Asian Economic and Financial Review
ISSN(e): 2222-6737
ISSN(p): 2305-2147
DOI: 10.55493/5002.v13i4.4763
Vol. 13, No. 4, 228-240.

URL: www.aessweb.com

An ARCH volatility analysis of real GDP, real gross capital formation, and foreign direct investment in Bangladesh

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Article History
Received: 23 December 2022
Revised: 14 February 2023
Accepted: 2 March 2023
Published: 27 March 2023

Keywords
ARCH
Economic growth
Net inflows
Return
Risk
Time series
Volatility
World bank indicators.

JEL Classification:
C22; C58; F21; F43.

ABSTRACT

This paper aims to investigate the volatility of the growth rates of Bangladesh's real GDP, real gross capital formation, and net inflows of foreign direct investment. The study used data on these indicators from the World Bank for the period between 1972 and 2020. Autoregressive integrated moving average (ARIMA) and the autoregressive conditional heteroscedastic (ARCH) methods were applied to model the conditional mean and conditional variance components for each growth rate. The validity of the selected volatility models was evaluated using a variety of diagnostic techniques, such as the time series graph of estimated residuals, cumulative periodogram, and the portmanteau test for white noise. The overall performance of the selected models is evaluated using the mean squared error (MSE) and the root mean squared error (RMSE). For all three indicators, the conditional means depend on the growth rates of the previous year or two years, whereas conditional variances depend on the previous year's rates. The outcomes of the study also indicate the existence of time-varying volatility in Bangladesh's economy. This study may be helpful in understanding the potential risks related to the volatile nature of macroeconomic growth rates.

Contribution/Originality: This is one of the few studies that strives to accurately reflect the volatility of the returns of the three most fundamental economic indicators and treats the volatility of these indicators as non-constant over time for Bangladesh, an economically developing nation.

1. INTRODUCTION

Volatility is an integral concept in finance (Bollerslev, Chou, & Kroner, 1992) and economics (Daly, 1999; Figlewski, 1997) that can be defined as a statistical measurement expressing the dispersion of the rate of return for a given variable or indicator. The strength or degree of variability in the returns of an indicator or variable is indicated by volatility. It also comes with instability, inconsistent prediction, uncertainty and risk (Ederington & Guan, 2005).

Economic indicators provide insight into the state of a country's economy. Macroeconomic indicators are the aggregated measurements of an economy that are utilized to understand recent and upcoming opportunities and activities of a nation's economy. This study analyzes the volatility of the growth rates of three crucial macroeconomic and financial indicators of Bangladesh – real gross domestic product (GDP), gross fixed capital formation (GFCF) and foreign direct investment (FDI) – to get a cumulative perception and investigate the dispersion from the expected change of return of these indicators as well as to determine whether new opportunities will be generated in Bangladesh's economy. Being a developing nation, Bangladesh's economy is expanding over time, making it vital to ascertain the presence of volatility in the growth rates of its key financial and macroeconomic indicators. The growth rates of the chosen financial indicators for Bangladesh are assumed to be volatile in the current study rather than being taken as constant over time. Since volatility is a measure of risk, it is intimately tied to both risk analysis and economic growth. Understanding how risk may affect decisions regarding present and future investments will have an impact on those decisions.

The economy and financial sector of Bangladesh are expanding rapidly despite having so many odds, and the purchasing power of the people is increasing through the diligent workforce, exports, committed entrepreneurs, expansion of domestic and international trade, escalating streaming of remittance, and the continuous development of the infrastructure sector, among others. According to the International Monitory Fund (IMF), the economy of Bangladesh was the 44th largest in the context of nominal GDP, and considering the purchasing power of parity, it gained the 32nd position in 2018 (High Commission for Bangladesh to Canada, 2020). The current overall improvement opens up new opportunities for more business cycles and makes the economy more lucrative for business. Thus, it becomes necessary to analyze the economic health of Bangladesh with more insight and volatility analysis of crucial financial indicators to understand the existence and certainty of the risks of economic growth in Bangladesh. This study employs the autoregressive conditional heteroscedasticity (ARCH) model developed by Engle (1982), which is immensely popular in financial time series analysis (Bollerslev et al., 1992; Daly, 2008) to capture the asymmetric property of the time series indicators of Bangladesh that change over time.

Conventional regression models assume that the variance of estimated error terms acquired from the models is constant over time, which is called homoscedasticity, and when this assumption is violated, the confidence intervals computed from the traditional procedures become very small along with a spurious perception of preciseness, even though the OLS estimates of regression coefficients are unbiased. The variance of the return or growth rate of a financial indicator implies the degree of risk of those growth rates. In financial applications, volatility indicates riskier times, and variance of the growth rates implies the level of risks of those returns. When it comes to financial data, volatility becomes more and more visible, and the volatility of the returns does not occur infrequently, rather they exist in cluster form. Often, high volatility remains persistent at certain time points with increasing volatility and vice versa in different quarterly and annual financial data with the presence of autocorrelation in the precariousness of those financial growth rates (Engle, 2001). Various researchers have applied the ARCH model along with its related models (Shephard, 1996) to explain the time-variant volatility (Bollerslev et al., 1992). Several researchers have attempted to evaluate the time-variant volatility of the real GDP growth rates of the three most industrialized nations in the world—the United States, the United Kingdom, and Japan. To serve this purpose, the GARCH model accompanied by two of its extensions, T-GARCH and M-GARCH, was applied to determine the suitable conditional means and variance equations where the GARCH model was found to obtain the most robust results (Hamori, 2000). These same growth rates were also investigated by employing a regime-switching approach, the Markov Switching specification, with two states (Bhar & Hamori, 2003). Another study with more modifications was conducted for the same growth rates where the results did not suggest any asymmetric pattern in the volatility (Ho & Tsui, 2003). An alternative method called the Markov Switching heteroscedasticity model captured the feature of the volatility of these three countries extremely well and successfully identified business cycle peaks (Chen, 2006). Previously, the effect of exports on the growth rate of Bangladesh's economy was explored by both a two-sector growth model and the ARCH model (Begum & Shamsuddin, 1998) where the results described the volatility of Bangladesh's economy and indicated a positive impact of investment on the growth rate. The time-variant volatility analysis and prediction of foreign direct investment (FDI) in China are performed through wavelet analysis, intervention analysis and ARIMA–GARCH–M model in terms of conditional mean and variance (Shi, Zhang, Su, & Chen, 2012). Volatility analysis is popular in determining stock pricing movements

(Fama, 1990; Kearney & Daly, 2010; Koutoulas & Kryzanowski, 1996; Richard & Ramon, 1990; Rossi, 1996; Shiller, 1992) and market volatility (Nelson, 1991).

To identify a significant regime switch in the behavior of both energy consumption and GDP volatility, the Markov Switching ARCH model, an extension of the ARCH model, was used to examine the connection between energy consumption volatility and unpredictable fluctuations in the real GDP of the United Kingdom. No significant contemporaneous relationship was found between them in the low volatile regime but a significant positive relation was found in the high volatile regime (Rashid & Kocaaslan, 2013). Another volatility analysis was conducted to investigate the relationship between FDI and economic growth in 180 countries with data from the World Bank indicators using the ARCH two-step dynamic panel system generalized method of moments estimation approach (Edwards, Romero, & Madjd-Sadjadi, 2016). Again, the extended volatility analysis procedure called the GARCH model was used to find the volatility of macroeconomic uncertainty, and the relationship between macroeconomic volatility and FDI was explored by employing the panel model estimation technique (Asamoah, Adjasi, & Alhassan, 2016). The influence of political unrest on the economy of Pakistan was inspected by the ARCH and GARCH models using several independent variables, and only terrorism was found to have an adverse effect on the volatility of GDP (Tabassam, Hashmi, & Rehman, 2016). Similarly, the effect of the volatility prices and the exchange rate on FDI inflows of 10 Latin American and Caribbean countries (Dal Bianco & Loan, 2017) and the trend analysis of the gross capital formation (GCF) using the World Bank time series from 1972 to 2016 in Kenya was determined by the ARCH and GARCH models, respectively (Benjack, 2019). The ARCH model was even employed to capture the market price volatility to estimate the risk in the energy commodity markets (Doran & Ronn, 2008).

Forecasting economic growth is important for making decisions regarding an economy, so careful analysis is required in this field. Often, shocks affect the expected growth rate of an economy and they also influence the volatility of the growth rates. Therefore, identifying suitable and appropriate volatility models with logically precise confidence intervals of the rate of returns is essential and fundamental to achieving accurate forecasting along with making decisions and accomplishing continuous economic improvement. The study takes the econometric difficulty of explaining the expected growth rates and the variance of the growth rates of the macroeconomic indicators of Bangladesh based on past information.

2. DATA

The current study explores the volatility growth rate of Bangladesh's three critical macroeconomic indicators: real GDP, GFCF, and net FDI inflows. The analysis uses annual time series data from the World Bank's DataBank that covers the period from 1972 to 2020 (World Bank Data, 2020a, 2020b, 2020c). Here, the real GDP is the inflation corrected value of nominal GDP, presenting the aggregated values of all products and services produced by an economy during a given year (Ganti, 2022; The World Bank, 2022a). Gross fixed capital formation, formerly known as gross domestic investment, is also an inflation-adjusted evaluation. It indicates the total expense of fixed assets (tangible or intangible), except the disposal on it, along with the net changes in the level of inventories (OECD, 2022; The World Bank, 2022b). Finally, FDI net inflows refer to the gross value of investment by a firm or individual in one country to serve business interests in another country and depicts the entire equity capital, reinvestment of earnings, and other short-term and long-term capital in the balance of payments (The World Bank, 2022c). Real GDP and GFCF are calculated in terms of USD price in a base year (2015), and FDI net inflows are computed in current USD.

To examine the volatility analysis of the above financial indicators, the annual growth rates for each selected indicator are calculated using the following equation:

$$r_t = \frac{Y_t - Y_{t-1}}{Y_{t-1}} * 100 \qquad (1)$$

Where, Y_t indicates the initial annual time series data for each variable under study at time t.

Table 1. Descriptive statistics of the growth rates.

Summary statistics	Real GDP	GFCF	FDI inflows
Minimum	-0.041	-0.221	-2.370
Mean	0.050	0.135	1.374
Skewness	-1.393	4.307	3.516
Kurtosis	7.830	22.612	16.793
Maximum	0.096	1.473	25.0
Standard deviation	0.022	0.244	4.575
Normality test (Jarque–Bera test)	62.18 [0.000***]	917.6 [0.000***]	479.4 [0.000***]

Note: The values within the parentheses indicate the p-values of the Jarque–Bera test
*** indicates a 1% level of significance.

Table 1 displays the summary statistics for each variable in the study. The results exhibit that, among the three financial time series indicators, the growth rate or return of the FDI net inflows carries the highest volatility as well as the highest mean. The real GDP is the least volatile compared to other macroeconomic indicators. Moreover, all the growth rates of the financial indicators appear to have fat-tailed distributions, as the kurtosis values exceed the value of 3, which represents normal distribution (Engle, 2001). Only the return of real GDP shows negative skewness, indicating that the left tail is particularly extreme, but the growth rates of GFCF and FDI inflows display positive skewness, specifying that the right tails are extreme. Additionally, the normality test results support the above results with p-values < 0.01.

3. METHODOLOGY

Volatility can be defined as the inconsistency or instability of any phenomenon over a period of time. In macroeconomics ARCH models developed by Engle (1982) are often applied to take into account this dynamic behavior of financial time series indicators. The ARCH model was specially designed to capture the flamboyant nature of time series indicators in terms of conditional variance, so the conditional means of the time varying measurements under study need to be determined (Bera & Higgins, 1993; Linton, 2010).

This study attempts to identify the best ARIMA model to obtain suitable conditional mean equations for each time series indicator under examination using the Box–Jenkins model or autoregressive integrated moving average (ARIMA) model. ARIMA models are statistical models that can be adapted for the projection of numerous time series variables. They are also regression models that assume that future occurrences are dependent on or influenced by past occurrences, and they anticipate data inputs from a particular time series. ARIMA models predict the future incidences of a time varying variable by regressing its past values in a procedure known as autoregression. ARIMA models incorporate three principles represented by three terms denoted by p, d and q. The principles are autoregression, the optimum level required to obtain stationarity, and the moving average that determines the robustness of the dependent variable concerning the regressors or the past values of the dependent time series variable.

A general ARIMA model with the trend can be written as follows:

$$\Phi_p(B)(1-B)^d Y_t = \theta_q(B)\, A_t \tag{2}$$

$$\text{Where, } \Phi_p(B) = \left(1 - \delta - \Phi_1 B - \Phi_2 B^2 - \Phi_3 B^3 - \cdots - \Phi_p B^p\right) \tag{3}$$

$$\text{and} \quad \theta_q(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3 - \cdots - \theta_q B^q\right) \tag{4}$$

B is the backshift operator, i.e., $BY_t = Y_{t-1}$, $B^2 Y_t = Y_{t-2}$, and so on.

A general ARIMA(p,d,q) model can be written as:

$$Y_t = \alpha + \sum_{i=1}^{p} \Phi_i \, r_{t-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + e_t \qquad (5)$$

Where p, d, and q denote the required order of autoregressive terms, the appropriate number of differences to convert the non-stationary time series variable into a stationary one, and the optimum order of moving average terms, respectively. This model is generally known as ARIMA(p,d,q).

This study assumes volatility in the growth rate of each time series variable and explores the appropriate volatility models of the rate of returns for all of them by employing the autoregressive conditionally heteroscedastic (ARCH) model in terms of conditional variance (Nelson and Foster, 1994). The ARCH model is also a statistical model that is designed to capture the dynamic behavior of conditional variance over time as well as volatility clustering that is often observed in various fields such as economics, finance, and risk management. The ARCH model considers the concept of autoregression to specify a model for financial time series data to capture any irregular or unusual movement.

A general ARCH model can be written as follows:

$$r_t = X_t{}'\beta + \varepsilon_t \qquad (6)$$

Where r_t, β, X_t and ε_t represent the $k \times 1$ vector of a growth rate or endogenous time series variable, $k \times 1$ vector of regression parameter, $k \times 1$ vector of the exogenous variable that can include the lagged values of the endogenous variable, and the white noise of the conditional variance, σ_t^2.

The elementary ARCH model by Engle presumes that ε_t is conditional on X_t and r_t, where $\varepsilon_t | (r_t, X_t) \sim N\,(0, \sigma_t)$.

Here,

$$\varepsilon_t = \sigma_t Y_t \qquad (7)$$

Where Y_t are identically and interdependently distributed random variables with means of 0 and variances of 1.

The ARCH model developed by Engle assumes that:

$$\sigma_t^2 = \omega + \textstyle\sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 \,; \omega > 0 \; and \; \alpha_i > 0 \qquad (8)$$

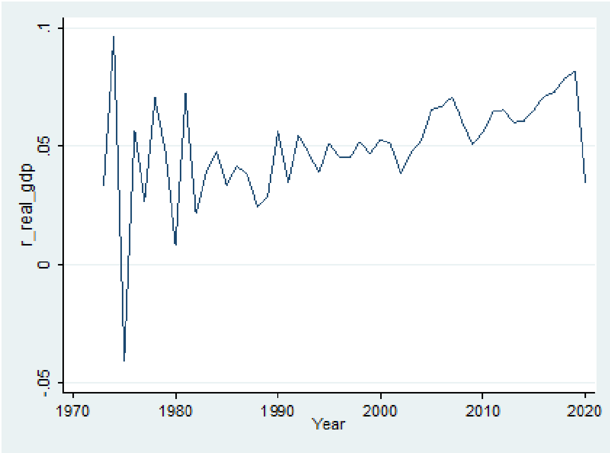
Where σ_t^2 may change over time, m refers to the number of ARCH terms of order m, and the conditional variance of the ARCH model is the weighted mean of the squared values of the lagged residuals. The main goal of the ARCH model is to determine or estimate the conditional variance, σ_t^2 . During the process of estimating the density function, often non-normal unconditional sampling distribution can be found, especially in data related to an asset or stock (Fama, 1990; Kearney & Daly, 2010; Koutoulas & Kryzanowski, 1996; Nelson, 1991). Even if the assumption that the conditional density function follows the normal distribution is violated, the estimates are not greatly affected (Alzghool & Al-Zubi, 2016). Throughout the application of the ARCH models, the main focus is to assess the dependency of the conditional variances on their previous values and arbitrate the time-varying volatility and forecast the volatility of the returns using the maximum likelihood estimation procedure, which is recommended (Bollerslev, 1986; Hamilton & Hansen, 1994), assuming that the conditional density follows the normal distribution.

Each model for each of the time series indicators is computed through STATA version 16.0, a statistical software package, and all the parameters are estimated using the maximum likelihood approach, where the optimum models are selected using information criteria such as the Bayesian information criterion (BIC) and the Akaike information criterion (AIC) (Hirotugu Akaike, 1979; H. Akaike, 1981; Cheung & Lai, 1995; Liew, 2004).

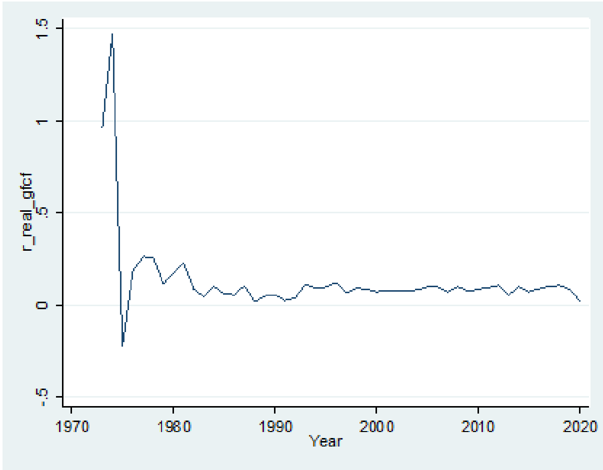
4. RESULTS AND DISCUSSION

4.1. Empirical Results

Figure 1 shows the time series plots of the growth rates of real GDP, GFCF and FDI inflows.



(a)



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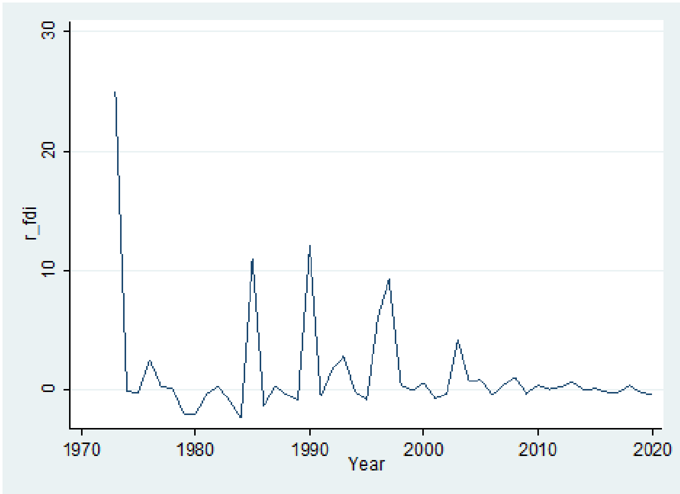


(c)

Figure 1. The overall growth rate behavior for (a) real GDP, (b) gross fixed capital formation, and (c) foreign direct investment inflows in Bangladesh.

Checking for stationarity is the first step in selecting the best ARIMA model for the growth rates under consideration, so the augmented Dickey–Fuller (ADF) and the Phillips–Perron (PP) tests are used to test the growth rates for three possible cases, which are (i) without a constant term, (ii) including a constant term, and (iii) including both a constant term and a time trend. Stationarity helps to obtain reliable parameter estimates and valid forecasting (Cheung & Lai, 1995; Dickey & Fuller, 1979; Phillips & Perron, 1988).

Table 2. Stationarity test results of the growth rates.

Case No.	Real GDP		GFCF		FDI inflows	
	ADF	PP	ADF	PP	ADF	PP
Case 1	-7.716 [0.000] ***	-1.662 [0.000] ***	-5.924 [0.000] ***	-5.558 [0.001] ***	-10.905 [0.000] ***	-10.218 [0.060] **
Case 2	-7.716 [0.000] ***	-1.662 [0.000] ***	-5.924 [0.000] ***	-5.558 [0.001] ***	-10.905 [0.000] ***	-10.218 [0.060] **
Case 3	-10.974 [0.000] ***	-11.795 [0.000] ***	-6.022 [0.000] ***	-6.549 [0.000] ***	-10.663 [0.000] ***	-11.068 [0.000] ***

Note: *** Significant at the 1% level; ** Significant at the 10% level.

The results in Table 2 reveal that, for all three cases, the null hypothesis of the presence of unit root for all the growth rates of the financial indicators in the study is rejected (Dickey & Fuller, 1981). This implies that all the growth rates of the time series variables are stationary.

Here, Equations 9 and 10 indicate general forms of the conditional mean and conditional variance equations of the selected growth rates of the study.

$$r_t = \alpha + \sum_{i=1}^{p} \Phi_i \, r_{t-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + e_t \quad (9)$$

Where r_t, Φ_i, θ_j and e_t denote the growth rate, the autoregressive and moving average coefficient, and the error term, respectively, obtained from the ARIMA model.

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \rho_i \varepsilon_{t-j}^2 \qquad (10)$$

Where σ_t^2 and ρ_i imply the variance of the growth rate and the ARCH coefficient, respectively.

Table 3. Empirical results of the ARIMA & ARCH model of the growth rates.

Coefficient	Real GDP			GFCF			FDI inflows		
	Estimated value	Standard error	P-value	Estimated value	Standard error	P-value	Estimated value	Standard error	P-value
α	0.056	0.005	0.000[a]	-0.679	0.005	0.140	0.107	0.047	0.022[b]
Φ_1	0.549	0.125	0.000[a]	-0.190	0.043	0.000[a]	-1.906	0.048	0.000[a]
Φ_2	0.394	0.147	0.000[a]	-	-	-	-0.928	0.046	0.000[a]
θ_1	-0.753	0.211	0.000[a]	-	-	-	1.904	0.045	0.000[a]
θ_2	-	-	-	-	-	-	0.931	0.042	0.000[a]
ω	0.000	0.262	0.067[c]	0.001	0.000	0.016[b]	0.024	0.127	0.852
ρ_1	1.228	0.584	0.036[b]	1.626	0.560	0.004[a]	10.699	2.062	0.000[a]

Note: a, b and c indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3 presents the empirical results of the optimum ARIMA and ARCH models for the growth rates of real GDP, GFCF and FDI inflows of Bangladesh. The above models were found to be most appropriate after comparing several other estimated models for each of the growth rates. The selected models satisfy all the criteria, such as the AIC and BIC values, the maximum log-likelihood estimates, and the p-values. For the selected models, the AIC and BIC values are the minimum and the log-likelihood values are the maximum (Higgins & Bera, 1992; Weiss, 1986). The results show that for the growth rate of real GDP, all the coefficients of the autoregressive terms and moving average terms up to lag 2 of the elected conditional mean equation are significant, including the constant terms. For the conditional variance equation, only the lag 1 coefficient together with the constant term were found to be significant, obtained using the ARIMA and ARCH models, respectively. For the growth rate of GFCF, only the autoregressive coefficient is significant for lag 1, the constant term is insignificant for the optimum ARIMA model, while both the constant term and the coefficient term of the ARCH model for lag 1 are significant according to the selection criteria. Furthermore, for the growth rate of FDI inflows of Bangladesh, all the autoregressive and moving average coefficients of the preferred ARIMA model are significant for lag 1 and lag 2 along with the constant term, when only the lag 1 ARCH coefficient is significant but not the constant term. No GARCH effect was found since the moving average coefficients of the conditional variance equations are insignificant.

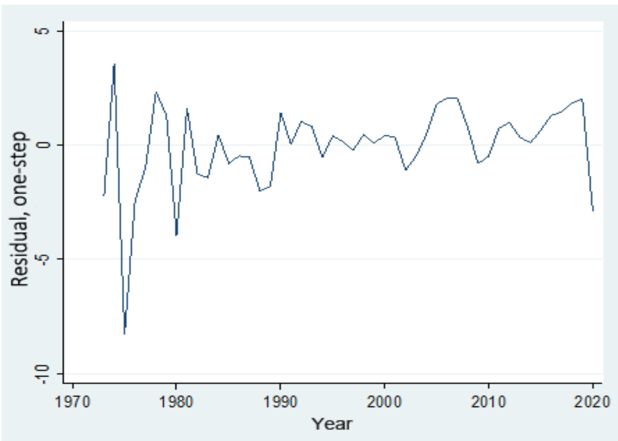
Table 4. Optimum models of the indicators.

Indicator	Estimated ARIMA model for the conditional mean equation	Estimated ARCH model for the conditional variance equation
Real GDP	ARIMA(2,0,1)	ARCH(1)
GFCF	ARIMA(1,1,0)	ARCH(1)
FDI (Inflows)	ARIMA(2,0,2)	ARCH(1)

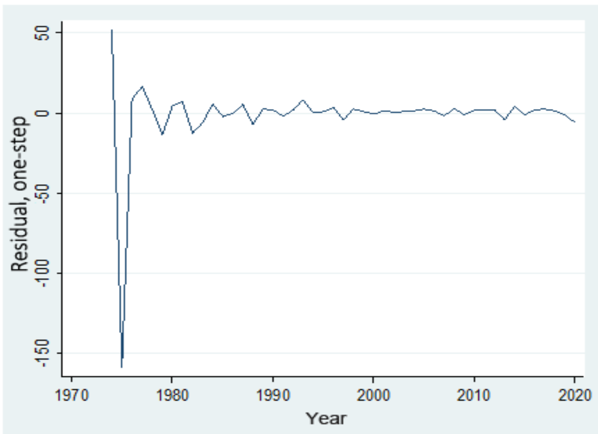
Table 4 displays the optimum ARIMA and ARCH models for the conditional mean and conditional variance equations for the growth rates under consideration in this study. An ARCH effect was found in the growth rates of the chosen financial indicators, and the presence of volatility was found in the return rate of real GDP, which was also found in various studies previously conducted in Japan, USA and UK (Burren & Neusser, 2010; Hamori, 2000; Ho & Tsui, 2003; Koulakiotis, Lyroudi, & Papasyriopoulos, 2011). A study by Edwards et al. (2016), which examined the relationship between foreign direct investment in 180 countries worldwide using the World Development Indicators dataset, also discovered a volatility effect. Also, another volatility analysis was carried out in 40 Sub-Saharan countries to explore the association between FDI and macroeconomic volatility (Asamoah et al., 2016) where volatility in FDI existed. Again volatility was found to be present in the growth rate of gross fixed capital formation in terms of macroeconomic volatility (Tokmakcioglu & Tas, 2014). So, the findings of the current study on the growth rates of these macroeconomic indicators in Bangladesh are not surprising after taking into account previous relevant studies.

4.2. Model Diagnosis

Model diagnosis is essential in time series analysis to evaluate the validity of the estimated models, Moreover, it helps to check the assumption of the time series models based on which the models are constructed, and it is also important to check the accuracy of the models and the forecasting estimates produced by the selected models. This study employed multiple diagnostic approaches to check the validity of the chosen volatility models for the time series indicators. Time series graphs of the estimated residuals were obtained from the selected ARCH models. Results were obtained from Bartlett's (B) test and the portmanteau (Q) test as well as a cumulative periodogram white noise test of the residuals of the chosen models for the macroeconomic indicators under examination.



(a)



(b)

(c)

Figure 2. Time series graphs of residuals estimated from the selected ARCH model for the growth rate of (a) real GDP; (b) gross fixed capital formation; and (c) foreign direct investment inflows.

Figure 2 shows that the time series graphs for the estimated residuals of the elected volatility time series models for each of the indicators present no pattern, so the graphs confirm the random nature of the estimated residuals obtained from the selected ARCH models.

Table 5. White noise test results.

Indicator name	Cumulative periodogram white noise test		Portmanteau test for white noise	
	Bartlett's (B) statistic	P-value	Portmanteau (Q) statistic	P-value
Real GDP	0.4352	0.9915	9.0257	0.9932
GFCF	1.1190	0.1634	7.7390	0.9962
FDI (Inflows)	0.4511	0.9871	14.7966	0.8708

The output results in Table 5 show that, for both Bartlett's (B) test and the portmanteau (Q) test, the p-values for the white noise or residuals obtained from the volatility models of the time series indicators are sufficiently large. Thus, it can be concluded that the null hypotheses of the residuals being white noise cannot be rejected for each of the indicators.

4.3. Model Evaluation

Model evaluation is necessary to evaluate the performance as well as examine the efficacy and accuracy of the selected models. The study utilized two very popular and effective residual measurements – the mean squared error (MSE) and the root mean squared error (RMSE) – to assess the efficiency of the chosen volatility models in the study.

4.3.1. Mean Squared Error (MSE)

The MSE is a frequently used performance measurement metric that is applied for different model comparisons and is the average squared difference between the observed and the forecasted values estimated from the fitted models. It has a special attribute of penalizing major errors with greater severity compared to other regular precision or evaluation measurements, and this specific quality of the MSE makes it one of the most suitable measurements in which a particular approach prevents massive residuals. The MSE can be calculated as:

$$MSE = \frac{\sum_{i=1}^{n} \varepsilon_i^2}{n}$$

Here, $\boldsymbol{\varepsilon_t} = \boldsymbol{r_t} - \boldsymbol{\hat{r}_t}$ where $\boldsymbol{r_t}$ and $\boldsymbol{\hat{r}_t}$ are the observed and predicted values at time t, respectively.

4.3.2. Root Mean Squared Error (RMSE)

The RMSE is the standard deviation of errors and it gives identical weights to all the residuals regardless of their time points. The root mean squared is the preferred performance evaluation metric among other assessment performance evaluation measurements and is popular both in applied fields and academics despite not being a unit-free measurement. The RMSE is computed as:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum_{i=1}^{n} \varepsilon_i^2}{n}}$$

Table 6. Estimated ARCH models and their respective MSE and RMSE.

Indicator name	Estimated ARCH model	MSE	RMSE
Real GDP	ARCH(1)	0.000	0.019
GFCF	ARCH(1)	0.059	0.244
FDI (Inflows)	ARCH(1)	21.768	4.666

Table 6 contains the MSE and RMSE values for the elected volatility models. The volatility model for the real GDP (ARCH (1)) gives the lowest MSE and RMSE values compared to the other growth rates. The chosen volatility model for Bangladesh's FDI growth rate provides the comparatively highest RMSE (4.6656036) among the three growth rates, which is not that large considering that the volatility analyses were conducted on annual time series data.

5. CONCLUSIONS

Volatility is closely related to risk, and the potential risk must be assessed carefully with greater comprehension. This study investigated volatility in the annual growth rates of three crucial financial indicators for Bangladesh: real GDP, gross fixed capital formation (GFCF), and foreign direct investment (FDI) net inflows using the ARCH model, which is popular in predicting and explaining volatility, especially in financial time series analyses. To understand the financial movements in terms of the aforementioned indicators, the consistency of Bangladesh's macroeconomic indicators' performance was analyzed. The study found ARCH effects for all three indicators. The volatility of all of these indicators depends on their previous return values. Moreover, the conditional mean of real GDP and FDI net inflows depend on the previous two years' return values of real GDP and FDI net inflows, respectively, whereas the current year's conditional mean of GFCF return is dependent on the previous year's return value.

The results of this analysis will open the door for more in-depth investigations of the financial growth of Bangladesh's economy and will support the formulation of important financial investment decisions. Investment opportunities are crucial for a developing nation such as Bangladesh and are closely linked to both financial progress and economic expansion. If the right policies are put in place, financial innovation will be possible with better financial services as they will stimulate financial activity and economic growth.

Funding: This study received no specific financial support.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study.

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