

Stock Return and Exchange Rate Changes Effect Case of Tunindex

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Abstract
This study aims to examine the macroeconomic environment effect on Tunisian stock market index (5 days a weak Tunindex) from 01/02/2011 to 19/11/2019. GARCHM-X type models are used to estimate volatility of the daily returns series of 2191 observations having no significant weakday's effect. Once using interaction variables, GARCHM-XS model results capture the effect of macro-economic instability via exchange rate growth and exchange rate volatility post 2016. Then macroeconomic environment have to be favourable to ensure growth in the Tunisian stock market. And, policies aimed to reduce exchange rate volatility are a necessity for Tunisian stock market.
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1. Introduction

Volatility is an important input to many investment decisions and portfolio selection. Understanding the pattern of stock market volatility is important to investors as well as for investment policy. A large number of empirical studies have been accomplished to address the concept of volatility of stock markets using the family of ARCH/GARCH processes. Greater volatility can reduce investor confidence to invest in stocks (Edwards, 2006). If volatility is changing at higher rate, it may results in high profits or huge losses (Hemanth & Basavaraj, 2016), and this should be boosted by providing empirical evidence from appropriate models.

The volatility of Tunindex will be modeled using daily return series consisting of 2191 observations from 01/02/2011 to 19/11/2019. ARCH effects test confirmed the use of GARCH family models. Then, several models as GARCH(1, 1), GARCHM(1, 1), EGARCH(1, 1), TGARCH(1, 1), PGARCH(1, 1) and APGARCH(1, 1) can be used to capture the most common features of the stock market like leverage effect and volatility clustering. But, the aim of this paper is to know in addition if macroeconomic environment can be favourable to ensure growth in the Tunisian stock market. Precisely, we seak policies that can reduce stock market volatility in the economy via exchange rate growth and exchange rate volatility.

Using more general GARCHM model (stable GARCHM-Xj model), that includes asymmetric effect of exchange rate volatility through partial sum concept, we get very little asymmetric significant effects. Then, once using instable GARCHM-Xj model (GARCHM-XjS model), we show that positive partial sum and negative partial sum of exchange rate volatility could affect the stock return volatility in an asymmetric manner. More precisely, GARCHM-XjS models will be considered to capture the effect of macro-economic instability via interaction variables from positive partial sum (depreciation) [or negative partial sum (depreciation)] of exchange rate and a dummy variable for prespecified date of structural change.

The rest of this paper is organized as follows. Following this introduction, Section 2 provides a brief empirical review of the methodology of modeling volatility using some well known symmetric and asymmetric GARCH models. A data description, summary statistics, and analysis is provided in Section 3. Methodology is given in section 4. The results of the estimated GARCH-Xj and GARCH-XjS type models are discussed in Section 5. Lastly, section 6 concludes the paper.

2. A selective empirical review

The volatility analysis of stock markets is important for the investors in measuring and managing market risks more accurately. In its turn, risk measure is useful in pricing capital assets, financial securities, and selecting portfolios. The main methodologies that are applied in modelling the stock market volatility are ARCH models introduced by Engle (1982) and generalized as GARCH by Bollerslev (1986) [1].

Volatility is generally higher after the stock market falls than after it raises. Therefore, volatility of returns has an asymmetric predictable response to the changes in stock prices. So that, there is a *negative correlation between volatility and returns*. This is so-called *leverage effect* and was reported by Black (1976) [2]. However, Black (1976) and Schwert (1989) found empirically that leverage alone cannot explain all the asymmetry. Asymmetric ARCH (AARCH) by Engle, et al. (1990), Exponential GARCH model (EGARCH) of Nelson (1991), Threshold ARCH model (TARCH) proposed by Zakonian (1990) and its modified version of Glosten, et al. (1993) (GJR) are able to capture the predictable asymmetric effect.

For instance, the reader might get benefit from the research done by (Shamiri & Isa, 2009; Kalu, 2010; Ahmed & Suliman, 2011; Naimy, 2013; and Maqsood et al., 2017) in which they used some models from GARCH family both symmetric and asymmetric to capture the stock market volatility. Ahmed & Suliman (2011) worked with the reference of Sudan stock market, while (Kalu, 2010) provides the volatility analysis of Nigerian stock exchange. Modeling volatility of Paris stock market using GARCH (1, 1) and compared with exponential weighted moving average (EWMA) was done in (Naimy, 2013). Similarly, Shamiri & Isa (2009) provide the comparison of usual GARCH model with the non-linear asymmetric NAGARCH models based on Malaysian stock market.

All these papers ignore the eventual instability due to macroeconomic conditions. However, Emeka & Aham (2016) used more general models; the GARCH-X and the GARCH-XS which take into account of macroeconomic factor as inflation and exchange rate effects. They conclude that a negative relationship exist between stock price volatility and inflation rate and a negative relationship is present between equity price volatility and the exchange rate. For more details reader can refer to Annex: A selective empirical review
Table A *1* in Annex giving a sum up about some empirical researchs.

3. Data Description and Basic Statistics

The time series data used for modeling volatility in this paper is the daily Tunisian stock market index (Tunindex) over the period from 2/01/2011 to 11/19/2019, resulting in total observations of 2191 daily observations from excluding public holidays (a 5 days a weak). We used time series data sourced from Bourse de Tunis of Tunisia. Figure 1 gives daily Tunindex and exchange rate evolution for this period. We could see from the graph that there were larger fluctuations in both series during 2017 until 2019 compared with the period between 2011 and 2016. The daily returns are calculated as the continuously compounded returns which are the first differences of log index of Tunindex of successive days. We denote by

$$R_t = LSP_t - LSP_{t-1} = \vartriangle LSP_t,$$

the return of Tunindex, where LSP_t = log(Tunindex) and LSP_{t-1} are the t and t −1 th day Stock price in log. Returns over the period is graphically shown below at Figure 1 (a).

The descriptive analysis of the underlying variables was carried out to check the characteristics of the series. Table A2 (in Appendix) show summary statistics of stock market return (R_t) and exchange rate (Exrate). Statistics consist of the daily sample mean return, standard deviation, minimum return and maximum return, skewness, kurtosis, and Jarque-Bera (JB) statistic.

The mean of return is 0.000205 with the standard deviation of 0.004899. The mean exchange rate is 2.035 with the standard deviation of 0.499. For instance, the standard deviations indicate that Exchange Rate is more unstable/volatile compared with Stock Market return (R). There is also an excess in kurtosis as can be seen clearly for Tunindex returns. A high value of kurtosis 13.12752 indicates a leptokurtic distribution that is an apparent departure from normality. Another important test of normality is the JB statistic, which reject the null hypothesis of normality for the daily Tunindex returns at 5% level of significance. We can thus summarize that the Tunindex return series do not conform to normality but actually tend to have negative skewness (i.e. the distribution has not a thick tail).

Figure 1 (b) show us that there is evidence of volatility clustering, meaning that large or small asset price changes tend to be followed by other large or small price changes of either sign (positive or negative). This implies that stock return volatility changes over time.

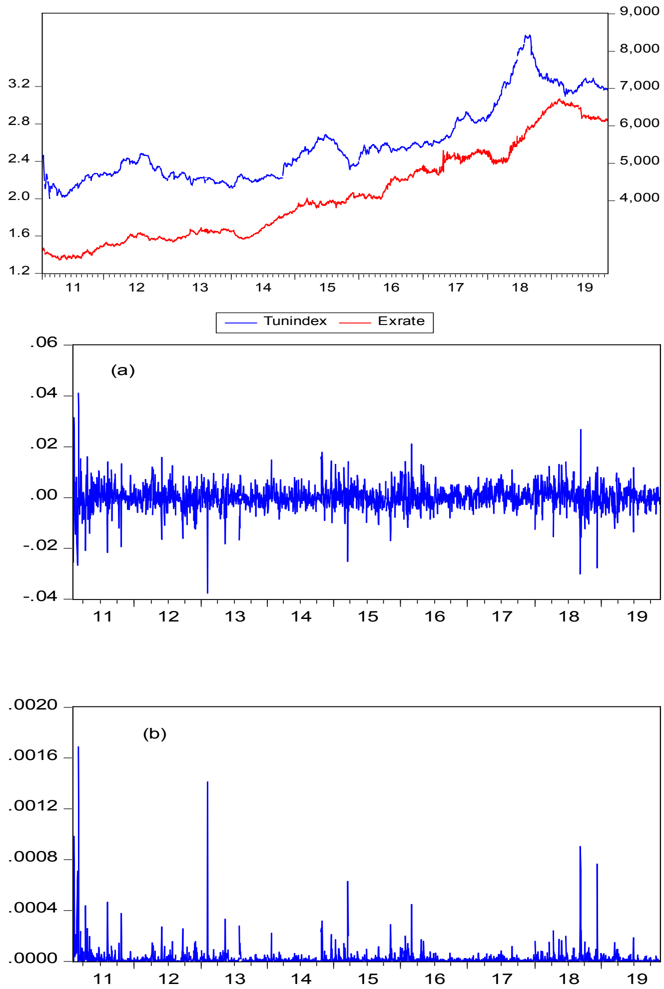

Figure 1: Daily mouvement of Tunindex and Exchange rate (Exrate), (a) Return (R_t), and (b) Squared return (R^2_t).

After the preliminary tests, the exchange rate growth (EXG) and its volatility (VEXG) are calculated using an AR(1)-GARCH(2, 1) model. Figure 2 gives the evolution of exchange rate growth volatily (VEXG). All these volatilities have different pattern *after 2016*. These revealed changes in volatility behavior have to be taken into account in modeling stock return volatility evolution.

Finally, it is important to examine the considered serie R_t that to find the evidence of heteroscedasticity before applying the methodology of modeling conditional variance. In order to test the presence of heteroscedasticity in the Tunindex return series, the Lagrange Multiplier (LM) test will be applied (to test against the hypothesis of q ARCH order effect [3]). Results of LM test for various ARCH order q = 1, 2, 3, which are presented in Table A 2**,** provide a strong evidence of rejecting the null hypothesis of constant variance for all lags included and then indicating the presence of ARCH effect in the Tunindex returns series R_t**.** Therefore we conclude that the variance of the return of Tunindex is not constant for all specified periods [4].

Once the volatility is confirmed in the data, we proceed our analysis further to estimate the parameters of both conditional mean and conditional variance. Before the application of AR(p)-GARCH technique, preliminary tests were conducted, such as the stationarity test of the variables (*Tunindex,* R_t*, and Exrate*) using the Augmented Dickey Fuller test (ADF), Philips Perron test (PP) and Kwiatkowski-Phillip-Schmidt-Shin (KPSS) test statistics. The results are presented in Table A 3 (see Appendix). Table A 3 reveals that *Tunindex* and Exrate series are not stationary. However the results for return R_t led towards the rejection of the null hypothesis of unit root, and hence stationarity is present in return series.

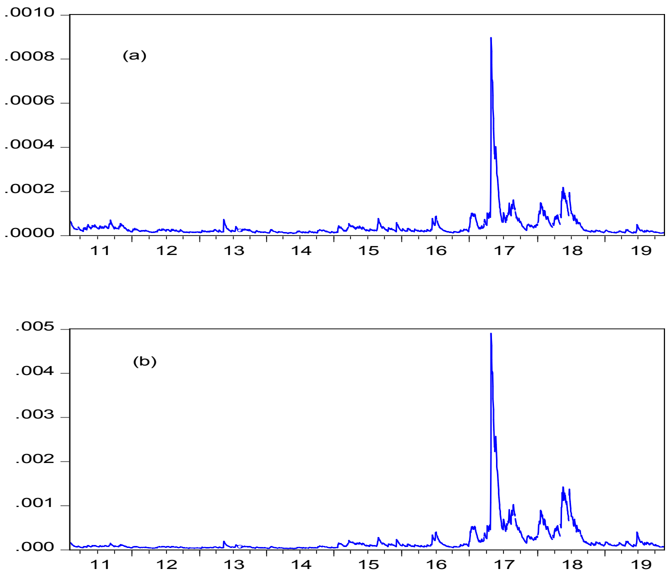

Figure 2: (a) Volatilty of Exchange rate growth (EXG) from AR(1)-GARCH(2, 1) and (b) volatility of Exchange rate (Exrate)

4. Methodology

Generalized Autoregressive Conditional Heteroskedasticity (GARCHM) models are widely used to determine volatility pattern. Three more egeneralized models, named GARCHM-Xj type, are considered when macro-economic variables are introduced in conditional mean and/or in conditional variance since macroeconomic factors (Xj) can effect stock market. In addition, when instability is taken into consideration, these models will be denoted by GARCHM-XjS (S refer to structural change). And then, three GARCH-XjS models will be build, j = 1, 2, 3. In all, we consider six models.

To examine the GARCHM models behavior, as suggested by Engle and Ng (1993), different diagnostics tests are used. These tests examine whether we can predict volatility by some variables observed in the past which are not included in the volatility model being considered [5]. The diagnostics tests are derived by writing the volatility model in the general form, of which the volatility model under the null hypothesis is a special case of

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2{}_{t-i} + \gamma' X_t,$$

where γ is the (m×1) vector of additional parameters, and X_t is the vector of the m corresponding additional explanatory variables, which are missing in the original volatility model. For example, these may be the variables which incorporate the instability and or more asymmetry in the volatility model. In order to approximate and quantify the asymmetry effect of exchange rate, we use the partial sums of negative changes and the partial sums of positive changes in exchange rate volatility (respevtively, VEX_t^- and VEX_t^+ as defined here after). Three models will be then considered. Since volatilty of exchange rate growth (VEXG), volatility of Exrate (VEX*)*, partial sums of negative and of positive changes in exchange rate volatility (VEX_t^-, and VEX_t^+) evolutions take different patturns after 2016 (see Figure 2), they may have different effects on Tunindex return volatility pre and post 2016. Then this type of models can be used to capture the effect of macro-economic instability. In order to approximate and quantify this instability, three other models will be then considered in which interaction effect variables will be used to take into account of possible structure change in the original three specifications. We begin by the more general models as given here after.

1) GARCHM-X1S model

For the first model, only macro-economic instability is introduced but in both conditional mean and conditional variance that are measered by the interaction effect $VEXG_{t2017}$. $VEXG_{t2017}$ gives the effect of volatility of the exchange rate growth post 2017. It is equal to

$$VEXG_{t2017} = VEXG_t \times D2017 \quad \text{for post 2017 } (t \geq 2017) \text{ and 0 if not,}$$

where

D2017 = 1 for post 2017 and 0 if not,

VEXG is the volatility of exchange rate Growth (EXG);

$$EXG = \Delta Log(EXRate),$$

with EXRate denote exchange rate.

Conditional mean and variance equations take the following forms:

$$\mu_t = c + \phi R_{t-1} + \lambda\, \sigma_t + \beta'\, EXG_t + \beta\;\, VEXG_{t2017} \qquad (1)$$

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2{}_{t-i} + \gamma_1\, VEXG_{t2017} \qquad (1')$$

where $VEXG_t$, EXG_t and R_t are stationary processes (see Table A 2 and Table A3 in Appendix).
The following two models suppose that macro-economic instability effect only the conditional variance but asymmetric effect is considered via appreciation and depreciation of Tunisian Dinar (TD).

2) GARCHM-X2S model :

$$\mu_t = c + \phi R_{t-1} + \lambda \sigma_t \qquad (2)$$

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2{}_{t-i} + \gamma_1 VEX^-_{t2017} + \gamma_2 VEX^-_t \qquad (2')$$

where VEX^-_{t2017} is the partial sums of negative changes in volatility of exchange rate (appreciation of TD). It is equal to

$$VEX^-_{t2017} = VEX^-_t \times D2017 = VEX^-_t \text{ for post 2017 } (t \geq 2017) \text{ and 0 if not,}$$

$$VEX^-_t = \sum_{j=1}^{t} \Delta VEX_j^- = \sum_{j=1}^{t} min\,(\Delta VEX_j, 0),$$

and VEX denote the volatility of exchange rate.

3) GARCHM-X3S model :

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2{}_{t-i} + \gamma_1 VEX^+_{t2017} + \gamma_2 VEX^+_t \qquad (3)$$

where

$$VEX^+_{t2017} = VEX^+_t \times D2017 = VEX^+_t \text{ for post 2017 } (t \geq 2017) \text{ and 0 if not,}$$

$$VEX^+_t = \sum_{j=1}^{t} \Delta VEX_j^+ = \sum_{j=1}^{t} max\,(\Delta VEX_j, 0),$$

is the partial sums of positive changes in volatility of exchange rate (depreciation of TD). Both VEX^-_t and VEX^+_t are stationary series (see Table A 2 in Appendix).

Note that if $\gamma_1 = 0$ in GARCHM-X2S and GARCHM-X3S, we get the stable models that are denoted respectively by GARCHM-X2 and GARCHM-X3. Also, if $\beta = 0$ and $\gamma_1 = 0$ in GARCHM-X1S, we get the stable model which is denoted by GARCHM-X1. We test the null hypothesis that the additional missing variables are not significant vs the alternative that they are significant. For example, to test H_0: $\gamma_1 = 0$, the test statistic will be computed as

$$LM = T.R^2,$$

where R^2 is the squared multiple correlation of the considered regression, and T is the sample number observations [6].

5. Empirical results

Since 2011 (Tunisian revolution), economic and political situation is instable in Tunisia. Then in the following, we investigate macroeconomic effects via exchange rate on Tunindex return volatility. This paper employed the AR(1)-GARCHM-Xj or GARCHM-XjS (S for structural shift) models to investigate the effect of exchange rate growth and exchange rate volatility on stock return volatility. All investigation results are given at Table A 4 for stable GARCHM-Xj models (see Appendix) and Table 1 for GARCHM-XjS models j =1, 2, 3 [7].

The performance of these estimated models are determined on the basis of some accuracy measures. We compute the Akaike information criteria (AIC), ARCH-LM test, Durbin-Watson (DW) statistic, and log of likelyhoud function (LL). The results are displayed at the end of Table A 4 for GARCHM-Xj and Table 1 for GARCHM-XjS. A look on these tables reveals that GARCHM-X2S is more suitable process to capture the main features of Tunindex return. Comparisons or selection of more accurate model based on Likelihood ratio (LR) tests and LM tests is also done. LM test results for GARCH(1, 1) against one model of the considered stable models (GARCHM- X1, GARCHM-X2, or GRCHM-X3) are also reported [8]. Only GARCHM-X2 and GARCHM-X1 which are significant. Then, LR test conclude that GARCHM-X2 is instable. That is, in all, only GARCHM-X2S model which will be then discussed.

ARCH and GARCH coefficients in GARCHM-X2S model are found to be significant. The significance of the parameters shows that there exists volatility clustering. Also, results indicate that coefficients α_1 (0.266561) and β_1 (0.533351) are less than ones. With low values of β_1, one can conclude that the volatilities do not last for long before it fades away. Also, the GARCH is greater than ARCH estimates in the model implying that the volatility of stock return is more affected by the past volatility than the related news from the previous period. GARCHM-X2S model reports a significant positive risk-premium (the λ estimated parameter 0.286812) indicating that data series is positively related to its volatility. This mean that agents are risk averse since they require a larger expected return from riskier asset within a period.

Now, with respect to exchange rate volatility, this result is predicted on the fact *bad news* about the volatilities of exchange rate (referred to as TD depreciation) correspond to positive volatility of stock return as it increases the conditional volatility; $\gamma_2 = 0.000743$ (see results from model GARCHM-X2S in Table 1). While that *good* *news* about the volatilities of exchange rate (referred to TD appreciation) correspond to negative volatility of stock return, since it reduces the conditional volatility; $\gamma_2 = -0.000718$ (see results from model GARCHM-X3S). This result is inconsistent with (Zakaria & Shamsuddin, 2012). However no significant effect of exchange rate volatility it self ($VEXG_{t2017}$) on stock return is found post 2017, while taking appreciation and depreciation effect seperatly (through interaction variables VEX^{-}_{t2017} *and* VEX^{+}_{t2017}), both have significant effect post 2016.

Table 1: Results of the three GARCHM-XjS (1, 1) models j = 1, 2, 3 with structural shift

Conditional variance

Conditional mean

$\mu_t = c + \phi R_{t-1} + \lambda\, \sigma_t + \boldsymbol{\beta EXG} + \boldsymbol{\beta}' VEXG_{t2017}$

C	$\emptyset_1$	λ	β	β'
−0.001091	00.227084*	0.284238*	0.009069	3.194222*

GARCHM − X1S: $\sigma^2{}_t = \alpha_0 + \alpha_1 u^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} + \boldsymbol{\gamma_1}\ VEXG_{t2017}$

α_0	α_1	β_1	γ_1
4.22E-06*	0.268286*	0.537486*	− 0.000194

GARCHM − X2S: $\sigma^2{}_t = \alpha_0 + \alpha_1 u^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} + \gamma_1\ \boldsymbol{VEX^{-}_{t2017}} + \gamma_2\ \boldsymbol{VEX^{-}_{t}}$

$\mu_t = C + \lambda\, \sigma_t + \emptyset_1 R_{t-1}$

C	λ	$\emptyset_1$	α_0	α_1	β_1	γ_1	γ_2
− 0.001030**	0.286812*	0.224690*	5.75E-06*	0.266561*	0.533351*	−0.000624*	0.000743*

GARCHM − X3S: $\sigma^2{}_t = \alpha_0 + \alpha_1 u^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} + \gamma_1\ \boldsymbol{VEX^{+}_{t2017}} + \gamma_2\ \boldsymbol{VEX^{+}_{t}}$

C	λ	$\emptyset_1$	α_0	α_1	β_1	γ_1	γ_2
−0.001024*	0.285318*	0.224959*	5.67E-06*	0.265448*	0.534769*	0.000606*	−0.000718*

Diagnostic	LL_N	LR	DW	AIC	ARCH LM (1)
GRCHM-X1S	8896.720	0.746	1.953829	-8.1166	0.9329
GRCHM-X2S	8898.488	8.848 > 5.99	1.943178	-8.1191	0.9725
GRCHM-X3S	8898.218	8.508	1.943841	-8.1189	0.9364

Note: LL_N: log-likelihood with Normal distribution. Chi-square critical points for LR test statistic are $\chi^2_{(1)} = 3.84$ and $\chi^2_{(2)} = 5.99$ at 5% and $\chi^2_{(1)} = 2.71$ and $\chi^2_{(2)} = 4.61$ at 10%. For ARCH LM test,only p-value is reported. LR = $-2(LL_R - LL_U)$ is test statistic to test GARCHM-Xj vs GARCHM-XjS model. LM = $T.R^2$ is test statistic to test GARCHM vs GARCHM-Xj model. * p<.1 ; ** p<.05 ; *** p<.01.

6. Conclusion

This paper present results from modeling volatility in an empirical investigation of equity return series from the Tunisian Stock Exchange; the daily Tunisian Stock index (5 days a weak Tunindex) for the period from 03/01/2011 to 19/11/2019. Previous studies assumed that exchange rate has symmetric effect. In this paper, we ue more general GARCHM-Xj model that includes asymmetric effect of exchange rate volatility through partial sum concept.

For policy, GARCHM-X2S (1, 1) turned to be the best model using both the AIC and LL criterions, with the presence of instability found to be significant using LR test results. The study concludes that positive and negative shocks impact differently on the stock market returns. Bad (and good) news will increase volatility of stock market returns in different magnitudes.

We conclude also that a positive relationship exist between stock return volatility and appreciation of exchange rate, while a negative relationship is present between equity return and the depreciation of exchange rate. These results remain true post 2016 but with less magnitudes.

The study result implies then that the investment climate including the stability in the macroeconomic environment should be favourable to ensure growth in the stock market. Investors require the predictability of the future appreciation of TD to make sound investment decisions. Policies to reduce volatility in the the economy (more stable exchange rate) are a necessity for stock Tunisian market.

Notes

1. The progress in such studies is generally provided for the purpose of estimation and prediction of the conditional variance of stock returns over the specified period.
2. When leverage of firms increases, uncertainty increases too.
3. The test procedure entails first obtaining the residuals u_t from the ordinary least square regression of Tunindex returns on a constant.
4. We assume a constant mean model and the LM test is applied to compute the test statistic value TR^2, where T is the number of observations and R^2 is the coefficient of multiple correlation obtained from regressing the squared residuals on q own lagged values.
5. If these variables can predict the squared normalized residual, then the variance model is misspecified. That is, if the test of significance of the other explanatory variables shows significant results, then we may conclude that the volatility model is not performing well.
6. The LM test statistic is distributed asymptotically as chi-square with m degrees of freedom, where m is the number of additional parameters in the model. We refer to (Engle, R. F., 1984) for more details on the asymptotic theory of the LM test.
7. Given, the predicted volatility for exchange rate growth, the relationship between the conditional volatility in exchange rate and stock return is examined by estimating the conditional mean and conditional variance equations.
8. There is no big difference between estimates results of GARCHM-X2 and GARCHM-3X model.

Annex: A selective empirical review

Table A 1 : Empirical review

Authors	**Variables**	**Model**	**Sample**	**Results**
(Al-Khazali, 2004)	Share prices -CPI -Industrial production index	-Johansen cointegration test -GARCH	**-Countries :** 21 emerging countries **-Period :** 1980-2001 -Monthly data.	-Negative short-term relationship between stock market returns and inflation. -Positive long-term relationship between stock market returns and inflation.
(Hammoudeh & Li, 2008)		GARCH model	Arab Gulf stock markets	Volatility was very high
(Surya, 2008)		GARCH (1,1)	Nepalese stock market 1297 observations from 2003 to 2009	No significant asymmetry in the conditional volatility of returns high persistence and predictability of volatility
(Ahmed & Suliman, 2011)	Khartoum Stock Exchange – KSE)		Sudan January 2006 to November 2010	Conditional variance process was highly persistent Existence of risk premium for the KSE index return series Presence of leverage effect.
(Goyal, 2012)		GARCH and PGARCH	Indian stock price daily returns from 2000 to 2010	Symmetric and asymmetric effect
(Ndako, 2012)			South Africa	Financial liberalisation is statistically important and not positive
(Sharaf & Abdalla, 2013)		GARCH(1,1), GARCH-M(1,1), EGARCH(1,1) and GJR-GARCH(1,1) models.	Khartoum Stock Exchange (KSE) daily closing prices over the period from 2nd January 2006 to 31st August 2010	High volatility process is present in KSE Index Existence of risk premium and indicates the presence of the leverage effect in the KSE index returns series

Authors	Variables	Model	Sample	Results
(Ananzeh, Jdaitawi, & Al-Jayousi, 2013)	Amman stock Exchange		Amman Stock Exchange for 27 individual stocks daily data for the period 2002-2012.	Trading volume has no significant effect on the reduction of the volatility persistence for majority of stocks Trading volume significantly contributes to the return volatility process
(Khositkulporn, 2013),		Multiple regression and GARCH	Thailand	S&P 500 had a major influence on Thailand's stock market, followed by the BSI and oil price
(Koima, Mwita, & and Nassiuma, 2015))		GARCH (1, 1)	Kenyan stock market	Iin a financial crisis ; the negative returns shocks have higher volatility than positive returns shocks
(Banumathy & Azhagaiah, 2015)	daily closing prices of S&P CNX Nifty Index for 10 years	GARCH (1,1) and TARCH (1,1), EGARCH (1,1) and TGARCH (1,1)	Indian stock Market Period: from 2003 to 2012.	Negative shocks have significant effect
(Cheteni, 2016)	Johannesburg Stock Exchange FTSE/JSE Albi index and the Shanghai Stock Exchange Composite Index	GARCH model	**Countries** South Africa and China stock markets **Period :** January 1998 to October 2014	Volatility was persistent in both exchange markets
(Emeka & Aham, 2016)	-Share price index -Inflation rates -Exchange rates	-Johansen's integration -AR (1) GARCH-S (1.1) - GARCH-X	**-Country :** Nigeria **-Period :** 1986-2012 -Quarterly data	-Negative relationship between stock price volatility and inflation rate. -Negative relationship between equity price volatility and the exchange rate.
(Murekachiro, 2016)	ZSE industrial index returns	GARCH (1,1) and EGARCH (1,1).	**Countries** Zimbabwe stock market **Period :** 19 February 2009 to 31 December 2014	Asymmetric EGARCH (1 ;1) model outperformed the symmetric GARCH (1 ;1)

Appendix

Table A 2: Descriptive analysis for daily data: Exchange rate growth (EXG), its volatility (VEXG), and partial sums of positive and negative changes in volatility of Exchange rate (VEX).

	EXRATE	EXG	VEXG	VEX_t^-	VEX_t^+	LSP	R_t	R_t^2
Mean	2.037434	0.000309	3.95E-05	-0.005632	0.005712	8.599037	0.000205	2.40E-05
Median	1.957500	0.000278	2.34E-05	-0.002334	0.002308	8.576524	8.72E-05	5.06E-06
Maximum	3.067100	0.044029	0.000898	0.000000	0.018373	9.039746	0.041086	0.001688
Minimum	1.343900	-0.095449	9.91E-06	-0.018422	2.77E-06	8.308577	-0.037572	0.000000
Std. Dev.	0.498802	0.006685	6.01E-05	0.006254	0.006365	0.177777	0.004899	8.36E-05
Skewness	0.505366	-1.055239	7.630818	-1.040332	0.994686	0.656896	0.012685	10.90062
Kurtosis	2.044746	26.81967	80.94890	2.406274	2.290192	2.356385	13.12752	159.0949
Jarque-Bera	176.5664	52441.65	578320.3	428.7633	408.5924	195.3907	9363.546	2267768.
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
T	2191	2201	2200	2198	2198	2191	2191	2191

Results of ARCH-LM test for different values of q.

ARCH order q	Test statistic TR^2	Probability
1	537.4039	0.0000
2	567.5435	0.0000
3	591.8380	0.0000

Unit root test results

Null Hypothesis : considered series has a unit root

	EXG	VEXG		VEX_t^-	VEX_t^+
PP test statistic	-69. 75309	-6.603327	**Min-t**	-5.72584	-5.61725
Prob.*	0.0001	0.0000	**Prob**	< 0.01	< 0.01
ADF test statistic	-34.22572	-6.881947	**Max-t**	3.807805	-5.597716
Prob.*	0.0000	0.0000	**Prob**	> 0.99	< 0.01
Conclusion	SL2	SL2		SL2	SL2

Heteroskedasticity Test: ARCH(1)

F-statistic	0.390477	Prob. F(1,2197)	0.5321
TR^2	0.390763	Prob. Chi-Square(1)	0.5319

Note : Min-t : Minimize Dickey-Fuller t-statistic is applied. Break Date: 4/25/2017 for VEX_t^- and 4/20/2017 for VEX_t^+. Max-t : Maximize intercept break t-statistic. Break Date: 5/12/2017 for VEX_t^- and 4/03/2017 for VEX_t^+.

Test critical values (for **PP test statistic**):

-3.433127, -2.862653, -2.567408 For **1% level** 5% level 10% level.

Test critical values (for Min-t):

-4.949133, -4.443649, -4.193627 For 1% level 5% level 10% level

Test critical values (for Max-t):

-4.734858, -4.193627, -3.863839 For 1% level 5% level 10% level

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Table A 3: Unit root results for original Tuindex series, and return series (Tunindex at first difference in log) for daily data.

PP test							
		Level			**1st Diff**		
		$TUNINDEX_t$	**R_t**	**$EXRATE_t$**	**$\Delta TUNINDEX_t$**	**ΔR_t**	**$\Delta EXRATE_t$**
With Constant	**t-Statistic**	-0.2139	-35.1895	0.2683	-37.0465	-326.1843	-74.7960
	Prob.	0.9343	0.0000	0.9766	0.0000	0.0001	0.0001
With Constant & Trend	**t-Statistic**	-2.4578	-35.2841	-2.3926	-37.0514	-325.6233	-74.8643
	Prob.	0.3494	0.0000	0.3833	0.0000	0.0001	0.0001
Without Constant & Trend	**t-Statistic**	1.0627	-35.2227	3.2466	-37.0503	-326.5386	-73.6475
	Prob.	0.9252	0.0000	0.9998	0.0000	0.0001	0.0001
ADF test							
		Level			**1st Diff**		
		$TUNINDEX_t$	**R_t**	**$EXRATE_t$**	**Δ $TUNINDEX_t$**	**Δ R_t**	**$\Delta EXRATE_t$**
With Constant	**t-Statistic**	-0.2505	-34.8711	0.4788	-36.6975	-22.2497	-35.7930
	Prob.	0.9295	0.0000	0.9860	0.0000	0.0000	0.0000
With Constant & Trend	**t-Statistic**	-2.5670	-34.8891	-2.2895	-36.7177	-22.2442	-30.1716
	Prob.	0.2957	0.0000	0.4390	0.0000	0.0000	0.0000
Without Constant & Trend	**t-Statistic**	0.9849	-34.8611	3.6985	-36.6817	-22.2557	-35.5003
	Prob.	0.9147	0.0000	1.0000	0.0000	0.0000	0.0000
KPSS test							
		Level			**1st Diff**		
		$TUNINDEX_t$	**R_t**	**$EXRATE_t$**	**$\Delta TUNINDEX_t$**	**ΔR_t**	**$\Delta EXRATE_t$**
With Constant	**t-Statistic**	4.9611	0.2164	5.9091	0.2550	0.0350	0.1759
	Prob.	***	n0	***	n0	n0	n0
With Constant & Trend	**t-Statistic**	0.8320	0.0972	0.9962	0.1155	0.0308	0.0788
	Prob.	***	n0	***	n0	n0	n0

Note: This Result is The Out-Put of Program Has Developed By Dr. Imadeddin AlMosabbeh , College of Business and Economics, Qassim University-KSA. For KPSS test, null Hypothesis: the variable is stationary.

Table A 4: Results of three stable GARCHM –Xj (1, 1) models.

			Conditional variance			
Conditional mean						
$\mu_t = c + \phi R_{t-1} + \boldsymbol{\beta}\,\mathbf{VEXG}_t + \lambda\,\sigma_t$						
C	$\emptyset_1$	β	λ			
−0.001114*	0.226460*	3.495209*	0.276129*			
		$\mathbf{GARCHM-X1}: \boldsymbol{\sigma^2}_t = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1 u^2}_{t-1} + \boldsymbol{\beta_1\sigma^2}_{t-1}$				
		$\boldsymbol{\alpha_0}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\beta_1}$		
		4.26E-06*	0.27143*	0.532988*		
		$\mathbf{GARCHM-X2}: \boldsymbol{\sigma^2}_t = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1 u^2}_{t-1} + \boldsymbol{\beta_1\sigma^2}_{t-1} + \gamma_1\ \boldsymbol{VEX}_t^-$				
$\mu_t = C + \lambda\,\sigma_t + \emptyset_1 R_{t-1}$						
C	λ $\emptyset_1$	$\boldsymbol{\alpha_0}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\beta_1}$	γ_1	
−0.000969*	0.271770* 0.227173*	4.44E-06*	0.26779*	0.54299*	5.19E-05*	
		$\mathbf{GARCHM-X3}: \boldsymbol{\sigma^2}_t = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1 u^2}_{t-1} + \boldsymbol{\beta_1\sigma^2}_{t-1} + \boldsymbol{\gamma_1}\ \boldsymbol{VEX}_t^+$				
C	λ $\emptyset_1$	$\boldsymbol{\alpha_0}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\beta_1}$	γ_1	
−0.00096*	0.270424* 0.227340*	4.43E-06*	0.26748*	0.54329*	−4.90E-05*	

Diagnostic	**LL_N**	**LM**	**DW**	**AIC**	**ARCH LM (1)**
GRCHM-X1		7.332 > 3.84	1.952708	-8.11812	0.8646
GRCHM-X2		2.766 > 2.71	1.949301	-8.11600	
GRCHM-X3	8896.347	2.566	1.949751	-8.11594	0.8425
	8894.064				
	8893.964				0.8414

Note: The Heteroskedasticity Consistent Covariance option is used to compute the quasi-maximum likelihood (QML) covariances and standard errors using the methods described by *(Bollerslev & Wooldridge, 1992)*. LL_N : log-likelihood with Normal distribution. Chi-square critical points for LR test statistic are $\chi2_{(1)} = 3.84$ and $\chi2_{(2)} = 5.99$ at 5% and $\chi2_{(1)} = 2.71$ and $\chi2_{(2)} = 4.61$ at 10%. For ARCH LM test, p-value is reported. LR = −2(LLR −LLU) is test statistic to test GARCHM-X vs GARCHM-XS model. LM = $T.R^2$ is test statistic to test GARCHM vs GARCHM-X model. * *p<.1 ;* ** *p<.05 ;* *** *p<.01.*

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