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Exploring the Food Inflation Volatility in Bangladesh: An Econometric Study

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Abstract

This study examines the volatility dynamics of food inflation in Bangladesh using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and its variants (EGARCH, TGARCH, and IGARCH) to capture the influence of past shocks, volatility persistence, and asymmetric responses. The analysis utilizes Consumer Price Index (CPI) data for food and its subgroups. The findings reveal significant heterogeneity in volatility behavior across commodities. Overall, food price volatility shows both significant persistence and asymmetry, where negative shocks reduce volatility more than positive shocks. The results highlight the strong persistence of price volatility in many food subgroups and the asymmetric response of prices to shocks, where price increases lead to higher volatility compared to price decreases. This has important implications for policy, particularly for inflation management and food security, as volatility disproportionately affects lower-income households. The study suggests targeted interventions to stabilize prices and improve supply chain efficiency, alongside long-term strategies for sustainable agricultural practices. The findings contribute to the broader discourse on economic stability and food price dynamics in Bangladesh. The estimated volatility along with the threshold effect (if any) will help to confirm the active intervention by the authority in the food markets to prevent unusual food price hikes.

Keywords: Food Price Volatility, GARCH Models, Asymmetric Shocks

JEL Classification: C22, E31, Q18.

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Views expressed in the article are author's own, which do not necessarily reflect the views of the institution in which she works.

1. Introduction

Food inflation is a critical economic indicator that significantly impacts the livelihood and well-being of individuals, particularly in developing nations like Bangladesh. In Bangladesh, food inflation has emerged as a pressing concern with far-reaching consequences. The volatility of food prices in Bangladesh not only affects household budgets but also influences broader economic stability and social equity. Over recent decades, Bangladesh has experienced substantial economic growth and development, yet this progress has been accompanied by considerable fluctuations in food prices. These fluctuations are driven by a complex interplay of factors including agricultural productivity, global commodity prices, supply chain disruptions, and climatic conditions. The volatility of food inflation in Bangladesh is particularly concerning given the significant role that food expenditure plays in the average household budget, especially among lower-income families who spend a larger proportion of their income on food. So, understanding the extent and accurate measurement and analysis of food inflation volatility can provide crucial insights into economic conditions and inform effective policy-making. As food inflation in lower income countries is more volatile and higher than non-food inflation, this has received considerable research attention in Bangladesh. This research paper aims to provide a comprehensive assessment of food inflation volatility in Bangladesh by employing advanced statistical methods and economic models. The study analyses historical price data and seeks to uncover patterns and provide a nuanced understanding of food price dynamics by focusing on both short-term fluctuations and long-term trends. This research will contribute to the broader discourse on economic stability and food security in Bangladesh, offering valuable insights for policymakers, economists, and stakeholders dedicated to fostering a resilient and equitable economic environment.

2. Literature Review

Food price volatility has significant macroeconomic implications, especially in developing economies where food constitutes a large portion of the consumption basket. Studies have demonstrated that food price volatility is not only a result of supply and demand shocks but is also influenced by macroeconomic variables such as exchange rates, interest rates, and global economic conditions (Roache, 2010). This section provides a synthesis of the existing literature on food price volatility with a focus on key concepts on volatility measurement including macroeconomic factors, market-specific conditions, and policy interventions.

Iddrisu et al. (2019) discusses various statistical approaches for analyzing inflation volatility, including the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and its variants. These models are commonly used to capture the time-varying nature of price volatility and are particularly relevant for studying food inflation, given its susceptibility to external shocks and seasonal effects. A study by Sekhar et al. (2018) explores food inflation and volatility in India, identifying key contributors to inflation. This study reveals that food inflation and volatility have been persistent due to supply-side factors like production shortfalls, wage rates, and government policies such as minimum support prices. Crain and Lee (1996) found that more market-oriented government programs in the United States contributed to increased volatility in wheat and corn prices. On the other hand, some studies suggest that price supports and subsidies may help in stabilizing prices, but the evidence remains inconclusive (Yang, Haigh, & Leatham, 2001).

Several empirical studies have explored food inflation volatility in Bangladesh, revealing important insights into its causes and impacts. Ahmed, Muzib, and Hasan (2016) explored the relationship between inflation, inflation uncertainty, and relative price variability in Bangladesh. Their study used disaggregated CPI data from 2002 to 2013 and found that food inflation played a significant role in overall price instability. The research indicated that food inflation volatility often results from external shocks such as global commodity price fluctuations, domestic supply chain inefficiencies, and policy mismanagement. Islam et al. (2022) examined the effect of climate change on food security and food loss in Bangladesh. Their findings suggested that climate-induced agricultural disruptions, such as floods and droughts, contribute to food price volatility. The study found that food grain losses significantly increase inflationary pressures by reducing domestic supply, thereby increasing reliance on food imports. This underscores the necessity of climate-resilient agricultural policies to stabilize food prices.

Hossain, Mujeri, and Chowdhury (2013) analyzed the impact of inflation on different household groups in Bangladesh. Their study emphasized that food inflation disproportionately affects low-income households, as food expenses constitute a larger share of their total consumption. They also identified structural issues such as supply chain bottlenecks, inadequate storage facilities, and inefficient distribution networks as contributors to food price instability. Uddin and Anika (2023) explored how inflation affects economic access to food in Bangladesh. Their study highlighted that rising food prices reduce purchasing power, particularly among lower-income groups. Additionally, they identified factors such as international price shocks, currency depreciation, and market syndicates as significant drivers of food inflation. The study called for improved market regulation and targeted subsidies to protect vulnerable populations. Akter and Basher (2013) investigated the impacts of food price and income shocks on household food security in rural Bangladesh. Their study, using longitudinal survey data, found that the 2007–2009 food price crisis significantly worsened food insecurity. Poor households bore the immediate brunt of rising food prices, although over time, market adjustments and economic growth alleviated some adverse effects. This study highlights the cyclical nature of food price volatility and its differential impact across income groups.

As consistent with literature, we have used Generalized Autoregressive Heteroskedastic (GARCH) Process to capture the underlying volatility of food inflation. GARCH models not only allow the incorporation of the effects of the conditional mean into the system but also "accommodate the effects of the inflation shock on inflation volatility, and, in turn, the effects of inflation volatility on economic activity," (Elder, 2003). This model is useful for modeling the changes in volatility over time. It explains volatility as a function of the errors which are often called 'shocks'. While investigating the reverse causality between inflation and inflation volatility by using a large panel of developing and developed countries data over the period of 1965 to 2007, Kim & Lin (2012) estimated the inflation volatility. In the study they used a five-year rolling window standard deviation of inflation to measure inflation volatility. Sethi (2015) modeled the inflation volatility as the five-point moving average of coefficient of variation of inflation. This paper found that the coefficient of inflation volatility is negative and significant.

Despite the contributions of existing research, several gaps remain in the literature. There is a need for more granular studies that explore variations in food inflation volatility in Bangladesh. Additionally, incorporating newer econometric techniques and real-time data could enhance the understanding of volatility dynamics.

In this study we have used both the commodity groups and commodity subgroups to assess the underlying volatility. They have found that the commodities with higher income elasticity of demand and limited processing and storage facilities, have higher volatility. To the best of our knowledge, in Bangladesh there is no such study of estimating food inflation volatility with commodity subgroup level data. So, our study will add some important insights to the literature of food inflation volatility of Bangladesh in commodity level.

Eisenstat & Strachan (2016) conducted a study on the US quarterly CPI data over the period of 1947: q2 to 2013: q3 to measure the inflation volatility. They employed the change-point model to estimate the evolving persistence and level of volatility and found that as the prior expected duration increases, the model will switch regimes less often and increasingly approximate the time-invariant stationary model. This model was chosen because of its efficiency of capturing the low frequency behavior of stationary process while measuring US inflation volatility.

However, the introduction of Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle in 1982 relaxed the assumption of constant variance of disturbances. He estimated the model with disturbances following an Autoregressive Heteroskedastic process rather than traditional econometric models based on UK inflation data which was concerned with the volatility of inflation. He found that UK inflation has significant ARCH effect with variances that increase substantially during the chaotic seventies.

After that many such volatility models using ARCH have been identified in the literature. Rizvi et al. (2014) investigated the inflation volatility in Asian perspective by exploiting quarterly CPI data of 10 Asian countries. In this paper inflation volatility has been modeled as a time-varying process through different symmetric and asymmetric GARCH specifications. The results of this study suggest that a statistically significant asymmetry has been found in inflation volatility in all countries.

Banarjee (2017) undertakes an empirical exercise on monthly CPI over the sample period of 1958 to 2016 for 41 countries using the GARCH (1, 1) model to estimate the inflation volatility. Sek & Har (2012) applied a GARCH (1, 1) model to calculate inflation volatility of three Asian countries namely Korea, Philippines and Thailand. Zivko & Bosnjak (2017) analyzed Croatian CPI volatility pattern using ARCH model. Nyoni (2018) used an AR (1) - GARCH (1,1) model to estimate the volatility of inflation in Zimbabwe using annual time series data. While investigating the causality among inflation volatility, economic growth and monetary policy Hossain (2015) estimated the CPI inflation volatility using GARCH (1,1)-in-mean model. The empirical results suggest that inflation positively affects inflation volatility and inflation volatility raises inflation.

Neyapti (2000) shows that inflation significantly raised uncertainty. Evidence in Nas and Perry (2000) supports this finding, while the evidence on the effect of inflation uncertainty on the level of inflation is mixed and depends on the time period analyzed. They used the EGARCH technique for modeling inflation uncertainty. Javed et al. (2012) applied ARMA-GARCH model to estimate conditional volatility of inflation in Pakistan using monthly data over 1957:01 to 2007:12. Sekhar et al. (2018) analyze the food price volatility in India using ARCH family models.

3. Methodology

Volatility is a symptom of market disruption which cannot be measured directly. It is associated with unpredictability, uncertainty and is usually realized through time varying conditional variance. To capture this time varying conditional variances, we have employed Autoregressive Conditional Heteroskedastic (ARCH) class of models of volatility in each series of the food CPI group containing monthly data from 2013M08 to 2023M03 collected from Bangladesh Bureau of Statistics (BBS).

To reach an ARCH process at first, we applied Box-Jenkins methodology in order to come up with the adequate ARMA models for the conditional mean equations of each CPI food group. After that we tested the residuals from the mean equations for ARCH effects. Therefore, applying different specifications of ARCH class of models such as GARCH, TARCH, IGARCH, and EGARCH models under appropriate error distributions, we have measured the time varying conditional variances hence the time varying volatility.

ARCH/ GARCH Specifications

An autoregressive conditional heteroscedasticity (Engle, 1982) model considers the variance of the current error term to be a function of the variances of the previous time period's error terms. ARCH relates the error variance to the square of a previous period's error. It can be described as follows:

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + b_1 a_1 \varepsilon_{t-2}^2 + b_1^2 a_1 \varepsilon_{t-3}^2 + \dots$$

Where, $a_0 > 0,\ 0 \leq a_1 < 1$

To capture the long lagged effects with fewer parameters, generalized ARCH model has been proposed by Bollerslev (1986) and Taylor (1986) independently. It tells us that the volatility changes with lagged shocks ε_{t-1}^2 but there is also momentum in the system working via h_{t-1}. A GARCH (1,1) model is as follows:

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + \mathrm{b}_1\mathrm{h}_{t-1}$$

Often in GARCH $\widehat{a_1} + \widehat{b_1} \approx 1$. Motivated by the stylized fact, Engle and Bollerslev (1989) proposed the IGARCH process. An IGARCH (1, 1) process is as follows:

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + (1 - a_1)h_{t-1}$$

To allow asymmetric effect in the standard GARCH model, a TGARCH model has been proposed by Jagannathan & Runkle (1993) and Zakoian (1994) as follows:

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + b_1 h_{t-1}$$

Where, the impact of good news is a_1 and bad news is $a_1 + \gamma$

Another variation is EGARCH model proposed by Nelson (1991) as described following:

$$\ln(h_t) = \delta + b_1 \ln(h_{t-1}) + a\left|\frac{e_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma\left(\frac{e_{t-1}}{\sqrt{h_{t-1}}}\right)$$

4. Results And Discussion

We have outlined the volatility of food inflation under Generalized Autoregressive Conditional Heteroskedastic (GARCH) framework. We considered the CPI of food along with food subgroups and estimated the volatility for each subgroup. We explored the sustained increases or decreases which are known as clustering and the asymmetry effects. Results indicate that the GARCH effects are strong for most of the CPI of food subgroups except Spices and Tobacco products. This suggests that the food price volatility in a period is impacted strongly by the volatility in previous periods. If the previous price volatility of a food subgroup is high then it can be concluded that the current price increase will be high for that food subgroups. Our findings support the Cukierman-Meltzer hypothesis which states that higher inflation volatility in the previous time increases inflation in the current time. We have found a stylized fact in food price movement is that volatility reacts asymmetrically to the good and bad news such as supply shortage, floods etc. which is evident from the significant threshold effects for most of the food subgroups. That is upward movements are followed by higher volatility than downward movements. It implies that price increase lead to an increase in volatility. Price declines have the reverse effect though smaller in magnitudes. It is also evident that most of the food subgroups experienced large spikes in volatility during the COVID-19 period. There is an increase in volatility along with significant threshold effect during that period.

Volatility in Commodity Subgroups

The EGARCH model for the CPI food group indicates significant findings about volatility dynamics. The AR (1) term of 0.86 shows strong persistence in volatility, meaning past volatility predicts current volatility. The ARCH term of -0.39 is negative, suggesting that past shocks reduce current volatility, which is unusual as volatility typically increases with past shocks. The significant GARCH term of 0.776804 confirms strong persistence of volatility, showing that past volatility impacts future volatility. Lastly, the threshold term of -0.366031 is negative, indicating that downward market movements cause lower volatility compared to upward movements, which highlights unique characteristics of the food CPI. The volatility dynamics across commodity groups reveal varying patterns. For cereals, past shocks (ARCH) significantly impact future volatility, but persistence (GARCH) is weaker indicating high reactivity. Markets for cereals are highly reactive to sudden shocks or news, but these shocks do not have a long-lasting impact on future volatility. Edible oils & fats show strong volatility persistence with significant ARCH and GARCH terms, highlighting the presence of volatility clusters. When a shock occurs, its impact tends to cluster and persist over time, indicating a market where volatility does not quickly settle down. This suggests strong volatility clusters, common in markets with higher uncertainty. Pulses exhibit strong volatility persistence, with an asymmetric response where negative shocks reduce volatility more than positive shocks. If volatility is high for a prolonged period, the asymmetric response (negative shocks reducing volatility more than positive ones) implies that the market stabilizes faster after negative events. For Rice, past shocks (ARCH) matter, but persistence (GARCH) and asymmetry are insignificant. Shocks to volatility do occur, but they do not last long, and the market reacts symmetrically to both positive and negative shocks. This suggests a relatively stable market. Spices show significant immediate shocks (ARCH) but limited persistence (GARCH) and no asymmetry. The market reacts to shocks, but their impact fades quickly. This indicates a market where short-term volatility spikes occur but are not sustained over time. Milk & milk products display strong volatility persistence and asymmetry, where negative shocks reduce volatility more than positive shocks. This asymmetry reflects the market's tendency to respond differently to adverse and favorable conditions.

Table 1: Conditional Variance Results

Food Groups	ARCH term	GARCH term	Threshold term
Food	-0.391950 (0.0000)	0.776804 (0.0000)	-0.366031 (0.0000)
Food Subgroups			
Cereals	0.638365 (0.0000)	0.361635 (0.0006)	na.
Edible oils & fats	0.757758 (0.0000)	0.242242 (0.0000)	na.
Egg & meat	2.180793 (0.0000)	0.860961 (0.0000)	-0.426596 (0.1449)
Fish	2.902208 (0.0011)	0.838337 (0.0015)	-0.331462 (0.5907)
Fruits	0.494452 (0.0000)	0.505548 (0.0000)	na.
Pulses	-0.408127 (0.0000)	0.858572 (0.0000)	-0.404349 (0.0000)
Rice	0.710324 (0.0000)	0.267696 (0.0000)	-0.061722 (0.7648)
Spices	0.581739 (0.0001)	-0.011138 (0.9040)	na.
Other cereals	1.312757 (0.0000)	0.811384 (0.0000)	-0.259857 (0.0001)
Vegetables	1.568777 (0.0000)	0.516665 (0.0000)	-0.584962 (0.0000)
Milk & milk products	2.172941 (0.0000)	0.813009 (0.0000)	-0.761856 (0.0000)
Tobacco products	0.519040 (0.0386)	0.480960 (0.0553)	na.

*Values in the parentheses indicate p-value. na. Not Applicable.
Source: Author's calculation

Table 2: Variance Equation

Food Groups	ARCH term	GARCH term	Threshold term
Food	-0.391950 (0.0000)	0.776804 (0.0000)	-0.366031 (0.0000)
Food Subgroups			
Cereals	0.638365 (0.0000)	0.361635 (0.0006)	na.
Edible oils & fats	0.757758 (0.0000)	0.242242 (0.0000)	na.
Egg & meat	2.180793 (0.0000)	0.860961 (0.0000)	-0.426596 (0.1449)
Fish	2.902208 (0.0011)	0.838337 (0.0015)	-0.331462 (0.5907)
Fruits	0.494452 (0.0000)	0.505548 (0.0000)	na.
Pulses	-0.408127 (0.0000)	0.858572 (0.0000)	-0.404349 (0.0000)
Rice	0.710324 (0.0000)	0.267696 (0.0000)	-0.061722 (0.7648)
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Tobacco products	0.519040 (0.0386)	0.480960 (0.0553)	na.

*Values in the parentheses indicate p-value. na. Not Applicable.
Source: Author's calculation

5. Policy Implications and Conclusions

This study has provided an in-depth analysis of food inflation volatility in Bangladesh by utilizing advanced time-series models such as EGARCH, GARCH, IGARCH, and TGARCH across various food groups. The findings reveal significant volatility in key food categories. Overall food price volatility shows both significant persistence and asymmetry, where negative shocks reduce volatility more than positive shocks. Subgroups such as eggs & meat, fish, and milk & milk products exhibit strong volatility persistence alongside large immediate shocks, including long-lasting market disruptions. In contrast, Cereals, Rice, and Spices are primarily influenced by immediate shocks with relatively limited persistence, suggesting more reactive but short-lived volatility. Asymmetric responses are observed in Pulses, Vegetables, and milk & milk products, where negative shocks stabilize volatility more effectively than positive ones. The results suggest critical policy implications, requiring commodity-specific policy interventions. For cereals like rice and wheat, prices react strongly to shocks but do not persist for long, indicating the need for strategic reserves, improved infrastructure, and early warning systems to stabilize prices. Edible oils & fats, characterized by strong volatility clustering, require diversified import sources, domestic oilseed cultivation, and tariff adjustments to smooth price fluctuations. Pulses, which exhibit persistent volatility with an asymmetric response, call for expanded local production, import hedging strategies, and government stockpiling to mitigate sharp price swings. Rice, though relatively stable, still benefits from seasonal buffer stocking, climate-resilient farming, and flexible trade policies to prevent shortages. Spices, highly reactive to shocks but without long-term volatility, require seasonal import planning, improved storage and transport facilities, and anti-hoarding regulations to curb price spikes. Milk & milk products, showing strong volatility persistence and asymmetry, need dairy farmer support, investment in cold storage, and price control mechanisms to ensure affordability. Broadly, a climate-resilient agriculture strategy, real-time price monitoring, flexible tariff policies, stronger public distribution systems, and strict market regulations are essential across all food commodities.

Overall, this research emphasizes the need for a multifaceted approach to managing food inflation volatility in Bangladesh, combining short-term stabilization measures with long-term agricultural policy reforms. Addressing the root causes of price instability will be crucial for ensuring food security, reducing inflationary pressures, and promoting economic stability in the country. Future research could also benefit from exploring the interactions between food inflation and other macroeconomic variables, such as employment and income distribution.

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