Modelling Exchange Rate Volatility in MIST Countries

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Abstract

ThisstudyexaminesthatmodellingMIST Countriesexchangerate volatilitywithAsymetric GARCH modelsand choosing the best forecasting volatility models. Then these models are used for out of sample forecasting. The best forecasting volatility models are choosed with choosing criteria. In our study we used monthly exchange rate against US dollar and investigated leverage effect and features of fat tailed over the period of between 1993.01 and 2012.12. The models are estimated the over the period between 1993.01and 2012.12 and models are evaluated for out of sample forecasting over the period between 2012.12 and 2013.03. The best forecasting models are choosed in these estimated models then the best forecasting models are estimated for three months until 2013.03. This forecastings are compared with the volatility for same real period and the model's forecastings are evaluated .The asymmetric and leverage effects are seen in the model estimations results.

Keywords: Exchange rates volatility, Asymmetric GARCH Model, Forecasting

1. *Introduction*

Volatility forecasting of exchange rates in general has been the focus of research related to invesment analysis, derivative securities, pricing, risk managementandso on. Financial marketsvolatility is a major concern for policy makers and in this context the volatility forecasts can play the role as a trigger factors for the financial markets and economy. (PoonandGranger 2003). There are some empirical studies which examine the exchange rate volatility in both developed and developing countries. For example, Marten (2001), McKenzie (1997), McKenzieandMitchell (2002), Sanchez-Fung (2003), Tse (1998), Andersen andBollerslev (1998), Vilasou (2002), BaillieandBollerslev (1989), BeineandLecourt (2000), Balaban (2004), Çağlayan and Dayıoğlu (2009) amongothers. In this paper we evaulate the volatility forecast performance of Asymmetric GARCH Models for dolar exchange rates of MIST countries.The MIST countriesarethe newest emerging market club that boasts a membership of Mexico, Indonesia, South Korea, and Turkey. The MIST represents the largest markets in Goldman's N-11 Equity Fund, which seeks long-term capital appreciation. The MIST countries undoubtedly share a great deal of economic situation. Mexico has a strong demographic foundation for future economic growth; something it shares with many of the other MIST countries. Indonesia also benefits from its geography. As Southeast Asia's largest economy, it is well placed to take advantage of the ASEAN-China Free Trade Area, and it has done just that- recording three consecutive years of GDP growth over 6 percent from 2009-2012. Indonesian economy is still connected to the wax and wane of the global economy. Its exports are dominated by commodities and natural resources, primarily heading to China, so it stands to reason that the Indonesian economy would suffer in the event of any Chinese slowdown. Turkey's position as one of the world's next big emerging economies has become unassailable in the past fifteen years. Unlike the aging populations that characterize other economic powers in the region. South Korea is somewhat of an exception within the MIST countries, but not for any lack of economic dynamism.

It stands apart because it can, in many respects, already be considered a developed economy, and it is often classified as such by everyone from the lowly student to the massive bureaucracy like the OECD.By most indications, South Korea is a developed economy: it boasts a per-capita income of US $27,000, its economy is export-driven and powered by high value-added manufacturing, and it has mature political institutions that help reduce corruption. South Korea might chafe at the categorisation – it has a far higher per capita GDP than the others and is a member of the OECD, but Turkey will likely be pleased. Some say the hype (not to mention investment) that could be spurred by MIST is warranted.The Istanbul stock exchange, in Turkey, one of the MIST, the four emerging economies in the next tier of large emerging economies.Still, all four countries have in common a number of factors: a large population and market, a big economy at about 1% of global GDP each, and all are members of the G20. South Korea might chafe at the categorisation – it has a far higher per capita GDP than the others ($27,000) and is a member of the OECD, but Turkey will likely be pleased. Some say the hype (not to mention investment) that could be spurred by MIST is warranted. Turkey became a much more attractive destination for FDI, breaking a new record in 2007 before the global crisis with $22bn of FDI [foreign direct investment] inflows." Investment has waxed and waned since then but, the country has a "large and as yet unsaturated market", which should make it attractive to investors. Turkey has relatively high labour costs and its main exports – such as cars and textiles – are under pressure from Asian rivals, while hi-tech investment does not as a rule go to Turkey (www.guardian.co.uk).

Each MIST country represents more than one percent of global gross domestic product (GDP). Each of these countries is a member of G-20, the group of finance ministers and central bank governors from 20 major economies. And real GDP growth in this group has been in the neighbourhood of 5 percent to 8 percent each year in recent years.Financial exchanges in some of the MIST countries are also increasingly forming partnerships that attract international investors. In March 2010, the parent company of the Mexican Derivatives Exchange (MexDer), BMV Group, entered into a strategic partnership with CME Group. The first phase of the in 2011 gave Mexican investors access to CME Group’s interest rates, foreign currencies, equity indexes, energy, metals and agricultural commodities. In August 2012, they announced the successful launch of their north-to-south order routing agreement, giving customers in the U.S. access to MexDer’s Mexican Stock Exchange Index Futures, Bond Futures and MXN Peso / US Dollar Futures contracts.

South Korea had already been on the radar screen for many investors. South Korea has a far higher per capita GDP than the other MIST countries at $27,000. The country is also one of the fastest-growing members of the the Organization for Economic Co-operation and Development (OECD). Korea Exchange’s main benchmark stock index is the KRX KOSPI 200. Futures and options contracts tied to the index’s value are the world’s most- traded derivatives contracts, according to the Futures Industry Association. The KOSPI is seen as one of most used indices by retail investors .Further, South Korea’s policy has become very integrated with Western policy. South Korea is a seen as a very mature market with a highly-educated workforce even though it has only been around for 64 years. The downside to South Korea is that, not unlike the U.S., their population is quickly aging.

For many investors, Mexico, Indonesia, South Korea and Turkey have taken over from the BRICS becoming the four biggest emerging markets, and growing faster than their major rivals. BRICS inventor Jim O’Neil from Goldman Sachs proposed the new term MIST term for Mexico, Indonesia, South Korea and Turkey, which are the four biggest markets in the Goldman Sachs N-11 Equity Fund.The MIST economies more than doubled during the last decade, according to Bloomberg, and continue surging despite global economy concerns. In Mexico, Latin America’s second-biggest economy, record auto exports are helping growth outpace Brazil’s for a second year amid waning Chinese demand for the South American nation’s commodities. Mexico’s IPC Index has climbed 11% this year, comparing with a 2.8% growth of Brazil’s Bovespa. Meanwhile Turkey’s ISE National 100 gained 28 percent, compared to 13% gain of BSE India Sensitive Index and 2.6% gain in Russia’s MICEX. Total GDP for the MIST nations was $3.9 trillion last year, compared to $13.5 trillion of BRIC economies and $7.3 trillion for China alone. Besides the MIST nations, the N-11 countries include Bangladesh, Egypt, Nigeria, Pakistan, the Philippines, Vietnam and Iran. However, Goldman Sachs says its fund does not invest in Iran because it isn’t an open market for foreign investors.TurkeyandMexicohavethe biggestpotancial in MIST countries .So the economicalrelationshipeffecteachotherespeciallytheirexchangerates fluctuation effectsthetheir economictrade.The purpose of this study is to evaluate the volatility forecast performance of various models for exchange rate returns of Mexico, Indonesia, South Korea and Turkey. For this purpose we used Asymmetric GARCH models. We also introduce different densities such as normal, student t, Generalized Error Distribution (GED).

The rest of the paper is organized as follows: The following section is including introduction. Section 2, 3 and 4 introduce estimation methods, data set used and empirical findings, respectively. The final section provides conclusions.

2. Autoregressive Conditional Heteroscedasticity Models

The GARCH model was introduced by Bollerslev (1986) as a generalized version of Engle's (1982) AutoRegressive Conditional Heteroscedasticity (ARCH). The GARCH(p,q) model suggest the conditional variance of returns is a linear function of lagged conditional variance terms and past squared error terms. The standard GARCH(p,q) model specification is as follows:

$$y_t = x_t'\theta + \varepsilon_t \qquad \varepsilon_t \sim N(0;\sigma_t^2) \tag{1}$$

$$\sigma_t^2 = \varpi + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

The mean equation given in (1) is written as a function of exogenous variables with an error term. Where ϖ constant term, ε_{t-i}^2 is an ARCH term and σ_{t-j}^2 is the GARCH term. This model is widely used especially in financial time series analysis. While the vast majority of the earlier studies relied on the ARCH framework, there is now a large and diverse time series literature on volatility modelling (for instance, Asymmetric GARCH modelling, such as EGARCH, GJR-GARCH, APARCH, ACGARCH). The Exponential GARCH (EGARCH) model advanced by Nelson(1991) is the earliest extension of the GARCH model that incorporates asymmetric effects in returns from speculative prices. The EGARCH model can be modelled as:

$$log(\sigma_t^2) = \varpi + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \beta_j log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{3}$$

The specification accounts for the volatility clustering observed in volatility behaviour following exogenous shocks through the parameter α and for the presence of leverage effect through parameter γ and lastly for persistence through the parameter β. Unlike GARCH(p,q) the form of the EGARCH(p,q) equation indicates that the conditional variance is an exponential function, there by removing the need for restrictions on the parameters to ensure positive conditional variance.The GJR-GARCH(p,q) model is another volatility model that allows asymmetric effects. This model proposed by Glosten, Jaganattan and Runkle (1993). Its generalized form is given by whereS_t^- is a dummy variable that is equal to 1 if $\varepsilon_{t-i} < 0$ and zero otherwise. This term allows for the asymmetric effect, as the impact of ε_{t-i}^2 on σ_t^2 depend on whether the shock is negative or positive.

$$\sigma_t^2 = \varpi + \sum_{i=1}^{p}\left(\alpha_i \varepsilon_{t-i}^2 + \gamma S_{t-i}^- \varepsilon_{t-i}^2\right) + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{4}$$

Asymmetric Power Autoregressive ConditionalHeteroskedastic (APARCH) model was introduced by Ding, Granger and Engle (1993). The APARCH model contains a particular power parameter that makes the conditional variance equation nonlinear in parameters. In the power ARCH model, the power parameter of δ the standard deviation can be estimated rather than imposed and the optinal γ parameters are added to capture asymmetry of up to order τ:

$$\sigma_t^\delta = \varpi + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}\right)^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta \tag{5}$$

where $\delta > 0$, $|\gamma_i| \leq 1$ for i=1,…, τ ; $\gamma_i = 0$ for all $i > \tau$ and $\tau \leq p$. Asymmetry or leverage effect in this model is captured by the term γ_i. Among other things, Ding et al. (1993) showed that by letting the power parameter approach zero, the APARCH family of models also includes the logarithmic GARCH model as a special case.

Engle and Lee (1993) proposed the component GARCH model in order to investigate the long-run and the short-run movement of volatility. The component GARCH or CGARCH model allows mean reversion to a time varying level q_t . The CGARCH (1,1) model is defined as:

$$\sigma_t^2 = q_t + \alpha_1(\varepsilon_{t-1}^2 - q_{t-1}) + \beta_1(\sigma_{t-1}^2 - q_{t-1}) \tag{6}$$

$$q_t = \varpi + \rho q_{t-1} + \emptyset(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{7}$$

The difference between the conditional variance and its trend, $\sigma_t^2 - q_t$, is the transitory or short component of the conditional variance, while q_t is the time varying long-run volatility.

Combining the transitory and permanent equations the model reduces to:

$\sigma_t^2 = (1 - \alpha_1 - \beta_1)(1 - \rho)\varpi + (\alpha_1 + \phi)\varepsilon_{t-1}^2 - (\alpha_1\rho + (\alpha_1 + \beta_1)\phi)\varepsilon_{t-2}^2 + (\beta_1 - \phi)\sigma_{t-1}^2 - (\beta_1\rho - (\alpha_1 + \beta_1)\phi)\sigma_{t-2}^2$(8)

which shows that the CGARCH (1,1) is a restricted GARCH (2,2) model. Moreover, because of the existence of the leverage effect, Engle and Lee (1993) combine the component model with GJR model to allow shocks to affect the volatility components asymmetrically. The asymmetric component GARCH, or the ACGARCH(1,1) model becomes:

$$\sigma_t^2 = q_t + \alpha_1(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma_1(d(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 - 0.5q_{t-1}) + \beta_1(\sigma_{t-1}^2 - q_{t-1}) \qquad (9)$$

$$q_t = \varpi + \rho q_{t-1} + \emptyset(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + \gamma_2(d(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 - 0.5\sigma_{t-1}^2) \qquad (10)$$

where$d(.)$ denotes the indicator function (i.e. $d(\varepsilon_{t-i} < 0) = 1$ if $\varepsilon_{t-i} < 0$, and . $d(\varepsilon_{t-i} < 0) = 0$ otherwise). In this model, the temporary leverage effect depends on the γ_1 coefficient significance.

In this study we used these models with different distributions. Financial time series generally have fat tailed and the GARCH models often do not fully capture the fat -tails property of high-frequency financial time series so this purpose the normal distributions can't be used. If the time series donot show normal distribution the student-t, skewed student t and GED distributions are suggested. On the other handsymmetric and asymmetric forecasting criteria are used to evaluate the performance of forecasting for the conditional heteroscedasticity models.In our study three different criteria, MAE(Mean Absolute Error),MAPE (Mean Absolute Percent Error) and TIC (Theil Inequality Criteria), are used.

3. Data

This paper examines monthly exchange rates against to USA dollar of MIST countries examined over the period from January 1993 to December 2012. All data used in this study are provided Economic Research Federal Reserve Bank of St Louise and International Financial Statictics website and (**http://research.stLouisfed.org** , respectively).We determine the exchange rate returns as:

$r._t = E_t - E_{t-1}$

WhereE_t denotes the log an exchange rate and $r._t$ denotes the returns for countries examined. We analyze the volatility forecasting of exchange rates between MIST countries. After estimate the models we expanded the range of data and we used period from December 2012 to March 2013 for the three months of volatility forecasting.

4. Empirical Findings

In this study, we estimate the exponential GARCH (EGARCH) model; GJR-GARCH model, asymmetric power ARCH (APARCH) and asymmetric component GARCH (ACGARCH) model beside symmetric GARCH model to determine the best performance of forecasting model of exchange rate volatility for the countries examined.

We also calculate the descriptive statistics for the exchange rate returns of each countries and summarize them in Table 1. In Table, skewness, kurtosis, Jarque-Bera (1980; JB, here after) normality test, Q and Q^2Ljung-Box test statistics and ARCH-LM test results are presented for all series.

Table 1. Descriptive Statistics of Returns Series

(i) r indicates the return series for each country.
(ii) Figures in parenthesis represent the p values.
(iii) Q, Q^2 denotes the Ljung-Box Test statistics for residual serial correlation
(iv) LM, TR^2 denotes the test statistics for ARCH (c)

Returns	Mean	Skewness	Kurtosis	J.B.	Q(12)	Q^2(12)	ARCH(2)
Mexico **rMEX**	0.594267	0.846078	26.84319	5689.806 (0.0000)	71.805 (0.0012)	113.44 (0.6588)	18.5972 (0.0000)
Indonesıa **rIND**	0.645453	4.163228	41.56887	15504.01 (0.0000)	55.567 (0.0003)	16.6321 (0.4388)	14.31084 (0.0007)
South Korea **rSK**	2.440535	10.35434	111.1100	120661.5 (0.0000)	0.04387 (0.8349)	0.05359 (0.0679)	0.03700 (0.0009)
Turkey **rTR**	2.211959	2.881293	21.10942	3596.538 (0.0000)	86.429 (0.0000)	9.9441 (0.6210)	8.23980 (0.0162)

The kurtosiscoefficients were found to be greater than 3, implying a fat–tailedempirical distrubution of there turns overall the periods.The JB normality test,based on skewness and kurtosiscoefficient rejects the null hypothesis of normal distribution for all countries any reasonable level. If we consider the sample, given the fact that there turn series exhibited some excess kurtosis,it can be predicted that a fatter-taileddistrubutions, such as the Student-t or may be a GED, should generate better results than simply a normal distrubution.The result of Q statistics show that the null hypothesis of no serial correlation cannot be rejected for return series.

The LM test indicatesthe presence of ARCH processes in theconditional variance at lag 2.The Q statisticsalsoindicatethe presence of statistically significant ARCH effects. All these evidences suggest that there turn series follow the ARCH –type dependencies, and therefore, it can be concluded that ARCH/GARCH-typemodelsareappropriateforvolatilityestimations. In this study, conditional mean equation was constructed to capture serial dependence in the data. In the specification of the conditional mean equation, the author followed the Box-Jenkins approach ande stimated ARMA(p,q) models.AR(p) and MA(q) orders were determined according tothe Akaike Information Criterion (AIC).The conditional mean of each returns series was modelled as ARMA(1,0),which was the best for all countries.We named the return series such as rMEX (Mexico), rIND (India), rSKOR (South Korea),rTR(Turkey).The models were estimated by assuming normal, Student-t and GED distributions.We used as ymmetric GARCH models and choosed the best volatility models using log likelihood(LL), AIC, Shwartz Information Criteria(SIC).Thebest model musthavethelowest AIC,SIC orhighest LL value.

Table 2. Estimationof ConditionalHetereroscedasticityModels

	ARMA(1,0) GJR-GARCH(1,1)	ARMA(1,0) EGARCH(1,1)	ARMA(1,0) GARCH(1,1)	**ARMA(1,0) APARCH(1,1)**	ARMA(1,0) GJR-GARCH(1,1)	ARMA(1,0) EGARCH(1,1)	ARMA(1,0) EGARCH(1,1)
Distribution	GED	GED	GED	GED	GED	GED	Student-t
Mean Equation							
Constant (M)	2.0681 [0.6459]* (0.0014)	-	-	0.2155 [0.0635]*	0.2511 [0.0.213]*	-0.2521 [0.0232]*	0.2302 [0.0264]*
AR(1)	0.1232 [0.0523]*	-0.0581 [0.0198]*	0.0587 [0.0120]*	0.3412 [0.0737]*	0.2787 [0.0494]*	0.2837 [0.0533]*	0.3135 [0.0605]*
MA(1)	-	-	-	-	-	-	-
Variance Equation							
Constant(V)	-	-	0.2795 [0.5063]*	0.1107 [0.0439]*	-	-0.4940 [0.0890]*	-0.5459 [0.0799]*
ARCH(α)	0.9291 [0.3855]* (0.0160)	-	0.3705 [0.1309]*	-	-1.0148 [0.3356]*	-	-
GARCH(β)	-0.3580 [0.1448]*	-	0.5724 [0.1072]*	-	0.6609 [0.0516]*	-	-
EGARCH(α)	-	0.3251 [0.0956]*	-	-	-	0.8066 [0.1711]*	0.9170 [0.2014]*
EGARCH(β)	-	0.0971 [0.0651]*	-	-	-	0.9640 [0.0177]*	0.9720 [0.0156]*
EGARCH(γ)	-	-0.3234 [0.9568]	-	-	-	-0.2337 [0.0965]*	-0.1914 [0.0664]*
GJRGARCH(γ)	0.0869 [0.3924]*	-	-	-	0.6827 [0.3363]*	-	-
A-CGARCH (γ)	-	-	-	-	-	-	-
APARCH(α)	-	-	-	0.1481 [0.2710]*	-	-	-
APARCH(β)	-	-		0.3497 [0.0776]*	-	-	-
APARCH(γ)	-	-		0.1415 [0.0647]*	-	-	-
APARCH(δ)	-	-		2.5061 [0.7617]*	-	-	-
t-distribution	-	-	-	-	-	-	3.1567 [0.7179]*
GED param.	0.8970 [0.0781]*	0.8807 [0.0818]*	0.8243 [0.0716]*	0.6144 [0.0958]*	0.8538 [0.0982]*	0.9241 [0.1059]*	-
AIC	4.4315	4.4215	4.5315	4.3135	4.0522	4.0121	4.0012
SC	4.6972	4.6802	4.7105	4.4303	4.1543	4.1142	4.1033
LL	551.9725	549.9547	471.8755	505.317	475.2182	470.4407	469.1482
Q(12)	0.1430 (0.2802)	15.937 (0.9883)	20.717 (0.0550)	17.245 (0.14129)	18.321 (0.1062)	11.480 (0.4880)	9.9159 (0.6237)
Q^2(12)	3.5845 (0.9902)	4.9195 (0.9614)	5.1145 (0.9540)	14.651 (0.2619)	13.477 (0.3357)	8.1701 (0.7721)	4.9235 (0.9601)
LM(2)	0.1988 (0.9053)	0.2300 (0.8913)	2.1571 (0.3400)	7.3093 (0.06582)	8.0783 (0.1761)	0.5046 (0.7769)	0.3494 (0.8396)
Wald δ=1	-	-	-	2.7548 (0.0070)*	-	-	-
δ=2	-	-	-	2.3631 (0.1242)	-	-	-

	rSKOR			rTUR				
	ARMA(1,0) GJR-GARCH(1, 1)	ARMA(1,0) EGARCH(1, 1)	ARMA(1,0) EGARCH(1, 1)	**ARMA(1,0) APARCH(1, 1)**	ARMA(1,0) GJR-GARCH(1, 1)	ARMA(1,0) EGARCH(1,1)	ARMA(1,0) EGARCH(1,1)	ARMA(1,0) ACGARCH(1, 1)
Distribution	**GED**	Normal	GED	**GED**	GED	GED	Student-t	GED
Mean Equation								
Constant (M)	-	1.0313 [0.0545]*	0.7214 [0.0416]*	0.5723 [0.2096]*	0.7569 [0.1794*	0.8872 [0.1799]*	0.8246 [0.187*	0.6868 [0.1678]*
AR(1)	0.0137 [0.0034]*	-0.0105 [0.0029]*	0.0506 [0.0204]*	0.5656 [0.0308]*	0.6844 [0.0519*	0.6636 [0.0494]*	0.6909 [0.0531 *	0.6550 [0.0402]*
MA(1)	-	-	-	-	0.6304 [0.3053*	-	-	-
Variance Equation								
Constant(V)	258.12 [126.38]*	0.7993 [0.0835]*	0.8243 [0.1205]*		2.0583 [0.8020]*	-	-	8.5550 [2.0017]*
ARCH(α)	-0.0105 [0.0028]*	-	-	-	0.7808 [0.3095]*	-	-	-
GARCH(β)	0.5563 [0.2286]*	-	-	-	0.5292 [0.0941]	-	-	-
EGARCH(α)	-	3.1260 [0.1054]*	2.8385 [0.0995]*	-	-	0.6102 [0.1826]*	0.6012 [0.1656]*	-
EGARCH(β)	-	0.0477 [0.0144]*	0.0827 [0.0270]*	-	-	0.8471 [0.0583]*	0.8917 [0.0423]*	-
EGARCH(γ)	-	-1.8751 [0.1156]*	-1.8963 [0.1141]*	-	-	-0.1717 [0.0473]*	-0.1546 [0.0431]*	-
GJRGARCH(γ)	5.8436 [2.6489]*	-	-	-	0.5644 [0.1752]*	-	-	-
A-CGARCH (γ)	-	-	-	-	-	-	-	0.0220 [0.0058]*
APARCH(α)	-	-	-	0.8019 [0.0634]*	-	-	-	-
APARCH(β)	-	-	-	0.9240 [0.0067]*	-	-	-	-
APARCH(γ)	-	-	-	0.9999 [0.0520]*	-	-	-	-
APARCH(δ)	-	-	-	0.6041 [0.0883]*	-	-	-	-
t-distribution	-		-	-	4.0645 [1.2856]*	-	3.9587 [1.1014*	-
GEDparam.	0.4480 [0.0345]*	-	0.4360 [0.0276]*	1.1226 [0.1310]*	-	1.1130 [0.1267]*	-	1.2688 [0.1368]*
AIC	8.2223	6.0772	6.8131	6.0922	5.3812	5.3965	5.3759	5.3868
SC	8.3093	6.1647	6.9006	6.1798	5.4833	5.4926	5.4743	5.4851
LL	972.4559	717.1887	593.0012	718.9810	633.3692	634.2810	632.2950	628.1717
Q(12)	1.6535 (0.0756)	12.384 (0.4152)	0.7819 (0.8773)	25.403 (0.0132)*	8.04010 0.7532	8.6599 (0.7325)	8.8250 (0.7653)	12.267 (0.4245)
$Q^2(12)$	0.0951 (0.9982)	9.8240 (0.6314)	0.1042 (1.0000)	13.350 (0.8774)	3.4653 (0.9914)	4.7616 (0.9657)	3.3759 (0.9901)	5.7233 (0.9293)
LM(2)	0.0236 (0.9882)	0.5705 (0.7518)	0.4013 (0.8181)	78.8195 (0.9363)	0.0461 (0.9772)	0.5091 (0.7752)	0.2436 (0.8852)	0.8810 (0.6437)
Wald δ=1	-	-	-	0.0759 (0.0000)*	-	-	-	
δ=2	-	-	-	1.0759 (0.9662)	-	-	-	

(i) Figures in parenthesis are p values and figures in brackets are standart deviation
(ii) LM, TR^2 denotes the test statistics for ARCH (c)
(iii) *indicates statistical significance at the 5% level.
(iv) Q, Q^2 denote the Ljung-Box Test statistics for residual serial correlation
(v) LM, TR^2 denotes the test statistics for ARCH (c)
(vi) ARMA(p,q) for the mean models and found ARMA(1,0)
(vii) M is mean equation V is variance equation

In Table2 all the parameters of them odels are statistically significant for all countries. GJR-GARCH –GED for Mexico, APARCH(1,1)-GED for India, GJR-GARCH-GED for South Korea, APARCH-GED for Turkey are founded the best volatility models. Inthe GARCH(1,1) –GED model for Mexico the persistence of volatility shocks primarily depends on thesum of α and β.If the sum approaches unity, then the persistence of shocks to volatility is considered permanent.$\alpha+\beta<1$ restrictionfor GARCH models is donewithWald test found that all models are stable(0.3705+0.5724 <1).

The APARCH model provides more flexibility of analysing the asymmetric volatility. According to the results of APARCH(1,1) models all estimated values of the asymmetry parameter γ is statistically significant and found positive(0.1415 ,0.9999) and confirming the importance of asymmetry in the return volatility for India and Turkey

.This condition shows that the negative shocks(bad news)are more effective than positiveshocks(good news) on volatility or bad news effect the volatility more than good news.For the APARCH models compare the restriction $\delta = 1$ ve $\delta = 2$ hypothesis the Wald test is done for two countries.The Wald statistics was used to test for the persistence of the conditional volatility model.

The most suitable APARCH models is null hypothesis $\delta = 1$ can be rejected and $\delta = 2$ hypothesis can be accepted for the APARCH models.The power parameters$\delta = 1$ (2.7548) with GED for İndia and $\delta = 1$ (0.0759) with GED for Turkey are founded statistically significant. This suggests that instead of modelling to conditional standard deviation ,it is more relevantin this case to model to conditional variance. In Table 2 shows the EGARCH models for rMEX (-0.3234), rIND (-0.2327), rSKOR(-1.8721),rTR(-0.1717) the leverage effect γ is statistically significant and found negative so this situation shows that the bad news (negative shocks) effect the volatility more than good news .

The best model GJR-GARCH-GED is founded for Mexico and South Korea .The leverage effects for Mexico (0.0869) and for South Korea(5.8436) are founded statistically significant and positive so γ leverage effect shows that bad news (negative shocks) effect the volatility more than good news for Mexico and South Korea.
As mentioned in this study the model selection criteria support the fact that the asymmetric GARCH (1,1) model can capture the best characteristic model performs in the period.In this study ,the diognastic test results of the asymmetric conditional –volatility models were also estimated and presented in Table 2 and continued ones.

TheLjung-Box-Pierce Q statistics evaluate the serial correlation in the raw (Q) and squared standartised residuals (Q^2) of the model up to lags 12 and show that the specified model has captured most of the conditional dependence in the returns and squared the returns well.The significant LM-test statistics suggest the absence of any further ARCH effect. As a result, the model diognastics show that the residuals of the models are reasonably wellb ehaved.

Tablo 2. Estimationof ConditionalHetereroscedasityModels (Continued)

In Table 2,A-CGARCH model is founded in the volatility models for Turkey. $\gamma_1 > 0$ there is a temporary leverage effect depends on the γ_1 coefficient significance and the restriction (0.0220>0)in the model shows that there is a temporary leverage effect for Turkey. All the models shows that the most suitable distributions GED and student-t . However these models are estimated with symmetric GARCH models but couldnot find statistically significant, so these results show that the asymmetric conditional heteroscedasticity models are better than symmetric conditional heteroscedasticity models.In our study we choosedthe sample range over the period from December 2012 to March 2012 for in sample forecasting. Then to compare all these models fit and choose the best forecasting models we used performance criteria such as MAE, MAPE and TICgiven in Table 3.Using these performance criteria we choose the best forecasting models and we did in sample forecasting 3 months and estimated the models. We can seethatthebestvolatility model and the best forecasting volatility models changed.

Table 3.Results of Forecasting Criteria

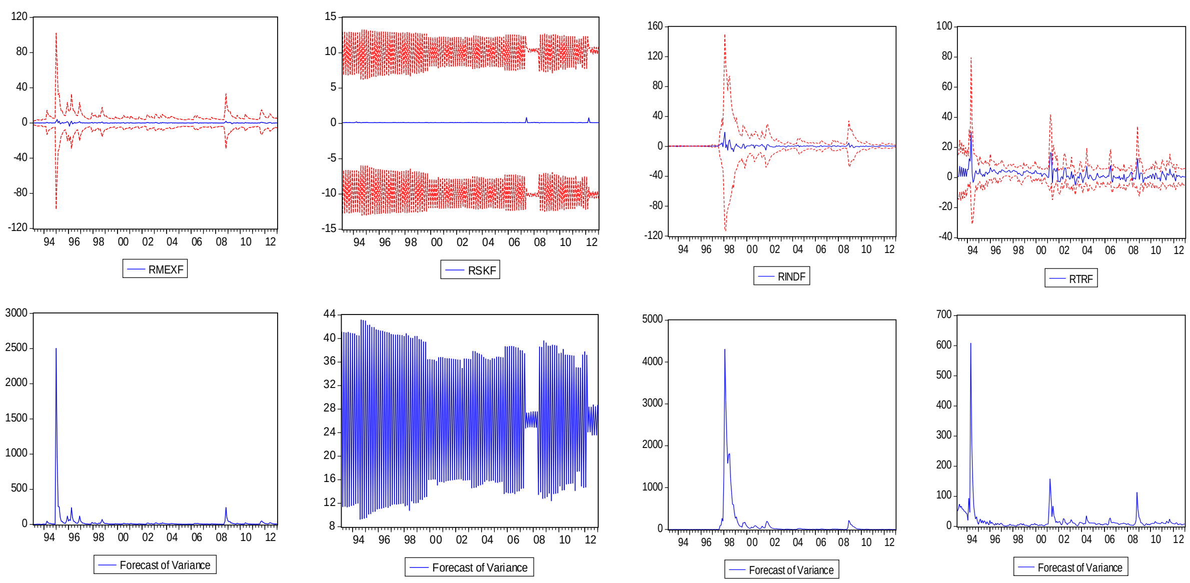
	Models	MAE	MAPE	TIC
Mexico rMEX	**EGARCH-student-t**	**2.2514**	**101.3288**	**0.9923**
	EGARCH-GED	2.2524	102.5574	0.9980
	GJR-GARCH-GED	2.2522	104.0282	0.9993
Indonesia rIND	**GJR-GARCH-GED**	**2.9508**	**184.1589**	**0.7506**
	EGARH-GED	2.9518	184.9426	0.7478
	APARCH-GED	2.9591	186.2886	0.7480
	EGARCH-student-t	0.9628	189.2018	0.7524
South Korea rSKOR	**EGARCH-GED**	**3.9076**	**211.8251**	**0.9372**
	EGARCH-normal	3.9357	255.8285	0.9487
	GJR-GARCH-GED	4.0716	313.2926	0.9584
Turkey rTUR	**ACGARCH-GED**	**3.0397**	**122.3332**	**0.5076**
	GJR-GARCH-GED	3.0413	124.3284	0.5081
	EGARCH-GED	3.0491	126.5083	0.5090
	APARCH-GED	3.0503	134.0468	0.5297
	EGARCH-student-t	3.0611	137.3621	0.5990

*the best volatility forecasting model

Table 3 shows the best forecasting model are different than the best conditional volatility models like GJR-GARCH –GED is the best volatility model but EGARCH student –t is the best forecasting model for Mexico.GJR-GARCH-GED is the best forecasting model for İndia and changed again .EGARCH-GED model is the best fit model for South-Korea. ACGARCH is the best forecasting model for Turkey and different than best volatility fit model .We can say that the GED and Student –t distribution are seen more effective in the forecasting models for all countries thus their exchange rate structure over the period.We can seetheforecastingvolatility in thestatisticalgraphs.Weevaluatetheforecastingvolatilitywithforecast of varianceandforecast of returnseriesforMIST Countries.Graph I showsstatisticalforecastingforreturnseries.

Graph 1. VolatilityForecasting

Graph (a) belongs to Mexico exchage rate volatility forecasting and both exchange rate and volatility decreased for three months.Graph(b)shows that South Korea Exchange rate volatility and exchange rate increased for three months but that's volatility very fluctuated ands how rising structure.ForIndonesia exchange rates volatility is shown in Graph (c). Indonesia exchange rate decreased but it'svolatility stayedstable. Graph (d)showsTurkey Exchange rate volatility.WhileTurkey'sexchange rate was increasing and fluctuating the volatility increased too.



Graph (a) **Graph(b)** **Graph(c)** **Graph(d)**

5. Conclusions

In the study, the comparison was focused on two different aspects: the difference between the best asymmetric GARCH models with asymmetric distributions and the best performance volatility forecasting models with forecasting criteria for MIST Countries. Then we have to continue to find the best forecasting volatility with the different conditional heteroscedasticity models which we used forecasting criteria. The estimation results show that the forecasting performance of asymmetric GARCH models, especially when the time series show fat-tailed asymmetric densities are taken into account in the conditional volatility is better than symmetric GARCH models for two countries examined. The distributions are usually GED and student-tin this for 3 months in sample forecasting. We saw the decreasing exchange rates but the volatility is increasing in Mexico. When we look at the South Korea the exchange rates increased minimal level so that the volatility of exchange rates will continue because of the value of decreased South Korea.The exchange rates are decreased in South Korea but the volatility is continuing stable but fluctuating structure will make the exchange rates increase. The increasing exchange rates and increasing volatility are founded for Turkey. This situation depends on the central bank reserve option mechanism policy against to payment of capital account. These policies can make the exchange volatility continue. Indonesia exchange rates decreased but it's volatility looks like stable this situation depend on the increasing Indonesia's GDP levels ,Indonesian economy is still connected to the global economy and it is the Southeast Asia's largest economy so this purpose effects the it's interest rates and exchange rates. So this situation the government will take good policies and made the exchange volatility stable in this period. These countries will be affected from the two points which is giving power to volatility risk. Firstly the central banks which firstly in Japan then in England will be done political for many countries. This political will be effected on countries exchange rates and economic situation mostly.Other point is in early time the response of the national countries to Japan dramatic volatility behaviours. So that except gold the many countries money units will loose their value and will show fluctuating structure even in MIST countries. The findings of this study might be interesting for investors, traders and regulators who interested in MIST countries.

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