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Exchange Rate Volatility in Bangladesh: An Exploration of the Leverage Effect of Positive and Negative Economic News

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ABSTRACT

Purpose of the Study: This research investigates the impact of leverage on exchange rate fluctuations in Bangladesh, with a specific focus on assessing whether negative news about the exchange rate generates a greater effect on volatility compared to positive news. **Methodology:** The study employs the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) (1,1) model to analyze monthly BDT/USD exchange rate data from January 1982 to May 2022. This approach captures the autoregressive conditional heteroskedasticity in the data, allowing for the assessment of volatility patterns in response to positive and negative shocks. **Main Findings**: The results reveal that positive shocks generate higher volatility in the BDT/USD exchange rate compared to negative shocks, contrary to conventional financial market expectations. Additionally, the study identifies a reversed leverage effect, where positive return changes lead to greater volatility than declining prices, challenging the typical pattern observed in financial markets. **Applications of This Study**: The findings have significant implications for policymakers, investors, and financial analysts. Understanding the asymmetric effects of exchange rate shocks can aid in designing more effective risk management strategies, monetary policies, and investment frameworks, particularly in emerging markets with volatile currencies. **Novelty**: This study contributes to existing literature by uncovering a reversed leverage effect in the BDT/USD exchange rate, which contrasts with standard financial market behavior. The application of the EGARCH (1,1) model to a long-term dataset provides new insights into the dynamics of exchange rate volatility and its response to macroeconomic shocks.

Keywords: Exchange rate, Volatility, GARCH, TGARCH, EGARCH, Leverage effect, Bangladesh

JEL Classifications: C50, C58, E44, F31, G10.

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INTRODUCTION

In the current period of growing globalization and elevated currency volatility, exchange rates have a substantial impact on the everyday operations and profitability of businesses, both public and private. Along with huge and multinational firms, medium-sized and smaller enterprises are equally affected by exchange rate volatility. Companies with headquarters in certain nations are also affected. Investors and business owners place a high value on comprehending and controlling exchange rate risk because of the substantial impact it has on their assets. Foreign currency values show their volatility tendency through exchange rate fluctuations against domestic currencies. Foreign currencies display value fluctuations relative to local currencies. These rates demonstrate their level of variation through their fluctuation frequencies as well as their magnitude of movement. Foreign business deals between companies from different countries together with investment agreements represent typical instances where exchange rate volatility creates market challenges (Havi, 2019).

The government retains various levels of control over exchange rates through four fundamental systems including pegged and managed to float and freely floating and fixed systems. A Managed Float Foreign Exchange Rate System grants free regular foreign exchange rate movements yet the local currency maintains its link to foreign currency with no impact from System changes. According to Madura (2020) market conditions set the external currency rate in a free-floating exchange system.

Market investors experience heightened concern due to excessive currency rate movement instability. In 1982 Engle presented the first volatility simulation model known as Autoregressive Conditional Heteroskedasticity (ARCH). The various features of volatility required separate models to capture them. The simulation of "volatility clustering" characterizes one group of models while the "leverage effect" serves as the main objective of another set. Financial and macroeconomic variables that include exchange rates display fat tail behavior due to higher kurtosis and greater data frequency data which causes levy distribution behavior (Mandelbrot, 1963). Regular error assumptions become essential to predict accurate volatility because such models rely on them. It is improper to make evaluations of volatility models when assuming the presence of serial correlation. Abdullah et al.'s (2017) model helps the research analyze the volatility of taka-to-US dollar exchange rate returns while solving distribution errors.

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This research studies how leverage affects exchange rate fluctuations in Bangladesh from January 1982 through January 2022. This study examined if negative news about the exchange rate creates a bigger impact than positive news when determining exchange rate volatility in Bangladesh.

This research contains two major parts: Next, the paper summarizes past market-related experiments. Section 3 explains the information and research techniques that this study utilizes. Section 4 presents the analysis outcomes and examines this information for evaluation purposes. In the final section the paper presents both its conclusions alongside policy recommendations.

LITERATURE REVIEW

According to Brooks and Burke (1998), proper modified information criteria helps us to favour GARCH models. We used selected GARCH family models to predict currency rate volatility of the conversion rate in US dollars. The new forecasting models selected by this method outperformed GARCH (1, 1) models in most cases but showed less success when measuring mean squared error. (1, 1) models are frequently chosen less than 20% of the time, according to an analysis of the models' selection orders based on the criteria.

In 2005 Hansen and Lunde tested how well 330 ARCH-type models explained volatility behavior. We compare both model types using IBM return data and DM-US dollar exchange rate results outside the testing sample. Through IBM return studies the researchers confirmed that more advanced models overperform a basic GARCH (1,1) model by measuring volatility impact. Valid modes of comparison for the models included the Superior Predictive Ability test (SPA) and the Reality Check for Data Snooping procedure (RC). Our research shows that the RC does not have enough power to identify differences between the very best and poorest models in our study.

Through different GARCH model versions Choo, Loo, and Ahmad (2002) analyzed volatility dynamics in the exchange rate between Malaysian ringgit and British pound. With daily data spanning 1990 to 1997 the researchers determined stability in RM-sterling exchange rate volatility. They determined GARCH models work better for accurate predictions while GARCH-in-mean models produce better forecasts than standard GARCH models.

Clement and Samuel (2011) sought to simulate the fluctuations of the Nigerian currency rate through the GARCH model and studied currency fluctuations between the Naira and US

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Dollar as well as Naira and Sterling exchange rates. They measured the Naira exchange rate against US dollars and British pounds during the 2007 to 2010 period on a monthly basis. They found that return data from the exchange rates had abnormal patterns and exchange rate return data was not stable over time. The researchers proposed more research about government policies because finding return volatility lasted permanently.

Bala and Asemota analyzed exchange-rate volatility through monthly Naira/US dollar and Naira/Euro exchange rate returns in GARCH models in 2013. They tested different GARCH models by setting up starting points for exchange rate changes in US dollar rates. Every currency type in the study showed price swings and most asymmetric volatility modeling techniques except for breaks and persistence tests rejected the leverage effect. Volatility predictability increased when researchers used models with structural breaks instead of GARCH models without breaks and many models displayed reduced market trend following after volatility break inclusion.

Rofael and Hosni applied both ARCH-type models and SS techniques to exchange rate volatility data between January 2003 and June 2013 to forecast market movements. They learned that exchange rate volatility impacts Egyptian market results and when measuring nominal rates the varying time schedule of exchange rate changes and the mismatch between market risks must be recognized.

To model exchange rate volatility Dhamija and Bhalla (2010) point out that conditionally heteroskedastic models produce effective results. During their analysis of currency variability Dhamija and Bhalla determined that TGARCH and I-GARCH outperformed other models in forecasting five daily exchange rates Euro, Indian rupee, Japanese yen, German mark, and British pound.

GARCH shows a high rate of accuracy in predicting exchange rate volatility according to Ramasamy and Munisamy (2012). They applied GARCH models plus additional variations such as GJR-GARCH and EGARCH to study daily exchange rate actions of the Australian USD and three other regional currencies. The additional leverage factor inside EGARCH and GJR-GARCH models failed to boost predictive power according to their results.

From 1975 to 1998 Herwartz and Reimers studied daily FX variations for DEM and its relation to USD and JPY. They demonstrated how fluctuations clump together using a GARCH(1,1) model with leptokurtic innovations. The moments when the business system changed linked directly to currency policy shifts in the US and Japan during that era.

DOI: 10.48165/sajssh.2024.6307

Çağlayan et al. (2013) employed asymmetric GARCH methods to measure MIST nation exchange rate movements with the US dollar based on their study. They did two tests using data series on monthly exchange rates from 1993 to 2013. Researchers found that MIST exchange rates with US dollars show non-uniform movement patterns between those markets and the United States.

Vee Gonpot and Sookia (2011) tested GARCH(1,1) forecast accuracy by applying Student's t-test and Generalized Error Distribution. They inspected GARCH(1, 1) model forecasting accuracy by looking at MAE and RMSE measures from day-to-day USD/MRU exchange rate data. GARCH(1, 1) showed better forecast accuracy when comparing the student's t-distribution to the GED error distribution.

Tse (1998) analyzed the statistical fluctuations that came with trading between the yen and US dollar currencies. They combined the fractionally integrated process into an asymmetric power model of autoregressive conditional heteroscedasticity. Empirical tests showed that the future market volatility levels were altered by shock movements of the yen relative to the dollar similarly to the movements found in equity markets. Stable models and fractional integrated models show equal results in estimating currency capital requirements since both test results rejected fractional integration.

In 2014 Pelinescu researched the leu/euro exchange rate volatility by looking at other currency variations plus regular economic numbers. Our research results show that leu/euro volatility follows an ARCH pattern while traders encounter significant uncertainty while predicting exchange movements with volatility and rate returns showing a direct relation.

The research team Zia ur Rehman et al. (2020) analyzed cryptocurrency volatility using GARCH 1,1 symmetric and EGARCH, TGARCH, PGARCH asymmetric GARCH family members. Cryptocurrency values move up and down unpredictably according to research performed across a complete period for specific currencies. PGARCH performs better with student t distribution and indicates positive market movements strongly increase risk level compared to negative shifts.

In 2019 Havi conducted multiple studies on exchange rate volatility by analyzing how volatility works under specific conditions including Ghana Cedi redenomination. The exchange rate return data showed its characteristics by analyzing both EGARCH(1,1)-ARMA(1,1)-ARMA(4,4) and GARCH(1,1)-ARMA(4,4) models with Student's t-distribution. His research revealed that news from yesterday triggered stronger market volatility on the

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following day. Following Cedi redenomination GARCH(1,1)-ARMA(4,4) produced the best forecast of daily exchange rate return volatility. The currency reform known as Cedi redenomination worked positively to reduce exchange rate return volatility between GHC and USD.

Erkekolu et al. (2020) tested one-step-ahead daily USD/UGX return data using standard GARCH models plus PARCH (1,1), EGARCH (1,1), TARCH (1,1), and IGARCH (1,1). Secondary stock market volatility tests confirmed large deviation from normality, volatility clustering, concentrated risk, leverage effects, and better fit with PARCH (1,1) and EGARCH (1,1) using GED distribution.

Lu et al. (2022) built an RMB exchange rate forecasting system through deep learning methods to enhance risk measurement of Value at Risk (VaR) data. They merged the ARMA-GARCH model with autoregressive moving average to design a VaR risk measuring system. Deep learning helps the proposed model predict exchange rates more accurately across different international foreign currency markets with 74.92% precision. ARMA-GARCH risk prediction model recorded good market results that showed better accuracy than established measurement methods.

Mia and Rahman (2019) analyzed the monthly exchange rates between BDT and USD to test the ARCH model system. They tested many models by checking AIC, SIC and Theil inequality metrics to find the best data fit. These accuracy measurements included RMSE, MAE, MAPE, and RMAE to determine how well the models performed. Studies show that GARCH (1,1) stands out as the top model for monthly exchange rate volatility prediction and counteracts the exchange rate leverage effect for Bangladesh.

Over seven years Abdullah et al. (2017) used daily exchange rates to fix the problem of incorrect error distribution used in volatility prediction between BDT and USD. The analysis tried to display volatility movement through GARCH, APARCH, EGARCH and TGARCH. The team identified that Student's t-distribution for errors improved the model's accuracy of forecasting because it surpassed diagnostic tests when replacing the normal distribution. A model that combines two lags of auto-regressions with one lag of GARCH produces the strongest results when using Student’s T-distribution to forecast volatility.

DATA AND METHODOLOGY

3.1 Data and Variables

DOI: 10.48165/sajssh.2024.6307

This study used monthly exchange rate data between 1982 and 2022 that came from the IMF. This paper uses exchange rate data downloaded from IMF sources. The term nominal exchange rate (r_t) shows the value at which you exchange one country currency for another country currency. The usual exchange rate shows an unchanging pattern. This research uses a natural logarithm transformation to analyze the exchange rate changes, which is in the following:

$$r_t = ln\left(\frac{x_t}{x_{t-1}}\right) \tag{1}$$

$$r_t = ln\,(x_t) - ln\,(x_{t-1}) \tag{2}$$

where x_t and x_{t-1} are the BDT–US dollar nominal exchange rates during periods t and (t–1), respectively, and r_t represents the return on the exchange rate during time t.

3.2 Statistical Tools

This study uses EViews 10 (Econometric Views Version 10) to perform econometric estimation and analyses.

3.3 Methodology

It is generally known that choosing the right mean equation specification is crucial for modeling volatility with GARCH family models. The volatility model's potential autocorrelation issue might not be addressed by that equation's incorrect formulation. The research utilizes the Autoregressive Conditional Heteroskedastic (ARCH) model together with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Threshold GARCH (TGARCH) and Extensive GARCH models along with a nonparametric specification test to find the best model for Bangladesh's foreign exchange market volatility. We begin by establishing the mean relationship through this procedure.

Mean equations:

$$r_t = \mu + \rho r_{t-1} + \varepsilon_t \tag{3}$$

DOI: 10.48165/sajssh.2024.6307

Three alternative GARCH family models are used in this study, each with a specific purpose, to determine the variance equation for modeling the presence of volatility in diverged logarithmic exchange rates, such as exchange rate returns. Furthermore, this work models the variance for the aforementioned mean equation using the GARCH, TGARCH, and EGARCH models. This research adheres to the t-distribution. Since the literature on returns on financial assets has demonstrated that kurtosis tends to increase with data frequency and suggesting a "levy distribution" with "fat tails" is more prone to be the return variable's pattern.

Variance equation:

$$\varepsilon_t = \sqrt{h_t} v_t \ \ where\ v_t \sim N(0,1) \tag{4}$$

There are various GARCH family models that might be used, depending on how h_t is specified in this study. This work evaluated the following GARCH family model specification to estimate volatility in logarithmic exchange rates.

Generalized-ARCH

The amount of volatility in a Bollerslev GARCH model (1986) depends on prior variations in its own past measurements. The number of ARCH lags typically decreases because volatility can be predicted using delayed results. You can designate the GARCH (1, 1) model as shown below:

$$h_t = \eta + \alpha\, \varepsilon_{t-1}^2 + \beta\, h_{t-1} \tag{5}$$

The GARCH (1, 1) model in this case is made up of one GARCH term, ash$_{(t-1)}$, and one ARCH term, $\varepsilon^2_{(t-1)}$. A few conditions have to be met: $\eta > 0$, $\alpha \geq 0$, and $\beta \geq 0$ in order for the variance to behave itself . The enduring nature of volatility shocks is determined by the sum of the GARCH and ARCH coefficients. To guarantee that the series ε_t is stationary and the variance is positive, their sum should be smaller than the unit ($\alpha + \beta < 1$).

Threshold-GARCH

Zakoian (1994) and Glosten, Jagannathan, and Runkle (1993) proposed threshold generalized autoregressive conditional heteroscedasticity (TGARCH), another model developed to investigate leverage effects.

DOI: 10.48165/sajssh.2024.6307

$$h_t = \eta + \alpha\varepsilon_{t-1}^2 + \lambda d_{t-1}\varepsilon_{t-1}^{2} + \beta h_{t-1}, \qquad d_{t-1} = \{1, if\ \varepsilon_{t-1} < 0 \quad 0, if\ \varepsilon_{t-1} \geq 0 \tag{6}$$

In the aforementioned TGARCH (1, 1) model, volatility is affected differently by $\varepsilon_{(t-1)} > 0$ (positive news) and $\varepsilon_{(t-1)} < 0$ (bad news). In this case,good news has a consequence of α, whereas bad news has a consequence of (α + γ). We can therefore conclude that there is a leveraging effect when γ > 0 since the rise in volatility brought on by negative information is larger than that caused by positive information. Here, we also require nonnegative limitations for α, γ, and β, just like in normal GARCH models.

Exponential-GARCH

According to the research of Nelson (1991) the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model provides the solution for explaining asymmetrical financial patterns. The persistence is represented by the asymmetry parameter within the EGARCH specification and the shock size is indicated by the size parameter while the asymmetry parameter depicts the leverage effect. The EGARCH specification breaks away from previous GARCH models because it eliminates non-negativity restrictions by using an exponential function for conditional variance evaluation.

$$lnh_t = \eta + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \beta lnh_{t-1} \tag{7}$$

According to the classical GARCH (1, 1) model, whether $\varepsilon_{(t-1)} > 0$ or $\varepsilon_{(t-1)} < 0$, the shock in $\varepsilon_{(t-1)}$ has the same effect. The fact that adverse shocks generate greater fluctuation compared to favorable shocks, however, is a common characteristic of financial data.

RESULTS AND DISCUSSION

Testing the stationary nature of the variable of interest is crucial when assessing a time series analysis. Regressions produced using econometric modeling with non-stationary data may be erroneous or fraudulent, where the findings of the study would be misleading, as well as not suitable for providing any inference. The study makes use of Augmented-Dickey Fuller (ADF) and Phillips-Perron (PP) tests to determine data stationarity. The investigation examines two possibilities through its null hypothesis: the existence of a unit root in the series as a sign of non-stationarity or absence of a unit root for stationary structure. In a

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divergence from tests we have examined, the KPSS test conducts the null hypothesis assessment from a series that contains a unit root whereas its alternative hypothesis evaluates a series without a unit root. The Bangladeshi exchange rate demonstrates the results from its unit root test in the following table.

Table 1: *Unit Root Test Results of Exchange Rate*

	ADF	**PP**	**KPSS**
Test Statistic	-15.75978***	-16.30432***	0.566955***

Note: (, ** and *** specify statistical significance, respectively, at the 10%, 5% and 1% levels for ADF & PP tests; *, ** and *** specify the null hypothesis cannot be rejected, respectively, at the 10%, 5% and 1% levels for KPSS test).*

Table 1 demonstrates that, at a 1% level of significance, both the ADF and PP tests reject the null hypothesis for the unit root in the series (r_t). Similarly according to the KPSS test result, the null hypothesis of stationarity cannot be disproved at the 1% level of significance.As a result, I (0), the variable exchange rate (r_t), is stationary.

Table 2 displays the estimation results for the Ordinary Least Squares (OLS)-based differed logarithmic exchange rate conditional mean models.

Table 2: *Testing for the ARCH effect and estimating various conditional mean models*

Variables	**Coefficients**
Dependent Variable, r_t	
μ	0.000963* (0.000166)
r_{t-1}	0.284578* (0.045395)
ARCH Effect (Dependent Variable, ε_t^2)	
Constant	3.27E-06* (2.08E-07)
ε_{t-1}^2	0.639665* (0.067024)
H_O: **No ARCH Effect**	
F- Statistic	18.39833*
Probability	0.0000

*Note: Parenthesis indicates standard errors. The symbols ***, **, and * denote significance at the 10%, 5%, and 1% levels, respectively.*

DOI: 10.48165/sajssh.2024.6307

Analysis utilized OLS as the regression technique because the series exhibited mean-reversion characteristics. The significance of additional AR terms failed to appear therefore the model did not include them. According to the findings, the constant and AR(1) terms are both significant in the model, and the F-statistic evaluates the null hypothesis regarding lack of the ARCH effect on the logarithmic difference in exchange rates, demonstrating statistical significance at the 1% level.Understanding that the Taka's conditionally heteroscedastic logarithmic exchange rate compared to the US dollar is crucial for modeling volatility clustering. Additionally, the residual plot demonstrates that the exchange rate reflects volatility clustering.Having confidence in the ARCH effects' presence or absence is necessary for modeling GARCH models. Researchers use Lagrange multiplier as an efficient test method to determine ARCH presence (Engle, 1982).

The ARCH-LM effect, which tests conditional heteroscedasticity, is proposed by the LM. It uses $\varepsilon_t = r_t - \mu - r_{(t-1)}$ as the residual for the mean equation ε_t^2 .The ARCH-LM test was run for the first lag after the AR (1) model was estimated for the conditional mean. The null hypothesis that there are no ARCH effects is rejected at a 95% confidence level according to the test findings displayed in Table 2 below. This suggests that ARCH effects are present and that the variance of the return series is fluctuating.

Multiple criteria were applied for GARCH estimation after detecting an ARCH effect in the model. Three distributional assumptions were tested in the initial estimation for the GARCH(1, 1) models starting with normal distribution followed by student's t distribution and ending with GED distribution assumptions. The purpose of monitoring time-varying volatility required the implementation of the GARCH model.

Table 3: *Evaluation of various conditional mean models and GARCH effect tests*

Coefficients	GARCH
μ	3.94E-06 (1.39E-05)
ρ	0.362126* (0.036651)
η	5.98E-09* (1.17E-09)
α	0.654349* (0.088538)
β	0.318345* (0.016876)
$Q1(4)$	0.6450
$Q1(8)$	1.0528
$Q2(4)$	0.0277

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$Q2(8)$	0.0541
Log Likelihood	2482.207
F statistic	0.006765
Probability	0.9345

*Note: Enclosed in parenthesis are robust standard errors. * denotes that at the 1% level, ** denotes that at the 5% level, and *** denotes that at the 10% level.*

The estimation results are shown in Table 3. The autoregressive coefficient for mean equations of the lagged dependent variable is clearly statistically significant in this case. In every specification, the GARCH components' coefficients—including α and β—are positive and statistically significant at the 1% level. However, as long as the sum of the regressions was more than 1, the variance would stay limitless since the residuals of the regressions would not be stationary. Given that the GARCH model residual ought to be white noise, the Ljung-Box Q-test was used as a diagnostic test using the null hypothesis (H_0: No Serial Correlation in the Error Term). Drawing inspiration from Tse (1998), the standardized residuals (Q1) and their squared values (Q2) were examined for the fourth and eighth lags using Q-statistics. Each and every Q1 statistic is significant at the five percent significance threshold. The null hypothesis, according to which the error term does not show serial correlation, was thus sufficiently supported by the data. The models' absence of ARCH effects was also verified by the F-statistic. The model satiated every nonnegativity criterion necessary for its legitimacy. Additionally, across all models, the parameter that gauges volatility's uneven reaction to shocks consistently produced negative and significant results, suggesting the potential for an asymmetric volatility effect.

Table 4: *Testing for the T-GARCH effect and estimating various conditional mean models*

Coefficients	**T-GARCH**
μ	1.21E-06 (1.04E-05)
ρ	0.362239* (0.032626)
η	1.78E-09* (4.31E-10)
α	0.914534* (0.157342)
γ	-0.690183* (0.152540)
β	0.354370* (0.014913)
$Q1(4)$	0.2256
$Q1(8)$	0.4078
$Q2(4)$	0.0277

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$Q2(8)$	0.0541
Log Likelihood	2507.295
F statistic	0.003529
Probability	0.9527

*Note: Enclosed in parenthesis are robust standard errors. * denotes that at the 1% level, ** denotes that at the 5% level, and *** denotes that at the 10% level.*

The estimator is only accurate under the student's t-distribution and the normal error distribution; therefore, it can be used safely. Furthermore, there are no additional ARCH effects or autocorrelation problems in this model. In addition to accounting for the asymmetric volatility effect, the computed EGARCH model removes the nonnegativity limits. Using several assumptions and the residual Student's t-distribution, the estimation results for the EGARCH model are shown in Table 5. In the present estimated EGARCH models, the autoregressive coefficients significantly affected the calculations. As a result, the variance equation represents the "size parameter" and the "asymmetry parameter," both of which are frequently called "parameters." The latter measures how shock intensity impacts their mean, whereas the former assesses the asymmetric influence on volatility. The size and asymmetry parameters are both significant at the 1% level, which suggests that there may be an asymmetric effect on volatility based on the student's t distribution. A review of the diagnostic indicators reveals that the model is free of the ARCH effect and that serial correlation is not a problem.

Table 5: *E-GARCH effect testing and estimation of various conditional mean models*

Coefficients	E-GARCH
μ	4.53E-05 (3.92E-05)
ρ	0.297517* (0.028758)
η	-2.884448* (0.268571)
α	9.940749* (3.200570)
γ	3.182085** (1.422214)
β	0.677940* (0.024238)
$Q1(4)$	1.9665
$Q1(8)$	11.727
$Q2(4)$	0.2112
$Q2(8)$	0.6473
Log Likelihood	2463.668

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F statistic	0.065722
Probability	0.7978

*Note:Enclosed in parenthesis are robust standard errors. * denotes that at the 1% level, ** denotes that at the 5% level, and *** denotes that at the 10% level.*

As a result,the return of the BDT/USD exchange rate demonstrates asymmetric fluctuation , and appreciation and depreciation may have differing effects on future volatility, according to the EGARCH specification. Using squared residuals, the models solved the autocorrelation issue based on the Ljung-Box Q-test. Additionally, the autocorrelation issue was not present when the test was run with normal residuals. EGARCH ignored the potential for an asymmetric volatility effect, thus we explored TGARCH as an alternative parameterization.

CONCLUSION

Using monthly data on the BDT/USD exchange rate for 40 years, the study attempted to explore the nature of the leverage effect on Bangladesh's exchange rate volatility. Given that the exchange rate trend was not stationary in nature, to alleviate the emergence of the spurious analysis, the natural logarithmic function of exchange return, results from the series as stationary. A brief summary of the findings of this study is presented in the followings:

i) The different unit root tests, namely ADF, PP, and KPSS tests confirm the stationarity of the research variable.

ii) The ARCH effect,a precondition to conduct ARCH family models, was found in the LM test.

iii) The estimation results of the GARCH (1, 1) model indicates that the model has no serial correlation and heteroscedasticity, and at a significance level of 1%, the model's coefficients are statistically significant.

iv) The asymmetry parameter is deemed statistically significant at the 1% level, according to the Threshold-GARCH (TGARCH) model's results, which also showed no issues with autocorrelation or heteroscedasticity. This suggests that exchange rate volatility is not symmetrically impacted by both the two extreme news.

v) According to the Exponential-GARCH (EGARCH) model's estimation results, the leverage parameter is positive and, at the 5% level, statistically significant. Surprisingly, this outcome guarantees that positive news rather than negative news

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will dominate and raise volatility in the foreign exchange market. The so-called stylized fact that negative news outweighs positive ones in terms of financial market volatility is completely contradicted by this result.

Limitation of the Study

The study's limitations include its exclusive focus on the BDT/USD exchange rate, which might not adequately represent the dynamics of other currency pairs or regional exchange rate patterns. The EGARCH (1,1) model is also useful, although it might not take into consideration all external factors that affect exchange rate volatility, like abrupt policy changes or geopolitical events. The results may not accurately represent future market circumstances or structural shifts in the global economy due to the time span (1982–2022). Investigating the role of external factors, such as geopolitical risks or monetary policy shifts, could provide a more comprehensive understanding of exchange rate volatility.

Conflict of interest: The authors state that none of the work described in this study could have been influenced by any known competing financial interests or personal relationships. No grants, funds, or other financial assistance were obtained from any group or entity that would be thought to have an impact on the study. This study was carried out impartially and independently, and neither its findings nor its conclusions were influenced by outside factors.

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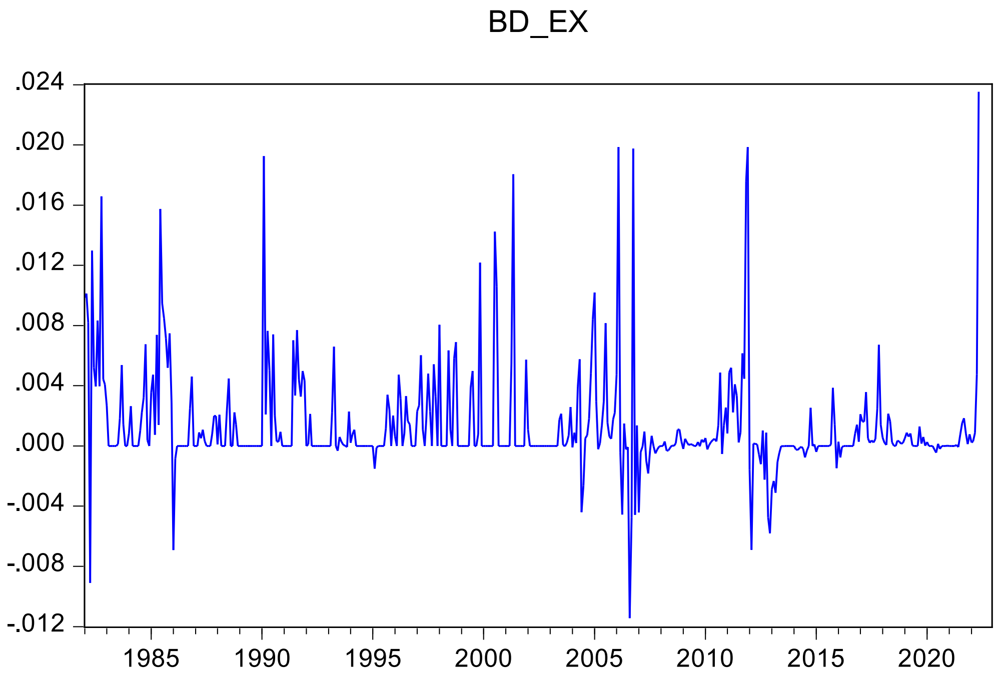
DOI: 10.48165/sajssh.2024.6307

Appendices

Appendix-1: Exchange Return Volatility of Bangladesh



Appendix-2: Unit Root Test Results

Null Hypothesis: BD_EX has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.75978	0.0000
Test critical values:	1% level	-3.443635	
	5% level	-2.867292	
	10% level	-2.569896	

Null Hypothesis: BD_EX has a unit root

Exogenous: Constant

Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

	Adj. t-Stat	Prob.*

DOI: 10.48165/sajssh.2024.6307

Phillips-Perron test statistic		-16.30432	0.0000
Test critical values:	1% level	-3.443635	
	5% level	-2.867292	
	10% level	-2.569896	

Null Hypothesis: BD_EX is stationary

Exogenous: Constant

Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.566955
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

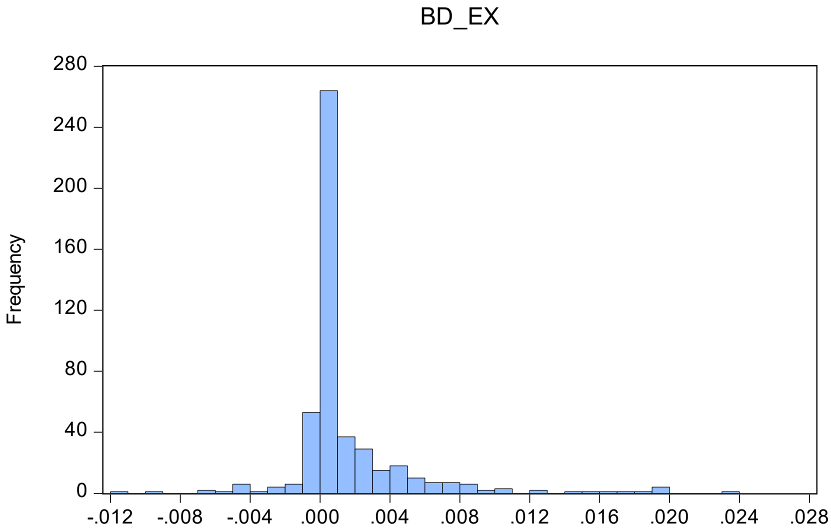
Appendix-3: ARCH-Effect Test

Heteroskedasticity Test: ARCH

F-statistic	18.39833	Prob. F(1,481)	0.0000
Obs*R-squared	17.79420	Prob. Chi-Square(1)	0.0000

Appendix-4: Distribution of the Variable

DOI: 10.48165/sajssh.2024.6307



Appendix-5: Mean Equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000963	0.000166	5.797544	0.0000
BD_EX(-1)	0.284578	0.045395	6.268873	0.0000

Appendix-6: GARCH(1, 1) Estimation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.94E-06	1.39E-05	0.282513	0.7776
BD_EX(-1)	0.362126	0.036651	9.880516	0.0000
Variance Equation				
C	5.98E-09	1.17E-09	5.117865	0.0000
RESID(-1)^2	0.654349	0.088538	7.390627	0.0000
GARCH(-1)	0.318345	0.016876	18.86328	0.0000

DOI: 10.48165/sajssh.2024.6307

T-DIST. DOF	2.772711	0.118968	23.30633	0.0000

Appendix-7: TGARCH Estimation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.21E-06	1.04E-05	0.117228	0.9067
BD_EX(-1)	0.362239	0.032626	11.10272	0.0000
Variance Equation				
C	1.78E-09	4.31E-10	4.133707	0.0000
RESID(-1)^2	0.914534	0.157342	5.812410	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.690183	0.152540	-4.524606	0.0000
GARCH(-1)	0.354370	0.014913	23.76222	0.0000
T-DIST. DOF	2.517804	0.103998	24.21002	0.0000

Appendix-8: EGARCH Estimation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.53E-05	3.92E-05	1.154280	0.2484
BD_EX(-1)	0.297517	0.028758	10.34544	0.0000
Variance Equation				
C(3)	-2.884448	0.268571	-10.74000	0.0000
C(4)	9.940749	3.200570	3.105931	0.0019
C(5)	3.182085	1.422214	2.237416	0.0253
C(6)	0.677940	0.024238	27.97005	0.0000

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T-DIST. DOF	2.000934	0.000567	3526.484	0.0000

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