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कृषि वस्तुओं के बाजार एकीकरण और मूल्य संचरण की गतिशीलता का अध्ययन

Studying the Dynamics of Market Integration and Price Transmission of Agricultural Commodities

भा.कृ.अनु.प लाल बहादुर शास्त्री युवा वैज्ञानिक पुरस्कार-2016

ICAR Lal Bahadur Shastri Young Scientist Award-2016

परियोजना रिपोर्ट

Project Report

हर कदम, हर डगर
किसानों का हमसफर
भारतीय कृषि अनुसंधान परिषद
Agrisearch with a human touch

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<u>प्रस्तावना</u>

कुशल कृषि बाजारों और एक कुशल कृषि उत्पादन प्रणाली को प्राप्त करने के लिए बाजार सुधारों की आवश्यकता है। जैसे - जैसे बाजार एकीकृत होते जा रहे हैं, मूल्य संकेत स्थानों पर प्रसारित होते हैं और अन्य स्थानों पर कीमतों को प्रभावित करते हैं। थोक और खुदरा बाजारों की परस्पर-निर्भरता के कारण बाजार एकीकरण महत्वपूर्ण हो गया है जो किसानों को लाभकारी मूल्य सुनिश्चित करता है।

भारत के प्रमुख बाजारों में गेहूं के थोक और खुदरा मूल्य में क्षैतिज और साथ ही लंबवत एकीकरण किया जाता है। सह.एकीकरण की पुष्टि करने पर संबंधित मूल्य चैनल में समायोजन की गति का पता लगाने के लिए वेक्टर एरर करेक्शन मॉडल (वीईसीएम) लागू किया जाता है। सह.एकीकरण का अध्ययन करने के अलावा, असममित सह.एकीकरण की उपस्थिति के परीक्षण के लिए थ्रेशोल्ड ऑटोरेग्रेसिव (टी.ए.आर) और मोमेंटम टी.ए.आर (एम.टी.ए.आर.) मॉडल लागू किए जाते हैं। तदनुसार दो पद्धति के साथ थ्रेसहोल्ड वीईसीएम (टीवीईसीएम) मॉडल लागू किया जाता है।

कीमतों में उतार-चढ़ाव और एक बाजार का दूसरे बाजार पर स्पिलओवर प्रभाव को समझना बहुत व्यावहारिक महत्व का है और शोधकर्ताओं के लिए मुख्य आकर्षण है। इसलिए मल्टीवेरिएट गार्च(एमगार्च) मॉडल पर विचार करने के लिए यूनीवेरिएट जेनरलाइज़्ड ऑटोरेग्रेसिव कंडीशनल हेटरोसेडेस्टिक (गार्च) मॉडल का विस्तार करना महत्वपूर्ण है। सहएकीकरण और वेक्टर एरर करेक्शन मॉडल के विभिन्न पहलुओं पर चर्चा की गई है। एमगार्च मॉडल में, बाबा.एंगल.क्राफ्ट.क्रोनर (बी.इ.के.के) और कॉन्स्टेंट कंडिशनल कोरिलेशन (सी.सी.सी) मॉडल को कर्नाटक भारत में प्याज के दो प्रमुख बाजारों में प्याज की कीमतों में उतार-चढ़ाव के मॉडलिंग के लिए उचित माना जाता है।

अस्थिरता आवेग प्रतिक्रिया विश्लेषण की अवधारणा एक ऐतिहासिक झटके के बाद सशर्त अस्थिरता के व्यवहार की कल्पना करने की अनुमति देती है। वर्तमान जांच में बाजार के बीच अस्थिरता स्पिलओवर पर एक विशिष्ट झटके के प्रभावों को देखने के लिए वोलैटिलिटी इंपल्स रिस्पांस फ़ंक्शन (वि.आई.आर. एफ) का उपयोग किया गया है। मल्टवेरीइट गार्च मॉडल की अनुभवजन्य तुलना की गई है।

परियोजना अन्वेषक लाल बहादुर शास्त्री युवा वैज्ञानिक पुरस्कार के तहत परियोजना के वित्त पोषण के लिए आईसीएआर को धन्यवाद देता है। परियोजना अन्वेषक भी निदेशक भाकृअनुप.भाकृसांअसं को उनके समर्थन और अनुसंधान कार्य को सफलतापूर्वक पूरा करने के लिए सभी आवश्यक सुविधाएं प्रदान करने के लिए धन्यवाद व्यक्त करता है। प्रमुख सांख्यिकीय आनुवंशिकी विभाग भाकृसांअसं और प्रभाग के अन्य वैज्ञानिकों से प्राप्त सहयोग के लिए आभार व्यक्त किया जाता है। परियोजना अन्वेषक डॉ शिव प्रसाद किमोथी एडीजी (टी.सी.), आईसीएआर और डॉ संजीव पंवार, प्रधान वैज्ञानिक आईसीएआर को परियोजना के सफल समापन के लिए धन्यवाद देते हैं।

परियोजना अन्वेषक

PREFACE

Market reforms are required for achieving efficient agricultural markets and hence an efficient agricultural production system. As the markets are becoming integrated, the price signals are transmitted across locations and influence prices at other locations. The market integration has become important due to the interdependence of wholesale and retail markets which ensures remunerative prices to the farmers.

Horizontal as well as vertical integration is carried out in wholesale and retail price of wheat in major markets of India. On confirming cointegration, Vector error correction model (VECM) is applied to find out speed of adjustment in the corresponding price channel. In addition to studying cointegration, threshold autoregressive (TAR) and Momentum TAR (MTAR) model are applied to test for presence of asymmetric cointegration. Accordingly, threshold VECM (TVECM) model with two regimes is applied.

Price volatility and understanding the spillover effect of one market on the others is of great practical importance and has been the main attention for the researchers. It is therefore important to extend the consideration univariate Generalized autoregressive conditional heteroscedastic (GARCH) model to Multivariate GARCH (MGARCH) model. Various aspects of cointegration and vector error correction model have been discussed. In the MGARCH model, Baba-Engle-Kraft-Kroner (BEKK) and Constant Conditional Correlation (CCC) models are considered for modeling volatility of onion prices in two major markets of onion in Karnataka, India.

The concept of volatility impulse response analysis allows to visualize the behavior of the conditional volatility after a historical shock. In the present investigation, Volatility Impulse Response Function (VIRF) has been used to see the impacts of a specific shock on the volatility spillovers among the markets. An empirical comparison of the multivariate GARCH models has been carried out.

The project investigator expresses sincere thanks to ICAR for funding the project under Lal Bahadur Shastri Young Scientist Award. The project investigator also expresses sincere thanks to the Director, ICAR-IASRI for his support and providing all necessary facilities to carry out the research work successfully. The cooperation received from Head, Division of Statistical Genetics, IASRI and other scientists in the Division are thankfully acknowledged. The project investigator is thankful to Dr. Shiv Prasad Kimothi, ADG (TC), ICAR and Dr. Sanjeev Panwar, Principal Scientist, ICAR for successful completion of the project.

Project Investigator

CONTENTS

Chapter 1

INTRODUCTION

1. Introduction

It has been argued that market reforms are required for achieving efficient agricultural markets and hence an efficient agricultural production system. Until agricultural markets are integrated, producers and consumers will not be able to realize the potential gains from the common market. As the markets are becoming integrated, the price signals are transmitted across locations and influence prices at other locations. The price mechanism or marketing process of agricultural commodities from producer's level to consumer's level involves wholesale market prices and retail market prices. The market integration has become important due to the interdependence of wholesale and retail markets. Another important feature is the production-consumption gap which has resulted in a rice in commodity prices, thereby pushing most of the agricultural commodities out of the reach of poor household leading to a negative effect on their nutritional status (Reddy, 2004). Market integration is an important component to ensure remunerative prices to the farmers which will eventually work as an incentive for them to bring more area under pulses. Therefore, the proposed study would examine the movement of prices of different agricultural commodities in spatially separated markets in the country and the transmission of price signals and information across these markets. The market integration can be measured in terms of strength and speed of price transmission between markets across various regions of a country (Ghafoor *et al*., 2009). The degree, to which consumers and producers can benefit, depends on how domestic markets are integrated with world markets and how the different regional markets are integrated with each other (Varela *et al.*, 2012). Although, several empirical studies have been done using cointegration techniques which concern the market integration of agricultural commodities in India (Reddy *et al.*, 2012; Bhardwaj *et al*., 2015; Wani *et al*., 2015a; 2015b; 2015c; Saxena *et al*., 2015; Paul *et al*., 2015; Paul and Sinha, 2015), but none of the above studies has taken care of the possibility of presence of any fractional integration among the market prices. A very few literatures is available on threshold cointegration and its application in agriculture. Along with the price series, the other information related to market may also be used during studying the price integration and transmission. Also testing the presence of cointegration by usual approach has some limitations. In order to overcome the limitations, test based on wavelet approach may be used. The wavelet approach is appealing, since it is based directly on the different behaviour of the spectra of a unit root process and that of a short memory stationary process. It decomposes the variance (energy) of the underlying process into the variance (energy) of its low frequency components and that of its high frequency components via the discrete wavelet transformation (DWT). Also, almost all these previous studies have been concentrated in finding integration in price of a commodity in different markets, but it is equally important to see market integration between wholesale and retail prices of the commodity, i.e. vertical transmission of information. The major crops which would be considered are major pulses, cereals, vegetables crops like tomato, potato etc.

The secondary data on wholesale and retail prices for different commodity would be collected from Agricultural Marketing Information Network (AGMARKNET), Ministry of Agriculture and Farmers' Welfare, Government of India; Department of Consumer Affairs (DCA), Ministry of Consumer Affairs, Food & Public Distribution; National Horticultural Research and Development Foundation (NHRDF) New Delhi etc.

2. Objective

The proposed study would be an attempt to investigate

- The volatility in agricultural commodity prices using Multivariate Generalized Autoregressive Conditional Heteroscedastic (MGARCH) models
- Whether the prices of major agricultural commodities in different zones of India are co-integrated and influenced by each other?
- The price linkages across vertical value chain
- What is the likely influence of changes in prices at one location/stage of value chain on the other location/stage of value chain?

The study will use different statistical methods namely testing stationarity, concept of cointegration, testing for rank of cointegration, vector error correction model (VECM), Granger causality testing and impulse response function. These techniques allow one to quantify the degree of interconnectedness between the markets. For testing the stationarity of time series data, the tests namely Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and Phillips-Perron Unit Root test (Philips and Perron, 1988) have been applied. The statistical techniques which are used in the present investigation are described below in brief.

3. Johansen Approach

Johansen (1988) multivariate cointegration approach was used to examine cointegration among price series. When the data are non-stationary purely due to unit roots (integrated once, denoted by I(1)), they could be brought back to stationarity by differencing. If a series must be differenced d-times before it becomes stationary, then it contains 'd' unit roots and is said to be integrated of order d, denoted by I(d). Let $\mathbf{y_t}$ be and n×1 set of I(1) variables. In general, any linear combination $\mathbf{a'y_t}$ will also be I(1) for arbitrary $\mathbf{a}\neq\mathbf{0}$. However, suppose there exists an n×1 vector $\boldsymbol{\alpha}_\mathbf{i}$ such that $\boldsymbol{\alpha}_\mathbf{i}'\mathbf{y_t}$ is I(0),$\boldsymbol{\alpha}_\mathbf{i} \neq \mathbf{0}$**,** then it is said that the variables in $\mathbf{y_t}$ are cointegrated of order one, denoted CI(1) and $\boldsymbol{\alpha}_\mathbf{i}$ is a cointegrating vector. It is to be mentioned that if $\boldsymbol{\alpha}_\mathbf{i}$ is a cointegrating vectors then so is the k$\boldsymbol{\alpha}_\mathbf{i}$ for any k≠0 since $k\boldsymbol{\alpha}_\mathbf{i}'\,\mathbf{y_t} \sim I(0)$.

There can be r different cointegrating vectors, where $0 \leq r < n$, i.e. r must be less than the number of variables n. In such a case, we can distinguish between long-run relationships between the variables contained in $\mathbf{y_t}$, that is, the manner in which the variables drift upward together, and the short-run dynamics, that is the relationship between deviations of each variable from their corresponding long-run trend.

4. Granger Causality Tests

Granger causality provides additional evidence as to whether and in which direction price transmission has occur between two series (Granger, 1980, 1988). Historically, Granger (1969) and Sims (1972) were the ones who formalized the application of causality in economics. We investigate the Granger causality tests by fitting VAR and VECM models for our data series in order to identify the direction of causality among the prices.

5. Error Correction Models (ECM)

In vector and matrix notation, the ECM can be written as per the following equation

$$\Delta\mathbf{y_t}=\boldsymbol{\alpha\beta}'\mathbf{y_{t-1}}+\boldsymbol{\Gamma}_\mathbf{1}\Delta\mathbf{y_{t-1}}+\mathbf{u_t}$$

Where, $\boldsymbol{\alpha}$=[α_1, α_2]′, $\boldsymbol{\beta}'$=[1, -β_1] and, $\boldsymbol{\Gamma_1}=\begin{bmatrix}\gamma_{11} & \gamma_{12}\\ \gamma_{21} & \gamma_{22}\end{bmatrix}$

The above equation can be reformulated into a vector error correction model (VECM) :

$$\Delta\mathbf{y_t}=\boldsymbol{\Pi}\mathbf{y_{t-1}}+\sum_{j=1}^{k-1}\boldsymbol{\Gamma_j}\Delta\mathbf{y_{t-j}}+\mathbf{u_t},\ \ t=k+1,\dots,T$$

where, $\boldsymbol{\Gamma_i}=-(\mathbf{A_{i+1}}+\dots+\mathbf{A_k})$, i=1,…,k-1, and $\boldsymbol{\Pi}=-(\mathbf{I}-\mathbf{A_1}-\dots-\mathbf{A_k})$. This way of specifying the system contains information on both the short-run and long-run adjustments to changes in $\mathbf{y_t}$, via the estimates of $\hat{\boldsymbol{\Gamma}}_\mathbf{i}$ and $\hat{\boldsymbol{\Pi}}$, respectively. $\boldsymbol{\Pi}=\boldsymbol{\alpha}\boldsymbol{\beta}'$, where $\boldsymbol{\alpha}$ represents the rate of adjustments to disequilibrium and $\boldsymbol{\beta}$ is a matrix of long-run coefficients such that the term $\boldsymbol{\beta}'\mathbf{y_{t-1}}$ represents up to (n-1) cointegration relationships in the multivariate model.

Thus, we examined relationship between the price series by using the IRF (impulse response function). The IRF is a useful instrument used to predict the effect of a shock on a specific series.

6. VECM

If price series are cointegrated we can estimate the following vector error correction model that can be seen as a VAR model including a variable representing the deviations from the long-run equilibrium. Following equation shows a VECM for three variables including a constant, the error correction term and a lagged term.

$$\begin{bmatrix}\Delta p_t^f\\ \Delta p_t^s\end{bmatrix}=\begin{bmatrix}c_1\\ c_2\end{bmatrix}+\begin{bmatrix}a_1\\ a_2\end{bmatrix}ECT_{-1}+\begin{bmatrix}b_{11} & b_{12}\\ b_{21} & b_{22}\end{bmatrix}\begin{bmatrix}\Delta p_{t-1}^f\\ \Delta p_{t-1}^s\end{bmatrix}+\begin{bmatrix}\varepsilon_t^f\\ \varepsilon_t^s\end{bmatrix}$$

Here the superscripts *f* stands for futures market, s stands for spot market. This VECM representation is particularly interesting as it allows for estimating how the variables adjust deviations towards the long-run equilibrium. The error correction coefficient (a_i) reflects the speed of adjustment.

7. BEKK (1,1) model

For individual series, the volatility pattern can be assessed by simply univariate specification of GARCH model of the form:

$$h_t = c_0 + a_1\varepsilon_{t-1}^2 + \cdots + a_p\varepsilon_{t-p}^2 + b_1 h_{t-1} + \cdots + b_q h_{t-q}$$

where *p* and *q* are the order of the GARCH model. This can be transferred into a multivariate GARCH model of the resulting variance-covariance matrixH_t as

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \quad \textit{for i=1,2}$$

Accordingly, the BEKK (1, 1) representation of variance of error term H_t is

$$H_t = C_0'C_0 + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + B_{11}'H_{t-1}B_{11}$$

where, A_i and B_i are *n*×*n* parameter matrix and C_0 is *n*×*n* upper triangular matrix. The bivariate BEKK(1,1) model can be written as

$$H_t = C_0'C_0 + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} +$$
$$\begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

The off diagonal parameters in matrix *B*, b_{12} and b_{21}respectively measures the dependence of conditional price volatility in the futures market on that of spot market and vice-versa. The parameters b_{11} and b_{22} represents persistence in volatility in their own market. The parameters a_{12} or a_{21} represent the cross markets effects whereas a_{11}, a_{22} represent the own market effects. Therefore, the significant level of each parameter indicates the presence of strong ARCH or GARCH effect.

From the above equation we can have the following equations of conditional variance and conditional covariance,

$$h_{11,t} = c_1 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} +$$
$$b_{21}^2 h_{22,t-1}$$

$$h_{22,t} = c_3 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2h_{22,t-1}$$

$$h_{12,t} = c_2 + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + b_{11}b_{12}h_{11,t-1}^2 + (b_{21}b_{12} + b_{11}b_{22})h_{12,t-1} + b_{21}b_{22}h_{22,t-1}^2$$

8. Dynamic Conditional Correlation (DCC) Model

According to Engle (2002), the DCC model set up can be expressed in the following manner:

$$H_t = D_tR_tD_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}}$$

where, $H_t$conditional variance co-variance matrix, R_t is the $n \times n$ conditional correlation matrix and the matrices D_t and R_t are computed as follows:

$$D_t = diag(h_{11t}^{\frac{1}{2}}, \dots, h_{nnt}^{\frac{1}{2}})$$

where h_{iit} is chosen to be a univariate GARCH (1,1) process;

$$R_t = (diagQ_t)^{-1/2}Q_t(diagQ_t)^{-1/2}$$

where $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u_{t-1}' + \beta Q_{t-1}$ refers to a $n \times n$ symmetric positive definite matrix with $u_{it} = {}^{\varepsilon_{it}}\big/_{\sqrt{h_{iit}}}$, $\bar{Q}$ is the $n \times n$ unconditional variance matrix of u_t and α and β are non negative scalar parameters satisfying $\alpha+\beta < 1$.

The conditional correlation coefficient ρ_{ij} between two markets i and j is then computed as follows:

$$\rho_{ij} = \frac{(1-\alpha-\beta)\bar{q}_{ij}+\alpha u_{i,t-1}u_{j,t-1}+\beta q_{ij,t-1}}{((1-\alpha-\beta)\bar{q}_{ii}+\alpha u_{i,t-1}^2+\beta q_{ii,t-1})^{1/2}((1-\alpha-\beta)\bar{q}_{jj}+\alpha u_{j,t-1}^2+\beta q_{jj,t-1})^{1/2}}$$

where ρ_{ij} refers to the element located in the i^{th} row and j^{th} column of the symmetric positive definite matrix Q_t .

9. Socio-economic, scientific, technological relevance and priority

In the context of volatility in agricultural commodity prices, it is of utmost important to study the linkages among the markets. The recent development in the area of statistics need to be properly applied for this purpose. In literature, traditional methodology is being used to see the price transmission. But the traditional methodology has its own disadvantages. Once we know the linkages properly, the price of the agricultural commodities will be controlled to some extent and obviously it will have a huge impact on the socio economic development of the farming community.

10. Plan of work and key technologies proposed to be used in the investigations

The project will be completed in three years. The following methodologies will be used for implementation of the project.

i. Stationarity testing: ADF test, PP test, KPSS test
ii. Testing presence of heteroscedasticity: ARCH- LM test
iii. Cointegration: Johansen’s test, Test using Wavelets
iv. MGARCH and its family of models
v. VECM model
vi. Granger Causality testing
vii. Impulse response function
viii. Other statistical techniques

Chapter 2

VOLATILITY AND SPILLOVER IN ONION PRICES IN MAJOR MARKETS OF KARNATAKA, INDIA

1. Introduction

For many agricultural products, data are usually collected over time. The importance of time series application in the field of agriculture is immense. The most widely used technique for analysis of time series data is undoubtedly the Box-Jenkins ARIMA (Autoregressive Integrated Moving Average) methodology (Box *et al*., 2013). Some of the applications of this model in agriculture can be seen in Paul *et al*. (2013a, 2013b), Paul and Das (2013), Paul *et al*. (2015). However, it is based on some crucial assumption like linearity, stationarity and homoscedastic error. In practical, many financial time-series show periods of stability, followed by unstable periods with high volatility. Therefore, nonlinear time-series models are usually needed to describe data sets in which variance changes through time. Data in which the variances of the error terms are not equal, in which the error terms may reasonably be expected to be larger for some points or ranges of the data than for others, are said to suffer from heteroscedasticity. In case of volatility modeling, the standard models have become the Autoregressive Conditional Heteroscedastic (ARCH) models (Engle, 1982) and Generalized ARCH (GARCH) models (Bollerslev, 1986). Most studies of price volatility examine the volatility of commodity price in a specified market. To cite a few one can be referred to Paul *et al* (2009), Ghosh *et al*. (2010), Paul *et al*. (2014), Paul (2015). But the manner in which volatility shocks is transmitted from one market to other markets necessitates the application of multivariate GARCH (MGARCH) model. Multivariate GARCH (MGARCH) model is the extension of univariate GARCH model, with the recognition that MGARCH models are potentially useful developments regarding the parameterization of conditional cross-moments. Although, the MGARCH methodology has been used extensively in modelling financial time series their applications to the field agriculture and modelling commodity prices is scarce. This model allows to assess spillovers among the variables in the mean equations as well as in their variances. While modeling volatility of the commodity has been the main center of attention, understanding the co movements of prices is of great practical importance. Multivariate GARCH models have also been used to investigate volatility, transmission and spillover effects. Some important applications of MGARCH models can be found in Silvennoinen and Teräsvirta (2009), Chevallier (2012), Lin and Li (2015). It is therefore important to extend the considerations to multivariate GARCH (MGARCH) models (Bauwens *et al*., 2006 and 2013) for modelling the price volatility of one of major vegetables crop in India i.e. onion in the major markets of Karnataka. The price volatility in onion has been a major concern in the recent decades. There are few works in the area of price transmission and volatility in the price of onion markets e.g. Paul *et al*. (2015), Paul *et al*. (2016). In order to find out the linkages among the markets with respect to the price of a commodity, Johansen's cointegration approach and vector error correction model (VECM) are used (Paul and Sinha, 2015; Wani *et al*. (2015a, 2015b); Paul *et al*., 2016).

The objectives of the present paper are (i) to apply VECM- MGARCH model for modelling the price volatility of two major markets of Onion (ii) To identify and describe the spillover effects among the studied markets.

2. Description of models and methodology

2.1 Testing stationarity

For testing stationarity of a time series the tests namely Augmented Dickey Fuller (ADF) test, Phillips- Perron (PP) test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test are applied.

2.2 Autoregressive integrated moving average (ARIMA) Model

A generalization of Autoregressive moving average (ARMA) models, which incorporates a wide class of nonstationary time-series, is obtained by introducing "differencing" in ARMA model. y_t is said to follow ARIMA model, denoted by ARIMA(p,d,q), if $\nabla^d y_t = (1-B)^d \varepsilon_t$ is ARMA(p, q). The model is written as

$$\emptyset(B)(1-B)^d y_t = \theta(B)\varepsilon_t \qquad (1)$$

Where ε_t are identically and independently distributed as $N(0,\sigma^2)$. The integration parameter d is a nonnegative integer. When d=0, the ARIMA (p, d, q) model reduces to ARMA(p, q) model. Estimation of parameters for ARIMA model is generally done through Nonlinear least square method.

2.3 ARCH Model

The ARCH (q) model for the series {ε_t} is defined by specifying the conditional distribution of ε_t given the information available up to time t −1. Let Ψ_{t-1} denotes this information. It consists of the knowledge of all available values of the series. In principle, it may even include the knowledge of the values of other related time-series, and anything else which might be useful for forecasting and is available by time t −1. We say that the process { ε_t } is ARCH(q) if the conditional distribution of { ε_t }given the available information Ψ_{t-1} is

$$\varepsilon_t|\Psi_{t-1} \sim N\ (0, h_t) \tag{2}$$

and

$$h_t = a_0 + \sum_{i=1}^{q} a_i\, \varepsilon_{t-1}^2 \tag{3}$$

where

$$a_0>0,\ a_i \geq 0 \text{ for all i and } \sum_{i=1}^{q} a_i<1.$$

For testing the presence of ARCH effect, the Lagrange Multiplier (LM) test is used. The details of the test can be found in (Engle, 1982).

2.4 The GARCH Model: Bollerslev (1986) proposed the Generalized ARCH (GARCH) model in which conditional variance is also a linear function of its own lags and has the following form

$$h_t = a_0 + \sum_{i=1}^{q} a_i\, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} b_j\, h_{t-j} \tag{4}$$

A sufficient condition for the conditional variance to be positive is $a_0 > 0$, $a_i \geq 0$, i= 1, 2,…,q and $b_j \geq 0$, j= 1, 2, …, p. In order to estimate the parameters of GARCH model, Method of maximum likelihood is used (Engle, 1982).

2.5 Johansen's Cointegration test

It is employed to investigate the causal relationship between prices after identifying the appropriate order of integration of each series (Johansen, 1988). The usual step has been followed by identifying the significant lag length of Vector autoregressive (VAR) model on the basis of suitable information criteria. To identify the cointegration relation between the two price series, two likelihood ratio tests employed such as λ_{trace} *and* λ_{max} respectively.

$$\lambda_{trace} = -T \sum_{t=r+1}^{n} \ln(1-\widehat{\lambda_t}) \text{ for } i = 0,1,\dots,n\text{-}1 \tag{5}$$

$$\lambda_{max} = -T ln(1-\hat{\lambda}_{r+1}) \tag{6}$$

where, T is the number of usable observations and are the estimated eigen values (also called characteristics roots). The trace test statistic (λ_{trace}) tests the null hypothesis of r cointegrating relation against the alternative hypothesis of less than or equal to *r* cointegrating relation while, the test statistic tests the null hypothesis of *r* cointegrating relation against *r+1* cointegrating relations.

2.6 Vector Error Correction Model (VECM)

The VEC Model takes the following form

$$\Delta \mathbf{y_t} = \mathbf{\Pi y_{t-1}} + \sum_{j=1}^{k-1} \mathbf{\Gamma_j \Delta y_{t-j}} + \mathbf{u_t}, \ t=k+1,\ldots,T \tag{7}$$

where,

$$\mathbf{\Gamma_i = -(A_{i+1} + \ldots + A_k)} i=1,\ldots,k-1, \text{ and } \mathbf{\Pi = -(I - A_1 - \ldots - A_k)}. \tag{8}$$

This way of specifying the system contains information on both the short-run and long run adjustments to changes in $\mathbf{y_t}$, via the estimates of $\widehat{\mathbf{\Gamma}}_\mathbf{i}$ and $\widehat{\mathbf{\Pi}}$ respectively. $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$, where $\boldsymbol{\alpha}$ represents the speed of adjustments to disequilibrium and $\boldsymbol{\beta}$ is a matrix of long run coefficients such that the term $\boldsymbol{\beta}'\mathbf{y_{t-1}}$ embedded in the model represents up to (n-1) cointegration relationships in the multivariate model.

2.7 MGARCH Model

For a multivariate time series the MGARCH model is given by:

$$y_t = H_t^{1/2} \varepsilon_t \tag{9}$$

where, H_t is $k \times k$ positive-definite matrix of conditional variance. k is the number of series and t = 1,2,…,*n (observations*). It is with the specification of conditional variance that the MGARCH model changes.

BEKK Model

Let us assume the form of H_t for two variable case is as follows:

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \tag{10}$$

Accordingly, the BEKK (1, 1) representation of the conditional variance H_t is

$$H_t = C_0' C_0 + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + B_{11}' H_{t-1} B_{11} \tag{11}$$

where, A_1 and B_1 are 2×2 parameter matrix and C_0 is 2×2 upper triangular matrix. The bivariate BEKK(1,1) model can be written as

$$H_t = C_0' C_0 + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} +$$

$$\begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \tag{12}$$

The off diagonal parameters in matrix B, b_{12} and b_{21} measures the dependence of conditional price volatility in the first market on that of second market and the dependence of conditional price volatility in the second market on that of first market. The parameters b_{11} and b_{22} represents persistence in volatility in own market. The parameters a_{12} or a_{21} represent the cross markets effects whereas the subscripts a_{11}, a_{22}represent the own market effects.

Constant Conditional Correlation (CCC) Model

A relatively flexible approach is the CCC model introduced by Bollerslev (1990). This model assumes the conditional correlations to be constant. This restriction strongly reduces the number of unknown parameter and thus simplified the estimation. In case of CCC model the H_t represented as follows

$$H_t = D_t R D_t \tag{13}$$

Where, $D_t = diag(h_{11,t}^{1/2}, \dots, h_{kk,t}^{1/2})$ and R is a symmetric positive-definite matrix whose elements are (constant) conditional correlations$\rho_{ij,i,j} = 1,2,..\ k(\rho_{ij} = 1, i = j)$. Thus each conditional covariance is given by

$$h_{ij,t} = \rho_{ij}\sqrt{h_{ii,t} h_{jj,t}} \tag{14}$$

3. MODELING OF ONION PRICE THROUGH MGARCH MODEL

For this study we have taken onion prices from two major markets of Karnataka i.e. Bangalore and Hubli to show the spillover effect of price in one market to another. Monthly data have been collected from January, 2010 to April, 2018 collected from National Horticultural Research and Development Foundation (NHRDF) (http://nhrdf.org). Markets have been selected based on the total arrival of onion in Karnataka and also based on the availability of the data. The time plot of the series indicate the presence of volatility and simultaneous moving in respect of price in two markets. A perusal of the plot also indicates that the price in Bangalore always remains high as compared to the Hubli market one of the reason may be Bangalore being the metro city. Also seasonality can be very clearly seen in the price pattern. The price generally goes high during September to December every year and goes down during February to May. Therefore, before going for further analysis the price is seasonally adjusted and the seasonally adjusted price series are depicted in figure 2. The summary statistics are presented in table 1.

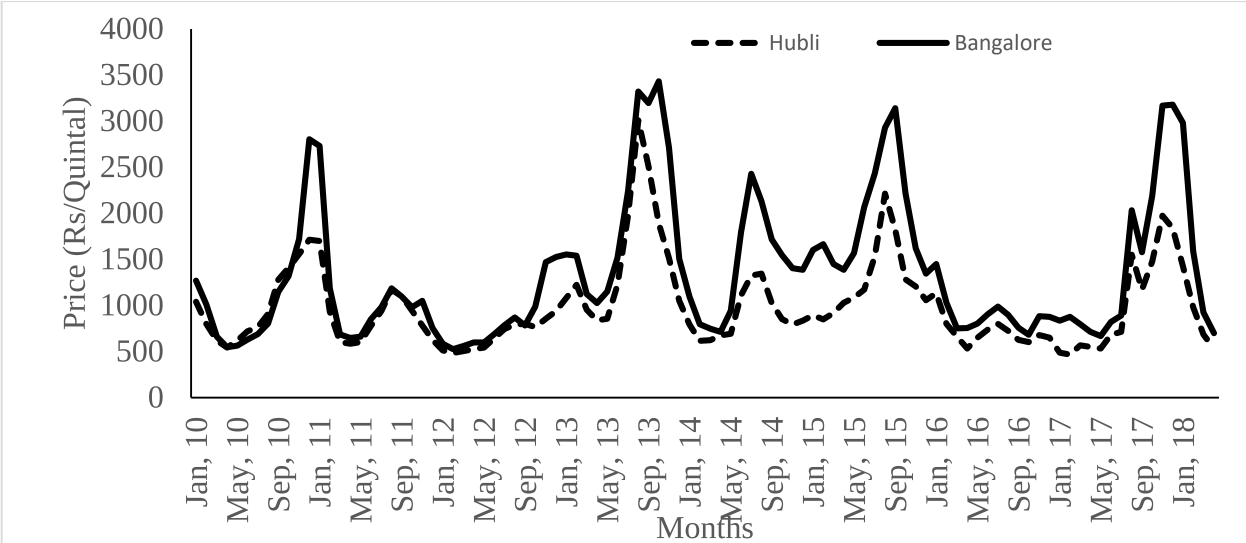


Fig. 1. Time plot of onion prices in Bangalore and Hubli Markets of Karnataka

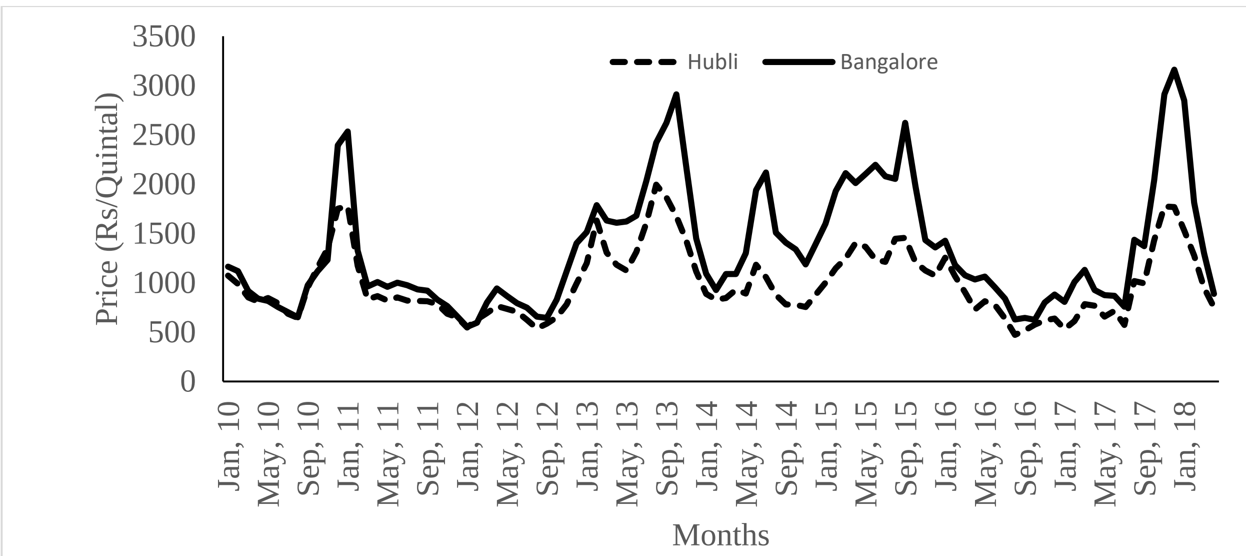


Fig. 2. Seasonally adjusted time plot of onion prices in Bangalore and Hubli Markets of Karnataka

3.1 Descriptive statistics

Various descriptive statistics of these two series separately has been computed and reported in table 1. Variability has been represented by coefficient of variation (CV). A perusal of table 1 indicates that the average price of onion is much more in Bangalore market and also the variability in as compared to Hubli market. Bothe the markets are positively skewed and leptokurtic.

Table 1. Descriptive statistics for the two market price

Statistics	Hubli	Bangalore
Mean	988.39	1349.98

Median	842.50	1071.00
Maximum	3007.00	3430.00
Minimum	466.00	524.00
Std. Dev.	469.06	759.05
Skewness	1.66	1.21
Kurtosis	6.27	3.53
Coefficient of Variation (CV)	47.46	56.23
Observations	100	100

3.2 Stationarity Test

The nature of stationarity for each series has been confirmed using KPSS, ADF, and PP tests. All the tests confirm that the seasonally adjusted price series are non-stationary. But after first differencing of level series, the series were found to be stationary.

3.3 Fitting of ARIMA Model

The univariate ARIMA models are fitted individually for both the series. Based on Akaike Information Criteria (AIC) the best models are obtained, and the result are given in table 2. In both the series ARIMA (1,1,0) model are found to be best fitted model and in both series the AR coefficients are highly significant.

Table 2: Parameter estimates of ARIMA model

	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Hubli	C	-3.039	27.258	-0.112	0.911
	AR(1)	0.356	0.096	3.716	<0.001
Bangalore	C	-4.327	49.199	-0.088	0.930
	AR(1)	0.343	0.097	3.551	0.001

3.4 ARCH-LM Test

The residuals of the individual ARIMA models are tested whether there exists any heteroscedasticity or not. For this, ARCH-Lagrange Multiplier (LM) test has been carried out and it is observed that for both the series there is significant presence of ARCH effect.

3.5 Fitting of GARCH Model

After confirming the significant presence of ARCH effect, the GARCH model is fitted to individual series. The best model is selected based on minimum AIC values. The parameters estimates of GARCH models are reported in table 3.

Table 3: Parameter estimates of GARCH model for Hubli and Bangalore markets

Hubli Market				
Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	29.066	26.030	1.117	0.264
AR(1)	0.452	0.113	3.981	<0.001
Variance Equation				
C	7468.527	4530.654	1.648	0.099
ARCH	0.658	0.227	2.905	0.004
GARCH	0.248	0.211	1.175	0.240
Bangalore market				
Mean Equation				
C	84.768	56.814	1.492	0.136
AR(1)	0.588	0.106	5.541	<0.001
Variance equation				
C	61373.430	10315.950	5.949	<0.001
ARCH	0.709	0.304	2.335	0.020
GARCH	0.052	0.135	0.388	0.698

In both the markets, ARCH coefficients are significant. Most importantly ARCH effect is more than that of GARCH, which means conditional variance is more dependent on the past square residual than that of lag variances.

3.6 Johansen's test for cointegration

The Johansen's cointegration test is carried out for Bangalore and Hubli market price of onion. Both trace and Maximum Eigen value statistics are used. The results are as reported in table 4.

Table 4: Testing rank of cointegration using Trace statistic

Hypothesized No. of CE(s)	**Trace Statistic**			
	Eigenvalue	Statistic	Critical Value	Probability
None	0.18	20.85	12.32	0.0015
At most 1	0.02	1.63	4.13	0.237

	Maximum Eigen value statistic			
None	0.18	19.23	11.22	0.0016
At most 1	0.02	1.63	4.13	0.237

From the above table it can be concluded that the null hypothesis with no cointegration is rejected, but the alternative hypothesis is accepted with at most one cointegration. Hence, there is one cointegration vector among the two series.

3.7 Vector Error Correction Model

Once the cointegration is established, the VEC model has been fitted in order to find out the speed of adjustment in both the series and also to see the dependency of lagged market price of own market and other markets in determining the change in price of individual market. The result of VECM is reported in table 5.

Table 5: Result of VECM model

Error Correction	D(Hubli)	D(Bangalore)
CointEq1	0.152	-0.464
Standard Error	0.099	0.120
t-statistic	1.530	-3.869
D(Hubli(-1))	0.238	0.205
Standard Error	-0.171	-0.156
t-statistic	1.393	1.313
D(Bangalore(-1))	0.071	0.448
Standard Error	-0.094	-0.283
t-statistic	0.752	1.585
C	-2.208	-2.073
Standard Error	-17.515	-28.967
t-statistic	-0.126	-0.072

Error correction terms as denoted by CointEq1 in table 5 show the speed of adjustments, here for Bangalore market the magnitude of this coefficient is higher than that of Hubli. Also the error correction term is highly significant in Bangalore market but it is not significant in Hubli market. It indicates that if Bangalore market price deviates from equilibrium, then it quickly approaches towards equilibrium.

3.8 MGARCH Model

Multivariate GARCH model has been fitted by two different models, those are:

MGARCH- BEKK Model

As discussed in the section 2.7 MGARCH-BEKK model is fitted to the data under consideration and the results are reported in table 6.

Table 61: Parameter estimates of MGARCH-BEKK model

Coefficients	Estimate	Standard Error	t-value
C11	-32.788	24.810	-1.322
C21	8.199	8.764	0.936
C22	4.227	6.094	0.694
A11	-0.740**	0.221	-3.341
A12	0.287	0.380	0.755
A21	0.566**	0.140	4.032
A22	0.077	0.238	0.322
B11	-0.527**	0.246	-2.139
B12	-1.612**	0.403	-3.996
B21	0.775**	0.084	9.264
B22	1.550**	0.135	11.505

Here, 11 parameters are estimated by this method among which 6 parameters are significant. Here the first market considered is Hubli and the second one is Bangalore market. The results obtained clearly indicates the transmission of volatility from Bangalore to Hubli (-1.612) and from Hubli to Bangalore (0.775). The negative value of -1.612 can be interpreted as the transmission of persistent negative impact on Hubli due to the presence of volatility in Bangalore. In a similar manner the value 0.775 is the positive impact that Hubli has on Bangalore in terms of transmission of volatility between them. For Bangalore, the individual effect on its past volatility (1.55) is higher than that of the Hubli.

Constant Conditional Correlation (CCC) Model

More flexible model that is CCC model as discussed in section 2.7 has been fitted to the data under consideration and the result obtained is reported in table 7.

Table 72: Parameter estimates of MGARCH-CCC mode

	Coefficient	Standard Error	t-Value
C11	28045.100	13954.710	2.010
A11	0.238	0.164	1.448
B11	0.431	0.237	1.821
C22	9318.188	5484.426	1.699
A22	0.358	0.187	1.914
B22	0.359	0.260	1.381
CCC	0.777	0.032	24.445

So, from CCC model we get 7 estimate of coefficients. Results of the CCC model clearly suggested the presence of conditional correlation in the conditional variance exhibited by the series. The magnitude of constant conditional correlation is 0.777 that means the conditional correlation between these two markets is very high.

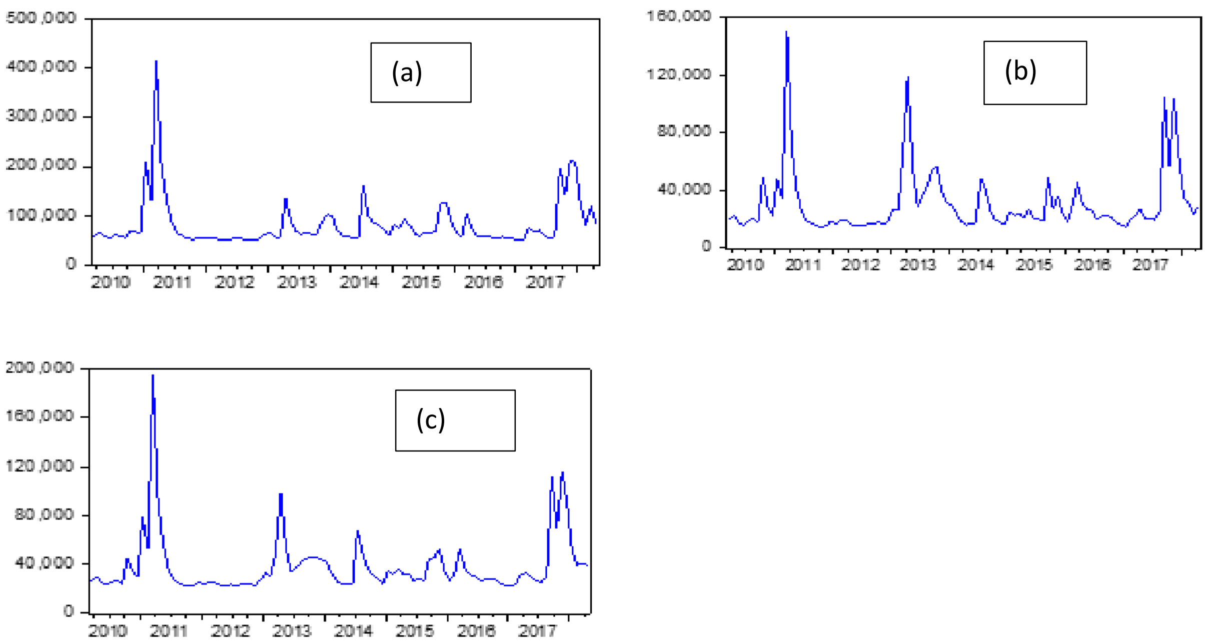


Fig. 3. Conditional variance of Hubli (a), Bangalore (b) market and conditional covariance of two markets (c) for fitted CCC model

4. Conclusions

ARIMA models are fitted using monthly Onion price data of two different markets, Bangalore and Hubli of Karnataka. The residuals were investigated for possible presence of ARCH effect followed by fitting of univariate GARCH models. It is seen that the magnitude of ARCH effects are more than the GARCH effects for both the series. The cointegration among the two series were tested by using both Trace statistic and Eigen value statistic and it is found that there was one cointegrated vector among the two series. Accordingly, VEC model was fitted and possible presence of MARCH effect was investigated on the residuals of VEC model. To this end MGARCH model was applied for modeling the conditional variance of the bivariate series. The performances of MGARCH models namely BEKK and CCC have been studied. High persistence of volatility has been observed in each market price. The interdependence and volatility spillover of onion price between Bangalore and Hubli markets has been established. The linkages among the markets, amount and direction of spill over will help the policy makers to take proper policy decision in order to stabilize the price of the commodity.

Chapter 3

ASYMMETRIC PRICE TRANSMISSION: A CASE OF WHEAT IN INDIA

1. Introduction

India ranks second in the world after China in terms of wheat production and consumption. India's share in global wheat production was recorded at 12.76 percent in the year 2016-17. India has been self-sufficient in wheat production. India's share in global exports was around 0.40 percent in the year 2015-16 (Directorate General of Commercial Intelligence and Statistics (DGCI&S). As per data of 2016-17 collected from Directorate of Economics and Statistics, Ministry of Agriculture and Farmers' Welfare, Government of India, it is revealed that the highest share of wheat comes from Uttar Pradesh (30% of total production), followed by Madhya Pradesh (18%), Punjab (17%), Haryana (12%), Rajasthan (9%), which together share about 86% of the total national wheat production while the remaining 14% is contributed by Gujarat, Maharashtra, Uttarakhand, West Bengal and other states of the country. The leading states in terms of area under wheat are Uttar Pradesh, Madhya Pradesh, Punjab, Haryana, Rajasthan accounting for more than 80 percent of wheat area in the country.

Market integration is a concept used to figure out the phenomenon in which markets of goods and services that are related to one another, experience similar patterns in terms of increase or decrease of the prices of the commodities. The term can also be related to circumstances in which the prices of relatable goods and services that are sold in a defined geographical location also start to move in some sort of similar pattern to one another. Therefore, Market integration is the phenomenon by which price interdependence takes place. Agricultural product markets that are established under market regulation programs play vital role in providing market places to the farmers to sell off their products. These markets also provide facilities and environment to the traders, processors and other market functionaries for smooth conduct of their trading activities. Nature of agricultural commodities can be characterized by seasonality, variability, perishability etc. Poor market integration is quite uncompetitive. The fragmented and small size farm with low volume of marketable surplus make the performance of marketing functions more difficult and expensive.

The marketed surplus from the production has also been rising and it is estimated that about 60-70 percent of the production now comes to the market (Directorate of Economic and Statistics, 2002). As a result, the marketing system and its efficiency is of major concern and interest in India. Poor efficiency in marketing can result in serious consequences for both producers and consumers as well as effecting the government budgets and the economy. Major concerns have been raised about the working of the market mechanisms and market related policies for wheat, being one of the staple food crop. The market price of wheat necessarily influences the demand of wheat. The demand-side market of wheat products needs to be explored in order to understand the impact on production and growth of the crop. It is necessary to look at the price movement of wheat in different markets due to mismatch between demand-supply and large-scale imports.

Market integration is generally of two types, viz. horizontal market integration and vertical market integration. Horizontal market integration indicates that the price of a commodity in one market responds to change in the price of same commodity in other markets. Vertical market integration represents integration of price of same product at different levels of value chain (farm price, wholesale price and retail price).

Usually market reforms are required for achieving efficient agricultural markets and an efficient agricultural production system. When the agricultural markets are integrated, producers and consumers can realize the potential gains from the common market. In this regard, the prices of wheat play a vital role. When the markets are integrated, the price signals are transmitted form one market to other and also influence prices of other markets. Both the wholesale market prices (producer's level) and retail market (consumer's level) prices are the important components of the marketing process. Studying market integration of wheat has become important due to the interdependence of wholesale and retail markets. Price transmission can be of two types: symmetric and asymmetric. In contrast to symmetric price transmission, asymmetric price transmission (APT) is said to exist when the adjustment of prices is not homogeneous with respect to external or internal characteristics to the system. Major causes of asymmetric price transmission are: the presence of non-competitive markets and existence of adjustment costs (Meyer and Von Cramon-Taubadel, 2004). Although other causes such as political intervention, asymmetric information and inventory management are also reported in literature.

2. Background

Several empirical studies have been carried out using cointegration techniques which concern the market integration of agricultural commodities in India (Gonzalez *et al*., 2012; Acharya *et al*., 2012; Bhardwaj *et al*., 2015; Wani *et al*., 2015a; Wani *et al*., 2015b; Wani *et al*., 2015c; Saxena *et al*., 2015; Paul *et al*., 2015; Paul and Sinha, 2015), however, a little work has been carried out on empirically evaluating wheat market integration in India particularly when price transmission is asymmetric. Asche *et al*. (2007) carried out vertical and horizontal price linkages for salmon. The authors found a high degree of price transmission in both supply chains, as well as integrated markets in salmon. von Cramon-Taubadel *et al*. (2006) studied the impact of cross-sectional aggregation over individual retail stores on the estimation and testing of vertical price transmission between the wholesale and retail levels in Germany. The authors reported that estimation with aggregated data can generate misleading conclusions about price transmission behavior at the level of the individual units. Meyer and Von Cramon-Taubadel (2004) studied different types and causes of asymmetric price transmission and described the econometric techniques used to quantify it. Powers (1995) reported that wholesale prices of iceberg lettuce move in accord with free-on-board shipping point (FOB) price changes. Bachmeier and Griffin (2003) applied error-correction model with daily spot gasoline and crude-oil price data over the period 1985-1998 and concluded no evidence of asymmetry in wholesale gasoline prices. Andrle and Blagrave (2020) studied market integration using monthly price data for 21 agricultural goods and 60 markets in India. The authors reported that there is no robust evidence that price integration has increased in recent years. Das and Bhattacharya (2008) attempted to examine whether there is price convergence across various regions in India. Their results indicated significant presence of cross-sectional dependence in prices in India. Gandhi and Zhou (2004) indicated that in India, wheat production is concentrated and growth is driven predominantly by yield increases, and to some extent by a shift in area from other crops. Jha et al. (2008) stated that if agricultural markets are not integrated, then any local food scarcity will tend to persist. Mellor et al. (2000) reported that depending on the rate and nature of economic growth, a 4 to 5 per cent annual rate of growth in the demand for wheat is likely in the near future in India. Sekhar (2012) studied the extent and degree of integration among selected agricultural markets in India and concluded that the like gram and edible oils, appear well-integrated but, rice market does not show integration at the national level. Balaguer and Ripollés (2014) studied integration among transport fuel retail markets in Spain. If the marketing environment is perfectly competitive, then the magnitude of price transmission will remain intact regardless of whether the change in price increasing or decreasing, i.e., adjustment is symmetric (Goletti and Babu 1994). However, in agricultural markets, price of many commodities including wheat are characterized by asymmetric adjustment (Powers, 1995; Gonzalo and Pitarakis, 2002; Meyer and Cramon-Taubadel, 2004;Gonzalo and Wolf, 2005; Cramon-Taubadel, et al., 2006; Asche at al., 2007; Ghoshray, 2008;Ghoshray, 2002;Hassanzoy*et al*. 2016, Hassanzoy *et al*. 2017).) If price adjustment is asymmetric, Enders and Siklos (2001) reported that the standard cointegration tests and their extensions are not correctly specified. Enders and Granger (1998) investigated the asymmetric movements towards the long-run equilibrium. Balke and Fomby (1997) pointed out that price movement towards long run equilibrium is not necessarily constant and subsequently, under an asymmetric adjustment process, the power of cointegration test reduces. In this situation, it is important to use Threshold cointegration approach which allows for asymmetric adjustment introduced by Enders and Siklos (2001). In literature, estimation methods of threshold cointegration have been extensively studied. To mention a few Balke and Fomby (1997), Hansen and Seo (2002)and Seo (2011) may be referred. Wang *et al*. (2016) studied the structure of interest rates by a two-threshold cointegration model. But application of threshold cointegration in agriculture is scarce. Moreover, there is no study of asymmetric cointegration in wheat prices in Indian markets. So, the present study attempts to examine the movement of prices of wheat in different markets across the states of India and the transmission of price signals and information across these markets. For this purpose, Threshold Autoregressive (TAR) and Momentum-TAR(MTAR) approaches have been applied (Tiwari and Mutascu, 2016).

3. Data and Methodology

The study selected seventeen major markets namely Delhi, Jammu, Amritsar, Ludhiana, Lucknow, Dehradun, Raipur, Ahmedabad, Bhopal, Mumbai, Jaipur, Patna, Bhubaneswar, Bengaluru, Thiruvananthapuram, Chennai, Hyderabad along with all India Maximum, Minimum and Modal price of wheat. Daily data on retail and wholesale prices of wheat of above markets for the period

January, 2010 to May, 2018 were collected from the Department of Consumer Affairs, Government of India. The daily data was converted into weekly data and the missing observations were imputed by using mean value i.e. if 3rd week of January, 2015 is missing, it is replaced by the mean of the 3rd week price of January of preceding years. Though usage of temporally aggregated data at weekly level could yield some degree of biasness in the analysis of the vertical price transmission process due to the omission of lagged information (Geweke, 1978; Bachmeier and Griffin, 2003).

The statistical methods used in the present investigations are: testing stationarity, concept of cointegration, testing for rank of cointegration, vector error correction model (VECM), testing presence of nonlinearity using BDS test, testing asymmetric cointegration followed by threshold VECM (TVECM), Granger Causality and Impulse response analysis. These techniques allow one to quantify the degree of interconnectedness between the markets. For testing the stationarity of time series data, the tests namely Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), Phillips-Perron Unit Root test (Philips and Perron, 1988) and KPSS test (Kwiatkowski *et al*., 1992) have been applied. The statistical techniques which are used in the present investigation are described below in brief.

3.1 Johansen's approach of cointegration

Johansen's(1988) multivariate cointegration approach was used to examine cointegration among price series. Let $\mathbf{y_t}$ be and $n \times 1$ set of I(1) variables (if the series is integrated of order d, it is denoted by I(d)). In general, any linear combination $\mathbf{a}'\mathbf{y}_t$ will also be I(1) for arbitrary $\mathbf{a} \neq \mathbf{0}$. However, suppose there exists an $n \times 1$ vector $\boldsymbol{\alpha}_i$ such that $\boldsymbol{\alpha}_i'\mathbf{y}_t$ is I(0),$\boldsymbol{\alpha}_i \neq \mathbf{0}$**,** then it is said that the variables in $\mathbf{y_t}$ are cointegrated of order one, denoted CI(1) and $\boldsymbol{\alpha}_i$ is a cointegrating vector. It is to be mentioned that if $\boldsymbol{\alpha}_i$ is a cointegrating vectors then so is the $k\boldsymbol{\alpha}_i$ for any $k \neq 0$ since $k\boldsymbol{\alpha}_i' \, \mathbf{y}_t \sim I(0)$. For total n series, there can be maximum r different cointegrating vectors, where $0 \leq r < n$.

3.2 Error Correction Models (ECM)

In vector and matrix notation, the ECM can be written as per equation (1)

$$\Delta \mathbf{y}_t = \boldsymbol{\alpha\beta}' \mathbf{y}_{t-1} + \boldsymbol{\Gamma}_1 \Delta \mathbf{y}_{t-1} + \mathbf{u}_t \tag{1}$$

Where, $\boldsymbol{\alpha}$=[α_1, α_2]′, $\boldsymbol{\beta}'$=[1, -β_1] and, $\boldsymbol{\Gamma_1}=\begin{bmatrix}\gamma_{11} & \gamma_{12}\\ \gamma_{21} & \gamma_{22}\end{bmatrix}$

Equation (1) can be reformulated into a vector error correction model (VECM):

$$\Delta\mathbf{y_t}= \boldsymbol{\Pi}\mathbf{y_{t\text{-}1}}+\textstyle\sum_{j=1}^{k\text{-}1}\boldsymbol{\Gamma_j}\Delta\mathbf{y_{t\text{-}j}}+\mathbf{u_t},\ \ t=k+1,\ldots,T \qquad (2)$$

where, $\boldsymbol{\Gamma_i}$=-($\mathbf{A_{i+1}}$+…+$\mathbf{A_k}$), i=1,…,k-1, and $\boldsymbol{\Pi}$=-(I-$\mathbf{A_1}$-…-$\mathbf{A_k}$). This way of specifying the system contains information on both the short-run and long-run adjustments to changes in $\mathbf{y_t}$, via the estimates of $\widehat{\boldsymbol{\Gamma}}_{\mathbf{i}}$ and $\widehat{\boldsymbol{\Pi}}$, respectively. $\boldsymbol{\Pi}=\boldsymbol{\alpha}\boldsymbol{\beta}'$, where $\boldsymbol{\alpha}$ represents the rate of adjustments to disequilibrium and $\boldsymbol{\beta}$ is a matrix of long-run coefficients such that the term $\boldsymbol{\beta}'\mathbf{y_{t-1}}$ embedded in Equation (2) represents up to (n-1) cointegration relationships in the multivariate model. A good description of cointegration can be found in Paul (2015). Relationship between the wholesale and retail price is also examined by using the IRF (impulse response function). The IRF is one of widely used techniques in order to predict the effect of a shock on a specific series.

3.3 Asymmetric cointegration

The standard cointegration tests and their extensions are mis-specified if adjustment is asymmetric (Enders and Siklos, 2001). In order to to account for asymmetry in cointegrating relationship, they extended the Threshold Autoregressive (TAR) and Momentum Threshold Autoregressive (M-TAR) models of Enders and Granger (1998) to a multivariate context. The aspects of ‘deep movements’ can be captured by TAR model whereas M-TAR captures aspects of ‘steep movements’ in a price series (Enders and Granger, 1998). Hassanzoy *et al*. (2017) reported that M-TAR model is superior to that of TAR and Engle and Granger tests. In the present investigation, in order to take care of the large changes in the price series, M-TAR model was applied. The consistent M-TAR model is defined by the Equations (3)-(5). Here, the speed of adjustment towards equilibrium depends on the direction of change in $\hat{\varepsilon}_{t-1}$, that is, $\Delta\hat{\varepsilon}_{t-1}$. Therefore, the speed of adjustment is $\rho_1\hat{\varepsilon}_{t-1}$, if deviations from the long-run equilibrium are positive, and $\rho_2\hat{\varepsilon}_{t-1}$otherwise.

$$\Delta\hat{\varepsilon}_t = I_t\rho_1\hat{\varepsilon}_{t-1} + (1-I_t)\rho_2\hat{\varepsilon}_{t-1} + \textstyle\sum_{i=1}^{p-1}\beta_i\Delta\hat{\varepsilon}_{t-i} + \omega_t \ (3)$$

$$I_t = \begin{cases} 1 & if\ \Delta\hat{\varepsilon}_{t-1} \geq a_0 \\ 0 & if\ \Delta\hat{\varepsilon}_{t-1} < a_0 \end{cases} \quad (4)$$

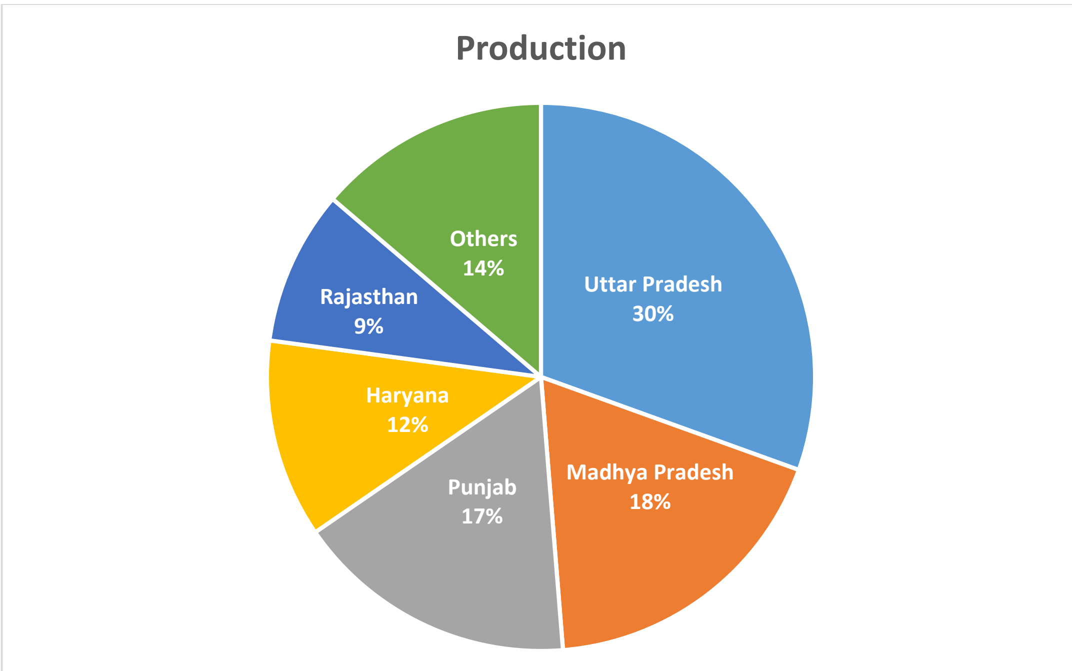
where a_0 is a consistent threshold value; ρ_1 and ρ_2 denote adjustment coefficients; $\beta_i$shows the coefficient(s) of lagged changes; and ω_t is i.i.d. disturbance term. The necessary and sufficient conditions for stationarity of $\hat{\varepsilon}_t$ are $\rho_1<0$, $\rho_2<0$ and $(1 + \rho_1)(1+ \rho_2) <1$ for any values of a_0(Hassanzoy *et al*. 2016;Hassanzoy *et al*. 2017). Tong (1990, 2007, 2011) showed that the least square estimates of ρ1 and ρ2 have an asymptotic multivariate normal distribution under the condition that $\hat{\varepsilon}_t$ is stationary. The M-TAR model is applied in this here to examine the long-run relationship among the pairs of wholesale and retail prices of wheat assuming asymmetric adjustment. For threshold cointegration, with M-TAR adjustment, five-step procedure as reported in Hassanzoy *et al*. (2017) is followed. First, a long-run relationship between the pairs of markets is estimated as follows:

$$y_{1,t} = \gamma_0 + \gamma_1 y_{2,t} + \varepsilon_t \quad (5)$$

where $y_{1,t}$ and $y_{2,t}$ are logarithm of wholesale and retail prices of wheat at time t; γ_0 *i*s constant term ; γ_1 is elasticity of price transmission; and ε_t is error term which may be serially correlated. In the second step, following Chan (1993), consistent estimates of threshold values for M-TAR models were obtained. Equations (3) and (4) are estimated for each of the possible threshold values. Finally, the threshold (a_0), is estimated by minimizing the sum of squared residuals from the fitted model. Third step involves testing the null hypothesis of no cointegration, that is, $\rho_1 = \rho_2 = 0$, for each of the M-TAR model. Fourth, given that the null hypothesis of no cointegration is rejected, the null hypothesis of no asymmetric adjustment, that is, $\rho_1 = \rho_2$, is tested for each of the M-TAR model using the standard F-test. In the last step, Ljung–Box Q-statistic is applied to test for white noise process of the estimated residuals from M-TAR models. Once the presence of cointegration is established among the markets, the dynamics of price transmission among them are analyzed using Asymmetric Vector Error Correction Models (AVECMs) with threshold (M-TAR) adjustment. It is observed that in TAR model, Asymmetric Cointegration is present in wholesale and retail price of wheat in the markets namely Ahmedabad, Bengaluru, Bhubaneswar, Hyderabad, Patna and All India Minimum Price. Whereas in MTAR model it is seen that Asymmetric Cointegration is present in most of markets.

4. Results and discussion

Summary statistics of the price data of different markets are computed and the same is reported in Table 1. It has been seen that both the wholesale and retail prices are more or less consistent in the markets as depicted by coefficient of variation (CV) value. The share of area and production of wheat by different states of India is depicted in Fig. 1. In market integration study, the first step is to check for the evidence of non-stationarity of data. Test for stationarity was performed by using ADF test PP test as well as KPSS test. The results of all three tests as reported in Table 2, revealed that all the variables were non-stationary at level. In order to achieve stationarity, the series were differenced to first order and all the series became stationary after first differencing. As all the series are found to be integrated of same order, data set is suitable for cointegration.



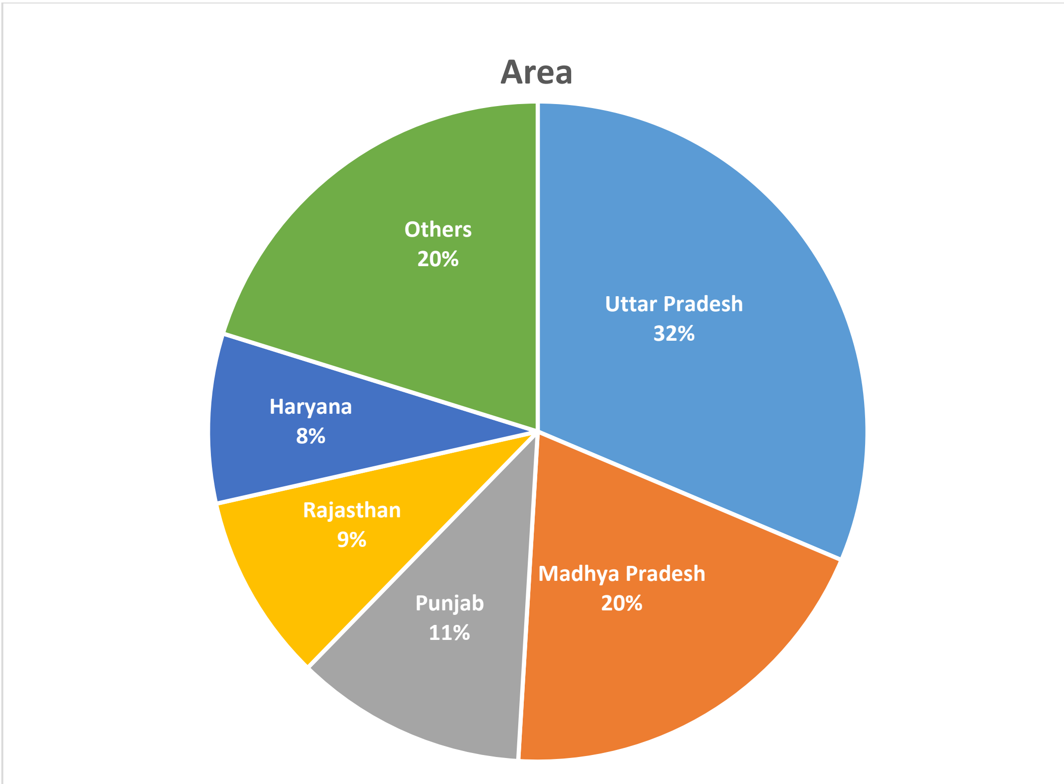


Fig. 1 State wise share of wheat production and area

Table 1. Descriptive statistics for wholesale and retail prices of individual markets

Markets		Wholesale Price						Retail Price					
		Mean	**Median**	**Max**	**Min**	**SD**	**CV(%)**	**Mean**	**Median**	**Max**	**Min**	**SD**	**CV(%)**
Ahmedabad	:	1647.75	1650.00	2000.00	1100.00	302.89	18.38	1851.49	1900.00	2300.00	1200	318.11	17.18
Amritsar	:	1491.28	1500.00	1900.00	1050.00	229.44	15.39	1688.93	1800.00	2200.00	1100	297.61	17.62
Bengaluru	:	2320.10	2500.00	2800.00	1671.43	418.44	18.04	2582.08	2700.00	3400.00	1800	530.42	20.54
Bhopal	:	1457.20	1500.00	1700.00	1050.00	170.97	11.73	1638.73	1700.00	2000.00	1100	234.91	14.33
Bhubaneswar	:	1512.65	1580.00	1580.00	1210.00	107.36	7.10	1803.18	1800.00	2014.29	1400	222.5	12.34
Chennai	:	2298.40	2342.86	2814.29	1800.00	204.42	8.89	2794.45	3000.00	3500.00	2000	439.36	15.72
Dehradun	:	1511.74	1512.86	1880.00	1120.00	218.85	14.48	1709.16	1600.00	2200.00	1200	310.24	18.15
Delhi	:	1590.37	1671.43	2227.86	1138.57	244.90	15.40	1800.62	1900.00	2414.29	1300	234.88	13.04
Hyderabad	:	2359.37	2400.00	2700.00	1490.71	356.55	15.11	2581.75	2700.00	2900.00	1700	353.88	13.71
Jaipur	:	1570.16	1600.00	2250.00	1150.00	233.97	14.90	1709.90	1700.00	2600.00	1300	256.55	15.00
Jammu	:	1562.63	1617.14	2560.00	1000.00	253.82	16.24	1698.18	1700.00	2200.00	1100	259.59	15.29
Lucknow	:	1445.64	1450.00	1900.00	1035.71	215.18	14.88	1576.59	1600.00	2000.00	1100	213.26	13.53
Ludhiana	:	1489.15	1350.00	1900.00	1114.29	242.65	16.29	1601.62	1592.86	2000.00	1200	243.15	15.18
Mumbai	:	2102.12	2200.00	2628.57	1453.57	313.44	14.91	2614.76	2700.00	3514.29	1700	447.64	17.12
Patna	:	1518.12	1600.00	2200.00	1100.00	238.40	15.70	1730.36	1800.00	2400.00	1200	292.66	16.91

Thiruvananthapuram	:	2331.98	2400.00	3200.00	1500.00	405.95	17.41	2557.70	2600.00	3500.00	1700	413.19	16.15
Maximum Price	:	2833.35	2850.00	4021.43	1833.00	546.88	19.30	3109.81	3100.00	4428.57	2100	632.25	20.33
Minimum Price	:	1276.89	1337.14	1471.43	100.00	169.09	13.24	1401.84	1500.00	1671.43	1000	177.20	12.64
Modal Price	:	1717.69	1667.86	2714.29	1100.00	395.82	23.04	1712.87	1797.64	2478.57	1200	267.59	15.62

Table 2. Stationarity test results

Markets		Original series						Differenced series					
		Wholesale Price											
		ADF test statistic	p-value	PP test statistic	p-value	KPSS test statistic	p-value	ADF test statistic	p-value	PP test statistic	p-value	KPSS test statistic	p-value
Ahmedabad	:	-1.43	0.57	-1.44	0.56	114.11	<0.001	-15.56	<0.001	-15.74	<0.001	0.89	0.37
Amritsar	:	-0.46	0.90	-0.49	0.89	136.34	<0.001	-14.92	<0.001	-14.77	<0.001	1.46	0.15
Bengaluru	:	-0.70	0.84	-0.55	0.88	116.30	<0.001	-15.37	<0.001	-16.64	<0.001	0.99	0.32
Bhopal	:	-0.71	0.84	-0.82	0.81	178.78	<0.001	-15.13	<0.001	-14.31	<0.001	0.88	0.38
Bhubaneswar	:	-1.89	0.34	-1.77	0.40	295.55	<0.001	-14.00	<0.001	-13.90	<0.001	0.29	0.77
Chennai	:	-2.48	0.12	-2.78	0.06	235.84	<0.001	-17.01	<0.001	-14.80	<0.001	0.46	0.65
Dehradun	:	-0.90	0.79	-0.69	0.85	144.90	<0.001	-13.66	<0.001	-13.28	<0.001	1.16	0.25
Delhi	:	-1.56	0.50	-1.46	0.55	136.22	<0.001	-15.00	<0.001	-15.04	<0.001	0.75	0.45
Hyderabad	:	-2.13	0.23	-2.10	0.24	138.80	<0.001	-18.50	<0.001	-18.50	<0.001	1.22	0.22
Jaipur	:	-1.71	0.43	-1.66	0.45	140.77	<0.001	-14.26	<0.001	-14.27	<0.001	0.89	0.37
Jammu	:	-1.80	0.38	-2.45	0.13	129.14	<0.001	-15.21	<0.001	-21.69	<0.001	0.33	0.74
Lucknow	:	-1.75	0.41	-1.50	0.53	140.92	<0.001	-13.14	<0.001	-13.86	<0.001	1.02	0.31
Ludhiana	:	-0.15	0.94	-0.19	0.94	128.73	<0.001	-15.79	<0.001	-21.58	<0.001	1.31	0.19
Maximum Price	:	-0.82	0.81	-1.58	0.49	108.68	<0.001	-18.52	<0.001	-77.21	<0.001	0.71	0.48
Minimum Price	:	-2.89	0.05	-3.14	0.02	158.40	<0.001	-20.26	<0.001	-22.65	<0.001	-0.01	0.99
ModalPrice	:	-2.64	0.09	-3.95	0.00	91.03	<0.001	-12.85	<0.001	-41.55	<0.001	0.03	0.98
Mumbai	:	-1.37	0.60	-1.02	0.75	140.68	<0.001	-14.51	<0.001	-15.25	<0.001	0.89	0.38
Patna	:	-2.01	0.28	-2.06	0.26	133.58	<0.001	-23.90	<0.001	-24.12	<0.001	0.33	0.74
Thiruvananthapuram	:	-1.97	0.30	-2.10	0.24	120.50	<0.001	-17.09	<0.001	-16.53	<0.001	0.31	0.76
Retail Price													
Ahmedabad	:	-1.32	0.62	-1.24	0.66	122.09	<0.001	-14.47	<0.001	-17.00	<0.001	0.31	0.76
Amritsar	:	-1.43	0.57	-1.23	0.66	119.04	<0.001	-14.73	<0.001	-14.08	<0.001	0.98	0.33

Bengaluru	:	-0.32	0.92	-0.26	0.93	102.11	<0.001	-15.56	<0.001	-15.52	<0.001	1.53	0.13
Bhopal	:	-0.94	0.78	-1.02	0.75	146.33	<0.001	-10.61	<0.001	-14.20	<0.001	0.91	0.36
Bhubaneswar	:	-0.84	0.81	-0.83	0.81	170.00	<0.001	-13.44	<0.001	-13.33	<0.001	0.89	0.37
Chennai	:	-1.59	0.49	-1.58	0.49	133.41	<0.001	-15.52	<0.001	-14.54	<0.001	1.08	0.28
Dehradun	:	-0.69	0.85	-0.79	0.82	115.56	<0.001	-12.12	<0.001	-13.87	<0.001	1.02	0.31
Delhi	:	-2.02	0.28	-1.43	0.57	160.81	<0.001	-13.96	<0.001	-13.72	<0.001	0.70	0.48
Hyderabad	:	-2.55	0.10	-2.49	0.12	153.03	<0.001	-13.80	<0.001	-13.09	<0.001	1.44	0.15
Jaipur	:	-2.07	0.26	-2.27	0.18	139.81	<0.001	-15.30	<0.001	-18.30	<0.001	0.51	0.61
Jammu	:	-1.38	0.59	-1.27	0.65	137.22	<0.001	-9.34	<0.001	-15.40	<0.001	0.70	0.48
Lucknow	:	-1.45	0.56	-1.45	0.56	155.07	<0.001	-16.67	<0.001	-15.30	<0.001	0.79	0.43
Ludhiana	:	-0.92	0.78	-0.66	0.85	138.17	<0.001	-16.03	<0.001	-18.52	<0.001	0.95	0.34
Maximum Price	:	-0.30	0.92	-0.09	0.95	103.17	<0.001	-19.55	<0.001	-31.50	<0.001	0.99	0.32
Minimum Price	:	-1.83	0.37	-1.69	0.44	165.94	<0.001	-20.83	<0.001	-20.98	<0.001	0.22	0.83
ModalPrice	:	-2.27	0.18	-3.24	0.02	134.27	<0.001	-21.57	<0.001	-62.84	<0.001	0.20	0.84
Mumbai	:	-1.37	0.60	-1.23	0.66	122.53	<0.001	-12.47	<0.001	-17.59	<0.001	0.85	0.40
Patna	:	-1.55	0.51	-1.42	0.57	124.02	<0.001	-10.28	<0.001	-16.48	<0.001	1.24	0.22
Thiruvananthapuram	:	-1.80	0.38	-1.85	0.35	129.85	<0.001	-16.67	<0.001	-18.33	<0.001	0.13	0.90

4.1 Cointegration in Price Series

The Johansen's cointegration test has been applied to investigate cointegration among different markets with respect to wholesale and retail prices. For horizontal integration, 11 markets were selected based on the production and consumption of wheat in different states of India. The 11 selected markets are: Ahmedabad, Amritsar, Bhopal, Dehradun, Delhi, Jaipur, Jammu, Lucknow, Ludhiana, Mumbai and Patna. It reveals that markets are perfectly cointegrated with respect to wholesale as well as retail price. Both the maximum eigen value statistic and trace statistics have been used for testing the cointegration and the result is reported in Table 3. In retail price, according to trace statistic, the no of cointegrating equations are six whereas eigen value statistic indicates the no of cointegrating equations are two. Similarly, for wholesale price, no of cointegrating equations are found out to be four and three respectively based on trace and eigen value statistics. In addition to the horizontal cointegration, the vertical cointegration between the wholesale and retail prices of wheat in individual market was also investigated. The results of Johansen's cointegration test are presented in Table 4 using the trace and eigen statistics. It is observed that wholesale and retail prices are integrated in all the markets.

Table 3. Cointegration among retail and wholesale prices of wheat

No. of cointegrating equations	Retail Price			
	Test Statistics (Trace)	5% Critical Value	Test Statistics (Eigen)	5% Critical Value
None	392.86	277.39	95.04	68.27
At most 1	297.82	232.49	75.47	62.42
At most 2	222.35	192.84	53.7	57
At most 3	168.65	157.11	40.3	51.07
At most 4	128.35	124.25	37.76	44.91
At most 5	90.59	90.39	33.95	39.43
At most 6	56.64	70.6	23.41	33.32
At most 7	33.23	48.28	14.69	27.14
At most 8	18.54	31.52	11.45	21.07
At most 9	7.09	17.95	6.91	14.9
At most 10	0.18	8.18	0.18	8.18
Wholesale Price				
None	438.07	277.39	126.4	68.27
At most 1	311.67	232.49	79.39	62.42
At most 2	232.28	192.84	73.67	57
At most 3	158.61	157.11	50.88	51.07
At most 4	107.73	124.25	34.12	44.91
At most 5	73.61	90.39	25.9	39.43

At most 6	47.71	70.6	17.71	33.32
At most 7	30	48.28	14.84	27.14
At most 8	15.16	31.52	8.71	21.07
At most 9	6.45	17.95	6.34	14.9
At most 10	0.11	8.18	0.11	8.18

Table 4.Market-wise cointegration between wholesale and retail prices of wheat

No. of cointegrating equations	Eigen Value	Test Statistics (Eigen)	5% Critical Value	Test Statistics (Trace)	5% Critical Value
			Delhi		
None	0.0054	22.43	14.90	24.85	17.95
At most 1	0.0499	2.41	8.18	2.41	8.18
			Ahmedabad		
None	0.0061	43.77	14.90	46.48	17.95
At most 1	0.0951	2.71	8.18	2.71	8.18
			Amritsar		
None	0.0023	9.54	14.90	10.58	17.95
At most 1	0.0215	1.04	8.18	1.04	8.18
			Bengaluru		
None	0.0016	8.75	14.90	9.47	17.95
At most 1	0.0197	0.72	8.18	0.72	8.18
			Bhopal		
None	0.0030	42.07	14.90	43.40	17.95
At most 1	0.0915	1.33	8.18	1.33	8.18
			Bhubaneswar		
None	0.0025	14.63	14.90	15.73	17.95
At most 1	0.0328	1.10	8.18	1.10	8.18
			Chennai		
None	0.0070	25.69	14.90	28.77	17.95
At most 1	0.0569	3.09	8.18	3.09	8.18
			Dehradun		
None	0.0026	13.67	14.90	14.84	17.95
At most 1	0.0307	1.16	8.18	1.16	8.18
			Hyderabad		
None	0.0089	37.59	14.90	41.53	17.95
At most 1	0.0822	4.00	8.18	4.00	8.18
			Jaipur		
None	0.0055	58.65	14.90	61.09	17.95

At most 1	0.1253	2.44	8.18	2.44	8.18
			Jammu		
None	0.0064	134.00	14.90	136.80	17.95
At most 1	0.2634	2.84	8.18	2.84	8.18
			Lucknow		
None	0.0068	52.58	14.90	55.61	17.95
At most 1	0.1131	3.03	8.18	3.03	8.18
			Ludhiana		
None	0.0015	31.19	14.90	31.88	17.95
At most 1	0.0687	0.69	8.18	0.69	8.18
			Mumbai		
None	0.0049	33.22	14.90	35.40	17.95
At most 1	0.0730	2.18	8.18	2.18	8.18
			Patna		
None	0.0061	21.00	14.90	23.67	17.95
At most 1	0.0467	2.69	8.18	2.69	8.18
			Thiruvananthapuram		
None	0.0101	52.46	14.90	56.95	17.95
At most 1	0.1128	4.49	8.18	4.49	8.18

Source: Authors' estimation

Before investigating the presence of asymmetric cointegration, presence of nonlinearity is tested using BDS test (Brock et al., 1996). The result of BDS test is reported in table 5. The result indicates that all the series are nonlinear in nature. After assuring cointegration among wholesale and retail price of wheat, test of presence of asymmetric cointegration was investigated by means of MTAR model as described in section 2.3. The results of testing asymmetric cointegration is presented in table 6. In Table 6, Phi determines whether retail and wholesale prices are cointegrated or not and APT (Asymmetric Price Transmission) checks whether price transmission between individual markets of retail and wholesale price is of symmetric or asymmetric nature. MTAR model revealed that Delhi, Ahmedabad, Bhopal, Chennai, Hyderabad, Jaipur, Jammu, Lucknow, Ludhiana, Maximum, Minimum and Modal series have the property of APT.

Table 5. BDS test for testing nonlinearity in each of the price series

Markets		**Dimension**	**epsilon (1)**	**epsilon (2)**	**epsilon (3)**	**epsilon(4)**
Ahmedabad_Retail	:	2	600.67	173.78	117.59	70.00
	:	3	1129.23	215.99	133.03	70.30
Ahmedabad_Wholesale	:	2	2173.76	319.87	108.27	72.50
	:	3	3950.85	431.49	119.93	72.39
Amritsar_Retail	:	2	93.81	117.40	91.05	69.29

	:	3	149.09	160.84	102.21	69.63
Amritsar_Wholesale	:	2	180.06	136.23	88.66	73.80
	:	3	329.51	181.74	96.50	71.81
Bengaluru_Retail	:	2	292.59	323.93	131.92	59.34
	:	3	522.18	439.46	147.52	57.72
Bengaluru_Wholesale	:	2	244.40	1255.52	181.84	72.96
	:	3	365.17	1663.65	217.31	73.67
Bhopal_Retail	:	2	137.42	165.38	101.25	62.23
	:	3	222.07	220.16	111.85	61.05
Bhopal_Wholesale	:	2	209.93	180.14	101.56	64.07
	:	3	421.36	247.94	111.55	62.80
Bhubaneshwar_Retail	:	2	166.81	84.49	74.55	61.24
	:	3	277.31	100.98	81.61	62.74
Bhubaneshwar_Wholesale	:	2	36.89	51.99	45.93	35.62
	:	3	47.80	63.11	50.41	35.26
Chennai_Retail	:	2	181.38	187.00	103.10	73.61
	:	3	295.91	241.48	116.06	74.61
Chennai_Wholesale	:	2	100.65	85.42	63.95	53.87
	:	3	156.00	103.09	67.05	51.98
Dehradun_Retail	:	2	669.71	166.61	107.52	73.71
	:	3	1230.74	210.35	121.92	72.53
Dehradun_Wholesale	:	2	539.88	199.04	90.49	75.48
	:	3	1033.83	276.57	96.11	73.98
Delhi_Retail	:	2	88.11	91.31	72.94	61.73
	:	3	135.25	115.87	80.75	61.20
Delhi_Wholesale	:	2	113.22	92.92	83.71	70.42
	:	3	177.46	118.92	95.89	70.09
Hyderabad_Retail	:	2	72.33	65.15	57.72	50.04
	:	3	118.83	80.06	62.26	49.80
Hyderabad_Wholesale	:	2	103.98	69.05	64.85	52.94
	:	3	185.87	83.48	71.01	53.02
Jaipur_Retail	:	2	158.78	97.03	65.89	52.97
	:	3	277.57	125.27	71.73	50.48
Jaipur_Wholesale	:	2	183.13	102.85	72.85	64.64
	:	3	315.12	133.01	79.83	63.58
Jammu_Retail	:	2	111.30	129.08	68.34	66.87
	:	3	194.38	173.25	76.45	63.79
Jammu_Wholesale	:	2	109.77	99.42	68.60	58.83
	:	3	191.54	129.57	74.86	56.69
Lucknow_Retail	:	2	125.41	117.73	79.20	67.49
	:	3	194.25	143.68	84.73	65.61
Lucknow_Wholesale	:	2	390.74	164.18	92.79	74.23
	:	3	741.61	216.04	100.56	73.06
Ludhiana_Retail	:	2	262.12	937.45	179.97	84.53

	:	3	397.97	1233.07	214.37	88.56
Ludhiana_Wholesale	:	2	247.35	683.00	211.98	81.38
	:	3	360.43	901.09	260.63	85.69
Maximum_Price_Retail	:	2	493.20	175.26	96.65	71.00
	:	3	939.21	234.04	105.91	70.88
Maximum_Price_Wholesale	:	2	677.41	189.46	92.78	70.06
	:	3	1324.58	253.50	103.21	71.68
Minimum_Price_Retail	:	2	79.60	112.47	83.43	57.51
	:	3	141.35	146.67	92.67	57.06
Minimum_Price_Wholesale	:	2	80.12	76.01	60.34	44.10
	:	3	121.74	90.87	65.72	43.64
Modal_Price_Retail	:	2	118.78	118.55	66.71	47.41
	:	3	201.10	155.97	72.70	48.17
Modal_Price_Wholesale	:	2	143.71	60.58	42.94	36.59
	:	3	236.28	73.09	45.92	36.09
Mumbai_Retail	:	2	294.76	165.60	94.41	75.08
	:	3	547.07	217.46	102.39	74.63
Mumbai_Wholesale	:	2	129.13	132.31	89.78	66.80
	:	3	205.21	166.97	100.58	67.68
Patna_Retail	:	2	388.63	277.51	91.02	74.61
	:	3	733.61	396.26	98.42	74.56
Patna_Wholesale	:	2	199.47	191.24	84.96	61.60
	:	3	357.21	254.22	94.33	60.17
Thiruvananthapuram_Retail	:	2	203.09	111.99	81.55	64.48
	:	3	349.40	141.54	88.10	63.15
Thiruvananthapuram_Wholesale	:	2	224.43	227.39	102.92	67.89
	:	3	387.76	290.76	113.16	66.63

Note: All values of epsilons are statistically significant at 1% level of significance

Table 6. Asymmetric cointegration

Markets	MTAR			
	PHI		APT	
	F Value	Pr. Value	F Value	Pr. Value
Ahmedabad	14.60	<0.05	3.55	0.05
Amritsar	6.03	<0.05	2.43	0.11
Bengaluru	3.48	<0.05	3.05	0.08
Bhopal	26.91	<0.05	4.88	<0.05
Bhubaneswar	6.38	<0.05	0.02	0.88
Chennai	11.05	<0.05	12.74	<0.05
Dehradun	4.61	<0.05	1.17	0.27
Delhi	13.33	<0.05	4.44	<0.05
Hyderabad	63.31	<0.05	96.47	<0.05
Jaipur	42.80	<0.05	47.64	<0.05
Jammu	49.47	<0.05	38.20	<0.05
Lucknow	40.52	<0.05	32.62	<0.05
Ludhiana	41.19	<0.05	54.91	<0.05
Mumbai	7.80	<0.05	1.93	0.16
Patna	43.31	<0.05	51.02	<0.05
Thiruvananthapuram	17.38	<0.05	1.13	0.28
Maximum	31.52	<0.05	23.55	<0.05
Minimum	35.72	<0.05	41.16	<0.05
Modal	20.84	<0.05	4.82	<0.05

PHI is testing presence of cointegration while APT stands for testing presence of asymmetric cointegration

The acceptance of cointegration between two series implies that there exists a long-run relationship between them and this means that an error-correction model (ECM) is applicable, which combines the long-run relationship with the short-run dynamics of the model. Accordingly, Vector Error correction model (VECM) was applied in order to find out the speed of adjustment and long run coefficient among wholesale and retail price of wheat in individual market. For fitting of VECM model, first an unrestricted VAR model was fitted and optimum lag was determined based on Akaike information criterion (AIC), Bayesian information criteria (BIC). The results of VECM is demonstrated in table 7. In the markets Delhi, Bhopal, Mumbai, Jaipur, Patna and Bhubaneswar, the optimum number of lags for wholesale and retail price is one lag; whereas in all the other markets, the optimum number of lags for wholesale and retail price is found to be second lags. It is to be noted that the most of the values of Error correction term (ECT) term which are significant are found to be negative. The value of ECT signifies the speed of adjustment at which the market approaches to the equilibrium once it deviates. The speed of adjustment (per week) is found to be highest in Jaipur (18.8%) followed by Bhopal (17.4%), Lucknow (13%) and Hyderabad (13%) in the retail price. But in case of wholesale price, Jammu market has the highest speed of adjustment (13.2%) towards equilibrium.

Table 7. Results of VECM model

Market			ECT	Intercept	Retail Lag 1	Wholesale lag 1	Retail Lag 2	Wholesale lag 2
Ahmedabad	Retail	:	-0.096	0.059	0.305	0.120	-0.018	-0.173
			(0.024)***	(0.014)***	(0.054)***	(0.069)	(0.055)	(0.070)*
	Wholesale	:	0.057	-0.034	0.041	0.284	-0.116	-0.118
			(0.018)**	(0.011)**	(0.041)	(0.053)***	(0.042)**	(0.054)*
Amritsar	Retail	:	-0.020	-0.002	0.392	-0.008	-0.147	-0.004
			(0.012)	(0.002)	(0.059)***	(0.077)	(0.060)*	(0.028)
	Wholesale	:	0.007	0.001	0.044	0.400	-0.051	-0.370
			(0.009)	(0.001)	(0.045)	(0.059)***	(0.046)	(0.044)***
Bengaluru	Retail	:	-0.008	-0.008	0.133	0.271	-0.256	0.055
			(0.015)	(0.018)	(0.063)*	(0.067)***	(0.060)***	(0.065)
	Wholesale	:	0.016	0.020	0.095	0.211	0.021	-0.198
			(0.015)	(0.017)	(0.060)	(0.064)**	(0.057)	(0.062)**
Bhopal	Retail	:	-0.174	-0.263	0.064	0.465		
			(0.029)***	(0.045)***	(0.058)	(0.086)***		
	Wholesale	:	-0.037	-0.056	-0.205	0.529		
			(0.022)	(0.034)	(0.044)***	(0.065)***		
Bhubaneswar	Retail	:	-0.003	-0.021	0.211	0.381		
			(0.007)	(0.051)	(0.047)***	(0.049)***		
	Wholesale	:	0.025	0.173	-0.043	0.424		
			(0.007)**	(0.052)**	(0.048)	(0.051)***		
Chennai	Retail	:	-0.009	-0.083	0.375	0.025	-0.242	0.005
			(0.005)	(0.045)	(0.048)***	(0.033)	(0.048)***	(0.034)
	Wholesale	:	0.022	0.186	0.020	0.404	0.014	-0.259
			(0.007)**	(0.064)**	(0.068)	(0.047)***	(0.068)	(0.049)***
Dehradun	Retail	:	-0.022	-0.027	0.295	0.292	-0.182	0.037
			(0.016)	(0.020)	(0.059)***	(0.093)**	(0.060)**	(0.094)
	Wholesale	:	0.011	0.014	0.025	0.436	0.041	-0.148
			(0.010)	(0.012)	(0.038)	(0.060)***	(0.039)	(0.060)*
Delhi	Retail	:	-0.058	0.091	0.340	0.162		
			(0.016)***	(0.026)***	(0.048)***	(0.045)***		
	Wholesale	:	0.027	-0.042	0.133	0.251		
			(0.019)	(0.029)	(0.055)*	(0.052)***		

Hyderabad	Retail	:	-0.130	0.152	0.617	-0.198	-0.161	0.055
			(0.032)***	(0.037)***	(0.070)***	(0.060)**	(0.073)*	(0.060)
	Wholesale	:	-0.026	0.030	0.762	-0.442	0.075	-0.188
			(0.038)	(0.045)	(0.083)***	(0.072)***	(0.087)	(0.072)**
Jaipur	Retail	:	-0.188	0.131	0.343	0.067		
			(0.026)***	(0.018)***	(0.049)***	(0.091)		
	Wholesale	:	0.005	-0.003	0.044	0.316		
			(0.014)	(0.009)	(0.026)	(0.049)***		
Jammu	Retail	:	-0.075	0.023	0.280	0.011	-0.056	-0.004
			(0.022)***	(0.006)***	(0.048)***	(0.026)	(0.049)	(0.028)
	Wholesale	:	-0.132	-0.069	0.022	0.435	-0.016	-0.370
			(0.035)***	(0.010)***	(0.075)	(0.041)***	(0.076)	(0.044)***
Lucknow	Retail	:	-0.130	0.103	0.249	0.265	-0.320	0.122
			(0.034)***	(0.026)***	(0.055)***	(0.080)**	(0.056)***	(0.081)
	Wholesale	:	0.031	-0.024	0.032	0.415	-0.152	-0.001
			(0.024)	(0.019)	(0.040)	(0.057)***	(0.040)***	(0.058)
Ludhiana	Retail	:	-0.066	0.045	0.165	-0.023	-0.123	-0.088
			(0.028)*	(0.018)*	(0.061)**	(0.068)	(0.061)*	(0.068)
	Wholesale	:	0.047	-0.030	-0.002	-0.030	-0.037	-0.230
			(0.024)	(0.016)	(0.054)	(0.060)	(0.054)	(0.060)***
Mumbai	Retail	:	-0.064	-0.025	0.269	-0.032		
			(0.016)***	(0.006)***	(0.047)***	(0.065)		
	Wholesale	:	0.043	0.017	0.001	0.254		
			(0.012)***	(0.004)***	(0.034)	(0.046)***		
Patna	Retail	:	-0.021	-0.017	0.215	0.027		
			(0.014)	(0.012)	(0.049)***	(0.028)		
	Wholesale	:	0.089	0.078	0.455	-0.170		
			(0.024)***	(0.021)***	(0.085)***	(0.049)***		
Thiruvananthapuram	Retail	:	-0.054	0.030	0.146	0.002	-0.211	0.021
			(0.030)	(0.017)	(0.061)*	(0.055)	(0.062)***	(0.056)
	Wholesale	:	0.109	-0.060	-0.049	0.296	-0.062	-0.147
			(0.033)**	(0.019)**	(0.067)	(0.060)***	(0.068)	(0.062)*

In this study, we employed the Sup-LM test developed by Hansen and Seo (2002) to test the null hypothesis of linear cointegration against the Two-Regime Threshold Cointegration. The result of the Sup-LM is reported in Table 8. It can be seen from table 8 that in the markets Delhi, Ahmedabad, Bhopal, Hyderabad, Jammu, Mumbai, Patna, Thiruvananthapuram, All India Minimum and Modal price the mechanism of the price transmission is not of linear rather it is of threshold type. Accordingly, to accommodate the asymmetricity and nonlinearity in price transmission as clearly evidenced from table 5 and 6, threshold VECM was fitted with two regimes and the results of same is depicted in table 9. The percentage of data points fall in the first regime and second regime is mentioned in last but one column of Table 9 and the threshold value as found out in individual market to divide the data in two regime is mentioned in the last column of Table 9. The approach followed to find out the optimum lag in TVECM model is same as that of VECM model. The optimum value as how it is obtained through grid search is depicted in Fig. 2. To save the space, the optimum value of threshold parameter and the cointegration parameter obtained through gird search only for selected markets namely Ahmadebad, Amritsar and Bhubaneswar are depicted in Fig. 2; for other markets the plots are available with the first author on request. In the present investigation, in almost all the markets there is significant difference in percent of observations fall into first and second regime except for Bhubaneswar and Chennai. In Bhubaneswar, 46.30 % of observations fall in first regime while 53.70 % of observations fall in second regime. Similarly, in Chennai, 45.50% of observations fall in first regime and 54.50 % of observations fall in second regime. According to Hansen and Seo (2002) we call it "Typical" regime, where more than half the observations belong to this regime and the regime which includes less percent of the observations is known as the "Extreme" regime. Therefore, the short-run dynamic effects of the retail and wholesale prices show significant differences between typical and extreme regimes.

Table 8: Result of the Sup-LM Test.

Markets	Test statistic	p value
Ahmedabad	17.27	0.03
Amritsar	10.88	0.77
Bengaluru	11.30	0.49
Bhopal	21.54	0.01
Bhubaneswar	14.07	0.39
Chennai	10.70	0.56
Dehradun	13.72	0.35
Delhi	22.66	0.01
Hyderabad	18.90	0.02
Jaipur	15.69	0.29
Jammu	22.91	0.01
Lucknow	9.36	0.88
Ludhiana	11.55	0.75
Mumbai	17.97	0.03
Patna	19.00	0.02
Thiruvananthapuram	19.17	0.02
Maximum	11.29	0.81
Minimum	25.77	0.01
Modal	35.03	0.001

Table 9. Results of TVECM model

Market		ECT	Intercept	Retail Lag 1	Wholesale lag 1	Retail Lag 2	Wholesale lag 2	Regime (I & II)	Threshold
Delhi	Retail	-0.036 (0.0195)*	8.9e-05 (0.8909)	0.299 (3.3e-09)***	0.198 (2.5e-05)***			92.70% (I)	0.099
	Wholesale	0.0200 (0.2432)	1.6e-05 (0.9828)	0.0665 (0.2299)	0.2803 (1.1e-07)***				
	Retail	-0.4043 (0.0178)*	0.0439 (0.0202)*	0.6390 (0.0004)***	-0.2393 (0.2640)			7.30% (II)	
	Wholesale	-0.3346 (0.0781).	0.0418 (0.0468)*	1.0437 (3.4e-07)***	0.0274 (0.9085)				
Jammu	Retail	-0.1134 (0.4216)	0.0010 (0.8646)	0.0545 (0.8365)	-0.0909 (0.3799)	0.1092 (0.7234)	-0.0553 (0.7645)	5.50% (I)	-0.028
	Wholesale	0.3565 (0.0334)*	0.0166 (0.0151)*	0.4780 (0.1274)	0.7458 (2.6e-09)***	-2.363 (2.7e-10)***	-0.6968 (0.0015)**		
	Retail	-0.1106 (0.0003)***	0.0030 (0.0182)*	0.2976 (4.3e-09)***	0.0666 (0.0514).	-0.0626 (0.2096)	-0.0125 (0.7092)	94.50% (II)	
	Wholesale	0.0983 (0.0069)**	-0.0012 (0.4188)	0.0723 (0.2197)	0.1084 (0.0075)**	0.1570 (0.0081)**	-0.0461 (0.2444)		
Amritsar	Retail	0.2037 (0.0389)*	0.0251 (0.0161)*	0.2255 (0.0204)*	0.3599 (0.0156)*	-0.1075 (0.2946)	0.0823 (0.6058)	28.60% (I)	-0.07
	Wholesale	0.2039 (0.0072)**	0.0213 (0.0079)**	-0.1056 (0.1564)	0.6543 (1.7e-08)***	-0.0820 (0.2977)	-0.0241 (0.8440)		
	Retail	-4.5e-05 (0.9980)	-0.0006 (0.5071)	0.4767 (6.0e-10)***	-0.1469 (0.1026)	-0.1414 (0.0601).	0.0039 (0.9648)	71.40% (II)	
	Wholesale	0.0070 (0.6158)	0.0006 (0.4225)	0.1295 (0.0255)*	0.2948 (2.4e-05)***	-0.0396 (0.4922)	-0.2175 (0.0015)**		
Ludhiana	Retail	-0.1763 (0.0013)**	0.0031 (0.0066)**	0.2147 (0.0037)**	-0.2216 (0.0126)*	-0.1579 (0.0329)*	-0.0994 (0.2605)	95% (I)	0.109
	Wholesale	0.0195 (0.6768)	0.0007 (0.4557)	0.0853 (0.1779)	-0.1756 (0.0214)*	-0.1464 (0.0214)*	-0.0572 (0.4512)		
	Retail	-0.2705 (0.0413)*	0.0380 (0.0838).	0.4537 (0.0021)**	0.2825 (0.0096)**	0.0607 (0.6523)		5% (II)	

	Wholesale	0.6416 (3.0e-08)***	-0.1040 (6.2e-08)***	0.3102 (0.0144)*	0.3716 (8.0e-05)***	-0.2152 (0.0637).			
Lucknow	Retail	-0.0176 (0.5702)	0.0011 (0.2898)	0.2288 (0.0001)***	0.2553 (0.0012)**	-0.1486 (0.0155)*	0.0029 (0.9705)	94.50%(I)	0.051
	Wholesale	0.0464 (0.0580)	0.0009 (0.2462)	0.0597 (0.1955)	0.4002 (2.3e-10)***	-0.1745 (0.0003)***	0.0145 (0.8158)		
	Retail	-0.7688 (1.6e-07)***	0.0572 (1.2e-10)***	0.4610 (0.0046)**	0.8234 (0.0125)*	-0.5288 (0.0006)***	-0.2052 (0.6143)	5.50% (II)	
	Wholesale	-0.0364 (0.7483)	0.0041 (0.5502)	0.0167 (0.8959)	0.2941 (0.2552)	-0.0875 (0.4675)	0.0451 (0.8880)		
Dehradun	Retail	-0.0479 (0.0092)**	0.0002 (0.7647)	0.2444 (0.0001)***	0.3040 (0.0010)***			83.60%(I)	0.067
	Wholesale	0.0017 (0.8850)	7.5e-05 (0.8900)	0.0268 (0.5191)	0.4072 (4e-11)***				
	Retail	-0.6545 (7.7e-05)***	0.0628 (5.6e-05)***	0.4697 (0.0032)**	-0.0089 (0.9801)			16.40% (II)	
	Wholesale	-0.1409 (0.1908)	0.0151 (0.1365)	0.1231 (0.2375)	0.1588 (0.4997)				
Ahmedabad	Retail	0.0046 (0.8777)	0.0010 (0.4893)	0.2923 (4.6e-05)***	0.1318 (0.0671).	-0.0785 (0.1722)	-0.1557 (0.0216)*	90.40%(I)	0.040
	Wholesale	0.0827 (0.0010)**	0.0030 (0.0161)*	0.0927 (0.1211)	0.2508 (3.9e-05)***	-0.1104 (0.0225)*	-0.1327 (0.0198)*		
	Retail	-0.5347 (1.2e-16)***	0.0369 (3.6e-09)***	0.3837 (1.2e-07)***	-40.6699 (3.0e-06)***	0.4828 (5.0e-05)***		9.60% (II)	
	Wholesale	0.0458 (0.3788)	0.0011(0.8345)	-0.0061 (0.9190)	-0.1473 (0.9837)	-0.1365 (0.1686)			
Bhopal	Retail	-0.0548 (0.0292)*	0.0016 (0.0273)*	0.0814 (0.1657)	0.2440 (0.0063)**			87.70%(I)	0.056
	Wholesale	-0.0141 (0.4900)	0.0009 (0.1546)	-0.1451 (0.0026)**	0.4204 (1.3e-08)***				
	Retail	-0.5232 (9.4e-07)***	0.0339 (4.4e-06)***	0.4956 (0.0021)**	0.6266 (0.0032)**			12.30% (II)	
	Wholesale	-0.0434 (0.6134)	0.0024 (0.6899)	-0.4598 (0.0005)***	0.8780 (5.3e-07)***				

Mumbai	Retail	-0.3146 (3.0e-13)***	-0.0529 (1.9e-07)***	0.4002 (1.2e-11)***	0.1931 (0.5111)			5% (I)	-0.106
	Wholesale	-0.0181 (0.5632)	-0.0099 (0.1847)	-0.0181 (0.6733)	0.0862 (0.6946)				
	Retail	-0.0137 (0.5389)	0.0007 (0.6147)	0.1802 (0.0221)*	-0.0007 (0.9915)			95% (II)	
	Wholesale	0.0627 (0.0002)***	0.0003 (0.7990)	0.0822 (0.1622)	0.2463 (8.1e-07)***				
Jaipur	Retail	-0.0307 (0.4728)	0.0007 (0.6684)	0.2233 (2.5e-05)***	0.1302 (0.1601)	-0.0342 (0.5183)	0.0047 (0.9597)	90.80%(I)	0.030
	Wholesale	0.0551 (0.0295)*	0.0017 (0.0737).	0.0507 (0.1023)	0.2890 (2.0e-07)***	0.0035 (0.9100)	0.0547 (0.3170)		
	Retail	-0.5521 (4.7e-23)***	0.0251 (1.2e-06)***	0.7200 (8.0e-15)***	0.6652 (0.0526).	0.4012 (0.0001)***	-0.5521 (4.7e-23)***	9.20% (II)	
	Wholesale	-0.0433 (0.1647)	0.0049 (0.1017)	0.0334 (0.5268)	0.2375 (0.2408)	0.0381 (0.5364)	-0.0433 (0.1647)		
Patna	Retail	0.1809 (0.0163)*	0.0143 (0.0333)*	-0.9078 (2.3e-06)***	0.0036 (0.9346)			7.10% (I)	-0.0655
	Wholesale	1.1181 (8.2e-19)***	0.0805 (4.4e-13)***	-0.6948 (0.0229)*	0.1074 (0.1237)				
	Retail	-0.0196 (0.2291)	0.0005 (0.5434)	0.2711 (7.5e-05)***	0.0569 (0.3461)			92.90% (II)	
	Wholesale	0.0087 (0.7381)	0.0018 (0.1887)	-0.0550 (0.6132)	0.3481 (0.0004)***				
Bhubaneswar	Retail	-0.0631 (0.0030)**	-0.0049 (0.0105)*	0.2243 (9.1e-06)***	0.0481 (0.4161)			46.30%(I)	-0.062
	Wholesale	0.0237 (0.3097)	0.0013 (0.5245)	-0.1123 (0.0427)*	0.3461 (1.8e-07)***				
	Retail	-0.0377 (0.0575).	0.0015 (0.0747).	0.2545 (0.0051)**	0.7920 (8.8e-24)***			53.70% (II)	
	Wholesale	-0.0903 (4.4e-05)***	0.0037 (7.2e-05)***	0.0467 (0.6407)	0.5280 (3.2e-10)***				
Bengaluru	Retail	-0.2817 (0.0091)**	-0.0178 (0.0043)**	0.0642 (0.5604)	0.1699 (0.1101)	-0.4547 (4.9e-05)***	0.5230 (3.6e-05)***	6.40% (I)	-0.026

	Wholesale	-0.1203 (0.2587)	-0.0153 (0.0130)*	0.1033 (0.3433)	0.1443 (0.1697)	-0.0745 (0.4971)	-0.0850 (0.4928)		
	Retail	-0.0044 (0.7962)	0.0009 (0.3218)	0.1125 (0.1992)	0.2526 (0.0072)**	0.0340 (0.6587)	-0.2702 (0.0008)***	93.60% (II)	
	Wholesale	-0.0064 (0.7043)	0.0014 (0.1102)	0.0215 (0.8038)	0.2865 (0.0021)**	0.1357 (0.0753).	-0.2901 (0.0003)***		
Thiruvananthap uram	Retail	-0.1043 (0.0053)**	-0.0007 (0.6179)	0.1492 (0.0111)*	-0.0431 (0.4254)	-0.2134 (0.0005)***	0.0331 (0.5568)	94.70%(I)	0.079
	Wholesale	0.0256 (0.5076)	-0.0002 (0.8893)	0.0131 (0.8295)	0.1637 (0.0037)**	-0.0271 (0.6674)	-0.1605 (0.0063)**		
	Retail	0.1290 (0.1256)	-0.0269 (0.0535).	3.4693 (1.4e-08)***	-0.1328 (0.5317)	-1.4247 (0.0002)***	0.0092 (0.9596)	5.30% (II)	
	Wholesale	0.1163 (0.1834)	0.0248 (0.0856).	2.9207 (3.6e-06)***	1.2404 (3.2e-08)***	-1.5578 (6.8e-05)***	0.0445 (0.8139)		
Chennai	Retail	-0.0277 (0.2316)	-0.0019 (0.5433)	0.3409 (4.0e-05)***	0.1260 (0.0446)*	-0.3480 (4.2e-05)***	0.1478 (0.0383)*	45.50%(I)	-0.035
	Wholesale	0.0225 (0.4881)	0.0031 (0.4766)	0.1909 (0.0985).	0.4814 (7.3e-08)***	-0.1462 (0.2161)	-0.1297 (0.1948)		
	Retail	-0.0079 (0.5901)	-0.0002 (0.8955)	0.3408 (4.4e-08)***	-0.0260 (0.5160)	-0.2368 (0.0001)***		54.50% (II)	
	Wholesale	0.0603 (0.0036)**	-0.0040 (0.0200)*	-0.1685 (0.0500).	0.3145 (3.9e-08)***	0.0060 (0.9450)			
Hyderabad	Retail	0.3198 (7.1e-07)***	0.0079 (1.7e-07)***	0.5926 (6.5e-05)***	-0.2200 (0.0752).			69.90%(I)	0.0180
	Wholesale	0.3156 (3.3e-05)***	0.0073 (4.0e-05)***	1.4428 (1.4e-15)***	-0.9544 (1.8e-10)***				
	Retail	-0.2546 (0.0001)***	0.0059 (0.0076)**	0.6780 (6.4e-16)***	-0.3188 (1.5e-05)***			30.10% (II)	
	Wholesale	0.1259 (0.1075)	-0.0027 (0.3089)	0.4571 (2.3e-06)***	-0.2769 (0.0014)**				

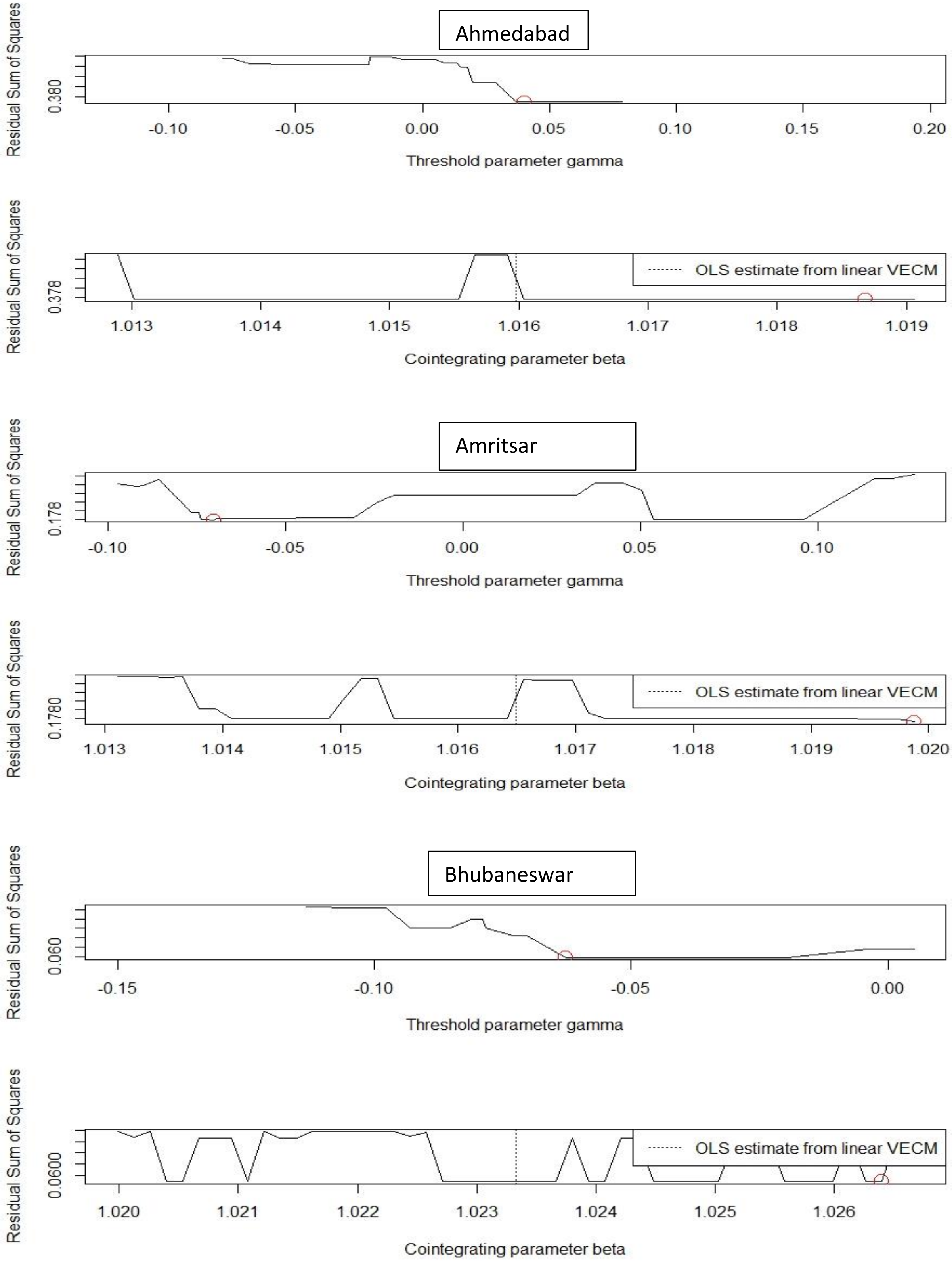
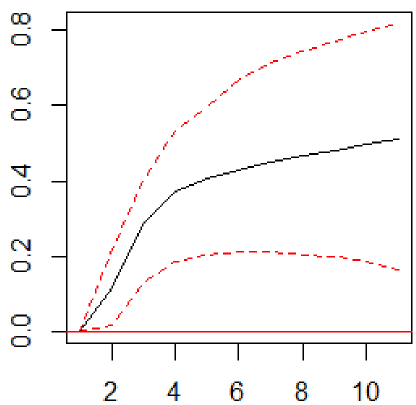
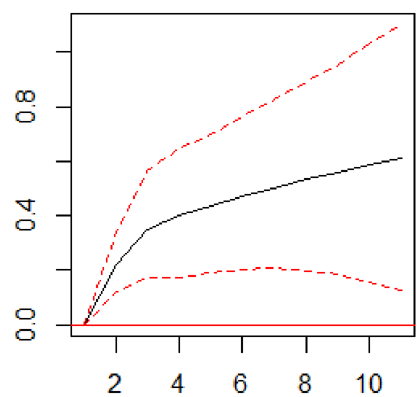


Fig 2. Grid search for finding optimum value of threshold parameter and cointegration parameter in TVECM

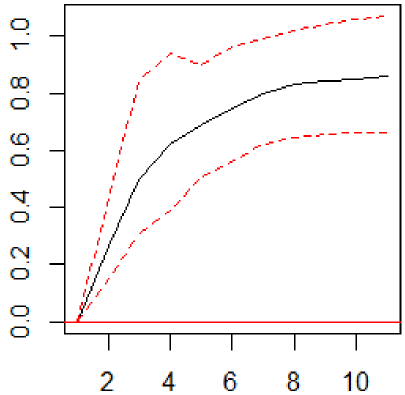
The effect of a positive shock of wholesale (retail) price on retail (wholesale) price is evaluated by performing impulse response analysis, which could be used to show the magnitude and lasting effects. Fig. 3 represents the IRF results with 95% confidence interval for the series under consideration. A perusal of Fig. 3 reveals that in general increase in wholesale price results in increase in retail price with difference in rate of change and also time lag at which both the prices stabilize. To this end, Granger causality is computed among the wholesale and retail prices of different markets in India and the result is reported in table S1. It is found that, in most of the pairs of markets the causality is bi-directional.



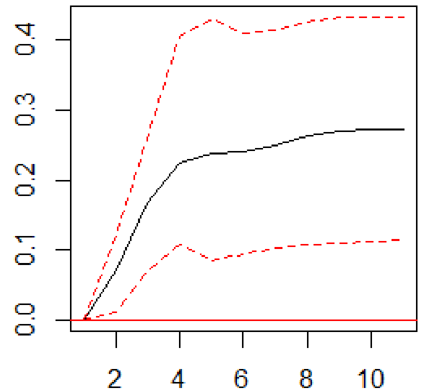
Response from Delhi_Retail to Delhi_Wholesale



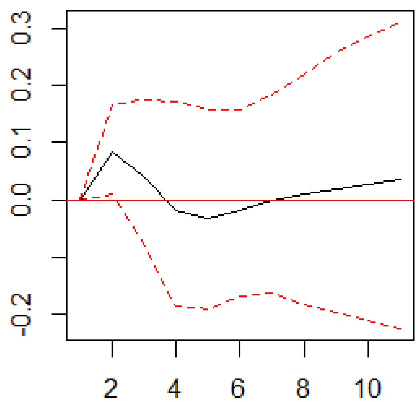
Response from Delhi_Wholesale to Delhi_Retail



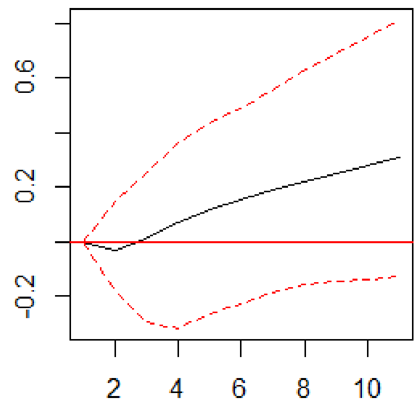
Response from Jammu_Retail to Jammu_Wholesale



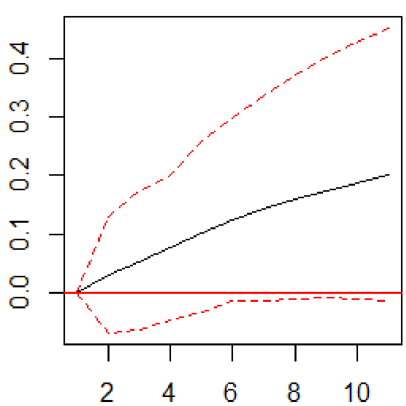
Response from Jammu_Retail to Jammu_Wholesale

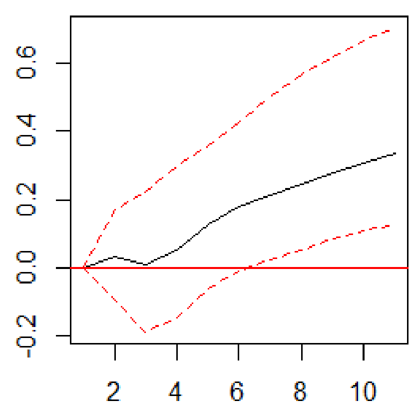


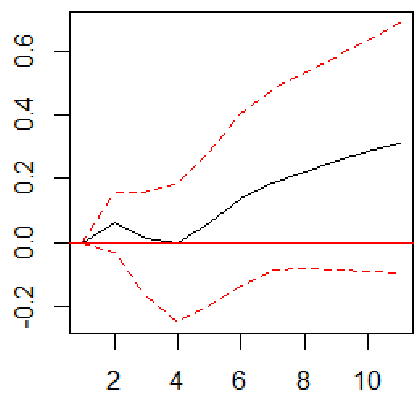
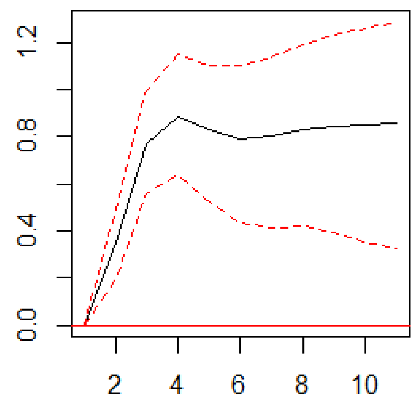
Response from Amritsar_Retail to Amritsar_Wholesale



Response from Amritsar_Retail to Amritsar_Wholesale





Response from Ludhiana_Retail to Ludhiana_Wholesale	Response from Ludhiana_Retail to Ludhiana_Wholesale
	
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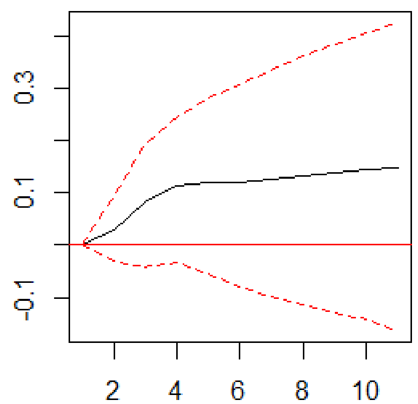
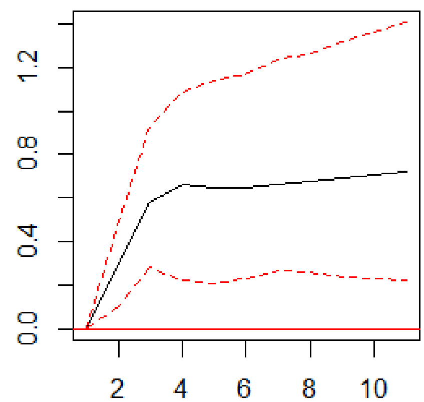
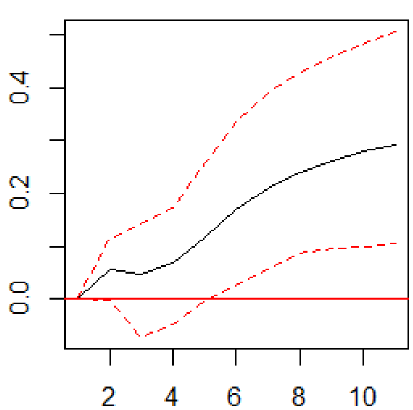
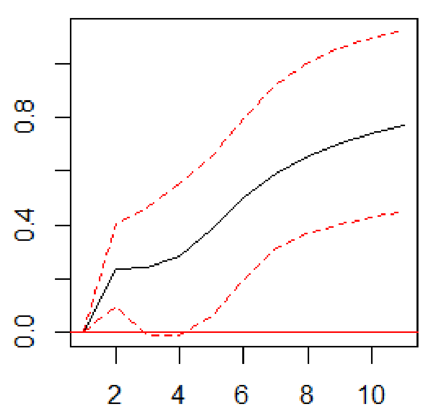
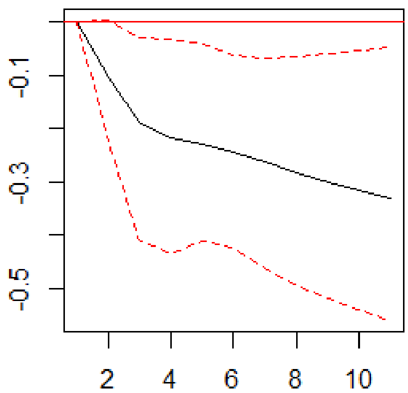
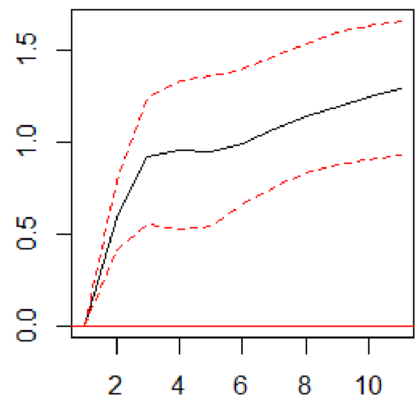
	
Response from Dehradun_Retail to Dehradun_Wholesale	Response from Dehradun_Retail to Dehradun_Wholesale
	

Response from Ahmedabad_Retail to Ahmedabad_Wholesale

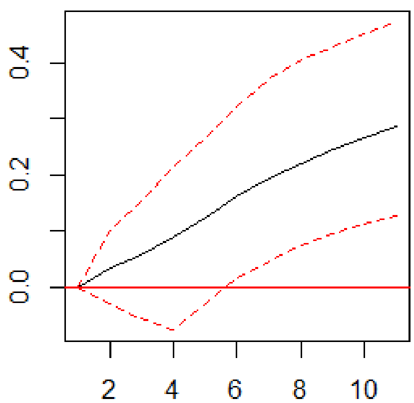
Response from Ahmedabad_Retail to Ahmedabad_Wholesale

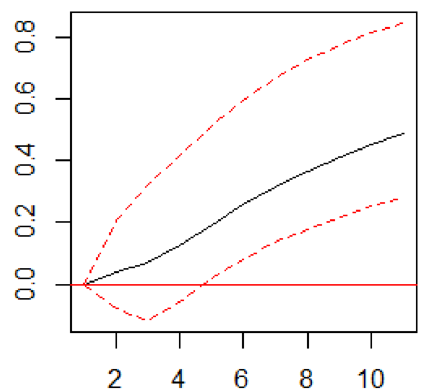




Response from Bhopal_Retail to Bhopal_Wholesale

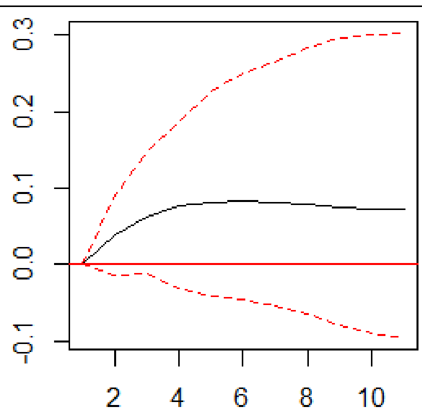
Response from Bhopal_Retail to Bhopal_Wholesale

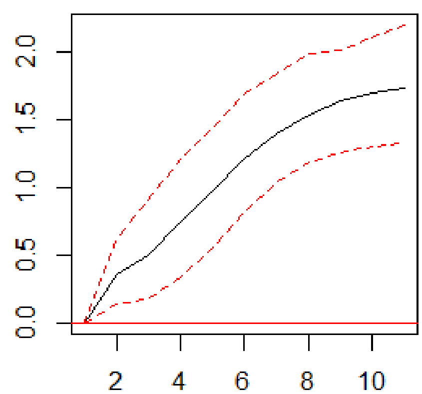




Response from Mumbai_Retail to Mumbai_Wholesale

Response from Mumbai_Retail to Mumbai_Wholesale





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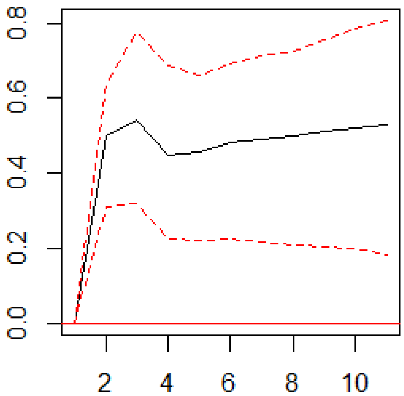
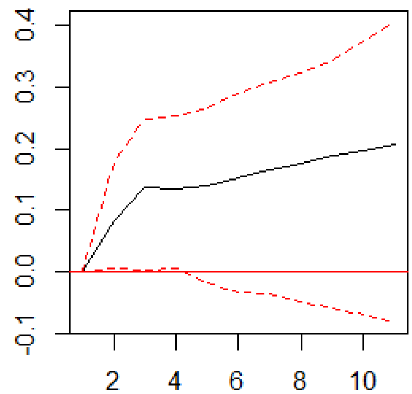
<tr><td>

Response from Patna_Retail to Patna_Wholesale</td><td>

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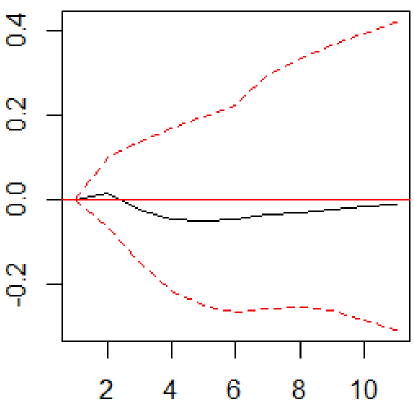
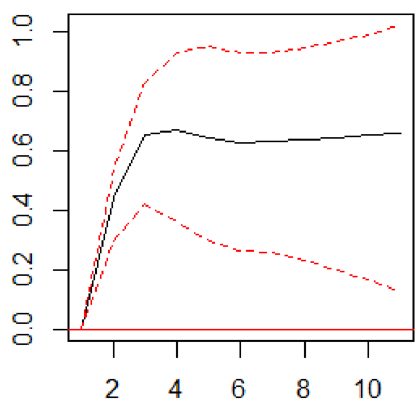
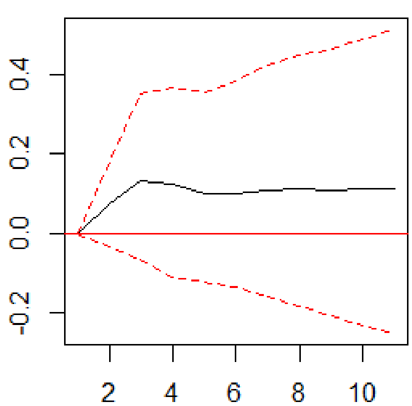
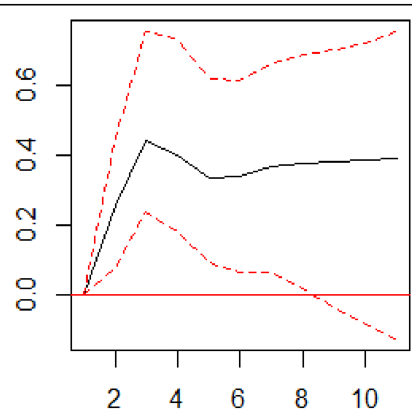
<tr><td>

Response from Bhubaneshwar_Retail to Bhubaneshwar_Wholesale</td><td>

Response from Bhubaneshwar_Retail to Bhubaneshwar_Wholesale</td></tr>
<tr><td>
</td><td>
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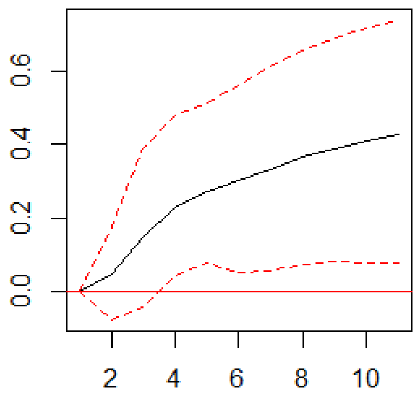
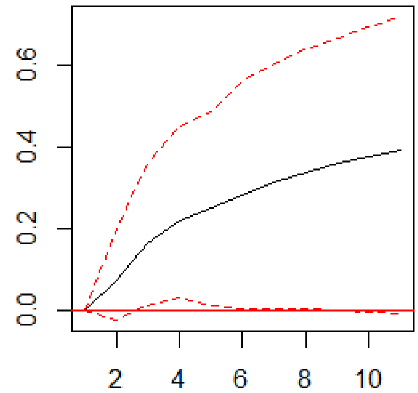
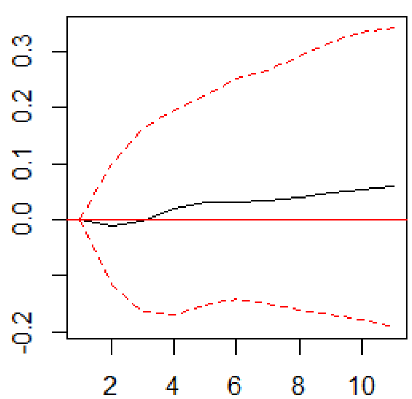
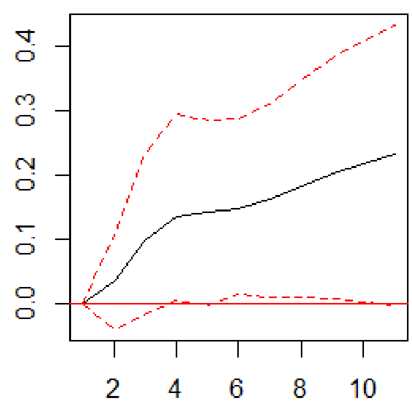
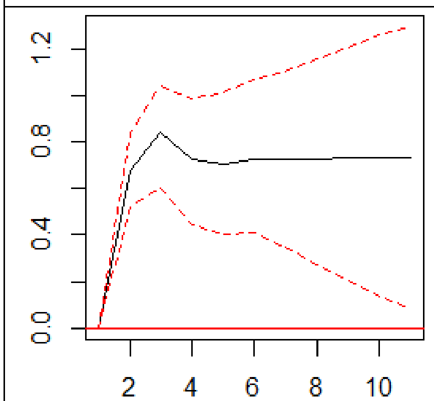
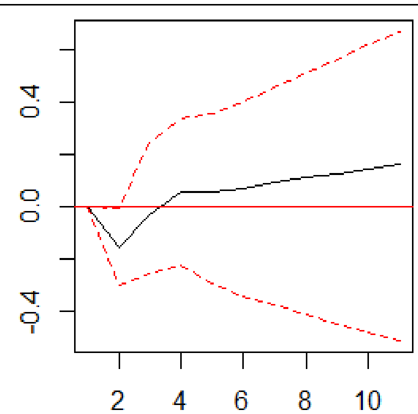
Response from Bengaluru_Retail to Bengaluru_Wholesale	Response from Bengaluru_Retail to Bengaluru_Wholesale
 Response from Thiruvananthapuram_Retail to Thiruvananthapuram_Wholesale	 Response from Thiruvananthapuram_Retail to Thiruvananthapuram_Wholesale
 Response from Chennai_Retail to Chennai_Wholesale	 Response from Chennai_Retail to Chennai_Wholesale
	

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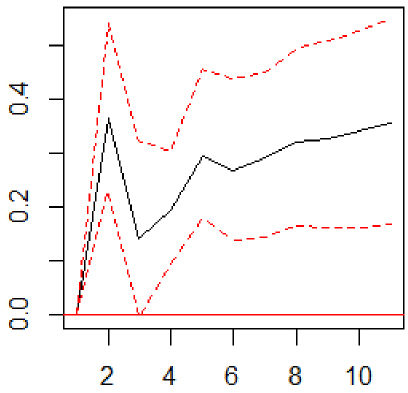

Response from Maximum_Price_Retail to Maximum_Price_Wholesale
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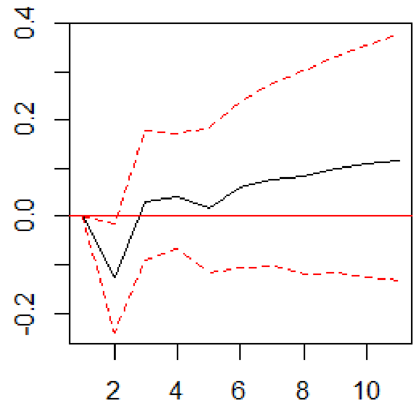

Response from Maximum_Price_Retail to Maximum_Price_Wholesale
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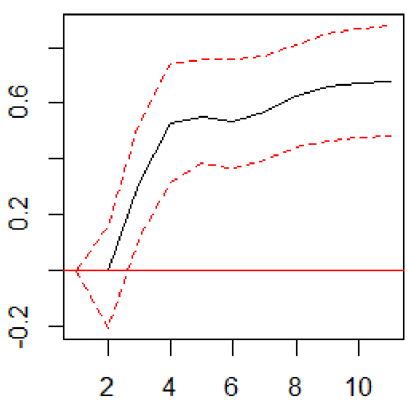

Response from Minimum_Price_Retail to Minimum_Price_Wholesale
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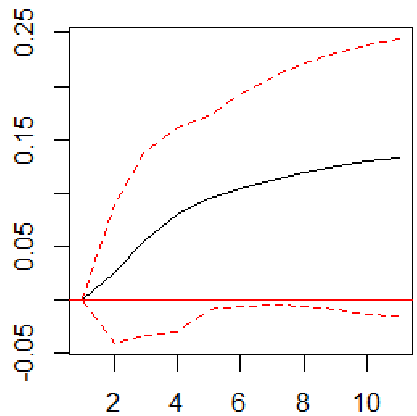

Response from Minimum_Price_Retail to Minimum_Price_Wholesale
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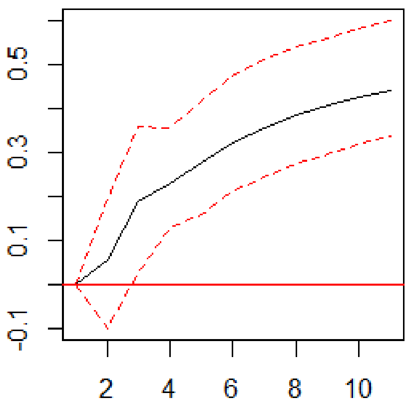

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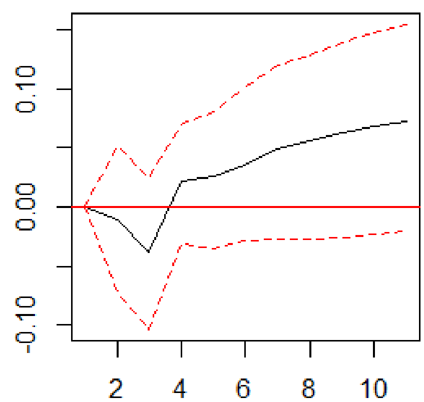

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Response from Modal_Price_Retail to Modal_Price_Wholesale	Response from Modal_Price_Retail to Modal_Price_Wholesale

Fig3. Response of change in wholesale price to retail price and vice-versa

5. Conclusions

In the present study, presence of cointegration was tested by using Johansen's approach. It was revealed that wholesale and retail price of wheat in all the market are cointegrated both horizontally as well as vertically. Asymmetricity in price transmission is investigated by means of Threshold Autoregressive (TAR) and Momentum Threshold Autoregressive (M-TAR) models. The application of MTAR model reveals that most of the markets under consideration are asymmetric in terms of price transmission from wholesale to retail markets. The acceptance of cointegration between two series implies that there exists a long run relationship between them and this means that an error-correction model (ECM) exists which combines the long-run relationship with the short-run dynamics of the model. The results indicate that most of the error correction term (ECT) are statistically significant implying that the system once in disequilibrium tries to come back to the equilibrium state. Moreover, findings pointed out that there are nonlinearities in the studied price adjustment process. To take care of asymmetricity as well as nonlinearity in cointegration and price transmission between wholesale and retail price of wheat, TVECM model was applied. Application of the Two- Regime Threshold Vector Error Correction Model (TVECM) demonstrated that the coefficient of Error Correction Term (ECT) is significant in retail for both the regimes in Delhi; wholesale for both the regime and retail in typical regime for Jammu, retail and wholesale in extreme regime for Amritsar; retail in both the regime but wholesale in extreme regime for Ludhiana; retail in extreme regime in Lucknow; retail in both the regime for Dehradun; wholesale in typical regime and retail in extreme regime for Ahmedabad; retail in both the regime for Bhopal; retail in extreme regime and wholesale in typical regime for Mumbai; wholesale in typical regime and retail in extreme regime for Jaipur; retail and wholesale both in extreme regime for Patna; retail and wholesale in both the regimes; retail in extreme regime for Bengaluru; retail in typical regime for Thiruvananthapuram; wholesale in second regime for Chennai; retail in both the regime and wholesale in typical regime for Hyderabad. This implies that retailers respond significantly to the deviations from the long-run equilibrium. Impulse response analysis has shown that changes in wholesale prices in a market will cause change in retail prices in that market with varying rate and time lags to price stabilization. It estimated the effect of a shock in one market price to another market, which can be used to show the magnitude and lasting effects. It is seen that the price signals are transmitted across both horizontal and vertical chain. However, the direction and intensity of price changes may be affected by the dynamic linkages between the demand and supply. The results from the study will help improve the information precision to predict the price movements used by marketing operators for formulating appropriate strategies. The study will help policy makers in order to design suitable marketing strategies in bringing efficiency in agricultural markets. It is to be noted, that price changes are temporary and would converge to an equilibrium within a given time span. Consideration of proper domestic supply management, international trade along with strong market surveillance will minimize the gap between wholesale and retail prices of agricultural commodities. The present study has some limitations as this did not highlight the factors that affect price of the commodity in cointegraton study. This may be figured out in future research. Furthermore, in studying vertical cointegration, the farm harvest price of the commodity may be included.

Chapter 4

MULTIVARIATE GARCH MODEL FOR MODELLING THE VOLATILITY OF POTATO PRICES IN DIFFERENT MARKETS OF INDIA

1. Introduction

Value of agricultural commodities are influenced by fluctuations in price that arise from various factors including unfavorable weather conditions, natural disasters, shifts in demand and supply, change in agricultural policies and exchange rate volatility. Huge and unforeseen variations in price create a scene of unpredictability which increases risks for producers, traders, consumers and government. Bellemare et al. (2013) stated agricultural commodity price volatility has been exceptionally high during the last decade when food price volatility reached almost a 30-year high in December 2010. The continuous fluctuations in prices of commodity has attracted interest and attention in field of economic and financial literature, it can also be viewed as one of the most important economic events (Engle, 1982). Prices of commodity are generally volatile in nature and agricultural commodities are especially known for their continuously volatile nature (Newbery, 1989). Further, volatility of prices has a direct impact on competition by increasing consumer costs (Zheng, Kinnucan and Thompson, 2008). Apergis and Rezitis (2011) in their study observed that volatility of price brings up situation of uncertainty and risk for both producers and consumers. Bernhardt (2017) discussed about impact of volatility and found that extreme weather events do have large impact on volatility. Furthermore, he stated that with the application of the spillover index, it is possible to calculate the quantity of volatility spillovers across time. Candila and Farace (2018) in their study investigated the presence, the size, and the persistence of volatility spillovers among five agricultural commodities (corn, sugar, wheat, soybean, and bioethanol) and five Latin American (Argentina, Brazil, Chile, Colombia, Peru) stock market indexes. The study also contributed towards the analysis that, in general, higher agricultural commodity volatilities may induce economic weakness, mainly in food-exporter countries. Furthermore, in turn, a more fragile economy can heavily undermine the food security. The concept of volatility impulse response analysis was coined by Hafner and Herwartz (2006), which is built on the methodology of multivariate GARCH model. The main aim of this method is the analysis of the conditional variance instead of the conditional mean. This analysis allows to visualize the behavior of the conditional volatility after a historical shock. In the present investigation, Volatility Impulse Response Function (VIRF) (Koop et al., 1996) has been used to see the impacts of a specific shock on the volatility spillovers among the markets. An empirical comparison the three multivariate GARCH models namely DCC and BEKK has been carried out.

Potato is a root vegetable that belongs to the Solanum tuberosum plant. A raw potato is basically 79% water, 17% carbohydrate, 2% protein and negligible fat to describe its nutritional value. India occupies the second position on the scale of largest producers of potatoes globally. India produces around 9.97% of world's total potato production in 2017 (FAOSTAT). The vast growth in production of potatoes in India can be attributed to expansion in area than improvement in yield per hectare. Agricultural markets are one of the most important global markets because of their correlation not only with markets like energy markets, commodities or stock markets, but they also have an impact on political and social events.

The highest producer of potato in India is Uttar Pradesh (30.32% of total production), followed by West Bengal (24.91%), Bihar (14.23%), Madhya Pradesh (6.36%), Gujarat (6.22%) and others (24.52%) (Horticultural Statistics at a Glance 2018). The leading states in terms of area under potato are Uttar Pradesh, West Bengal, Bihar, Gujarat and Madhya Pradesh in total covering around 94% of total area. Area coverage under Rabi potato has increased slightly in India as compared to previous year. The production of potato during the year 2017-18 is estimated to be 5.57 % higher as compared to that of the previous year i.e. 2016-17. Harvesting of the crop is usually dependent on the weather conditions and market prospects. If the demand is higher in the market, harvesting is done slightly early. In short, potato can be concluded being a staple food as wheat and rice in India. Total demand of potatoes in India during 2017-18 was estimated to be 47.15 million tonnes. Other than this, India is also involved in exporting of potato and total export during the year 2017-18 was 395.75 thousand million tonnes (Horticultural Statistics at a Glance). Since potato is one of the most staple food in

India, it is in high demand throughout the year and around 80-85% produce of Rabi potato is stored in different cold storages of the major Potato growing states. In terms of market arrival, Potato arrives in Azadpur (Delhi) market (one of the major potato consuming state) from Uttar Pradesh, Punjab, Himachal Pradesh and Haryana.

2. Data and Methodology

To study the volatility of price of potatoes among different markets, monthly price data set starting from January, 2005 to July, 2019 is considered. The daily return has been calculated for each market using the formulae: $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$.

MGARCH Model

Multivariate GARCH (MGARCH) models are used commonly to estimate volatility spillovers among different markets. For a multivariate time series the MGARCH model is given by:

$$y_t = H_t^{1/2}\varepsilon_t$$

where, H_t is $k \times k$ positive-definite matrix of conditional variance.*k*is the number of series and t = 1,2,…,*n (observations*). It is with the specification of conditional variance that the MGARCH model changes.

BEKK Model

The study makes use of the famous BEKK model which is given by the Baba, Engle, Kraft and Kroner (Baba *et al.* 1991). The BEKK (1,1) model is :

$$H_t = CC' + A \in_{t-1}\in'_{t-1} A' + BH_{t-1}B'$$

It can be transferred into multivariate GARCH model with a generalization of the resulting variance matrix *Ht* is

$$H_t = \begin{bmatrix} h_{11} & h_{12} & h_{13} & h_{14} & h_{15} \\ h_{21} & h_{22} & h_{23} & h_{24} & h_{25} \\ h_{31} & h_{32} & h_{33} & h_{34} & h_{35} \\ h_{41} & h_{42} & h_{43} & h_{44} & h_{45} \\ h_{51} & h_{52} & h_{53} & h_{54} & h_{55} \end{bmatrix}$$

Accordingly, the BEKK (1, 1) representation of variance of error term H_t is

$$H_t = C_0' C_0 + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + B_{11}' H_{t-1} B_{11}$$

Each element of H_t depends on the *p* delayed values of the squared ε_t, the cross product of ε_t and on the *q*delayed values of elements from H_t. The BEKK(1,1) model with five variables can be written as

$$H_t = \begin{bmatrix} h_{11} & h_{12} & h_{13} & h_{14} & h_{15} \\ h_{21} & h_{22} & h_{23} & h_{24} & h_{25} \\ h_{31} & h_{32} & h_{33} & h_{34} & h_{35} \\ h_{41} & h_{42} & h_{43} & h_{44} & h_{45} \\ h_{51} & h_{52} & h_{53} & h_{54} & h_{55} \end{bmatrix}$$

$$H_t = C_0' C_0 + \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,\,t-1}^2 & \varepsilon_{1,\,t-1}\varepsilon_{2,\,t-1} & \varepsilon_{1,\,t-1}\varepsilon_{3,\,t-1} & \varepsilon_{1,\,t-1}\varepsilon_{4,\,t-1} & \varepsilon_{1,\,t-1}\varepsilon_{5,\,t-1} \\ \varepsilon_{2,\,t-1}\varepsilon_{1,\,t-1} & \varepsilon_{2,\,t-1}^2 & \varepsilon_{2,\,t-1}\varepsilon_{3,\,t-1} & \varepsilon_{2,\,t-1}\varepsilon_{4,\,t-1} & \varepsilon_{2,\,t-1}\varepsilon_{5,\,t-1} \\ \varepsilon_{3,\,t-1}\varepsilon_{1,\,t-1} & \varepsilon_{3,\,t-1}\varepsilon_{2,\,t-1} & \varepsilon_{3,\,t-1}^2 & \varepsilon_{3,\,t-1}\varepsilon_{4,\,t-1} & \varepsilon_{3,\,t-1}\varepsilon_{5,\,t-1} \\ \varepsilon_{4,\,t-1}\varepsilon_{1,\,t-1} & \varepsilon_{4,\,t-1}\varepsilon_{2,\,t-1} & \varepsilon_{4,\,t-1}\varepsilon_{3,\,t-1} & \varepsilon_{4,\,t-1}^2 & \varepsilon_{4,\,t-1}\varepsilon_{5,\,t-1} \\ \varepsilon_{5,\,t-1}\varepsilon_{1,\,t-1} & \varepsilon_{5,\,t-1}\varepsilon_{2,\,t-1} & \varepsilon_{5,\,t-1}\varepsilon_{3,\,t-1} & \varepsilon_{5,\,t-1}\varepsilon_{4,\,t-1} & \varepsilon_{5,\,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{pmatrix} +$$

$$\begin{pmatrix} b_{11} & b_{12} & b_{13} & b_{14} & b_{15} \\ b_{21} & b_{22} & b_{23} & b_{24} & b_{25} \\ b_{31} & b_{32} & b_{33} & b_{34} & b_{35} \\ b_{41} & b_{42} & b_{43} & b_{44} & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{pmatrix}' \begin{pmatrix} h_1^2 & h_1h_2 & h_1h_3 & h_1h_4 & h_1h_5 \\ h_2h_1 & h_2^2 & h_2h_3 & h_2h_4 & h_2h_5 \\ h_3h_1 & h_3h_2 & h_3^2 & h_3h_4 & h_3h_5 \\ h_4h_1 & h_4h_2 & h_4h_3 & h_4^2 & h_4h_5 \\ h_5h_1 & h_5h_2 & h_5h_3 & h_5h_4 & h_5^2 \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} & b_{13} & b_{14} & b_{15} \\ b_{21} & b_{22} & b_{23} & b_{24} & b_{25} \\ b_{31} & b_{32} & b_{33} & b_{34} & b_{35} \\ b_{41} & b_{42} & b_{43} & b_{44} & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{pmatrix}$$

The off diagonal parameters in matrix *B*, b_{12} and b_{21} respectively measures the dependence of conditional price volatility of first market to the second market and vice-versa. The parameters b_{11} and b_{22} represents persistence in volatility in their own market. The parameters a_{12} or a_{21} represent the cross markets effects whereas a_{11}, a_{22} represent the own market effects. Therefore, the significant level of each parameter indicates the presence of strong ARCH or GARCH effect.

From the above equation we can have the following equations of conditional variances for first and second variables respectively:

$$
\begin{aligned}
h_{11,t} = c_1 &+ a_{11}^2\varepsilon_{1,t-1}^2 + a_{12}^2\varepsilon_{2,t-1}^2 + a_{13}^2\varepsilon_{3,t-1}^2 + a_{14}^2\varepsilon_{4,t-1}^2 + a_{15}^2\varepsilon_{5,t-1}^2 + 2a_{11}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
&+ 2a_{11}a_{13}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{11}a_{14}\varepsilon_{1,t-1}\varepsilon_{4,t-1} + 2a_{11}a_{15}\varepsilon_{1,t-1}\varepsilon_{5,t-1} \\
&+ 2a_{12}a_{13}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 2a_{12}a_{14}\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 2a_{12}a_{15}\varepsilon_{2,t-1}\varepsilon_{5,t-1} \\
&+ 2a_{13}a_{14}\varepsilon_{3,t-1}\varepsilon_{4,t-1} + 2a_{13}a_{15}\varepsilon_{3,t-1}\varepsilon_{5,t-1} + 2a_{14}a_{15}\varepsilon_{4,t-1}\varepsilon_{5,t-1} \\
&+ b_{11}^2h_{11,t-1} + b_{12}^2h_{22,t-1} + b_{13}^2h_{33,t-1} + b_{14}^2h_{44,t-1} + b_{15}^2h_{55,t-1} + 2b_{11}b_{12}h_{12,t-1} \\
&+ 2b_{11}b_{13}h_{13,t-1} + 2b_{11}b_{14}h_{14,t-1} + 2b_{11}b_{15}h_{15,t-1} + 2b_{12}b_{13}h_{23,t-1} \\
&+ 2b_{12}b_{14}h_{24,t-1} + 2b_{12}b_{15}h_{25,t-1} + 2b_{13}b_{14}h_{34,t-1} + 2b_{13}b_{15}h_{35,t-1} \\
&+ 2b_{14}b_{15}h_{45,t-1}
\end{aligned}
$$

$$
\begin{aligned}
h_{22,t} = c_{22} &+ a_{22}^2\varepsilon_{2,t-1}^2 + a_{21}^2\varepsilon_{1,t-1}^2 + a_{23}^2\varepsilon_{3,t-1}^2 + a_{24}^2\varepsilon_{4,t-1}^2 + a_{25}^2\varepsilon_{5,t-1}^2 + 2a_{22}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
&+ 2a_{21}a_{23}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{21}a_{24}\varepsilon_{1,t-1}\varepsilon_{4,t-1} + 2a_{21}a_{25}\varepsilon_{1,t-1}\varepsilon_{5,t-1} \\
&+ 2a_{22}a_{23}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 2a_{22}a_{24}\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 2a_{22}a_{25}\varepsilon_{2,t-1}\varepsilon_{5,t-1} \\
&+ 2a_{23}a_{24}\varepsilon_{3,t-1}\varepsilon_{4,t-1} + 2a_{23}a_{25}\varepsilon_{3,t-1}\varepsilon_{5,t-1} + 2a_{24}a_{25}\varepsilon_{4,t-1}\varepsilon_{5,t-1} \\
&+ b_{22}^2h_{11,t-1} + b_{12}^2h_{22,t-1} + b_{23}^2h_{33,t-1} + b_{24}^2h_{44,t-1} + b_{25}^2h_{55,t-1} + 2b_{21}b_{21}h_{12,t-1} \\
&+ 2b_{21}b_{23}h_{13,t-1} + 2b_{21}b_{24}h_{14,t-1} + 2b_{21}b_{25}h_{15,t-1} + 2b_{22}b_{23}h_{23,t-1} \\
&+ 2b_{22}b_{24}h_{24,t-1} + 2b_{22}b_{25}h_{25,t-1} + 2b_{23}b_{24}h_{34,t-1} + 2b_{23}b_{25}h_{35,t-1} \\
&+ 2b_{24}b_{25}h_{45,t-1}
\end{aligned}
$$

Dynamic conditional correlation (DCC) Model

The dynamic nature of time varying correlations has been studied using DCC-GARCH model developed by Engle (2002). The DCC model can be formulated in a following manner:

$$y_t = \mu_t(\theta) + \varepsilon_t$$

where ε_t is a n ×1 vector of zero mean in which innovations conditional on the information available at time *t-1*. The conditional variance co-variance matrix can be written as:

$$H_t = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}}$$

where, R_t is the $n \times n$ conditional correlation matrix and the matrices D_t and R_t are computed as follows:

$$D_t = diag(h_{11t}^{\frac{1}{2}}, \dots, h_{nnt}^{\frac{1}{2}})$$

h_{iit} is chosen to be a univariate GARCH (1,1) process; $R_t = (diagQ_t)^{-1/2} Q_t (diagQ_t)^{-1/2}$, $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1}$ refers to a $n \times n$ symmetric positive definite matrix with $u_{it} = {\varepsilon_{it}}/{\sqrt{h_{iit}}}$, $\bar{Q}$ is the $n \times n$ unconditional variance matrix of u_t and α and β are non negative scalar parameters satisfying $\alpha + \beta < 1$.

The conditional correlation coefficient ρ_{ij} between two markets *i* and *j* is then computed as follows:

$$\rho_{ij} = \frac{(1-\alpha-\beta)\bar{q}_{ij} + \alpha u_{i,t-1}u_{j,t-1} + \beta q_{ij,t-1}}{((1-\alpha-\beta)\bar{q}_{ii} + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1})^{1/2}((1-\alpha-\beta)\bar{q}_{jj} + \alpha u_{j,t-1}^2 + \beta q_{jj,t-1})^{1/2}}$$

where ρ_{ij} refers to the element located in the i^{th} row and j^{th} column of the symmetric positive definite matrix Q_t .Maximum likelihood method is used to estimate all the multivariate GARCH models which will be employed in this study.

Volatility Impulse Response Functions

As stated in Hafner and Herwartz (2006), the fact that the residual vector ε_t is simultaneously correlated, the error vector cannot be assumed to be received from independent sources. That means that a change in one component of ε can not be regarded without considering a change in another component. For this reason, we need to orthogonalize the components. In order to ensure orthogonally residuals, the residual were decomposed into vector ε_t

$$\varepsilon_t = P_t \xi_t$$

With $P_t P_t' = \Sigma_t$ and ξ_t is a i.i.d. random vector. To identify $\xi_t = P^{-1}\varepsilon_t$, Hafner and Herwartz (2006) recommend using a Jordan decomposition to obtain the symmetric matrix $\Sigma_t^{1/2}$ with

$$\Sigma_t^{1/2} = \Gamma_t \Lambda_t^{1/2} \Gamma_t'$$

Whereas $\Lambda_t = diag(\lambda_{t,1}, \dots, \lambda_{t,k})$ is a a matrix with Eigenvalues of Σ_t on its main diagonal and $\Gamma_t = (\Upsilon_{t,1,} \dots, \Upsilon_{t,k})'$is the matrix which contains the corresponding Eigenvectors $\gamma_{t,i}$. Knowing that $\Sigma_t = \Sigma_t^{1/2}\Sigma_t^{1/2}$ we can set $P_t = \Sigma_t^{1/2}$and calculate $\xi_t = \Sigma^{-1}\varepsilon_t$

BEKK model can be represented by the vec representation as:

$$vech(H_t) = Q + R \times vech(\varepsilon_{t-1} \times \varepsilon_{t-1}') + P \times vech(H_{t-1})$$

where $H_t$stands for the conditional covariance matrix at time t and vech(.) stands for the operator that stacks the lower triangular fraction of an $N \ X \ N$ matrix into an $N^* = N(N+1)/2$ dimensional vector. The vector Q contains N^*coefficients, and R and P are parameter matrices each containing $(\frac{N(N+1)}{2})^2$ parameters. According to Engle and Kroner (1995), every BEKK model has a unique and equivalent vec representation. If every sequence of innovations ε_t generates the same sequence of conditional volatilities (H_t) for both models, then the BEKK and vec representations are said to be equivalent. More specifically, the parameters of Q, R, and P matrices of the vec model are linked to the parameters of the BEKK model given in equation as follows:

$$Q = \begin{bmatrix} c_{11}^2 \\ c_{11}c_{21} \\ c_{11}c_{31} \\ c_{21}^2 + c_{22}^2 \\ c_{31}c_{21} + c_{32}c_{22} \\ c_{31}^2 + c_{32}^2 + c_{33}^2 \end{bmatrix},$$

$$R = \begin{bmatrix} a_{11}^2 & 2a_{11}a_{12} & 2a_{11}a_{13} & a_{12}^2 & 2a_{12}a_{13} & a_{13}^2 \\ a_{11}a_{21} & a_{12}a_{21} + a_{11}a_{22} & a_{13}a_{21} + a_{11}a_{23} & a_{11}a_{22} & a_{13}a_{22} + a_{12}a_{23} & a_{13}a_{23} \\ a_{11}a_{31} & a_{12}a_{31} + a_{11}a_{32} & a_{13}a_{31} + a_{11}a_{33} & a_{12}a_{32} & a_{13}a_{32} + a_{12}a_{33} & a_{13}a_{33} \\ a_{21}^2 & 2a_{21}a_{22} & 2a_{21}a_{23} & a_{22}^2 & 2a_{22}a_{23} & a_{23}^2 \\ a_{31}a_{21} & a_{31}a_{22} + a_{21}a_{32} & a_{31}a_{23} + a_{21}a_{33} & a_{32}a_{22} & a_{32}a_{23} + a_{22}a_{33} & a_{23}a_{33} \\ a_{31}^2 & 2a_{31}a_{32} & 2a_{31}a_{33} & a_{32}^2 & 2a_{32}a_{33} & a_{33}^2 \end{bmatrix} \text{ and}$$

$$P = \begin{bmatrix} b_{11}^2 & 2b_{11}b_{12} & 2b_{11}b_{13} & b_{12}^2 & 2b_{12}b_{13} & b_{13}^2 \\ b_{11}b_{21} & b_{11}b_{22} + b_{12}b_{21} & b_{11}b_{23} + b_{13}b_{21} & b_{12}b_{22} & b_{12}b_{23} + b_{13}b_{22} & b_{13}b_{23} \\ b_{11}b_{31} & b_{11}b_{32} + b_{12}b_{31} & b_{11}b_{33} + b_{13}b_{31} & b_{12}b_{32} & b_{12}b_{33} + b_{13}b_{32} & b_{13}b_{33} \\ b_{21}^2 & 2b_{21}b_{22} & 2b_{21}b_{23} & b_{22}^2 & 2b_{22}b_{23} & b_{23}^2 \\ b_{21}b_{31} & b_{21}b_{32} + b_{22}b_{31} & b_{21}b_{33} + b_{23}b_{31} & b_{22}b_{33} & b_{22}b_{33} + b_{23}b_{32} & b_{23}b_{33} \\ b_{31}^2 & 2b_{31}b_{32} & 2b_{31}b_{33} & b_{32}^2 & 2b_{32}b_{33} & b_{33}^2 \end{bmatrix}$$

This study uses the vec representation to eliminate the parameters which appear twice in the conditional covariance matrix. This reduction in the number of parameters does not have any adverse impact in terms of the generality of the model. Hafner and Herwartz (2006) define VIRF as the expectation of volatility conditional on an initial shock and history, subtracted by the baseline expectation that only conditions on history, given by:

$$V_t(z_t) = E[vech(H_t)|I_{t-1}, z_t] - E[vech(H_T)|I_{t-1}]$$

Where z_t is an initial specific shock hitting the system at time t and I_{t-1} is the observed history up to time $t-1$. $V_t(z_t)$ is the $N(N+1)/2$ dimensional vector of the impact of the identical and independent shock components of z_t on the t-step ahead conditional variance covariance matrix components. For example, for a BEKK (1,1) model, if $N = 3$ there will be six components in the vec model of equation above: the first, fourth, and sixth elements of $V_t(z_t)$ represent the impulse responses of the conditional variance of the first, second, and third variables, respectively. Similarly, the second, third, and fifth elements of $V_t(z_t)$ represent the impulse responses of the conditional covariance between the first and second, first and third, and second and third variables, respectively.

The one-step ahead VIRF can easily be obtained based on the application of a BEKK(1,1) model, and then the vec model is given as:

$$V_t(z_t) = R\, D_N^+(H_t^{\frac{1}{2}} \otimes\, H_t^{\frac{1}{2}})D_N vech(z_t z_t' - I_N)$$

where H_t is the conditional variance covariance matrix at time t; D_N represents the duplication matrix defined by the property $vec(Z) = D_N vech(Z)$ for any symmetric $N \times N$ matrix Z; D_N^+ represents the Moore-Penrose inverse of matrix Z; I_N is the identity matrix; $\otimes$ is the Kronecker Tensor product; and R is the parameter matrix containing $(\frac{N(N+1)}{2})^2$ parameters. For any $t \geq 2$, VIRF is given as:

$$V_t(z_t) = (R + P)V_{t-1}(z_t)$$

The volatility impulse response functions describe the impact of an independent shock on the volatility of the variables. The nature of independence of the given shock from other previous shocks allow the construction of volatility impulse response function from historical data. However, in a multivariate setup it is hard to assume that shocks are independent if they all occur at the same time. In such cases Cholesky decomposition is used for the orthogonalization of residuals. Hafner and Herwartz (2006) as an alternative used the Jordan decomposition to obtain independent shocks. This makes the obtained impulse responses to be free from issues involving ordering of the variables.

VIRFs have the following distinctive properties:

1. The VIRF is a symmetric function of the shock, which can be shown by the feature of $V_t(z_0) = V_t(-z_0)$

2. The VIRF is not a homogeneous function of any degree.

3. The VIRF depends on the history through the volatility state H0 at the time when the initial shock occurs.

4. The decay or persistence of shocks is measured by the moving average matrices

3. Results and Discussion

The pattern of prices of potato in different markets is displayed in fig.1. It can be visualized that the prices vary a lot over the time period leading to volatility. Results obtained for descriptive statistics are reported in Table 1. A perusal of table 1 reveals that mean monthly price of potatoes is maximum in Bangalore i.e. 1139.58/quintal and minimum in Agra at 671.19/quintal. Similarly, maximum price of potatoes was observed in Bangalore at 2480/quintal followed by Delhi. The CV as depicted in table 1 indicates that Agra markets has highest variation in price followed by Delhi market. Considering the fact that price of potatoes is highly fluctuating in all the markets with marginal difference in standard deviation values, it can be concluded that all markets are subject to high shocks.

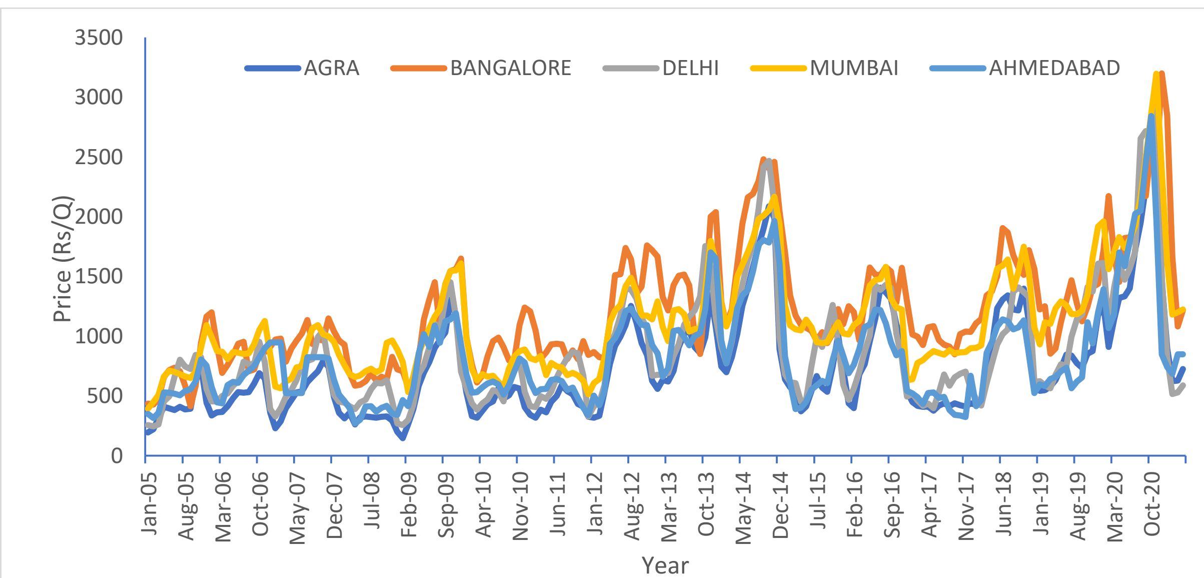


Fig. 1. The time plot of potato prices in studied markets

Table 1. Descriptive Statistics

Markets	Mean	Median	Maximum	Minimum	Standard Deviation	CV
Agra	671.19	548.00	2086.00	147.00	367.13	54.70
Ahmedabad	763.06	661.00	1965.00	271.00	335.40	43.95
Bangalore	1139.58	1037.00	2480.00	414.00	417.46	36.63
Delhi	797.75	695.00	2467.00	245.00	399.66	50.10
Mumbai	1029.38	953.00	2167.00	394.00	351.20	34.12

The study applied various unit root tests for validating the stationarity of the potato data. Tests included Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller, Phillips–Perron (PP) test proposed by Phillips and Perron and Kwiatkowski–Phillips– Schmidt–Shin (KPSS) test proposed by Kwiatkowski et al. The results of the unit root tests are reported in Table 2. It may be seen that all the log return series are stationary at level.

Table 2. Unit root test Results

Markets	ADF test		PP test		KPSS test	
	t stat	p-value	t stat	p-value	t stat	p-value
Agra	-5.04	0.00	-3.85	0.00	24.18	0.00
Ahmedabad	-4.57	0.00	-3.68	0.01	30.10	0.00
Bangalore	-3.40	0.01	-3.06	0.03	36.11	0.00
Delhi	-5.57	0.00	-4.19	0.00	26.41	0.00
Mumbai	-4.45	0.00	-3.58	0.01	38.77	0.00

Table 3. Results of BEKK (1,1) model

Constant (C)					
	Agra	Bengaluru	Delhi	Mumbai	Ahmedabad
Agra	0.157	-0.035	0.151	0.081	0.075
Bengaluru	0.000	0.022	-0.096	0.050	0.061

Delhi	0.000	0.000	0.072	0.031	0.073
Mumbai	0.000	0.000	0.000	-0.014	-0.010
Ahmedabad	0.000	0.000	0.000	0.000	-0.034
ARCH Coefficients (A)					
	Agra	Bengaluru	Delhi	Mumbai	Ahmedabad
Agra	0.218	0.226	0.165	0.279	0.267
Bengaluru	0.047	0.097	-0.276	-0.119	-0.022
Delhi	0.328	0.029	0.134	0.129	-0.216
Mumbai	-0.413	0.230	-0.169	-0.165	-0.198
Ahmedabad	0.094	-0.076	0.251	0.034	0.368
GARCH Coefficients (B)					
	Agra	Bengaluru	Delhi	Mumbai	Ahmedabad
Agra	0.552	-0.254	0.125	-0.261	0.573
Bengaluru	-0.465	-0.810	-0.463	-0.315	-0.712
Delhi	-0.256	0.291	-0.102	0.256	-0.391
Mumbai	0.533	0.404	0.341	-0.086	-0.281
Ahmedabad	0.028	0.347	0.309	0.232	0.304
Standard Error of Coefficient of Constant					
	Agra	Bengaluru	Delhi	Mumbai	Ahmedabad
Agra	0.028	0.031	0.026	0.015	0.028
Bengaluru	0.000	0.030	0.031	0.018	0.018
Delhi	0.000	0.000	0.038	0.014	0.050
Mumbai	0.000	0.000	0.000	0.012	0.185
Ahmedabad	0.000	0.000	0.000	0.000	0.048
Standard Error of ARCH coefficients					
	Agra	Bengaluru	Delhi	Mumbai	Ahmedabad
Agra	0.107	0.157	0.212	0.030	0.112
Bengaluru	0.098	0.112	0.134	0.061	0.104
Delhi	0.210	0.127	0.271	0.069	0.115

Mumbai	0.192	0.185	0.237	0.058	0.171
Ahmedabad	0.099	0.073	0.083	0.051	0.091
Standard Error of GARCH coefficients					
	Agra	Bengaluru	Delhi	Mumbai	Ahmedabad
Agra	0.207	0.261	0.205	0.097	0.327
Bengaluru	0.215	0.107	0.182	0.127	0.206
Delhi	0.295	0.343	0.288	0.136	0.372
Mumbai	0.103	0.254	0.189	0.143	0.650
Ahmedabad	0.206	0.152	0.199	0.082	0.302

The results of the estimated MGARCH- BEKK model for log return series of monthly price of potatoes for five cities namely Agra, Bengaluru, Delhi, Mumbai and Ahmedabad are presented in table 3. In table 3, the ARCH effect of own market and cross markets are represented by matrix A whereas the GARCH effect of own market and cross markets are represented by matrix B. The significant coefficients are indicated by *.

We often get number of negative parameters in the typical BEKK output. One thing to note is that the BEKK model isn't global identified— we get exactly the same fit if we change the sign of the entire A or B matrix, or even any column of C. However, the guess values used by GARCH will steer it in the direction of positive "own" contributions, so it would be very rare that we get the parameters with the opposite from the expected set of signs.

Table 4 reports the results of DCC model. Here the parameter α measures the reaction of conditional volatility to market shocks and parameter β measures the persistence in conditional volatility irrespective of anything happening in the market. The condition that $0 < \alpha + \beta < 1$ are all satisfied, for all the five markets. The maximum value occurring for Agra at 0.962 and minimum value for Bengaluru at 0.695. In all the markets, value of α is less than β except. The low value of α and high value of β indicates the importance of long-run persistence in comparison to short-run persistence. A close analysis of dcca1 and dccb1 showed that both the coefficeints are statistically significant and clearly indicate that system of series as a whole makes sense to fit DCC model.

Table 4. Results of DCC model

Agra				
Parameter	Estimate	Std. Error	t value	Pr(>|t|)
c	0.007	0.034	0.202	0.840
ω	0.000	0.008	0.007	0.995
α	0.163	0.069	2.354	0.015
β	0.799	0.008	97.450	0.000
Bangalore				
c	0.004	0.012	0.354	0.724
ω	0.009	0.005	1.753	0.080
α	0.142	0.064	2.225	0.026
β	0.553	0.211	2.628	0.009
Delhi				
c	0.005	0.016	0.286	0.775
ω	0.000	0.002	0.049	0.961
α	0.215	0.034	6.288	0.000
β	0.594	0.001	502.113	0.000
Mumbai				
c	0.006	0.011	0.537	0.591
ω	0.000	0.000	0.063	0.950
α	0.236	0.025	9.489	0.000
β	0.599	0.002	346.643	0.000
Ahmedabad				
c	0.005	0.014	0.352	0.725
ω	0.000	0.001	0.146	0.883

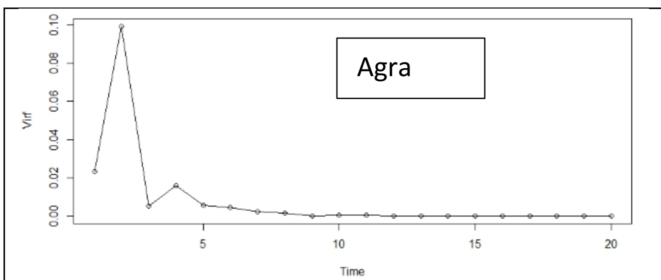
α	0.149	0.019	7.995	0.000
β	0.758	0.001	615.584	0.000
dcca1	0.042	0.017	2.494	0.013
dccb1	0.753	0.120	6.257	0.000

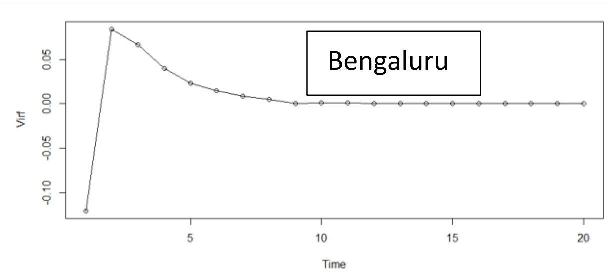
Note: c, ω, α and β denotes respectively the constant in mean equation, constant in variance, ARCH effect and GARCH effect.

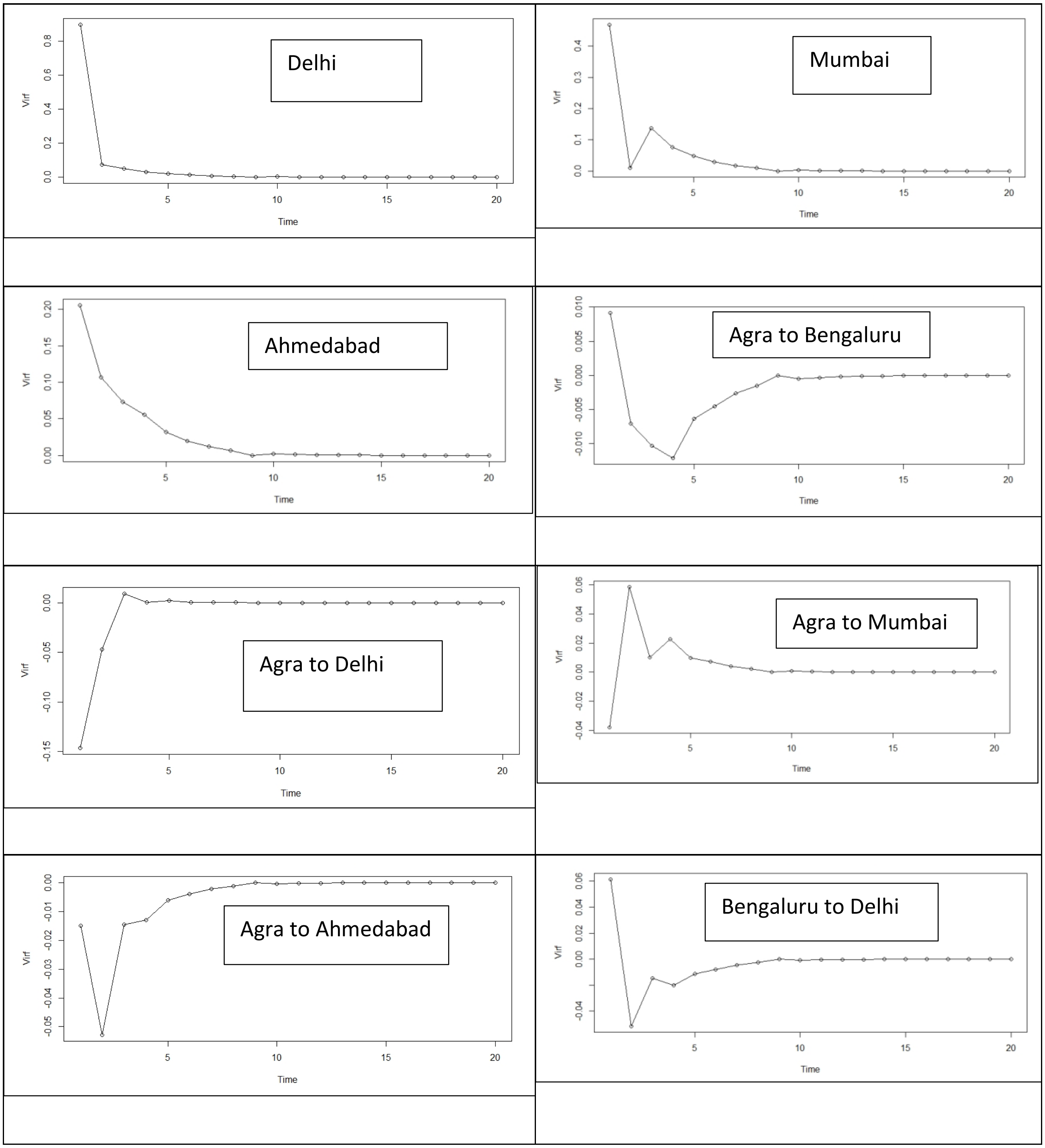
The VIRF depends on the initial volatility Ht given to the system. The value of initial volatility can be either the volatility state at the time of the shock incurred, or any other date chosen from the sample period. In the present scenario the shock to the system was given at time June, 2012.

Figure 2 shows the volatility impulse responses. The impact of the shock appears not only in the expected conditional variances but also evident in the expected conditional covariances. The impact of the shock on expected conditional variances in all the cities can be evaluated from first month itself.

The initial impact of the shock on expected conditional covariances between all the cities was noticeable at point of initial shock and the peak response was reached in about second or third month. Regarding the die down of the impact of the shock on expected conditional covariances, it can be seen that impact of shock didn't sustain after ten months in all the cities. The continuous fluctuations in initial months confirms the fact that volatility transmission across markets is usually attributed to news and cross-market hedging which dynamically changes expectations across markets. A key result to be noted is that even if impact of shock is negative initially for some markets, in terms of both variances and covariances, but duration was very short.






Delhi
Mumbai
Ahmedabad
Agra to Bengaluru
Agra to Delhi
Agra to Mumbai
Agra to Ahmedabad
Bengaluru to Delhi
Virf
Time

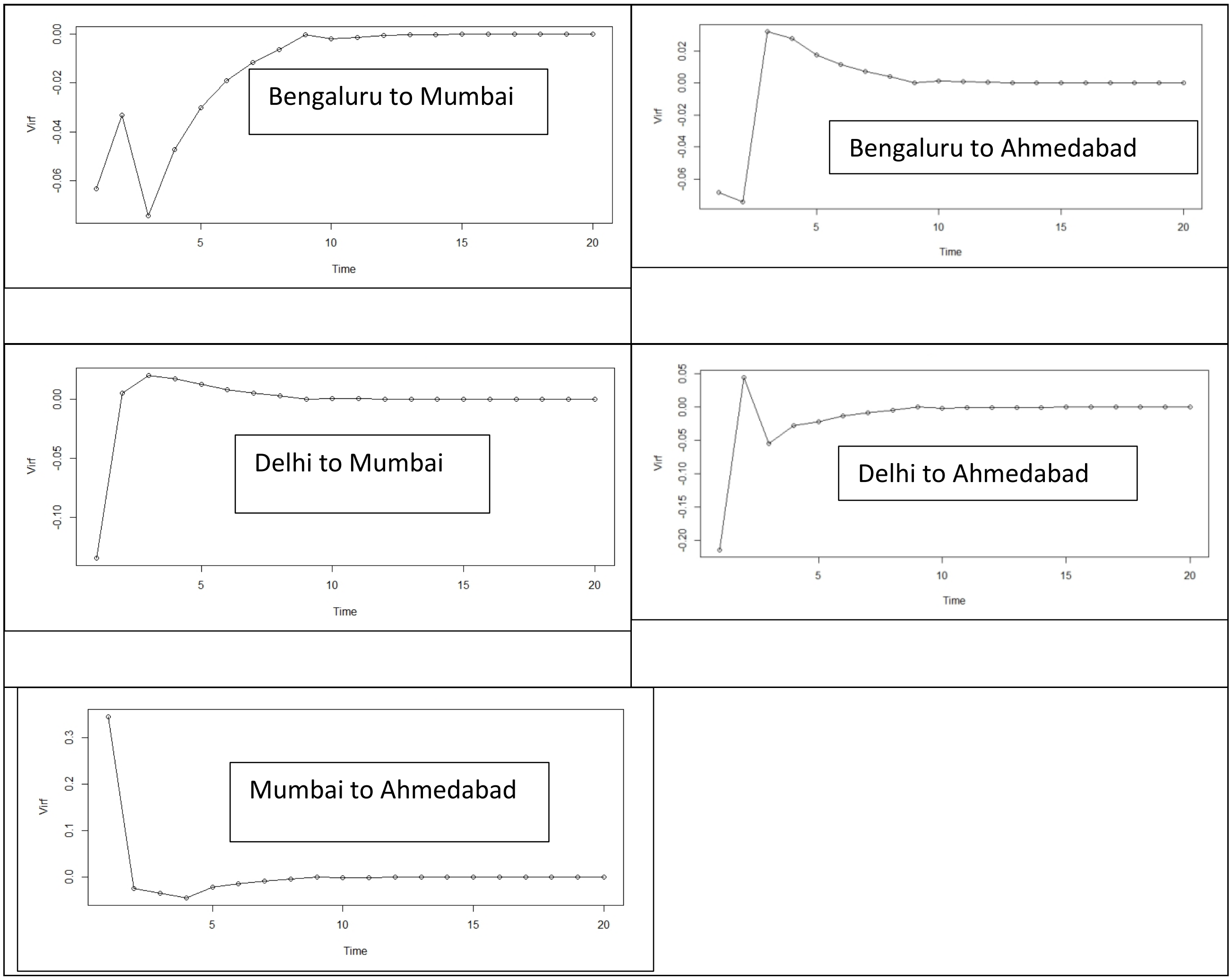


Fig. 2. VIRF of different markets

4. Conclusions

The present study investigated the effect of volatility spillovers in monthly potato price of five different markets Agra, Ahmedabad, Bengaluru, Delhi, and Mumbai from January, 2005 to April, 2021. The empirical results support the presence of ARCH and GARCH effects in all the markets. Accordingly, to accommodate the conditional heteroscedasticity as well as inter dependence of studied markets, MGARCH models namely BEKK and DCC have been applied. It is observed that price volatility is not only dependent on its own market's past volatility but also depends on cross market volatility. Finally, the application of VIRF demonstrated volatility spillover of all the studied markets and it also showed the impacts of impulse responses on expected conditional variances and expected conditional covariances took almost ten months to recover. To this end one can conclude that changes in the volatility of one market will often trigger reactions in other markets.

सारांश

कीमतों में उतार-चढ़ाव के साथ साथ एक बाजार का दूसरे बाजार पर स्पिलओवर प्रभाव को समझना शोधकर्ताओं के लिए ध्यान का मुख्य केंद्र रहा है। इसलिए मल्टीवेरिएट गार्च (एमगार्च) मॉडल पर विचार करने के लिए यूनीवेरिएट जेनरलाइज़्ड ऑटोरेग्रेसिव कंडीशनल हेटरोसेडेस्टिक (गार्च) मॉडल का विस्तार करना महत्वपूर्ण है। सहएकीकरण और वेक्टर त्रुटि सुधार मॉडल के विभिन्न पहलुओं पर चर्चा की गई है। एमगार्च मॉडल में, बाबा क्रोनर.क्राफ्ट.एंगल.(बी.इ.के.के) और कॉन्स्टेंट कंडिशनल कोरिलेशन (सी.सी.सी) मॉडल को कर्नाटक भारत में प्याज के दो प्रमुख बाजारों में प्याज की कीमतों में उतार-चढ़ाव के मॉडलिंग के लिए उचित माना जाता है। यह निष्कर्ष निकाला गया है कि दो बाजार सह.एकीकृत हैं और उनके बीच स्पिलओवर प्रभाव मौजूद है। ऐरीमा मॉडल कर्नाटक के दो अलग-अलग बाजारों बैंगलोर और हुबली के मासिक प्याज मूल्य डेटा का उपयोग करके फिट किए गए हैं। रेसिडुअलस की जांच आर्च प्रभाव की संभावित उपस्थिति के लिए की गई, जिसके बाद एकतरफा गार्च मॉडल की फिटिंग की गई।। यह देखा गया है कि आर्च प्रभावों का परिमाण दोनों श्रृंखलाओं के लिए गार्च प्रभावों से अधिक है। ट्रेस स्टेटिस्टिक और ईजेन वैल्यू स्टेटिस्टिक दोनों का उपयोग करके दो श्रृंखलाओं के बीच सह.एकीकरण का परीक्षण किया गया और यह पाया गया कि दो श्रृंखलाओं के बीच एक सह-एकीकृत वेक्टर था। तदनुसार, वीईसी मॉडल फिट किया गया था और वीईसी मॉडल के अवशेषों पर मार्च प्रभाव की संभावित उपस्थिति की जांच की गई थी। इसके लिए एमगार्च मॉडल को द्विभाजित श्रृंखला के सशर्त विचरण के मॉडलिंग के लिए लागू किया गया था। बी.इ.के.के और सी.सी.सी नामक एमगार्च मॉडल के प्रदर्शन का अध्ययन किया गया है। प्रत्येक बाजार मूल्य में अस्थिरता की उच्च सतत देखी गई है। बैंगलोर और हुबली बाजारों के बीच प्याज की कीमत की अन्योन्याश्रितता और अस्थिरता स्पिलओवर स्थापित की गई है। बाजारों के बीच जुड़ाव, मात्रा और स्पिल ओवर की दिशा नीति निर्माताओं को वस्तु की कीमत को स्थिर करने के लिए उचित नीतिगत निर्णय लेने में मदद करेगी।

वर्तमान अध्ययन में, जोहान्सन के दृष्टिकोण का उपयोग करके सह-एकीकरण की उपस्थिति का परीक्षण किया गया था। यह पता चला कि सभी बाजारों में गेहूं के थोक और खुदरा मूल्य क्षैतिज और साथ ही लंबवत रूप से सह-एकीकृत हैं। एंडर्स एंड ग्रेंजर (1998) के थ्रेशोल्ड ऑटोरेग्रेसिव (TAR) और मोमेंटम थ्रेशोल्ड ऑटोरेग्रेसिव (M-TAR) मॉडल के माध्यम से मूल्य संचरण में विषमता की जांच की जाती है। एमटीएआर मॉडल के अनुप्रयोग से पता चलता है कि विचाराधीन अधिकांश बाजार थोक से खुदरा बाजारों में मूल्य संचरण के संदर्भ में असममित हैं। दो श्रृंखलाओं के बीच सह-एकीकरण की स्वीकृति का तात्पर्य है कि उनके बीच एक दीर्घकालिक संबंध मौजूद है और इसका अर्थ है कि एक त्रुटि-सुधार मॉडल (ईसीएम) मौजूद है जो मॉडल के अल्पकालिक गतिकी के साथ दीर्घकालिक संबंध को जोड़ता है। परिणामों से संकेत मिलता है कि अधिकांश त्रुटि सुधार शब्द (ईसीटी) सांख्यिकीय रूप से महत्वपूर्ण हैं, जिसका अर्थ है कि एक बार असमानता में प्रणाली संतुलन स्थिति में वापस आने की कोशिश करती है। इसके अलावा, निष्कर्षों ने बताया कि अध्ययन की गई मूल्य समायोजन प्रक्रिया में गैर-रैखिकताएं हैं। हैनसेन और एसईओ (2011) द्वारा परीक्षण के आवेदन द्वारा थ्रेसहोल्ड सह-एकीकरण की महत्वपूर्ण उपस्थिति सुनिश्चित की गई थी। गेहूं के थोक और खुदरा मूल्य के बीच सह-एकीकरण और मूल्य संचरण में विषमता के साथ-साथ गैर-रैखिकता का ख्याल रखने के लिए TVECM मॉडल लागू किया गया था। टू-रेजीम थ्रेशोल्ड वेक्टर एरर करेक्शन मॉडल (TVECM) के अनुप्रयोग ने प्रदर्शित किया कि त्रुटि सुधार अवधि (ECT) का गुणांक दिल्ली में दोनों शासनों के लिए खुदरा में महत्वपूर्ण है; शासन के लिए थोक और जम्मू के लिए ठेठ शासन में खुदरा, अमृतसर के लिए चरम शासन में खुदरा और थोक; दोनों शासन में खुदरा लेकिन लुधियाना के लिए चरम शासन में थोक; लखनऊ में चरम शासन में खुदरा; देहरादून के लिए दोनों शासन में खुदरा; अहमदाबाद के लिए ठेठ शासन में थोक और अत्यधिक शासन में खुदरा; भोपाल के लिए दोनों शासन में खुदरा; चरम शासन में खुदरा और मुंबई

के लिए विशिष्ट शासन में थोक; जयपुर के लिए ठेठ शासन में थोक और अत्यधिक शासन में खुदरा; पटना के लिए खुदरा और थोक दोनों चरम शासन में; दोनों व्यवस्थाओं में खुदरा और थोक; बेंगलुरू के लिए चरम शासन में खुदरा; तिरुवनंतपुरम के लिए ठेठ शासन में खुदरा; चेन्नई के लिए दूसरी व्यवस्था में थोक; हैदराबाद के लिए दोनों शासन में खुदरा और ठेठ शासन में थोक। इसका तात्पर्य यह है कि खुदरा विक्रेता दीर्घकालीन संतुलन से विचलन के लिए महत्वपूर्ण रूप से प्रतिक्रिया करते हैं। आवेग प्रतिक्रिया विश्लेषण से पता चला है कि बाजार में थोक कीमतों में बदलाव से उस बाजार में खुदरा कीमतों में बदलाव होगा और मूल्य स्थिरीकरण के लिए अलग-अलग दर और समय अंतराल होंगे।

वर्तमान अध्ययन ने जनवरी, 2005 से अप्रैल, 2021 तक आगरा, अहमदाबाद, बैंगलोर, दिल्ली और मुंबई के पांच अलग-अलग बाजारों में आलू की मासिक कीमत में उतार-चढ़ाव के प्रभाव की जांच की। अनुभवजन्य परिणाम आर्च और गार्च प्रभावों की उपस्थिति का समर्थन करते हैं। अंत में, वीआईआरएफ़ ने प्रदर्शित किया कि अपेक्षित सशर्त भिन्नताओं और अपेक्षित सशर्त सहप्रसरणों पर आवेग प्रतिक्रियाओं के प्रभाव को ठीक होने में लगभग दस महीने का समय लगा। इसके लिए कोई यह निष्कर्ष निकाल सकता है कि इसमें परिवर्तन होता है

SUMMARY

Price volatility as well as understanding the spillover effect of one market on the others has been the main center of attention for the researchers. It is therefore important to extend the consideration univariate Generalized autoregressive conditional heteroscedastic (GARCH) model to Multivariate GARCH (MGARCH) model. Various aspects of cointegration and vector error correction model have been discussed. In the MGARCH model, Baba-Engle-Kraft-Kroner (BEKK) and Constant Conditional Correlation (CCC) models are considered for modeling volatility of onion prices in two major markets of onion in Karnataka, India. It is concluded that that the two markets are cointegrated and there exists spillover effect among them. ARIMA models are fitted using monthly Onion price data of two different markets, Bangalore and Hubli of Karnataka. The residuals were investigated for possible presence of ARCH effect followed by fitting of univariate GARCH models. It is seen that the magnitude of ARCH effects are more than the GARCH effects for both the series. The cointegration among the two series were tested by using both Trace statistic and Eigen value statistic and it is found that there was one cointegrated vector among the two series. Accordingly, VEC model was fitted and possible presence of MARCH effect was investigated on the residuals of VEC model. To this end MGARCH model was applied for modeling the conditional variance of the bivariate series. The performances of MGARCH models namely BEKK and CCC have been studied. High persistence of volatility has been observed in each market price. The interdependence and volatility spillover of onion price between Bangalore and Hubli markets has been established. The linkages among the markets, amount and direction of spill over will help the policy makers to take proper policy decision in order to stabilize the price of the commodity.

In the present study, presence of cointegration was tested by using Johansen's approach. It was revealed that wholesale and retail price of wheat in all the market are cointegrated both horizontally as well as vertically. Asymmetricity in price transmission is investigated by means of Threshold Autoregressive (TAR) and Momentum Threshold Autoregressive (M-TAR) models of Enders and Granger (1998). The application of MTAR model reveals that most of the markets under consideration are asymmetric in terms of price transmission from wholesale to retail markets. The acceptance of cointegration between two series implies that there exists a long run relationship between them and this means that an error-correction model (ECM)

exists which combines the long-run relationship with the short-run dynamics of the model. The results indicate that most of the error correction term (ECT) are statistically significant implying that the system once in disequilibrium tries to come back to the equilibrium state. Moreover, findings pointed out that there are nonlinearities in the studied price adjustment process. The significance presence of threshold cointegration was ensured by application of test by Hansen and Seo (2011). To take care of asymmetricity as well as nonlinearity in cointegration and price transmission between wholesale and retail price of wheat, TVECM model was applied. Application of the Two- Regime Threshold Vector Error Correction Model (TVECM) demonstrated that the coefficient of Error Correction Term (ECT) is significant in retail for both the regimes in Delhi; wholesale for both the regime and retail in typical regime for Jammu, retail and wholesale in extreme regime for Amritsar; retail in both the regime but wholesale in extreme regime for Ludhiana; retail in extreme regime in Lucknow; retail in both the regime for Dehradun; wholesale in typical regime and retail in extreme regime for Ahmedabad; retail in both the regime for Bhopal; retail in extreme regime and wholesale in typical regime for Mumbai; wholesale in typical regime and retail in extreme regime for Jaipur; retail and wholesale both in extreme regime for Patna; retail and wholesale in both the regimes; retail in extreme regime for Bengaluru; retail in typical regime for Thiruvananthapuram; wholesale in second regime for Chennai; retail in both the regime and wholesale in typical regime for Hyderabad. This implies that retailers respond significantly to the deviations from the long-run equilibrium. Impulse response analysis has shown that changes in wholesale prices in a market will cause change in retail prices in that market with varying rate and time lags to price stabilization.

The present study investigated the effect of volatility spillovers in monthly potato price of five different markets Agra, Ahmedabad, Bangalore, Delhi, and Mumbai from January, 2005 to April, 2021. The empirical results support the presence of ARCH and GARCH effects. Finally, the VIRF demonstrated that the impacts of impulse responses on expected conditional variances and expected conditional covariances took almost same time of ten months to recover. To this end one can conclude that changes in the volatility of one market will often trigger reactions in other markets.

References

Andrle, M., & Blagrave, P. 2020. Agricultural Market Integration in India. IMF Working Paper WP/20/115.

Apergis, N. and A. Rezitis (2011). Food price volatility and Macroeconomic factors: Evidence from GARCH and GARCH-X estimates. Journal of Agricultural and Applied Economics, 43 (1): 95-110.

Asche, F., Jaffry, S., & Hartmann, J. (2007). Price transmission and market integration: vertical and horizontal price linkages for salmon. Applied Economics, 39(19), 2535-2545.

Bachmeier, L. J., & Griffin, J. M. (2003). New evidence on asymmetric gasoline price responses. Review of Economics and Statistics, 85(3), 772-776.

Balaguer, J., and Ripollés, J. (2014). Are the transport fuel retail markets regionally integrated in Spain? Evidence from price transmission. *Economic Modelling*, 42, 323-332.

Balke, N.S., and Fomby, T.S. (1997). Threshold cointegration. *International Economic Review*,38(3), 627-645.

Bauwens, L., Hafner, C. M., and Pierret, D. (2013). Multivariate volatility modeling of electricity futures. *Journal of Applied Econometrics*, **28(5),** 743-761.

Bauwens, L., Laurent, S., and Rombouts, J. V. (2006). Multivariate GARCH models: a survey. *Journal of applied econometrics*, **21(1**), 79-109.

Bellemare, M., Barrett, C., and Just, D. (2013). The Welfare Impacts of Commodity Price Volatility: Evidence from Rural Ethiopia. American Journal of Agricultural Economics, 95(4), 877-899.

Bhardwaj, S.P., Paul, R.K. and Kumar, A. (2015). Future trading in soybean – An econometric analysis. *Journal of the Indian Society of Agricultural Statistics*, 69(1): 11-17.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of econometrics*, **31(3),** 307-327.

Bollerslev, T. (1990). Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. *The Review of Economics and Statistics*, **72(3)**, 498-505

Box, G. E., Jenkins, G. M., Reinsel, G. C., and Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.

Brock W, Dechert D, Scheinkman J, LeBaron B. (1996). A test for independence based on the correlation dimension. *Econometric Reviews* 15: 197–235.

Candila,V. and Farac, S. (2018). On the Volatility Spillover between Agricultural Commodities and Latin American Stock Markets. Risks, 6(4)

Chan, K. S. (1993). Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. *The Annals of Statistics*, **21**, 520–533.

Chevallier, J. (2012). Time-varying correlations in oil, gas and CO2 prices: an application using BEKK, CCC and DCC-MGARCH models. *Applied Economics*, **44(32),** 4257-4274.

Das, S., & Bhattacharya, K. 2008. Price convergence across regions in India. *Empirical Economics*, 34, 299-313.

Dickey, D.A., and Fuller, W.A. (1979) Distribution of the estimators for autoregressive time series with a unit root. Journal of the American *Statistical Association*, **74**(3):427–31.

Enders, W. and C. W. J. Granger (1998). Unit root tests and asymmetric adjustment with an example using the term structure of interest rates. *Journal of Business and Economic Statistics*,**16**, 304–311

Enders, W. and P. L. Siklos (2001). Cointegration and threshold adjustment. *Journal of Business and Economic Statistics*,**19**, 166–176.

Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, **50(4),** 987-1007.

Engle, R. and Kroner, K. (1995). Multivariate Simultaneous GARCH. Econometric Theory, 11: 122-150

Gandhi, V.P., & Zhou, Z. Y. 2004. India's Wheat Economy: Will Demand Be a Constraint or Supply? *Economic and Political Weekly*, 39(43):4737-4746

Geweke, J. (1978). Temporal aggregation in the multiple regression model. *Econometrica: Journal of the Econometric Society*, 643-661.

Ghosh, H., Paul, R. K. and Prajneshu, (2010). The GARCH and EGARCH Nonlinear Time-Series Models for Volatile Data: An Application. *Journal of Statistics and Applications*, **5** (**2**), 177-193.

Ghosh, M., &Ghoshray, A. 2018. Rice market integration in India, n Global Commodity Markets and Development Economics (Pfaffenzeller, S. (Ed.)) London: Routledge https://doi.org/10.4324/9781315708683

Ghoshray, A. (2002). Asymmetric price adjustment and the world wheat market. *Journal of Agricultural Economics*,**53**, 299–317.

Ghoshray, A. (2008). Asymmetric adjustment of rice export prices: the case of Thailand and Vietnam. *International Journal of Applied Economics*,**5**, 80–91.

Goletti, F. and Babu, S. (1994). Market liberalization and integration of maize markets in Malawi. *Agricultural Economics*, **11**, 311–324.

Gonzalo, J. and Pitarakis, J.-Y. (2002). Estimation and model selection based inference in single and multiple threshold models. *Journal of Econometrics*,**110**, 319-352.

Gonzalo, J. and Wolf, M. (2005). Subsampling inference in threshold autoregressive models. *Journal of Econometrics*,**127**, 201-224.

Granger, C.W.J. (1988) Some recent developments in the concept of causality. *Journal of Econometrics*, **39**(2):199-211.

Hafner C, Herwartz H. (1998). Time-varying market price of risk in the CAPM. Approaches, empirical evidence and implications. Finance 19: 93– 112.

Hansen, B.E., &Seo, B. (2002). Testing for two regime threshold cointegration in vector error-correction models. *Journal of Econometrics*, **110**(2),293-318

Hassanzoy, N., Ito, S., Isoda, H. and Amekawa, Y. (2017). Cointegration and spatial price transmission among wheat and wheat-flour markets in Afghanistan. *Applied Economics*,**49**(30): 2939-2955

Hassanzoy, N., Ito, S.,Isoda, H. and Amekawa, Y. (2016). A comparison of asymmetric price transmission from global to domestic markets between high and low quality grains: a case of Afghan rice markets. *Economics Bulletin*,36(1), 537-552

Huang, D., Wang, H., and Yao, Q. (2008). Estimating GARCH models: when to use what? *The Econometrics Journal*, **11(1),** 27-38.

Jha, R., Bhanu Murthy, K.V., & Sharma, A. 2008. Market Integration in Wholesale Rice Markets in India, in Jha R. (eds) The Indian Economy Sixty Years After Independence. Palgrave Macmillan, London.

Johansen, S. (1988) A statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, **12**(3): 231-54.

Koop, G., Pesaran, M.H and Potter, SM., (1996). Impulse response analysis in nonlinear multivariate models," Journal of Econometrics, 74(1): 119-147

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P. and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54 (1–3): 159–178

Lin, B., and Li, J. (2015). The spillover effects across natural gas and oil markets: Based on the VEC– MGARCH framework. *Applied Energy*, **155**, 229-241.

Mellor, J. & Zhou, Z. Y., & Gandhi, V. P., 2000. Wheat Economy of India: A Study Of The Growth, Development and International Trade Prospects," IIMA Working Papers WP2000-06-11.

Meyer, J., & Von Cramon-Taubadel, S. (2004). Asymmetric price transmission: a survey. Journal of Agricultural Economics, 55(3), 581-611.

Newbery D.M. (1989). The Theory of Food Price Stabilization. The Economic Journal, 99, 1065-1082.

Paul, R. K. (2015). ARIMAX-GARCH-WAVELET Model for forecasting volatile data. *Model Assisted Statistics and Application*, **10**(3), 243-252.

Paul, R. K. (2015). Cointegration. Data Analysis in Social Sciences Research Using SAS, SSCNARS (https://iasri.icar.gov.in/sscnars/socialsci/20-Cointegration.pdf)

Paul, R. K. and Das, M. K. (2013). Forecasting of average annual fish landing in Ganga Basin. *Fishing chimes*, **33** (3), 51-54

Paul, R. K., and Ghosh, H and Prajneshu. (2009). GARCH nonlinear time series analysis for modelling and forecasting of India's volatile spices export data. *Journal of the Indian Society of Agricultural Statistics*, **63(2),**123-131.

Paul, R. K., Ghosh, H. and Prajneshu (2014). Development of out-of-sample forecast formulae for ARIMAX-GARCH model and their application. *Journal of the Indian Society of Agricultural Statistics*, **68**(1), 85-92.

Paul, R. K., Gurung, B. and Paul, A. K. (2015). Modelling and Forecasting of Retail Price of Arhar Dal in Karnal, Haryana. *Indian Journal of Agricultural Science*, **85**(1), 69-72

Paul, R. K., Panwar, S., Sarkar, S. K., Kumar, A. Singh, K. N., Farooqi, S. and Chaudhary, V. K. (2013a). Modelling and Forecasting of Meat Exports from India. *Agricultural Economics Research Review*, **26** (2), 249-256.

Paul, R. K., Prajneshu, and Ghosh, H. (2009). GARCH Nonlinear Time Series Analysis for Modeling and Forecasting of India's Volatile Spices Export Data. *Journal of the Indian Society of Agricultural Statistics*, **63** (2), 123-131.

Paul, R. K., Prajneshu, and Ghosh, H. (2013b). Statistical modelling for forecasting of wheat yield based on weather variables. *Indian Journal of Agricultural Science*, **83** (2), 180-183

Paul, R. K., Rana, S. and Saxena, R. (2016). Effectiveness of price forecasting techniques for capturing asymmetric volatility for onion in selected markets of Delhi. *Indian Journal of Agricultural Sciences*, **86** (3): 303–309

Paul, R. K., Saxena, R., Chaurasia, S., Zeeshan and Rana,S. (2015). Examining export volatility, structural breaks in price volatility and linkages between domestic & export prices of onion in India. *Agricultural Economics Research Review*, **28**, 101-116

Paul, R. K., Sinha, K. (2015) Spatial market integration among major coffee markets in India. *Journal of the Indian Society of Agricultural Statistics*, 69(3): 281-287

Paul, R.K., Saxena, R. and Bhat, S.A. (2016). How Price Signals in Pulses are Transmitted across Regions and Value Chain? Examining Horizontal and Vertical Market Price Integration for Major Pulses in India. *Agricultural Economics Research Review*, **29**: 75-86.

Phillips, P.C.B., and Perron, P. (1988). Testing fora unit root in time series regression. *Biometrika*, 75,335–346

Powers, N. J. (1995). Sticky short-run prices and vertical pricing: Evidence from the market for iceberg lettuce. Agribusiness, 11(1), 57-75.

Ravallion, M. 1986. Testing market integration. American Journal of Agricultural Economics, 68, 102-109.

Saxena, R., Paul, R.K., Rana, S., Chaurasia, S., Pal, K., Zeeshan and Joshi, D. (2015) Agricultural trade structure and linkages in SAARC: an empirical investigation. *Agricultural Economics Research Review*,28(2): 311-358.

Sekhar, C.S.C. 2012. Agricultural market integration in India: An analysis of select commodities. Food Policy, 37(3), 309-322.

Seo, M. H. (2011). Estimation of nonlinear error correction models. *Economic Theory*,**27**, 201-234.

Silvennoinen, A., and Teräsvirta, T. (2009). Multivariate GARCH models. *Handbook of financial time series* (pp. 201-229). Springer, Berlin, Heidelberg.

Tiwari, A.K. and Mutascu, M. (2016). The revenues-spending nexus in Romania: a TAR and MTAR approach, *Economic Research-Ekonomska Istraživanja*, 29 (1), 735-745

Tong, H. (1990): *Non-Linear Time Series: A Dynamical System Approach*. Oxford Science Publications.

Tong, H. (2007). Birth of the threshold time series model. *StatisticaSinica*,17, 8–14.

Tong, H. (2011). Threshold models in time series analysis — 30 years on. *Statistics and Its Interface*, **4**, 107–118

von Cramon-Taubadel, S., Loy, J. P., & Meyer, J. (2006). The impact of cross-sectional data aggregation on the measurement of vertical price transmission: An experiment with German food prices. Agribusiness: An International Journal, 22(4), 505-522.

Wang, M., Chan, N.H. and Yau, C.Y. (2016). Nonlinear error correction model and multiple-threshold cointegration. *Statistica Sinica*,26, 1479-1498

Wani, M. H., Paul, R. K., Bazaz, N. H. and Manzoor, M. (2015a). Market Integration and Price Forecasting of Apple in India. *Indian Journal of Agricultural Economics*, **70** (2), 169-181.

Wani, M.H., Bazaz, N.H., Paul, R.K., Showkat A.I. and Bhat, A. (2015a). Inter-Sectoral linkages in Jammu & Kashmir economy-an econometric analysis. *Agricultural Economics Research Review*, 28(1): 11-24.

Wani, M.H., Paul, R.K., Bazaz, N.H. and Manzoor, M. (2015b). Market integration and price forecasting of apple in India. *Indian Journal of Agricultural Economics*, **70**(2): 169-181.

Wani, M.H., Sehar, H., Paul, R.K., Kuruvila, A. and Hussain, I. (2015c). Supply response of horticultural crops: a case of apple and pear in Jammu and Kashmir, India. *Agricultural Economics Research Review*, 28(1): 83-89.

Zheng, Y., H.W. Kinnucan, and H. Thompson (2008). News and volatility of food prices, Applied Economics, 40: 1629-1635.