AN EMPIRICAL ANALYSIS OF PRICE VOLATILITY OF TURMERIC IN INDIA

ABSTRACT

The objective of the present study aimed at examining the price volatility of turmeric in major markets of the state. The secondary data on monthly modal prices for the period January 2011 to December 2023 were collected from Duggirala and Kadapa (Andhra Pradesh), Nizamabad and Warangal (Telangana), Sangli (Maharashtra) and Erode (Tamil Nadu) by using purposive sampling method. The findings of ARCH-GARCH analysis revealed that the price series of Duggirala, Nizamabad and Erode markets showed the presence of price fluctuations as indicated by the sum of Alpha and Beta co-efficient which were nearer to one whereas in the remaining markets, the volatility shocks were not quite persistent.

Key words: Price volatility, ARCH, GARCH, Turmeric

INTRODUCTION

Volatility refers to variance. The origin of volatility differs for different groups of commodities. Volatility in agricultural commodities originates mainly from the supply shocks whereas for industrial raw materials (both agricultural and metallic), it originates mainly from demand disturbances. These disturbances coupled with the short-run demand and supply elasticity co-efficients give rise to acute price fluctuations. Commodity markets reveal that information flow on prices, hedging and speculation and physical availability of commodities are the crucial factors that influence the volatility in prices. Primary agricultural commodities generally fall into the former group while industrial products often confirm to the latter. A price series can be highly volatile, yet change over longer periods of time show little volatility but a considerably large change over time through discrete adjustments.

In general, any price series exhibit a tendency of volatility clustering *i.e.,* periods of high and low market uncertainty. Specifically, agricultural commodity prices require modelling within a flexible and unified framework. Despite several models exist to capture the volatility in price series, the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) is used to measure the extent of volatility in agricultural commodity prices. (Li, et al., 2017; Roux, 2018) . Bollerslev (1986) generalised the Engel's ARCH model which distinguishes not only between predictable and unpredictable components of prices but also allows the variance of unpredictable element to be time varying. Evidence of ARCH and GARCH is widespread in series that are partly driven by speculative forces. However, these may also be present in the behaviour of agricultural commodity prices with an expected positive transmission of volatility across commodities. Hence the choice of widely used model in estimating the volatility in agricultural commodity prices is preferred for the present study.

Hitherto, the use of GARCH models in capturing the agricultural commodity price volatility has been limited in India unlike analysing the financial instruments. Autoregressive Conditional Heteroscedasticity models (ARCH) are specially designed to model and forecast conditional variances. The variance of the dependent variable is modelled as a function of past values of the dependent variable and independent or exogenous variables. These models are widely used in various branches of econometrics, especially in financial time series analysis. However, Mahalik *et al.* (2009), Vasisht and Bharadwaj (2010), Sundarmoorthy *et al.* (2014), Sendhil *et.al* (2014), Katsiampa *et al.* (2017) and Ding *et al.* (2018) and few others analysed the volatility in agricultural commodities.

Turmeric is the ancient and sacred spice of India, known as 'golden spice' in the world. It is widely cultivated in different countries such as India, China, Myanmar, Nigeria, Bangladesh, Pakistan, Sri Lanka, Taiwan, Burma, Indonesia, etc. India contributes nearly 85-90 per cent of global turmeric production and its annual production ranges between 10.5-11 lakh tonnes. Major turmeric growing states are Andhra Pradesh, Telangana, Tamil Nadu, Karnataka, Odisha, West Bengal and Maharashtra. Indian turmeric is considered as the best in the world because of its high curcumin content. The various varieties of turmeric that are traded in India are Allepey finger (Kerala), Erode turmeric (Tamil Nadu), Salem turmeric (Tamil Nadu), Rajapore turmeric (Maharashtra), Sangli turmeric (Maharashtra), Nizamabad bulb (Telangana), Duggirala finger (Andhra Pradesh) etc.

India is the largest producer, consumer and as well as exporter of turmeric in the world. This makes turmeric prices very open to price changes in Indian demand and supply. Good availability in physical markets provides cash and carry opportunity for arbitragers. It serves as a hedging platform for the producers and exporters. Turmeric content is highly liquid and provides easy entry and exit to a speculator and thus turmeric contract provides space for every investor category.

In the present study, ARCH-GARCH analysis was carried out to assess the persistence of volatility in turmeric prices in the selected markets.

MATERIALS AND METHODS

Arrivals of turmeric in major markets of the country for three years preceding 2023 were recorded and the markets were arranged in the descending order of the average arrivals. The top six markets of turmeric with maximum quantity of arrivals were purposively selected. The six markets thus selected for the study were Nizamabad and Warangal (Telangana), Duggirala and Kadapa (Andhra Pradesh), Sangli (Maharashtra) and Erode (Tamil Nadu) as these are the major trading centres of turmeric in India. These markets were purposively selected to study the market integration. Monthly data for the period January 2011 to December 2023 were collected from their respective APMC's.

GARCH Model

The commonly used GARCH (1,1) model is defined below.

$$Y_{it} = a_0 + b_1 Y_{it-1} + b_2 Y_{it-2} + \varepsilon_{it} \quad \text{...} (1)$$

where, Y_{it} is the price of i^{th} commodity in t^{th} period and t is the time period ranging from 1, 2, 3… n. The variance of the random error is given as

$$\sigma^2_{i,t} = \omega + \alpha_{i,} \varepsilon^2_{i,t-i} + \beta_i \sigma^2_{i,t-i} \quad \text{..} (2)$$

The conditional variance equation specified in equation (2) is a function of three terms *viz.*, the mean (ω), news about volatility from the previous period measured as the lag of the squared residual from the mean equation (ε_{t-1}^2, the ARCH term) and the last period's forecast variance (σ_{t-1}^2, the GARCH term). The (1, 1) in GARCH (1, 1) refers to the presence of a first-order GARCH term (the first term in parentheses) and a first-order ARCH term (the second term in parentheses). The sum of (σ_i+ β_i) gives the degree of persistence of volatility in the price series. Closer the sum to one, greater is the tendency of price volatility to persist for long time. If the sum exceeds one, it indicates an explosive time series with a tendency to meander away from mean value. The mean term (w) given in equation (2) is written as a function of exogenous variables with an error term. Since $\sigma_t^2$is the one-period ahead forecast variance based on past information, it is called the conditional variance.

An ordinary ARCH model is a special case of a GARCH specification in which there are no lagged forecast variances in the conditional variance equation. Higher order GARCH models, denoted by GARCH (p,q), can be estimated by choosing either p or q or both greater than one. The representation of the GARCH (p,q) is given as,

$$\sigma_{i,t}^2 = \omega + \sum_{i=1}^{p} \beta_{i,} \varepsilon_{t-i}^2 + \sum_{i=1}^{n} \alpha_{i,} \varepsilon_{t-i}^2$$

This model can be generalized to a GARCH (p,q) model in which there are '*p'* lagged terms of the squared error term and *'q'* terms of the lagged conditional variances.

EVIEWS 13 software was used for estimating the GARCH/ARCH set of models used in the present study.

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RESULTS AND DISCUSSION

ARCH-GARCH analysis was carried out in order to capture the volatility persisting in the price series of turmeric in selected markets. GARCH (1,1) model was employed to measure the extent of volatility in turmeric prices.

From the results presented in Table, it could be inferred that the prices of turmeric in Duggirala, Nizamabad and Erode markets were volatile during the study period. The sum of co-efficients of α (ARCH) and β (GARCH) gives the degree of persistence of volatility in the prices of turmeric. The closer the sum to one, greater is the tendency of volatility to persist for longer time. If the sum exceeds one, it is indicative of an explosive series with a tendency to meander away from mean value.

The sum of ARCH and GARCH co-efficient values closer to one indicated persistence of price volatility. The prices in Duggirala, Nizamabad and Erode markets witnessed volatility as indicated by the sum of co-efficients for the ARCH (α) and GARCH (β) values which were 0.9892, 0.9883 and 0.9841 respectively. Large GARCH co-efficients indicated persistence of volatility and large ARCH co-efficients indicated volatility spikier (Pati, 2008). GARCH parameter β was statistically significant at 5 per cent level for the price series of turmeric in the three markets indicating the persistence of volatility. Price volatility was due to supply shocks and the extent of the volatility was determined by the variances of these shocks and by the elasticity co-efficients of the supply and demand functions.

The remaining price series of turmeric in Kadapa, Warangal and Sangli markets indicated absence of volatility in the prices as indicated by GARCH parameter 'β' which was statistically insignificant at 5 per cent level. The volatility was extremely high in Sangli market prices ($\alpha + \beta = 1.23$) clearly indicating the explosive nature of the price series. The prices in Kadapa and Warangal markets were less volatile when compared to other markets.

ARCH-GARCH analysis

Particulars	**Kadapa**	**Duggirala**	**Nizamabad**	**Warangal**	**Sangli**	**Erode**
Alpha (α)	0.968428	0.979882	0.981475	0.956583	0.986694	0.968886
Beta (β)	-0.256312	0.009366	0.006892	-0.288428	0.246504	0.015282
α +β	0.712116	**0.989248**	**0.988367**	0.66815	1.233198	**0.984168**

The volatility of prices was more influenced by acerage adjustments driven by the lagged prices, production variation in the country, distribution of rainfall, prices of the competing crops and export demand. When all or some of these factors operated, turmeric prices exhibited volatility under these conditions. If the farmers are given right market advisory, they can take advantage of the same for the additional net returns.

The results of GARCH model indicated that the price series of Duggirala, Nizamabad and Erode markets showed the presence of price fluctuations during the study period whereas in the remaining markets (Kadapa, Warangal and Sangli) the volatility shocks were not quite persistent. These results are in line with that of Ajjan *et al.* (2012) on red chillies, Lakshmi (2014) on red chillies and Khatkar *et al.* (2014) on mustard and Lama *et al.* (2015) on cotton, Lama *et al.* (2020) on spices and Thakur *et al.* (2021) on wheat..

Conclusions

Volatility represents an important risk factor of supply, especially in agricultural commodities. Those who claim that price volatility will be higher over a long period must believe either that shock variances have increased or elasticity coefficients of demand and supply functions have declined. Analysing the existence of volatility spillover effects across regions and markets requires special attention to the data. The results of the present study with GARCH model indicated that the price series of Duggirala, Nizamabad and Erode markets showed the presence of price volatility during the study period as indicated by the sum of Alpha and Beta co-efficients which were nearer to one whereas volatility shocks were not quite persistent in Kadapa, Warangal and Sangli markets. The main reasons for increased price volatility are uncertainty in production, international trading prices, rainfall, domestic and export demand. Ensuring improved market information system and analysis and more predictable government policies reduces uncertainty and helps producers, traders and consumers to make better decisions. The study concludes that market intelligence and effective dissemination of information to the farmers will check the price volatility as well as decision-making for profitable agri-business, especially on sowing, stocking and transportation from surplus to deficit areas.

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