markets are expected to bring about spillover effects to other close economies, for example, trading partners especially if they are emerging economies. In other words, the contribution is made by addressing the gap in the literature that identifies which volatility model outperforms other models in terms of in-sample and out-of-sample forecasting accuracy for the Egyptian and Japan stock markets.

The findings of GARCH (1, 1) model show nonlinear structure in the conditional variance of the returns and this dynamic may be simulated with the GARCH (1, 1) model. Estimates of the model $(\alpha_1 + \beta_1)$ for EGX30 show the variance of the series has long memory and shocks on volatility are quite persistent, and this supports the mean reverting process. The sum of ARCH and GARCH terms for Nikkei225 indicate that the random error series is non-stationary.

The findings of GARCH-in-MEAN model show that for EGX30 returns, there is a negative feedback from the conditional variance to the conditional mean. Here an investor would be advised to exit quickly from this financial portfolio. On the contrary, for Nikkri225 index, the estimated parameter on the mean equation has a positive sign but is statistically not significant.

The findings of EGARCH and GJR-GARCH models show that the series have leverage effect, and the impact of the shocks is asymmetric, and consequently it can be stated that the impact of negative shocks on volatility are higher than positive shocks of the same size for both EGX30 and Nikkei225 indices. This finding is consistent with the literature. Multivariate GARCH model indicates no relationship at all between rEGX30, and rNikkei225.

According to the results obtained by the two selection criteria —AIC, and BIC—it is concluded that the most appropriate models for modeling the volatility of EGX30 and Nikkei225 for the full sample is Nelson EGARCH model. Furthermore, the results of this study support those of previous studies (Abdalla and Winker, 2012; Abdelhafez , 2018), in which it is concluded that, compared with linear GARCH-class models, non-linear GARCH-class models are a better fit for measuring the volatility of stock market returns (e.g., Gabriel and Ugochukwu, 2012; Al Rahahleh and Bhatti, 2017).

In addition, the results suggest that emerging stock markets can have higher volatilities than those in developed markets. Further, these results imply that the EGARCH model might be more useful than other models when implementing risk management strategies and developing stock pricing model.

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