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Market Intelligence in India: Methods and Effectiveness of Agricultural Commodity Price Forecasts

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Foreword

In the past one decade or so, the global food prices have become more volatile, particularly vegetables and pulses have exhibited extreme volatility in prices. High volatility in prices may distort production and investment decisions, leading to inefficient allocation of resources. Managing food price volatility is, thus, a big challenge for policymakers. Farmers benefit from higher prices, but not necessarily from its high volatility. They lack information about the expected changes in prices of food commodities. If they are aware of the likely trends in future prices, it can guide them to take informed decisions regarding choice of crop, allocation of area, time of sowing and harvest, choice of market, and time of sale. It is assumed that sufficient information about the prices would strengthen the otherwise weak link between production and marketing. In order to enable farmers to take informed decisions, ICAR-National Institute of Agricultural Economics and Policy Research (NIAP) collaborated with 14 centres across the country and undertook the Network Project on Market Intelligence to generate price forecasts for important agricultural commodities. The forecasts were disseminated to the farmers before sowing and at the time of harvest.

This area of market intelligence holds paramount importance, particularly when the Government is committed to increase the income of farmers. Globally, continuous efforts are being made to capture the trends in prices and commodity outlook/projections to gain from the market dynamics in terms of demand-supply interplay. The present work is a substantial effort in the area of agricultural price forecasting. As the project was conceptualized during my stay at this institution, it was made sure that due emphasis is given on the inclusion of high-value crops, particularly fruits, vegetables and spices. I am happy to see the outcome of this project in the form of a policy paper, which will be extremely useful to the stakeholders in the Department of Agriculture, Cooperation & Farmers Welfare (DAC&FW) and other relevant organizations. This policy paper includes the detailed analysis of price forecasts and their dissemination in selected states from 2014-15 to 2016-17. I congratulate the Director and the project team for bringing out this useful document.

Ramesh Chand
Member NITI Aayog

Acknowledgments

In recent years, the agricultural prices have exhibited very high volatility. The issue of high price volatility in agricultural commodities in domestic as well as international market has assumed critical importance in the changing context of trade liberalization. The volatility in the agricultural prices has a catastrophic effect on all the stakeholders involved in the supply chain of various commodities and has increased the financial risk of the farming community. The fluctuation in prices of agricultural commodities is a matter of concern among farmers, policy makers and stakeholders. For the Government, unforeseen variations in agricultural price can complicate the entire planning. Thus, their accurate forecasting is extremely important for efficient planning and monitoring. This paper provides the summary results of the 'Network Project on Market Intelligence' from 2014-15 to 2016-17. In this paper, we are presenting the efficacy of our results and effectiveness of various models used for price forecasting. We worked with a number of time series models. It was observed that ARIMA family has serious limitations and is not capable of modelling the datasets that depict volatility. Considering this, other non-linear and hybrid models were relied upon to capture the volatility in prices.

The authors express their sincere thanks to ICAR for providing with financial support to carry out this important research work. The project team is grateful to Prof Ramesh Chand, former Director, NIAP and presently Member (Agriculture), NITI Aayog, Government of India for providing strong support and motivation to carry out this exercise. Our sincere thanks are due to Dr Suresh Pal, Director, NIAP for continuous motivation, guidance, and support in bringing out this paper. We duly acknowledge the cooperation by Director IASRI. We would like to place on record the support of project teams (at Annexure A) of our collaborative institutions, who played key role in generating and disseminating the price forecasts to the farmers.

The network mode of operation provided the scope in building the effective linkages and capacity building of the project teams which resulted in delivery of location specific outcomes. The stakeholders reflected a lot of confidence in this exercise. We are trying to institutionalize the efforts through the Department of Agriculture, Cooperation and Farmers' Welfare. We understand that these efforts will be beneficial for the stakeholders and farmers to maximize the gains from effective information delivery.

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Executive Summary

In recent years, the issue of high price volatility in agricultural commodities in domestic as well as international market has assumed critical importance. Considering the extreme price situations and volatility, the market intelligence plays a significant role in farmers' decisions regarding production and marketing of agricultural commodities. The present work is a substantial effort in the area of agricultural price forecasting, wherein more than 40 agricultural commodities were selected to provide reliable and timely price forecasts to farmers in 13 major states across the country from 2014-15 to 2016-17, in order to enable them to make informed production and marketing decisions. This policy paper includes the detailed analysis of price forecasts and their dissemination in selected states. The commodities were mainly selected on the basis of market arrivals besides other concerns such as global linkages in terms of international trade, which could influence the prices.

The price behaviour was decomposed into trend, seasonal, cyclical and irregular fluctuations in order to ascertain the causal factor for price volatility and the price series were adjusted accordingly, wherever required. Cereal prices have exhibited less volatility as compared to other crop categories. However, the price volatility has been more evident after the year 2012. In case of pulses, pigeon pea has shown very stable WPI from January, 2005 to March, 2009. Oilseeds exhibited very stable price behaviour specially groundnut and rapeseed & mustard. However, soybean exhibited very high seasonal and irregular variations. Cotton prices also exhibit high fluctuations with high irregular variations during June, 2011 to September 2011 and May, 2016 to September, 2016. Fruits and vegetable crops exhibited highest price volatility among all agricultural commodities.

The forecasts were developed based on the scientific modeling framework along with the consideration of price expectations of farmers and traders to provide short-term forecasts to farmers at an appropriate time for effective production and marketing decision making. In case of perishable commodities, the forecasting was done on a weekly basis. An autoregressive integrated moving average (ARIMA) model was applied for price forecasting in case of cereals such as fine paddy, pearl millet and finger millet, and pulses. The forecast accuracy in cereals stood at about 90 per cent. This was due to relatively stable prices of cereals, except in the case of maize, wherein the forecast accuracy ranged between 77-89 per cent for Dhule market in Maharashtra. The estimates of parameters along with corresponding standard error and p-value of the selected model were worked out. ARIMA model was applied in initial years for price forecasting of pulse crops. Following the volatility in the prices of pulse crops, generalized autoregressive conditional heteroskedasticity (GARCH) models were adopted to forecast green gram price in 2014-15. In order to capture the seasonal effects, seasonal ARIMA (SARIMA) models were successfully used to forecast green gram price during 2015-17. As cluster bean prices are extremely volatile, exponential GARCH (EGARCH) model was applied for price forecasting to capture the symmetric and asymmetric patterns. The price forecasts were more than 80 per cent accurate in pulses during 2014 and 2015. In the year 2016, pre-sowing forecast accuracy was lesser than 2014 and 2015. In case of pulses, it was evident that pre-harvest (PH) forecasts are more precise than pre-sowing (PS) forecasts.

An ARIMA model was employed for oilseeds and fibre crops as well. In majority of markets, the accuracy of price forecasts was higher for oilseeds in 2016 as compared to 2014 and 2015. In general, forecast accuracy was high for PH forecasts (precision >90 per cent) even in the case of oilseeds. Cotton was the major fibre crop selected for price forecasts where 90 per cent precision was observed.

Prices of horticultural commodities, especially vegetables, were the most volatile during the study period. Thus, a combination of different forecasting models proved to be effective in case of these commodities, depending on the price trends. ARIMA, GARCH, SARIMA, vector auto-regression (VAR), E-GARCH and autoregressive conditional heteroskedasticity (ARCH), GARCH models were used for modeling and forecasting the prices of major horticultural crops in India. Weekly forecasts were done for Karnataka state where ARIMA model was found suitable. ARIMA was quite successful in forecasting the prices of turmeric, black pepper, coconut, castor, green pea, chilli, mango and tapioca. SARIMA models were used to forecast cabbage, coconut, ginger, pineapple, tomato and turmeric prices due to very high seasonality factor. ARIMA models are subject to assumption of linearity and homoscedastic error variance and hence, were not adequate to deal with price volatility. Thus, GARCH models were used to forecast price volatility more efficiently and were used for apple, cherry, coriander and ginger.

Among all the sub-sectors, vegetables showed lowest forecast precision for three consecutive years. Though the forecast accuracy was high (>90%) for cabbage, chilli and green pea, extreme fluctuations were observed in prices of onion, potato and tomato, resulting in a lower accuracy in price forecasts for vegetable crops as a whole. In case of fruits (banana, pear, pineapple, plum, mango and cherry), the forecast accuracy for 2015 was lesser as compared to 2016. Forecast accuracy for fruits was more than 80 per cent, except pear, cherry and pineapple, and 60% for mango in 2016 for Uttar Pradesh. Price forecast for walnut was more than 80 per cent accurate throughout the study period.

The forecasts were disseminated to farmers through regional newspapers, websites of the regional academic institutes, information bulletins, personal meetings and interactions, social media and other relevant means. Besides, a minimum of 30 farmers were identified for each commodity in each state in order to regularly disseminate the forecasts and monitor the impacts of the price information provided to them. The same sets of farmers were monitored over the study period to assess the impact of price forecasts. Print media had wider dissemination across states and was the preferred mode. This comprised national dailies, regional newspapers, magazines, pamphlets and brochures. Websites were also widely used for the purpose. Other modes of communication comprised voice and text SMSs, and broadcast on television and radio. Farmers' fairs in the universities and institutes also proved to be a good platform for interaction and price forecast dissemination purpose.

The study made continuous efforts in terms of improving the forecast accuracy through modeling and its dissemination through institutional interventions. A lot can be done to improve the forecast accuracy in terms of data dimensions, modeling innovations and further institutionalization of the concept of market intelligence (basically aiming at generating short-term price forecasts). Price data are the key input in generating the price forecasts and a mismatch in the data series provided by different agencies has been noted. This accentuates that the data reporting mechanisms at the Agricultural Produce Market Committees (APMCs) need to be standardized. Harmonizing the efforts of different organizations in terms of data recording and availability will be effective. The data discrepancies need to be addressed as reliable data are crucial for technically sound forecasts. Thus, the real-time data on price realized by the farmers is required for generating precise forecasts.

Besides its own volatility, the prices of agricultural commodities are affected by many climatic and policy variables. Therefore, the methodological improvements for incorporating the effects of critical variables are the need of the hour. The multivariate modeling framework needs to capture the variables which emanate from climatic and policy shocks. Thus, the real-time data on these critical variables must be available to capture the external shocks. Besides, the use of remote-sensing and artificial intelligence should be promoted in order to get the advanced information about the crop conditions at field level. The forecast accuracy can further be improved by incorporating the future prices in the modeling framework as a lot of indicative trends can be observed through the movement in futures prices.

The study also revealed that most of the markets for a given commodity are co-integrated and price signals are transmitted from one market to the other with varying speed. The rate of adjustments is high when prices are assumed to be influenced by the changes in each other's price. In most of the agricultural commodities, there are some dominating markets from the production zones which quickly transmit the price signals to other markets. Though, initially own price volatility remains an important and major driving force for price change in a given market, the effect of the dominating market's volatility are spilled over in other markets and changes the price in those markets. Thus, focused regional and commodity studies are required to provide the updated market dynamics to appraise the policy makers to take any preventive or corrective actions. Proper emphasis on domestic supply management along with international trade, coupled with strong market surveillance and intelligence efforts would help control the price distortions.

In the long run, the market intelligence efforts need to be actively taken up by the Department of Agriculture and Department of Marketing, both at the central and state levels. The academic institutions can play an important role in capacity building. The project activities may be linked with line departments for effective dissemination and institutionalization. A proactive approach needs to be adopted to create awareness and acceptability of price forecasts among the farmers. The impact studies in this context would be extremely useful for generating the system feedback and improving the market intelligence framework. To create longer and larger impact and acceptability in the system, e-solution for market intelligence can be developed by combining various algorithms of suitable techniques and models in single software package, which would be easy to use even by the line departments.

1 Chapter

Introduction

Agricultural prices hold tremendous importance in the agricultural economy of India. It has a significant influence on the crop acreage (Mesfin, 2000; Mythili, 2001; Mythili, 2008) as well as the marketing decisions of the farmers and other stakeholders (Saxena et al., 2017). Agricultural prices determine the farm income and thus have a significant impact on the farmers' well-being (Chand, 2017). A notable turnaround observed in terms of trade after 2004-05 was attributed to the faster growth in agricultural prices (at about 30% higher) than those of non-farm commodities (Chand and Parappurathu, 2012). Hence, volatility in agricultural commodity prices has been a major concern for policy makers in India as it significantly affects the gains to farmers (Saxena and Chand, 2017).

Market Intelligence and the dissemination of market information plays an important and significant role in the farmers' decisions regarding production and marketing of agricultural commodities. Thus, the availability of accurate, timely and adequate market-related information enables farmers to take informed decision as to when and where to sell their produce (Acharya, 2003). Market Intelligence is the process of collecting relevant information related to the existing market prices, domestic and global agricultural supply and demand conditions, policy environment and other relevant factors; converting the information into usable form through scientific modeling and stakeholders' perceptions; and disseminating through effective means so that informed and effective decisions can be taken by the farmers and other stakeholders.

In recent years, the agricultural prices have exhibited very high volatility. The issue of high price volatility in agricultural commodities in domestic as well as international market has assumed critical importance in the changing context of trade liberalization. The volatility in the agricultural prices has a catastrophic effect on all the stakeholders involved in the production, marketing and consumption of the food commodities (Sekhar, 2004). This has increased the risk faced by the farming community. Besides temporal volatility, there also exists wide spatial variability in the prices of agricultural commodities. Varying climatic conditions and differences in resource endowments of country result in regional specialization of the agricultural commodities which are marketed through alternate marketing channels to consumers spread across the country. Thus, it is assumed that sufficient information about the prices, based on an efficient marketing intelligence, would strengthen linkages between production and marketing.

Globally, continuous efforts are being made to capture the trends in prices and commodity outlook/projections to gain from the market dynamics in terms of demand-supply interplay. The comparison of annual medium-term projections issued by the OECD-FAO, Food and Agricultural Policy Research Institute (FAPRI) and the US Department for Agriculture (USDA) provide common and diverging trends across projections as well as identify uncertainties that could significantly impact markets for grains, oilseeds, meat, dairy, biofuel and sugar over the next ten years (OECD/FAO, 2011).

In India, 14 Market Intelligence Units (MIU) were established by the Directorate of Economics and Statistics as early as in 1954. These units were set up in Andhra Pradesh, Assam, Bihar, Delhi, Gujarat, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal following the recommendation of the Agricultural Prices Enquiry Committee. However, there is a need to reevaluate the activities, functions and staff requirements of the MIUs (GOI, 2019). After a prolonged gap, the next initiative to provide the farmers with the agricultural price information was led by the Indian Council of Agricultural Research (ICAR) in 2009. ICAR implemented the sub-project "Establishing and Networking of Agricultural Market Intelligence Centres in India" as part of the National Agricultural Innovation Project (NAIP) with the objective to establish an institutionalized network of Agricultural Market Intelligence Centres in India; enabling and empowering farmers and entrepreneurs. It aimed at providing up-to-date information on prices and other market factors enabling farmers to negotiate with the traders and also facilitating spatial distribution of products among markets. Therefore, the ICAR set up the Domestic and Export Market Intelligence Cell (DEMIC) in order to provide price forecasts for various crops (FICCI, 2017). The DEMICs were established to help the farmers to realise higher prices, provide improved regional linkages to generate, disseminate, and sharing market information for better decision making and also improve the access and use of market intelligence to all stakeholders in the marketing chain for better production and marketing strategies.

Scientists from the state agricultural universities (SAUs) who were involved as collaborating centres, developed the price forecasts (FICCI, 2017) whereas the lead team, based in Tamil Nadu Agricultural University (TNAU), monitored the overall implementation of the project activities. The collaborative centres were Kerala Agricultural University, University of Agricultural Sciences (Dharwad), University of Agricultural Sciences (Bangalore), Acharya N G Ranga Agricultural University (Guntur), Dr Panjabrao Deshmukh Krishi Vidyapeeth (Akola), Junagadh Agricultural University, Maharana Pratap University of Agriculture & Technology (Udaipur), Chaudhary Charan Singh Haryana Agricultural University (Hissar), Punjab Agricultural University (Ludhiana), and Govind Ballabh Pant University of Agriculture & Technology (Pantnagar).

The team regularly brought out pre-sowing and pre-harvest price forecasts for 34 crops (including cereals, pulses, oilseeds, cotton, vegetables and spices) with 90 to 100 per cent accuracy, the price forecasts were widely disseminated through print and visual media, mobile applications, radio broadcasts and also through tie-ups with organizations having networks with farmers. Regular feedbacks were received from stakeholders and analysed (Acharya, 2017). Two types of price forecasts viz., pre-sowing forecast and pre-harvest-forecast were provided to help the farmers on sowing and area allocation decisions as well as the decisions on immediate sale or stocking period to take advantage of the price rise in the commodity markets and the price forecasts were validated by interacting with traders, farmers, and other commodity specific websites and also in futures platform (Acharya, 2017; NAIP, 2014[a]).

The impact assessment of the forecast advisory provided showed that the income of the adopters of market advisory was higher compared to the non-adopters (ICAR, 2014). The Monitoring and Evaluation Committee of the NAIP project emphasized that the market advisories will have a bearing on the sowing and harvesting decisions, while commodity outlook will have a bearing on the cropping pattern. It was further suggested that the market intelligence should be continued at ICAR-National Institute of Agricultural Economics and Policy Research (NIAP) (Acharya, 2017; NAIP, 2014 [C]). Besides this, NIAP also implemented a decision support system (DSS) for commodity market outlook. An India-specific model namely, Cereal Outlook Model, was developed for three major cereals, viz. rice, wheat and maize, which could generate commodity outlook based on four key components of the food balance sheet, viz., demand, supply, trade and prices (Shinoj et al., 2014). An online database repository, Commodity Market Outlook Statistics (CMOS), was developed as a part of the sub-project for providing time-series and cross commodity data (NAIP, 2014[a & b]).

This work was continued at NIAP with ICAR funding with a network of 14 institutions (covering 12 state/central agricultural universities and 2 ICAR institutes) and was named 'Network Project on Market Intelligence'. The project intended to provide the short-term price forecasts of regionally important commodities and also focused on policy studies with relevance to price behaviour, price transmission, market infrastructure along with market linkages. More than 40 agricultural commodities, most of them being high-value commodities (horticulture), were selected to provide reliable and timely price forecasts to farmers in 13 major states across the country, in order to enable them to make informed production and marketing decisions based on the price and arrival data gathered from APMCs and AGMARKNET portal. Appropriate forecast models were used and the results were delivered to farmers through regional newspapers, regional websites, information bulletins, personal meetings and interactions, social media and various other relevant means. As personal dissemination method is more effective in such cases, a minimum of 30 farmers were identified for each commodity in each state in order to regularly disseminate the forecasts and monitor the impact of the price information provided to them. The same sets of farmers were monitored over the study duration to assess the impact of price forecasts provided. The project focused on continued capacity building of the project teams to build forecast precision. The project was launched in June 2013 and concluded in March 2017 with the collaborating partners (Annexure A). This policy paper includes the detailed analysis of price forecasts and their dissemination in selected states from 2014-15 to 2016-17.

Chapter 2

Price Behaviour and Market Linkage

2.1 Price Behaviour

Time series models and components

The time series (TS) movements of chronological data can be decomposed into trend, periodic (seasonal, etc.), cyclical, and irregular variations. A basic assumption in any TS analysis is that some aspects of the past pattern will continue to remain in the future. The successive observations are statistically dependent and TS modelling is concerned with techniques for the analysis of such dependencies, the prediction of values in TS modelling for the future periods is based on the pattern of past values of the variable under study, but not generally on explanatory variables which may affect the system. An important step in analysing TS data is to consider the types of data patterns, so that the models most appropriate to those patterns can be utilized. Four types of TS components can be distinguished –

(i) horizontal: when data values fluctuate around a constant value;

(ii) trend: when there is a long-term increase or decrease in the data;

(iii) seasonal: when a series is influenced by a seasonal factor which recurs on a regular, periodic basis; and

(iv) cyclical: when the data exhibit rises and falls that are not of a fixed period. Many data series include combinations of the preceding patterns.

(v) After identifying the existing patterns in any TS data, the pattern that remains unidentifiable forms the 'random' or 'error' component.

Time plot (data plotted over time) and seasonal plot (data plotted against individual seasons) help in visualizing these patterns while exploring the data. Trend analysis of TS data analyses a variable over time to detect or investigate long-term changes. Trend is 'long-term' behaviour of a TS process, usually in relation to the mean level. The trend of a TS may be studied because the interest lies in the trend itself, or may be to eliminate the trend statistically in order to have an insight into other components, such as periodic variations in the series. A periodic movement is one which recurs with some degree of regularity, within a definite period. The most frequently studied periodic movement is that which occurs within a year and which is known as seasonal variation. Sometimes the TS data are de-seasonalized for the purpose of making the other movements (particularly trend) more readily discernible. Climatic conditions directly affect the production system in agriculture and hence, in turn, their patterns of prices. Thus, they are primarily responsible for most of the seasonal variations exhibited in such series. A crude yet practical way of decomposing the original data (including the cyclical pattern in the trend) is to go for a seasonal decomposition either by assuming an additive or multiplicative model such as,

$$Yt = Tt + St + Et \text{ or } Yt = Tt \,.\, St \,.\, Et$$

Where, Yt - original TS data, Tt - Trend, St - Seasonal component, Et - Error/ Irregular component

If the seasonal variations of a TS increase with the level of the series, then a multiplicative or an additive model should be adopted. The decomposition methods may enable one to study the TS components separately or may allow de-trending or seasonal adjustments, if needed for further analysis. Decomposition methods usually try to identify two separate components i.e. trend-cycle and seasonality of the basic underlying pattern that tend to characterize economic and business series. Any residual is considered as an irregular or a remainder component, identified as the difference between the combined effect of the two sub-patterns of the series and the actual data.

We considered a TS model which is additive in nature with seasonal period 12 such that, preserving the earlier mentioned notations, Yt = Tt + St + Et. The trend cycle Tt is computed using a centered moving average MA i.e. a 2 × 12 MA. The de-trended series is computed by subtracting the trend-cycle component from the data, leaving the seasonal and irregular terms:

$$Yt - Tt = St + Et.$$

The seasonal component St is obtained by stringing together this set of 12 values called seasonal indices (one for each month), repeated the same for each year of data. The irregular series Et is computed by subtracting the estimated seasonality and trend - cycle from the original data series. The analysis was done on the wholesale price indices of selected commodities from January 2005 to March 2017. Figures 1 to 7 present the price decomposition in major commodities groups/commodities based on the wholesale price indices (WPI).

Cereals: Cereal prices have exhibited less volatility as compared to other crop categories. However, the price volatility has been more evident after the year 2012. The selected cereals exhibited very little seasonal and irregular variations in spite of an increasing trend (Fig. 1). A relatively steeper increasing price trend was observed in ragi. Higher WPI for ragi, pearl millet and maize were observed from July, 2012 to March, 2014.

Pulses: In case of pulses, pigeon pea has shown very stable WPI from January, 2005 to March, 2009. Sudden increase in pigeon pea price was observed in March 2009 which continued till December, 2010 due to higher irregular variation. However, a lower price has been observed during December, 2010 to June 2015. In spite of seasonal variation, higher irregular variation was also observed after June, 2015 to February, 2017 (Fig 2). In case of gram, WPI was very stable from January, 2005 to April, 2012 with very little fluctuations. A dramatic increase in WPI after April, 2016 was pronounced. A steep increasing trend for moong was pronounced from 2005 to 2017 with high fluctuations as the prices witnessed higher irregular variations with little seasonal variations. Prices of moong suddenly accelerated from August, 2009 to December, 2010. Prices remained higher from September, 2014 to May, 2016, though declined thereafter.

Oilseeds: Oilseeds exhibited very stable price behaviour specially groundnut, rapeseed & mustard. However, soybean exhibited very high seasonal and irregular variation. Cotton price also exhibit high fluctuations with high irregular variations between June and September, 2011 and then between May and September, 2016.

Horticulture: Fruits and vegetable crops exhibited the highest price volatility among all the agricultural commodities. Onion witnessed extremely high seasonal and irregular variations from June 2013 to December 2015. Potato price fluctuations occurred largely due to seasonal variations. Banana price was quite stable with few seasonal and irregular variations. The prices of spices were quite stable, except for coriander and turmeric. Coriander prices suddenly accelerated during December, 2007 to June, 2008 and reflected higher fluctuations during December, 2013 to July, 2015 due to higher irregular variations. Turmeric prices were peak in 2010-2011.

Fig 1. Price Decomposition for Cereals

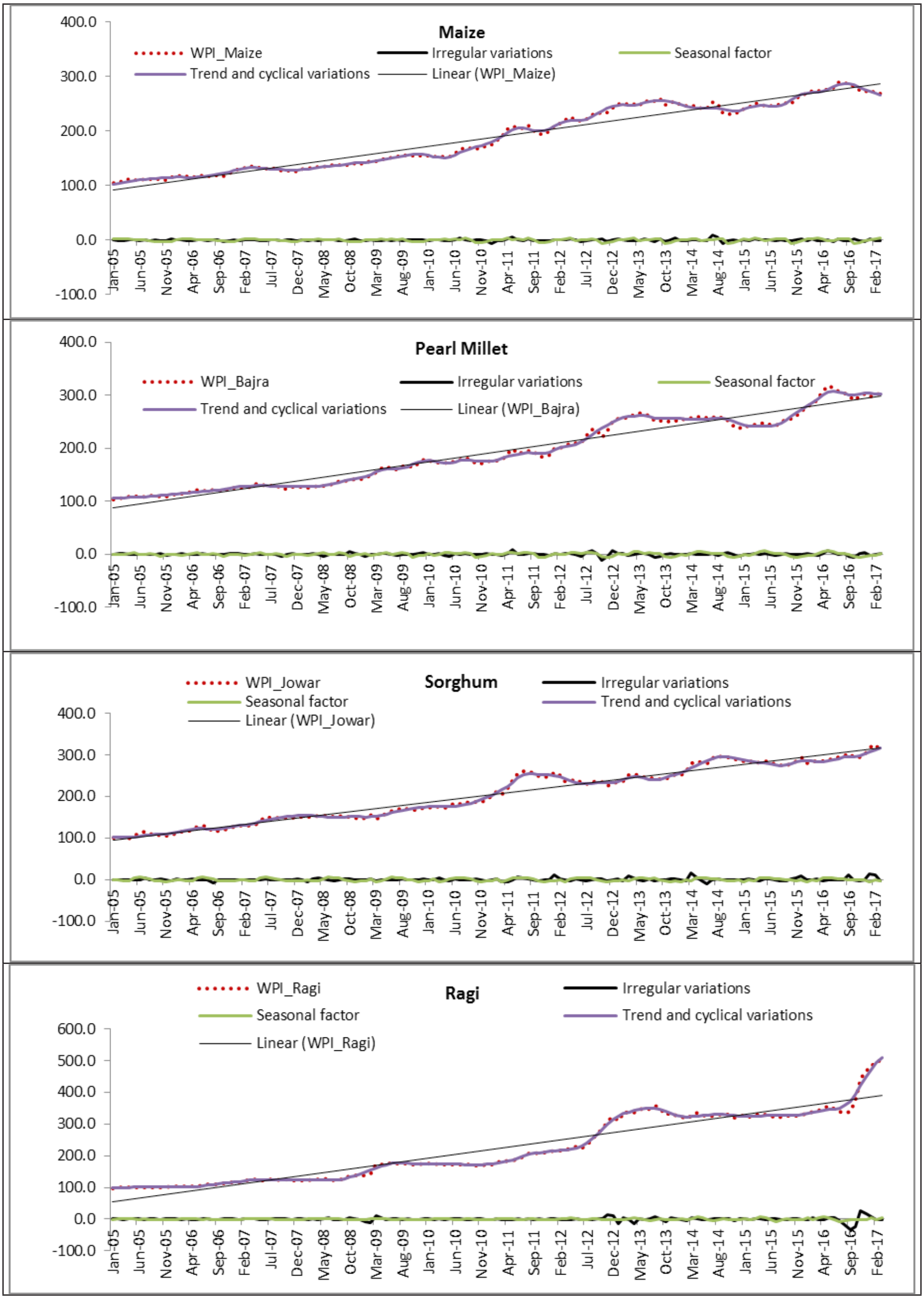


Fig 2. Price Decomposition for Pulses

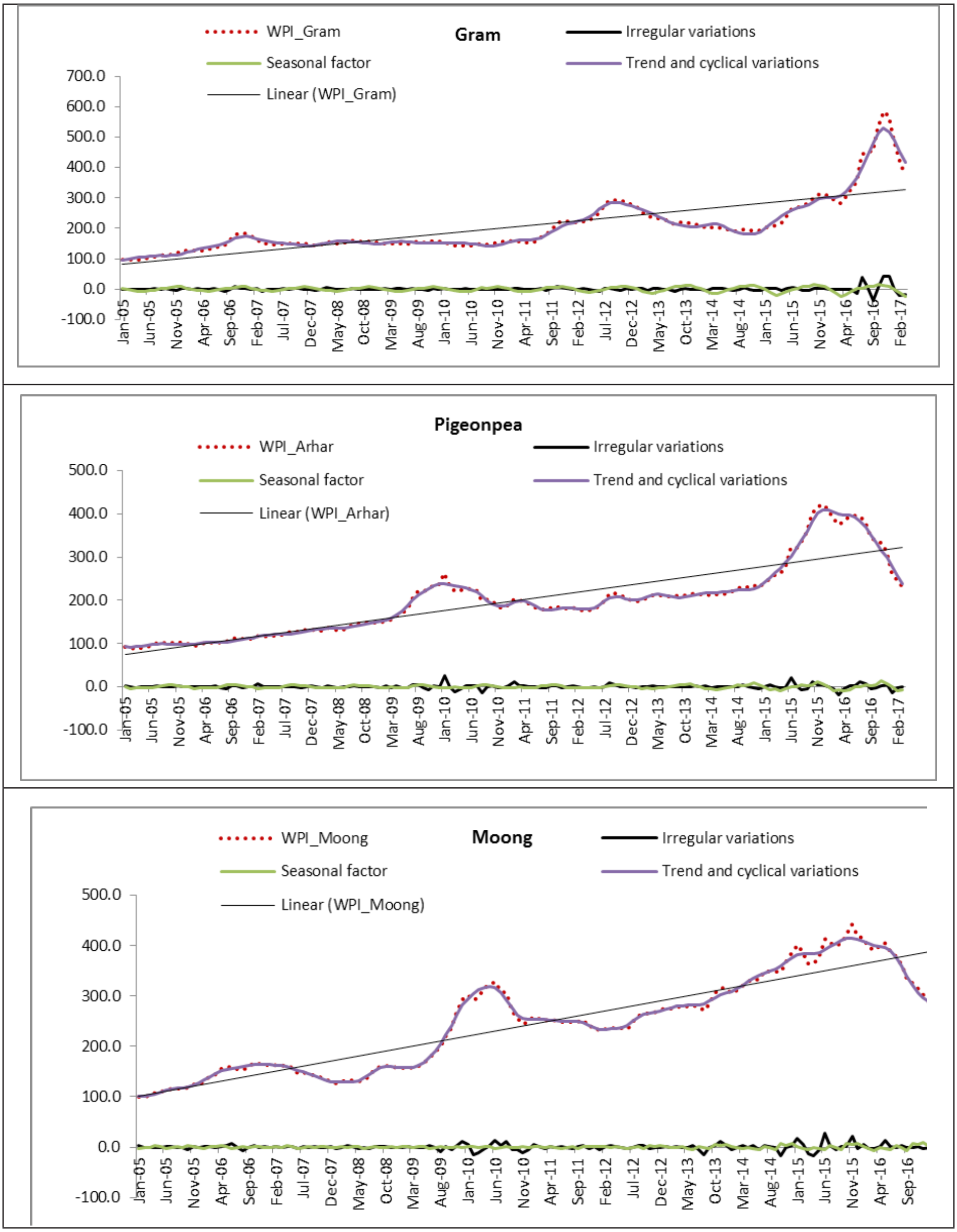


Fig 3. Price Decomposition for Oilseeds

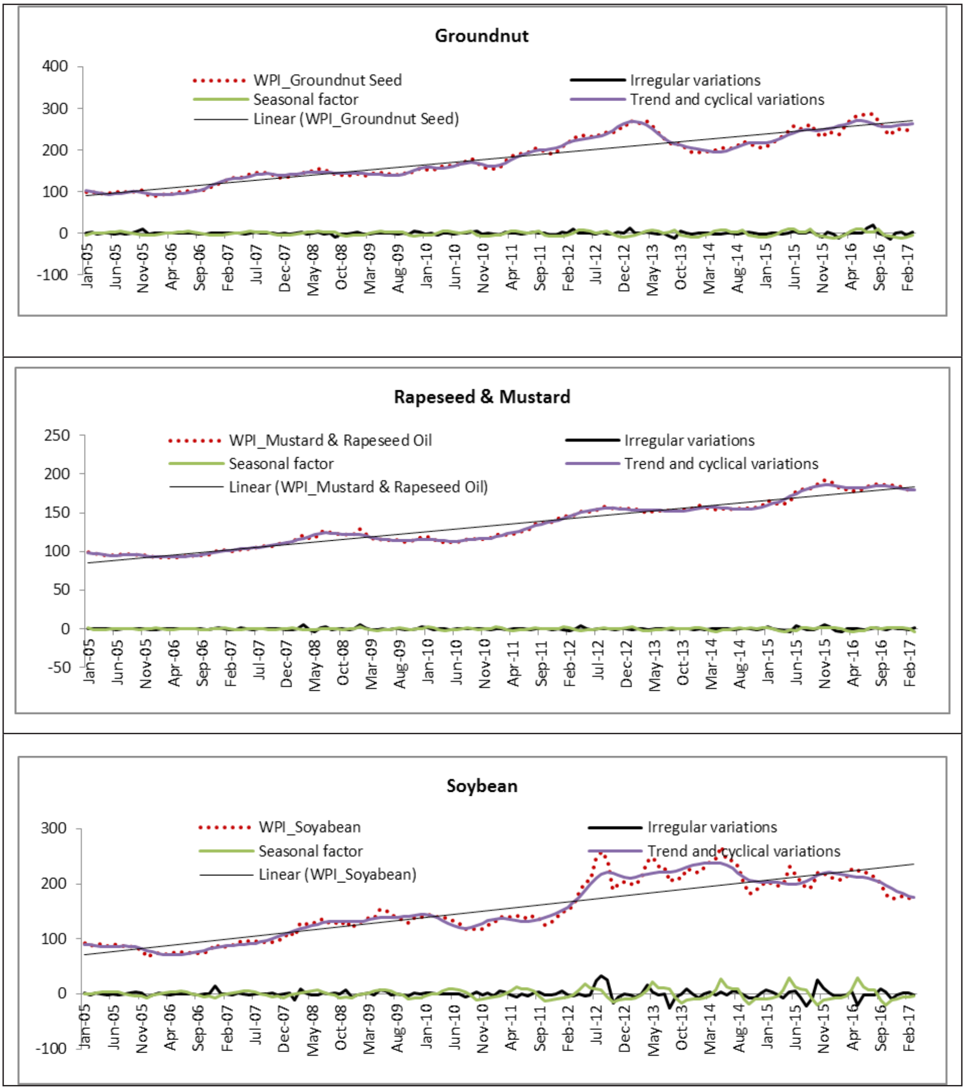


Fig 4. Price Decomposition for Cotton

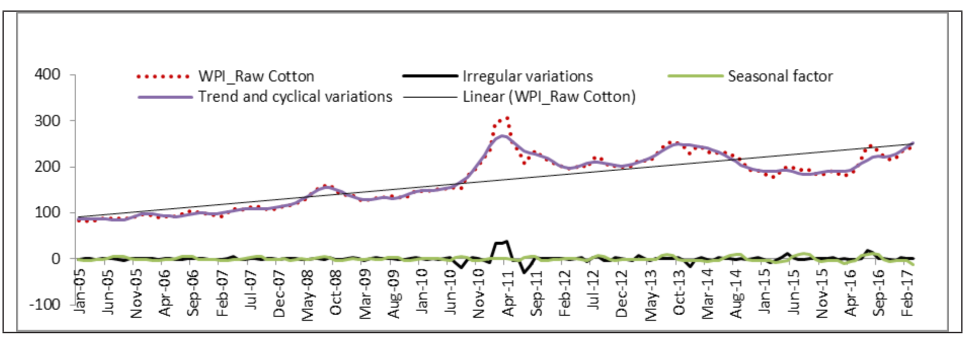


Fig 5. Price Decomposition for Vegetables

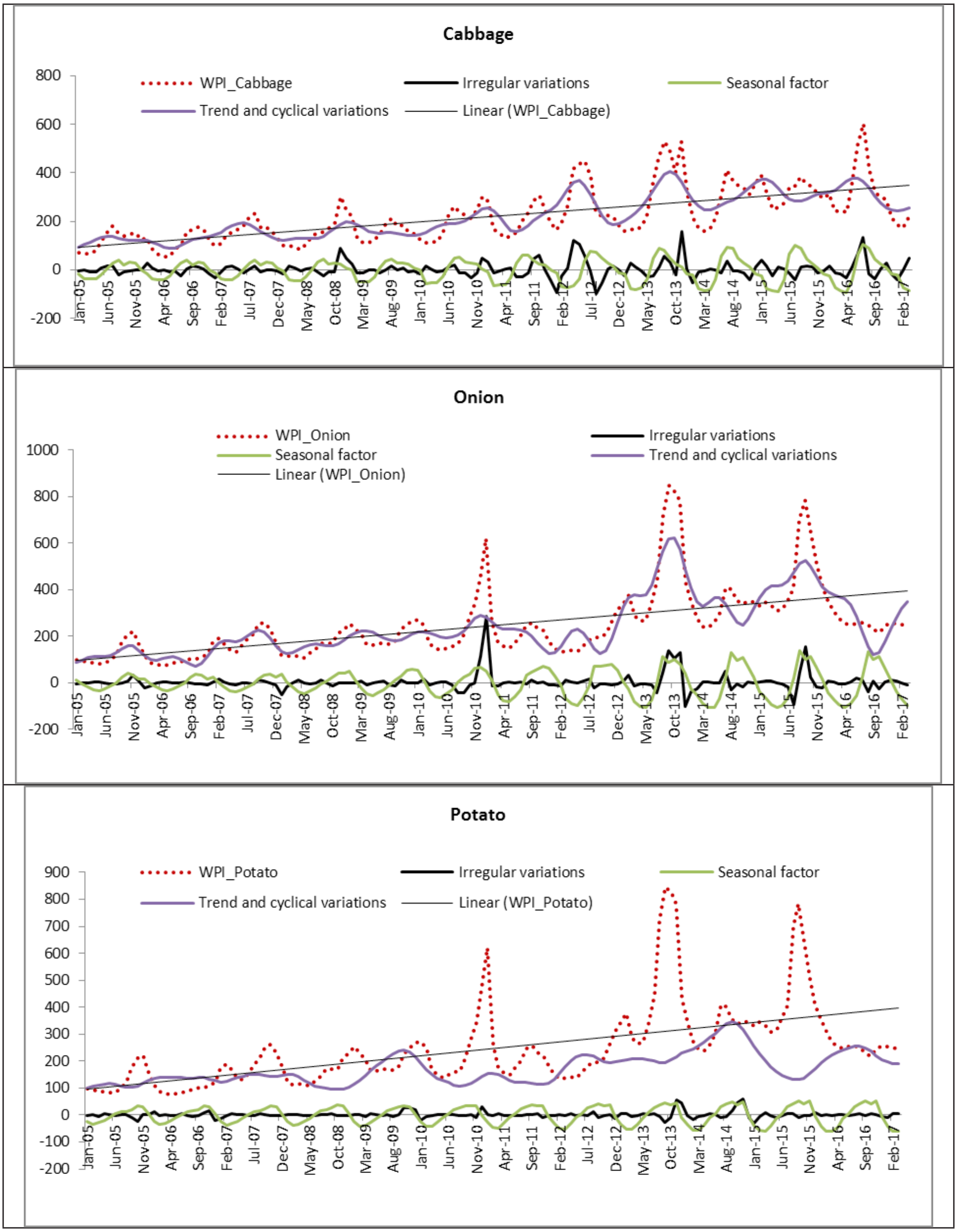


Fig 6. Price Decomposition for Fruits

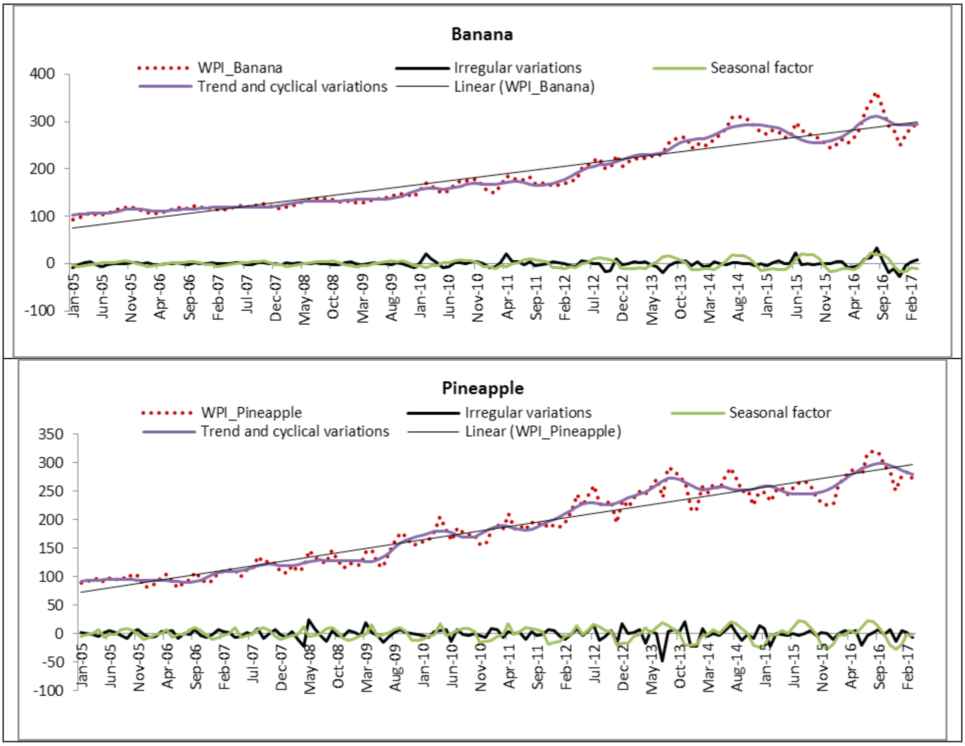


Fig 7. Price Decomposition for Spices

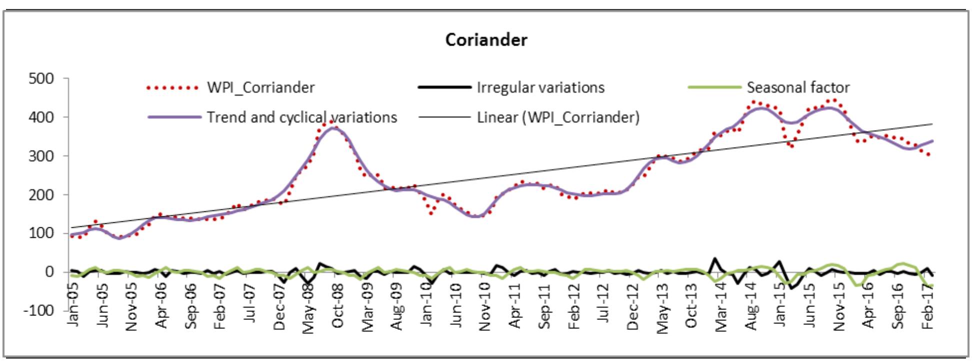
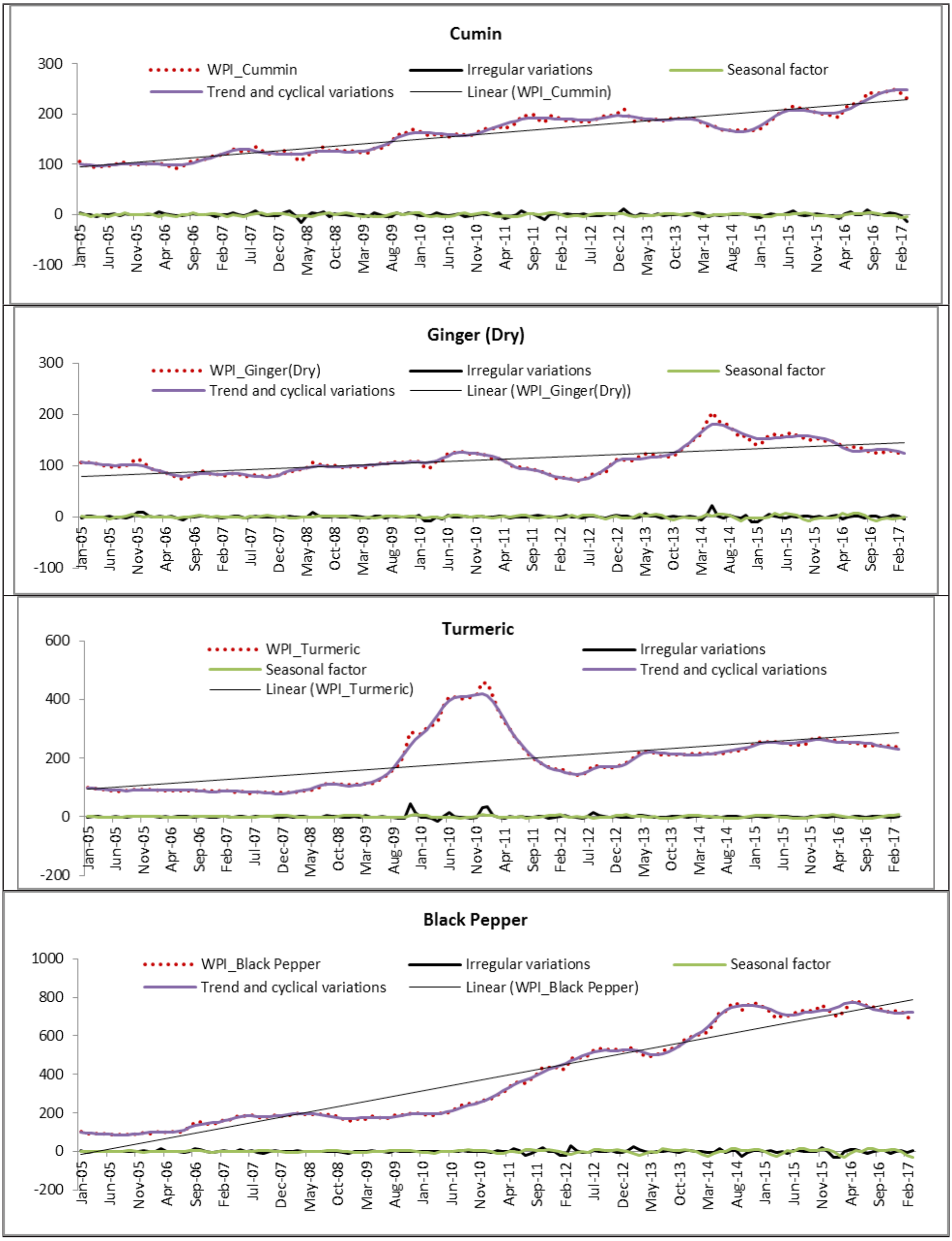


Fig 6. Price Decomposition for Fruits



2.2 Price Transmission Analysis

Testing the Stationarity

The price series were considered stationary if its underlying generating process is based on a constant mean and a constant variance. In general, the price series are non-stationary in nature. The unit root tests are used to test the stationarity of a series. A statistical test for stationarity or test for unit root has been proposed by Dickey and Fuller (1979), referred to as the Augmented Dickey Fuller (ADF) test. The test is applied for the parameter ρ in the auxiliary regression

$$\Delta_1 y_t = \rho\, y_{t-1} + \alpha_1\, \Delta_1 y_{t-1} + \varepsilon_t$$

where, Δ_1 denotes the differencing operator i.e. $\Delta_1 y_t = y_t - y_{t-1}$.

The relevant null hypothesis is $\rho = 0$, i.e. the original series is non-stationary and the alternative is $\rho < 0$ i.e. the original series is stationary. Usually, differencing is applied until the ACF shows an interpretable pattern with only a few significant autocorrelations.

Cointegration and Long-term Causality

The cointegration depicts long-term relationship between the variables. It means even if two or more series are non-stationary, they are said to be cointegrated if there exists a stationary linear combination of them. For examining the long-term causality, Granger causality test was applied. According to the test, if a variable Y is Granger caused by a variable X, it means that values of variable X help in predicting the values of variable Y and vice-versa. The Granger causality test, conducted within the framework of a Vector Auto-regression (VAR) model, is used to test the existence and the direction of long-run causal price relationship between the markets (Granger, 1969). It is basically the F-test of whether changes in one price series affect another. The causality relationship between two price series, as an example, based on the following pairs of ordinary least squares (OLS) regression equations through a bivariate VAR, is given by equations below:

$$\ln X_t = \sum_{i=1}^{m} \alpha_i\, lnX_{t-i} + \sum_{i=1}^{m} \beta_j\, lnY_{t-j} + \varepsilon_{1t} \tag{1}$$

$$\ln Y_t = \sum_{i=1}^{m} \alpha_i\, lnY_{t-i} + \sum_{i=1}^{m} \beta_j\, lnX_{t-j} + \varepsilon_{2t} \tag{2}$$

Where, X and Y are two different market prices series, In stands for price series in logarithm form and t is the time trend variable. The subscript stands for the number of lags of both variables in the system. The null hypothesis in Equation (1), and Equation (2) is a test that In X_t does not Granger cause ln Y_t . In each case, a rejection of the null hypothesis will imply that there is Granger causality between the variables (Gujarati, 2010).

Estimating Error Correction Model for Short-term Relationship

The cointegration analysis reflects the long-run movement of two or more series, although in the short-run they may drift apart. Once the series are found to be cointegrated, the next step is to find out the short-run relationship along with the speed of adjustment towards equilibrium using error correction model, represented by Equations (3) and (4):

$$\Delta \ln X_t = \alpha_0 + \Sigma + \beta_{1i} \Delta \ln Y_{t-i} + \Sigma \beta_{2i} \Delta \ln X_{t-i} + \gamma ECT_{t-1} \quad \ldots (3)$$

$$\Delta \ln Y_t = \beta_0 + \Sigma \alpha_{1i} \Delta \ln X_{t-i} + \Sigma \alpha_{2i} \Delta \ln Y_{t-i} + \gamma ECT_{t-1} \quad \ldots (4)$$

where, ECT_{t-1} is the lagged error correction term; X_t and Y_t are the variables under consideration transformed through natural logarithm; and X_{t-i} and Y_{t-i} are the lagged values of variables X and Y. The parameter γ is the error correction coefficient that measures the response of the regressor in each period to departures from equilibrium. The negative and statistically significant values of γ depict the speed of adjustment in restoring equilibrium after disequilibria.

Impulse Response Function

Granger causality tests help establish the direction of price causation within the selected time span, but do not determine the relative strength of causality effects beyond the selected duration. The best way to interpret the implications of the models for patterns of price transmission, causality and adjustment are to consider the time paths of prices after exogenous shocks, i.e. impulse responses (Vavra and Goodwin, 2005). The impulse response function traces the effect of one standard deviation or one-unit shock to one of the variables on current and future values of all the endogenous variables in a system over various time horizons (Rahman and Shahbaz, 2013). Generalized impulse response function (GIRF), originally developed by Koop et al. (1996) and suggested by Pesaran and Shin (1998), is used. The GIRF in the case of an arbitrary current shock, δ, and history, $\omega t-1$ is given in Equation (5).

$$\text{GIRF } Y(h, \delta, \omega_{t-1}) = E[Y_t + h \mid \delta, \omega_{t-1}] - E[y_t + h \mid \omega_{t-1}] \text{ for } n = 0, 1, \ldots \quad (5)$$

Variance Decomposition

To identify the price triggers in major influencing markets, variance decomposition technique was applied. The variance decomposition provides information about the relative importance of each random variable/shock/innovation in affecting the variables in the VAR.

Variance decomposition separates the variation caused in an endogenous variable due to the shocks in other variables in the system. It provides information about the relative importance of each random innovation, i.e. price change in one market in affecting the variables in the vector auto-regression, i.e. price changes in other markets.

$$\mathrm{Var}(Y)=\mathrm{E}(\mathrm{Var}[Y \mid X])+\mathrm{Var}(\mathrm{E}[Y \mid X]) \quad \ldots\ldots\ldots (6)$$

In the relationship between X and Y, the variance of Y (dependent variable) is comprised (i) the expected variance of Y with respect to X, plus (ii) the variance of the *expected variance of* Y with respect to X. In other words, the variance of Y is its expected value plus the *variance of this expected value*. This is sometimes summarized as: $\mathrm{E}(\mathrm{Var}[Y \mid X])$ = explained variation directly due to changes in X and $\mathrm{var}(\mathrm{E}[Y \mid X])$ = unexplained variation comes from somewhere other than X.

2.3 Market Linkages: Regional Evidences on Price Transmission

Market integration is an important component, which indicates that integrated markets respond to the price signals in other markets and thus, will ensure market efficiency in long run. Also, farmers can decide their marketing pattern in accordance to the price signals and will eventually create a more competitive environment. 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). Several empirical studies have been undertaken using cointegration techniques related to the market integration of agricultural commodities in India (Reddy et al., 2012; Bhardwaj et al., 2014; Wani et al., 2015a; 2015b; 2015c; Saxena et al., 2015; Paul et al., 2015; Paul and Sinha, 2015). In order to understand the market integration and price transmission across markets, several case studies were taken up in different regions across the country. The excerpts from these studies are provided in the following section.

Cointegration of maize prices in Telangana[1]

Maize was grown in an area of 8.8 million hectares, producing of

1 This has been extracted from the policy study conducted by PJTSAY, Hyderabad under the ICAR-NIAP Network Project on Market Intelligence.

22.57 million tonnes with the productivity of 2.56 tonnes/ha during 2015-16 in the country. The major producing states are Karnataka, Telangana, Maharashtra, Madhya Pradesh, Bihar and Rajasthan. Karnataka was the largest maize producing state in India and produced 3.31 million tonnes in 2015-16 while Telangana stood at 5th position. The major producing districts in Telangana are Mahabubnagar, Medak, Karimnagar, Warangal and Nizamabad, which contributed around 80 per cent of the state production in 2015-16. The area, production, and productivity of maize in Telangana have increased significantly during the last few decades. The arrival season of the crop is from September to November which reaches peak during October. Maize prices remain higher from July to September in almost all the major markets of the state. This study investigated the price behaviour and linkages among maize markets in Telangana state (Box 1).

Box 1. Price Transmission for maize in Telangana

Markets	Badepalli, Nizamabad, Siddipet, Warangal and Nagarkurnool in Telangana
Data	January, 2011 to December, 2014
Methods	Co-integration, Granger Causality
Conclusions	There is bidirectional causality in maize prices between Nizamabad-Nagarkurnool, while unidirectional causality exhibited in the markets Badepalli-Warangal and Siddipet-Warangal. In case of price disturbance, Nagarkurnool and Warangal markets attain short run equilibrium rapidly.

The study established that maize markets in Telangana were co-integrated. The studies across globe also prove that markets are cointegrated. The degree of market integration of maize markets in Malawi was examined and found that liberalization had increased market integration (Goletti and Babu, 1994). Though future prices may be an effective instrument in predicting the spots, however, it was not confirmed in case of maize markets in Bulgaria (Penov and Zarkova, 2001). They examined the possibility of using futures prices in predicting spot prices of commodities.

Price transmission in pulses, India[2]

The production of pulses in the recent years has increased. Total pulse production in India has remarkably increased from 15.77 million

2 This has been extracted from the study conducted by NIAP under the ICAR-NIAP Network Project on Market Intelligence and published in the Agricultural Economics Research Review, 2016).

tonnes in 2010-11 to 23.13 million tonnes during 2016-17. In India, the most important pulse crops grown during 2015-16 were chickpea (covering 41% of total pulse growing area), pigeon pea (15%), urad bean (10%), moong bean (9%), cowpea (7%), lentil (5%) and field pea (5%). During the year 2015-16, the highest share in pulse production came from Madhya Pradesh (27.8 % of total pulse production), followed by Rajasthan (13.7%), Uttar Pradesh (9.13%), Maharashtra (8.6%), Karnataka (7.2%) and Andhra Pradesh (7.18%). These states together contribute for more than 70% of the total pulse production in the country (Government of India, 2017). This study applied time series model to investigate the wholesale and retail price market integration of major pulses (tur, gram, moong, urad, masoor) in five major regions namely north zone (NZ), south zone (SZ), east zone (EZ), west zone (WZ) and north-east zone (NEZ) in the country (Box 2).

Box 2. Price transmission for pulses in India

Region	North Zone (NZ), South Zone (SZ), East Zone (EZ), West Zone (WZ) and North-East Zone (NEZ)
Data	Monthly wholesale and retail price from January, 2009 to July, 2016
Methods	Johansen's multiple co-integration test, Granger causality test, VECM, impulse response function
Conclusions	The long run relationship (co-integration) between wholesale and retail prices of pulses in different zones revealed that wholesale and retail prices of gram are co-integrated in EZ and WZ zones, cointegrated in NZ, EZ, WZ for masoor, cointegrated in EZ, NZ, NEZ for moong, co-integrated in all zones except NEZ for tur. The wholesale prices of selected pulses were co-integrated in all zones except EZ. All the error correction terms (ECTs) were negative and most of these terms were statistically significant implying that the system in disequilibrium tries to come back to the equilibrium situation. which can be used to show the magnitude and lasting effects. Impulse response analysis shows that changes in wholesale prices of these five pulses in one zone will cause change in wholesale prices in other zones.

The study proved that the price signals are transmitted across regions indicating that price changes in one zone are consistently related to price changes in other zones and are able to influence the prices. However, the direction and intensity of price changes may be affected by the dynamic linkages between the demand and supply of pulses. Manasa (2009) analysed the spatial movement of prices and arrivals of pigeon pea in major five markets in Karnataka and established that prices across Karnataka markets were cointegrated to varying degrees and the zero-order correlation between market prices revealed strong integration among all the markets.

Price Transmission in Chickpea, Maharashtra[3]

Chickpea is a major pulse crop in India and accounts for 40% of the total pulse production. India produced 7.06 million tonnes of chickpea from 8.4 million ha area. Madhya Pradesh, Rajasthan, Maharashtra, Andhra Pradesh and Karnataka are the major chickpea producing states in India. Maharashtra ranks third in area (16.46 per cent) with around 12 per cent share in production. The area and production of chickpea exhibited an increasing trend during the recent decade. India contributes 70 per cent of the global chickpea production. The major chickpea producing clusters in Maharashtra are located in Vidarbha and Marathwada regions. Therefore, Akola, Daryapur Latur, and Jalgaon markets were selected for analysis from Vidarbha and Marathwada regions, respectively (Box 3). The arrival season of chickpea is from February and continues for next three to four months while July to January is the lean period when prices also remain on higher side.

Box 3. Price transmission for chickpea in Maharashtra

Markets	Latur, Akola, Jalgaon & Daryapur of Maharashtra
Data	Monthly data from January 2004 to December 2015
Methods	Johansen's multiple co-integration test, Granger causality test and vector error correction model
Conclusions	Unidirectional causality was found in all the selected markets. Prices in Latur market influenced the chickpea prices in Akola, Jalgaon and Daryapur markets, while Daryapur market exhibited unidirectional causality for Akola and Jalgaon markets. Latur is the lead market amongst the selected chickpea markets; hence, the price change in Latur market influence all other selected markets. Akola market influenced the Jalgaon market in unidirectional manner. The volatility coefficients (sum of Alpha and Beta) was less than 1 i.e. 0.313, 0.331, 0.331 & 0.327 for Latur, Akola, Jalgaon and Solapur markets, respectively, indicating that the price shocks in the prices of chickpea were quite persistent in these markets.

The chickpea markets were co-integrated. Hussain et al. (2010) studied the market integration of gram in Pakistan and showed that all gram markets were highly co-integrated in the long-run.

3 This has been extracted from the policy study conducted by PDKV, Akola under the ICAR-NIAP Network Project on Market Intelligence.

Price Transmission in Cotton, Gujarat[4]

Gujarat has rapidly emerged as India's largest cotton producing state. The adoption of Bt cotton by farmers in this state (and others) is believed to be the dominant contributing factor of the rapid rise with increased use of irrigation. Along with Gujarat, the northern zone states of Punjab, Haryana, and Rajasthan also produce higher-yielding cotton. The price of cotton showed instability and fluctuations in the last decade. Most of the cotton markets in Gujarat and India are co-integrated that affected the prices of each other. The cotton season spans from October to February, during which the crop arrives in bulk in the markets and prices remain on the lower side in different markets of Gujarat. The lowest arrivals were observed from May to September; hence, higher prices prevailed during this period. This study examined the price transmission for cotton in major markets of Gujarat and conclusions are provided in Box 4.

Box 4. Price transmission for cotton in Gujarat

Markets	Gondal, Amreli, Jamnagar, Rajkot and Junagadh
Data	Monthly price from January 2004 to October 2014
Methods	Johansen's multiple co-integration test, Granger Causality test
Conclusions	Lower price values were observed during October to March months while the highest values of price indices were observed during lean period from May to September in different markets. The model variables had a long-run equilibrium/co-movement among the Amreli, Rajkot, Gondal, Jamnagar and Junagadh market price series during the period under study. As far as market linkages with other important cotton markets are concerned, Gondal market transmits the price signals to Adoni. Budalada, Parbhani, Sendhava and Sangriya market while the Sangriya market transmits the price signal to Adoni, Budalada, Parbhani and Sendhava market. No integration was found with international prices but the price signals were transmitted from domestic hybrid-4 variety of cotton Sankar-6 variety prices.

The markets witnessed long-run equilibrium/co-movement among the Amreli, Rajkot, Gondal, Jamnagar and Junagadh markets.

4 This has been extracted from the policy study conducted by JAU, Junagadh under the ICAR-NIAP Network Project on Market Intelligence.

Price Transmission in Potato of Northern Hills and Plains[5]

Potato occupies more than 9 per cent area of total horticultural crops of Uttarakhand and contributes around 24 per cent to total horticultural production of India. Hill potato (kharif crop) is preferred by the consumers because of its taste and lower starch content as compared to potato grown in plains and is supplied to the entire northern India. Potatoes are available throughout the year in the markets either from plain/hill regions or cold storages: first four months of the year are dominated by the supply of plain potato; whereas, hill potato is available in the markets for rest of the eight months. The hill potato is available for a longer duration in the markets due to higher shelf life. The spatial and temporal variations in potato supply are supposed to be linked to the variations in its price. Such variations in potato prices have become more evident in the recent years with high volatility in prices. This study examined the market linkages in major northern hill and plain markets (Box 5).

Box 5. Price transmission for potato in northern hills and plains

Markets	Haldwani, Dehradun and Haridwar from Uttarakhand, Agra and Lucknow in Uttar Pradesh and Delhi as a consuming market
Data	Monthly data from January 2005 to March 2015
Methods	Johansen's multiple co-integration test, Granger causality test, impulse response, variance decomposition
Conclusions	There existed a bi-directional causality in potato price transmission between Haldwani and Dehradun markets. In case of markets of plain region of northern India, there was a bi-directional causality between Haldwani-Delhi and Haldwani-Lucknow. However, Haldwani market shares unidirectional causal relationship with Agra market wherein causality runs from Agra market towards Haldwani market. This is justified as Haldwani market receives lower arrivals as compared to Agra market, though the produce in both the markets are distinctly different.

5 This has been extracted from the study conducted by NIAP under the ICAR-NIAP Network Project on Market Intelligence and published in the Indian Journal of Agricultural Marketing (Saxena et al., 2016).

	The speed of adjustment ranges from 17 per cent to 42 per cent. The highest adjustment speed (42.3%) was noticed when potato prices in Lucknow were assumed to be determined by the prices in Haldwani market, while the lowest adjustment share (17.9%) was observed when the prices in Haldwani market were assumed to be dependent on prices in Delhi market. The error correction terms for potato in all the markets exhibited the desired negative sign which clearly exhibited the price convergence between Haldwani and other markets in the short run with markets mainly Delhi, Lucknow from plain region and Dehradun from hill region of northern India showed greater speed of adjustment as compared to Agra market. Agra market was mostly affected by its own shocks and very less affected by Haldwani and Dehradun markets. In the long run, the price shock in Agra market can cause more than 81 per cent fluctuation in the price volatility of its own market. Although, after its own price-shock, Agra market is largely affected by Haldwani market (i.e., 8.51 per cent) followed by Dehradun market (7.88 per cent) and the contribution of Haldwani as well as Dehradun market has been increasing remarkably in recent times. However, Haldwani market is largely affected by price shocks of the same market.

Movement in prices is prominent from markets with early and high arrivals. A bidirectional relationship was observed among Haldwani and all the markets of northern India except for Agra. There is a convergence in prices between Haldwani and other markets in the short run with markets from Delhi and Lucknow from the plains and Dehradun from the hill region of northern India, showing greater speed of adjustment as compared to the Agra market. Basu and Dinda (2003) studied the spatial integration of three potato markets of Hooghly district of West Bengal using the wholesale and retail prices and established that the wholesale and retail prices in all the markets were co-integrated.

Price Transmission in Onion, India[6]

Onion is one of the commodities with a high volatility in prices showing increasing instances of unexpected price spikes and falls. Such extreme movement in its prices has drawn the attention of policy makers in the recent years. Maharashtra is the leading onion producing state and accounted for 34 per cent of onion area and 29 per cent of onion production in the country in triennium ending (TE) 2014-15. Onion area witnessed very high growth from TE 2006-07

6 This has been extracted from the study conducted by NIAP with NITI Aayog and published as NIAP Policy Paper 33 (Saxena and Chand, 2017).

to TE 2014-15 in Bihar, Madhya Pradesh and Maharashtra, which resulted in a sharp increase in onion production during the above period. Though Maharashtra is the largest onion producing state in the country, it stands very low in terms of onion productivity. Within the state, onion is largely produced in Nasik, Pune and Ahmednagar districts. Three crops of onions are marketed in Maharashtra with about 10-15 per cent during kharif, 30-40 per cent as late kharif and 50-60 per cent rabi crop harvested during summer season. The results of price transmission analysis across major onion markets are given in Box 6.

Box 6. Price transmission for onion in India

Markets	Delhi; Lasalgaon, Pune and Solapur markets in Maharashtra; Bengaluru and Hubli markets in Karnataka; and Indore market in Madhya Pradesh.
Data	Monthly price data from January 2005 to March 2017 along with WPI
Methods	Johnson-co-integration, Granger causality, Vector Error Correction, Variance decomposition
Conclusions	The markets prices and WPI are cointegrated. Lasalgaon prices Granger cause prices in all the markets except Hubli and Solapur. In terms of arrival, Solapur receives higher quantity as compared to Lasalgaon, thus, Solapur market Granger causes the prices in Lasalgaon, while the reverse is found not true. Lasalgaon shares bidirectional causal relationship with Pune only. Lasalgaon also Granger causes WPI. Delhi, being a consuming market, is affected by the price changes emanating from other markets. Prices in Delhi Granger cause prices in Bengaluru, Hubli and WPI. It does not Granger cause prices in Lasalgaon, Pune and Solapur. However, prices in all the other markets Granger cause prices in Delhi. When Lasalgaon is considered to be dependent on other markets, the speed of adjustment is very low in general in Lasalgaon. This is probably due to the reason that only one-way transaction exists between the markets i.e. Lasalgaon only supplies the produce to the other markets. However, in some cases, especially Solapur and Hubli, the speed of adjustment is found to be higher in Lasalgaon. As Solapur is the nearby secondary market of onion, the stored quantity might be released due to which faster error correction mechanism takes place.

	When a price shock is given to Lasalgaon market, an immediate and a high response was noticed in almost all markets between second and fourth month, reaching a peak in the third month. After fourth month, the response starts to decline and reaches negative in case of Bengaluru, Delhi and Pune. If a shock is arising in Lasalgaon market it gets transmitted to all other markets with a higher response in the approaching months; thus, exhibiting a dominance of Lasalgaon market in onion price determination in the country. The response was found to be higher in case of Pune market.

Paul et al. (2015) investigated the long-run and short-run relationships between export price and domestic prices of onion. The analysis of structural breaks in volatility revealed the situations of price shocks in the years 2007, 2010, 2011 and 2013, when onion prices went abnormally high and created disturbances in the markets. The study established the long-term relationships across domestic market prices as well as between domestic market prices and exports prices. Export prices share bidirectional causality with the markets at Delhi, Bangalore, Hubli and Solapur and unidirectional causality with Pune and Lasalgaon markets. The markets at Delhi, Bangalore, Pune and Lasalgaon have shown higher speed of adjustment as compared to other markets.

Price Transmission in Apple, Kashmir[7]

India produced 1.7 million tonnes of apple from an area of 0.136 million ha in 2015-16 and was ranked as the fifth largest apple producer in the world. Jammu and Kashmir (J&K) contributes around 65 per cent of total apple production in the country with the productivity of 12.25 metric tonnes per ha, highest in India and is comparable to the productivity of China. Despite tremendous progress in production and productivity of apple in the state, there are various issues pertaining to production and marketing of apples which require due attention. Apples are characterized by strong seasonality and perishability. This induces competition and affects their prices and quantities supplied. The state does not have specialized markets, and these fruits are traded in distant markets such as Delhi, Ahmadabad, Bengaluru, Mumbai and Kolkata and other major terminal markets of India.

Apple is produced in most of J&K and is disposed to different primary/secondary wholesale markets. Apple is marketed in almost every major primary wholesale markets of the country. However, based on the highest volume of the apple arrivals, eight terminal markets (Delhi, Mumbai, Kolkata, Bangalore, Ahmadabad, Amritsar, Sopore and Parimpora) were

7 This has been extracted from the policy study conducted by SKAUST, Srinagar under the ICAR-NIAP Network Project on Market Intelligence.

selected (Box 7). The arrivals of apple were recorded maximum during October and minimum in April. The arrivals start picking up from June onwards; accordingly, the prices move opposite to the arrivals in August and had remained constant during later part of the year. The seasonal indices for prices are lowest in April and the highest in August.

Box 7. Price transmission for apple in India

Markets	Delhi, Mumbai, Kolkata, Bangalore, Ahmadabad, Amritsar, Sopore and Parimpora
Data	Weekly data on wholesale prices from 2005 to 2015
Methods	Johansen's multiple co-integration test, Granger Causality test and
Conclusions	Existence of long run relationship among the market prices Unidirectional causality exists, where Delhi market prices affect the prices of apple in Kolkata, Sopore, Parimpora, Amritsar and Ahmadabad. These unidirectional relationships wherein the prices of one market affects the prices of other markets without having a reciprocal impact on the prices would imply that the market for such varieties/grades is not very efficient in terms of influencing the prices of the other markets and also would increase prices in such markets. The bi-directional causation was observed in Parimpora and Kolkata, Ahmadabad and Sopore, Kolkata and Sopore and between Ahmadabad and Kolkata.

Another study investigated the strength of the spatial market integration of five apple markets of India and revealed that the selected markets were strongly cointegrated and converge on the long run equilibrium; the prices are linked together even if there is a geographical dispersion of markets (Wani et al., 2015). Vasishi et al. (2008) studied the price behaviour in fruits and vegetable markets and provided evidence of high volatility in the prices of fruits and vegetables in major markets, long-run relationship across some markets for apple was present.

Many other studies have also analysed extent of market integration in agricultural commodities. Anitha (1994) studied the groundnut marketing in Gujarat and concluded that the groundnut oil prices at terminal market influenced the groundnut prices in the lower level market structure and thus groundnut markets were integrated vertically. Dittok and Breth (1994) analysed the market integration of dry season vegetables in Nigeria, the observations indicated that there were little and a low degree of integration of markets in the study area. Kumawat and Kumar (2006) studied market integration of rapeseed-mustard markets of Rajasthan and revealed that almost all the selected markets were mutually integrated, however, the degree of integration varied from the market pair to another within and across the years. Reddy (2008) analysed the market integration of the price series of soybean spot and soybean futures, indicating markets integration. Reddy et al. (2009) studied the price trends in soybean and integration of markets for soybean and soya oil. The study reveals that markets and prices were integrated. Soe and Fukuda (2010) analysed the spatial market integration of oilseed crop markets in Myanmar and the results indicated that the markets in the producing area were highly integrated in the long-run.

Key Extracts

Most of the researchers analysed the market integration for agriculture commodities (Anitha, 1994; Basu and Dinda, 2003; Kumawat and Kumar, 2006; Reddy, 2008; Vasishi et al., 2008; Reddy et al., 2009; Manasa, 2009; Hussain et al., 2010; Wani et al., 2015) in Indian context. The Augmented Dickey Fuller (ADF) test was performed to check the stationarity of the time series data before conducting cointegration test. The effects of shocks in the short run and long run equilibrium were examined by using Vector Error Correction Model (VECM). Researchers found that the most of the price time series data were stationary at first difference. The co-integration tests revealed that most of the markets and price series were co-integrated in case of agriculture commodities.

It was revealed that most of the markets are co-integrated and rate of adjustments is high when prices are assumed to be influenced by the changes in each other's price. In most of the agricultural commodities, there are some dominating markets from the production zones which quickly transmit the price signals to other markets. Though, initially own price volatility remains important and major driving force for price change in a given market. However, the dominating markets volatility effects are spilled over in other markets and affect the price change in those markets. For example, Agra and Lasalgaon are the most important markets for rabi onion and plain potato, respectively; the price signals from these markets become the major change agents in price fluctuations in other markets. A special case in apple price transmission exhibits that price signals are even transmitted from a major consumers' market (Delhi) and influenced other markets including producers' markets. Thus, it can be inferred that price changes are temporary and would converge to an equilibrium within a given time span. A proper focus on domestic supply management along with international trade coupled with strong market surveillance and intelligence efforts would help control the price distortions.

Chapter 3

Price Forecasting

3.1 Commodities, Markets and Data

The total commodity arrivals indicate the strategic importance of a market for a given commodity, thus, major criterion for selection of market was the commodity arrivals. However, regionally important commodities were selected based on other relevant criteria such as global linkages in terms of international trade, which could influence the prices (Box 8). The wholesale price data for selected commodities were obtained majorly from the respective APMCs, nonetheless, secondary sources published by the Government of India and other regional sources/publications were also used for data on other parameters like area, production, exports etc.

Box 8. Selected Commodities for Price Forecasts

Sl. No.	State	Commodities Selected
1.	Gujarat	Castor, Pigeon pea, Potato, Cotton, Groundnut, Maize
2.	Jammu & Kashmir	Apple, Walnut, Cherry, Pear, Plum
3.	Karnataka	Onion, Tomato, Mango, Pomegranate, Grapes, Maize, Banana, Ragi, Red gram, Potato, Turmeric
4.	Kerala	Pepper, Tapioca, Coconut
5.	Madhya Pradesh	Soybean, Chickpea, Maize, Mustard, Pigeon pea
6.	Maharashtra	Green gram, Pigeon pea, Onion, Maize, Soybean
7.	North-east	Ginger, Turmeric, Potato, Pineapple, Tomato, Banana
8.	Odisha	Coconut, Cotton, Turmeric, Maize, Green gram, Ginger, Groundnut
9.	Rajasthan	Cumin, Chickpea, Pearl millet, Cluster bean, Coriander
10.	Telangana	Chickpea, Groundnut, Maize, Cotton, Chilli
11.	Uttar Pradesh	Tomato, Potato, Mango, Maize, Rapeseed
12.	Uttarakhand	Potato, Fine Paddy, Tomato, Cabbage, Pea
13.	West Bengal	Jute, Mustard, Onion, Pineapple, Potato

The forecasts were based on weekly/monthly wholesale modal prices of the selected commodities using at least 10 years historical time series (TS) data, depending upon the price behaviour. The missing observations[1] in the data were taken care of using appropriate imputation techniques.

Appropriate forecast models were developed to capture the price trend of each commodity; forecasts were developed based on modelling framework along with consideration of price expectations of farmers and traders. The basic objective of this exercise was to provide short term forecasts to farmers at an appropriate period for effective decision making. Price forecasting for the selected commodities was done in the preceding month of sowing and harvesting of the crop so that it provided sufficient time for production and marketing decisions of the farmers. In case of perishable commodities, the forecasting was done on a weekly basis. The choice of forecast model depended on the trends in historical prices and the extent of volatility. The final forecasts were given in the plausible range. The data on critical variables other than the arrivals could have an impact on commodity prices hence, the same was also considered in relevant cases for efficient forecasting.

3.2 The Modelling Approach

For many agricultural commodities, data are usually collected over time. Forecasts for these can be obtained using different modelling techniques; however, the choice of method depends on the purpose. Various statistical methods viz., regression, time series analysis and, of late, machine learning approaches are in vogue for statistical modelling of time series data. These models typically attempt to forecast market behaviour and estimate future values of key variables by using past values of core economic indicators. Most widely used technique for the analysis of time-series data is the Box Jenkins' ARIMA methodology, as these models are found to be more flexible in handling different patterns of time series data.

Husain and Bowman (2004) assessed the performance of three types of commodity price forecasts— a) based on judgment, b) relying exclusively on historical price data, and c) incorporating prices implied by commodity futures for close to 15 commodities using spot and future prices. They concluded that spot prices tend to move toward futures prices over the long run, and error-correction models exploiting this feature

1 The historically price data in certain cases contained missing values. Such gaps were filled by applying appropriate methods. In some cases, the missing values were replaced with the corresponding mean value or the growth rates in the neighbouring markets. Missing data were also intrapolated based the general seasonal pattern.

produce more accurate forecasts. Their analysis indicated that based on statistical- and directional-accuracy measures, futures-based models yield better forecasts than historical-data-based models or judgment, especially at longer horizons. They recommended the use of a composite forecast model if both types of data are available, i.e. the time-series (historical) and the option implied. In addition, the results of this paper are consistent with the section of literature that emphasizes the difficulty of forecasting the volatility in returns on asset prices accurately. This is because the explanatory power (coefficient of determination) calculated in the forecast regressions were relatively low.

Chen et al. (2010) predicted agri-commodity prices using asset pricing approach and demonstrated the prevalence of structural breaks, emphasizing the importance of controlling the same. The study investigated whether information in the asset markets of major commodity producers can help forecast future agri-commodity price movements. The asset-pricing approach provides additional advantages; the asset prices are easy to observe at high frequencies and are not subject to revisions. Combining market information from several markets, one can readily obtain a forecast for the aggregate world agri-commodity market.

In addition to the historical price data, our modelling framework also considered inclusion of other relevant factors to capture the price volatility. We mainly relied on the time-series analysis for price projections. An important characteristic of time series data is that the successive observations are dependent on the past values of the series. Each observation of the observed data series, Y_t, may be considered as a realization of a stochastic process $\{Y_t\}$, which is a family of random variables $\{Y_t, t \in T\}$, where T $\{0, \pm 1, \pm 2, \ldots\}$. Applying standard time-series approach to develop an ideal model will adequately represent the set of realizations and also their statistical relationships in a satisfactory manner, denoted by Y_t, the observations made at time t ($t = 1, 2, \ldots, n$). Thus, a time-series involving "n" points may be represented as sequence of n observations ($Y_1, Y_2, \ldots, Y_n$). Contrary to the assumption of statistical independence of observations in the classical regression analysis, it is assumed that the time sequenced observations ($Y1, Y_2, \ldots, Y_{t-1}, Y_t, Y_{t+1}, \ldots$) may be statistically related to the past observations in the same series, in the Box-Jenkins method (Box et al., 2007).

Forecasting with ARIMA

Box-Jenkins models are especially suited to short-term forecasting because most ARIMA models place greater emphasis on the recent past rather than the distant past. The Box-Jenkins method applies to both discrete data as well as to continuous data. However, the data should be available at equally spaced discrete time intervals. A time series requires a minimum of about 40-50 observations to use ARIMA for forecast. ARIMA model assumes stationarity of the series. A time series is said to be stationary if its underlying generating process is based on a constant mean and constant variance. In general, unit root tests are used to test the stationarity of a series. A statistical test for stationarity or test for unit root has been proposed by Dickey and Fuller (1979). This test is also referred to as the Augmented Dickey Fuller (ADF) test. The test is applied for the parameter ρ in the auxiliary regression

$$\Delta_1 y_t = \rho\, y_{t-1} + \alpha_1\, \Delta_1 y_{t-1} + \varepsilon_t$$

where, Δ_1 denotes the differencing operator i.e. $\Delta_1 y_t = y_t - y_{t-1}$.

The relevant null hypothesis is $\rho = 0$, i.e. the original series is non-stationary and the alternative is $\rho < 0$, i.e. the original series is stationary. Usually, differencing is applied until the ACF shows an interpretable pattern with only a few significant autocorrelations.

The ARIMA methodology is carried out in three stages, viz., identification, estimation and diagnostic checking. Parameters of the tentatively selected ARIMA model at the identification stage are estimated at the estimation stage and adequacy of tentatively selected model is tested at the diagnostic checking stage. If the model is found to be inadequate, the three stages are repeated until satisfactory ARIMA model is selected for the time-series under consideration. An excellent discussion of various aspects of this approach is given in Box et al. (2007). Paul (2010, 2014), Paul and Das (2010, 2013), Paul et al. (2013a, 2013b, 2014) applied ARIMA model in the field of agriculture as well as livestock and fisheries.

Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

A key feature of seasonal time-series with period S is that observations which are S intervals apart are similar. In this situation, SARIMA model is advocated. Therefore, the operation $L(y_t)\, y_{t-1}$ plays a particularly important role in the analysis of seasonal time-series. Two sets of parameters are used here; one is seasonal and another is non-seasonal.

Forecasting with ARIMA-X

Forecasting a response series using an ARIMA model with exogenous variables whose values correspond to the forecast periods may generate price forecasts driven by these shocks, captured through the selected critical variable. ARIMA-X model includes exogenous covariates (input variables in the forms of external shocks resulting from climate, production/supply, marketing/trade policy changes etc.) along with the dependent variable (prices, in this case) of the time series observation. In this study, historical data on arrivals were taken as explanatory variables for application of ARIMAX model in potato. In addition to the past values of the response series and past errors, we can also model the response series using the current and past values of other series, called input series.

Forecasting with ARCH/GARCH

ARIMA model is based on the assumptions of linearity and homoscedastic error variances. However, underlying relationships among variables are highly complex and cannot be described satisfactorily through a linear modelling approach. There are many features of time series data, such as the existence of threshold value, which can be captured only through non-linear methods. Under this, there are basically two approaches, viz., parametric and non-parametric. Evidently, if in a particular situation, we are quite sure about the functional form of estimation/model, one should use the parametric approach. Otherwise, the latter may be employed.

While dealing with nonlinearities, Campbell et al. (1997) made the distinction between:

- *Linear Time-Series:* The shocks are assumed to be uncorrelated but not necessarily identically and independently distributed (*iid*).
- *Nonlinear Time-Series:* The shocks are assumed to be *iid*, but there is a nonlinear function relating the observed time-series $\{X_t\}_{t=0}^{\alpha}$ and the underlying shocks, $\{\varepsilon_t\}_{t=0}^{\alpha}$

A nonlinear process is described as

$$X_t = g(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) + \varepsilon_t h(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots).\ E[X_t / \psi_{t-1}] = g(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots)$$

$$Var[X_t / \psi_{t-1}] = E\left[\{(X_t - E(X_t)) / \psi_{t-1}\}^2\right] = \{h(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) / \psi_{t-1}\}^2$$

where function $g(\cdot)$ corresponds to the conditional mean of X_t, and function $h(\cdot)$ is coefficient of proportionality between the changes in X_t and shock ε_t. The general form above leads to a natural division in nonlinear time-series literature in two branches:

- Models Nonlinear in Mean: $g(\cdot)$ is nonlinear;
- Models Nonlinear in Variance: $h(\cdot)$ is nonlinear.

The most promising parametric nonlinear time series models are ARCH and GARCH models.

Forecasting volatility by GARCH and *Exponential GARCH* (EGARCH) Model

The exponential GARCH or EGARCH model was first developed by

Nelson (1991). Forecasts of a GARCH model can be obtained using methods similar to those of an ARMA model. GARCH models are mean reverting and conditionally heteroscedastic, but have a constant unconditional variance. The multi-step ahead volatility forecast of a GARCH (*1,1*) model converge to the unconditional variance of shocks (ε_t) as the forecast horizon increases to infinity provided that Var (ε_t) exists. In order to estimate the parameters of GARCH model, many estimators are available in literature viz, conditional maximum likelihood estimator, Whitle's estimator and the least absolute deviation estimator. The Lagrange multiplier (LM) test is used to test for presence of conditional heteroscedasticity.

ARCH model has some limitations. Firstly, when the order of ARCH model is very large, estimation of a large number of parameters is required. Secondly, conditional variance of ARCH (q) model has the property that unconditional autocorrelation function (ACF) of squared residuals; if it exists, decays very rapidly compared to what is typically observed, unless maximum lag q is large. So, in order to have a parsimonious model, GARCH model is preferred over ARCH model. The EGARCH model allows for asymmetric effects of volatility, thus, making forecasts more accurate. Some of the applications of ARCH/GARCH and EGARCH model can be found in Paul et al. (2009, 2014b, 2015) and Paul (2015).

Validation of the Forecasts

It is important to evaluate/validate the forecasts obtained in terms of accuracy of the predicted values. The commonly used measures for validation are Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Standard Error. In this study, validation of the forecasts was done by computing MAPE (Mean Absolute Percentage Error) for the hold out data[2] as it is a scale independent measure. The estimates of parameters along with corresponding standard error and p-value of selected model were worked out. The best forecast models were selected based on Akaike Information Criteria (AIC) / Schwartz Bayesian Criteria (SBC). The

2 Generally, it is recommended not to use the entire data series for forecasting and rather to hold a set of time series observations (may be recent 4-5 price observations) and develop the forecasts based on the remaining historical observations. The 'hold out set' may be used to evaluate the forecasting model using the forecast error based measures. If one is interested in slightly long forecasting, say 12 months, the short term forecast of 4-5 time periods need to be developed first. These forecasts are plugged in the original dataset and forecasts are developed based on this new dataset. The process is repeated once more to get the complete forecasts of 12 months.

residuals of fitted models were examined for adequacy of fitted model. The final forecasts were validated using statistical criteria along with the qualitative information collated from traders'/farmers' survey in the respective locations/markets.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

Where, A_t is the actual value and F_t is the forecast values of prices.

3.3 Modelling for Improving Forecast Precision

ARIMA technique is widely used for forecasting of relevant variables especially agricultural prices. Though our initial emphasis was on the use of ARIMA methodology, volatility in the price of agricultural commodities, especially that of vegetables, prompted the use of other statistically advanced and non-linear models which could capture the volatility in prices and render more efficient forecast values. The details have been given in Tables 2 and 3. Boxes 9 and 10 exhibit the application of various methods in improving the forecast precision in the most price volatile crops i.e. potato and onion.

Field Crops

The ARIMA model was applied for price forecasting in case of cereals such as fine paddy, pearl millet and finger millet. Khan et al. (2010) forecasted the future price of three different agricultural commodities in Bangladesh for the period March 2010 to February 2012 using the ARIMA model based on model selection criteria and error statistics among the competing models. In our study also, ARIMA model was applied in initial years for price forecasting in case of pulse crops. Following the volatility in the prices of pulse crops, GARCH models were adopted for green gram price forecasting in 2014-15. In order to capture the seasonal effects, SARIMA models were successfully used for green gram price forecasting during the years 2015-16 and 2016-17. As cluster bean prices are extremely volatile, E-GARCH model was applied for price forecasting which could capture the leverage effects and symmetric & asymmetric patterns. ARIMA model was employed for oilseeds and fibre crops as well. Maize exhibited quite stable price pattern in Uttar Pradesh, thus, a simple model like Winter's additive model was found effective in some cases.

Horticulture Crops

Prices of horticultural commodities, especially that of vegetables were the most volatile during the study period. Thus, a combination of different forecasting models proved to be effective in case of these commodities depending on the price trends. ARIMA, GARCH, SARIMA, VAR, E-GARCH and ARCH GARCH models were used for modelling and forecasting for major horticultural crops in India. ARIMA was effective for banana in Karnataka where weekly forecasts were done. However, SARIMA was more effective for banana in the north-eastern states to capture the seasonality effect. ARIMA was quite successful in turmeric, black pepper, coconut, castor, greenpea, chilli, mango and tapioca. SARIMA models were used to forecast cabbage, coconut, ginger, pineapple, tomato and turmeric due to very high seasonality factor. In order to deal with price volatility, ARIMA models were not precise enough as it is subjected to assumption of linearity and homoscedastic error variance. Thus, GARCH models were used to forecast price volatility more efficiently and were used for apple, cherry, coriander, and ginger. In recent time, tomato prices shown both symmetric and asymmetric patterns, in such condition ARIMA or GARCH models are inefficient which deal only with the magnitude not the positive or negative shocks. To overcome this, the exponential GARCH (EGARCH) model was applied.

Table 1. Modelling approach for field crops

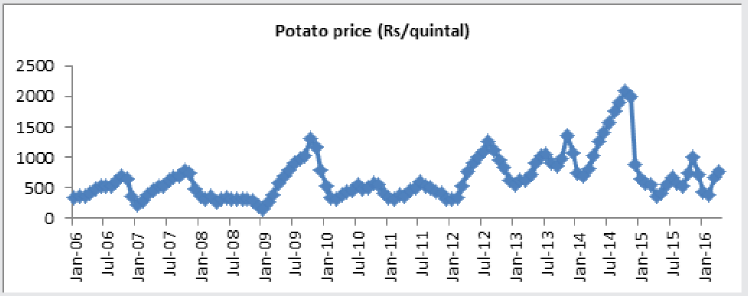
Crop Sub-roup	Commodity	State	Forecast models used in the study		
			2014-15	2015-16	2016-17
Cereals	Fine paddy	Uttarakhand	ARIMA	ARIMA	ARIMA
	Maize	Uttar Pradesh	ARIMA	WINTER'S ADDITIVE	ARIMA
		Telangana	ARIMA	ARIMA	ARIMA, SARIMA, GARCH
		Odisha	SARIMA	SARIMA	SARIMA
		Gujarat	ARIMA	ARIMA	SARIMA
		Maharashtra	GARCH	ARIMA	ARCH, ARIMA
		Karnataka	ARIMA	ARIMA	ARIMA
	Pearl millet	Rajasthan	ARIMA	ARIMA	ARIMA
	Finger millet	Karnataka	ARIMA	ARIMA	ARIMA
Pulses	Chickpea	Rajasthan	ARIMA	ARIMA	ARIMA
		Madhya Pradesh	ARIMA	ARIMA	ARIMA
		Uttar Pradesh			ARIMA
		Telangana	ARIMA	ARIMA	ARIMA, GARCH SARIMA
	Green gram	Maharashtra	GARCH	ARIMA	ARIMA, GARCH
		Odisha	GARCH	SARIMA	SARIMA
	Pigeon pea	Madhya Pradesh	ARIMA	ARIMA	ARIMA
		Gujarat	ARIMA	ARIMA	SARIMA
		Maharashtra	ARIMA	ARCH	ARCH, ARIMA
		Karnataka	ARIMA	SARIMA	ARIMA, SARIMA
	Lentil	Madhya Pradesh		ARIMA	ARIMA
		Uttar Pradesh	ARIMA	ARIMA	ARIMA
	Cluster bean	Rajasthan	E-GARCH	E-GARCH	E-GARCH
Oilseeds	Groundnut	Telangana	ARIMA	ARIMA	ARIMA
		Odisha	SARIMA	SARIMA	SARIMA
	Soybean	Madhya Pradesh	ARIMA	ARIMA	ARIMA
		Maharashtra	GARCH	ARIMA	ARCH, ARIMA
	Mustard	West Bengal			SARIMA
		Madhya Pradesh	ARIMA	ARIMA	ARIMA
	Castor	Gujarat	ARIMA	ARIMA	ARIMA
Fibre crops	Cotton	Gujarat	ARIMA	ARIMA	SARIMA
		Odisha	SARIMA	SARIMA	SARIMA
		Telangana	ARIMA	ARIMA	ARIMA
	Jute	West Bengal			ARIMA

Table 2. Modelling approach in horticultural commodities

Crop Sub-group	Commodity	State	Forecast models used in the study		
			2014-15	2015-16	2016-17
Fruits and dry fruits	Apple	Jammu & Kashmir	ARIMA, GARCH	VAR	VAR
	Banana	Karnataka	ARIMA	ARIMA	ARIMA
		Meghalaya			SARIMA
	Cherry	Jammu & Kashmir	ARIMA, ARCH, GARCH	ARIMA	VAR
	Coconut	Kerala	ARIMA	ARIMA	ARIMA
		Odisha	SARIMA	ARIMA	SARIMA
	Mango	Uttar Pradesh		ARIMA	ARIMA
	Pear	Jammu & Kashmir			VAR
	Plum	Jammu & Kashmir			ARIMA
	Pineapple	Meghalaya	ARIMA	SARIMA	SARIMA
	Walnut	Jammu & Kashmir	ARIMA	ARIMA	VAR
Vegetables	Cabbage	Uttarakhand	SARIMA	SARIMA	SARIMA
	Chilli	Telangana	ARIMA	ARIMA	ARIMA
	Green pea	Uttarakhand	ARIMA	ARIMA	ARIMA
	Onion	Karnataka	ARIMA	ARIMA	E-GARCH
		Maharashtra	SARIMA	ARIMA	ARIMA, ARCH-GARCH
		West Bengal		ARCH-GARCH	ARCH-GARCH
	Potato	Uttar Pradesh	ARIMA	WINTER'S ADDITIVE	ARIMA
		Karnataka	ARIMA	ARIMA	ARIMA, SARIMA
		Uttarakhand	SARIMA	SARIMA	SARIMA
		Gujarat	ARIMA	SARIMA	SARIMA
		Meghalaya	ARIMA	SARIMA	SARIMA
		West Bengal			ARIMA, SARIMA, GARCH
		Maharashtra	GARCH	ARIMA	ARIMA, ARCH
	Tomato	Uttar Pradesh	ARIMA	ARIMA	ARIMA
		Meghalaya	ARIMA	SARIMA	SARIMA
		Uttarakhand	SARIMA	SARIMA	SARIMA
		Karnataka	ARIMA	E-GARCH	E-GARCH
Spices and tuber crops	Black pepper	Kerala	ARIMA	ARIMA	ARIMA
	Coriander	Rajasthan	GARCH	E-GARCH	ARIMA
	Cumin	Rajasthan	ARIMA	E-GARCH	E-GARCH
		Gujarat			ARIMA
	Ginger	Odisha	GARCH	SARIMA	SARIMA
		Meghalaya	ARIMA	SARIMA	GARCH
	Tapioca	Kerala	ARIMA	ARIMA	ARIMA
	Turmeric	Odisha	SARIMA	SARIMA	SARIMA
		Meghalaya	ARIMA	SARIMA	GARCH
		Karnataka	ARIMA	ARIMA	ARIMA, SARIMA

Box 9. Price forecast for Potato through different models

Selected market: Agra



1. **Scenario I: No seasonality in potato prices**

   Series found stationary at level, thus no differencing required.

   ARIMA applied

   ✓ ARIMA (2 0 3), (2 0 2), (2 0 0), (2 0 1), (1 0 0) applied

   ✓ ARIMA (2 0 0) chosen based on the number of parameters and SBC values

   MAPE: 33.3%

2. **Scenario II: With seasonal effects in potato prices**

   Though the series is stationary at level, the plot does not exhibit such behaviour Thus, the series may contain seasonality and need to be adjusted accordingly

   ✓ SARIMA applied: SARIMA (2 0 0) (1 0 0) and SARIMA (1 0 0) (1 0 0)

   SARIMA (2 0 0) (1 0 0) chosen based on the number of parameters and SBC values

   MAPE: SARIMA without differencing: 28.8%, SARIMA with differencing: 48.3%

   ✓ The series adjusted for seasonal effects and applied ARIMA (2 0 0).

   MAPE: 16.1%

3. **Scenario III: Inclusion of Critical Variables**

   Arrival was considered as the closest proxy variable to capture climate and supply effects and was included in the model. Though the correlation between price and arrival was found to be lower, the variable was included since the parameter estimates were statistically significant.

   MAPE 16.6 %

4. **Scenario IV: Capturing volatility through GARCH model**

   Different variants of GARCH models (EGARCH, SGARCH) were applied after testing for GARCH effect in the price series.

   Models applied: EGARCH

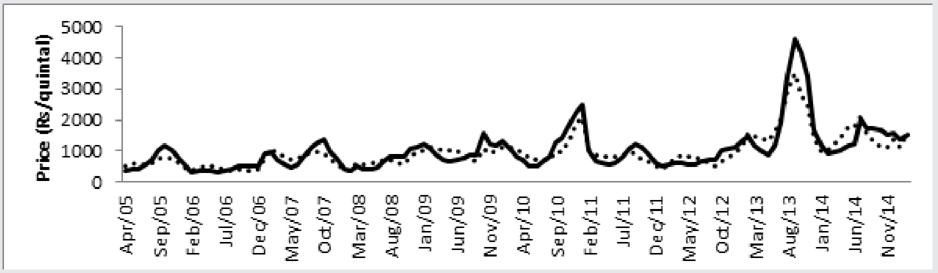
   MAPE: 3.4%

   In a nutshell, application of GARCH model was able to capture the volatility in potato prices and led to enhancement in forecast accuracy. ARIMAX model didn't prove much effective in capturing the volatility due to non-existent of a clear association between the potato arrivals and prices.

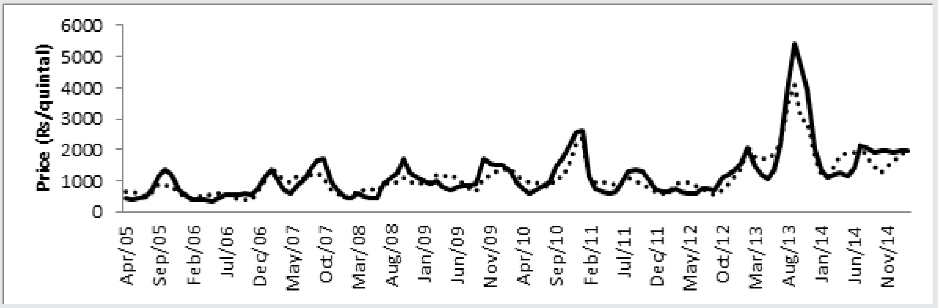
Box 10. Price forecast for onion through different models

Selected market: Azadpur market, Keshopur market, Shahdara market in Delhi

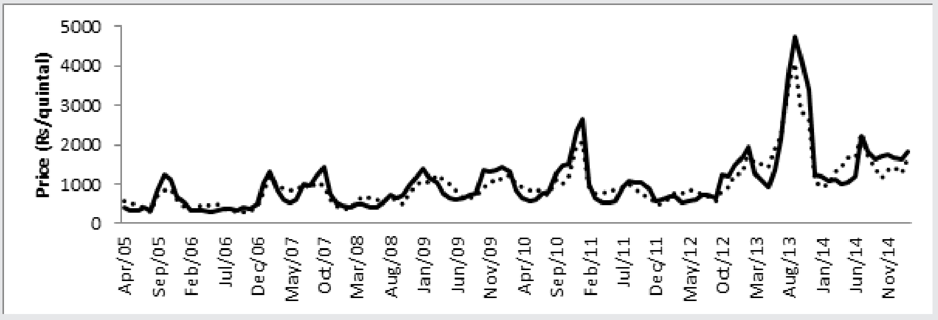
Actual (bold line) and seasonally adjusted price series (dashed line) for Azadpur market



Actual (bold line) and seasonally adjusted price series (dashed line) for Keshopur market



Actual (bold line) and seasonally adjusted price series (dashed line) for Shahdara market



RMAPE value (%) for different models in three markets

Market	ARIMA (1,1,0)	ARIMA(1,1,0)-GARCH(1,1)	ARIMA(1,1,0)-EGARCH(1,1)
Azadpur	26.61	25.96	21.91
Keshopur	30.40	51.92	20.72
Shahdara	30.57	23.06	30.82

In onion also, application of GARCH model was able to capture the volatility in prices and led to enhancement in forecast accuracy.

3.4 Forecasts Precision

Forecast accuracy percentage was derived from the Mean Absolute Percentage Error (MAPE) for eight crop categories across states for three consecutive years, i.e. 2014-15, 2015-16 and 2016-17, denoted as 2014, 2015 and 2016 to have better clarity and avoid repetition. The results are provided in Tables 4 and 5. The estimated values of forecast accuracy are presented in Fig 8. In general, pre-harvest (PH) forecasts were more precise as compared to pre-sowing (PS) forecasts due to limited scope to consider climatic or market uncertainty due to proximity in time of forecasts.

Cereals: Across all the crop categories, high forecast accuracy was found in cereals, which stood at about 90 per cent. This was due to relatively stable prices of cereals, except in the case of maize, wherein the forecast accuracy ranged between 77-89 per cent for Dhule market in Maharashtra.

Pulses: In case of pulses, the PH price forecasts were more than 80 per cent accurate during 2014 and 2015. In the year 2016, pre-sowing forecast accuracy was lesser. However, in the following exercises the accuracy of forecasts improved with the use of suitable modelling techniques. Yet, the forecast accuracy for green gram prices in Maharashtra was not satisfactory. In case of pulses, the evidence of PH forecasts being more precise than PS forecasts was much stronger. For illustration, accuracy of pigeon pea PS price forecasts in Maharashtra and Karnataka for 2015 and 2016, respectively, were much lower than PH forecasts.

Oilseeds: In majority of markets, the accuracy of price forecasts was higher for oilseeds in the year 2016 as compared to 2014 and 2015. In general, forecast accuracy was high for PH forecasts (precision >90 per cent) even in the case of oilseeds. Exception to this was the PS forecasts obtained for soybean in Madhya Pradesh, which showed lower accuracy in the initial year i.e. 2014. The price forecasts obtained for soybean in Maharashtra were accurate to the extent of 99 per cent.

Fibre crops: Cotton was the major fibre crop selected for price forecasts. Jute was added in the year 2016 for West Bengal. Close to 90 per cent precision was observed in cotton price forecasts. Cotton forecasts fluctuated for the selected years (2014-16) due to higher cotton price volatility in Gujarat.

Vegetable crops: Among all sub-sectors, lowest forecast precision was noted for vegetables crops for three consecutive years. Though the forecast accuracy was high (>90%) for cabbage, chilli and green pea, however, extreme fluctuations were observed in prices of onion, potato and tomato crops, resulting in lower accuracy in price forecasts for vegetable crops as a whole. However, in general, accuracy of price forecasts for tomato was high

(>85%) across markets except Kanpur wherein the accuracy of PS forecasts was 66.1% in 2014. This perhaps was due to production instabilities and other local factors which could not be captured through our models.

In case of potato crop, Haldwani, Mawiong and Hassan markets displayed higher forecasting accuracy over the years while the markets of Uttar Pradesh displayed very low forecast accuracy (Table 5). In UP, the pre-sowing price forecast accuracy was 37.6% in 2014 that increased to 64.7% in 2015. Forecast accuracy was high (>90%) for onion in the Hubli market, while in rest of the markets, accuracy was highly instable over the years. For instance, pre-harvest forecast accuracy for 2014 was 89.2% in Lasalgaon market that declined to 38.8% in 2015 and further increased to 87.6% in 2016. The most prominent reason for less accuracy of price forecasts among vegetables was the high price volatility in onion, potato and tomato crops.

Fruits and dry fruits: In case of fruits (banana, pear, pineapple, plum, mango and cherry), the forecast accuracy was observed to be more than 80 per cent, except for pear, cherry and pine apple in 2015, mango (60%) in 2016 in Uttar Pradesh. Price forecast for walnut showed more than 80 per cent accuracy throughout the study period.

Plantation crops: Coconut and tapioca were selected under the plantation crops category for price forecasting. Accuracy of forecasts remained more than 80 per cent for both these crops, average precision of the estimates increased for plantation crops in the later years.

Fig 8. Forecast accuracy for major crop categories

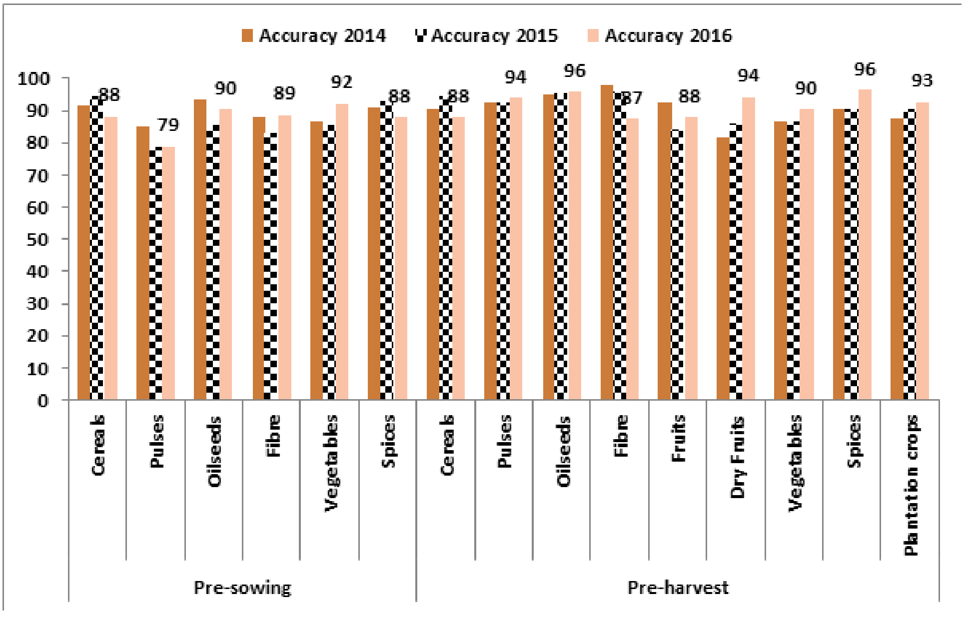


Table 3. Forecast accuracy in field crops (%)

Sub-Sector	Commodity	State	Market	Pre-sowing			Pre-harvest		
				2014	2015	2016	2014	2015	2016
Cereals	**Fine Paddy**	Uttarakhand	Rudrapur	98.6	99.2	95.3	77.0	98.6	95.6
	Maize	Gujarat	Dahod	97.0	99.1	96.0	95.4	93.1	97.1
		Karnataka	Davanagere		93.5	98.7	78.0	95.7	96.0
		Madhya Pradesh	Chhindwara	89.0	86.0		94.9	94.2	
		Maharashtra	Dhule	77.9	79.3		89.0	79.3	
		Odisha	Nawarangpur	99.8	98.5	96.7	97.6	98.2	97.9
		Telangana	Warangal	92.1	96.8	99.3	94.2	97.6	99.0
		Uttar Pradesh	Mainpuri	90.2	95.8	96.3		91.2	90.7
	Ragi	Karnataka	Hassan		92.7	66.9	98.2	95.1	66.9
	Pearl Millet	Rajasthan		88.8	93.8		93.4	96.7	93.8
Pulses	**Chickpea**	Uttar Pradesh							97.3
		Madhya Pradesh	Ujjain, Shujalpur, shajapur and Dewas	81.6			91.6	99.5	
		Rajasthan	Bikaner	82.0	96.2		99.1	98.2	
		Telangana	Kurnool	100.0	94.2	94.0	93.5		96.8
	Cluster Bean	Rajasthan	Sriganganagar	78.5	82.4		93.8	96.8	97.7
	Green Gram	Maharashtra	Latur, Akola	73.6	67.5	78.0	92.4	85.5	77.7
		Odisha	Bhubaneswar	95.9	83.3	88.7	93.9	94.6	97.3
		Telangana			91.2	75.0		100.0	86.5
	Lentil	Madhya Pradesh						98.2	
	Pigeon Pea	Gujarat	Karjan	96.9	80.5	67.0	97.3	90.6	91.9
		Karnataka	Gulbarga, Sedam	86.9	71.0		84.4	85.4	87.3
		Madhya Pradesh	Piparia (Hoshangabad)	72.8			87.7	99.6	
		Maharashtra	Latur, Akola	85.3	48.1	63.7	89.2	80.2	99.4
Oilseeds	**Groundnut**	Odisha	Berhampur & Jajpur	85.9	93.7	97.8	91.7	96.2	97.2
		Telangana	Gadwal	93.6	88.1	94.9	91.8	97.4	97.2
		Gujarat	Gondal-Rajkot	93.5	88.9	95.6	95.8	99.0	96.0
	Mustard	Madhya Pradesh	Morena	99.5	77.9		95.8	99.3	
		Uttar Pradesh	Agra		85.2	85.1		93.7	98.0
	Castor	Gujarat	Patan	96.6	80.3	71.6	95.7	91.4	90.2
	Soybean	Madhya Pradesh	Ujjain, Shujalpur, shajapur and Dewas	41.3	92.1	99.2	93.5	93.5	98.8
		Maharashtra	Latur, Washim, Akola	91.8	82.8	90.8	98.4	82.8	99.6
Fibre	**Cotton**	Gujarat	Gondal-Rajkot	80.9	74.5	84.6	97.9	96.9	82.3
		Odisha	Kesinga	95.1	97.4	91.0	99.1	96.8	94.1
		Telangana	Warangal	88.2	94.9	91.8	97.6	92.9	95.7
	Jute	West Bengal	Beldanga			92.3			87.3

Note: The grey cells indicate that price forecasts were not generated for that season.

Table 4. Forecast accuracy for horticultural crops (%)

Sub-Sector	Commodity	State	Market	Pre-sowing			Pre-harvest		
				2014	2015	2016	2014	2015	2016
Vegetables	**Cabbage**	Uttarakhand	Haldwani		95.4	91.3			96.1
	Chilli	Telangana	Guntur	99.4	93.2	97.7	97.7	97.0	93.1
	Green Pea	Uttarakhand	Rudrapur		94.9	96.0		88.0	95.9
	Onion	Karnataka	Hubli	95.8	94.3	96.4	97.0	95.2	93.8
		West Bengal	Barra Bazar						87.0
		Maharashtra (Kharif)	Lasalgaon		55.7	96.2	89.2	38.8	87.6
		Maharashtra (Rabi)	Lasalgaon				45.8	98.3	
	Potato	Gujarat	Deesa			88.4			94.6
		Karnataka	Hassan		74.3	96.5	91.9	87.3	76.6
		Meghalaya	Mawiong	90.9	96.9			99.9	94.1
		Uttar Pradesh	Agra, Kanpur, Varanasi	37.6	64.7		61.2		
		Uttarakhand	Haldwani		95.3	84.0		95.0	97.2
	Tomato	Karnataka	Kolar	91.8	95.4	90.3	89.8	92.1	91.4
		Meghalaya		95.8	87.9		94.9	92.5	
		Uttar Pradesh	Kanpur	66.1	96.2			81.6	77.2
		Uttarakhand	Haldwani	96.1	97.2	94.8	96.1	93.3	94.8
Fruits and Dry Fruits	**Banana**	Karnataka	Binny mill APMC, Bengaluru					91.0	89.4
	Pear-Nakh	Jammu & Kashmir	Delhi, Amritsar					64.3	84.7
	Pineapple	Meghalaya					92.6	95.8	94.2
	Pineapple	West Bengal							83.5
	Plum	Jammu & Kashmir	Parimpora, Delhi						95.6
	Mango	Uttar Pradesh	Lucknow, Varanasi					90.6	59.5
	Cherry	Jammu & Kashmir	Parimpora, Delhi, Mumbai, Amritsar, Ludhiana					78.9	90.8
	Pear-Babugosha	Jammu & Kashmir	Delhi, Amritsar, Mumbai, Ahmadabad					74.9	
	Walnut	Jammu & Kashmir	Narwal Jammu				81.6	86.3	94.1
Spices	**Coriander**	Rajasthan	Kota	73.6	89.0		83.9	87.4	
	Cumin	Rajasthan	Merta	96.6	97.3		92.8	99.2	
	Ginger	Meghalaya		97.4	98.7	94.4	94.0	67.4	95.1
	Ginger	Odisha	Bhubaneswar	98.3		55.2	97.1	73.4	
	Turmeric	Meghalaya		95.4	97.7	91.0	97.6	89.2	95.2
	Turmeric	Odisha	Phulbani	85.3	73.6		94.0	93.0	
	Black Pepper	Kerala	Kochi				86.8	96.4	97.1
Plantation	**Coconut**	Kerala	Thrissur, Alappuzha				87.4	89.7	96.0
	Coconut	Odisha	Kesinga				88.2	95.1	85.2
	Tapioca	Kerala	Thrissur, Calicut, Ernakulam, Trivandrum				92.5	84.2	90.0

Note: The grey cells indicate that price forecasts were not generated for that season.

The forecast accuracy can further be improved by incorporating the future prices in the modelling framework as a lot of indicative trends can be observed through the movement in futures prices. The same can be confirmed from some of the efforts, which applied composite approach incorporating both spot and future prices. Rausser and Just (1979) computed the agricultural commodity price forecasting accuracy using futures markets versus commercial econometric models for eight commodities, comparing them using the root mean squared error. The combined forecasts for spot and future prices provide dramatic improvements in accuracy – the performance of the composite forecast is 50 per cent better than the best individual forecasts. They also demonstrated that econometric and futures market forecasts contain enough independent information which can be valuably combined. Kastens et al. (1998) provided futures-based price forecasts for agricultural producers and businesses and determined the forecasting accuracy of five competing naive and futures-based localized cash price forecasts. The commodities included major grains, slaughter steers, slaughter hogs, several classes of feeder cattle, cull cows, and sows. Relative forecast accuracy across forecast methods was compared using regression models of forecast error. The traditional forecast method of deferred futures plus historical basis had the greatest accuracy – even for cull cows. They concluded that adding complexity to forecasts, such as including regression models to capture non-linear bases or biases in futures markets, does not improve accuracy.

3.5 Dissemination of Price Forecasts

Dissemination of reliable price information and market outlook can play a vital role in minimizing the impacts of price risk. We relied heavily on print media for the dissemination of price forecasts, as it had a wider acceptability and was a preferred mode of dissemination across states. This comprised national dailies, regional newspapers, magazines, pamphlets and brochures. We also widely used websites for the purpose. Other modes were voice SMS, text SMS, television and radio broadcasting (Table 6). As personal dissemination method is more effective, a minimum of 30 farmers were identified for each commodity in each state in order to regularly disseminate the forecasts and monitor the impacts of the price information provided to them. The same sets of farmers were monitored over the study duration to assess the impact of price forecasts. Farmers' fair in the universities and ICAR institutes also proved to be a good platform for interaction and price forecast dissemination. The major sources of price information for the farmers were obtained through farmers' survey. These include fellow farmers visiting the mandi, traders/commission agents, regional newspapers and personal dissemination through local R&D

organizations (Box 11).

Box 11. Major sources of price information for the farmers

State	Top five sources of agricultural price information for the farmers				
	Rank I	Rank II	Rank III	Rank IV	Rank V
Uttar Pradesh	Fellow farmers	Traders/ Commission agents	Personal contact, Call	SMS	National/ Regional Newspaper
Rajasthan	Traders/ Commission agents	Regional newspapers	Fellow farmers	Local mandi	Television
Meghalaya	Personal contacts	SMS	Institutional website	Local newspapers	Farmers fair/ Agri- exhibition
Gujarat	Regional newspapers	Farmers' training & CCS scheme assistance	Fellow farmers	SMS	By telephonic contact with scientist
Madhya Pradesh	Radio	Regional newspapers	Fellow farmers	Trader/ Commission agent	Others (KCC, CCS, ATIC)
Kerala	Training	Visit to KVK/ College	Phone calls	Personal contact	Institutional website
Odisha	Personal contact	Regional newspapers	Fellow farmers	TV/Radio	
Maharashtra	Regional newspapers	Regulated mandi	SMS	Academic research organization	TV/Radio
Telangana	Fellow farmers	Traders/ Commission agents	Personal Contact, Call	APMC	Newspaper
Jammu & Kashmir	Personal contact	KVK	Newspaper	Fellow farmers	TV/Radio

Community radio service in Uttarakhand, administered by G B Pant University of Agriculture & Technology, was able to connect with villages within the radius of 15 to 20 Km on day-to-day basis. The information was also circulated through IFFCO Kisan Sanchar Limited (IKSL), which provided very large connectivity to farmers and thus the price forecasts were disseminated on a wider scale. Regional *Doordarshan Kendras* and All India Radio broadcast awareness programmes on price forecast of the commodities. Modern social networking modes like YouTube, WhatsApp and Facebook were also used for disseminating the forecasts.

In collaboration with IFFCO Kisan Sanchar Ltd., price forecasts were disseminated to 71,735 farmers through 31.56 lakh voice mails SMS in Gujarat. A special biweekly programme titled "*Sawal kisano ke Jawab Vigyaniko dwara*" was initiated in collaboration with AIR, Jabalpur, Bhopal, Indore and other stations in Madhya Pradesh to reply to the farmers' queries, which also included discussion on markets and prices. In Kerala, the maximum number of beneficiaries was covered through personal contact. The number farmers covered were 1500 for black pepper, 1000 for coconut and 400 for tapioca. IFFCO's free voice service was also used to deliver price forecasts to the subscribers. Each voice message of one-minute duration covered contextual alerts and advisories on diverse subjects such as soil management, weather forecasts, weather based agro-advisory, crop management, plant protection, market prices, dairy and animal husbandry. It was found that SMS through mobile phones has reduced the gap among traders and farmers and farmers can directly communicate with the best buyers providing better prices.

In Jammu and Kashmir, the regional newspapers such as Greater Kashmir and Kashmir Uzma were used for dissemination. The dissemination efforts were institutionalized and liaison was created with the Department of Horticulture and Directorate of Information, Government of Jammu & Kashmir, and it became one of the important modes of price forecasts dissemination. Doordarshan Kashmir and Radio Kashmir played a major role in the dissemination of the price forecast of the crops by broadcasting several programmes on the television and radio.

Table 5. Price forecast dissemination through different modes

State	Dissemination Modes	
	Print Media	**Electronic and Other Media**
Gujarat	Newspapers (Gujarat Samachar, Divya Bhaskar, Kesari, Krushi Prabhat, Agro-sandesh, Commodity world, Krushi Prabhat, Indian Express and Market outlook (Newsletter)	Website (www.jau.in), Radio talk Broadcast by Junagadh Janvani 91.2 FM, Voice mail-IFFCO portal, Farmer meeting and Trainings
Jammu & Kashmir	Bulletin	Personal contact, SMS, Website, Farmer Fair, Television, Radio, Regulated Mandi, KVK
Karnataka	Pamphlets	Voice SMS through IFFCO, Krishisewa and Agropedia, Website, KVK and RSK, Elec. Media, Television, Radio Social networking sites, Personal contact
Kerala	Newspapers (The Hindu and Deshabhimani -Malayalam Daily) and Magazines	Personal contact, e-mail, Website, Farmer Fair & Workshop, Training Programmes, SMS, Sensitization Programmes, College of Agriculture, Padannakkad-http://www.kaupad.edu.in
Madhya Pradesh	Newspapers (हरिभूमि, पीपुल्ससमाचार, देशबंधु, जबलपुर एक्सप्रेस, राजएक्सप्रेस, नईदुनिया, यशभारत, पत्रिका, नवभारत, स्वतंत्रमत, दैनिक भास्कर, हितवाद), Magazines- 1. कृषक दूत–भोपाल, 2. खेती दुनिया–पटियाला	Pamphlets, Bulletin, forecasted prices through KCC and ATIC, Farmers' meetings and interface, Farmers' Fair, Website (www.jnkvv.org)

Maharashtra	Newspapers (Sakal, Deshonnati, Lokmat, Agrowon, Matrubhumi, Tarun Bharat, Divya Marathi, and Dainik Bhaskar**),** Farmer Workshop, Bulletin of Onion	Website(https://www.pdkv.ac.in/) and other electronic modes, Personal contactWebsite (https://www.pdkv.ac.in/), Others Elect. Mode of Media
North-East (Meghalaya)	Local Newspapers (Mawphor & Nongsain Hima), One Bulletin on "Commodity Profile of Ginger, Turmeric, Potato, Tomato and Pineapple in Meghalaya"	Website- Mawphor (first Khasi daily), M4AgriNEI (Mobile Based Agricultural Extension System in North-East India), KIRAN (www.kiran.nic.in, knowledge Innovation Repository of Agriculture in North east), KMAS, All India Radio and Shillong, Doordarshan Kendra Shillong, Personal contact
Odisha	Newspapers, SMS, Website, IFFCO portal (Voice SMS), KCC	Telephone, Television/radio broadcasting, Personal contact
Rajasthan	Chokhi Kheti (SKRAU, Monthly Bulletin for Farmers)	SMS (IFFCO Kisan Sanchar Limited (IKSL)), KVK-Kota APMC, Sriganganagar APMC, Nagaur Merta City APMC, Jaipur APMC and Bikaner APMC), Website(http://iabmbikaner.org/MbaProgramme.aspx), Elec. Media, Farmer interaction at Krishi Haat, Personal contact
Telangana	Newspapers	Voice SMS through IFFCO Kisan Sanchar, Website, Farmer Fair & Workshop, Farmers' Meeting and Interface, Training Programmes, SMS, Radio, Bulletin, Personal contact
Uttar Pradesh	Newspapers (Rashtriya Sahara, Hindustan (hindi), Jansandesh Times, The Times of India, Denik Jagran, Amar Ujala, Gaon Connection and Sahara**),** Pamphlets	SMS panel (http://mobisol4u.com/), Website(http://www.bhu.ac.in/), Farmer Fair, Television, Radio, Farmers' Meeting and Interface, Exhibition, Personal contact
Uttarakhand	Newspapers (Dainik Jagran, Dainik Uttar Ujala, Amar Ujala, Hindustan, Punjab Kesari and AAJ)	Website (http://www.gbpuat.ac.in/, www.gbpuat.ac.in/pantnagarnews.htm), Farmer's fair - Pantnagar Kisan mela, Radio-Pantnagar Janvani broadcast 90.8 MHz Sunna hai, *Sunana Hai Khushiyon Ka Khajana Hai***,** Personal contact
West Bengal	Newspapers, Bulletin/ Magazines/ Pamphlets	SMS, Website, Farmer Fair, Social Network sites, KVK

4

Chapter

Conclusion

4.1 Major Findings

The present work is a substantial effort in the area of agricultural price forecasting, wherein more than 40 agricultural commodities were selected to provide reliable and timely price forecasts to farmers in 13 major states across the country, in order to enable them to make informed production and marketing decisions. This policy paper includes the detailed analysis of price forecasts and their dissemination through media in selected states from 2014-15 to 2016-17. The forecasts were developed based on modeling frameworks and considering the price expectations of farmers and traders to provide short-term forecasts to farmers at an appropriate time for effective decision making. Price forecasting for the selected commodities was done in the month preceding sowing and harvesting of the crop so that the farmers have sufficient time for production and marketing decisions.

In case of perishable commodities, the forecasting was done on a weekly basis. The ARIMA model was applied for price forecasting in case of cereals such as fine paddy, pearl millet and finger millet. The forecast accuracy in cereals stood at about 90 per cent. This was due to relatively stable prices of cereals, except in the case of maize, wherein the forecast accuracy ranged between 77-89 per cent for Dhule market in Maharashtra. The estimates of parameters along with corresponding standard error and p-value of selected model were worked out. ARIMA model was applied in initial years for price forecasting in case of pulse crops. The price forecasts were more than 80 per cent accurate in pulses in 2014 and 2015. In the year 2016, pre-sowing forecast accuracy was lesser than the previous years. In case of pulses, pre-harvest (PH) forecasts were more precise than pre-sowing (PS) forecasts. ARIMA model was employed for oilseeds and fibre crops as well. In majority of the markets, the accuracy of price forecasts was higher for oilseeds in the year 2016 as compared to 2014 and 2015. In general, forecast accuracy was high for PH forecasts (precision >90 per cent) even in the case of oilseeds. Cotton was the major fibre crop selected for price forecasts. Jute was added in the year 2016 for West Bengal. More than 90 per cent precision was observed in cotton price forecasts.

Prices of horticultural commodities, especially of vegetables, were the most volatile during the study period. Thus, a combination of different forecasting models proved to be effective in case of these commodities depending on the price trends. ARIMA, GARCH, SARIMA, VAR, E-GARCH and ARCH GARCH models were used for modelling and forecasting for major horticultural crops in India. As the weekly forecasts were done for Karnataka state, ARIMA model was found suitable. ARIMA was quite successful in forecasting prices for turmeric, black pepper, coconut, castor, green pea, chilli, mango, and tapioca. Among all sub-sectors, the lowest forecast precision was noted for vegetables for three consecutive years. Though the forecast accuracy was high (>90%) for cabbage, chilli and green pea, extreme fluctuations were observed in prices of onion, potato and tomato, resulting in lower accuracy in price forecasts for vegetable crops as a whole. However, in general, accuracy of price forecasts for tomato was high (>85%) across markets except for Kanpur wherein the accuracy of PS forecasts was 66.1% in 2014 that declined to 31.8% in 2016. In case of fruits (banana, pear, pineapple, plum, mango and cherry), the forecast accuracy for 2015 was lesser than 2016. Forecast accuracy was observed to be more than 80 per cent, except for pear, cherry and pineapple in 2015, and mango (60%) in 2016 for Uttar Pradesh. Price forecast for walnut showed more than 80 per cent accuracy throughout the study period.

The forecasts were disseminated to farmers through regional newspapers, websites of the regional academic institutes, information bulletins, personal meetings and interactions, social media and other relevant means. Besides, a minimum of 30 farmers were identified for each commodity in each state in order to regularly disseminate the forecasts and monitor the impacts of the price information provided to them. The same sets of farmers were monitored over the study period to assess the impact of price forecasts. Print media had wider dissemination across states and was the preferred mode. This comprised national dailies, regional newspapers, magazines, pamphlets and brochures. Websites were also widely used for the purpose. Other modes of communication comprised voice and text SMSs, and broadcast on television and radio. Farmers' fair in the universities and ICAR institutes also proved to be a good platform for interaction and price forecast dissemination purpose.

This exercise has witnessed the use of scientific methods like ARCH-GARCH family based models in bringing precision in price forecasts. This exercise will also prove helpful for other stakeholders in various departments for effective decision making. More specifically, the forecasts can be used by state governments and related agencies for advance planning and preparation of action plan for timely and effective implementation of MSP policy and MIS to solve the problems against which farmers are agitating all over the country (Acharya, 2017).

4.2 Way Forward

The study made continuous efforts in terms of improving the forecast accuracy through modelling and its dissemination through institutional interventions. However, it was realized that a lot can be done to improve the forecast accuracy in terms of data dimensions, modelling innovations and further institutionalization of the concept of market intelligence (basically aiming at generating short term price forecasts). Following can be done to make these forecasting more effective for farmers' welfare in the county:

Data Harmonisation

Price data are the key input in generating the price forecasts. The wholesale price data compiled by the DAC&FW and made available through AGMARKNET portal is used for the forecasting. Besides, National Horticultural Research and Development Foundation (NHRDF) also provided the wholesale price data for selected horticultural commodities. A mismatch has been noted in the data series provided by these different agencies. Even the data available with AGMARKNET and APMC records do not match. This accentuates that the data reporting mechanisms at the APMCs need to be standardized. It would be effective if the data recording and availability efforts of different organizations are harmonised. Further, there are a lot of data gaps, especially in very short seasoned crops such as mango and green peas. Hence, the forecasts could not be generated for a few seasons. The data discrepancies need to be addressed as reliable data is crucial for technically strong forecasts. Thus, the real-time data on price realized by the farmers is required for generating precise forecasts.

Inclusion of Critical Variables

Besides its own volatility, the prices of agricultural commodities are affected by many climatic and policy variables. Thus, considering only the price in univariate modelling does not remain effective, especially in highly price-sensitive commodities such as onion and potato. Hence, the modelling framework needs to capture the variables other than prices that influence the price forecasts. Therefore, the methodological improvements for incorporating the effects of critical variables are the need of the hour. The multivariate modelling framework needs to capture the variables which emanate from climatic and policy shocks. The proxy variables could be arrivals, rainfall, temperature, exports, import duty, inter-state commodity transactions, etc. We could not capture these due to non-availability of a longer and disaggregated (across locations) series fit for scientific modelling. Thus, the real-time data on critical variables must be available to capture the external shocks. Besides, the use of remote sensing and artificial intelligence should be promoted to get the advanced information about the crop conditions at field level. There are advanced tools and hybrid models for capturing such shocks which can further bring precision in forecasts. The forecast accuracy can further be improved by incorporating the future prices in the modelling framework as lot of indicative trends can be observed through the movement in futures prices.

Strengthening Institutionalization of Market Intelligence

In the long run, the market intelligence efforts need to be actively taken up by the Department of Agriculture and Department of Marketing, both at central and state levels. A lot of continuous capacity building was done for the project teams under the 'Network Project on Market Intelligence', particularly for the young project associates, which contributed in building their capacity in understanding forecasting techniques and projections, and would be extremely useful. The academic institutions can play an important role in capacity building of the market intelligence teams.

Effective Dissemination

The ultimate beneficiaries of price forecasts are farmers. Thus, the project activities may be linked with line departments for effective dissemination and institutionalization. The state departments in Telangana and Jammu and Kashmir have taken keen interest and supporting the state agricultural universities in carrying out these efforts. The proactive approach should be adopted to create awareness and acceptability of price forecasts among the farmers. The impact studies in this context would extremely useful for generating the system feedback and improving the market intelligence framework.

Focus on Commodities with high price volatility

Focus needs to be given to horticultural commodities like potato, onion, tomato and others which find an important place in the daily consumption of masses but are highly volatile. To make effective use of price signals and price forecasts, the role of logistics management is important. Thus, the holistic solutions in terms of efficient supply chains and logistics will work more effectively.

Use of Information Technology as a Long Term Solution

To create longer and larger impact and acceptability in the system, e-solution for market intelligence can be developed by combining various algorithms of suitable techniques and models in single software package, which would be easy to use even by the line departments.

Focus on Regional Studies

The study revealed that most of the markets for a given commodity are co-integrated and price signals are transmitted from one market to the other with varying speed. The rate of adjustments is high when prices are assumed to be influenced by the changes in each other's price. In most of the agricultural commodities, there are some dominating markets from the production zones which quickly transmit the price signals to other markets. Though initially own price volatility remains important and major driving force for price change in a given market, volatility effects in the dominating markets are spilled over to other markets and changes the price therein. Thus, focused regional and commodity studies are required to provide the updated market dynamics to appraise the policy makers to take any preventive or corrective actions. Proper emphasis on domestic supply management along with international trade coupled with strong market surveillance and intelligence efforts would help control the price distortions.

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