

Financial Forecasting by Autoregressive Conditional Heteroscedasticity (ARCH) Family: A Case of Mexico

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To cite this article:

Vina Javed Khan, Abdul Qadeer, Bezon Kumar. Financial Forecasting by Autoregressive Conditional Heteroscedasticity (ARCH) Family: A Case of Mexico. *Journal of Public Policy and Administration*. Vol. 2, No. 3, 2018, pp. 32-39. doi: 10.11648/j.jppa.20180203.13

Received: October 8, 2018; **Accepted:** October 29, 2018; **Published:** November 27, 2018

Abstract: Understanding and modeling the volatility measurements is important for forecasting the risk and for evaluating asset allocation decisions of stock market. The study have used the daily frequency data from January 1, 2002 to September 30, 2016 as an in-sample period to perform empirical analyses for modeling and predicting the volatility dynamics of Mexican stock market (IPC). To facilitate the variance forecast, the competing models are ARCH (p, q), GARCH (p, q), and its variations i.e. Glosten Jagannathan Runkle GARCH, GARCH in Mean, Exponential GARCH, and Quadratic GARCH. The results of residual diagnostics suggested that stock market of Mexico is characterized by heteroskedasticity, multicollinearity, non-normality, and serial correlation. Volatility measurements by ARCH and GARCH signify that the current conditional variance of Mexico is determined by its past price behavior and previous day volatility. Today's volatility does impact the current stock returns as indicated by GARCH-M. Results of EGARCH explained that any large size news produces high volatility as compared to small size news. Effects of bad news are greater on the volatility of the Mexican stock market than good news. GJR GARCH described the asymmetric behavior of returns and variance in the politically conflicted regime during 2006-2012. Moreover, QGARCH effect is not linear. Findings have the implications for individuals and corporate investors about retaining their risky stocks.

Keywords: Volatility, ARCH Family, Mexican Stock Market

1. Introduction

Financial forecasting is a broad subject with various subcategories and aspects. It may concern with estimating future profits and expenses of companies, impending financial and economic condition of countries, business valuation, risk accompanying the investment, and so forth. Predicting time series is one of the most challenging tasks due to its non-stationary and noisy characteristics [1-2]. Specifically concerned with stock markets, this study has investigated the volatility of Mexico Capital Market index. According to Figlewski, volatility is a departure from mean and this deviance entails risk [3]. Markowitz employed the volatility as a measure of risk in modern portfolio theory [4]. Forecasting volatility has plentiful implications for (a)

options pricing like in option pricing model, (b) asset pricing like in Capital Asset Pricing Model (CAPM) introduced by Sharpe, Lintner and Mossin (c) risk management such as Value at Risk (VaR) models and hedging, (d) portfolio management, and (e) macroeconomic stability [5-7].

Many models have been developed so far to account for the stylized facts of heavy tails and sharply peaked distribution (leptokurtosis), leverage effect¹, and volatility clustering² in stock market returns. These include ARCH models, Autoregressive Moving Average (ARMA) models, Stochastic Volatility (SV) models, threshold models, and

1 Leverage effect explains the negative correlation between asset's present returns and its future volatility [8]

2 Volatility clustering means that large changes lead towards large changes (negative/positive) and similar is for small changes [9]

regime switching models. ARCH family models are used for modeling and forecasting conditional volatility of asset returns. Engle developed ARCH and its extensions consist of Generalized ARCH (GARCH) which was proposed by Bollerslev and Taylor [10-12]. Variations of GARCH include GARCH in Mean (GARCH-M), Exponential GARCH (EGARCH), and Integrated GARCH (IGARCH) developed by Nelson, Glosten Jagannathan Runkle GARCH (GJR-GARCH) by Glosten *et al.*, Quadratic GARCH (QGARCH) by Engle and Ng, and Asymmetric GARCH (AGARCH) by Engle [13-16]. Past studies have shown consensus that no model is superior however these are alternative specifications and extensions of one model that are aimed to capture the characteristics of financial time series.

Stock markets' volatility forecasting has been done on various developed and developing countries by utilizing many econometric models. For example, Brooks and Burke used the stock market data of the United States and found the GARCH family models perform better [17]. Brailsford and Faff forecasted the volatility of the Australian stock market index using GARCH models [18]. For modeling the stock market volatility, Mcmillan *et al.* worked upon the United Kingdom stock market; Franses and Ghijsels analyzed the capital markets of Netherlands, Spain, Germany, and Italy; Wei studied the Chinese equity market; Pandey analyzed the Indian stock market; and Miron and Tudor worked upon daily stock returns of US and Rumania [19-23].

None of the studies, as per researchers' knowledge are targeted on the emerging market of Mexico for scrutinizing conditional volatility using ARCH, GARCH, GARCH-M, EGARCH, QGARCH, and GJR-GARCH models. So, this research would fill this gap by answering the following research questions.

- (1) Is the current volatility of Mexbol estimated by squared residuals and volatility of previous periods?
- (2) Is there any relationship (positive/negative) between Mexbol stock returns and current volatility?
- (3) What is the impact of size (large/small) and sign (good/bad) of news on current volatility?
- (4) Does the bad news impact higher on the conditional volatility or the good news?

The paper is organized in different sections. After reviewing the relevant literature, data and methodology is given in section 2. Section 3 presents the results and discussion. Section four concludes the study.

Numerous empirical studies have been conducted on the forecasting of conditional volatility using ARCH family models contextualizing the developing and developed countries. Claessen and Mittnik employed GARCH models on the German (DAX) options market and found that historical returns do not provide useful information to predict the current volatility [24]. Another study predicted the Japanese stock market volatility concerning some macroeconomic variables using GARCH models and discovered no influence of these on volatility. Su applied GARCH and EGARCH models on the Chinese stock market and concluded that its volatility is more sensitive to crisis

period and bad news [25].

ARCH family models have been applied to encapsulate different characteristics of stock markets' conditional returns and variances. Using non-linear GARCH models, Iranian capital market assessed to have the same impact of good and bad news of equal size and the absence of asymmetric volatility [26]. By employing ARCH and GARCH models, Midhra found time-varying volatility of Indian stock market to be more sensitive to bad news from 1991 to 2009. Through applying GARCH models on the Saudi capital market, Abdalla and Suliman discovered the persistence of previous period volatility and presence of risk premium with the positive sign [27-28]. Ahmed and Suliman applied some univariate GARCH models on the Khartoum Stock Exchange (KSE) of Sudan and revealed that there is the high persistence of prior period volatility and leverage effect exists [29]. Chowdhury and Ratan performed volatility forecasting on Dhaka Stock Exchange of Bangladesh using GARCH and GJR-GARCH models and concluded equity returns are not always a function of its variance and conditional volatility exhibits symmetric behavior [30]. Arshad *et al.* identified the Karachi Stock Exchange of Pakistan as highly volatile [31]. Its current volatility depends upon previous periods residuals and absence of leverage effect indicates that greater volatility is caused by positive returns. Wong and Kok studied equity markets' conditional volatility of Malaysia, Thailand, Singapore, Philippines, and Indonesia using ARCH-M, TARCH, and EGARCH and identified the insignificant asymmetric behavior of their stock returns [32].

Some studies are aimed at comparison of different ARCH family models or among several forecasting models. Kuen and Hoong declared Exponentially Weighted Moving Average (EWMA) method as superior to the GARCH model and naive method based on the historical variance in forecasting volatility of Singapore stock market [33]. AbdElaal worked upon EWMA, ARCH, GARCH, GJR-GARCH, and GARCH models for Egyptian stock market and found EGARCH to be the best model among these [34]. Alberg *et al.* analyzed the conditional variance of Tel Aviv Stock Exchange (TASE) indices of Israel using GARCH, EGARCH, GJR-GARCH, and Asymmetric PARARCH (APARCH) models and realized the EGARCH to be more useful than others in inculcating dynamic behavior of stock returns [35]. Further, comparison was made between Heterogenous Auto Regressive (HAR) and GARCH class modeling for their performance to capture the asymmetric volatility in 19 equity indices from Asia, America, Australia, and Europe. The results indicated significant accuracy of GARCH models during high volatility (asymmetric volatility in equity markets around the world). Opposing, Vortelinos regarded HAR model better than nonlinear models like GARCH, neural networks, and Principal Components Combining for realized volatility forecasting [36].

None of the studies, as per researchers' knowledge have targeted forecasting the conditional volatility of Mexico despite its important place in North American Free Trade

Area (NAFTA) and well as in Next Eleven (N-11) emerging economies [37-38].

2. Data and Methods

Mexican Stock Exchange is the only stock exchange of Mexico, usually referred to as Mexican Bolsa (Mexbol). It is ranked the second largest by market capitalization in Latin America. Índice de Precios y Cotizaciones (IPC) is the benchmark index. For modeling and forecasting the volatility of the Mexican Stock Exchange Index, this paper used daily closing prices for the sample period January 1, 2002 to September 30, 2016. The dataset was obtained from Yahoo Finance and comprised 5832 observations. Continuously compounded returns R_t for daily stock prices of Mexbol Index were calculated using the formula $R_t = \ln(P_t/P_{t-1})$ where P_t and P_{t-1} represent the closing stock prices of Mexbol Index for two successive days.

Before application of univariate ARCH and GARCH models, authors firstly examine the residuals for autocorrelation and heteroscedasticity issues. To check for these econometric problems, residuals e_t were obtained by estimating the conditional mean equation through ordinary least square (OLS) method. For estimating residuals, conditional mean equation using autoregressive (AR) process is:

$$R_t = \alpha + \beta R_{t-1} + e_t \quad (1)$$

After finding the residuals, existence of serial correlation was checked through Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) Test. The decision was based on the p-value of chi-square for the null hypothesis of no serial correlation. Heteroscedasticity problem was tested against the null hypothesis that there is no ARCH effect or there exists heteroscedasticity. P value less than 0.05 provides a base for acceptance or rejection of the null hypothesis.

Volatility Models

Volatility is not exactly similar to risk, however, both terms are related. Commonly, risk is linked with some unfavorable outcome while volatility is specifically for uncertainty which might occur due to any positive event [39]. This study have used variance to measure the volatility of Mexican stock returns.

2.1. Autoregressive Conditional Heteroscedasticity (ARCH) Model

The ARCH model was first introduced by Engle being the first model to accommodate heteroscedasticity problem for volatility measurement of stock returns [10]. The ARCH model evaluates the variance of returns as a function of previous period innovations or disturbances. Conditional mean and variance equation of q order Autoregressive Conditional Heteroscedasticity i.e. ARCH (q) is specified as:

$$\text{Mean equation } R_t = \omega + \sum_{i=1}^q \theta_i R_{t-i} + \varepsilon_t \quad (2)$$

$$\text{Variance equation } \sigma_t^2 = \alpha + \sum_{i=1}^q \gamma_i \varepsilon_{t-i}^2 \quad (3)$$

R_t is the current period return of an asset. This study is related to stock returns so R_t will be stock returns of Mexbol Index and these are predicted by its own lags and residual term ε_t . σ_t^2 denotes the volatility of stock returns at the time t i.e. current period and measured by sigma square. Current period volatility is predicted by squared errors of prior periods i.e. ε_{t-i}^2 . α is the constant term and γ is the coefficient of ε_{t-i}^2 . ω and θ are parameters.

2.2. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

Bollersley propounded the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model which suggested that current volatility of an asset return is not only determined by squared errors of previous periods but also by its own lags [11]. Conditional mean and variance equation for GARCH (p, q) model is formed as:

$$\text{Mean equation } R_t = \omega + \sum_{i=1}^q \theta_i R_{t-i} + \varepsilon_t \quad (4)$$

$$\text{Variance equation } \sigma_t^2 = \alpha + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 + \sum_{j=1}^q \gamma_j \varepsilon_{t-j}^2 \quad (5)$$

Here, p represents the order of lagged volatility (GARCH term) and q is the lagged order of squared error (ARCH term). σ_{t-i}^2 denotes the lagged values of volatility. α , β and γ are parameters.

2.3. GARCH in Mean (GARCH-M) Model

In the finance world, the stock returns may be determined by its own volatility. Engel et al. developed GARCH in Mean model to account for this aspect. GARCH-M is an extension of ARCH family models which permits the condition to mean the return to being estimated by its standard deviation or variance [40]. GARCH-M (p, q) can be written as:

$$\text{Mean equation } R_t = \omega + \sum_{i=1}^q \theta_i R_{t-i} + \varphi \sigma_t + \varepsilon_t \quad (6)$$

$$\text{Variance equation } \sigma_t^2 = \alpha + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 + \sum_{j=1}^q \gamma_j \varepsilon_{t-j}^2 \quad (7)$$

In the conditional mean equation, the coefficient of σ_t is called risk premium parameter φ . The positive sign of φ shows that the asset return has a positive relation with its volatility and vice versa. It signifies that if risk (standard deviation, σ_t) of the security increases, returns will grow. β and γ are coefficients of GARCH and ARCH term respectively.

ARCH, GARCH, and GARCH-M models, discussed above, do not account for the leverage effects in stock returns. Leverage effect is described as the negative relationship between the stock returns and future volatility [41]. In these models, the conditional variance was dependent upon the past conditional volatility and lag values of squared errors. Increase or decrease in the ε_t did not influence the conditional variance. In other words, the variance of the returns was only affected by the size, but not by the sign of returns. Hence, to inculcate this aspect, asymmetric GARCH models like EGARCH, TARCH, and QGARCH were developed by researchers.

2.4. Exponential GARCH (EGARCH) Model

In 1991, Nelson developed the EGARCH model that encapsulate leverage effect and the asymmetric responses of conditional variance as a result of shocks [13]. Mean equation is similar to equation (4) and following are the specifications of conditional mean and variance for EGARCH (p, q) model.

$$\text{Mean equation } R_t = \omega + \sum_{i=1}^q \theta_i R_{t-i} + \varepsilon_t \quad (8)$$

$$\text{Variance equation } \ln \sigma_t^2 = \alpha + \sum_{j=1}^p \gamma_j \left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}^2} \right| + \sum_{j=1}^p \rho_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}^2} + \sum_{i=1}^q \beta_i \ln(\sigma_{t-i}^2) \quad (9)$$

In this model, ρ signifies the asymmetric impact of shocks on conditional volatility. The second term signifies the magnitude impact which shows that large size news causes high volatility and small size news leads to low volatility. The third term of equation (9) indicates the sign effect. This means that zero value of ρ will reveal the absence of leverage impact and its positive or negative value ensure the presence of asymmetric behavior of stock returns [29]. The last term denotes the persistence of previous periods of volatility.

2.5. Glosten Jagannathan Runkle GARCH (GJR-GARCH) Model

GJR-GARCH that is also known as Threshold GARCH (TGARCH) is another model for volatility measurement that can handle the leverage effect. Volatility forecasting using TGARCH process permits to analyze the impacts of good or bad news on the conditional volatility by introducing a dummy variable. Conditional mean and variance for TGARCH (p, q) process can be generally specified as:

$$\text{Mean equation } R_t = \omega + \sum_{i=1}^q \theta_i R_{t-i} + \varepsilon_t \quad (10)$$

$$\text{Variance equation } \sigma_t^2 = \alpha + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 + \sum_{j=1}^q \gamma_j \varepsilon_{t-j}^2 + \sum_{j=1}^q \rho_j (D * \varepsilon_{t-j}^2) \quad (11)$$

D represents the dummy variable in equation (11) and its value is 1 for the time period December 1, 2006 to November 30, 2012. This period represents the presidential tenure of Felipe Calderón of Mexico which is characterized by a large increase in organized crime, illegal drug trade, lawlessness, and political corruption. Use of army by president Calderón to resolve these issues worsened the situation [42]. For the rest of the sample, the value of the dummy variable was zero. ρ measures the leverage effect and if its value was found to be significant and positive then bad news or negative shocks impact higher on the conditional volatility.

2.6. Quadratic GARCH (QGARCH) Model

Engle and Ng developed another model that can account for the asymmetric impact of shocks [15]. This model adds error term as a regressor in the variance equation. QGARCH (p, q) then can be written as:

$$\text{Mean equation } R_t = \omega + \sum_{i=1}^q \theta_i R_{t-i} + \varepsilon_t \quad (12)$$

$$\text{Variance equation } \sigma_t^2 = \alpha + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 + \sum_{j=1}^q \gamma_j \varepsilon_{t-j}^2 + \sum_{j=1}^q \rho_j \varepsilon_{t-j} \quad (13)$$

GARCH effect would be quadratic, and non-linear if ρ_j value was found to be significant.

3. Results and Discussion

Figure 1 displays the result of descriptive statistics and normality test for Mexbol index returns. The daily average return for the chosen time series was close to zero. A normal distribution has 0 skewness and a kurtosis of 3. In this study, skewness coefficient of 0.07 is positive and not equal to zero which suggests that the distribution is positively skewed to right. Kurtosis of 11.89 indicates the empirical distributions is leptokurtic, being greater than 3. It also reveals the presence of extreme values and hence, fat tails. P-value against the Jarque-Bera test of normality rejects the null hypothesis of normality as its value is significant at 5% level of significance.

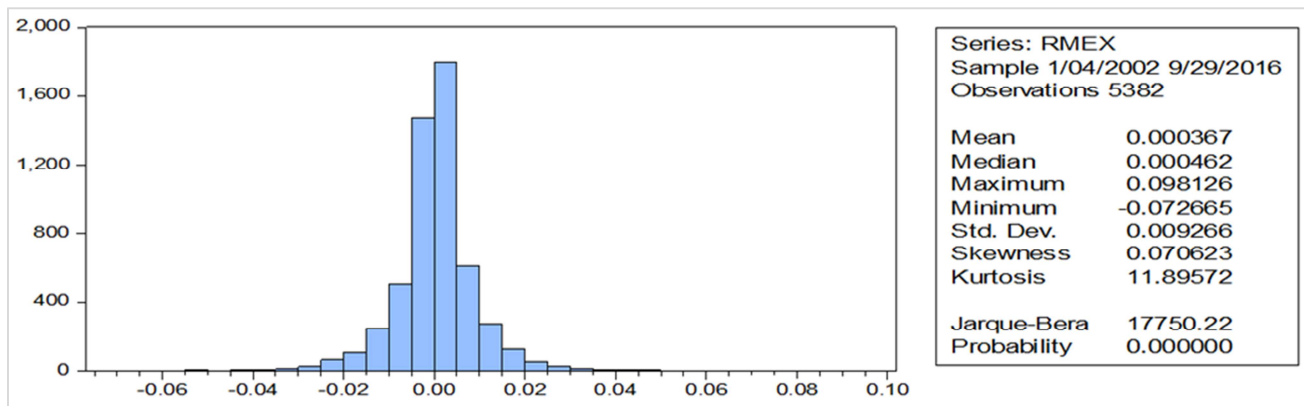


Figure 1. Summary statistics and normality test of Mexico's return time series for the period 1st January 2002 to 30th September 2016.

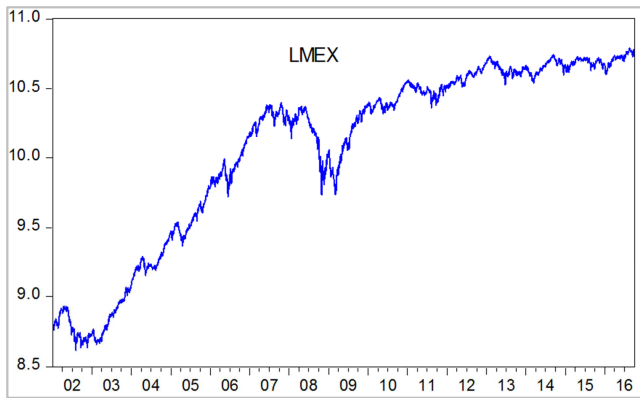


Figure 2. Daily closing log prices of Mexican Stock Exchange Index (Mexbol) from 1st January 2002 to 30th September 2016.

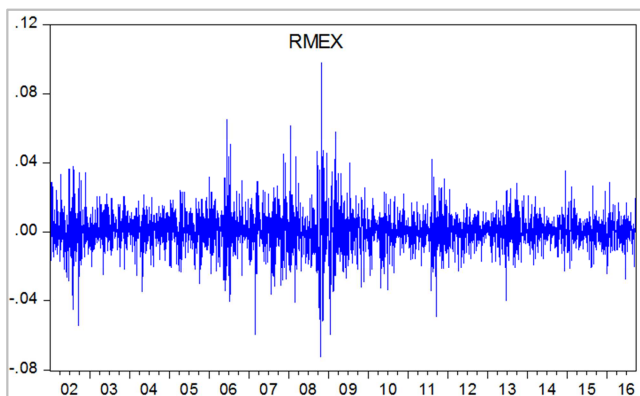


Figure 3. Daily Stock Returns of Mexican Stock Exchange Index (Mexbol) from 1st January 2002 to 30th September 2016.

Daily closing log prices of Mexbol exhibit an upward trend as evident from Figure 2. The major downward trend in its prices was observed in late 2007 to 2009 which might be due to financial crisis of 2007 occurred in United States (US). Daily returns of Mexican Bolsa (Mexbol) also show the greater volatility during this crisis as displayed in figure 3.

Table 1. Unit Root Analysis.

Variables/series	Augmented Dickey Fuller	
	Levels	1st Difference
Mexico	-62.51	-27.99
Critical Values		
1% Level	-3.96	-3.96
5% Level	-3.41	-3.41
10% Level	-3.13	-3.13

Stationarity of sample return series was tested by employing Augmented Dickey Fuller test as displayed in Table 1. Test results revealed the stationarity of Mexbol stock returns series at levels and at first difference. Decision was based on the comparison between the absolute values of t-statistic and corresponding critical values at 5% significance level. Greater absolute t-statistic value suggested the stationarity of Mexbol daily stock return series.

Pre-requisites of applying ARCH family models for financial forecasting are presence of heteroscedasticity and autocorrelation in the residuals. For this purpose, equation (1) is estimated through autoregressive process (1) using least square method and residual diagnostics are applied. Results for diagnostic tests are given in table 2.

Table 2. Diagnostic Tests on Standardized Residuals.

	Heteroscedasticity Test -ARCH	Breusch-Godfrey Serial Correlation LM Test
F-statistic	169.18	3.17
Prob. F(1,5378)	0.00	0.04
Obs*R-squared	164.09	6.33
Prob. Chi-Square(1)	0.00	0.04

Heteroscedasticity of the residuals is present as Prob. Chi-Square is less than 0.05 (see table 2). So, null of no ARCH effect is rejected. Breusch-Godfrey serial correlation LM test identified the autocorrelation problem in residuals (see table 2) as its Prob. Chi-Square value of less than 0.05 rejected the null of no serial correlation.

Results of financial time series was detected to have the characteristics of heteroscedasticity and autocorrelation in residuals. So, ARCH family models can be applied for forecasting the conditional volatility of Mexbol's returns.

Conditional volatility is estimated using one lag. According to Brooks and Bruke lag order one is enough to encapsulate the impact of volatility clustering [17]. By using simple ARCH family models, Table 3 shows the conditional mean and conditional variance equations of ARCH, GARCH, and GARCH-M.

Table 3. Estimation of Conditional Volatility Using ARCH (1), GARCH (1, 1), and GARCH-M(1, 1) Process.

	Mean equation			Variance equation		
	ω	θ	ϕ	α	γ	β
ARCH (1)	0.00 (0.00)	0.09 (0.00)		0.00 (0.00)	0.39 (0.00)	
GARCH(1, 1)	0.00 (0.00)	0.12 (0.00)		0.00 (0.00)	0.04 (0.00)	0.94 (0.00)
GARCH-M (1, 1)	- 0.001 (0.09)	0.12 (0.00)	0.15 (0.00)	0.00 (0.00)	0.04 (0.00)	0.95 (0.00)

Note: Figures in the brackets indicate p-values.

In ARCH (1) process, the significant p-value of θ suggests that today's return of Mexico stock market index is predicted by the past return. Its positive coefficient of 0.09 shows that

current return will be 9% more than the previous day return. In variance equation of ARCH (1) process, significant p value (i.e. less than 0.05) of ARCH term β indicates that

previous day innovations explain the current volatility. Positive coefficient of lagged squared residuals β exhibit today's volatility will be greater.

Estimation of GARCH (1, 1) model also accounts for the previous period volatility in the analysis of today's volatility. It captures the persistence of last period volatility. Variance equation of GARCH (1, 1) process (see table 3) depicts that today's conditional volatility is significantly dependent upon prior day innovations β as well as previous period volatility γ that is GARCH term. The positive value of γ revealed that 95% volatility of last day transfers to the next day.

GARCH in Mean (1, 1) model consider that today's stock return might be affected by today's volatility. As p-value of GARCH-M that is ϕ is significant which suggests that today's return of Mexico stock market is predicted by today's volatility and 1% increase in current volatility cause 14% increase in today's stock return. The coefficient of GARCH-M term is the risk premium parameter of equation (6). Variance equation signifies that previous period's squared residuals and variance positively and significantly determines the today conditional volatility.

As discussed previously, EGARCH model incorporates the

asymmetric responses of variance to the shocks. Conditional volatility in this model is determined by the size as well as by sign of news (positive or negative). For EGARCH (1, 1) process, errors were estimated using equation (8). Intercept term [α of equation (9)] is negative and significant. It suggests that there are many other variables or factors that might affect the today's stock market volatility and should be part of the equation. The coefficient of size effect $\sum_{j=1}^q \gamma_j \left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}^2} \right|$ and has the positive sign; its p-value is significant which suggest that large size news leads to high volatility and small size cause little volatility. ρ of equation (9) which represents the sign effect $\sum_{j=1}^p \rho_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}^2}$. The P-value

of ρ is negatively significant which means that the leverage effect exists and bad news impact higher on the volatility of stock returns as compared to the good news. These results entail that the impact of market crashes have higher on the volatility than the market bubble because of greater perceived uncertainty [9]. The significant value of coefficient β indicates that previous day volatility persists and contribute 98.42% to next day conditional volatility.

Table 4. Estimation of Conditional Volatility Using EGARCH (1, 1), GJR-GARCH(1, 1), and QGARCH(1, 1) Process.

	Mean equation		Variance equation			
	ω	θ	α	β	γ	ρ
EGARCH (1, 1)	0.00 (0.04)	0.11 (0.00)	-0.22 (0.00)	0.98 (0.00)	0.09 (0.00)	-0.08 (0.00)
GJR-GARCH(1, 1)	0.00 (0.00)	0.12 (0.00)	0.00 (0.00)	0.94 (0.00)	0.01 (0.00)	-0.001 (0.00)
QGARCH (1, 1)	0.00 (0.99)	0.16 (0.00)	0.00 (0.00)	0.94 (0.00)	-0.65 (0.00)	0.69 (0.00)

Note: Figures in the brackets indicates p-values.

Next asymmetric model of ARCH family in table 4 is Threshold GARCH model. It also takes into account the leverage effect on the conditional volatility by introducing a dummy variable into the TGARCH (1, 1) model. The dummy variable is a politically corrupt period of Mexico 1st December 2006 to 30th November 2012 as discussed before.

TGARCH (1, 1) model also measure the leverage effect. In table 4, coefficient ρ of dummy variable that measure the impact of good news and bad news. As p-value of the dummy is significant that is less than 0.05 which signifies the asymmetric behavior of stock returns along with the different influence of good and bad news on the Mexbol stock market. Coefficient ρ of dummy variable in variance equation (see table 4) is negative which indicates that good news has greater sensitivity than the bad news to the conditional volatility. It is evident from the minor value of coefficient of dummy.

Results of QGGARCH indicates that conditional volatility of Mexbol's stock returns is not lagged squared residuals and lagged volatility but also by previous day's residuals. Significant p-value of ε_{t-j} suggests that GARCH effect on conditional volatility exist and it is not linear but quadratic.

4. Conclusion

Financial forecasting of stock market's volatility has

several knocks on effects. Variation in the stock market volatility influence the consumer spending through the wealth effect, investors' readiness for retaining the risky assets and securities, and also the companies' decisions about investment. Forecasting of conditional volatility is thus important for risk management, portfolio allocation, and asset pricing decisions. This study on Mexico stock market would definitely contribute academically to the present literature related to modeling and forecasting of conditional volatility using ARCH and GARCH family models within the context of emerging countries. Results of GARCH (1, 1) have indicated that the conditional volatility of Mexbol's returns depends upon the previous day disturbances and volatility. GARCH-M determined that current return is forecasted by current volatility along with its lagged returns. The large size and negative news were discovered to be highly associated with greater volatility as indicated by EGARCH (1, 1) process. Conditional volatility was uncovered to have asymmetric behavior and observed greater sensitivity to good news. In future, this research can be extended by comparing the performance of these ARCH family models in capturing the stock market volatility of Mexico. These ARCH models can be applied to other unexplored emerging markets for the same purpose.

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