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Modelling Ethiopian Birr/Dollar Exchange Rate Volatility: Application Of GARCH And Asymmetric Models

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Abstract:

This paper investigated the volatility of Birr/Dollar exchange rates in Ethiopia using GARCH (1, 1), GJR-GARCH (1, 1), EGARCH (1, 1), Component ARCH (1, 1) and Asymmetric Component ARCH (1, 1) models. Using monthly data over the period January 1957 to December 2008. The impact of the deregulation of foreign exchange market on volatility was investigated separately for the period before deregulation, fixed exchange rate period until 1992 and managed float regime (September 1992- January 2010). The results from all the models show that volatility is less persistent and low unconditional volatility. The result is not the same for the fixed exchange rate period and managed float rate regime. The results of GJR-GARCH and EGARCH models have leverage effect, which is in confirmatory with the result of Nelson (1990). Based on AIC and SIC, the EGARCH and GJR-GARCH models are found to be the best models.

Keywords: *Volatility, persistence, leverage and asymmetric properties of exchange rate.*

Introduction

Prior to the introduction of structural adjustment programme of Ethiopia in 1992, the country adopted a fixed exchange rate regime supported by exchange control regulations that engendered significant distortions in the economy.

The foreign exchange market in the fixed exchange rate period was characterized by high demand for foreign currency, which cannot be adequately met with the supply of foreign exchange by the National Bank of Ethiopia (NBE). The inadequate supply of foreign currency by the NBE promoted the parallel market for foreign exchange and created uncertainty in foreign exchange rates. The introduction of structural adjustment programme (SAP) in Ethiopia in September 1992, which deregulated the foreign exchange market led to the introduction of market-determined exchange rate, managed floating rate regime. This introduction of managed floating rate regime tends to increase the uncertainty in exchange rates, thus, increasing the volatility of exchange rate by the regime shifts. This made the exchange rate to be the most important asset price in the economy. Understanding the behaviour of exchange rate is important to monetary policy (Long more and Robinson, 2004). The exchange rate has been found to be an important element in the monetary transmission process [Robinson and Robinson (1997), Allen and Robinson (2004)] and movements in this price have a significant pass-through to consumer prices (see Robinson (2000a and 2000b) and McFarlane (2002)). According to Long more and Robinson (2004), because of the thinness and volatility of the market, the policy makers focus on the information content of the short-term volatility especially in deciding intervention policy. The uncertainty of the exchange rate shows how much economic behaviours are not able to perceive the directionality of the actual or future volatility of exchange rate, that is, it is a different concept from the volatility of the exchange rate itself in that it means that the more forecast errors of economic behaviours made, the higher the trends in the uncertainty of the exchange rate are shown (Yoon and Lee, 2008).

Researchers have introduced various models to explain and predict these patterns in volatility. Engle (1982) introduced the autoregressive conditional Heteroscedasticity (ARCH) to model volatility. Engle (1982) modelled the heteroscedasticity by relating the conditional variance of the disturbance term to the linear combination of the squared disturbances in the recent past. Bollerslev (1986) generalized the ARCH model by modelling the conditional variance to depend on its lagged values as well as squared lagged values of disturbance, which is called generalized autoregressive conditional

Heteroscedasticity (GARCH) . Since the work of Engle (1982) and Bollerslev (1986), various variants of GARCH model have been developed to model volatility. Some of the models include IGARCH originally proposed by Engle and Bollerslev (1986), GARCH-in-Mean (GARCH-M) model introduced by Engle, Lilien and Robins (1987),the standard deviation GARCH model introduced by Taylor (1986) and Schwert (1989), the EGARCH or Exponential GARCH model proposed by Nelson (1991), TARCH or Threshold ARCH and Threshold GARCH were introduced independently by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993), the Power ARCH model generalised by Ding, Zhuanxin, C. W. J. Granger, and R. F. Engle (1993) among others.

The modelling and forecasting of exchange rates and their volatility has important implications for many issues in economics and finance. Various families of GARCH models have been applied in the modelling of the volatility of exchange rates in various countries. Some other studies on the volatility of exchange rates include Meese and Rose (1991), McKenzie (1997), Christian (1998), Longmore and Wayne Robinson (2004), Yang (2006) Yoon and Lee (2008) among others. Little or no work has been done on modelling exchange rate volatility in Ethiopia particularly using GARCH models. The study conducted on the effect of devaluation on the Ethiopian macroeconomic performance (Kidane, 1994 and Kidane 1999) showed that the Birr exchange rate was pegged to US dollar and lead to over evaluation to Ethiopian Currency and which in turn resulted in an ever increasing to budgetary deficiency to the country. The government was forced to balance the deficit through money creation. The study also showed that the fixed exchange rate led to the increase in domestic credit, which enhanced to demand in tradable and non-tradable goods, while the former lead to trade deficit, the later resulted in higher price. The two kidane's study outputs are descriptive statistics and did not sufficiently express the volatility of exchange rate return in a model pattern. Furthermore, it does not show the current situation of the flexible exchange rate in Ethiopia. The purpose of this paper is to model exchange rate volatility in Ethiopia using family of GARCH models. This study will examine the volatility and asymmetry of exchange rates in Ethiopia using GARCH, GJR-GARCH, EGARCH, component ARCH and asymmetric components models. The exchange rate volatility has implications for many issues in the arena of finance and economics.

The deregulation of foreign exchange market in September 1992 could have affected the volatility of exchange rates in Ethiopia. The study, apart from presenting full sample results, will separate to present the results of volatility in a fixed exchange rate regime and floating exchange rate regime.

Models For Variance Evolution

Models Of Time Varying Volatility

The need of long lag to improve the goodness of fit when we adopt the autoregressive conditional Heteroscedasticity (ARCH) model occurs at times. To overcome this problem, Bollerslev (1986) suggested the generalized ARCH (GARCH) model, which means that it is a generalized version of ARCH. The GARCH model considers conditional variance to be a linear combination between square of residual and a part of lag of conditional variance. This simple and useful GARCH is the dominant model applied to financial time series analysis by the parsimony principle. GARCH (p, q) model can be summarized as follows:

$$y_t = \alpha + \varepsilon_t \text{ , } \varepsilon_t/\phi_t \sim N(0, \sigma^2) \qquad (1)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_t^2 + \beta_1 \sigma_t^2 \qquad (2)$$

where, σ^2 is conditional variance of ε_t and $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$. Equation (2) will be stationary if the persistent of volatility shocks, $\alpha_1 + \beta_1$ is lesser than 1 and in the case it comes much closer to 1, volatility shocks will be much more persistent. To complete the basic ARCH specification, we require an assumption about the conditional distribution of the error term. There are three assumptions commonly employed when working with ARCH models: normal (Gaussian) distribution, Student's t-distribution, and generalized error distribution (GED). Bollerslev (1986, 1987), Engle and Bollerslev (1986) suggest that GARCH (1,1) is adequate in modelling conditional variance.

The normality assumption for the error term in (1) is adopted for most research papers using ARCH. However, other distributional assumptions such as Student's t-distribution and General error distribution can also be assumed. Bollerslev (1987) claims that for some data the fat-tailed property can be approximated more accurately by a conditional Students-distribution. If sum of α and β is equal to 1 in GARCH model (2), then shocks to volatility persist forever, and the unconditional variance is not determined by the model.

Engle and Bollerslev (1986) call this type of process 'Integrated-GARCH'. They call this model the integrated GARCH' or IGARCH' model. The IGARCH model is, thus, given as follows:

$$\sigma_t^2 = \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (3)$$

where, $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j = 1$

A weakness of the GARCH model is that the conditional variance is merely dependent on the magnitude of the previous error term and is not related to its sign. It does not account for skewness or asymmetry associated with a distribution. Thus, GARCH model cannot reflect leverage effects, a kind of asymmetric information effects that have impact that is more crucial on volatility when negative shocks happen than positive shocks do (Yoon and Lee, 2008). Because of this weakness, a number of extensions of the GARCH (p, q) model have been developed to explicitly account for the skewness or asymmetry. The popular models of asymmetric volatility includes, the exponential GARCH (EGARCH) model, Glosten, Jogannathan, and Rankle (1992) GJR-GARCH model, asymmetric power ARCH (APARCH), Zakoian (1994) threshold ARCH (TARCH).

The TS-GARCH model developed by Taylor (1986) and Schwert (1990) is a popular model used to capture the information content in the thick tails, which is common in the return distribution of speculative prices. The specification of this model is based on standard deviations and is:

$$\sigma_t = \sum_{i=1}^{p} \alpha_t |\varepsilon_{t-i}| + \sum_{j=1}^{q} \beta_j \sigma_{t-j} \quad (4)$$

The GJR-GARCH (p, q) model was introduced by Glosten, Jogannathan and Runkle (1993) to allow for asymmetric effects. The model is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k I_{t-k}^{-} \varepsilon_t^2 \quad (5)$$

where I_t (a dummy variable) = 1 if $\varepsilon_t < 0$ and 0 otherwise. In the GJR-GARCH model, good news $\varepsilon_{t-i} > 0$ and bad news, $\varepsilon_{t-i} < 0$, have differential effects on the conditional variance, good news has an impact of α_i while bad news has an impact of $\alpha_i + \gamma$. If $\gamma_i > 0$, bad news increases volatility, and there is a leverage effect for the i^{th} order. If

$\gamma \neq 0$. 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 is defined as follows:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-j}} - \sqrt{\frac{2}{\pi}} \right| + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-i}}{\sigma_{t-j}} \qquad (6)$$

The EGARCH (p, q) model, unlike the ARCH (p, q) model, indicates that the conditional variance is an exponential function, thereby removing the need for restrictions on the parameters to ensure positive conditional variance. The asymmetric effect of past shocks is captured by the γ coefficient, which is usually negative, that is, keeping constant positive shocks generate less volatility than negative shocks (Longmore and Robinson, 2004). The leverage effect can be tested if $\gamma < 0$. If $\gamma \neq 0$, the news impact is asymmetric.

We use the Component GARCH (CGARCH) models to analyse data throughout the study. Component models are based on the idea that there is a long-run component in volatilities, which changes smoothly, and a short-run one, changes more quickly and fluctuating around the long-run component. The component model of Engle and Lee (1999) is additive and consist of the equations of Component-ARCH (1, 1):

Transitory $\sigma_t^2 = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(\sigma_t^2 - q_{t-1}\right)$

(7)

Permanent $q_t = \omega + \lambda\left(q_{t-1} - \omega\right) + \phi\left(\varepsilon_t^2 - \sigma_{t-1}^2\right)$

where q_t is the permanent component, $\left(\varepsilon_t^2 - \sigma_{t-1}^2\right)$ serves as the deriving force for the time dependent movement of the permanent component(trend) and $\left(\sigma_{t-1}^2 - q_{t-1}^2\right)$ represents the transitory component of the conditional variance. The sum of parameters $\alpha+\beta$ measures the transitory shock persists and λ measures the long run persistence derived from the shock to a permanent component given by β

Asymmetric Component model combines the component model with the asymmetric TARCH (Threshold ARCH) model. This specification introduces asymmetric effects in transitory equation and estimates models of the form:

$$y_t = x_t^T \pi + \varepsilon_t$$
$$q_t = \omega + \lambda\left(q_{t-1} - \omega\right) + \phi\left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2\right) + \theta_1 z_{1t} \qquad (8)$$
$$\sigma_t^2 - q_t^2 = \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \gamma\left(\varepsilon_{t-1}^2 - q_{t-1}\right)d_{t-1} + \beta\left(\sigma_{t-1}^2 - q_{t-1}\right) + \theta_2 z_{2t}$$

Where z is exogenous variables and d is dummy variable indicating negative shocks. $\gamma > 0$ indicates the presence of transitory leverage effects in the conditional variance and λ is the estimate of persistence of the long run component.

Diagnostic Testing

The modelling process consists of four stages: identification, specification, estimation, and diagnostic checking (Cromwell, Labys, and Terraza; 1994).

Most of the theories of time series require stationarity, therefore, it is critical to determine whether a time series is stationary. Two non-stationary time series are fractionally integrated time series and autoregressive series with random coefficients. However, more often some time series are non-stationary due to an upward trend over time. Either of the following two models can capture the trend. The difference stationary process:

$$(1 - L)\, y_t = \alpha + \beta(L)\varepsilon_t \qquad (9)$$

where L is the lag operator, and ε_t is a white noise sequence with mean zero and variance σ^2. Hamilton (1994) also refers to this model the unit root process. The trend stationary process is

$$y_t = \alpha + \delta t + \beta(L)\,\varepsilon_t \qquad (10)$$

When a process has a unit root, it is said to be integrated of order one or I(1). An I(1) process is stationary after the first difference. The trend stationary process and difference stationary process require different treatment to transform the process into stationary one for analysis. Therefore, it is important to distinguish the two processes. Bhargava (1986) nested the two processes into the following general model:

$$y_t = \gamma_0 + \gamma_1 t + \alpha\left(y_{t-1} - \gamma_0 - \gamma_1 (t-1)\right) + \beta(L)\,\varepsilon_t \qquad (11)$$

However, a difficulty is that the right-hand side is nonlinear in the parameters. Therefore, it is convenient to use a different parameterization model of like:

$$y_t = \gamma_0 + \gamma_1 t + \alpha\, y_{t-1} + \beta(L)\,\varepsilon_t \qquad (12)$$

The test of null hypothesis of that $\alpha = 1$ against the one-sided alternative of $\alpha \angle 1$ is called a unit root test. Dickey-Fuller unit root tests are based on regression models similar to the previous model and

$$y_t = \gamma_0 + \gamma_1 t + \alpha\, y_{t-1} + \varepsilon_t \qquad (13)$$

where ε_t is assumed to be white noise.

The t statistic of the coefficient α does not follow the normal distribution asymptotically. Instead, its distribution can be derived using the functional central limit theorem. Three types of regression models including the preceding one are considered by the Dickey-Fuller test. The deterministic terms that are included in the other two types of regressions are either null or constant only.

An assumption in the Dickey-Fuller unit root test is that it requires the errors in the autoregressive model to be white noise, which is often not true. There are two popular ways to account for general serial correlation between the errors. One is the augmented Dickey-Fuller (ADF) test, which uses the lagged difference in the regression model. This was originally proposed by Dickey and Fuller (1979) and later studied by Said and Dickey (1984) and Phillips and Perron (1988) proposed another method; it is called Phillips-Perron (PP) test. The tests adopt the original Dickey-Fuller regression with intercept, but modify the test statistics to take account of the serial correlation and heteroscedasticity. A problem of the augmented Dickey-Fuller and Phillips-Perron unit root tests is that they are subject to size distortion and low power. It is reported in

Schwert (1989) that the size of distortion is significant when the series contains a large moving average (MA) parameter. DeJong et al. (1992) find that the ADF has power around one third and PP test has power less than 0.1 against the trend stationary alternative, in some common settings. Among some more recent unit root tests that improve upon the size distortion and the low power are the tests described by Elliott, Rothenberg, and Stock (1996), Ng, and Perron (2001). These tests involve a step of detrending before constructing the test statistics and are demonstrated to perform better than the traditional ADF and PP tests.

Most testing procedures specify the unit root processes as the null hypothesis. Tests of the null hypothesis of stationarity have also been studied, among which Kwiatkowski et al. (1992) is very popular.

Economic theories often dictate that a group of economic time series are linked together by some long-run equilibrium relationship. Statistically, this phenomenon can be modelled by co integration. One way to test the relationship of co integration is the residual based co integration test, which assumes the regression model

$$y_t = \beta_1 + X_t{}'\beta + \varepsilon_t \qquad (14)$$

where $Y_t = Z_{1t}$, $X_t = (Z_{2t},..,Z_{kt})'$, and $\beta = (\beta_2,..\beta_k)^T$. The OLS residuals from the regression model are used to test for the null hypothesis of no co integration. Engle and Granger (1987) suggest using ADF on the residuals while Phillips and Ouliaris (1990) study the tests using PP and other related test statistics.

Augmented Dickey-Fuller Unit Root And Engle-Granger Co Integration Testing

Common unit root tests have the null hypothesis that there is an autoregressive unit root $H_0 : \alpha = 1$ and the alternative is $H_a : |\alpha| < 1$, where α is the autoregressive coefficient of the time series

$$y_t = \alpha y_{t-1} + \varepsilon_t \qquad (15)$$

This is referred to as the zero mean models. The standard Dickey-Fuller (DF) test assumes that errors ε_t are white noise. There are two other types of regression models that include a constant or a time trend as follows:

$$y_t = \mu + \alpha y_{t-1} + \varepsilon_t \qquad (16)$$

$$y_t = \mu + \beta t + \alpha y_{t-1} + \varepsilon_t \qquad (17)$$

These two models are referred to as the constant mean model and the trend model, respectively. The constant mean model includes a constant mean μof the time series. Campbell and Perron (1991) claimed, "the proper handling of deterministic trends is a vital prerequisite for dealing with unit roots". Hayashi (2000) suggests to using the constant mean model when we think there is no trend, and using the trend model when we think otherwise. The null hypothesis of the Dickey-Fuller test is a random walk, possibly with drift. The differenced process is not serially correlated under the null of I (1). The augmented Dickey-Fuller (ADF) test, originally proposed in Dickey and Fuller (1979), adjusts for the serial correlation in the time series by adding lagged first differences to the autoregressive model,

$$\Delta y_t = \mu + \delta t + \alpha y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta y_{t-j} + \varepsilon_t \qquad (18)$$

where the deterministic terms δt and μ can be absent for the models without drift or linear trend. The test statistics is using t value:

$$t = \frac{\hat{\alpha} - 1}{se\left(\hat{\alpha}\right)} \text{ where, s.e} = \sqrt{1 - \alpha^2} \qquad (19)$$

Phillips-Perron Unit Root And Co Integration Testing

Besides the ADF test, another popular unit root test is valid under general serial correlation, heteroscedasticity developed by Phillips (1997), Phillips, and Perron (1988). The tests are constructed using the AR (1) type regressions, unlike ADF tests, with corrected estimation of the long run variance of Δy_t. In the case without intercept, consider the drift less random walk process,

$$y_t = y_{t-1} + \varepsilon_t \qquad (20)$$

where the disturbances might be serially correlated with possible heteroscedasticity. Phillips and Perron (1988) proposed the unit root test of the OLS regression model

$$y_t = \rho y_{t-1} + \varepsilon_t \qquad (21)$$

Testing For Normality

Based on skewness and kurtosis, Jarque and Bera (1980) calculated the test statistic

$$T_N = \left[\frac{n}{6} b_1^2 + \frac{n}{24} (b_2 - 3)^{(2)}\right] \qquad (22)$$

where $b_1 = \frac{\sqrt{n}\sum_{t-1}^{n} \hat{\varepsilon}_t^3}{\left(\sum_{t=1}^{n} \hat{\varepsilon}_t\right)^{\frac{3}{2}}}$ $\quad b_2 = \frac{n\sum_{t-1}^{n} \hat{\varepsilon}_t^4}{\left(\sum_{t=1}^{n} \hat{\varepsilon}^2{}_t\right)^2}$

The X^2 (2) distribution gives an approximation to the normality test T_N.

When the GARCH model is estimated, the normality test is obtained using the standardized residuals $\frac{\hat{\varepsilon}_t}{\sigma_t}$. The normality test can be used to detect misspecification of the family of ARCH models.

Ljung-Box (Modified Box-Pierce) or Portmanteau Lack-of-Fit Test: Box and Pierce (1970) have developed a test to check the autocorrelation structure of the residuals.

The test statistic:

$$Q = n(n+2)\sum_{k=1}^{K}(n-k)^{-1}\hat{\rho}_k^2 \quad (23)$$

Where k is the maximum lag length, n is number of observations and $\hat{\rho}$ is sample autocorrelation at lag k. If the correct model is estimated then,

$$Q \sim \chi^2_{K-m} \text{ where } m = p + q \quad (24)$$

If Q> χ^2_{Table}, reject the null. This means that, the autocorrelation exists in residuals and the assumption is violated. In this case, it is better to add another lag in AR or MA part of the model to check the model again.

Methodology

The Data

The time series data used in this analysis consists of the average monthly Birr/Dollar exchange rate from January 1957 to December 2010 obtained from annual report of the National Bank of Ethiopia.

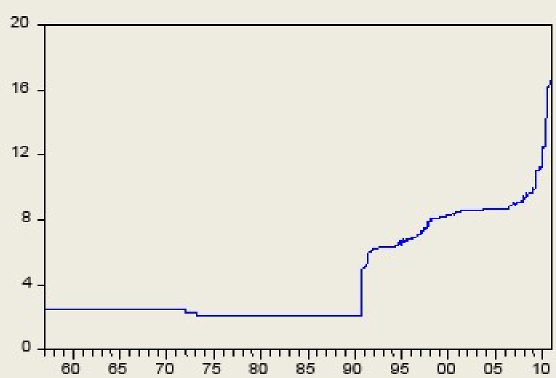

Figure 1: Plot of exchange rate series from 1957-2010

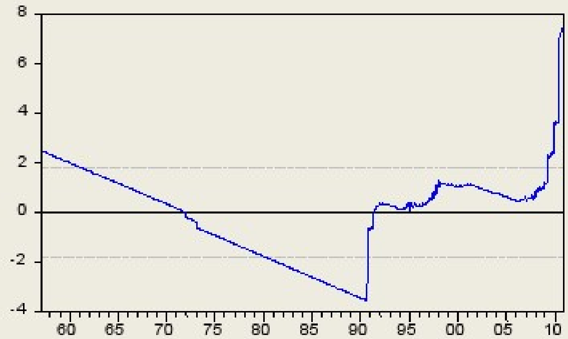

Figure 2: plot of residuals

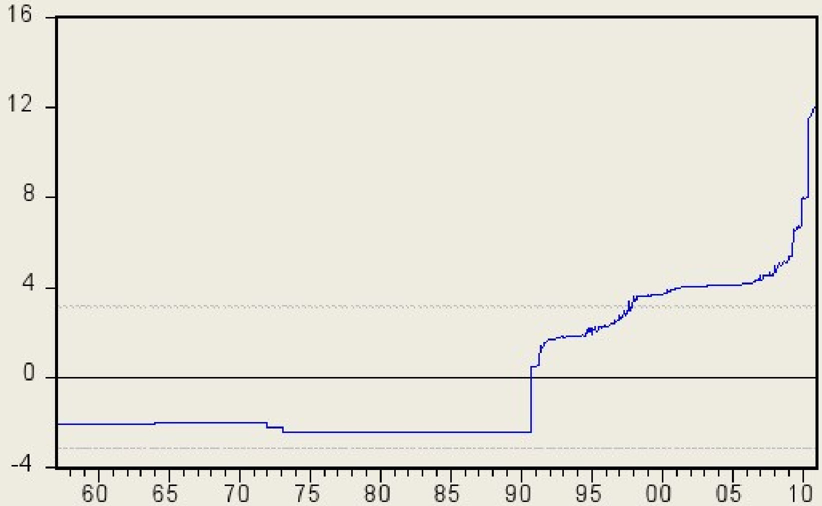

Figure 3: Plot of stadardized residuals

If we observe the graph of foreign exchange rate of Birr/dollar, residuals and standardized residuals (figure 2 & figure 3) clearly, the graph shows that there was a structural break in September 1992. Furthermore, the Ljung-Box test Q statistics in for the full sample (Table 1) are insignificant at 5% for all reported lags confirming the absence of autocorrelation in the exchange rate series. The Jarque –Bera test shows that the series is not normally distributed, whereas, the skewness and kurtosis, which are 1.1025 and 3.5 show that the distribution is actually non-normal. Since the observation is ratio (foreign exchange rate), the best distribution is identified by change of relatives. In this study, we use the exchange rate return as:

$$r_t = \log e_t - \log e_{t-1} = \log(\frac{e_t}{e_{t-1}}) = \log(1 + \frac{e_t - e_{t-1}}{e_{t-1}}) \tag{25}$$

Where e_t and e_{t-1} denote Birr/dollar exchange rate at time t and t-1 respectively. If r_t, t =

0, 1. . . n, be a time series of exchange rate of return at time t, instead of analysing e_t, which is often displays unit-root behaviour and thus cannot be modelled as stationary. The r_t of Equation (25) will be used in investigating the volatility of exchange rate in Ethiopia over the period, 1957 – 2010 and by using Taylor-expanding series the above equation of r_t is almost equivalent to the relative return, $\frac{e_t - e_{t-1}}{e_{t-1}}$. The reason we typically consider log-returns instead of relative returns is the additive property of log-returns, which is not shared by relative returns.

The foreign exchange market in Ethiopia was deregulated in November 1992 and the exchange rate is revised.

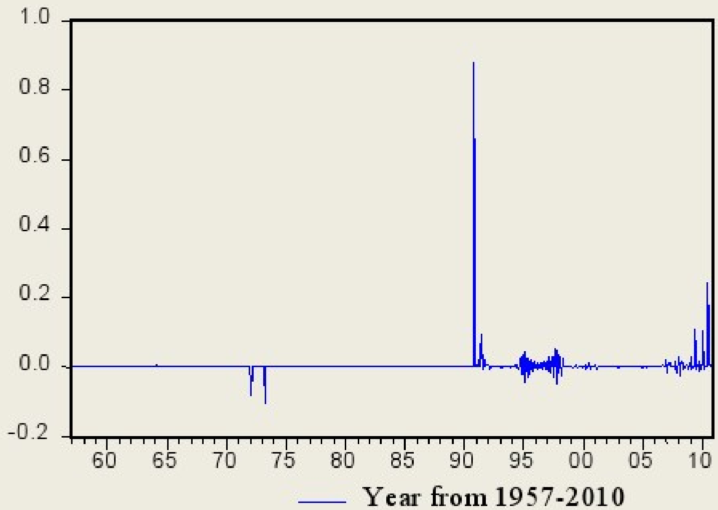

Figure 4: Graph of exchange rate of return from 1957-2010

Properties Of The Data

The summary statistics of the exchange rate return series is given in Table 1. The mean return for the full sample, pre-deregulation era and deregulation are 0.002927, 0.002163 and 0.001958, respectively while their standard deviations are 0.037606, 0.043479 and 0.022109 respectively. The standard deviation appears lower after the deregulation of exchange rate market following the introduction of market-determined exchange rates. The skewness for the full sample and the two sub periods (Fixed rate and Managed floating rate regimes) are 20.17995, 19.395041 and 6.462694 respectively. This shows that the distribution is positively skewed relative to the normal distribution (0 for the normal distribution). The kurtosis for the full sample and the two sub periods (Fixed rate and Managed floating rate regimes) are very much larger than 3, which is the kurtosis for a normal distribution. Skewness indicates non-normality, while the relatively large kurtosis suggests that distribution of the return series is leptokurtic, signalling the necessity of a peaked distribution to describe this series.

This suggests that for the exchange rate return series, large market surprises of either sign are more likely to be observed, at least unconditionally. The Ljung-Box test Q statistics for the full sample and the fixed rate regimes are all insignificant at the 5% for all reported lags confirming the absence of autocorrelation in the exchange rate return series. Jarque-Bera normality test rejects the hypothesis of normality for the full sample and the two sub periods (Fixed rate and managed floating rate regimes).

Figures 5, 6 and 7 show the quantile-quantile plots of the exchange rate return for the full sample and the two-sub period. This figure clearly shows that the distribution of the exchange rate returns series show a strong departure from normality. The usual method of testing for conditional homoscedasticity by transforming the autocorrelation of the squared return series might not be appropriate here in view of the non-normality of the exchange rate return series or not (see Mckenzie (1997)). According to Mckenzie (1997), volatility clustering is by no means unique to the squared returns of an assets price. In general, the absolute changes in assets price will exhibit volatility clustering and the inclusion of any power term acts so as to emphasise the periods of relative stability and volatility by highlighting the outliers in that series. If a data series is normally distributed, then we are able to characterise its distribution by its first two moments. Following, Mckenzie (1997), the test for conditional homoscedasticity was carried out by calculating the autocorrelation of power transformed exchange rate return series using powers of 0.25, 0.5 and 0.75. The Ljung-Box $Q^{0.25}$ and $Q^{0.5}$ statistics for the full sample and the two sub periods (Fixed rate and Managed floating rate regimes) are significant at the 5% for all reported lags confirming the presence of heteroscedasticity in the exchange rate return series. The Ljung-Box $Q^{0.75}$ statistics are significant at the 5% level for the full sample and second sub-period (floating exchange rate period). However, the Ljung-Box test $Q^{0.75}$ statistics are insignificant at the 5% level for all lags for the first sub-period. In view of the significance of the Ljung-Box $Q^{0.25}$ and $Q^{0.5}$ test statistics for the first sub-period, it will be safer to reject conditional homoscedasticity for this sub period too.

Table 3 shows the results of unit root test for the exchange rate return series. The Augmented Dickey-Fuller test and Phillips-Perron test statistics for the exchange rate return series are less than their critical values at the 1% and 5% level. This indicates that the exchange rate return series has no unit root.

Summary statistics	Full sample	Fixed exchange rate	Managed float
Mean	0.002927	.002163	0.001958
Standard deviation	0.037608	.043479	0.022109
Skewness	20.17995	19.39504	6.462694
Kurtosis	464.99037	393.6129	65.31979
Jarque-Bera	5804566	2747816	37142.42
	(0.0000)	(0.0000)	(0.0000)
Observation	648	428	220
Ljung-Box			
Q(1)	0.1075	0.0038	4.2999*
	(.743)	(0.951)	(0.038)
Q(2)	0.1101	0.998	4.3632
	(0.946)	(0.0041)	(0.113)
Q(4)	1.0909	0.2047	11.301*
	(0.896)	(0.995)	(0.023)
Q(6)	1.3593	0.2060	18.233*
	(0.968)	(6.6375)	(0.006)
Q(12)	9.9541	6.6375	23.440*
	(0.620)	(0.881)	(0.024)
Q(24)	11.194	(1.000)	42.698*
	(0.988)		(0.011)

Note: p-values in parenthesis * indicates significant at the 5%

Table 1: Summary statistics and autocorrelation of the raw exchange rate return series

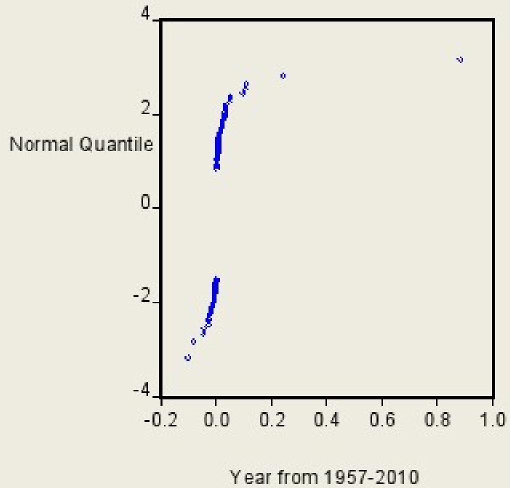

Figure 5: Quantile-Quantile plot of exchange rate return series based on the full sample (1957-2010)

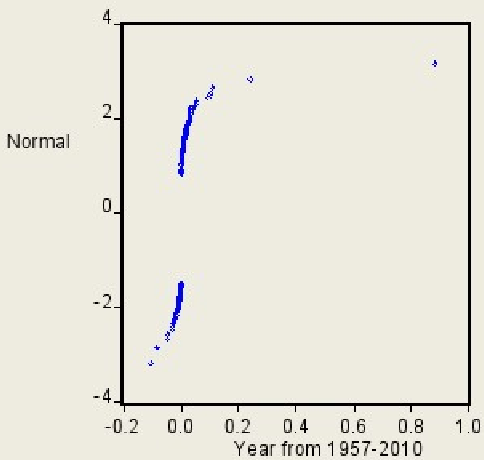

Figure 6: Quantile-Quantile plot of exchange rate return series on fixed period (1957-1992)

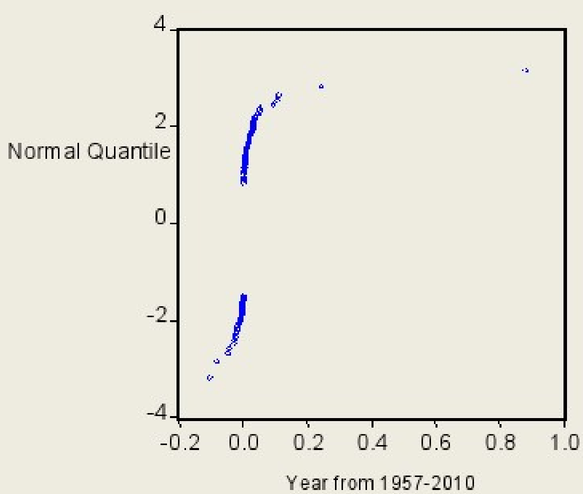

Figure 7: Quantile-Quantile plot of exchange rate return series based on floating manage regime (1992-2010

	Full samples	Fixed exchange ate	Managed float
Ljung-box $Q^{.25}$			
$Q^{.25}(1)$	246.27 (0.000)	37.556 (0.000)	44.425 (0.000)
$Q^{.25}(2)$	457.54 (0.000)	66.445 (0.000)	73.810 (0.000)
$Q^{.25}(4)$	941.00 (0.000)	160.36 (0.000)	151.99 (0.000)
$Q^{.25}(6)$	1340.90 (0.000)	210.81 (0.000)	204.88 (0.000)
$Q^{.25}(12)$	2349.10 (0.000)	368.10 (0.000)	270.84 (0.000)
$Q^{.25}(24)$	3704.10 (0.000)	417.64 (0.000)	298.55 (0.000)
Ljung-Box $Q^{.5}$ (1)	73.229 (0.000)	3.6788 (0.055)	31.250 (0.000)
$Q^{.5}$ (2)	131.46 (0.000)	5.8664 (0.053)	52.204 (0.000)
$Q^{.5}(4)$	303.74 (0.000)	20.779 (0.000)	126.32 (0.000)
$Q^{.5}(6)$	419.93 (0.000)	24.068 (0.001)	176.39 (0.000)
$Q^{.5}(12)$	752.56 (0.000)	87.754 (0.000)	239.09 (0.000)
$Q^{.5}(24)$	1085.10 (0.000)	103.38 (0.000)	279.80 (0.000)
Ljung-Box$Q^{.75}$ $Q^{.75}(1)$	6.1324 (0.013)	0.1623 (.687)	10.865 (0.001)
$Q^{.75}(2)$	10.330 (0.006)	0.2030 (0.903)	17.972 (0.000)
$Q^{.75}(4)$	30.251 (0.000)	1.7597 (0.780)	50.845 (0.000)
$Q^{.75}(6)$	41.891 (0.000)	1.7926 (.938)	84.209 (0.000)
$Q^{.75}(12)$	96.561 (0.000)	22.002 (0.037)	111.21 (0.000)
$Q^{.75}(24)$	121.65 (0.000)	23.944 (0.465)	137.87 (0.000)

Table 2: Autocorrelation of the power transformed return series using powers of .25, .5 and .75

Note: p values are in parenthesis

	Augmented Dickey-Fuller test			Phillips-Perron test		
	statistics	Critical value (%)		statistics	Critical value (%)	
		1%	5%		1%	5%
Full sample	-10.75097	-3.4430*	-2.8664	-25.72520	-3.4429*	-2.8664
Fixed rate	-8.964937	-3.4479*	-2.8686	-20.55581	-3.4478*	-2.8686
Managed float	-3.127293	-3.4615	-2.8747	-12.16136	-3.4615*	-2.8747

*Table 3: unit root Test of the exchange rate return series over the period, January1957 – December 2010. Note: * indicates significant.*

In summary, the analysis of exchange rate return indicates that the empirical distribution of returns in the foreign exchange rate market is non-normal, with very thick tails for the full sample and the two sub periods (fixed rate and managed floating rate regimes). The empirical distribution confirms the presence of non-constant variance or volatility clustering. This study will attempt to model the volatility of monthly exchange rates return. The mean equation that will be used in this study is given as:

$$r_t = c + \varepsilon_t \qquad \varepsilon_t \,/\, \varphi_{t-1} \sim t(0, \sigma^2, v) \qquad (26)$$

where r_t is the exchange rate of return which is approximately to a t-distribution with zero mean of error and constant variance and v is degree of freedom. This distribution has a v degrees of freedom parameter, which allows greater kurtosis. The t likelihood function is

$$l_t = \ln(\Gamma(0.5(v+1))\Gamma(0.5v)^{-1}(v-2)^{-1/2}(1+z_t(v-2)^{-1})^{-(v+1)/2}) - 0.5\ln(\sigma^2_t) \qquad (27)$$

where Γ the gamma function and v is is the degrees of freedom as $v \to \infty$ this tends to the normal distribution.

In September 1992, the government deregulated the foreign exchange market in Ethiopia and that paving the way for the introduction of market-determined exchange rates (managed floating exchange rate).

Wooldridge's (1990) robust LaGrange multiplier (LM) tests for autocorrelation and ARCH have no power to detect structural breaks in GARCH models. However, CUSUM and LM-based structural break tests have excellent size when the data is Gaussian, but the CUSUM tests tend to over reject even in quite large samples when returns have fat tails. Instead of CUMSUM and LM-based structural break tests to account for the introduction of managed floating exchange rate system, this paper divides the full sample in to two sub periods. For the two sub-periods, Fixed/Pegged exchange rate regime and Floating exchange rate regime, Equation (26) will still be used as the mean equation.

The volatility parameters to be estimated include ω, α, β, and γ. As the exchange rate, return series shows a strong departure from normality, all the models will be estimated with Student t as the conditional distribution for errors and are evaluated using the Akaike and Schwarz criteria with statistical software Eviews version 3.1 and estimation is done in such a way as to achieve convergence.

The Results

The results of estimating Equations of the GARCH family models are presented in Tables 4, 5 and 6. Table 4 shows that, in the mean equation, the constant variable is significant at the 5% level in GARCH, GJR-GARCH and Component ARCH models. The parameters of the mean equation in all GARCH family models are significant in managed floating system (Table 6).

The variance equation of Table 4 shows that ω, constant variance are significant in EGARCH and asymmetric component and α, the coefficient of ARCH is not statistically significant in all models. This appears to show that the absence of volatility clustering in these models.

A breakdown of the results shows that the statistical coefficients of α in Table 5 (Fixed rate period) are significant at 5% level in EGARCH model. However, in Table 6 (managed floating rate regime), the coefficients of α are statistically significant at the 5% level in the GARCH and GJR-GARCH models. This shows that the shift from fixed rate regime to managed float affected the statistical significance of α in the EGARCH model.

Table 4 shows that the coefficients of β (a determinant of the degree of persistence) are not statistically significant in all GARCH family models. This coefficient β is significant in EGARCH for the first sub periods (Fixed rate) as shown in Tables 5 and significant in the GARCH, GJR_GARCH and EGARCH model in Table 6 showing the shift from fixed rate regime to managed float affected the statistical significance of β. The sum of α and β in the GARCH model in Tables 4 and 5 is less than one whereas sum of α and β in the GARCH and GJR_GARCH exceeds one in table 6. This appears to show that the shocks to volatility are very high in managed floating rate for such models and will remain forever, as the variances are not stationary under the GARCH and GJR-GARCH model.

Table 4 and Table 5 show that there is low persistence volatility in these models, shocks to volatility are very low, and the variances are stationary in the full sample and fixed exchange rate regime.

The volatility persistence for the GARCH, GJR-GARCH and E-GARCH models in Table 5 are lower than those of Table 6 indicating that volatility persistence is higher in the Managed floating rate regime than fixed rate regime. However, in view of the insignificance of α in either of table 5 or table 6, this result is inconclusive. Anyhow, in sum, the Ethiopian Foreign exchange market is characterized by high volatility persistence in managed floating regime.

In Table 5, γ, represented in the output of EGARCH model is significantly positive and there appears to be asymmetric effect. Table 6 shows the leverage effect term, γ, of GJR-GARCH model is negative and statistically different from zero at 5% level, indicating the existence of the leverage effect in future exchange rate whereas the leverage of EGARCH model is positive and significantly different from zero at 5% level, indicting that there exist to appear asymmetric effect. In other GARCH family models, the leverage, γ, is not significantly positive so there does not appear to be asymmetric effect. Therefore, it is important that to use quasi-likelihood robust standard errors since the residuals are highly leptokurtic. The results of asymmetry and leverage effects are not the same for the fixed rate and managed float regimes.

Diagnostic checks

Tables 7, 8 and 9 show that the Ljung-Box Q-test statistics of the standardized residuals for the remaining serial correlation in the mean equation shows that autocorrelation of standardized residuals are statistically insignificant at the 5% level for all lags and models confirming the absence of serial correlation in the standardized residuals. This shows that the mean are well specified in all models in Tables 4, 5 and 6.

The Ljung-Box Q^2-statistics of the squared standardized residuals in Tables 7, 8 and 9 are all insignificant at the 5% level for all lags and models confirming the absence of ARCH in the variance equation. The ARCH-LM test statistics in Tables 7, 8 and 9 for all models further showed that the standardized residuals did not exhibit additional ARCH effect.

This shows that the variance equations are well specified in all models of Tables 4, 5 and 6. The Jarque-Bera statistics still shows that the standardized residuals are not normally distributed. In sum, all the models are adequate for forecasting purposes.

Model Evaluation

Based on this study, Table 10 shows that the ranking of the model in terms of the maximum log-likelihood, lowest Akaike information and Schwarz criteria. The best model for the full sample and fixed exchange rate regime in terms of maximum log-likelihood and lowest Akaike and Scwarz criteria is EGARCH model whereas GJR-GARCH model is the best for float managing exchange rate regime.

	GARCH	GJR_GARCH	EGARCH	component ARCH	Asymmetric Component
Mean equation					
C	0.003265*	0.00351*	-7.17E-08	0.00283*	0.002007
	(0.0215)	(0.0133)	(0.9944)	(0.0319)	(0.0953)
Variance equation					
ω	0.000933	0.00095	-5.794353*	0.001313	0.00127*
	(0.1261)	(0.1149)	(0.0004)	(0.2750)	(0.0444)
α					
	-0.002743	-0.0028	-0.831170	0.021499	0.023146
β	(0.0832)	(0.0839)	(0.2693)	(0.8363)	(0.8346)
	0.56095	0.5634	0.129298	0.010662	0.006289
γ	(0.2487)	(0.2335)	(0.2663)	(0.9764)	(0.9841)
λ		0.0075	0.196996		0.009610
		(0.9808)	(0.5833)		(0.9890)
φ					
				0.232655	0.229085
				(0.8590)	(0.8475)
				-0.009552	-0.009579
				(0.9203)	(0.9319)
LL	1680.343	1183.761	1226.983	1206.752	1205.021
Persistence	0.5582	0.56435	0.129298	0.232655	0.229085
AIC	-3.650859	-3.638153	-3.771551	-3.706025	-3.697595
SC	-3.623243	-3.603632	-3.737031	-3.664600	-3.649266
DW	2.025516	2.025245	2.013467	2.025666	2.024468
S.E of Regression	0.037695	0.037727	0.037837	0.037753	0.037793
N	647	647	647	647	647
Convergence rate (iteration)		47	242	99	20

Table 3: unit root Test of the exchange rate return series over the period, January1957 – December 2010.

Note: p- values are in parenthesis.

LL, AIC, SC, DW and N are the maximum log-likelihood, Akaike information criterion, Schwarz criterion, Durban Watson and number of observations respectively.

	GARCH	GJR_GARCH	EGARCH	component ARCH	Asymmetric Component
Mean equation					
C	0.002492	0.003636	0.000294*	0.001702	-2.80E-06
	(.1304)	(0.0575)	(0.0000)	(0.1988)	(0.9989)
Variance equation					
ω	0.001275	0.001202 (0.1185)	-5.258698*	0.001770	0.001889
α	(0.1308)	-0.003553	(0.0000)	(0.3352)	(0.3200)
β	-0.003628	(0.1474)	-2.58666*	0.028969	0.038918
	(0.1315)	0.562823 (0.2816)	(0.0000)	(0.8464)	(0.9167)
	0.546525		0.161302*	0.007609	0.014866
γ	(0.3134)	0.024194	(0.0000)	(0.9825)	(0.9839)
		(0.9450)			
λ			2.038295*		0.038608
			(0.000)		(0.8747)
ϕ				0.232182	0.238234
				(0.8692)	(0.7647)
				-0.013192	0.035412
				(0.9267)	(0.9297)
LL	724.2309	725.0747	780.6672	736.4708	730.8974
Persistence	0.542897	0.571367	0.161302	0.232182	0.238234
AIC	-3.365565	-3.364835	-3.624613	-3.413415	-3.382698
SC	-3.327629	-3.317415	-3.577193	-3.356511	-3.316310
DW	1.993916	1.991738	1.990346	1.993806	1.989086
S.E of Regression	0.807273	0.808156	0.808721	0.807317	0.809233
N	428	428	428	428	428
Convergence rate (iteration)	40	43	20	100	19

Table 5: parameter estimates of GARCH models for the fixed rate period, January 1957-September 1992

	GARCH	GJR_GARCH	EGARCH	Component ARCH	Asymmetric Component
Mean equation					
C	0.000599	0.000643	0.004163	0.004317	0.004317
	(0.0000)*	(0.0000)*	(0.0006)*	(0.0003)*	(0.0000)*
Variance equation					
ω					
α	2.85E-07	5.30E-07	-2.803513	0.000464	0.000488*
	(0.3805)	(0.1537)	(0.1933)	(0.0726)	(0.0017)
β	0.671282	1.026684	-0.066424	0.013753	0.036451
	(0.0077)*	(0.0030)*	(0.9058)	(0.9487)	(0.9510)
	0.729236*	0.721995	0.659727*	0.008376	0.015035
γ	(0.0000)	(0.0000)*	(0.0121)	(0.9973)	(0.9951)
λ		-1.219588	1.023609*		0.038126
ϕ		(0.0101)*	(0.0005)		(0.9520)
				0.237157	0.239431
				(0.7529)	(0.7552)
				-0.021970	0.033446
				(0.9170)	(0.9575)
LL	738.9428	752.8998	617.06051	529.5740	524.6670
Persistence	1.400518	1.138885	0.659727	0.237157	0.239431
AIC	-6.681298	-6.799089	-5.564186	-4.759763	-4.706063
SC	-6.619596	-6.721961	-5.392695	-4.667210	-4.598084
DW	2.212091	2.213570	2.277279	2.278205	2.277415
S.E of Regression					
N	0.022593	0.022638	0.022319	0.022366	0.022423
Convergence rate (iteration)	220	220	220	220	220
	54	56	106	300	20

Table 6: parameter estimates of GARCH models for the floating management exchange rate period, January 1992-December 2010

	Ljung-Box Q-statistics			Ljung –Box Q^2 statistics			ARCH LM		
	Q(4)	Q(6)	Q(12)	$Q^2(4)$	$Q^2(6)$	$Q^2(12)$	F	$N^* R^2$	JB
GARCH	1.3779 (.848)	1.5707 (.955)	9.2878 (.678)	0.0084 (1.000)	0.0118 (1.000)	0.0681 (1.000)	0.002825	0.002834	54845869
TARCH	1.2910 (.863)	1.4870 (.960)	9.2041 (.685)	0.0084 (1.000)	0.0119 (1.000)	0.0685 (1.0000)	0.002821	0.002830	5853891
EGARCH	5.1730 (.270)	5.6565 (.463)	28.595 (.005)	0.0053 (1.000)	0.0092 (1.000)	0.4893 (1.000)	0.001999	0.002005	4052196
Component ARCH	1.7452 (0.782)	1.9324 (0.9260)	10.345 (0.586)	0.0077 (1.000)	0.0112 (1.000)	0.0684 (1.000)	0.002803	0.002812	5779710
Asymmetric component	1.7298 (.785)	1.9135 (0.927)	10.289 (0.591)	0.0076 (1.000)	0.0111 (1.000)	0.0704 (1.000)	0.002790	0.002799	5806872

Table 7: Autocorrelation of standardized residuals, autocorrelation of squared standardized residuals and ARCH LM test of order 4. Since leptokurtic, we have to check up to order 4(full sample)

	Ljung-Box Q-statistics			Ljung –Box Q^2 statistics			ARCH LM		
	Q(4)	Q(6)	Q(12)	$Q^2(4)$	$Q^2(6)$	$Q^2(12)$	F	$N^* R^2$	JB
GARCH	1.6623 (0.798)	1.6759 (0.947)	7.5454 (0.820)	0.0059 (1.000)	0.0120 (1.000)	0.0681 (1.000)	0.00272 4	0.002736	227072
TARCH	1.8408 (.765)	1.8561 (.932)	7.7212 (.807)	0.0058 (.000)	0.0115 (.000)	0.0510 (.000)	0.00273 1	0.002744	272284 2
EGARCH	1.6623 (0.798)	1.6759 (.947)	7.5454 (.820)	0.0059 (.000)	0.3344 (.000)	0.0515 (1.000)	0.00272 4 (*)	0.002736 (*)	272707 2 (*)
Component ARCH	1.1287 (0.890)	1.1454 (.979)	7.4428 (.827)	0.0075 (.000)	0.0132 (.000)	0.0530 (.000)	0.00270 0	0.002712	272753 1
Asymmetric component	0.1834 (.996)	0.1841 (.000)	6.2586 (.902)	0.0101 (.000)	0.0159 (.000)	0.0580 (.000)	0.00267 1	0.002684	275818 8

Table 8: autocorrelation of standardized residuals, autocorrelation of squared standardized residuals and arch Lm test of order 4. Since leptokurtic we have to check up to order 4(fixed rate)

	Ljung-Box Q-statistics			Ljung –Box Q^2 Statistics			ARCH LM		
	Q(4)	Q(6)	Q(12)	$Q^2(4)$	$Q^2(6)$	$Q^2(12)$	F	$N*R^2$	JB
GARCH	8.1715 (0.085)	16.488 (0.011)	21.268 (0.047)	0.0695 (0.999)	5.3745 (0.497)	5.5949 (0.935)	0.025296	0.025526	45222.19
TARCH	7.9994 (0.092)	16.342 (0.012)	21.109 (0.049)	0.0703 (0.999)	5.3820 (0.496)	5.6017 (0.935)	0.025474	0.025706	45859.69
EGARCH	39.702 (0.000)	40.083 (0.000)	55.978 (0.000)	16.823 (0.002)	27.581 (0.000)	40.762 (0.000)	13.62595*	12.93906*	438.4761
APARCH component	9.1147 (0.058)	15.826 (0.015)	21.071 (0.049)	0.0573 (1.000)	5.4743 (0.485)	5.7246 (0.929)	0.000289	0.000292	35670.23
Asymmetric component	0.0050 (0.040)	17.415 (0.008)	22.439 (0.033)*	0.0836 (0.999)	5.2032 (0.518)	5.4236 (0.942)	0.022947	0.023156	43093.83

Table 9: autocorrelation of standardized residuals, autocorrelation of squared standardized residuals and arch Lm test of order 4. Since leptokurtic we have to check up to order 4(float manage exchange rate)

Rank	Full sample	Fixed rate regime	Managed float
1st	EGARCH	EGARCH	GJR-GARCH
2nd	COMPONENT ARCH	CONPONET APARCH	GARCH
3rd	GJR-GARCH	Asymmetric component	EGARCH
4th	GARCH	GJR-GARCH	COMPONENT APARCH
5th	Asymmetric component	GARCH	Asymmetric component

Table 10: Ranking of GARCH models in order of maximum log likelihood, Akaike information criterion and Schwarz criterion

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