Movement of Agricultural Commodity Prices in Post-reform India

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Submitted by

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Declaration

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I hereby declare that the thesis titled "**Movement of Agricultural Commodity Prices in Post-reform India**" is the result of research work carried out by me in the Department of Humanities and Social Sciences, Indian Institute of Technology Guwahati, India, under the supervision of Professor Mrinal Kanti Dutta, Professor of Economics in the Department of Humanities and Social Sciences, Indian Institute of Technology Guwahati, India.

In keeping with the general practice of reporting scientific observations, due acknowledgment has been made whenever the work described is based on findings of other investigations.

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Certificate

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This is to certify that the thesis titled "**Movement of Agricultural Commodity Prices in Post-reform India**" submitted by Ms. Prerona Baruah for the degree of Doctor of Philosophy in Economics in the Department of Humanities and Social Sciences at the Indian Institute of Technology Guwahati embodies bona-fide record of research work carried out under my supervision and guidance.

The present thesis or any part thereof has not been submitted to any other University for award of any degree or diploma. All assistance received by the researcher has been duly acknowledged.

(**Prof. Mrinal Kanti Dutta**)

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List of Abbreviations

ADF test	Augmented Dickey-Fuller test
AoA	Average value of assets per household
AoDL	Average amount of debt per indebted household
AP	Andhra Pradesh
APMC	Agricultural Produce Market Committee
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedaticity
ARMA	Autoregressive Moving Average
BBY	The Bhavatar Bhugtan Yojana
CV	Coefficient of Variation
DAR	Debt-to-asset ratio
DES	Directorate of Economics and Statistics
df	degrees of freedom
DMI	Directorate of Marketing & Inspection
DS process	Difference-stationary process
E-GARCH)	Exponential-GARCH
FAO	Food and Agriculture Organization
GARCH	Generalised Autoregressive Conditional Heteroskedaticity
GoI	Government of India
HP	Hodrick-Prescott
i.i.d	Independently and identically distributed
INR	Indian National Rupee
IoI	Incidence of Indebtedness
K-density	Kernel Density
LM	Lagrange Multiplier
MLE	Maximum Likelihood Estimation
MoA&FW	Ministry of Agriculture and Farmer Welfare
MP	Madhya Pradesh
MSP	Minimum Support Price
MSR	Marketed Surplus Ratio

NCT	National Capital Territory
ND	Normal Distribution
NE	Northeast
NSSO	National Sample Survey Office
OLS	Ordinary Least Squares
PP test	Phillips-Perron test
P-S	Prebisch-Singer
SD	Standard Deviation
SG	Seasonal Gap
S-K	Skewness-Kurtosis
SMF	Small and marginal farmers
ST	Scheduled Tribe
T-GARCH	Threshold-GARCH
TS process	Trend-stationary process
UP	Uttar Pradesh
USD	US Dollar
WB	West Bengal
WTO	World Trade Organisation
y.o.y	year-on-year

Abstract

The masses of farmers in developing countries have a limited resource base. This makes farm decision-making contingent on both the level and predictability of agricultural prices. At a time when several Asian countries are reeling under acute agrarian distress, this dissertation focuses on India to conduct disaggregated univariate time-series analysis on the behaviour of prices for four major agricultural commodities produced in the country. The study specifically analyses two important time-series components, *viz.* seasonal variations and irregular fluctuations (or volatility). To meet its objectives, the study examines prices reported in over 300 wholesale markets (*mandis*) across the country and uses monthly data spanning more than a decade (2003-2016). In order to obtain reliable and robust results, care has been taken not to compromise on the methodological rigour. Towards this end, the work has adapted from recent contributions made to the literature on price-behaviour estimation for agricultural commodities.

The research objectives taken up in this study have been guided by a critical review of the academic literature. Works of Prebisch (1950), Singer (1950) and Lewis (1954) hypothesize a theoretical downward trend in primary commodity prices over time owing to the changing nature of demand.

When commodity prices are low in general, the nature of intra-year variability has crucial implications for farmers as the price received against harvest is a basic determinant of their income-streams. Recent studies have highlighted the importance of examining price-seasonality in developing and less developed economies (Gilbert et al., 2017; Kaminski et al., 2016; Hatzenbuehler et al., 2018). If primary agricultural-markets are prone to large seasonal price drops, it is an indication that certain constraints may be inhibiting farmer-sellers from behaving as rational economic agents. As there is a dearth of works on seasonality covering the recent periods in India, this study makes some contribution towards this area. To obtain the estimates of price-seasonality, the dissertation tests harvest-pattern based specifications of seasonality (*viz.* trigonometric and saw-tooth functions) against an unrestricted dummy-variable specification to reduce estimation bias. The results show that there is a considerable variation in magnitudes of seasonal price gaps across space and commodity. In several cases, the seasonal price drops in domestic markets are higher than in international prices. Further, a cross-sectional analysis of the estimated seasonal gaps over socio-economic indicators reveals that the magnitude of the seasonal price drop has a direct relationship with the proportion of resource-poor smallholders in the district to which a particular *mandi* belongs. Thus, the study infers that the smaller farmers are the ones who mostly engage in the sub-optimal behaviour of "sell-low" and this leads to a glut in the market. Thus, they are the ones who receive the lowest price for their produce. Given their high economic vulnerability, negative shocks to income-streams of smallholder households may threaten their livelihood sustainability. Therefore, this finding raises critical concerns and calls for policy makers' attention.

Since the global food-crisis of the last decade, volatility in food prices has become a major concern world over (Gilbert & Morgan, 2010; Ott, 2012; Bathla, 2012; Tripathi, 2014; Baffes & Haniotis, 2016; Gilbert *et al.*, 2017). Although, volatility, in itself, is a short-run phenomenon, it can have adverse long-run implications in a country like India, which is teeming with resource-poor farmers. Therefore, this dissertation engages in a detailed investigation of the nature and degree of volatility in realised wholesale prices across the country. To accommodate for the possibility of time-changing variance, the study uses appropriate pre-estimation tests on each of the individual *mandi*-level series under study. Wherever the variance is non-stationary, a suitable generalised autoregressive conditional heteroscedasticity (GARCH) model has been identified to obtain an estimate of the price volatility. The findings, once again, highlight the wide dispersion in both the nature and magnitude of commodity price volatility across the country. On an average, for most of the commodities under study, the domestic market volatility estimates are close to international levels. Several markets also show evidence of time-varying volatility with marked clustering and persistence. The presence of volatility clustering and persistence implies that past volatility is an important determinant of future volatility in several wholesale markets of India. A crucial finding of this analysis is that price volatility is high in locations where a majority of cultivators are not in a position to economically sustain frequent shocks to their revenue stream. Moreover, both seasonal price drops and price volatility are found to be high in the districts dominated by smallholders. As such farmers have high economic vulnerability, continuation of such trends may result is adverse welfare outcomes for the economy as a whole.

Based on its findings, the study concludes that effective delivery of policy necessitates location-specific approaches. The diversity observed in price behaviour (both across and within the different states of the country) is an important contribution of this dissertation. It points out that certain locations are in more urgent need of policy support than others. Thus, continuing with blanket policy responses to the agrarian crisis may end up aggravating existing inequalities.

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1 | INTRODUCTION

"Everything else can wait, but not agriculture."

- Jawaharlal Nehru, 1947

Agriculture is that sector of our economy, which has persistently called out for urgent attention. The irony of Nehru's remark is that, although it was made at the dawn of our independence, it has stayed pertinent throughout the post-independence years. At the turn of the present millennium, academicians, policy makers, social activists and prominent scientists alike have expressed deep concerns about the state of agriculture across the country. Yes, the challenges facing the sector have changed over the years. However, even as the rest of the economy could register sustained growth in the past decades, agriculture continues to struggle to keep up. This assumes profound importance when we recognize the fact that this sector is directly responsible for the wellbeing of about 55 per cent of the country's workforce (Census of India, 2011.

1.1 Background and Motivation

In newly-independent India, the biggest concerns related to attaining sufficiency in food production. While some of these concerns were addressed to a great extent by 1980s after the spread of the technology revolution in agriculture (the 'Green Revolution'), the problem of access to food continues to haunt the average Indian (Patnaik, 2009). By the nineteen-eighties, regional inequalities in agricultural development emerged as a prime concern. The decade of the nineties saw major economic reforms and a clear shift in agricultural policy towards greater reliance on market forces. In addition, beginning in the eighties, agriculture has seen a shrinkage in the public investment in real terms, which led academicians to raise serious concerns about agricultural growth prospects (Rath, 1989; Shetty, 1990; Chand and Mishra, 1995). All of these have contributed towards bringing the agricultural sector to the state in which it presently is.

An agrarian crisis is manifesting in various forms across the country. When we entered the present millennium, many Indian farmers had stopped thinking of agriculture as a remunerative occupation (Government of India, 2006). The problems aggravated over the course of the first decade and by 2012-13 about 42 per cent of those engaged in agriculture expressed that they wish to quit farming if given a choice (NSSO, 2014). Government data shows that during this period, there has been a marked rise in the proportion of small and marginal farmers on the one hand and fragmented landholdings on the other (Census of India, 2011). Such holdings are often uneconomically sized, which prevents cultivators from reaping economies of scale. Moreover, India's agricultural markets are highly imperfect and there is a marked imbalance of bargaining power between farmers and traders (Government of India, 2006; Acharya, 2007; Government of India, 2017). As a result, the costs of both production and marketing end up being considerably high for farmers. At the same time, there is increased casualisation in the rural areas and most of the smallholders have now been pushed to become landless agricultural labourers (Census of India, 2011). The culmination of these has resulted in an environment of farmer distress and, each year, India sees a disturbingly large number of suicides by farmers (Mishra, 2006; Gill and Singh, 2006; Vaidyanathan, 2006; Mohanty, 2013).

In such a scenario, agricultural policy needs to actively engage with the question of catering to the interest of masses who are engaged in agriculture. The government should not assess agricultural progress in terms of physical production volumes only. Rather it should take into account the net income of farm families. As the National Commission on Farmers (GOI, 2006) puts it, there is a need “to place faces before figures”.

Each of the aforementioned issues requires focused policies. However, ‘price’ is a variable, which has close associations with several of these issues. Acharya (2007) asserts that right farm economics is as simple as remunerative price and assured market for the farmers. Thus, by and large, if the prices received by farmers become remunerative (especially, for the smaller farmers), the rising disillusionment with agriculture as a primary occupation in the country may be averted.

Over the decades, producers, consumers, food industry interest groups, legislators and others have debated over the efficiency and equity of price transmission in the marketing channel for agricultural and food products. An inspection of the country's policy decisions in the recent decades shows that a lot of effort has gone into 'setting prices right'. The question therefore is: *how is this right price achieved?* The neo-classical and new classical schools assert their confidence in the forces of competition. They argue that if a system (here the agricultural market) can be taken closer to a competitive model, 'right prices' will be automatically achieved. In his seminal work, Timmer (1986) argues that to determine the right price of food, we have to take into account a wide variety of effects of prices, both on efficiency and on income distribution. It is only in a world of perfect information, with competitive markets, without other government interventions and without political concerns for the impact on income distribution that such a 'right price' is easy to determine. What we observe in reality is that India's agricultural markets are characterized by several imperfections (Bhattacharyya and Kumbhakar, 1997; Vijayshankar and Krishnamurthy, 2012; Bhattacharyya et al., 2013). These hinder the realization of an optimal competitive equilibrium. And, hence, the system remains stuck in some sub-optimal equilibrium.

A substantial strand of literature comes from the new Keynesian economists, who highlight the bottlenecks that prevent market forces from ensuring optimal outcomes on their own (Lipsey and Lancaster, 1956; Dollery and Wallis, 1999; Winston, 2006; Cunningham, 2011; Samuelson and Nordhaus, 1992). Taking cue from this school of thought, this dissertation moves forward with the assumption that in the immediate future, given the ground realities in India, it is not too plausible for agricultural prices to correct themselves on their own. A meaningful approach in the time being is, therefore, to try and understand the prices themselves. Efforts need to be channelised towards obtaining more information on how prices of agricultural commodities get determined, how they move and what implications the nature of price movements have. If prices are not efficient on their own, we need to understand these inefficiencies and take required measures to protect the welfare of the masses whose sustainability is contingent on returns from agriculture.

Now, the realities of the economy, in general, and agriculture, in particular, have undergone a major change with economic reforms in India and the formation of the World Trade Organisation (WTO). With so many changes in policy and market dynamics, the post-reform period warrants separate analysis. The changed realities have had a significant impact not only on the movement of prices but also on the various factors affecting agricultural prices. Although the WTO impacts several countries, it is important to conduct country-specific studies as each country is affected differently. Moreover, in countries that are vast and diverse, the impact of opening up the economy to the world may even differ across regions within the country. Furthermore, farmers belonging to different socio-economic classes within these regions may be impacted differently by the policy shifts. Therefore, only a disaggregated study can answer such questions and reveal the true picture.

Given the present realities, a better understanding of price behaviour as well as of farmers' response to price movements can help in addressing several burning problems faced by agriculture in our country. This, in a broad sense, has been the motivation behind my dissertation. The answers for India may also carry lessons for several other developing countries at large, many of which have smallholder-dominated agrarian sectors and are in the process of implementing structural reforms. It is in this broad backdrop that this dissertation is placed.

Before moving ahead, it is important to introduce the reader to the way agricultural marketing takes place in India. The following section presents a brief discussion on the same.

1.2 Agricultural Marketing in India: The role of the *Mandis*

Agricultural marketing in India is characterised by long-supply chains with numerous intermediaries between the farmer-producer and the final consumer (Acharya, 2007). As a result, the price being paid for any agricultural produce also varies at every point of this supply chain. This dissertation focuses on the price received by the farmers and therefore, its interest is in the prices being realised at the beginning of this supply chain.

The marketing of primary agricultural produce in India has mostly been governed by two important Acts,*viz.* the Essential Commodities Act 1955 and the state-specific Agricultural Produce Marketing (Regulation) Acts. While the former lays out rules to prevent the hoarding and black-marketing of essential commodities in the country, the latter are intended to safeguard the farmers from exploitation by traders. As per the Agricultural Produce Market Committee (APMC) Acts, trade in agricultural commodities can only take place through APMC designated wholesale markets (or *mandis*). Hence, this is where farmers sell their produce to traders. Over the years, all primary wholesale markets have functioned under the ambit of these Acts, which divide the entire geographical area of a state and declares 'market areas'. The respective APMCs are responsible for enforcing the rules in each market-yard and sub market-yard. These Acts mandate that farmers have to bring the produce to the *mandi* and price discovery has to take place through 'open auctions' supervised by licensed commission agents.

A point to note is that *mandis* are usually located quite far from the villages where farms are located. Therefore, it is difficult (and often not viable) for smaller farmers to bring their produce to these *mandis*. Small and marginal farmers often do not come directly to the *mandis*, and instead sell through large farmers. Hence, Farm Harvest prices (FHP) better reflect the actual price received by farmers.

With time, the APMC markets have largely been rendered restrictive and monopsonistic (Government of India, 2017). Therefore, the APMC Acts were replaced by the Agricultural Produce and Livestock Marketing (Promotion & Facilitation) Act, 2017, which sought to make agricultural marketing more competitive across the country. More recently, in 2020, three new Farm Bills have been passed, which seek to change the nature of agricultural marketing in India. However, as these new reforms are not relevant to the period of reference of this study, they are not discussed here.

Having given a brief sketch of where (and how) farmers sell their produce, this dissertation now moves forward to define the problem being investigated in this work of research.

1.3 Statement of the problem

The nature of agricultural price movements has crucial implications for the economy at different levels. At the microeconomic level, it affects the farmer-households' income, cropping-pattern decisions, and, in general, the attitude towards continuing with farming as an occupation. At the macroeconomic level, it influences the relative distribution of income across the sectors and classes. Thus, in the long-run, the nature of these prices can impact the social and political stability of the economy.

In developing countries, the returns from agriculture has crucial implications as the masses of farmer-households are resource-constrained. The 'price' that farmers receive against their harvest has substantial influence on the size of these returns. Studies, however, show that the prices received by farmers in India during the last couple of decades have, in general, been quite low (Government of India, 2006; NSSO, 2014b; Nair and Eapen, 2015). In an environment of low prices, the nature of intra-year variability in prices has crucial implications for households whose livelihood depends primarily on the returns from agriculture. The works of Claessens & Duncan (1993), Gilbert (2003) as well as Dana & Gilbert (2012) discuss how the exposure to high price variability can have adverse consequences for farm households in countries like India, which have underdeveloped financial markets and a poor outreach of banks to the agricultural sector.

The intra-year variation in prices may be broadly classified into two types, *viz.* predictable and unpredictable. While volatility (irregularity/unpredictability) is desirable for making profits through speculation, too much volatility in agricultural commodity prices in developing countries can have adverse welfare implications of both consumers and producers (Chandrasekhar and Ghosh, 2002; Grimwade, 2004; Hoda and Gulati, 2008; Bathla, 2012). While such volatility raises food-security concerns for the former, it may raise concerns of livelihood sustainability for the latter. These occur because a large proportion of cultivating households in our country have a constrained resource-base and are, therefore, risk-averse. Again, when the predictable variations in price (like, say, seasonal drops in price) are too large, it indicates that farmers have not been able to smoothen price shocks through optimal trading and storage strategies. This indicates non-conformity to the competitive storage theory of Deaton and Laroque (1992), and implies sub-optimal behaviour from the farmer-sellers. Such behaviour could be a strong indication of the constraints being faced by farmers, which prevent them from behaving as rational economic agents.

Thus, understanding the nature of agricultural-commodity price behaviour can shed a lot of light on the empirical picture of agricultural market outcomes in India. Effective agrarian crisis mitigation policies can only be formulated when we have a fair understanding of agricultural prices. We, therefore, need to obtain information on how these prices move, and about how their movements differ across space, commodity and time. Given the gaps in the existing literature on these topics (discussed in section 2.4 of Chapter 2), the present work attempts to contribute to this literature by making a relatively disaggregated study of some important time-series components of price behaviour. The specific research objectives being pursued in the dissertation are listed in the following sub-section.

1.3.1 The Research Objectives

The aim of this study is to examine the time-series behaviour of the prices of some widely cultivated and traded agricultural commodities in India during the recent decades.

The specific research objectives of this dissertation are as follows:

(1) To examine the seasonal behaviour of *mandi* prices of a selected basket of commodities over the period from 2003 to 2016 across India.

(2) To examine the volatility in *mandi* prices of the selected commodities over the period from 2003 to 2016 across India.

(3) To examine the spatial variation in price-behaviour of these commodities and its implications for cultivating households across India.

1.3.2 Hypotheses and research questions

To meet each of the specified research objectives, this dissertation has formulated a specific set of testable hypotheses. Each is posed as a null hypothesis, which is empirically tested using the available data. The formulated hypotheses are serially listed below as per the research objective they help pursue.

Research Objective (1)

The null hypothesis is that there is no statistically significant seasonal pattern exhibited by agricultural commodity prices in India, *i.e.*

H_0 : *The coefficients of all the seasonal factors are not different from zero.*

Research Objective (2)

Two null hypotheses are tested to pursue this objective.

(A) The first relates to the degree of irregular variation in prices and states that all variation in prices are explained by structural factors and there is no irregular/idiosyncratic variation in prices over time, *i.e.*

$$H_0 : \epsilon_t = 0, \quad for\ all\ \ t,$$

Here ϵ_t represents the random disturbance at time t in de-trended and de-seasonalised prices.

(B) The second null hypothesis relates to the nature of volatility and it states that the studied prices are homoskedatic, *i.e.*,

H_0 : *The variance of the disturbances remain constant over time.*

Research Objective (3)

Two null hypotheses are formulated to pursue this objective.

(A) The nature of price behaviour is uniform across all markets of India and there is no statistically significant spatial dispersion in the studied components of commodity price-behaviour, *i.e.*

H_0 : *Dispersions of both the seasonal gap estimates and volatility estimates for prices across India are not different from zero.*

(B) There is no statistically significant association between the nature of price behaviour and the socio-economic conditions prevailing in a location, *i.e.*

H_0 : *The coefficients of all variables representing socio-economic indicators are not different form zero.*

In addition to these, some sub-research questions have been formulated at different points in the thesis to obtain better clarity on the issue being examined. These are specified within the respective chapters as and when they are investigated.

1.4 Methodology

This section engages with the broad methodological framework of the study. It begins with a brief introduction to the approach taken up in my thesis to study the time-series behaviour of commodity prices and touches upon the general framework within which the study is conducted. The section also elaborates on the time-period of reference and on the choice of the commodities.

This dissertation conducts its investigations within a general framework of time-series econometric analysis. Structurally, the time-series behaviour of agricultural commodity prices can be characterized in terms of trend, seasonality and volatility. While the former two represent predictable aspects, the third component relates to the irregularity or unpredictability in these prices. The study, thus, aims to separate the systemic component from the idiosyncratic components of each series. It specifically focuses on two of these aspects, *viz.* seasonality and volatility. Each component is assessed across (a) space, and (b) commodity type.

Specific approaches are adopted to estimate and analyse each of the studied components of price behaviour. Their choice has been guided by a review of seminal works, policy documents and recent methodological advances made in the respective fields (discussed in Chapter 2). First, the seasonal pattern is analysed by testing the statistical significance of the mean effect of seasonal components on each *mandi*-level price series using tools from time-series econometrics. The magnitude of price seasonality is then discussed by laying focus on the dispersion of the estimates across space and commodities. Next, to examine the volatility in prices, the nature of volatility is first investigated using standard tests. After this, appropriate frameworks are identified on case-by-case basis to model the volatility exhibited by each of the *mandi*-level series under study. A detailed discussion of the estimates obtained is then undertaken to understand how price volatility varies across *mandis* of India.

1.4.1 Time-period of reference

The period of reference for the study is from 2003 to 2016, which is chosen based on several considerations:

(i) Sufficient time is allowed for the lagged effects of the major policy changes initiated during the nineties to phase in. These reforms include the New Economic Policy adopted by India in 1991, opening up of the agricultural sector through the *i.e.* the Agreement on Agriculture of 1995, and the shrinking public investment as well as subsidy and credit cuts to agriculture in India.

(ii) Several studies have reported that, globally, the movement of commodity prices entered a new phase in and around 2005-06 (Ott, 2012; Baffes and Haniotis, 2016; Harvey et al., 2017);

(iii) There is a reported increase in irregular movements in this period, because of which it warrants investigation (Ott, 2012; Bathla, 2012; Tripathi, 2014; Baffes & Haniotis, 2016).

The year 2016 is taken as the cut-off-year because of two reasons. The first is that two major policy reforms were initiated in quick succession around this period, *viz.* demonetisation (November, 2016) and the Goods and Services Tax (GST) regime (July, 2017). Although a full assessment of their impact on agriculture (as well as the aggregate output of the economy) will require some time, studies have highlighted that they have adversely affected the sector, at least in the short-run, due to severe cash constraints and administrative hindrances (Govindasami, 2017; Goel, 2018; Khan and and, 2018; Browske, 2019; Baig, 2019; Chodorow-Reich et al., 2020; Lahiri, 2020). The second reason is that the years from 2015 have seen back-to-back droughts in India (Government of India, 2018; Todmal, 2019; Global Drought Observatory, 2019). As about 56% of the net cultivated area of the country is rain-fed, successive droughts can severely affect agricultural production (Government of India, 2016). Considering these factors, it is decided to not include data from the years after 2016, as they may have been unduly affected by abnormal conditions.

1.4.2 The commodities under study

To meet its objectives, the dissertation has chosen four major commodities cultivated widely across India to conduct its analyses, *viz.* paddy, wheat, mustard and groundnut. This choice is guided by the following considerations:

(i) *Representativeness across major crop types of India*: Representation is given to major crop categories by including two cereals (paddy and wheat) and two oilseeds (mustard and groundnut). Care is also taken to ensure that crops of the two major cropping seasons of India are represented *i.e.* Kharif (paddy and groundnut) and Rabi (wheat and mustard).

(ii) *The geographical spread of their cultivation across the country*: The four selected commodities not only constitute a large proportion of the total agricultural production, but their cultivation is widely spread across several states of India (Appendix A.1).

(iii) *The share of marketed surplus*: The four selected commodities also form some of the most highly traded commodities across the country as is evident from their marketed surplus ratio (MSR). Data available from the Directorate of Economics and Statistics (DES), Government of India shows that, for the oilseeds, the estimated MSR has mostly remained above 90%. For the cereals, the same varies within the range of 70-85% (see Appendix A.1 for the detailed figures).

(iv) The availability of consistent and credible data throughout the study period.

1.4.3 The unit of study: *Mandi*-level prices

As stated, given the vastness and diversity of India, country-wide averages are not sufficient in providing a meaningful picture of ground realities. Therefore, this dissertation conducts its analysis at a disaggregated level, *i.e.* at the level of the wholesale markets (*mandi*). Although *mandi* prices are not exactly the farm-gate price, they are better reflective of the price received by farmers than any other price for which data are available for substantially continuous periods at a relatively disaggregated level (Chand, 2012; Singh, 2012).

The line of analysis in each chapter moves from general to specific. Accordingly, the *mandi*-level estimates are examined at the various levels, *i.e* regional, state as well as at the level of the individual *mandis* (wherever appropriate). India consists of 28 states and 8 union territories, which fall under are six broad geographical regions, *viz.* North, South, Central, West, East and Northeast (NE). In the NE region, *mandis* from only one state (Assam) has qualified for analysis due to very low reporting from the rest of the states in the dataset used in this study (elaborated in Section 1.5). Therefore, Assam is clubbed under the Eastern region for the purpose of this study.[1]

1.5 Data

The primary variable of interest of this study is the wholesale market (*mandi*) price of agricultural commodities that are widely cultivated and traded across India. This study is conducted with the help of secondary data. Subject to their availability, the data on price are considered for the entire period of reference (2003-2016) to obtain estimates of the specific time-series components studied here. The obtained estimates are then further examined in the light of socio-economic indicators to attain insight into their implications. A point to be noted here is that, since the data on socio-economic indicators are collected through surveys, they are only available for specific points of time. This study has, therefore, used data from survey reports falling in roughly the middle of its period of reference to attain a representative picture of the prevailing socio-economic realities.

1.5.1 Data sources

Data on each variable are collected from credible secondary sources. Data on the daily prices (maximum, minimum and modal price) reported at the APMC *mandis* are available from AGMARK's database maintained by the Directorate of Marketing & Inspection (DMI), Government of India (GoI) (*http://agmarknet.gov.in*). Appendix A.2 elaborates more on the dataset and on the *mandi*-level series that are included from each commodity for this study. While data on the administered price or Minimum Support Price (MSP) are obtained from the publications of Ministry of Agriculture and Farmer Welfare, data on international price and USD-INR exchange rates are obtained from 'The Pink Sheets' of the World Bank[2] and the Economic Research Division of the Federal Reserve Bank of St. Louis (*https://fred.stlouisfed.org*) respectively.

Among the socio-economic indicators, while the data on landholding distribution are obtained from the Agricultural Census 2010-11 published by the GoI on the Agricultural Census Portal (*http://agcensus.nic.in*), the data on debt-related factors are obtained from the 70th Round of the National Sample Survey Office (NSSO), Government of India published in 2014.

1.5.2 Specification and transformations of data

This dissertation conducts uni-variate econometric analysis on the *mandi*-prices to decompose the price variation into some of their characteristic components. There are various choices that the dissertation had to make regarding the particular specification of data that it uses. At times, for sound econometric analysis, the raw data are also subjected to some arithmetic transformations. These are elaborated in the following paragraphs.

1.5.2.1 Real vs. nominal price

This dissertation uses the nominal *mandi* price of the four commodities to conduct the analysis of time-series components. Belsley (1972) shows that deflation of variables changes the functional and stochastic specification of a linear model, which may lead to incorrect least squares estimates. Wang and Tomek (2007) too show that deflation alters the features of a time series. Deflation may also remove part of the variation of interest and, therefore, many studies on price behaviour choose not to deflate unless there is a strong justification (Gilbert et al., 2017; Ott, 2012; White and Dawson, 2005). All analyses carried out in this dissertation are univariate. Thus, as there is no fear of spurious correlation arising out of a common trend in the prices, this dissertation does not deflate the available price data.

1.5.2.2 Absolute vs. log prices

Across India, the price of the same commodity differs in their mean level due to several reasons like differences in variety, location, market policies etc. (Chatterjee and Kapur, 2016). If we use absolute prices for the analysis of time series components, the resulting estimates may not be comparable with each other. In absolute terms, the estimates for the higher-mean priced series may be unduly large. Making comparisons with estimates obtained from lower priced series will not reflect the true picture. Hence, it makes more sense to compare percentage changes in price rather than the absolute changes. Therefore, to be able to make meaningful comparisons of the estimates obtained from the different *mandi*-level series, all prices are transformed to their natural logarithms before conducting any time-series analysis.

1.5.2.3 Choice of data frequency

Agricultural prices show wide variations within a year and, therefore, annual prices are often not very representative. Monthly frequency is the most convenient frequency to deal with seasonality inherent to agricultural commodities (Ott, 2012). Although high frequency data (daily prices) are reported in the data set, the reporting is inconsistent and has several missing observations. The proportion of missing observations gets reduced when we aggregate the daily modal prices to find monthly averages of the price. Therefore, this dissertation analyses the monthly prices of the selected commodities from across *mandis* of India.

1.5.2.4 Choice of international reference prices

For India, international prices are often either not available for several commodities or are inconsistent. The international price series for common rice

(25% broken kernels) exported from India is discontinuous due to export restrictions imposed from time to time (two major such gaps are from October 2003 to April 2005, and again from February 2008 to August 2011). Therefore, the dissertation uses the price of 25 percent broken rice supplied by Thailand, which is comparable to India's common rice (Saini and Gulati, 2017). Examination of the data shows that there is a high statistical correlation (92.97 per cent) between the two series from January 2003 to October 2018). Similarly, for wheat, the international price series used is the US Soft Red Winter Wheat. Although the international price series is available for groundnuts from the World Bank, no international price series is available for mustard. Therefore, for the latter commodity, the dissertation has not been able to analyse any international reference price.

1.6 Layout of the Dissertation

The entire dissertation is divided into six chapters. Chapter 1, the present chapter, is introductory. Chapter 2 presents a critical review of the literature examining various components of agricultural price behaviour. The gaps in this literature are also highlighted. The chapters 3, 4 and 5 form the core of my thesis and they engage with an empirical investigation of some important time-series components of agricultural commodity prices across various markets of India.

Chapter 3 examines the seasonal component of price behaviour. Rigorous analyses have been carried out on *mandi*-level data to understand the nature and magnitude of seasonality across India. Further, the implications of this seasonal behaviour is also examined in the chapter.

Chapter 4 engages with the concept of volatility (or unpredictability) in agricultural commodity prices. It begins by assessing the nature of volatility, *i.e.* it examines whether the degree of volatility varies over time. the chapter then goes on to measure the degree of volatility observed in the *mandi*-level prices of the country.

Chapter 5 investigates the spatial diversity in price volatility of *mandi*-prices across India. It also examines the implications of high volatility in the light of socio-economic indicators of risk-bearing capacity of farmer-households.

The sixth and the final Chapter presents the major conclusions of this study. It discusses the implications of the findings and also presents a section containing prescriptions for policy. Towards the end, a list of conferences and workshops attended throughout my doctoral research tenure is presented. There is also a mention of the publications that have resulted out of this research. The dissertation ends with the Appendices, Notes and the Bibliography.

The present chapter has provided a broad introduction to the work carried out in this dissertation. The chapter that follows is the 'Review of Literature' chapter and it engages with various theories and empirical investigations that have been carried out over the years to understand agricultural commodity price movements and their implications. It shall put the present study in perspective and also introduce the readers to several considerations that have been taken up while deciding on the methodology adopted for this dissertation.

2 Review of literature

Agriculture is indispensable for the sustenance of any economy. The literature on agriculture and the issues concerning it is, therefore, quite vast. It covers numerous aspects encompassing dynamics of supply, demand, price determination, technology adoption, farmer welfare, trade policies and so on. The present dissertation, however, is primarily engaged with studying the nature of agricultural prices. Agricultural price movements comprise of several components, which are associated with cyclical, seasonal, trend and irregular factors. The recent commodity price boom of 2004-05 has led to an increased momentum across the world in the efforts towards understanding agricultural prices. Several old debates are being revisited and evaluated in terms of present realities. The present chapter makes an attempt to bring together some of the key discourses on the subject.

The chapter comprises of four broad sections. While the first section discusses the existing theoretical and empirical literature on long-term price movements, the second section examines the literature on short-term price fluctuations. Further, the third section presents a critical review of the methodological approaches undertaken by different studies to understand specific components of commodity price movements. This chapter ends with a final section that identifies important research gaps. These gaps have guided the choice of the research problem taken up in this dissertation.

2.1 Long-term Movements in Agricultural Price: Theory and Evidence

The review is initiated with a discussion of some important theoretical works on long-term agricultural price movements. The chronological evolution of economic theory is traced in order to attain insights on how the existing theories have taken shape over time. This is followed by a review of empirical works conducted on long-term price movements. Towards the end, a summary is presented, which evaluates the empirical evidences in light of the existing theories. Major debates are also pointed out.

2.1.1 Review of Theoretical Discourses

Some of the widely discussed aspects of agricultural price behaviour are its trend and cyclical components. Price cycles have baffled academicians for a long time now. This is evident from the numerous theories put forward from various schools of thought to explain them. However, there is relatively lesser theoretical insight into the causes of agricultural price cycles. Among early works, economists like Clarke, Jevons, Juglar, Tugan-Baranovski, Marx, Engels, Pareto, Wicksell and Gelderen have recognized the presence of long-term economic fluctuations in commodity prices (Schumpeter, 1934; Schumpeter, 1939; Louçã, 1999; Erten and Ocampo, 2013). However, the credit for developing major analytical frameworks on commodity price cycles is given to Nikolai Kondratiev (1892-1938) and Joseph Schumpeter (1883-1950).

Kondratiev was a Russian economist whose major contributions were published in the 1920s. He is credited with formalizing the concept of long waves (*i.e.* long periods of upswing and downswing) observed in historical data of commodity prices, industrial production, interest rates and foreign trade. He also argues that irreversible and reversible processes coexist in the economy. Kondratiev stresses that among the major drivers of the long waves, endogenous factors such as technological changes inherent in capital accumulation are more important than any exogenous changes such as wars, revolutions, or gold production (Louçã, 1999). Austrian school economist, Joseph Schumpeter also agrees with the idea of endogeneity of drivers. According to his analysis, the main explanation of price cycles is to be found in entrepreneurial innovations. He is credited with the identification of overlapping cycles of various durations: long Kondratiev cycles lasting about 50 years, shorter Juglar cycles lasting about 9 years, and the rather short Kitchen cycles of around 3 years in length. He finds commodity prices to be directly related to the phases of prosperity and stagnation which form the long cycles. In the prosperity phase, the initial competition for productive inputs (metals, minerals, agricultural goods) tends to increase their prices relative to products that are directly influenced by innovation. The gradual imitation of innovations by other producers and the resulting reduced opportunities to obtain economic rents slows down the demand for commodities, making them relatively cheaper again. Schumpeter's important assertion is that prices are pushed by declining output growth, and not vice versa. Thus, he focuses on the demand-side (Schumpeter, 1934; Schumpeter, 1939).

Over the years, the concept of super-cycles has emerged. Erten and Ocampo (2013) emphasise that such cycles stand out on two important respects: they span a very long period of time (with upswings of 10-35 years, generating 20-70 year complete cycles), and they are observed over a broad range of commodities (mostly inputs for industrial production and urban development of an emerging economy). It has often been pointed out that these cycles are usually demand-driven. This implies that the individual commodity prices tend to move together with strong positive correlation (Pindyck and Rotemberg, 1990; Cuddington and Jerrett, 2008).

The trend component of agricultural commodity prices becomes a subject of intense discussion in mid-twentieth century. Towards the end of 1940s, a controversy emerges around the issue of terms of trade (*i.e.* the relative price of exports and imports) faced by developing countries. Drawing from Engel's Law, Prebisch (1950) and Singer (1950) independently advance a hypothesis that developing countries will experience a secular deterioration in their terms of trade as they export more of primary commodities. The hypothesis is that as incomes grow, the prices of such commodities, especially food, is expected to depict a general downward trend relative to manufactured goods. The two economists have put forward several theoretical explanations for this disadvantage faced by primary commodity exporters. One major argument is that such commodities have low-income elasticities of demand and, therefore, Engel's law would operate. In addition, while primary commodities are often comparatively homogeneous leading to highly competitive commodity markets, markets of manufactured goods tend to be oligopolistic. This leads to asymmetric market structures, which favor sellers of the latter kind of goods. Yet another explanation put forward to explain this hypothesis is that there are productivity differentials between core (industrial) and periphery (non-industrial) countries. The original Prebisch-Singer (P-S) hypothesis is extended by Singer (1998) with reference to Schumpeter's theory of creative destruction. He shows that the terms of trade between standardized and innovative products has a tendency to deteriorate. Thus, even though developing countries could industrialize and produce mature manufactured products, standardized products will not create new economic rents. Therefore, the long cycles following innovations in output growth generate cyclical fluctuations of similar durations for relative prices of primary commodities.

The 1950s also sees the emergence of an important framework for interpreting price movements of agricultural goods in the developing ('tropical') regions, which is put forward by Arthur Lewis through his concept of duality (Lewis, 1954). He postulates that price of agricultural produce from tropical regions is held down by the existence of unlimited supplies of labour in these countries. He argues that benefits from improvements in productivity of agro-based industries do not reach the workers. Rather, such benefits chiefly accrue to industrial purchasers in the form of lower commodity prices. For the price of any agro-produce to increase, the productivity of the tropical subsistence food economies has to increase. Lewis (1954) asserts that the contribution of the temperate world to the tropical world, whether in capital or in knowledge, mainly remains confined to the commercial crops for export. Unless, for a change, capital and knowledge are put at the disposal of the subsistence producers to increase the productivity of tropical food production for home consumption, the prices of tropical commercial crops will always permit only subsistence wages to the workers. Thus, he predicts that increases in the real commodity prices must wait for the elimination of poverty in the tropics. This analysis can be applied to all tropical commercial products for which an unlimited supply can be produced (because unlimited natural resources exist) in relation to demand.

Apart from trend and cycles, there is another component of long-term price behaviour which has generated academic interest, *viz.* seasonal variation. Seasonality refers to those fluctuations in price that tend to recur over time. Some seasonality is expected in agricultural commodity prices as their production is cyclical in nature. Thus, while prices tend to rise in the lean season as supply dwindles, they tend to fall with the coming of new harvest to the market. However, the works of Goetz and Weber (1986); Deaton and Laroque (1992), Deaton and Laroque (1996) discuss how seasonal fluctuations in price get smoothened out if markets are able to adjust the demand-supply dynamics through trade and storage. The competitive storage model proposed by Deaton and Laroque (1996) postulates that storage has an effect of smoothing price shocks (esp. downward shocks) through the “buy low, sell high” principle. However, other studies highlight the limited scope of the competitive-storage model in developing and less developed countries. Acharya and Agarwal (1994) discuss how the extent of seasonal price variation not only depends on storage costs but also on the degree of seasonal concentration of sales, perishability of the product, risks involved in holding the product over time as well as on the availability of storage, warehousing and credit facilities. Relatively recent works like Stephens and Barrett (2011) and d'Hotel and Cotty (2018) too engage with the theoretical factors that lead to wider seasonal price gaps in developing countries. These factors include poorly integrated markets, trade restrictions, high transaction costs, asymmetric market power along the marketing chain, heterogeneous price expectations as well as liquidity and credit constraints on farmer-households. Thus, seasonality continues to be an important element of price variation in several parts of the world.

2.1.2 Review of Empirical Works

With the above theoretical groundings in mind, this sub-section moves forward to examine findings of some important empirical works conducted to study the way agricultural prices move over time. Although the focus is primarily on the present realities, the review takes into account works examining historical movements as well so that meaningful insight can be attained.

Some notable empirical works on long-term commodity price movements include, among others, Deaton and Laroque (2003), Erten and Ocampo

(2013) and Harvey et al. (2017). Deaton and Laroque, 2003, based on Lewis' (1954) framework, statistically model real price movement of six different commodities for the period from 1900 to 1987. The commodities include cocoa, coffee, rice, sugar, copper and tin. They observe that there is a remarkable lack of long-run trend in these commodity prices. This is consistent with Lewis' account (as discussed in the preceding sub-section). The authors further point out that the results are statistically significant only in the case of two commodities, *viz.* cocoa and coffee, whose production was then confined to the tropics, which are less developed regions of the world. This lends further support to Lewis' account.

- Erten and Ocampo (2013), in an important work on long-term price movements, assess commodity price movements from 1865 to 2009. They approach this analysis from the super-cycle framework and decompose real commodity price movements observed during their period of reference into four super-cycles ranging between 30-40 years. For the total real non-fuel commodities, the cycles are: (a) from 1894 to 1932, peaking in 1917, (b) from 1932 to 1971, peaking in 1951, (c) from 1971 to 1999, peaking in 1973, and (d) the post-2000 episode. Each cycle possesses large amplitudes varying between 20 to 40 percent above or below the long-run trend. The mean of each super-cycle for non-oil commodities show a tendency to be lower than that of the previous cycle, which suggests a step-wise deterioration over the entire period. This is especially true for agricultural prices. They also find evidence of co-movement among all non-fuel commodity indices across the entire sample period. Among the agricultural indices, tropical agriculture exhibits super-cycles with much larger amplitude relative to non-tropical agriculture. Tropical agriculture is also found to have experienced the strongest and steepest long-term downward trend among all commodities through the twentieth century. This is followed by non-tropical agriculture and metals. The authors interpret the gradual evolution of long-term trends as providing an alternative interpretation of the Prebisch-Singer (P-S) hypothesis. Like Deaton and Laroque (2003), their findings also lend support to Lewis (1954).

Recently, Harvey et al. (2017) have taken up an even longer-term perspective to study historical price movements. They examine export values of 23 commodities spanning the period from 1650 to 2014. Employing multiple-break techniques, they report that each of the studied price series can be partitioned into four regimes: 1650 to early 1820s, early 1820s to early 1870s, early 1870s to mid-1940s, and the mid-1940s to 2014. They also find that over the entire industrial age, commodity prices have presented a long-run downward trend, with breaks. This fall is reported to have accelerated post 1870s, and especially in the 20th century. The authors interpret this as clear support to the P-S hypothesis. They argue that such acceleration suggests that the economic forces underlying the hypothesis have intensified over this recent period.

Although the very long-run framework gives important insights, it misses out on capturing a lot of variations occurring within these periods. More information about the behaviour of prices in the recent decades can be obtained from studies that have concentrated on relatively shorter time-periods of, say, two to three decades. One such study is by Tripathi (2014) who studies world price trends of some major agricultural commodities for the period from 1981-82 to 2004-05. He finds three distinct phases within this period for each commodity. The studied commodities include cereals (rice and wheat), oilseeds and edible oils (soybean, rapeseed and groundnut oil) and sugar. During the study period, the world price of wheat is found to have moved in cycles of eight to ten years, with troughs observed at 1987 and 2000 respectively. After 1997, wheat price fall sharply, and revive only after 2001. In case of the world price of rice, three different periods are observed. Up to 1986-87, prices show a sharp downward trend, which is followed by a period of relatively stable prices until 1995. The downward trend resumes in the post World Trade Organisation (WTO) period, reaching their lowest trough since the 1960s in 2000-01. It is only by mid-2003 that international rice prices start recovering. As for oilseed and oil prices, Tripathi (2014) observes three distinct patterns: a downward trend till 1986-87, an upward movement from 1987-88 to 1996-97, and finally, a strong downward trend from 1997 to 2002. By 2003-04, prices are found to have returned to their high level of mid-1990s.

The neo and new classical schools of thought advocate the power of market forces in bringing prices back to some optimal equilibrium. Applied to price-cycles, this has encouraged a lot of academic efforts towards looking for evidence of any tendency in price-series to drift towards some long-term mean (formally, 'mean-reversion'). A time-series is said to be 'stationary' if its statistical properties such as mean, variance, autocorrelation, etc. remain constant over time. Wang and Tomek (2007) argue that if commodity prices are non-stationary, it would imply that a shock has a permanent effect on the price dynamic and that it never dies out. Studies have tried to prove the hypothesis that the effect of price-shocks disappear in the long-run. Bessembinder et al. (1995) show that because of supply response, spot prices of agricultural commodities revert back to production costs. Peterson and Tomek (2000) also find empirical evidence of mean reversion in grain prices. Deaton and Laroque (2003), however, find that reversion of prices to their long-run base is very slow. They also stress that there is no strong empirical evidence to reject the alternatives of mean-reversion. Later empirical works argue that the evidences for stationarity of agricultural commodity prices is inconclusive. Newbold et al. (2000) find that grain prices are mean-reverting only if a structural break is taken into account. In a relatively recent work, Ott (2012) also finds that grain prices are mean reverting only by period. He finds that all grain prices have experienced a new period of higher prices starting around 2007.

The academic interest in investigating price seasonality in developing countries has seen a resurgence in recent decades. A number of studies highlight the implications of excess price seasonality on food-security, agricultural household incomes, and coping strategies of rural households in countries of Asia and Africa (Dercon and Krishnan, 2000; Khandker, 2012; Kaminski et al., 2016). Food price seasonality in countries of sub-Saharan Africa has raised concerns as it has been recorded to be two to three times higher than in global markets (Kaminski et al., 2016;Gilbert et al., 2017; Hatzenbuehler et al., 2018). Gilbert et al. (2017) study price seasonality in seven African countries covering 193 markets and 13 food commodities. They find that the nature and magnitude of seasonal variations show a lot of diversity across crops, regions and market places. Through their study on Nigeria for the from 2000-2016, Hatzenbuehler et al. (2018) too stress on the importance of conducting disaggregated studies. They find that the effect of common factors like policy changes differ across individual markets. They show that even when price paths of different markets follow similar trends, there are unique market-specific deviations in the price paths.

The literature analyzing long-term price movements specifically for India is not very extensive. Most of these studies examine agricultural prices within the framework of inflation or price rise, rather than in the more general framework of long-term cycles (Chand, 2010; Agrawal and Kumarasamy, 2014; Nair and Eapen, 2012; Sasmal, 2015; Nair and Eapen, 2015). Nair & Eapen (2015) examine long-term trends in food inflation in India in relation to the performance of Indian agricultural sector under various agricultural policy regimes. They find that in the post reform period (1992 to 2013), food prices are relatively low compared to the period from 1960s to early-1990s. In another study Gil-Alana and Tripathy (2014) examine mean-reversion in the prices of seven agricultural commodities: rice, wheat, maize, bajra, jowar, black gram and arhar. They do not find sufficient evidence of mean reversion in case of arhar and black gram. This indicates that shocks in the price of these commodities have a permanent nature. Further, for rice and bajra too, their findings are ambiguous. It is important to note that all of these are important food-grains (esp. rice and arhar). They not only comprise a large share of an average household's consumption basket, they also form a major share of the traded agricultural products. Thus, if price shocks have a permanent effect on these, it will substantially affect both consumers and producers. The authors stress on the need to adopt strong measures in the event of a negative shock in prices of arhar or black gram since the shocks will otherwise persist forever.

The aspect of seasonal price behaviour remains less examined in India. Some of the studies that have been conducted do find evidences in favour of the presence of commodity price seasonality (Sarkar, 1993; Sharma and Kumar, 2001; Kumar and Sharma, 2006; Makama et al., 2016; Meera and Sharma, 2016). Kumar and Sharma, 2006 analyse monthly indices of wholesale prices of wheat, rice and coarse-grains during the 1980s and 1990s. They find that the nature of seasonal variations show inter-crop differences in the two decades under study. Makama et al. (2016) study rice price seasonality in India using monthly prices from 2004 to 2014 and find seasonality to be one of the major causes of price variation. The work by Meera and Sharma (2016) studies monthly wheat prices in Sriganganagar district of Rajasthan from 2005 upto 2014. They too find statistically significant seasonal variations in the studied prices. However, leaving aside the relatively dated works mentioned here, the more recent works on India are wanting in terms of methodological rigor, as will be discussed in the later sections (2.3 and 2.4).

2.1.3 Section Summary

To paint a quick summarizing picture of the present section, it finds that both theory and empirical studies suggest that the price of all commodities depict cyclical movements over the long term. In the case of agricultural commodities, most of the discourses have been built up on the P-S hypothesis, followed by Lewis' contention that agricultural prices in the tropics shall tend to stay low. Since the mid-twentieth century, a lot of empirical effort has been directed towards proving (or disproving) the P-S hypothesis. However, these studies provide an ambiguous picture, with no conclusive evidence to support its holding. They argue that the tendency of primary commodity prices to deteriorate relative to manufactured goods is not an inevitable persistent effect. It is rather an evolving dynamics dependent on global demand trends and the effects of technological innovations. The studies on long cycles show that the mean of each price cycle significantly declines over the course of the twentieth century, which lends support to the original P-S hypothesis. However, the commodity price boom of the last decade has led many commentators to claim that it challenges all of the above. On the one hand, the findings of both Erten and Ocampo (2013) and Harvey et al. (2017) lend support to the P-S hypothesis. They, in fact, suggest that the economic forces underlying the hypothesis may have intensified in the late 20^{th} century. On the other hand, Ott (2012) reports that all grain prices depicted a new period of higher prices starting around 2007. The evidence on mean-reversion in price series also remains inconclusive. At most, studies have been able to show that, for some commodities, prices are mean-reverting only if a structural break is taken into account. Furthermore, the literature on price seasonality in developing countries has attracted attention towards the observations of relatively more pronounced seasonal variation in these countries.

2.2 Short-term Movements and Price volatility

Short-term movements of agricultural prices are a theoretically less explored area compared to long-term movements. This is striking since the agricultural sector is characterized by sharp year-to-year as well as intra-year fluctuations. Also, as will be highlighted in Section 2.2.2, the implications of short-term fluctuations can be severe and far-reaching for smaller farmers in developing countries. Therefore, while discussing the implications of price volatility, the section lays focus on developing countries in general and on India in particular.

2.2.1 Fluctuations in Agricultural Commodity Prices

What drives prices? This is a question, which economics has tried to answer for a very long time now. The basic debates in literature can be classified into two broad heads. These surround the relative importance of demand side versus supply side factors on the one hand, and that of microeconomic versus macroeconomic factors on the other. During the period of US recession in early 1980s, movements in agricultural commodity prices have been demonstrated to be adequately explained by demand side factors: mainly US dollar real exchange rate and industrial production of industrialized countries (Chu and Morrison, 1986; Gilbert, 1989). However, even when the industrial countries started to recover after 1984, prices continued to be weak. The demand-side framework failed to explain this. In response, Borensztein and Reinhart (1994) have extended the traditional framework to include supply-side factors like the relative price of oil. They have also modified the definition of demand to encompass output changes from Eastern Europe and the Soviet Union. This model greatly improves empirical explanation of commodity price movements over the 1980s and early 1990s. However, a major change takes place in the mid-1990s.

In 1995, the WTO is formed and the Agreement on Agriculture (AoA) comes into force, which considerably transforms the realities of trade in agricultural commodities. Although agricultural prices have always shown high fluctuations due to their susceptibility to weather shocks, a number of studies point out that volatility has increased in the recent decades across the world (FAO, 2009; Ott, 2012; Bathla, 2012; Tripathi, 2014; Baffes and Haniotis, 2016). In the case of India too, the prices of important cereals and pulses has seen very sharp increases from around 2005, which led food price inflation to rise as high as 20 per cent in 2010 (Gil-Alana & Tripathy, 2014). Thus, almost a decade after the AoA was signed, a commodity price boom begins to manifest across the world. All this has renewed the interest in the analysis of price behaviour as academicians begin to look for more fitting explanations.

Most of the research on short-term fluctuations comes under the literature on volatility. The work of Erten and Ocampo (2013) points out that unlike in the case of price-cycles, historically, short-term fluctuations in agricultural commodity prices have mostly been attributed to microeconomic factors. Moreover, price volatility has often been found to remain limited to individual commodities or sectors. However, Baffes and Haniotis (2016) highlight that, in the recent decades, commodity price movements show three distinct features, *viz.* high price volatility, significant co-movement, and higher real price levels for all commodity groups. Gilbert & Varangis (2004) discuss the flipside of liberalization in developing countries where the resulting lower world prices benefited consumers rather than producers. The rapid pass-throughs from international markets resulted in increasing price variability for producer (farmers).

In the post-WTO world, output and stock-holding policies of major exporting countries have been found to influence stability of commodity market prices in world markets. Some important studies that have focused on globalisation and opening up of markets include Bathla (2012), Frankel and Rose (2010), Minot (2011) and Ott (2012). Highlighting the impact of the Uruguay Round Agreement on Agriculture, Bathla (2012) states that agricultural trade has grown rapidly in recent years and developing countries' markets are now increasingly aligning with the world markets. At the same time, this sector is now exposed to drifts, which can be attributed to fluctuations in commodity prices and tariffs, imposition of non-tariff barriers, high domestic support against the WTO stipulations, demand and supply conditions within the country and other unexpected exogenous impulses. Her work attributes the abnormal surge in wheat prices in India within the three months from July to September, 2010 to drought-fueled crop losses in Russia and a subsequent export ban by the Russian Federation.

Frankel and Rose (2010) review some of the popular explanations of the recent commodity price boom, which include strong global growth, especially from China and India; easy monetary policy as reflected in low real interest rates or expected inflation; a speculative bubble resulting from bandwagon expectations; and risk, possibly resulting from geopolitical uncertainties. In addition to macroeconomic factors, they also highlight microeconomic determinants like inventory levels, uncertainty, and the spot-forward spread. Minot (2011) also attributes the recent food crisis to similar factors, *viz.* the increasing cost of oil, bio-fuel subsidy in the US, US dollar depreciation, demand-supply disequilibrium, export restrictions by some countries and the impact of futures markets. Ott (2012) classifies the drivers of price volatility into common global factors and market specific shocks. The former includes exchange rate, investment in futures markets, monetary expansion, and word economic activity. The latter encompasses factors like weather shocks, the bio-fuel mandate etc., which have implications on stocks of the commodity.

In case of India, some of the specific causes attributed to the persistent inflation and increased price volatility in the period after the economic reforms include supply-side constraints, growing demand for protein-rich food items and the rising cost of food production (Chand, 2010; Basu, 2010; Nair & Eapen, 2012). Nair & Eapen (2015) argue that in the period after the economic reforms in India (1992-2013), some major drivers of price are food output stability, food consumption pattern, price-support policy, buffer stocks and the public distribution system (PDS), trade policies, and the cost of production. Basu (2011) critically examines standard ideas behind inflation management policies. He lays stress on the need to recognise the realities of a globalised world which is suffering from stagflation. Chand (2010) feels that the debate on the causes of inflation in India is full of confusion and most experts do not distinguish between long-run and short-run inflation. He undertakes a detailed examination of the factors affecting food inflation in India during the recent commodity price boom and concludes that the main reason for the food price surge was a supply shock caused by drought in 2009. He points out that while the imbalance between demand and supply is often mentioned as an important factor affecting food prices, an adequate understanding of this imbalance is missing. He also argues that the long-run implications of the emerging trends in food production have also received little attention.

Among empirical works, Ott (2012) investigates prices in the grain sector of the United States (US) in terms of three concepts of volatility: intra-year, inter-year and conditional volatility. The study finds that during the period from 1978 to 2011, volatility in grain prices shows increase in the five years preceding his study. This is especially true for the inter-year volatility. Tripathi (2014) undertakes a detailed analysis of international price volatility of some major agricultural commodities for the period from 1980-81 to 2005-06 using both conditional and unconditional estimates. Although the unconditional estimates report relatively higher volatility, he argues that a significant proportion of this can be attributed to the presence of trend component in monthly price series. After the removal of this predictable trend component, overall inter-year volatility turns out to be lower for all commodities. In case of intra-year volatility, international prices show a cyclical movement. With the exception of rice and wheat, the study finds the decade of 1990s to be more stable than the 80s for agricultural prices. However, the reverse is true for the period following the 90s, when volatility in rice and wheat declines, while that in other commodities increase.

On analysing the price volatility for India separately, Tripathi (2014) finds that the domestic market exhibits lower inter-year volatility but higher intra-year volatility than the international market. Thus, the Indian market is found to be more prone to within-year fluctuations. The highest volatility is observed in 1980s, after which there has been a continuous decline in volatility till about 2004-05. Thus, at a time when world markets exhibit increasing volatility, India is found to be witnessing reduced volatility for most crops. Another study examining food-grain prices in India is by Chatterjee and Kapur (2016) for the period from 2005 to 2014. They find the variance in prices to have remained high since 2005. However, they do not find any trend in the price fluctuations over time. They also find evidence of wide spatial variations as the real prices across *mandis* within states show high variation. This points towards the fact that all spatial variation may not be because of quality differences only.

Having documented the nature of agricultural commodity price fluctuations over time, it is important to understand how these short-term fluctuations affect the economy. The following sub-section (Section 2.2.2) takes up this issue.

2.2.2 Implications of Agricultural Price Variation

Although volatility may be a short-run phenomenon, it can have severe and adverse implications, many of which are long-run. This is especially true for a developing country like India. The works of Claessens & Duncan (1993), Gilbert (2003) as well as Dana & Gilbert (2012) discuss the unintended consequences of market liberalization in developing countries, which exposed their farming sectors to international price volatility. The studies point out that this led to adverse outcomes as financial markets are underdeveloped and banks have poor outreach to the agricultural sector in most of these countries.

Concerns have, therefore, been raised on the likely impact of increased volatility on domestic prices, exports, imports, farm income, food security, employment and poverty (Chandrasekhar and Ghosh, 2002; Grimwade, 2004; Hoda and Gulati, 2008; Bathla, 2012). This sub-section compiles the different effects of volatility in prices as documented in existing literature.

Dana & Gilbert (2012) point out that liberalization had the effect of increasing the extent and speed of pass-throughs from international markets to domestic markets. Although the effects of volatility amplification have been felt throughout the supply chain, their impact has been most acute at the farm-gate because farmers are the residual claimants on commodity revenues. They argue that this volatility generates risk management problems in developing countries. Therefore, let us first discuss the effects of price volatility on farmers and rural areas. Volatility in commodity prices leads to uncertainty over future revenue and cost streams. This uncertainty can inhibit planning and deter investment by all the relevant agents in the commodity supply chain (household farmers, cooperatives, larger commercial farmers, and governments). The shortfalls in investment subsequently act as a drag on future growth and poverty reduction prospects (Blattman, Hwang, & Williamson, 2007; Poelhekke & van der Ploeg, 2009). Volatile output prices can impact land use decisions in case of risk-averse behaviour as they lead to a fluctuating profitability (shadow price) of agricultural land. Boere et. al (2012) in a study on Netherlands covering the first decade of 2000s, find that there is a negative effect of volatility on land shares of crops. Producer's output responses are consistently affected by risk-averse behaviour. Commenting on farmers' response to price-cycles, Nuppenau (2012) point out that experience from past phases of high price volatility is that, after a certain time, markets have difficulties in forming price expectations. Crashes have long term effect on farmers, especially when year on year (y.o.y) fluctuation is severe. Sekhar (2004)discusses how small farmers in countries like India, with low propensity to save and poor access to efficient saving instruments, cannot cope with the revenue variability resulting from fluctuations in output prices. Thus, along with the economic impact on livelihood sustainability of smallholders, this can also lead to political and social instability.

Price volatility can have equally adverse effects for consumers as well. The primary concern is food-security. In the recent commodity price boom, consumers in both developed and developing countries have felt the impact of higher food prices. Soaring commodity prices are feared to raise the cost of basic food staples in many developing countries. This makes life difficult for the poorest people who spend between 60 and 80 per cent of their meagre income on food (Bathla, 2012). The high food prices erode the purchasing power of urban households and other net buyers of food. They are thus forced to reduce their non-food spending and shift to cheaper foods (Minot, 2011).

Furthermore, Swinnen (2010) points out that many rural households in developing countries are both producers and consumers of food. Thus, they are affected in different ways by price changes. The net household effect depends on their net consumption status. Also, households that spend higher proportion of income on food will be affected more by price changes. Lower the income elasticity of food demand of a household, more adverse will be the effect on their welfare with price increase. He argues that at the level of the macro-economy, countries that consume more of food but produce little lose most from price increases and benefit most from price decreases. Volatility also has a fiscal impact. Increased volatility tends to lead to greater government intervention in agricultural markets. The cost of operating food and nutrition programmes also rise. This often leads to sizable fiscal costs (Gil-Alana & Tripathy, 2014).

2.2.3 Section Summary

In recent decades, the variability in food prices has been regarded as a major concern by many of the studies discussed above. Although agricultural prices have always shown high fluctuations due to their susceptibility to weather shocks, several studies point out that volatility has increased in the recent decades. Studies also find that Indian markets are more prone to intra-year fluctuations in prices relative to year-on-year fluctuations. A number of works argue that such variability is short-lived as the effect of price-shocks disappear in the long-run. However, this is questionable as the evidence on mean-reversion in price series remains inconclusive. At most, some studies have been able to show that, for some commodities, prices are mean-reverting only if a structural break is taken into account. The reversion of prices to their long-run base is also reported to be very slow. Furthermore, even if volatility is a short-run phenomenon, studies show that increased volatility can have several effects on welfare.

To sum up, studies find that increased price volatility affects exports, imports, farm income, food security, employment and poverty. Net food importing countries are at a loss when it comes to price volatility as price spikes lead them to face balance-of-payment pressure due to the rising cost of food imports. Moreover, increased volatility often results in sizable fiscal costs as they lead to greater government intervention in agricultural markets.

2.3 Methodological Approaches to Understand Price Movements

Studies examining price movements over time can be grouped under two broad perspectives. On one hand are those that try to characterise the movements as portraying some long-run pattern, while on the other are those that attempt to understand short-run fluctuations in prices. An assessment of the former involves examination of time series components like trend, cyclical and seasonal components. Short-term fluctuations in price are captured by the concept of 'volatility'. A statistical measure of dispersion, volatility measures are concerned with assessing the uncertainty (or risk) associated with the size of changes in the value of a variable. As is explicit from the preceding discussion, instability is a characteristic feature of agricultural commodity markets. Over time, the tools used by studies to estimate price instability have evolved.

We begin with studies that examine the movements of agricultural prices over the long-run. The concept of stationarity has been well discussed in literature. A time-series is said to be 'stationary' if its statistical properties such as mean, variance, autocorrelation, etc. remain constant over time. If a time-series possesses a unit-root, it is said to be non-stationary. Shocks in a non-stationary series will result in permanent changes in the level of the series. On the other hand, in trend-stationary series, fluctuations will be transitory and the series will return to its original trend sometime in the future. Discussing trend-stationarity and non-stationarity, Gil-Alana & Tripathy (2014) point out that the order of integration of a series can have serious implications for understanding the economy and economic planning. In most of the studies reviewed in the preceding sections, a combination of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests have been used to check for unit root (Conforti, 2004; Frankel & Rose, 2010; Ott (2012); Baffes & Haniotis, 2016; Harvey et al, 2017). In addition to the above tests, Ott (2012) used the ERS test (Elliott, Rothenberg & Stock, 1996) to examine stationarity as it is more robust compared to the other two and allows errors to be ARMA. The ADF and PP tests have very low power against I(0) alternatives for series which are close to be I(1). To distinguish between trend-stationary (TS) and differences-stationary (DS) process, Ott (2012) adopts a strategy described in Bourbonnais and Terraza (2010).

It has often been pointed out that that relative commodity prices may not be optimally represented by a single, secular trend but by some segmented alternative (Kellard & Wohar, 2006; Ghoshray, 2011; Gil-Alana & Tripathy, 2014; Hayvey et al, 2017). In Statistics, this is termed as the presence of some structural break in the series. Some tests used to ascertain the presence of a structural break are the Harvey, Leybourne, and Taylor (2009) test and the Bai and Perron (1998) (Harvey, Kellard, Madsen, & Wohar, 2010; Enders & Holt, 2012). The former helps circumvent the issues surrounding the identification of the order of integration, as it does not assume any a priori knowledge as to the order of integration of series. Harvey et al (2017) point out that in long time series, there may be multiple breaks in trend. To determine the number of breaks, they use a framework proposed by Kejriwal & Perron (2010) based on a sequential application of the Perron and Yabu (2009) test, which is robust to the order of integration of the errors. Taking different approach Ott (2012) uses the Cavaliere, Harvey, Leybourne, and Taylor (CHLT) unit root test, which is robust to structural breaks and allows non-stationary variance. The CHLT test extends the original Harris, Harvey, Leybourne, & Taylor (2009) test by assuming time varying variance. Gil-Alana & Tripathy (2014) bring up another important issue, i.e. the possibility that the order of integration of a time-series may not necessarily be an integer value. It can be a fractional value, and thus the series may be fractionally integrated. In such cases, the higher the value of the order of integration (denoted by 'd') is, the higher is the level of dependence and more persistent is the series.

As price often moves in cycles over the long run, some studies have tried to understand trend in price series in light of such cyclical movement. Recent studies like Erten & Ocampo (2013) and Harvey et al (2017) have approached price movements from a historical perspective taking very long time-periods spanning more than one century. Harvey et al (2017) point out that most of the earlier studies had taken up relatively shorter time-periods. The relatively large variance observed in commodity prices and the possibility of trend structural breaks could inhibit the statistical determination of any trend magnitude and direction in such datasets. As an innovation over the traditional approach of analysing of trends and structural breaks, Erten and Ocampo (2013) advocate the super-cycle framework. This framework allows analysis of the gradual change in long-term trends instead of a priori assuming a constant deterministic or stochastic trend. Several recent works in business cycle research use filtering methods for the purpose of isolating particular frequencies in an economic series. The band-pass (BP) filter approach allows the economic time series to be decomposed into cyclical components of a range of periodicities or frequencies. One of the advantages of the BP filter is that it can be used to decompose the time series into different frequency components regardless of the underlying dynamics (Christiano & Fitzgerald, 2003). The Hodrick-Prescott (1997) filter (HP) is the most commonly used BP filter. Baxter & King (1999), provide an alternative to the HP filter by extracting stochastic cyclical components with a specified range of periodicities from individual time series.

The methodological approaches to understand price seasonality has also seen marked advances in the recent decades. One of the important early works that studies seasonality across commodities is by Sahn and Delgado (1989). They first remove the trend by assuming it to be linear and then use eleven dummies for the months of the year by normalising the effect of the twelfth month to be zero. However, as it is possible for the trend to be variable (instead of linear), other studies (Allen, 1954; Goetz and Weber, 1986), have attempted to estimate the trend as a centered moving average, which can vary from month to month. In an important work, Gilbert et al. (2017) argue that while the conventional approach of estimating seasonal influences by assigning dummies to the months of a calender year may yield acceptable results, there could be an over estimation bias in the seasonal gap estimation when the study period is relatively shorter (5-10 years). This happens because most often, the exact timing of seasonal peaks and troughs varies across crop-location pairs, even within countries. They also discuss how the problems of underreporting and missing data in developing counties lead to estimation issues for seasonality. Their work presents an alternate approach to seasonality estimation which is based on the harvest pattern of crops. They show through Monte-Carlo simulations that this approach reduces the over-estimation bias in the seasonal gap compared to the conventional dummy-variable approach.

Next, we come to studies, which have attempted to understand the degree of variability in prices in the short-run. The conclusions drawn about any data series are often sensitive to the particular measure used. Recognizing this, Offutt and Blandford (1986) provide an extensive review of the different techniques used to measure instability in prices, revenues, expenditures etc. These include percentage range (PR), different versions of average percentage change (APC), moving averages (MA), Coppock index (CI), and the coefficients of variation (CV). Building up on the above, a recent work by Tripathi (2014) extends the review to include advancements in volatility measure like the Black-Scholes-Merton model, the ratio method and the GARCH approach. Several measures like the PR and some variations of the APC are disproportionately affected by presence of outliers. The advantage of the APC measures is that they provide an idea of average yearly changes, while most other measures are an index of relative dispersions from some standard. The CV has most wide applicability and it is a common tool used by several researchers. An important aspect related to the study of instability is the separation of predictable and unpredictable components. 'Variability' and 'uncertainty' are two key connotations of volatility and cannot necessarily be equated. It is argued that policy-makers are typically better able to cope with predictable variation, which may comprise of the effects of factors like inflation, trend, seasonality, adaptive expectations of farmers etc. (Offutt & Blandford; 1986; Ott, 2012; Tripathi, 2014). It is the unpredictable movements that form the primary concern. Offutt and Blandford (1986) point out that several studies have advocated the removal of trend elements from the data before measuring instability. This implies that a judgment is made as to what constitutes 'acceptable' versus 'unacceptable' variability. However, most often, studies do not provide an explicit rationale regarding why a particular specification of trend was adopted. Gardner (1977) stresses that studies should not only provide a rationale for exclusion of trend, they should also justify why certain types of fluctuation are treated as instability.

Another crucial issue discussed in the literature on volatility concerns the influence of past levels of price as well as volatility on current and future realizations. If a measure does not distinguish between known and unknown components of price series, it will lead to overestimation of the degree of uncertainty (Tripathi, 2014). The CI makes use of the log of first differences, which removes linear trend, and at the same time moderates the influence of outliers. However, while the index involves a lot of computational burden, it is found to be highly sensitive to the choice of period of the evaluated series. Although unconditional CV cannot account for trend, Offutt and Blandford (1986) prescribes the use of CV on detrended data, i.e. application of CV to residuals of regression. This allows instability to be measured using deviations from trend. Another commonly used method that distinguishes between predictable and unpredictable (irregular) components of price series is the Black-Scholes-Merton model. The model assumes that prices follow a geometric Brownian motion with constant drift and volatility. The drawback of this method is that it assumes price volatility to remain time-invariant and hence is unable to account for periods of changing volatility (Tripathi, 2014).

A method that takes care of separation of predictable components and also allows the variance of the unpredictable components to be time-varying is the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) approach, which was developed by Bollerslev (1986) by extending on the initial work of Engle (1982). Williams and Wright (1991) highlight that commodity prices are closer to a GARCH process than an ARMA process. Due to storage, agricultural commodity prices display autocorrelation and the variance might not be constant over time. In recent literature, this approach has been widely used (Gilbert & Morgan, 2010; Gardebroek & Hernandez, 2013; Ott, 2012; Tripathi, 2014).

2.4 Gaps in the literature

The scrutiny of the existing literature has brought out several areas where more research is needed. The first observation is that while long-term movements in agricultural prices have been much examined, there has been less research about short-run fluctuations. This is especially true for India. Such fluctuations can have long-term adverse implications for smaller farmers and hence need to be understood carefully.

While a few studies have focused their attention on price volatility in India (Sekhar, 2004; Kumar and Sharma, 2006; Bathla, 2012; Tripathi, 2014), other aspects of price behaviour like seasonal price drops remain less discussed. As quite a number of notable works have discussed that seasonality tendsto be more pronounced in developing countries, this aspect requires more comprehensive studies.

Another fact that comes to light in this section is that, for India, studies of price behaviour (esp. seasonality and volatility) carried out using rigorous methods on disaggregated data are either very few in number or have become relatively dated. Moreover, most of these works have been carried out in the framework of inflation rather than in a more general framework of time-series behaviour. A better understanding of price movements can only come with a more general framework.

Again, most studies on India have been conducted using annual data.

Such data does not capture seasonal price variations. Further, as agricultural prices in India have been found to show high intra-year variations, the complete picture of volatility cannot be captured unless studies use data of lower frequency (quarterly, monthly, weekly, daily).

Finally, there is a dearth of works that examine the spatial variation in price behaviour. Given India's vast size and diversity, studies based on country-wide averages do not provide much ground-level insight. Therefore, to understand the ground realities prevailing across different parts of the country, we need more rigorous studies using disaggregated data sources.

The present work makes a humble attempt in this direction. The research objectives taken up in this dissertation have been guided by the identified gaps in the existing academic literature. The next three chapters form the core chapters of my thesis and they empirically examine two crucial components of agricultural commodity price behaviour across India, *viz.* seasonal variation and volatility.

3 | Seasonality in Commodity Price Behaviour

This dissertation focuses on understanding agricultural commodity price behaviour across India. The broad aim is to contribute to the empirical literature examining the nature and degree of variation exhibited by these prices over time. The preceding chapter, which reviews the academic literature on the subject, elaborates on how the time-series behaviour of agricultural commodity prices can be decomposed into several components. The long-term direction, if any, in these prices is captured by the trend. The variation around a trend can be decomposed into two important time-series components, *viz.* seasonality and volatility. While the former is a predictable component, the latter represents the unpredictability or stochastic component in the behaviour of the time-series.

Accordingly, while the present chapter is devoted to a discussion of seasonality, the next chapter investigates the volatility in these prices around their trend. All analyses are carried out using *mandi*-level data for the period from 2003 to 2016 (as elaborated in sections 1.4 and 1.5 of Chapter 1)

This chapter is divided into four broad sections. While the first one engages with the conceptual framework under which seasonality is studied, the second lays down the detailed methodological approach. The third section presents the results of the analysis on seasonal patterns observed in the *mandi* prices across India. It also discusses the spatial variation in the estimated seasonal gaps and the possible sources of their dispersion. Finally, it presents a summary of the major findings and discusses them in light of the existing scholarship on this subject. The last section presents the inferences and conclusions drawn from the analyses carried out in the chapter.

3.1 Theoretical and conceptual framework

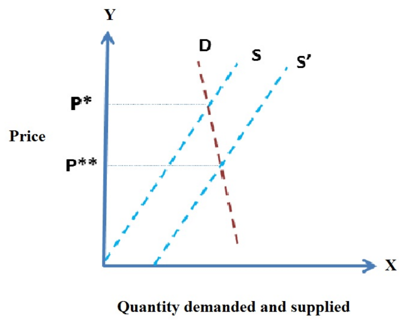
In the context of time-series behaviour, the term 'seasonality' describes any fluctuation or pattern in data that recurs over time. Seasonality in prices, thus, relates to the presence of a predictable structure restricted to one production cycle (often related to the calendar year). Seasonality measures, therefore, seek to capture that part of intra-annual variability, which is related to the crop cycle.

Investigating the extent and magnitude of price-seasonality in domestic markets of a developing economy has important implications. The difference between a higher pre-harvest price and lower post-harvest price is termed as the seasonal gap in prices. The persistence of wide seasonal gaps for storable commodities goes against the competitive storage principle of

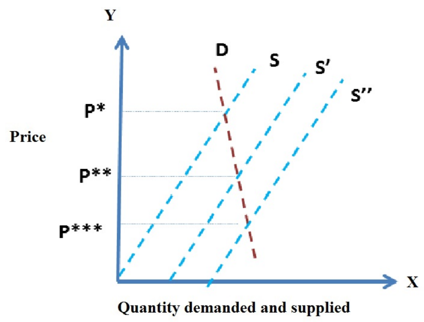
Deaton & Laroque (1996), which postulates that storage has an effect of smoothening price shocks. A large seasonal gap in a market means that it is prone to price drops in specific months. Such drops may be caused by a glut-like situation in the market when a large number of farmers sell their produce immediately after harvest. Through comparative statics, Figure 3.1 illustrates how sub-optimal trading behaviour by a large number of players (farmers) selling in a particular market can lead to a wide seasonal gap.

Figure 3.1: Illustration of market forces behind seasonal gaps: Sub-optimal trading by farmers

(a)



(b)



The figure consists of two panels: 3.1a and 3.1b, where both the quantity of produce arriving at the market and the quantity being demanded are represented on the X-axis and the realized market price (p) is represented on the Y-axis. DD and SS represent the demand and supply curves respectively.

Let us consider the time immediately before the harvest, when the demand-supply equilibrium is at price p^*. After the harvest, there will be an increase in supply and, therefore, the supply curve shifts to the right as shown in Figure 3.1a. Since there is no simultaneous change in demand, the new equilibrium price will be relatively lower (p^{**}). With a drop in price, rational players are expected not to bring in more supply as it will further depress the market price. However, if more produce keeps coming to the market, the supply curve will shift further to the right and take the equilibrium price to p^{***} (as shown in 3.1b). The difference between p^{***} and p^* gives the seasonal gap.

In case of commodities that are storable and not highly perishable, such behaviour goes against the economic logic of adopting a profitable trading strategy of holding on to stocks when prices are low (Sahn and C.Delgado, 1989; d'Hotel and Cotty, 2018. A few possible explanations of such sub-optimal behaviour can be need for immediate cash in hand, lack of access to storage facilities, off-farm income and credit and so on. Such factors can have influences on crop sales and purchase behaviours, which often leads to 'sell-low, buy-back-high' behaviour (Stephens and Barrett, 2011; d'Hotel and Cotty, 2018). It is the resource-poor smallholders who are most likely to encounter such constrains. Larger farmers, on the other hand, are unlikely to engage in distress sale. This implies that not only are post-harvest price drops likely to occur due to sub-optimal trading by resource-poor farmers, it is also these farmers who are the ones selling most of their produce at the lowest prices realised in a year.

The above conceptual framework is relevant to India as our agriculture is dominated by smallholders in terms of their numbers. As per the Agricultural Census of 2010-11, around 84.5% of the total operational holdings in India fall under the small and marginal categories of size classes measuring less than 2 hectares in size (Government of India, 2015). Hence, it is important to examine how the magnitude of seasonality varies across India. In this study, the estimates of the seasonal gaps are discussed in relation to the socio-economic conditions of farmers in various locations of the country. Through its findings, the dissertation investigates the following: *In general, does the magnitude of the seasonal gap show any positive association with proportion of small and marginal farmers in a location?*

Having outlined the conceptual framework, I now proceed to elaborate on the tools and methods.

3.2 Methodological Framework: Modelling seasonality

This section presents the broad methodological framework that has been adopted in my dissertation to estimate and analyse seasonality. The time-series behaviour of agricultural commodity prices can be structurally characterised in terms of trend, seasonality and volatility as follows:

$$p_{ym} = \mu_{ym} + s_m + \varepsilon_{ym} \tag{3.1}$$

Here, p_{ym} is the price in month m of year y, μ is the stochastic trend, and ε is a disturbance (volatility). The seasonal effect is captured by the seasonal factor (s_m), which is the average effect of a particular month on the price level.

A standard measure of the magnitude of seasonality in a particular series is the seasonal gap, which is reflected in the difference between the highest and lowest seasonal factor.

$$Seasonal\ gap(SG) = Max(s_m) - Min(s_m) \tag{3.2}$$

Thus, a seasonal gap estimate of x indicates that, on an average, prices are lower by x percent in the trough month compared to the peak month. Here, 'peak' and 'trough' months are defined as follows: the peak month is the month reporting the highest seasonal factor and the trough month is the one with the lowest seasonal factor.

To obtain estimates of the seasonal factors, the parameters of Equation 3.1, are estimated using standard econometric procedures on each individual price series under study. Now, such procedures necessitate pre-testing of the dynamic properties of each series for stationarity. However, stationarity tests require continuous series and cannot be conducted in the presence of missing data points. Unfortunately, a major issue with datasets of developing countries is the presence of considerable missing observations. This is true for the data source being considered in this dissertation as well. As elaborated in section 1.5, the *mandi* prices available from the Directorate of Marketing & Inspection (DMI), Government of India (GoI) has several missing values in the data for the period of reference of this study (*i.e* 2003-2016).

One strategy is to opt for interpolation techniques. However, interpolation of any series exhibiting seasonality requires making prior assumptions about the seasonal structure. In a recent work, Gilbert, Christiaensen and Kaminski (2017) argue that adding seasonal dummies at this point imposes a seasonal structure during the interpolation itself, which makes the problem of estimating seasonality circular. Their work addresses this exact issue: seasonality estimation in relatively short samples (10-15 years), which are characterized by missing observations. Therefore, the seasonality estimation in this paper closely follows the approach elaborated in their work. This approach is explained in the following paragraphs.

First, we have to make some assumptions about the trend (μ_{ym}) in equation 3.1. There is no theoretical basis to assume that the trend component of food prices remains constant over time. Therefore, this thesis allows the trend to be stochastic. To keep things simple, it is assumed that the trend varies over time by a constant monthly increment (γ). Thus, the trend component of Equation 3.1 is re-expressed as under:

$$\mu_{ym} = \mu_{y,(m-1)} + \gamma + \upsilon_{ym} \tag{3.3}$$

Here v_{ym} is a random disturbance term.

Although nominal prices are usually non-trend-stationary, they are generally difference-stationary(Nelson and Kang, 1984). Thus, it is reasonable to re-define the data-generating process (DGP) in its differenced form. Differencing Equation 3.1 and substituting Equation 3.3 gives us:

$$\Delta p_{ym} = \gamma + \Delta s_m + \mu_{ym} \tag{3.4}$$

Here, μ_{ym} is a compound error term.

When there are any missing observations in a series, this approach allows the administration of a method that is robust to the presence of missing data points. This procedure treats missing observations as missing and it is termed as 'skip-estimation' of differences. This is formally represented by Equation 3.5:

$$\Delta_k p_{ym} = p_{ym} - p_{y,m-k-1} = k\gamma + \sum_{i=1}^{k-1} s_{m-i} + w_{ym} \tag{3.5}$$

The term $\Delta_k p_{ym}$ can be better understood with the help of an example. Let us consider an arbitrary time-series in which three data points are missing before the month of July, 2003, i.e. $k = 3$.

The differenced price for July 2003 will then be calculated as the difference between the price in July and the last recorded observation (i.e. March, 2003) as shown in Table 3.1.

Table 3.1: Illustration of the calculation of skip-difference

Trend	Time	Price	(d.Price)	
1	Jan-03	100		
2	Feb-03	120	20	
3	Mar-03	112	-8	
4	Apr-03			
5	May-03			
6	Jun-03			
7	Jul-03	140	28	$(= P_{Jul-03} - P_{Mar-03})$ (i.e. 140 - 112)
8	Aug-03	122	-18	
9	Sep-03	123	1	

Thus, the term $\Delta_k p_{ym}$ of equation 3.5 has three components:

a. The increment in trend during the intermediate months:

$$\gamma + \gamma + \gamma = 3\gamma \quad (i.e.\ k\gamma)$$

b. The monthly seasonal influence of all intermediate months

$$s_{April-03} + s_{May-03} + s_{Jun-03} = \sum_{i=1}^{k-1} s_{m-i}$$

where, $i = 7$ (resp. to July-03)

c. Some disturbance term: w_{ym}

By defining price-differences in this way, the estimation is able to do away with the need for interpolating missing data before the seasonality estimation.

This reduces the possibility of bias creeping in from the nature of a chosen interpolation technique(Gilbert et al., 2017). The estimation of the seasonal effect is now reduced to estimation of the parameters of Equation 3.5.

Before the estimation, the seasonal factors (s_m) have to be defined. The conventional way is to go for a dummy variable specification for capturing the seasonal effects by introducing eleven dummies in the equation (to account for the 12 months of a calender year). However, this results in a large number of parameters and, hence, a loss of degrees of freedom (df). The parameters to be estimated can be reduced by imposing some restrictions of the dummies by recognising the fact that seasonal variation arises from the crop-cycle (as will be elaborated shortly). If the parameters to be estimated can be reduced, the degrees of freedom lost are lesser. Further, Gilbert et al. (2017) demonstrate through Monte Carlo simulations that, in relatively shorter samples, estimation using a dummy-variable specification is prone to bias in the form of overestimation of the seasonal gap. They attribute this bias to three factors that interact with each other: the number of observations used to estimate the coefficients of the peak and trough month dummy variables is small in short samples; there is a possibility of incorrect identification of peak and trough months from data; and the estimated gap may be a non-linear function of the dummy variable coefficients. They also demonstrate that adopting harvest-pattern based specifications lead to a reduction of overestimation bias.

Considering the above facts, this dissertation again takes recourse to the approach taken in Gilbert *et al* (2017) whereby three alternate functional specifications are tested against each other to capture seasonality through Equation 3.5. The first specification is the conventional dummy-variable specification. The latter two are inspired by the nature of harvest-patterns and are more parsimonious.

3.2.1 The Dummy-variable Specification

The dummy variable approach specifies a set of twelve seasonal factors for each month of the year, *viz.* $s_1, \ldots, s_{12}$.

For the estimation, eleven dummies are taken and all their coefficients (δ_j) are normalised with respect to the 12^{th} month by assigning the effect of December as 0, *i.e.* $\delta_{12} = 0$ (If we had 12 dummies and no intercept, δ_{12} would be the effect of the month December on price). Since there is no dummy for December, we interpret the coefficients of each dummy as the effect of its respective month in relation to the effect of the month December on price.

The equation being estimated is:

$$\Delta p_{ym} = \gamma + \sum_{j=1}^{11} \delta_j \Delta z_{mj} + \mu_{ym} \tag{3.6}$$

Here, the effect of the 12^{th} month is normalized to be zero, *i.e.* $\delta_{12} = 0$

The raw dummy coefficients obtained from the estimated equation defines the effect of each month in relation to some other month (here, December).

To obtain a generalized estimate, the seasonal factor of a particular month (i.e its net effect on the price) is defined as the deviation of the 'average effect of all months' from the effect of the particular month (in relation to December). This is formally expressed as:

$$s_m = \delta_m - \frac{1}{12}\sum_{j=1}^{12}\delta_j \tag{3.7}$$

$for\ m = 1, ..., 12.$

Thus, all the eleven estimates of δ_j are used to estimate each month's 'seasonal factor'. The seasonal factor of December will be the negative of the average effect of all other months combined. If the average effect of all other months is negative in relations to December, the seasonal factor for December will be positive.

Now, Equation 3.6 of my report expresses the differenced price as a function of differenced dummies[1]: ΔZ_{mj} is the differenced form of the level dummy Z_{mj} ($Z_{mj} = 1$ if $m = j$ and 0 if $m \neq j$). The differenced dummy takes the values as under:

(a) when $m = j$

$$\begin{aligned}\Delta Z_{mj} &= Z_{mj} - Z_{(m-1)j} \\ &= Z_{jj} - Z_{(j-1)j} \\ &= 1 - 0 \\ &= 1\end{aligned}$$

(b) when $m = j + 1$

$$\begin{aligned} \Delta Z_{mj} &= Z_{(j+1)j} - Z_{(j+1-1)j} \\ &= 0 - 1 \\ &= -1 \end{aligned}$$

(c) For all other values of m,

$$\Delta Z_{mj} = 0$$

An Ordinary Least Squares (OLS) regression is run on Equation 3.6. The objective is to test whether there is any statistically significant effect of a particular month on the average price level (*i.e.* seasonal effect). Therefore, the null hypothesis of the estimation is that the coefficients of the differenced dummies are all equal to zero, *i.e.*

$$H_0 : \delta_1 = \delta_2 = \delta_3 = \ldots = \delta_{12} = 0$$

After the estimation, a joint significance test (F-test) is conducted taking the coefficients of all the 11 dummies to ascertain whether any of the them shows evidence of being different from zero. If the statistic is significant at 5% level, we reject the null hypothesis that there is no seasonal pattern in the data.

If the seasonal factors are found to be significant for any series, the seasonal gap is obtained as the difference between the largest and the smallest seasonal factor (as in Eq. 3.2). An illustration is provided in the Appendix A.3.

3.2.2 The Trigonometric Specification

Now we come to the harvest-based specifications of seasonality. It is expected that prices fall at the time of harvest (due to excess supply) and then rise in later months as supply dwindles over time. This pattern may be approximated by a trigonometric specification. In this approach, the seasonal pattern is defined as a pure sine wave:

$$s_m = \alpha cos\left(\frac{m\pi}{6}\right) + \beta sin\left(\frac{m\pi}{6}\right) \tag{3.8}$$

For trending data, the equation to be estimated is thus:

$$\Delta p_{ym} = \gamma + \alpha cos\left(\frac{m\pi}{6}\right) + \beta sin\left(\frac{m\pi}{6}\right) + \mu_{ym} \tag{3.9}$$

The seasonal factor s_m can be re-expressed as a pure cosine function:

$$s_m = \lambda cos\left(\frac{m\pi}{6} - \omega\right) \tag{3.10}$$

Where $\lambda = \sqrt{\alpha^2 + \beta^2}$ and $\omega = tan^{-1}\left(\frac{\alpha}{\beta}\right)$.

If the specification is valid, least squares estimation of Eq. 3.9 yields unbiased and consistent estimates of the α and β coefficients.

The parameter λ measures the amplitude of the seasonal cycle and implies a seasonal gap of 2λ (see Appendix A.3.1.2 for an illustration).

However, this specification is restrictive as it assumes that the post-harvest price decline is symmetric with respect to the pre-harvest price rise. In reality, the prices tend to drop more rapidly with on-coming of harvest and then rise gradually (Samuelson, 1957; Goetz and Weber, 1986).

3.2.3 The Saw-tooth Specification

An alternate harvest-pattern based specification is the saw-tooth specification. This specification is an improvement over the trigonometric specification as it removes the restrictive assumption of symmetry in price drop and price rise. The sawtooth specification comes very near to describing the expected seasonal pattern in storable agricultural commodities that are harvested once a year (Goetz & Weber, 1986).It is formulated by assuming that the peak price occurs in the month prior to the harvest and then prices drop sharply in the month of harvest and the next, after which prices gradually rise over the remainder of the year. More specifically, this approach assumes that the peak seasonal factor of k occurs in month $m^{\star}$ and then the price falls by the seasonal gap of 2λ to $-\lambda$ in the harvest month $m^{\star}$. The seasonal factor then rises steadily by an amount 5λ over the remainder of the year. To choose $m^{\star}$, a grid search is performed by selecting the value for $m^{\star}$, which gives the maximum R^2 fit statistic. Once we know the peak price month $m^{\star}$, the amplitude parameter λ is estimated from the regression of the equation:

$$\begin{aligned}\Delta p_{ym} &= \gamma + \Delta s_m + \mu_{ym} \\ &= \gamma + \lambda \Delta z_m(m^*) + \mu_{ym}\end{aligned} \tag{3.11}$$

Here,

$$\Delta z_m(m^\star) = \begin{cases} -1 & \text{if } m = m^\star + 1 \; or \; m = m^\star + 2 \\ \frac{1}{5} & \text{otherwise} \end{cases}$$

If the specification is valid, least squares estimation of Eq. 3.11 yields unbiased and consistent estimates of the coefficients.

The parameter λ measures the amplitude of the seasonal cycle and implies a seasonal gap of 2λ. An illustration is provided in Appendix A.3.1.3).

3.2.4 Choice of Appropriate Seasonality Specification

The preceding sub-section has defined three alternate functional specifications of the seasonal pattern. Although the more parsimonious approaches to seasonality estimation reduce bias in the seasonal gap estimation, the estimates will not be very accurate if the actual seasonal structure does not conform to the imposed structure. For example, if there are two harvests in a year, there may be two troughs corresponding to the respective harvest months within a calander year. In such a case, neither of the two parsimonious models will capture the actual seasonal pattern. The dummy variable model is a better choice in such cases as it allows for more flexibility (since there are no restrictions on the parameters). By recognising this issue, this dissertation follows the three-step procedure proposed in Gilbert et al. (2017) to identify the most suitable specification of seasonality (or the "preferred model"). This procedure allows the data to decide the appropriate choice of seasonality specification on a case-by-case basis.

As the estimates of the trigonometric and saw-tooth specifications are nested within the dummy specification, the choice of the appropriate model is done for each series by conducting F-tests. The detailed rules for selection of a preferred model are:

(A) The estimates of the trigonometric and saw-tooth specifications are compared against those of the dummy variable model. If the F-test rejects both models, the dummy variables estimates are retained.

(B) If only one of the parsimonious specifications is not rejected by the F-test (and the other is rejected), the non-rejected parsimonious model is taken as an acceptable simplification of the dummy procedure.

(C) If the F-test fails to reject both the parsimonious models, the one with the better fit (given by R^2 statistic) is selected.

The selected model is termed as the 'preferred model' for that particular case. For each *mandi* level series, it is only the estimates of the preferred model that are taken as the final estimates and reported in the dissertation.

All estimations in this chapter are carried out using the matrix programming language GAUSS 16 developed by Aptech Systems.

3.2.5 Framework for analysis of results

Once the analysis is carried out, from each preferred model, we obtain an estimate of the seasonal factors, the seasonal gap, the R^2 statistic (proportion of price variation attributable to seasonal factors) and the statistical significance level of the seasonal pattern for every individual *mandi* price series. These results are then analysed to investigate how the nature and magnitude of seasonality varies across space and commodity. The standard deviation (SD), coefficient of variation (CV) and box-plots are extensively used to understand the spread of the estimates. The statistical distributions of the estimates for each commodity are examined using different tools: (1) the skewness and kurtosis test (S-K test) described by D'Agostino, Belanger, and D'Agostino (1990) with the empirical correction developed by Royston (1991), and (2) the Kernel density estimate. If these tests find that the distributions of the seasonal gap estimates approximate a normal distribution, we would infer that average values are more common than extremes.

Next, the thesis explores the variation in the estimates (if any) to investigate whether such variation is attributable to location or commodity-specific differences. The traditional F test for the homogeneity of variances and Bartlett's generalization of this test to K samples are sensitive to the assumption that the data are drawn from an underlying Gaussian distribution. Levene's (1960) test statistic is robust under non-normality and, therefore, this test is chosen over the other two to conduct equality of variance tests across the studied commodities as well as across the different states (locations) of India. The alternative formulations of Levene's test statistic by Brown and Forsythe are also reported as they use more robust estimators of central tendency (*i.e.* the median and the 10% trimmed mean respectively) in place of the mean, which have been demonstrated to be more robust when dealing with skewed populations (Brown and Forsythe (1974)). The results of these tests give insights about how the influence of seasonal factors differs across space and commodity in wholesale markets of India.

Finally, given the conceptual framework outlined in Section 3.1, the dissertation examines whether the magnitude of the seasonal gap shows any association with the presence of smallholders in a location. Towards this end, an OLS regression is run on the seasonal gap estimates to identify whether the proportion of small and marginal farmers and other related demographic/socio-economic factors have any significant influence on its magnitude.

3.3 Findings and Discussion

This section discusses the results of the seasonality analysis and is divided into two broad sub-sections. While the first section discusses the estimates and their distribution across commodity and space, the second investigates some possible sources that may explain the variation in magnitudes of seasonal gaps.

3.3.1 Seasonality across India: prevalence, magnitude, distribution & dispersion

The prevalence, patterns and the magnitude of seasonal behaviour are examined here with respect to the results obtained from the seasonality analysis. The findings presented in the present sub-section answer several empirical questions: How prevalent is seasonality across India? Are there any typical patterns in the seasonal structure of price? How much of the variability in these prices does seasonality explain? And, most importantly, what are the magnitudes of the seasonal gaps observed in the different *mandis* of India?

3.3.1.1 Prevalence and patterns of seasonal behaviour

Here, I present the results related to the prevalence and patterns of seasonal variation. Table 3.2 provides the state-wise break-up of the percentage of cases showing statistically significant seasonal patterns (at 5% level). The results show that seasonality in prices of the studied commodities is common across India. The null hypothesis of 'no seasonality' is rejected (at a significance level of 5% or less) in most of the considered *mandi* level price-series for all of them- paddy (75%), wheat (91%), mustard (86%) and groundnut (74%).

Table 3.2: Significance of seasonality in *mandi* prices of some major agricultural commodities across states of India

State	Percentage of cases exhibiting statistically sig. seasonality (at 5% level)			
	Paddy	Wheat	Mustard	Groundnut
(1)	(2)	(3)	(4)	(5)
Andhra Pradesh	66.67	100.00		62.50
Assam	100.00		100.00	
Chhattisgarh	90.91	100.00	50.00	
Gujarat	100.00	92.86	91.67	69.23
Haryana		100.00	71.43	
Jharkhand	85.71	61.54	100.00	
Karnataka	63.64	80.00	0.00	77.78
Madhya Pradesh	57.14	86.67	100.00	75.00
Maharashtra	66.67	94.12	50.00	100.00
NCT of Delhi	20.00	100.00	100.00	
Odisha	80.00			
Puducherry	100.00			100.00
Punjab		100.00		
Rajasthan	66.67	100.00	85.71	50.00
Tamil Nadu	85.71			81.82
Telangana	100.00			81.82
Uttar Pradesh	50.00	100.00	100.00	100.00
Uttarakhand	80.00			
West Bengal	85.71	100.00	100.00	
Total	74.85	91.13	86.36	73.85

Note: The table reports, for each state, the percentage of cases for which the preferred model's seasonality coefficients are significant at the 5% level or less.

Source: Author's calculations

Next, to obtain information on the general pattern of seasonality, let us come to the results of the F-tests that compare the three alternate functional specifications of seasonal structure. For each individual series, the particular model chosen using the F-tests (see sub-section 3.2.4 is termed as the 'preferred model' in this dissertation. Unless otherwise specified, all future uses of the term 'preferred model' would be in this context.

Now, if a particular functional specification is found to qualify as the preferred model more frequently than the others do, it can be identified as a widely prevalent pattern. Table 3.3 presents the percentage distribution of preferred models across the different commodities.

Table 3.3: Percentage distribution of preferred seasonality models across commodities.

Preferred model type	Paddy	Wheat	Mustard	Groundnut
(1)	(2)	(3)	(4)	(5)
Dummy	24.55	56.45	50.00	16.92
Trigonometric	17.96	10.48	18.18	36.92
Saw-tooth	57.49	33.06	31.82	46.15
Total	100.00	100.00	100.00	100.00

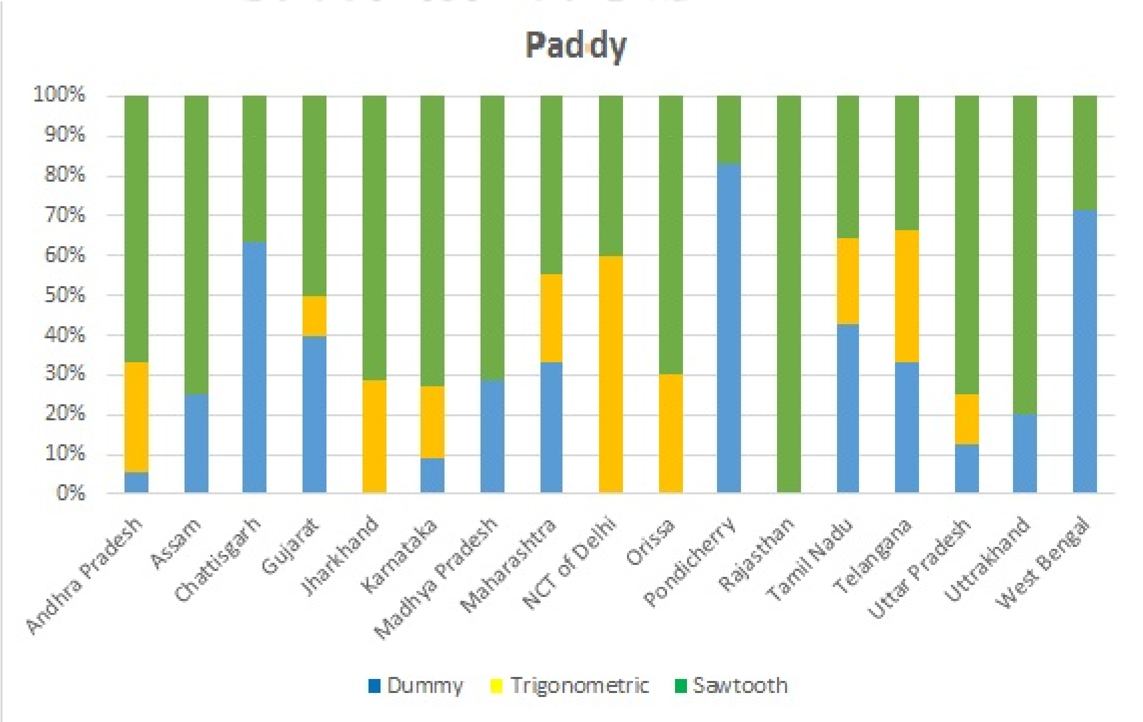
Note: The table reports the percentage of cases in which a particular seasonality specification is identified as the preferred model through the F-tests.

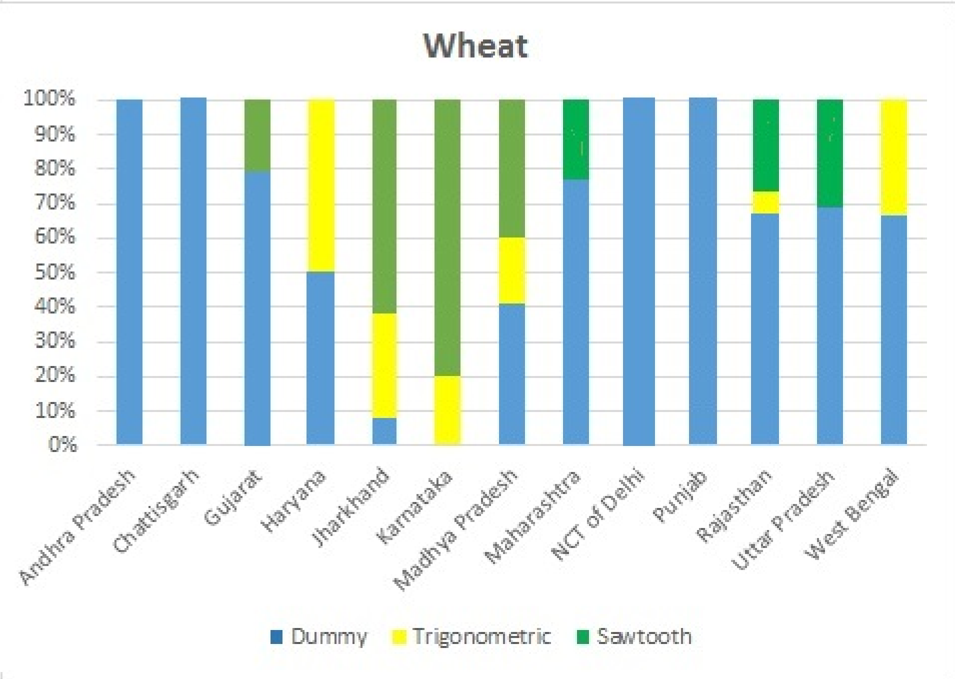
Source: Author's calculations

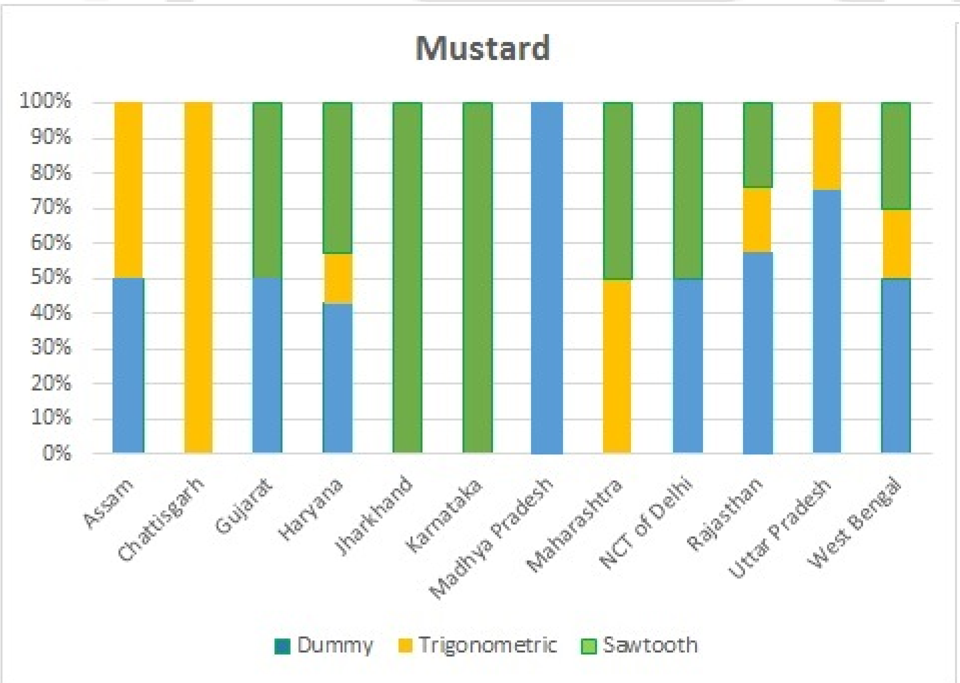
Table 3.3 shows that, in most instances, it is either of the two harvest-pattern based parsimonious specifications that qualify as the preferred model over the dummy-specification: paddy- 76%, wheat- 44%, mustard-50%, groundnut-83%. Between the two, the saw-tooth specification gets preferred more often than the trigonometric specification. Therefore, we infer that a common seasonal pattern across some major agricultural commodities of India is an asymmetric structure: the prices reach a peak just before the harvest month and then drop sharply for a month or two, after which prices rise gradually until the next harvest month.

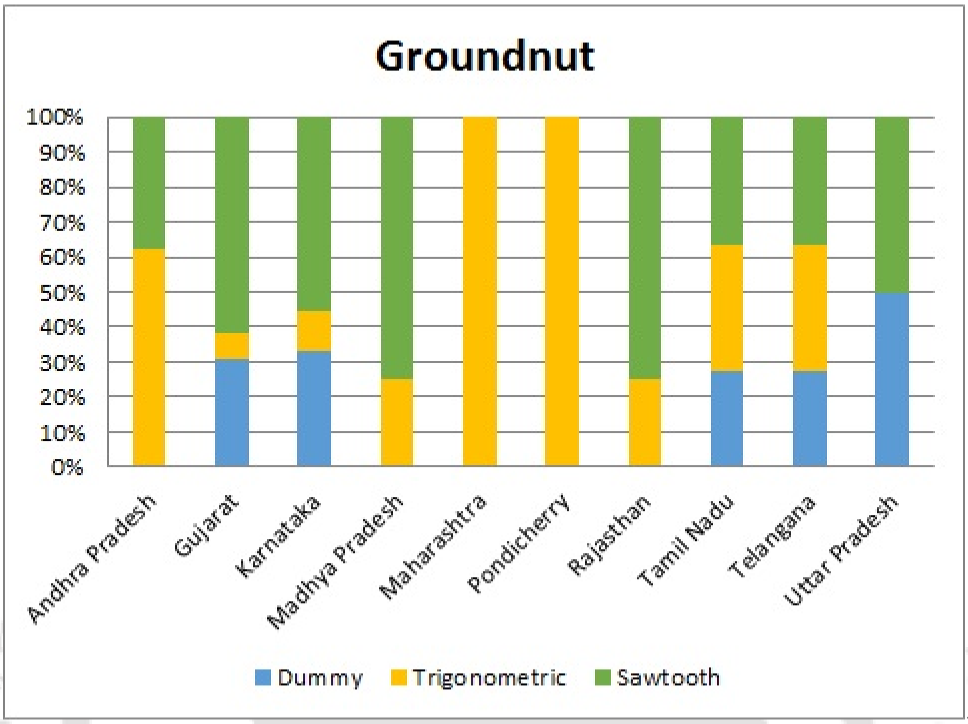
A detailed state-wise break-up of the preferred model is presented through bar diagrams in Figure 3.2.

Figure 3.2: Distribution of 'Preferred Models' of seasonality across States




Wheat
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Andhra Pradesh
Chatisgarh
Gujarat
Haryana
Jharkhand
Karnataka
Madhya Pradesh
Maharashtra
NCT of Delhi
Punjab
Rajasthan
Uttar Pradesh
West Bengal
Dummy
Trigonometric
Sawtooth


Mustard
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Assam
Chattisgarh
Gujarat
Haryana
Jharkhand
Karnataka
Madhya Pradesh
Maharashtra
NCT of Delhi
Rajasthan
Uttar Pradesh
West Bengal
Dummy
Trigonometric
Sawtooth



A close look at the bars in Figure 3.2 shows us that while the sawtooth specification gets generally preferred, there are a few apparent exceptions. For paddy, there a few states where the dummy variable specification gets preferred more often over both the parsimonious specifications. These are Puducherry, West Bengal and Chhattisgarh. Similarly, this is the case in Madhya Pradesh and Uttar Pradesh for the commodity Mustard. These locations, therefore, merit further examination of the observed patterns of seasonality. Again, the observed seasonal patterns for wheat may be explored further since the parsimonious models have most often not been preferred in several states. This thesis does not engage with this discussion as they would require some in-depth research, which is beyond its scope.

3.3.1.2 Extent and magnitude of seasonality

We now turn our attention to the results on the extent of seasonal behaviour in prices. The value of R^2 tells us how much of the intra-annual price variation in a particular series can be explained by seasonal factors. Table 3.4 presents the state-wise averages of the seasonal gap estimates as well as the respective R^2 statistics for each of the four commodities.

Table 3.4: Average Seasonality in *mandi* price of some major agricultural commodities across various states of India (2003-2016)

	Seasonal gap Estimate (in %)				**R-squared statistic**			
State	Paddy	Wheat	Mustard	Groundnut	Paddy	Wheat	Mustard	Groundnut
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Andhra Pradesh	6	12		7.42	0.08	0.23		0.07
Assam	11		20.32		0.17		0.36	
Chhattisgarh	8	14	7.05		0.23	0.32	0.05	
Gujarat	9	10	9.77	11.81	0.17	0.27	0.18	0.15
Haryana		12	10.48			0.28	0.16	
Jharkhand	8	6	8.31		0.08	0.09	0.12	
Karnataka	5	5	6.59	15.64	0.06	0.05	0.02	0.16
Madhya Pradesh	18	9	11.33	25.91	0.13	0.18	0.24	0.11
Maharashtra	11	8	9.25	12.67	0.14	0.23	0.06	0.14
NCT of Delhi	14	12	9.06		0.05	0.47	0.18	
Odisha	4				0.09			
Puducherry	20			20.18	0.35			0.12
Punjab		9				0.27		
Rajasthan	13	8	9.60	7.96	0.06	0.28	0.19	0.06
Tamil Nadu	13			16.71	0.18			0.13
Telangana	9			22.23	0.19			0.13
Uttar Pradesh	4	10	9.22	13.81	0.06	0.33	0.21	0.21
Uttarakhand	16				0.23			
West Bengal	9	13	14.86		0.22	0.39	0.28	
All India average	**8.74**	**8.93**	**10.71**	**13.27**	**0.13**	**0.24**	**0.19**	**0.12**
(Standard Deviation)	(6.79)	(3.59)	(5.64)	(9.73)				
International Prices	**12**	**18.62**		**19.93**	**0.21**	**0.19**		**0.23**

Note: The table reports regression estimates of average seasonal gap in *mandi*-level prices of the four commodities (Columns (2) to (5)) and the seasonal R^2, representing the proportion of intra-annnual variation attributable to seasonal factors (Columns (6) to (9)) across states of India. The all-India averages are unweighted arithmetic means of the estimates taken across *mandis*. The bottom column reports the estimates for the international reference prices, *i.e.* Thai rice (25% broken kernels), Wheat (US Soft Red Winter) and Groundnuts.

Source: Author's calculations

The table shows us that in case of wheat, a large proportion of cases report an R^2 value ranging between 20 to 50 per cent. However, for the other crops, the R^2 value is relatively lower and mostly remains below 20%. There are a few exceptions in some states where the R^2 value for a few *mandi*-level series is slightly higher and range between 35 – 60%. These include Puducherry, Chhattisgarh, Uttrakhand (for paddy); Assam, West Bengal and Rajasthan (for mustard); and Karnataka (for groundnut). However, we can infer that, more generally, seasonal factors do not explain a major part of the variation in prices over time.

The seasonal gap estimates reported in Table 3.4 tell us about the magnitude of seasonality. Among the commodities, the oilseeds report a higher average seasonal gap estimate compared to the cereals. The highest is for groundnut with the average peak price being about 13 percent higher than the average trough price. Table 3.4 also reports the seasonal gaps that I have estimated for the international reference prices of paddy, wheat and groundnut using the same methodology as for the domestic mandi-level prices. For each of these commodities, the all-India average (arithmetic mean of the seasonal gap estimates of all the studied *mandis*) is relatively lower compared to the estimates for their corresponding international reference price. However, if we look at the individual estimates, there are several instances where a *mandi*-level seasonal gap estimate is higher than that of the international series. The incidence of large seasonal drops is not found to be confined to any particular geographical region. For paddy, this is true for all the *mandis* covered from Puducherry and for large proportions of the *mandis* covered from Uttrakhand, Maharashtra and Madhya Pradesh. Similarly, for groundnut, a number of *mandis* in Telangana, Tamil Nadu, Karnataka and Madhya Pradesh have seasonal gap estimates higher than that estimated for the international price series. In the case of wheat, however, the seasonal gap estimates are found to be relatively lower in almost all the studied *mandis*, with just two exceptions from Jharkhand and Madhya Pradesh. Thus, we infer that although, on an average, seasonal price drops in the domestic wholesale markets are lower relative to that observed in the international markets, there are a number of notable exceptions.

The results reported so far show that individual seasonal gap estimates appear to differ quite a lot in their magnitudes. Therefore, the next sub-section goes on to explore in detail how the seasonal gaps vary across commodity and space.

3.3.1.3 Variation in the magnitudes of seasonality

To understand how the estimated seasonal gaps vary across the studied commodities, the skewness-kurtosis (S-K) test described by D'Agostino et al. (1990) is conducted on the seasonal gap estimates for each of the commodities separately as well as for all the commodities taken together. The results of the test are reported in Table 3.5, which also include the empirical correction developed by Royston (1991). The Kernel density functions are also estimated to check the distribution of the estimated seasonal gaps and Figure 3.3 plots the respective graphs along with the theoretical normal distributions.

Table 3.5: Skewness/Kurtosis tests for normality on seasonal gap estimates

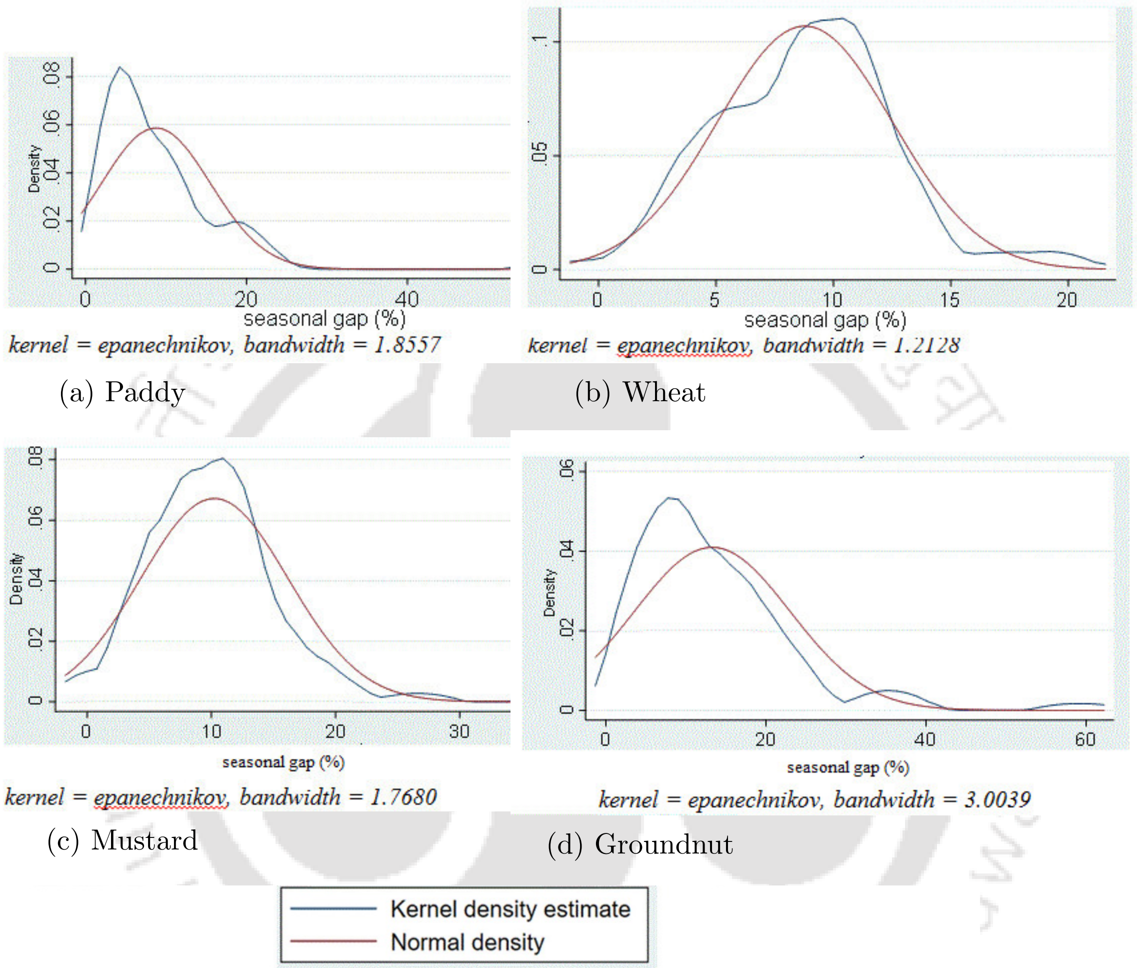
				joint	
Variable	n	Pr (Skewness)	Pr (Kurtosis)	Adjusted chi^2	Prob>chi^2
(1)	(2)	(3)	(4)	(5)	(6)
Paddy	167	0.00	0.00	.	0.00
Wheat	126	0.1441	0.1823	3.99	0.1357
Mustard	69	0.00	0.00	28.54	0.00
Groundnut	65	0.00	0.00	32.75	0.00
All crops	422	0.00	0.00	.	0.00

Note: Column (1) specifies the commodity and Column (2) reports the number (n) of observations (*i.e.* estimated seasonal gaps) for each crop. Pr in the columns (3) and (4) represent the probability of falsely rejecting the null hypothesis of zero skewness and kurtosis respectively. Columns (5) and (6) respectively report the adjusted Chi-square statistic and its associated p-value. A dot (.) in column (5) represents as a very large number, which indicates that the data are, most certainly, not normal.

Source: Author's calculations

Table 3.5 presents results of the skewness and kurtosis test conducted on the estimates of seasonal gap obtained from *mandi*-level prices for each studied commodity. Pr in the columns (3) and (4) represent the probability of falsely rejecting the null hypothesis of zero skewness and kurtosis respectively. The reported results are discussed shortly along with the estimated k-density functions presented in Figure 3.3

Figure 3.3: Kernel density function for the seasonal gap estimates across the studied commodities



(a) Paddy (b) Wheat

(c) Mustard (d) Groundnut

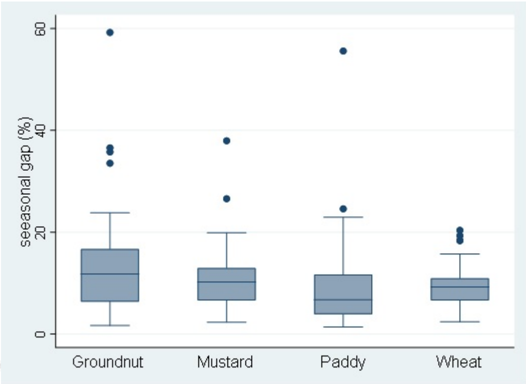
Note: The figure presents Kernel-density estimates of the estimated seasonal gaps obtained from *mandi*-level prices across India for each of the studied commodities respectively. The normal distribution curve is superimposed for comparison.

Source: Author's calculations

The results of both the statistical tools lead us to conclude that, except in the case of wheat, the estimated seasonal gaps do not show evidence of being normally distributed. The nature of deviations from the theoretical normal distribution becomes clearer from Figure 3.3. It shows that the Kernel-density plots are noticeably skewed to the right for paddy and groundnut, and slightly so for mustard. In a right-skewed distribution, the left-tail is shorter and the mode lies to the left of the mean value, indicating that lower values (*i.e.* values lesser in magnitude than the average) are more common in the distribution. However, the right-tail is longer, which indicates that there are more extreme values towards the higher end of the distribution. Another observation is the presence of small bumps in the Kernel density plots for almost all the commodities. Even though these bumps are not large enough to categorize the distributions as bi-modal, they are still noticeable. Some insights to these bumps may be found in the analysis of spatial differences in the magnitude of seasonality.

To better understand the distribution of the estimated seasonal gaps of each commodity, Figure 3.4 presents box–plots of the estimates across the four commodities. This gives a visual representation to their distribution around their respective median values. The spread of the estimates visibly differ across commodities with wheat showing the lowest spread, whereas groundnut and paddy show the highest. Furthermore, the plots show that there is a marked presence of outliers (on the higher end) in case of all the commodities, especially for groundnut and paddy, and for mustard to some extent. This explains the long right tails observed in the distribution of the seasonal gap estimates for these commodities (in Figure 3.3).

Figure 3.4: Distribution of Seasonal gaps across major agricultural commodities (2003-2016)



Note: The figure presents a box-plot of the regression estimates of seasonal gap in *mandi*-level prices categorized by crop.

Source: Author's calculations

To formally ascertain whether the apparent differences in dispersion are statistically significant, this dissertation conducts the test for equality of variance developed by Levene (1960). Since the distribution of the estimates is found to be significantly skewed, the alternative formulations of Levene's test statistic by Brown and Forsythe are also reported. They use more robust estimators of central tendency (*i.e.* the median and the 10% trimmed mean respectively) in place of the mean and have been demonstrated to be more robust when dealing with skewed populations (Brown and Forsythe, 1974). The results are presented in Table 3.6, which reports the Levene's robust test statistic (W_0), Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the four studied commodities. The figures in parenthesis are the respective p-values. All the three test statistics confirm that the spread of the seasonal gap magnitudes do differ across the studied commodities at much less than 5 percent level of significance. Therefore, their average values are not comparable *per se*.

Table 3.6: Test results for Equality of Variance in seasonal gap estimates across commodities

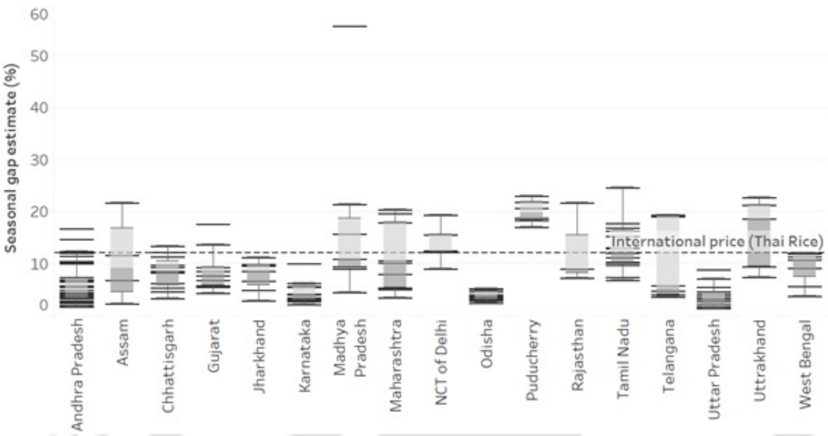
	W_0	W_{50}	W_{10}	Degrees of freedom $(k-1, n-k)$
(1)	(2)	(3)	(4)	(5)
Test statistic	13.56	10.66	11.48	df (3, 418)
p-value	(0.00)	(0.00)	(0.00)	

Note: The table reports the Levene's robust test statistic (W_0), Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the groups (commodities). The figures in parenthesis are the respective p-values. The final column reports the respective degrees of freedom ($k-1$, $n-k$), where k is the number of groups and n is the number of observations in the group.

Source: Author's calculations

The dispersion in the estimates is also evident in their geographical distribution. The figures 3.5 to 3.8 present the spread of the regression estimates of seasonal gap in *mandi*-level paddy prices categorized by states of India. In the figures, each horizontal line above a particular state represents the estimate for a particular *mandi*. Box-plots are superimposed to show the spread of the estimates within that state. The estimated seasonal gap for the international price of the respective commodity is also added as a reference line.

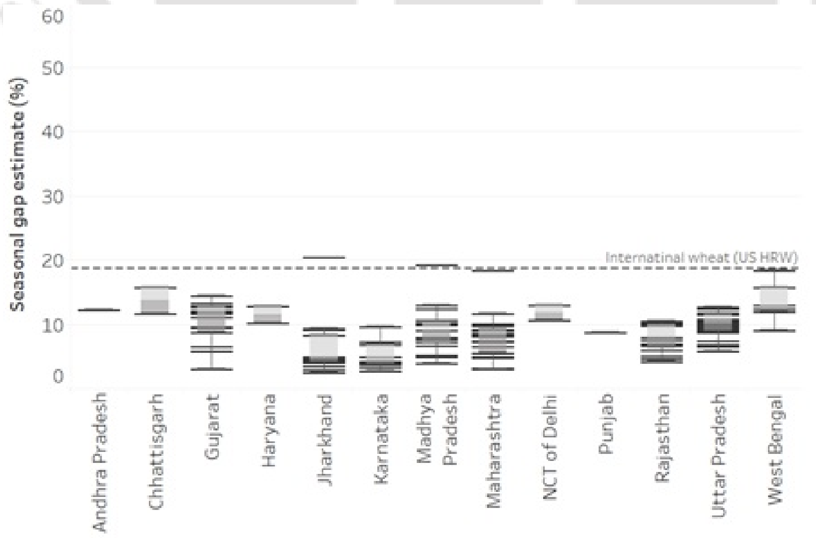
Figure 3.5: Seasonal gaps in *mandis* across states of India for Paddy (2003-2016)



Note: The figure shows the regression estimates of seasonal gap in *mandi*-level paddy prices categorized by states of India. Each horizontal line represents the estimate for a particular *mandi.* Box-plots are superimposed to show the spread of the estimates within a state. The seasonal gap in the international price of paddy is added as a reference line.

Source: Author's calculations

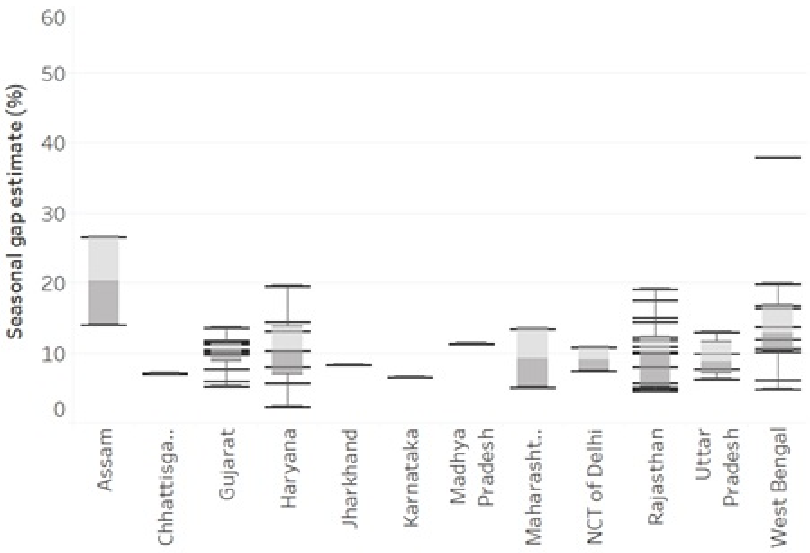
Figure 3.6: Seasonal gaps in *mandis* across states of India for Wheat (2003-2016)



Note: The figure shows the regression estimates of seasonal gap in *mandi*-level wheat prices categorized by states of India. Each horizontal line represents a particular *mandi.* Box-plots are superimposed to show the spread of the estimates within a state. The seasonal gap in the international price of wheat is added as a reference line.

Source: Author's calculations

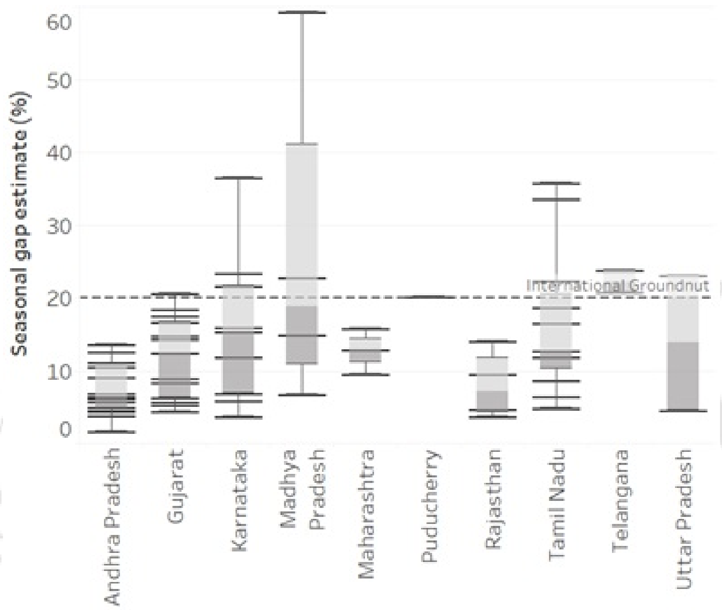
Figure 3.7: Seasonal gaps in *mandis* across states of India for Mustard (2003-2016)



Note: The figure shows the regression estimates of seasonal gap in *mandi*-level mustard prices categorized by states of India. Each horizontal line represents a particular *mandi*. Box-plots are superimposed to show the spread of the estimates within a state.

Source: Author's calculations

Figure 3.8: Seasonal gaps in *mandis* across states of India for Groundnut (2003-2016)



Note: The figure shows the regression estimates of seasonal gap in *mandi*-level groundnut prices categorized by states of India. Each horizontal line represents a particular *mandi*. Box-plots are superimposed to show the spread of the estimates within a state. The seasonal gap in the international price of groundnut is added as a reference line.

Source: Author's calculations

Table 3.7 presents the CV of the seasonal gap estimates from the different states for the four commodities. Notable states that have a relatively higher dispersion in the *mandi*-level seasonal gap estimates within them are: Madhya Pradesh (paddy, groundnut); Telangana (paddy); Uttar Pradesh (groundnut, paddy); Assam (paddy); Andhra Pradesh (paddy, groundnut); Tamil Nadu (groundnut); Gujarat (paddy, groundnut); Karnataka (paddy, groundnut); Rajasthan (paddy, groundnut); and Maharashtra (paddy). Each of these states report *mandi* level seasonal gap estimates that range from very low values ($1-2\%$) to values higher than that for the respective international reference price.

Table 3.7: Dispersion in seasonal gap estimates across states by crop

State	Paddy		Wheat		Mustard		Groundnut	
	CV (%)	n	CV (%)	n	CV (%)	n	CV (%)	n
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Andhra Pradesh	64	36	-	1			46	16
Assam	76	4			44	2		
Chhattisgarh	41	11	20	2	02	2		
Gujarat	45	10	32	14	25	12	47	13
Haryana			16	2	55	7		
Jharkhand	37	7	80	13	-	1		
Karnataka	44	11	44	10	-	1	67	9
Madhya Pradesh	97	7	43	15	01	2	89	4
Maharashtra	60	9	45	17	63	2	25	3
NCT of Delhi	28	5	13	2	26	2		
Odisha	24	10						
Puducherry	12	6					-	1
Punjab			-	1				
Rajasthan	61	3	28	15	47	21	59	4
Tamil Nadu	36	14					61	11
Telangana	85	6					10	2
Uttar Pradesh	53	16	19	26	32	4	94	2
Uttrakhand	44	5						
West Bengal	37	7	25	6	63	10		
Total	78	167	40	124	53	66	73	65

Note: The table reports the coefficients of variation (CV) of the *mandi*-level estimates of seasonal gap from the different states of India across the four commodities. The n in (Columns (3), (5), (7) and (9) represents the number of *mandi*-level series included from each state. The bottom column reports the CV for all the estimates taken together, classified by commodity.

Source: Author's calculations

Further, to ascertain whether the inter-state differences in the dispersion of the seasonal gap estimates are statistically significant, Levene's test for equality of variances between groups is conducted across states for each commodity individually. Table 3.8 reports the Levene's robust test statistic (W_0) along with Brown's (W_{50}) and Forsythe's (W_{10}) alternative statistics for each commodity.

Table 3.8: Test statistics for Equality of Variance among seasonal gap estimates across states

	W_0	W_{50}	W_{10}	Degrees of freedom $(k-1, n-k)$
(1)	(2)	(3)	(4)	(5)
Paddy	5.36	2.08	5.27	df(16, 150)
	(0.00)	(0.01)	(0.00)	
Wheat	1.17	0.66	0.88	df(12, 111)
	(0.31)	(0.79)	(0.57)	
Mustard	1.77	1.41	1.49	df(11, 54)
	(0.08)	(0.19)	(0.16)	
Groundnut	5.03	2.18	4.84	df(9, 55)
	(0.00)	(0.04)	(0.00)	

Note: The table reports the Levene's robust test statistic (W_0), Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the groups (states). The figures in parenthesis are the respective p-values. The final column reports the respective degrees of freedom ($k-1$, $n-k$), where k is the number of groups and n is the number of observations in the group.

Source: Author's calculations

The results presented in Table 3.8 show that for wheat and mustard, the null hypothesis of equal variances across groups (states) cannot be rejected at a significance level of 5 percent or less. Hence, the differences in mean (or median) values are comparable for these two commodities. Now, since the median value is not unduly affected by the presence of extreme values, it makes sense to compare the median of the seasonal gap estimates instead of their means. For wheat, states having a median seasonal gap estimate that is relatively higher are West Bengal, Chhattisgarh, NCT of Delhi and Haryana. These could explain the small bump on the right tail of the K-density function for wheat. Similarly, states like Jharkhand, Karnataka, Rajasthan and Maharashtra have relatively lower median seasonal gaps, which may explain the noticeable hump on the left of the K-density plot. Again, for Mustard, states with relatively higher median seasonal gaps are Assam, West Bengal and Haryana, which may explain the two small bumps on the K-density function on the right tail.

Now, for paddy and groundnut, Table 3.8 shows that the null hypothesis of equal variance can be rejected at significance levels of less than 1 percent each. This indicates that in case of these two commodities, certain states have significantly higher dispersion in the *mandi*-level seasonal gap estimates than others and therefore the differences in the mean (and median) level of seasonality are not comparable.

The high dispersion observed in the seasonal gap estimates raises a question, *i.e.* what causes the seasonal gaps to differ from one another. The high intra-state dispersions tell us that state and crop related differences may not be sufficient to explain the variation in seasonal gaps. Therefore, the dissertation proceeds to explore other factors that may influence the magnitude of seasonal gaps. The next sub-section, conducts a disaggregated examination of the seasonal gaps in terms of their location and crop-specific differences.

3.3.2 Understanding the variation in seasonality across India

Drawing from the conceptual framework presented in the begining of this chapter, a likely source of the variation in seasonal gaps may be traced to the trading strategies opted for by the farmer-seller. The seasonal gap in a particular *mandi* is expected to be larger if the majority of the sellers take up the sub-optimal trading strategy of "sell low", *i.e.* selling their harvest even when prices are relatively low (discussed in section 3.1).

This dissertation, therefore, investigates whether the proportion of small and marginal farmers (SMF) in a location affects the magnitude of the seasonal gap. The Agricultural Census of India operational classifies all holdings that are less than 2 hectares in size as small and marginal holdings. Within these, the 'small' category refers to holdings ranging from 1.00 - 2.00 Ha. The marginal category is further subdivided into two groups: one with holdings ranging between $0.5 - 1.00$ Ha and the other with all holdings below 0.5 Ha (Government of India, 2015).

The intuition behind this investigation comes from the assumption that SMFs are likely to sell their stocks immediately after harvest if they face constraints like, *inter alia*, a poor resource base, lack of access to credit, lack of access to storage facilities and so on, which restrict their ability to hold on to their harvest (Stephens and Barrett, 2011; d'Hotel and Cotty, 2018). If such conditions hold true for a very large proportion of farmers selling in any *mandi*, it would depress the realised wholesale price (because of excess supply) and lead to a high seasonal gap. This has been discussed more elaborately in the conceptual framework presented in section 3.1.

To ascertain the empirical validity of the above proposition, a set of measurable variables are identified to capture possible socio-economic factors influencing the magnitude of the seasonal gaps. An ordinary least squares (OLS) regression is then run by taking these variables as the explanatory variables for the magnitude of the seasonal gap estimates. A description of included variables and the rationale for their inclusion is presented in the following paragraphs.

Proportion of smallholders selling in the location: To examine whether the magnitude of the seasonal gap shows any association with the proportion of smallholders in a location, two continuous variables (SMF_a and SMF_b) are included. They represent the proportion of operational holdings belonging to the size classes 0.5 to 1.00 Ha and 1.00 to 2.00 Ha respectively within the district to which a particular *mandi* belongs. Data on these parameters are obtained from the Agricultural Census of India 2010-11 (Government of India, 2015). Given the theoretical framework presented above, the coefficients of each of these variables is expected to have a positive sign. Although there are three sub-categories of SMF, severe multi-collinearity issues arise if all three are included in the model. Therefore one of the size classes (‘less than 0.5 Hectares’ category) is dropped from the estimation. The assumption is that farmers cultivating on such small-sized holdings will be cultivating for subsistence and not for marketing. Thus, their proportion is unlikely to affect market outcomes. See table 3.12 for the Variance Inflationary Factors (VIF) of the included variables.

Backwardness: The Planning Commission of India classified all rural districts of India into three categories in terms of their backwardness for the phased implementation of the Mahatma Gandhi National Rural Employment Guarantee Scheme. The districts that fall under Phase I of this classification are identified as falling in the 'most backward district' category (Planning Commission, 2003). It is also expected that as most farmers in such districts are expected to be asset poor, their capacity to practice optimal trading and storage strategies is limited. Hence, the seasonal gaps may be higher in regions that are categorised as "the most backward". Therefore, a dummy variable (backward district) is created, which takes the value of one (1) when a *mandi* belongs to any district that features in the most backward district category. Otherwise, it takes a value of zero (0). We expect a positive sign for this variable.

Value of assets: Since the value of assets owned by a household influences its capability to bear risks, it is expected that higher the value of assets, larger will be the ability to hold on to stocks after harvest. This is represented by the average value of assets (AoA) of households in a district as reported in the NSSO 70^{th} round (NSSO, 2014a). As seasonal gaps are postulated to be lower when farmers are able to hold on to stocks, we expect a negative sign for its coefficient.

Credit and indebtedness: Access to affordable credit may enable cultivators to hold on to stocks for a while and prevent them from being forced to opt for the sub-optimal trading strategy of "sell-low". The dissertation uses the incidence of indebtedness (IoI) in a district to represent the access to credit, which is expected to have a negative sign. Another variable included here is the average amount of debt per indebted household (AODL) in a district, which represents the degree of indebtedness. This variable may, however, affect farmer's trading strategies in more than one way. Availing more credit enables farmers to hold on to stocks for some time after harvest. At the same time, given the problems associated with credit markets in developing countries, a high outstanding debt may also increase the pressure for needing immediate cash in hand and lead to distress sale after the harvest. Therefore, there is no clear expectation for the sign of this variable's coefficient. Data for both these variables is obtained from NSSO (2014a)

Crop: To incorporate inter-crop differences in the seasonal gap, three dummies are included for paddy, mustard and groundnut respectively, while wheat represents the base category. There are no prior expectations about the sign associated with these dummies.

The regression model is represented in Equation 3.12. A summary of the included variables is presented in Table 3.9 and their descriptive statistics are presented in Table 3.10.

$$SG_{x,y} = A_0 + \sum_{i=1}^{3} A_{1,i} d\_crop_i + A_2 d\_Backward_y + A_3 SMFa_y + A_4 SMFb_y + A_5 AoA_y + A_6 IOI_y + A_7 AODL_y + \varepsilon_{x,y} \tag{3.12}$$

On the left-hand-side, SG represents the seasonal gap estimate for commodity x in *mandi* y. On the right-hand-side, d_crop_i represents a set of three crop dummies that take the value of one (1) if $i = x$ and zero (0) otherwise. Wheat is taken as the base category. A point to be noted here is that there is an absence of clarity on which villages are allowed to sell in a particular *mandi*. Therefore, district level characteristics are taken as an approximation of the indicators of socio-economic conditions prevailing for cultivators selling in each *mandi*. For instance, AoA_y represents the AoA per household in the district to which *mandi* y belongs.

Table 3.9: Regression on seasonal gaps: Description of included variables and their expected association

Variables	Description of variable	Type of variable	Expected sign
(1)	(2)	(3)	(4)
$SG_{x,y}$	Seasonal gap estimate (for crop x in $mandi_y$)	Continuous	
d_crop_1	Paddy	Dummy	.
d_crop_2	Mustard	Dummy	.
d_crop_3	Groundnut	Dummy	.
SMF_a	Prop. of $0.5 - 1.00$ Ha holdings	Continuous	+
SMF_b	Prop. of $1.00 - 2.00$ Ha holdings	Continuous	+
$d_$backward	Backward district	Dummy	+
AoA	Average value of assets per household	Continuous	−
IOI	Incidence of Indebtedness	Continuous	−
AODL	Average Amount of Debt per indebted household	Continuous	+/− (ambiguous)

Note: The table presents a list of measurable variables that are included in an OLS regression on the seasonal gap estimates. The variable name and its description are provided in Columns (1) and (2) resp. Column (3) describes the type of the variable (discrete, continuous, binary/dummy). The final column presents the theoretical expectation regarding the direction of association between the regressor and the dependent variable. A dot(.) in column(4) indicates that there is no prior expectation regarding the direction of association.

Table 3.10: Regression on seasonal gaps: Descriptive statistics of variables

Variables	n	Mean	SD	Min	Max
$SG_{x,y}$	422	10.56	8.08	1.37	80.81
SMF_a	420	0.22	0.05	0.01	0.34
SMF_b	420	0.22	0.08	0.05	0.41
AoA	397	5052818.00	13700000.00	677035.00	100000000.00
AODL	397	161566.80	130535.70	38529.00	754239
IOI	397	43.53	16.70	1.17	73.85

Note: Only the continuous variables are included

Source: Author's calculations based on data obtained from DMI, MoA&FW, Govt. of India, Government of India (2015), NSSO (2014a)

It is to be noted that the model uses robust standard errors. Otherwise a problem of heteroscedasticity is encountered in the model. Model diagnostic statistics are reported in the Tables 3.11 and 3.12.

Table 3.11: Model Diagnostic Statistics for Regression on Seasonal gap estimates: Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Dependent variable: Seasonal gap estimates
H_0: Constant variance
$chi^2(1) = 54.62$ Prob $> chi^2 = 0.0000$

Source: Author's calculations

Table 3.12: Variance Inflationary Factor and Tolerance of explanatory variables
(Regression on seasonal gap estimates)

Variable	VIF	1/VIF
Average value of Assets	3.12	0.32044
Average debt outstanding per indebted household	3.00	0.333086
Paddy (dummy)	1.53	0.653724
Groundnut (dummy)	1.44	0.692785
Prop. of 1.00 - 2.00 Ha holdings in district	1.31	0.760769
Incidence if Indebtedness	1.30	0.769534
Mustard (dummy)	1.30	0.770474
Prop. of 0.5-1.00 Ha holdings in district	1.13	0.88458
Backward district (dummy)	1.11	0.898375
Mean VIF	1.69	

Source: Author's calculations

The results of the OLS regression are reported in Table 3.13 The fitted model, as a whole, is statistically significant with the F-statistic having a p-value of less than 0.001. The coefficients of the crop dummies indicate that seasonal gaps are significantly higher in case of both the oilseeds (substantially for groundnut) compared to the two food grains. Most importantly, the results indicate that the identified socio-economic factors do have significant influence on the magnitude of seasonal gaps. Especially, the proportion of smallholders has a strong and direct relation with the magnitude of seasonal gap in any location.

Table 3.13: Regression results: Factors affecting the magnitude of seasonal gaps

Explanatory Variables	Coef.	Robust Std. Err.	$p > t$	
(1)	(2)	(3)	(4)	
Paddy (Dummy)	-0.03	0.94	0.975	
Mustard (Dummy)	1.95	0.88	0.027	**
Groundnut (Dummy)	4.48	1.88	0.018	**
SMFa_y	2.26	7.11	0.750	
SMFb_y	15.45	5.14	0.003	***
Backward district (Dummy)	0.34	0.92	0.713	
AoA$_y$	0.00	0.00	0.000	***
IoI$_y$	-0.08	0.02	0.000	***
AODL$_y$	0.00	0.00	0.009	***
Constant	9.22	1.65	0.000	***
n	395			
F(9, 385)	21.86	***		
R^2	0.151			
Root MSE	7.3452			

Note: The table presents the results of the regression on the estimated *mandi*-level seasonal gaps on various factors including crop type and district characteristics (socio-economic condition and proportion of smallholders). The stars represent the level of significance: $^{***}p < 0.01$, $^{**}0.05 > p > 0.01$, $^{*}p < 0.10$. n represents the number of observations included in the regression.

Source: Author's calculations

The results show that, in general, the magnitude of the seasonal gap rises significantly with an increase in the proportion of smallholders in a district. The coefficient of variable representing the small farmer category ($1-2$ ha sized holdings) is highly significant and has a value of 15.45. This is much higher compared to the coefficients of all other variables. Thus, when the percentage of small farmers increases by 1%, the magnitude of the seasonal price drop rises by more than 15%. This large coefficient is strongly in favour of the proposition that smaller farmers face certain constraints that force them to opt for the sub-optimal behaviour of 'sell-low'. As most sell immediately after harvest, the market price falls as a result of the excess supply. These smallholders continue to sell even at the lower prices, taking prices to a low trough, which results in higher seasonal gaps.

The regression results do not find the coefficient of the marginal farmer category ($SMFa_y$) to be statistically significant. This may be attributed to the possibility that most marginal farmers in India cultivate for subsistence and, therefore, do not affect market supply.

The study also finds some other significant variables. One among them is access to credit. Since the coefficient of incidence of indebtedness has a significant negative sign, access to credit is found to have a dampening effect on the seasonal gap. This finding is in line with theoretical expectations (Stephens and Barrett, 2011; d'Hotel and Cotty, 2018). As for the two other significant variables, *i.e.* the average value of assets of households and the amount of debt outstanding per indebted household, their coefficient magnitudes are nearly equal to zero. This indicates that they have a negligible impact on the magnitude of seasonal gap. Furthermore, the 'backward district' dummy is not significant. This indicates that the incidence of large seasonal gaps is not only confined to the poorer districts, but such phenomenon is observed in other districts as well.

Here, it is important to note that although the model as a whole is significant, it has low explanatory power. The R^2 value is quite small and the constant term is highly significant, which means that there are several other important explanatory variables that have not been captured here. This opens up the work for further research by expanding the model to include other relevant variables identified by literature (like access to storage facilities, collusion among traders, farmers' access to and awareness about state procurement facilities, trade restrictions, transportation facilities to market, alternate sources of household income in rural areas and so on). These variables could not be included at this point as village or district level data on these factors are not readily available. Nevertheless, the model presented here is still able to give us crucial insights concerning those variables that have been considered here. Most importantly, it does find strong statistical evidence in favour of the proposition that seasonal gaps are larger in smallholder-dominated regions.

3.3.3 The chapter's findings and the existing literature

The specific component of price behaviour that this chapter addresses is seasonality. The present section sums up the findings on the different aspects of seasonality and compares them to findings by similar studies on this area. Through its analysis, the study finds statistically significant evidences in favour of the presence of seasonal patterns in most of the wholesale markets across India for all the commodities studied. This indicates that the prices of some of the most widely cultivated commodities across India tend to experience periodic drops in specific months of a calendar year. Furthermore, such drops in prices are common across the country. The existing literature reports evidence of similar seasonal behaviour of prices in other developing countries like Bangladesh[2] (Salam, Alam & Moniruzzamam, 2012) as well as countries of sub-Saharan Africa (SSA) (Gilbert et al, 2017; Hatzenbuehler et al., 2018).

Earlier works on India (Sarkar, 1993; Sharma and Kumar, 2001; Kumar & Sharma, 2006) have established the presence of seasonality in the previous decades (1980s and 90s). Sarkar (1993) shows that an important explanation of the post-harvest price drop lies in the fact that small sellers sell off their entire stocks before the large sellers do. The results of the present study show that seasonal factors have continued to affect prices across India in the recent periods as well. Furthermore, it is still the smallholders who get the lowest returns on their harvest.

Although evidence of price seasonality in India has been documented by other studies covering a similar time-period (Makama et al., 2016; Meera & Sharma; 2016), the present work not only adopts a more rigorous methodology, it is also conducted at a highly disaggregated level (*i.e.* at the level of the *mandi*). Thus, this dissertation is able to give a more comprehensive picture of how seasonal price behaviour varies across India. Specifically, it brings our attention to the differences in the seasonal behaviour of prices across India and the findings highlight the diversity in both the influence of seasonal factors and the magnitude of seasonal gaps across location and commodity. Interestingly, the estimates of seasonal gaps do not just differ across states. In several cases, the dispersion of the estimates within specific states is quite high. This is specifically true for paddy and groundnut. In general, the average of the seasonal gap estimates for the domestic wholesale markets are lower than that estimated for their corresponding prices in the international market. However, there exist quite a number of cases where the *mandi*-level seasonal gap is much higher than that for the corresponding international price.

Among the commodities, on an average, both the oilseeds tend to have relatively higher seasonal gaps compared to the two cereals. Being commercial crops, the incurrence of loss can adversely affect income-streams of producers. While those selling at the peak price would benefit, the ones selling at (or near) the though price may be incurring substantial losses depending on how low the trough price is. For the two cereals, the average of the estimated seasonal gaps is similar for both at a little less than 9 per cent. However, the dispersion in the estimates is much higher for paddy (compared to wheat). For all the crops except wheat, the distributions of the *mandi*-level seasonal gap estimates are positively skewed. This means that in several *mandis*, commodities report seasonal gap estimates that are much higher than the average value. In case of wheat, however, the distribution of the estimated seasonal gaps approximates a normal distribution and they stay mostly around the mean value. Similar findings have been reported for cereal price seasonality in the neighbouring country of Bangladesh, where Salam et al. (2012) find that both the magnitude of and dispersion in the seasonal price drops are larger in the case of paddy compared to wheat.

The work on price-seasonality by Kumar & Sharma (2006) tells us that in the two previous decades in India, the picture was different. The band of seasonality (or the seasonal gap) in rice prices remained lower compared to wheat in both the 1980s and the 1990s. More importantly, in the case of rice, they find that the seasonal price difference recorded a decrease in the latter decade (from about 8 percent to a little less than 4 percent).[3] They attributed this dampening in seasonal fluctuations in rice to government intervention (specifically procurement policies). In an earlier work, Sarkar (1993) provides theoretical justification of public procurement (in addition to land reform) for ensuring welfare gains to smaller farmers. However, the efficiency of state procurement in the later decades has been repeatedly questioned (Bathla, 2012; Chatterjee and Kapur, 2016; Chatterjee, 2019). Therefore, we can draw from the inference of Kumar and Sharma (2006) that prices tend to be lower in locations where procurement is lower. There are large differences in procurement levels both across and within regions and in several cases the farmers are unaware of the policy of Minimum Support prices (NSSO, 2014b). In those locations where there is an absence of access to price support measure, there is no mechanism to prevent price crashes. Thus, the ineffective delivery of the price support policy may explain this dissertation's finding that seasonal fluctuations are high (for paddy) after the 2000s.

3.4 Conclusion

The objective of the present chapter has been to understand seasonal fluctuations in the wholesale price of four major agricultural commodities in *mandis* spread across the country. As the study filters out the seasonal components of price behaviour, a related and important question emerges: what do the nature and magnitudes of the estimates imply? This section presents the inferences and conclusions that can be drawn from the findings presented in this chapter.

What do large seasonal gaps in specific markets mean? They mean that these markets are prone to price crashes immediately after the harvest. The spatial variation observed in the seasonal gaps raises a critical. First, The seasonal price drops are significantly high in districts where resource-constrained smallholders are larger in number. As they are unable to hold on to stocks and sell soon after the harvest, they are the ones who receive the lowest price for their produce. Given their high economic vulnerability, negative shocks to income-streams of smallholder-households can threaten their livelihood sustainability. Furthermore, as the relatively larger farmers have the means to hold on to stocks, they may be selling when prices are nearer to the peak price. Thus, large seasonal gaps could indicate that the more vulnerable lose out, while the relatively better off are able to gain disproportionately.

Drawing from the findings for India, the study infers that agricultural crisis mitigation policies in smallholder-dominated developing countries will be more meaningful if they are directed towards addressing the constraints faced by smallholders.

While this chapter has tried to conduct a comprehensive study of seasonality, it finds that a lot of the intra-annual variation in commodity prices is not seasonal. Examining the nature and extent of unexplained variations in prices is important. The next chapter, therefore, moves ahead to examine these unexplained idiosyncratic variations in prices of the commodities under study. Finally, the fifth chapter investigates whether locations facing wide seasonal price drops are also facing high price volatility (section 5.3). If this is true in smallholder dominated locations, then these locations may be in need of urgent policy attention.

4 | VOLATILITY IN COMMODITY PRICE BEHAVIOUR

This chapter engages with the concept of volatility (or unpredictability) in agricultural commodity prices. While presenting the review of literature, Chapter 2 discusses how volatility can have severe and adverse implications for developing economies like India despite it being a short-run phenomenon in itself. Further, one important inference drawn from the preceding chapter (Chapter 3) is that for almost all the studied commodities, a major portion (over 80 percent) of the variation in prices is not attributable to seasonal factors. Thus, most of this variation may be categorised as idiosyncratic (*i.e.* irregular or volatile). This gives added weight to conducting the analysis of price-volatility at a disaggregated level.

In case of price movements over time, volatility refers to that part of the variation which is not accounted for by the trend and seasonal components. Economic theory attributes the marked volatility observed in agricultural commodity prices to their low short-term production and consumption elasticities. Binswanger (1989) discusses how problems arise in responding to price-signals in the short-run because the main factors of agricultural production (land, capital, and labour) are fixed. Moreover, planting decisions are made before prices are known and hence production (and supply) decisions depend more on expected prices and not price realisations. Dana & Gilbert (2012) discuss how variability in agricultural prices has been large all around the world throughout the twentieth century and how, since the 1980s, interventions in agricultural commodity markets have become the norm to prevent or offset these movements. India too has seen such stabilisation policies in the form of price support measures (MSP) and buffer stock schemes.

In countries like India, increased volatility is likely to impact not just exports and imports but also farm income, food security, employment and poverty (Chandrasekhar and Ghosh, 2002; Grimwade, 2004; Sekhar, 2004; Hoda and Gulati, 2008, Bathla, 2012). Although increased agricultural price volatility is being recognised as undesirable in several parts of the world, it has more serious implications for resource poor-households in developing countries with imperfect credit markets and skewed land-relations (Government of India, 2006; Acharya, 2007; Government of India, 2017). While for the relatively larger farmers some volatility is desirable for making profits through speculation, severe volatility may raise livelihood sustainability concerns for resource-poor small-farmers. Hence, it is of utmost importance that more and more works concentrate on investigating the ground-level picture of volatility.

In this context, this chapter aims to contribute towards the study of commodity price volatility facing farmers of India. It comprises of three sections. The first is related to the methodological approach adopted to estimate price volatility in this dissertation. It also discusses the post-estimation and/or model diagnostic tests conducted to ensure the appropriateness of the fitted volatility models. The second section discusses the results of the estimation. In the final section, the implications of the findings are discussed.

4.1 Methodological Framework: Modelling Volatility

As indicated, volatility is that part of price-variation which is not explained by any systemic component. Equation 3.1 in Chapter 3 structurally characterises the time-series behaviour of an agricultural price series p_{ym} in year y and month m. This is presented as Equation 4.1 here:

$$p_{ym} = \mu_{ym} + s_m + \varepsilon_{ym} \tag{4.1}$$

Here, trend μ_{ym} and seasonality s_m represent the predictable components, while ε_{ym} is the unpredictable component. It is the variation in ε_{ym} that gives us a measure of the volatility.

4.1.1 Removal of structural components

The first step in the estimation of volatility is the removal of predictable components. This is done by identifying and de-seasonalising those *mandi*-level price series for which seasonal variations are found to be significant (*i.e.* the F-statistic of the preferred model is significant at 5 per cent level or less). De-seasonalising is done by subtracting the respective seasonal factors (estimated in Chapter 3) from the each of these series.

The next step is trend elimination. For this purpose, this dissertation uses the Hodrick-Prescott (HP) filter, which enables extraction of non-linear trends from a series (Hodrick and Prescott, 1997). This filter belongs to a class of band-pass (BP) filters, which allows an economic time series to be decomposed into cyclical components of a range of periodicities or frequencies. One of the advantages of the BP filter is that it can be used to decompose the time series into different frequency components regardless of the underlying dynamics (Christiano and Fitzgerald, 2003).

The HP-filter is a model-free approach that "smooths" the original time series (here price, *i.e* p_t) to estimate its trend component (μ_t). This can be represented as follows:

$$p_t = \mu_t + c_t \tag{4.2}$$

The difference between μ_t and the original price series (p_t) gives the random and cyclical components (c_t). For the HP-filter, μ_t is constructed to minimize the following:

$$\sum_{1}^{T}(p_t - \mu_t)^2 + \lambda \sum_{2}^{T-1}[(\mu_{t+1} - \mu_t)–(\mu_t - \mu_{t-1})]^2 \tag{4.3}$$

Here, λ is called the 'smoothing parameter', which imposes a penalty for changes in the trend's growth rate. There have been debates about the appropriate value of this parameter as there may be a risk of removing too much of the stochastic component. The work by Ravn and Uhlig (2002) derives appropriate smoothing parameters applicable for different frequencies of data. Following them, the smoothing parameter used for trend elimination in this chapter is taken as 129600, which is has been prescribed for data of monthly frequency.

An advantage of using the HP filter is that it has been shown to obtain a better fit to data compared to models assuming a linear deterministic trend. It also allows us to relax the assumption about the nature of the stochastic trend taken for the seasonality estimation. However, the application of HP filter requires continuous series. The data on *mandi*-level prices obtained from the e-governance portal (AGMARKNET) of the Ministry of Agriculture, Govt. of India has missing observations in certain months within the period of reference of this study (2003-2016). As those series exhibiting seasonality have already been de-seasonalised, the missing observations in each series can now be interpolated. For this, an $AR(1)$ model is fit to each series and the predicted values are substituted wherever missing data points are encountered. The suitability of the model fit is checked on two criteria:

(a) the p-value of the $chi-squared$ statistic is less than or equal to 5 percent;

(b) the AR parameters satisfy the stability condition, *i.e.* all eigenvalues lie inside the unit circle.

Once this is done, the HP-filter is applied to each series.

4.1.2 Modelling Volatility

A commonly used measure of volatility is the standard deviation (SD) of the de-seasonalized and de-trended prices, which is a unit-free measure. For low levels of volatility, the log standard deviation is approximately equal to the coefficient of variation (Gilbert and Morgan, 2010). However, the SD is not a fair measure if all disturbances in time-series behaviour are not white noise. Studies point out that agricultural prices display autocorrelation due to storage and, therefore, they tend to exhibit time-varying variance or conditional heteroscedasticity (Aradhyula and Holt, 1988; Williams and Wright, 1991; Saphores et al., 2002). In situations when the variance of a series is not constant over time, it is apt to use an autoregressive conditional heteroskedaticity (ARCH) model or a generalized-ARCH (GARCH) approach, as elaborated in the works of Engle (1982) and Bollerslev (1986) The advantage of such models is that they can capture the behaviour of those series that follow different processes at different points in time and exhibit a time-varying non-linear variance.

The basic GARCH model consists of two equations: a mean equation and a variance equation. The mean equation describes the behaviour of the mean of the time series being modelled and is applied to de-mean the series before its variance is modelled. It is a linear regression function consisting of a constant (and possibly some explanatory variables) and an error term.

Suppose p is the time series being modelled which has a constant mean x:

$$p_t = x + \varepsilon_t \tag{4.4}$$

Here, the error (ε_t) is a stochastic process, which is normally distributed and heteroskedastic. This error term can be represented as:

$$\varepsilon_t = \sigma_t Z_t, \tag{4.5}$$

where, σ_t^2 is the conditional variance of ε_t, while Z_t is a series of independent random variables with zero mean and unit variance (*i.e.* $\varepsilon_t \sim N(0, \sigma_t^2)$. The term 'conditional' implies that σ_t^2 is an one-period-ahead estimate for the variance calculated based on any past information thought relevant.

GARCH modelling is primarily involved with appropriately identifying the functional specification of this conditional variance. Formally, the variance equation of a $GARCH(p, q)$ process is a sum of two components:

(a) ARCH component: This component models the 'autocorrelation in volatility' by allowing the conditional variance of the error term, σ_t^2, to depend on the previous values of the squared error $(\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \dots \varepsilon_{t-q}^2)$.

(b) GARCH component: This component models the conditional variance as being dependent upon its own previous lags $(\sigma_{t-1}^2, \sigma_{t-2}^2, , \dots, \sigma_{t-p}^2)$.

Thus, in a GARCH model, the variance is expressed as an auto regressive moving average ($ARMA(p, q)$) model of squared residuals.[1] The complete specification of the conditional variance of a time-series following a $GARCH(p, q)$ process is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-p}^2 \qquad (4.6)$$

Where,

$$\alpha_0 : constant \ (\text{`}ambient\ volatility') \\ \alpha_j : ARCH\ component\ coefficients \\ \beta_i : GARCH\ component\ coefficients$$

The parameters $(\alpha_0, \alpha_1 \ldots \alpha_q, \beta_1 ... \beta_p)$ are estimated by Maximum Likelihood estimation (MLE). Engle (1982), in his seminal paper published in *Econometrica*, demonstrates that MLE is more efficient than OLS here and he also calculates the amount by which this is so.

Since σ_{t-1}^2 is a conditional variance, its value must always be strictly positive to be meaningful. Therefore, non-negativity constraints are imposed on the parameter coefficients

$$i.e.\ \ (\beta_i, \alpha_j) \geq 0, \qquad for\ \ all\ \ i, j.$$

The estimated parameters give us information on the nature of the time-varying volatility, which are well articulated in the works of Alexander (2008) and Brooks (2008). In sum, the main features of time-varying volatility include the following:

(a) *Volatility clustering:* This relates to the presence of autocorrelation in the magnitude of absolute changes in a time-series. In the model, $\sum \alpha_i$ measures volatility clustering, *i.e.* the extent to which volatility shock in past periods feed through into the current period's volatility. Because of clustering, large and small changes tend to cluster together over time. Larger the value of $\sum \alpha_i$, higher is the sensitivity of volatility to market events.

(b) *Volatility persistence:*This relates to the presence of higher-order autocorrelation in the absolute magnitude of changes, so that present volatility feeds into the volatility of a number of time-periods in the future. $\sum \beta_i$ measures the persistence in conditional volatility, *i.e.* the rate at which the effect of a shock in one period dies over time. When β is relatively large (say, above 0.9) then volatility takes a long time to die out following a crisis in the market.

(c) *Convergence and Half-life:* The sum $\sum(\alpha_i + \beta_i)$ determines the rate of convergence of the conditional volatility to the long term average level. The larger the sum, the slower is the decay of shocks and current changes in volatility continue to affect future volatilities for a long period of time. Closer the sum is to one, greater is the tendency of price volatility to persist over time. Another common indicator of the persistence of volatility is the half-life of volatility, which refers to the time taken by the volatility in a series to come halfway down to its unconditional mean level. The higher the persistence, the longer will be the half-life.

(d) *Explosive volatility:* If the spill-over effect of a shock is greater than unity, the series is not covariance stationary. In such cases, the volatility level does not converge to any long-term average and is termed as 'explosive'. Such a series can still be strictly stationary in mean and ergodic, and hence, the standard asymptotically based inference procedures are generally valid (Nelson,1990; Bougerol &Picard, 1992; Wang, 2008). Explosive volatility is inferred if the sum of the parameter estimates exceeds unity, *i.e.* $\sum(\alpha_j + \beta_i) > 1$.

4.1.3 Specification of volatility model: Pre and Post Estimation Tests

4.1.3.1 Pre-estimation Tests and Choice of Volatility Model

A pre-estimation test checks whether a particular data series shows conditional heterosckedasticity. Following Engle (1982), the Lagrange Multiplier (LM) test for ARCH errors is applied individually on each series to ascertain whether the data follow an ARCH (or GARCH process). Given below is the sequence of steps that guide the choice of the volatility estimation model:

(1) *Identification of the mean equation:* The Box-Jenkins method is applied to each series to determine whether the mean equation should contain any lagged values of the dependent variable. This is done to control for the presence of any serial correlation in the series itself.

(2) *Test for conditional heteroscedasticity:* Once the apt mean equations are identified, the ARCH-LM test is conducted on each de-meaned series.

(3) *Specification the model:* If the LM test finds ARCH effects to be significant

in a particular de-meaned series, its results are used to choose the appropriate orders (p and q) of a GARCH(p,q) fit.

Now, the literature on the estimation techniques for series exhibiting conditional volatility is very dynamic and has evolved to capture asymmetric responses to shocks, leverage effects, regime-switching, non-normal distributions and so on. Therefore, alternate specifications like threshold-GARCH (T-GARCH) and exponential-GARCH(E-GARCH) are tested on a series if and when the post-estimation statistics are not strong enough to provide statistically significant evidence that the symmetric GARCH model is sufficient in capturing all the serial correlation in that series.

4.1.3.2 Calculation of Volatility

A measure of the volatility of each individual *mandi* level series is calculated based on the nature of its variance in the following way:

1. In those series where no significant ARCH effects are identified by the LM test, the standard deviation (SD) of log prices (de-seasonalised and de-trended price) is taken as a measure of the volatility.

2. In those series where ARCH effects are identified by the LM test, the results of a suitable $GARCH(p,q)$ model fit give us estimates of the conditional variances (σ_t^2), *i.e.* the one-period ahead forecast variance based on past information. In the long-run, it is possible that there is a finite average to which the variance converges. This average is termed as the unconditional variance (V), which can be obtained from the estimated GARCH parameters:

$$V = \frac{\alpha_0}{1 - \left(1 - \sum_{i=1}^{max(p,q)} (\alpha_i + \beta_i)\right)} \tag{4.7}$$

The square root of V gives us a measure of the long-run-volatility of the series.

If $\sum \beta_i + \sum \alpha_j \geq 1$, the unconditional variance of the model is not defined, and the variance is non-stationary.

4.1.3.3 Post-estimation tests for model diagnostics

In those cases where a GARCH specification is fitted to arrive at a measure of volatility, post-estimation tests (or model diagnostic tests) are conducted to ascertain whether the model has been sufficient in capturing all of the relevant features of the data. If a fitted model captures the underlying time series behaviour adequately, there will be no remaining serial correlation in the residuals, *i.e.* the standardised residuals will be white noise. Brooks (2008) points out that traditional tools of time series analysis (like autocorrelation and partial autocorrelation functions, spectral analysis etc.) are not appropriate for series exhibiting conditional heteroskedasticity. Even if these tools find no evidence of linear structure in the data, it would not necessarily imply that the same observations are independent of one another.

This dissertation, therefore, uses the Portmanteau (Q) test for white noise, which can test for non-linear patterns and is designed to be able to detect many departures from randomness in data. This test is administered on both the standardised residuals (r_s) and the squared standardised residuals (r_s^2) of the model. The standardized residuals are calculated by dividing the residuals (r) of the fit by the predicted conditional variances (v) as follows:

$$r_s = \frac{r}{\sqrt{v}}$$

$$r_s^2 = r_s^2$$

If the null hypothesis cannot be rejected at less than 5 percent level of significance, it is inferred that there is not enough statistical evidence to suggest any remaining serial dependence and that the specified model has a fair fit.

All estimations in this chapter are carried out using the statistical software package Stata (version 15) developed by StataCorp.

4.1.4 Framework for analysis of results

Once the estimation procedures are executed, we obtain estimates of the unconditional volatility of each series individual *mandi* price series (provided that it exists). We are also able to identify those markets where volatility is not stationary so that no long-run average volatility level exists. The obtained results are then analysed to investigate how the nature and magnitude of volatility varies across the commodities. Simple tools like the coefficient of variation (CV) and box-plots are first used to understand the spread of the estimates. The estimates are also compared with that estimated for the international reference prices of each commodity.

The statistical distributions of the estimates for each commodity are examined using: (1) the skewness and kurtosis test (S-K test) described by D'Agostino, Belanger, and D'Agostino (1990) with the empirical correction developed by Royston (1991), and (2) the Kernel density estimate. If these tests find that the distributions of the volatility estimates approximate a normal distribution, we infer that average values are more common than extremes.

Further, to understand whether the variation in the estimates shows commodity specific differences, equality of variance tests are conducted using the Levene's (1960) test statistic, which is robust under non-normality. Like in Chapter 3, the alternative formulations of Levene's test statistic by Brown and Forsythe (1974) are also reported. The results of these tests give insights about how the average magnitude of volatility and its dispersion differs across India.

4.2 Results and Discussion

This section presents and discusses the results of the price volatility analysis conducted on the four commodities under study. Through its findings, this chapter tries to answer some important empirical questions: *How volatile have wholesale prices of some of the most widely-cultivated commodities been across India? Is volatility time-varying? Do large and small price shocks* *show a tendency to cluster together over time? How long does it take for a price shock to die down? Which are the locations and/or commodities where the effect of a price shock takes longer to die down?* Answers to each of these questions can provide crucial inputs to effective policy making.

This section is divided into two broad sub-sections. While the first engages with the nature of volatility, the second discusses the magnitude of volatility. The discussions attempt to provide a general picture of commodity price volatility in addition to highlighting the crop specific features of volatility.

4.2.1 The nature of price volatility

Following the approach outlined in Section 4.1, the nature of price volatility has been examined for a total of 427 *mandi*-level price series. Table 4.1 reports a break-up of the number of series exhibiting the different characteristics of time-varying volatility across the four commodities under study. Both the number of cases and their percentage share in total cases is presented in adjacent columns. The first key finding is that past volatility is an important determinant of future volatility in several domestic wholesale markets of India as the ARCH-LM test results have identified that nearly half of the considered series for each commodity exhibit evidence of time-varying volatility- paddy (40%), wheat (63%), mustard (55%) and groundnut (46%). The specific characteristics are discussed in the sub-sections that follow.

Table 4.1: Cases exhibiting different features of time-varying volatility

Crop	Clustering		Persistence		Explosive Volatility		Total no. of series
	No. of cases	(%)	No. of cases	(%)	No. of cases	(%)	
Paddy	66	40.52	22	13.17	18	10.78	167
Wheat	79	62.7	23	18.25	5	3.97	126
Mustard	38	55.07	6	8.70	3	4.35	69
Groundnut	30	46.15	5	7.69	6	9.23	65
Total	213	49.88	56	13.11	32	7.49	427

Note: The table reports a break-up of the number of series exhibiting the different characteristics of time-varying volatility across the four commodities under study. Both the number of cases and their percentage share in total cases is presented in adjacent columns. The final column reports the total number of series included in this study.

Source: Author's calculations

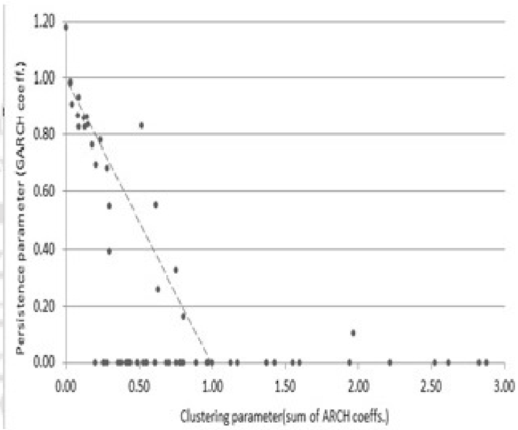
4.2.1.1 Clustering and Persistence

Two important features of a series showing autoregressive conditional heteroscedasticity are clustering and persistence. A high value of the *clustering* parameter coefficient implies that periods of high volatility tend to cluster together as one period's shock has a strong impact on the next period's price realisation. A high *persistence* parameter coefficient indicates that the effect of a shock in one period is carried over to several time-periods in the future and thus shocks take much longer to die down. Table 4.1 elaborates on these features of time-varying volatility estimated for the *mandi*-level series of each commodity.

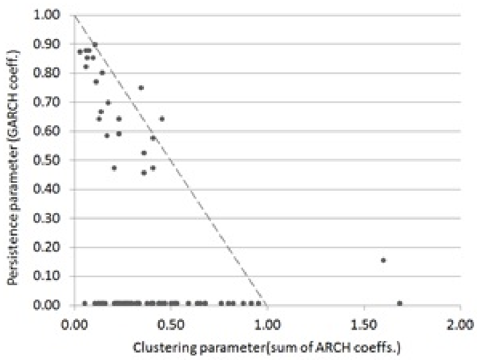
While volatility clustering is observed in 50% of the total cases, evidence of volatility persistence is found in about 13%.

To summarise the results, Figure 4.1 plots the estimated parameters for clustering ($\sum \alpha_j$), and persistence (β_i) for *mandi*-level series of the four commodities.

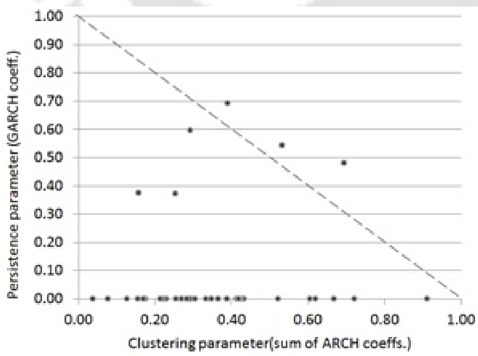
Figure 4.1: Price-volatility clustering and persistence in *mandis* across India (2003-2016)



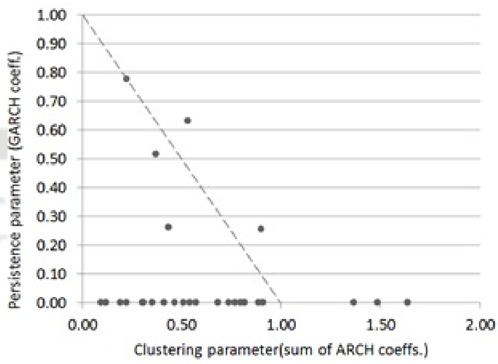
(a) Paddy



(b) Wheat



(c) Mustard



(d) Groundnut

Note: The figure depicts the nature of time-varying volatility in prices of respective *mandis* for each commodity. In the x-axis we plot the clustering parameter (α) and in the

y-axis the persistence parameter (β) estimates of the GARCH Model.

Source: Author's calculations

The stronger the clustering and/or persistence in a series, the longer it takes for the effect of a shock to die down. Figure 4.1 shows that for paddy and wheat, a majority of the dots lie close to the diagonal line joining unity to unity on either axis. These represent strong persistence effects. The points lying to the right of this diagonal line represent cases of explosive volatility.

In a contemporary study on price behaviour in the commodity exchanges of India, Shanmugam and Armah (2017) discuss the marked presence of clustering and persistence in spot and futures prices of several agricultural commodities. Although agricultural markets function under a relatively protectionist policy environment in the country, the nature of time-varying behaviour exhibited by *mandi* price volatility are quite similar to that seen in countries where market forces are allowed to operate with lesser state intervention. For instance, the high persistence parameters estimated for several *mandi*-level series in this dissertation is comparable to findings of Guerrero et al. (2017) for commodity price volatility in markets of Mexico for a similar time period (2006-2011). A developing country from North America, Mexico has actively encouraged the use of market-based mechanisms for more than two decades now.

4.2.1.2 Half-life of Volatility

To understand the persistence of volatility and gauge the extent of its effect, the half-life of volatility is calculated for each series. A half-life represents the time taken by the volatility in a series to come halfway down to its unconditional mean level (Engle & Patton, 2001). Formally, the half-life (τ) of a volatility shock in a series is given by:

$$\tau = \frac{\ln\left(\frac{1}{2}\right)}{\ln\left(\sum(\alpha_j + \beta_i)\right)} \tag{4.8}$$

Here, α and β are the ARCH and GARCH parameter coefficients respectively. The more persistent the volatility, the longer will be the half-life. Thus, as $\sum(\alpha_i + \beta_i)$ approaches unity, the half-life approaches infinity. If $\sum(\alpha_i + \beta_i) > 1$, the volatility is explosive or non-stationary. Thus, no long-run unconditional mean level of volatility exists for such series.

Table 4.2 presents the descriptive statistics for the estimated half-lives of volatility of the *mandi*-level prices of each commodity. Results of S-K tests conducted on these estimates are also reported in the table. The distributions show significant skewness and kurtosis, implying that extreme values are more common than averages.

Table 4.2: Descriptive statistics of the estimated half-lives of volatility across the four commodities

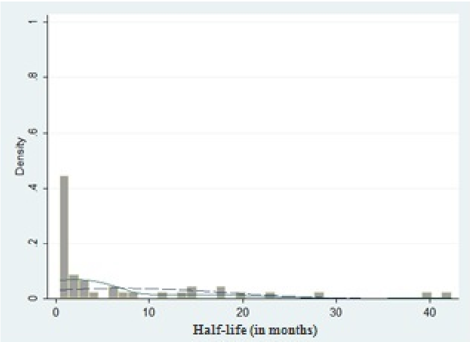
Crop	Avg.	Median	SD	CV	*Sk.*	$p(S)$	*Kr.*	$p(K)$	S-K Test joint $p > \chi^2$
Paddy	7.12	1.85	10.33	1.45	2.00	0.000	6.52	0.002	0.00
Wheat	3.12	0.88	5.33	1.71	3.64	0.000	19.49	0.000	0.00
Mustard	1.08	0.63	1.47	1.36	3.43	0.000	14.14	0.000	0.00
Groundnut	1.96	1.08	1.95	1.00	1.33	0.004	4.06	0.112	0.01

Note: The table reports descriptive statistics for the estimated half-life of volatility for each of the four commodities. 'Half-life' refers to the time (in months) taken by the volatility level in a series to come down to half of what it was. The more persistent the volatility, the longer will be the half-life. Results of S-K tests conducted on the estimates are also reported.

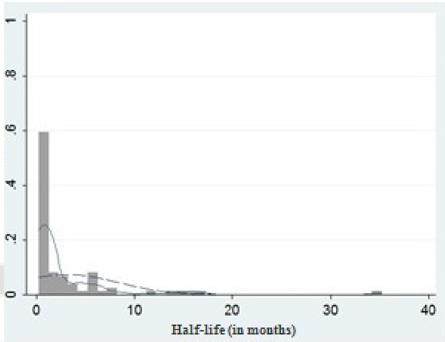
Source: Author's calculations

Next, Figure 4.2 presents histograms of these estimated half-lives. The Kernel density function and the theoretical normal distribution (dashed line) are also plotted for reference.

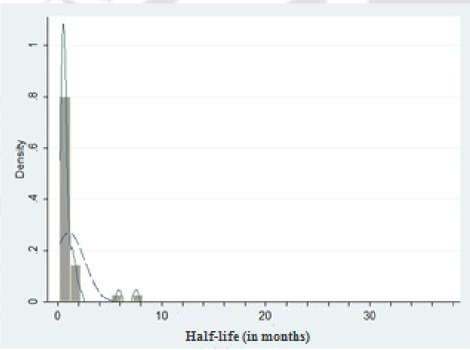
Figure 4.2: Histograms for half-life of price-volatility in *mandi* prices of the four commodities across India (2003-2016)



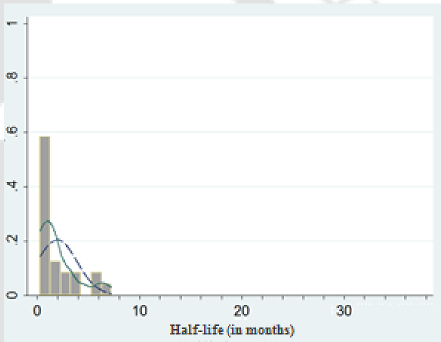
(a) Paddy



(b) Wheat



(c) Mustard



(d) Groundnut

Note: The figure depicts histograms for the estimated half-life of volatility for each of the four commodities. 'Half-life' refers to the time (in months) taken by the volatility level in a series to come down to half of what it was. The more persistent the volatility, the longer will be the half-life. The Kernel density (solid curve) and theoretical normal distribution (dashed curve) plots are also plotted for reference.

Source: Author's calculations

From both the table and the figure, it can be seen that half-life of volatility is relatively shorter for the two oilseeds compared to the foodgrains. The average half-life is the largest for paddy (7 months), followed by wheat (3 months). Although the median values of half-life do not differ much across the four commodities, the histograms in Figure 4.2 clearly show that in almost all cases, the half-life is found to remain between $1-2$ months for mustard and less than 5 months for groundnut. However, the half-lives exceed well beyond a year in several instances for the two foodgrains. This indicates that, price shocks show a tendency to take longer to die down in case of the foodgrains considered here.

Here, we may touch upon the literature examining the role of speculative markets on price stabilization. Recent empirical works on Indian commodity exchanges have highlighted the efficiency of futures trading in price discovery and risk management (Ali and Gupta, 2011; Shanmugam and Armah, 2017). It is interesting to note that while the oilseeds have been more freely traded in the commodity derivatives markets of India since 2003, futures-trading in the two cereals has been relatively restricted and it has faced several bans, especially since 2007. Thus, it may the case that the futures trading in the oilseeds could be playing a stabilising role, leading to shorter half-lives of volatility. For the cereals, contemporary studies do not find the futures market to be efficient for either wheat or rice (Ali & Gupta, 2011; Ghosh and Chakravarty, 2010). The possible reasons listed by these studies include market manipulation by large traders, policy intervention like MSP and procurement as well as the fact that futures commodity exchanges are less-developed. These studies, therefore, advocate the developing the derivatives market for price stabilisation. However, works like **?** caution against drawing generalised inferences on this aspect. In their study of four oils and oilseeds (mentha oil, soya oil, palm oil and mustard seed), they find that, except in the case of mustard seed, there are significant destabilisation impact of futures trading on prices of the other three commodities. While discussing the exceptional case of mustard, the possible explanations that the authors put forward include the existence of price support for mustard (MSP) and India's near self-sufficiency in mustard seed production (which keeps mustard seed prices relatively independent of international price movements). As the academic literature on this subject is inconclusive, this dissertation refrains from making any comment on the role of futures trading in lowering persistence of volatility.

4.2.1.3 Explosive Volatility

As has been observed in table 4.1, there are about 7.5% cases which exhibit explosive volatility. In these cases, the volatility level does not show any evidence of convergence over time. In figure 4.1, these cases have been represented by the dots lying to the right of the diagonal line joining unity to unity. The individual cases are specified in Table 4.3. In each of these price series, the feedback effect of a price shock increases in future periods. Thus, the variance does not converge to any finite long-term mean variance and no estimate of an unconditional volatility exists.

Table 4.3: Cases of Explosive Volatility in *mandi* prices of the four commodities

Region	State	Commodity	*mandi*	n
(1)	(2)	(3)	(4)	(5)
North				
(4)	NCT of Delhi	Paddy	Narela (Basumati)	1
	Uttar Pradesh	Paddy	Faizabad	1
	Uttrakhand	Paddy	Kashipur, Rudrapur, Sitarganj	2
South				
(17)	Andhra Pradesh	Paddy	Banaganapalli, Badvel, Dharmavaram, Nagaram, Naidupet, Ponnur, Thottambedum, Vijayanagaram, Vuyyur (BPT)	9
		Groundnut	Dharmavaram, Kalyandurg, Madakasira, Pulivendala	4
	Karnataka	Paddy	Davangere (paddy medium)	1
		Wheat	Bhadravathi	1
		Mustard	Bangalore	1
	Tamil Nadu	Groundnut	Ulundurpettai	1
East				
(3)	Chhattisgarh	Mustard	Bhatapara	1
	Jharkhand	Wheat	Deoghar	1
	Odisha	Paddy	Bhadrak	1
West				
(4)	Gujarat	Mustard	Unjha	1
		Groundnut	Jamnagar	1
	Haryana	Wheat	Shahabad	1
	Maharashtra	Paddy	Alibagh	1
Central				
(3)	Madhya Pradesh	Paddy	Bichhiya	1
		Wheat	Harda, Jabalpur	2
Total				32

Note: The table reports, for each region, the names of the *mandis* for which the price series of a particular commodity is found to exhibit explosive volatility. The figure in parenthesis in column (1) represents the total number of such series in that particular region. In cases where there are more than one series of the same commodity from a particular *mandi*, the specific variety which is found to exhibit explosive volatility is reported in parenthesis beside the name of the *mandi*. The n in the final column represents the number of explosive volatility exhibiting series from the respective state.

Source: Author's calculations

Among commodities, paddy reports the highest number of such cases (18), followed by groundnut (6), wheat (5) and mustard (3). Most of the cases of explosive volatility are observed in the Southern region of India with the state of Andhra Pradesh alone reporting 9 such cases. However, instances of explosive volatility are observed in all the geographical regions of India. In the North, all the cases of explosive volatility (among the series under study) are found to be confined to the commodity paddy only.

The above findings can be related to the emerging literature on trending volatility. Some notable works find that commodity prices have shown increasing volatility since the food crisis beginning in 2005-06. These works include Minot (2014) for grain prices and Gilbert and Morgan (2010) for rice and groundnut oil prices. Although the studies do not find strong evidence to suggest the presence of long-term trends in volatility, they nevertheless confirm that the recent years have seen increased volatility. Gilbert and Morgan (2010) specifically highlight that the volatility in rice prices has shown a greater tendency to increase than is suggested by historical experience. This is in line with the findings of this dissertation.

4.2.2 The degree of price volatility

Now we come to findings regarding the degree of price volatility, *i.e. how volatile have the prices of major agricultural commodities been in domestic wholesale markets of India?* Table 4.4 presents the arithmetic mean and coefficient of variation (CV) of the estimates from all the *mandi*-level series included in the study. The estimates for the respective international reference prices are also presented for comparison.

Table 4.4: Price volatility estimates for some major agricultural commodities in India (2003-2016)

	Paddy	Wheat	Mustard*	Groundnut	All Crops
Average volatility	10.79	6.12	7.94	12.44	9.13
(CV)	(55)	(42)	(42)	(52)	-
Intl. reference price	11.10	17.94	-	11.06	-

Note: The table reports the arithmetic mean of the volatility estimates obtained from the domestic wholesale markets included in the study along with the estimates of volatility for their respective international reference prices. The figures in the parenthesis represent the coefficient of variation (CV) of the estimates.
*No international reference price series exists for mustard and, therefore, there is no comparable estimate for volatility.

Source: Author's calculations

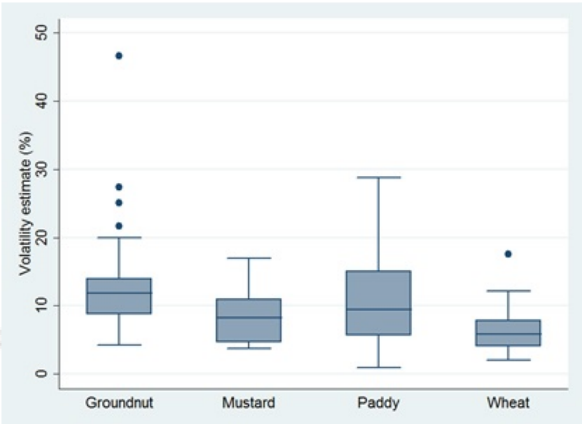
The table shows that in case of two commodities (paddy and groundnut), the domestic market estimates are similar to that observed in their respective international prices. However, while international wheat prices have been highly volatile during the study period, the average of the volatility estimates for domestic wheat prices is much lower in comparison.

Here, it is important to note that for those series that exhibit evidence of explosive volatility, no unconditional volatility estimate could be estimated due to absence of convergence. Hence, the descriptive statistics reported herein do not reflect these cases of explosive volatility (32 in total).

The CV values reported in Table 4.4 show that the estimates for each crop show substantial dispersion. A quick look at the individual estimates show that instances of high volatility are not confined to any particular geographical region. To understand inter-crop and intra-crop differences in the level of price volatility, a series of statistical tools is applied to the obtained estimates. These tools are outlined below.

First, Figure 4.3 presents the distribution of the volatility estimates across each commodity in the form of box plots. Then, to formally investigate whether the spread of the estimates differs across commodity, Levene's Equality of Variance tests is conducted. The result of this test are presented in Table 4.5, which reports Levene's robust test statistic (W_0), Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the groups (commodities).

Figure 4.3: Distribution of volatility estimates across major agricultural commodities (2003-2016)



Note: The figure presents a box-plot of the volatility estimates for *mandi*-level prices categorized by commodity. The dots lying outside the plots represent outliers.

Source: Author's calculations

Table 4.5: Test results for Equality of Variance in volatility estimates across commodities

	W_0	W_{50}	W_{10}	Degrees of freedom $(k-1, n-k)$
(1)	(2)	(3)	(4)	(5)
Test statistic	22.72	18.74	20.94	df (3, 391)
p-value	(0.00)	(0.00)	(0.00)	

Note: The table reports the Levene's robust test statistic (W_0), Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the groups (commodities). The figures in parenthesis are the respective p-values. The final column reports the respective degrees of freedom ($k-1$, $n-k$), where k is the number of groups and n is the number of observations in the group.

Source: Author's calculations

The box-plots in Figure 4.3 show that the median volatility differs from crop to crop. It is the highest for groundnut and lowest for wheat. The statistical tests conducted for equality of variance show that even the spread of the estimated volatility levels differs significantly across the studied commodities (Table 4.5). Wheat has the lowest spread, while paddy has the highest. There is also a marked presence of outliers (on the higher end) in case of groundnut. In addition, almost all the commodities have instances of explosive volatility, with paddy reporting the highest number of such cases.

The two sets of tests conducted on the statistical distribution of the estimates find significant evidence against the null hypothesis that the estimates follow a normal distribution (which is rejected at less than 5 percent level of significance for all the four commodities). Hence, we infer that extreme values are quite common and that the estimates do not show a tendency to cluster around their respective average values.

Next, to better understand how the estimated volatility levels are statistically distributed, skewness-kurtosis (S-K) tests are conducted for each commodity separately as well as for all the commodities taken together. The results of these tests are presented in Table 4.6. Additionally, to give a visual representation of their distribution, Figure 4.4 plots their respective Kernel density estimates along with the theoretical normal distribution graphs. Here too, the analysis does not reflect the cases of explosive volatility.

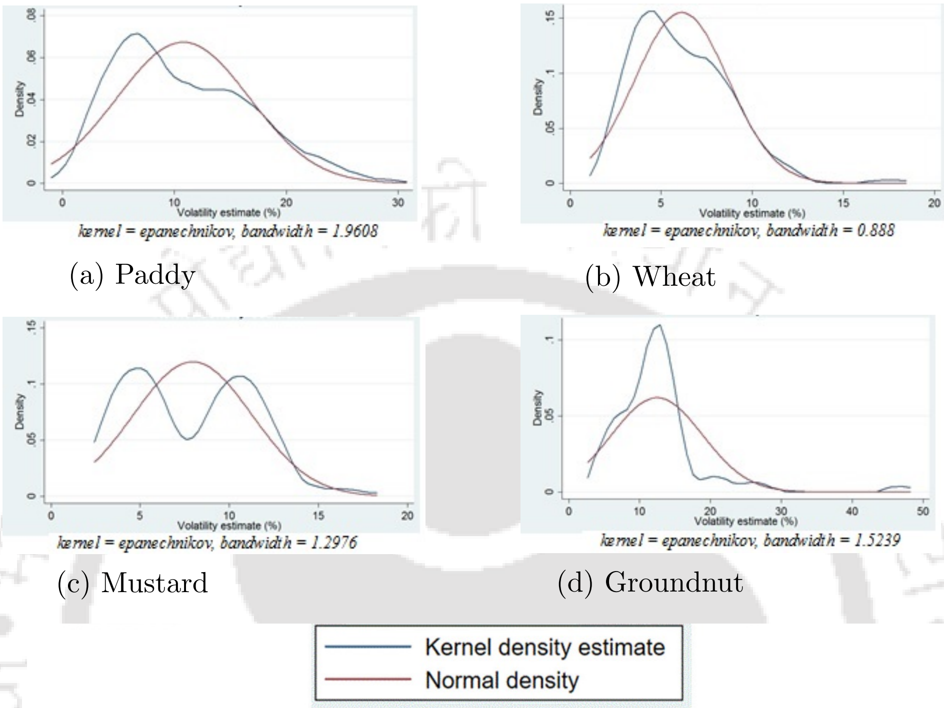
Table 4.6: Skewness/Kurtosis tests for normality on volatility estimates

Variable	n	Pr (Skewness)	Pr (Kurtosis)	joint Adjusted chi^2	joint Prob>chi^2
(1)	(2)	(3)	(4)	(5)	(6)
Paddy	149	0.002	0.458	8.97	0.0113
Wheat	121	0.000	0.003	20.20	0.0000
Mustard	66	0.247	0.013	6.87	0.0321
Groundnut	59	0.000	0.000	42.93	0.0000
All crops	395	0.000	0.00	.	0.0000

Note: The table presents results of the skewness and kurtosis test on the estimates of volatility obtained from *mandi*-level prices across India. Column (1) specifies the commodity whose estimates are tested and Column (2) reports the number (n) of observations (*i.e.* volatility estimates) for each crop. This excludes a total of 32 price-series for which an unconditional volatility estimate could not be arrived at since the GARCH model estimation finds evidence in favour of explosive volatility in them. Pr in the columns (3) and (4) represent the probability of falsely rejecting the null hypothesis of zero skewness and kurtosis respectively. Columns (5) and (6) respectively report the adjusted Chi-square statistic and its associated p-value. A dot (.) in column (5) represents as a very large number, which indicates that the data are, most certainly, not normal.

Source: Author's calculations

Figure 4.4: Kernel density function for the volatility estimates across the studied commodities



(a) Paddy (b) Wheat

(c) Mustard (d) Groundnut

The S-K test results in Table 4.6 show that volatility estimates for two of the commodities (wheat and groundnut) show both significant skewness and kurtosis in their statistical distributions. While the estimates for paddy report significant skewness, those for mustard report significant kurtosis. The exact nature of how the distribution of estimates obtained for each commodity deviates from the normal distribution (ND) becomes clearer from their Kernel-density plots presented in Figure 4.4. The deviations from the ND are more pronounced in case of the two oilseeds (mustard and groundnut).

Since the examination of estimates reveals wide commodity specific differences, this dissertation moves on to engage in a crop-wise discussion of the findings in the following paragraphs.

4.2.2.1 Paddy

Out of the 167 *mandi* level series examined in this dissertation, a total of 66 cases (*i.e.* 40.5%) shows evidence of time varying volatility. The median of the *mandi*-level volatility estimates is around 9.5%, which is only slightly lesser than the volatility calculated for the international price of rice (11%). However, the estimates have a large spread, which ranges from as low as 1% to as high as 29%. Furthermore, the results have identified as many as 18 cases of explosive volatility. The distribution of the estimates is positively skewed with a value of 0.64, which is found to be statistically significant at less than 5% level by the S-K test. Furthermore, the right tail is not just longer, but it is also slightly fatter relative to the normal distribution, while the left tail is much shorter and thinner. This implies that although most of the estimates fall towards the left of the mean, several notable extreme values are observed on the right of the modal value of the estimates. Put simply, this means that although the price volatility observed in a large number of the studied *mandis* are lower than the average of the total, there also exist certain *mandis* where price volatility is considerable higher than this average. Several *mandi*-level estimates for paddy are also comparable to those of Minot (2014) for rice in Sub-Saharan Africa, which is regarded as a high price volatility region.

4.2.2.2 Wheat

Out of the 126 *mandi* level series examined in this dissertation, a total of 79 cases (*i.e.* 63%) shows evidence of time varying volatility. The median of the estimates is 5.8%, which is much below the volatility calculated for the international price of wheat (nearly 19%). The spread of the estimates around their median value is also relatively smaller compared to that of the other three crops and most of the estimates lie between 2% and 12%. However, there are some significant outliers, which include five cases of explosive volatility. The distribution of the estimates is positively skewed with a value of 1.02, which is found to be significant at less than 5% level by the S-K test. Here too the right tail is slightly fatter relative to the normal distribution, while the left tail is much shorter and thinner. Thus, the presence of extreme values is more commonly observed on the right of the modal value of the estimates. The distribution of the estimates also shows positive kurtosis of 4.9, which is statistically significant at less than 5% level.

4.2.2.3 Mustard

Out of the 69 *mandi* level series examined in this dissertation, a total of 38 cases (*i.e.* 55%) shows evidence of time varying volatility. The estimates have a median value of around 8% and they are spread across a range of 4% to 17%. In addition, three cases are identified as showing explosive volatility. An interesting feature of the estimates for mustard is that, unlike the other commodities under study, the distribution of the estimates is bi-modal. The two modal values lie around 5% and 11% respectively, with the former having a relatively taller peak compared to the latter. In the next chapter, which is devoted to examining how price-movements vary across locations, this dissertation investigates whether the two modes observed here can be attributed to spatial sources.

4.2.2.4 Groundnut

Out of the 65 *mandi* level series examined in this dissertation, a total of 30 cases (*i.e.* 46%) shows evidence of time varying volatility. The median of the estimates is nearly 12%, which is in fact slightly higher than the volatility calculated for the international price of groundnuts (11%). Most of the estimates range between 4% and 20%. However, there are quite a few significant outliers. In addition, there are six cases for which the nature of volatility is identified as explosive. A notable feature of the distribution of the volatility estimates for groundnut is their kurtosis, which has a value of 15.2 significant at less than 5% level. Thus, the concentration of the estimates immediately around the modal value is substantially high. The distribution is also positively skewed with a value of 2.83, which is found to be significant at less than 5% level by the S-K test. The right tail is pretty long and shows a small bump towards the end of tail. This may be explained by the notable presence of outliers on the higher end. Further investigations on this aspect are conducted in the next chapter.

The findings highlight that the stability (or instability) of prices over time can be very different across individual markets for all the studied commodities. In a contemporary work, Ramadas et al. (2014) argue that domestic prices of commodities like rice and wheat show relatively lower volatility than in international markets. Bathla (2012) too finds that domestic wheat prices exhibit lower volatility at a time when the international wheat prices have been highly volatile. She attributes the relative stability in wheat prices to policy measures like price support, procurement and trade regulation. However, these studies are based on aggregated all-India data. The findings of this dissertation show that although wheat prices, on an average, show relatively lower volatility, the same cannot be said for all regions of the country. Additionally, the rest of the commodities show volatility levels that are at par with that of international prices. These findings are in line with the findings by Sekhar (2004) and Tripathi (2014) covering earlier periods for commodity prices in India. Both the works find that intra-year volatility in domestic markets has been as high as in the international markets, if not higher.

The results reported so far show that volatility estimates for individual price series differ quite a lot in their magnitudes. In addition to inter-crop differences, there is substantial intra-crop variation in volatility levels as well. The issue of location in price volatility is examined in the next chapter, which goes on to explore how the estimated volatility levels vary across different locations of the country.

4.3 Conclusion

The aim of the present chapter has been to understand the unpredictability (or volatile fluctuations) in the wholesale price of four major agricultural commodities across the country. It has examined both the nature and the degree of volatility in *mandi*-level prices and made efforts to present a disaggregated picture. This section presents the inferences and conclusions that can be drawn from the reported findings.

The study finds that both the nature and magnitude of price volatility varies widely across individual markets. In addition, time-varying volatility is found to be common across India as around half of the total cases studied show statistically significant evidence of autoregressive conditional heteroscedasticity. In these markets, the effect of a price shock in one period is carried over to the future period(s). Moreover, in a sizable number of markets, any increase in the volatility level is found to persist for several months before returning to its long-term average level. The presence of such volatility clustering and persistence implies that past volatility is an important determinant of future volatility in several wholesale markets of India. Such a finding strengthens the inferences made by Conforti (2004) that, despite being deeply regulated by public intervention, agricultural prices tend to show considerable degree of linkage with international price movements in countries like India, Pakistan, Egypt and Indonesia.

On the research question related to the magnitude of volatility, the findings show that the estimates of volatility differ widely across individual markets. Furthermore, while the averages of the estimated figures are quite close to international levels for two commodities- paddy (a foodgrain) and groundnut (an oilseed), several individual markets exhibit volatility levels that are much higher than this. Another finding of this dissertation is that volatility shows a tendency to be non-stationary (or explosive) in a number of cases. In these price series, an increase (or decrease) in volatility is sustained over time and the volatility level never returns to any long-run average. The highest number of cases of explosive volatility is found to be exhibited by the commodity paddy. As paddy is very widely cultivated and marketed across India (see Appendix A.1), returns from paddy affects the livelihood of a large section of cultivators. High volatility in these returns may not be sustainable for the smaller farmers who form a major proportion of India's cultivators (Government of India, 2015).

Among the four commodities being studied in this dissertation, wheat reports relatively lower price volatility as well as much lower dispersion in the individual estimates. Here, it needs to be noted that wheat is more widely cultivated in states of the Western and Northern region of India, which have relatively greater proportions of larger operational landholdings. As per the Agricultural census 2010-11, within the Northern and Western regions, the proportion of 'large' operational holdings (*i.e.* greater than 10 ha in size) is the highest in Punjab (6.62%), followed by Rajasthan (5.86%) and Haryana (2.83%) (Government of India, 2015). Historically, these regions have also performed well in terms of agricultural productivity and states like Punjab and Haryana have seen the emergence of a class of commercial farmers. With relatively stronger resource bases, such farmers may be in a position to control large portions of the supply in wholesale markets and thus smoothen price shocks through optimal trading strategies. The seminal works of Kalecki (1971) and Mitra (1977) provide theoretical arguments in line with such possibilities.

Coming to paddy, it is much more widely cultivated across the country and is the staple crop in the Eastern and Southern regions. While the policy measures existing for paddy (price support, procurement etc.) are similar to those for wheat, this dissertation finds that such policies are not able to insulate paddy prices from exhibiting volatility levels that are as high as seen in the international market. This finding too reminds us of Mitra's (1977) relative analysis of the administered prices of wheat and paddy, which are found to favour the former.

Taken together, the results reported in this chapter show that volatility estimates for individual price series differ quite a lot in their magnitudes. Therefore, a detailed examination of these differences and their implications is taken up in the next chapter, which goes on to explore how the estimated volatility levels vary across different locations of India.

5 | SPATIAL VARIATION IN PRICE VOLATILITY

5.1 Introduction

India is a vast country marked by geographical, cultural and institutional diversity. When it comes to agriculture, each corner of the country differs in terms of aspects like production, marketing, state policies and so on. Results based on aggregated data are unable to capture this diversity. As there is no 'one general picture', therefore, averages can give only a limited idea of the ground level pictures. In fact, the results and discussions presented in the two preceding chapters bring this diversity to light by showing that both the nature and degree of price movements vary widely across individual markets of the country. Now, the risk environment for farmers in India differs across the country because of the vast diversity of climate, growing conditions, market structures and so on (Ramaswami et al., 2003). The present chapter, therefore, goes ahead to investigate the spatial diversity in the unpredictability (volatility) of *mandi* prices in India in the light of certain factors that influence the risk-bearing capacity of farmer-households.

Risk and uncertainty can have an impact not just the production decisions of farm households, but also on their consumption decisions (Newbery and Stiglitz, 1981;Morduch, 1995). Households that have limited economic means are expected to have lower capacity to bear risks. When farmers make decisions on whether to invest in any agricultural enterprise, the household's risk bearing ability is their last critical line of defence in the face of any adversity (Kahlon and Singh, 1980). Farm households often cope using mechanisms such as cutting down on consumption, asset depletion or dis-saving (Rosenzweig and Stark, 1989; Deaton, 1992; Rosenzweig and Wolpin, 1993). Such mechanisms will, however, severely affect the welfare of low income and resource-poor households who are characterised by a low net worth as well as low levels of saving and consumption. As has been repeatedly pointed out in this dissertation, the majority of India's cultivators are resource poor, which constrains their ability to economically sustain price crashes. In addition, land ownership distribution is uneven across India, and the average landholding size differs from state to state (Government of India, 2015). As farmer-households in a socio-economically backward locations show a high degree of risk-aversion (Senapati, 2020), price volatility can have more adverse consequences for welfare in certain locations relative to others. Given this backdrop, the present chapter is devoted to a detailed discussion of such spatial differences. There are two broad questions that this chapter addresses:

(1) *How do the magnitudes of irregular price variation differ across the country?*

(2) *Are volatility levels high in locations having large proportions of resource-poor farmers?*

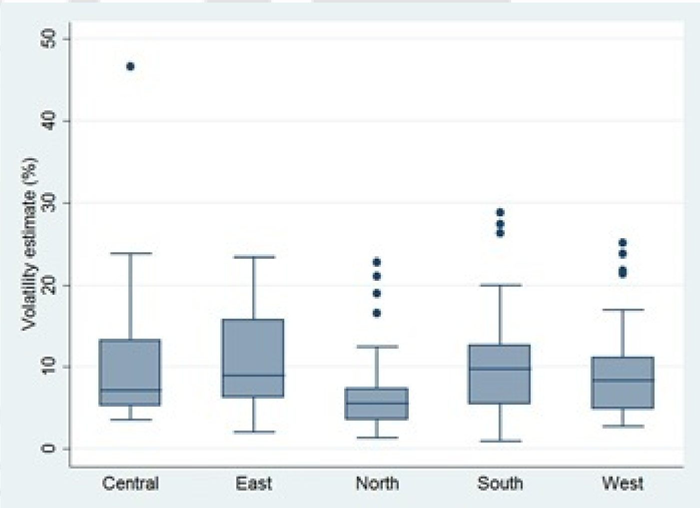
The chapter is divided into three sections. The first section (*i.e.* the current one) is introductory. It has laid out the motivation behind the analysis conducted in this chapter and has also presented the research questions. The second section discusses the spatial variation in the volatility estimates across the various regions (and states) of the country. The third section investigates the question: *'who faces how much volatility?'*. It does this by examining the dispersion in the estimated volatility levels in relation to various socio-economic indicators of farmers' risk-bearing capacity. Finally, the fourth section presents a summary of the findings along with the inferences and conclusions drawn from them.

5.2 Spatial variation in volatility levels

This section begins its analysis by examining price volatility across the major regions of India. There are six broad geographical regions in the country, *viz.* North, South, Central, West, East and Northeast (NE). As *mandis* from only one state (Assam) belonging to the NE region has qualified for analysis (due to very low reporting from the rest of the states), Assam is clubbed under the Eastern region for the purpose of this study.

To give a crude general picture of the spatial variation in volatility levels, Figure 5.1 illustrates the spread of the estimates across the five geographical regions. In the figure, a box-plot of the volatility estimates obtained for *mandi*-level prices of all the four studied commodities is presented. These estimates are categorized by region. Here, the estimates of all the four crops are pooled together. Crop specific-differences are taken up for study in subsequent sections. The horizontal bars across the boxes in Figure 5.1 represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Figure 5.1: Distribution of volatility estimates across regions (2003-2016)



Note: The figure presents a box-plot of the volatility estimates for *mandi*-level prices of all the four crops categorized by region. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

A visual inspection of the box plots in Figure 5.1 brings out some interesting observations. Although the median of the estimates differs for each region, the spread of the estimates around their respective medians also visibly differs across them. While the Northern and Western regions show relatively smaller spreads, the Eastern, Central and Southern regions show much larger spreads. To formally ascertain whether these apparent differences in the intra-regional dispersions are significant, Levene's equality of variance test is conducted. The results of this test are reported in Table 5.1, which reports Levene's robust test statistic (W_0) along with Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the groups (regions).

Table 5.1: Test results for Equality of Variance in volatility estimates across regions

	W_0	W_{50}	W_{10}	Degrees of freedom $(k-1, n-k)$
(1)	(2)	(3)	(4)	(5)
Test statistic	5.75	3.33	4.44	df (4, 390)
p-value	(0.000)	(0.011)	(0.002)	

Note: The table reports the Levene's robust test statistic (W_0), Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the groups (regions). The figures in parenthesis are the respective p-values. The final column reports the respective degrees of freedom ($k-1$, $n-k$), where k is the number of groups and n is the number of observations in the group.

Source: Author's calculations

The table shows that we can reject the null hypothesis of equal variances across groups (regions) at much less than 5% level of significance. Thus, the differences in variance of volatility levels across regions are highly significant. Hence, at this juncture, we are not in a position to interpret the apparent differences in median (and mean) volatility levels seen across the regions. For instance, although the Northern region reports the lowest median (and mean) volatility level with relatively low dispersion, it is marked by the presence of certain outliers. A more formal investigation of the inter-regional differences in the estimated volatility levels is taken up in the next sub-section.

In what follows, the inter- and intra-state variations in volatility levels are examined closely. The discussion is aimed at shedding light on the geographical distribution of volatility levels. First, Table 5.2 provides the state-wise break-up of the volatility estimates obtained for the four commodities. For each state, the arithmetic average and coefficient of variation (CV) of the volatility estimates obtained for the four commodities under study from their respective *mandi*-level price series are presented. Kindly note that this table excludes a total of 32 price-series for which an unconditional volatility estimate could not be arrived at since the GARCH model estimation finds evidence in favour of explosive volatility in them.

Table 5.2: Volatility in *mandi*-prices of the studied commodities: Average of the estimates for different states of India (2003-2016)

State	Paddy			Wheat			Mustard			Groundnut		
	Volatility	CV	*n*	Volatility	CV	*n*	Volatility	CV	*n*	Volatility	CV	*n*
Andhra Pradesh	8.74	69.44	27	7.35	-	1	-	-	-	9.05	37.13	12
Assam	16.46	33.24	4	-	-	-	11.28	1.60	2	-	-	-
Chhattisgarh	7.02	46.90	11	4.87	8.18	2	12.83	-	1	-	-	-
Gujarat	7.79	30.91	10	7.46	40.82	14	7.81	41.37	11	12.87	39.33	12
Haryana	-	-	-	6.72	-	1	9.69	18.10	7	-	-	-
Jharkhand	12.24	46.65	7	6.79	54.98	13	9.79	-	1	-	-	-
Karnataka	6.96	47.01	10	5.78	36.24	9	-	-	-	12.88	24.14	9
Madhya Pradesh	16.94	39.67	6	6.73	35.85	13	5.09	25.65	2	24.28	63.27	4
Maharashtra	11.07	25.78	8	6.54	40.66	17	12.34	34.91	5	7.54	40.28	3
NCT of Delhi	18.79	23.98	4	4.36	48.64	2	8.19	47.02	2	-	-	-
Odisha	15.89	27.39	9	-	-	-	-	-	-	-	-	-
Puducherry	10.79	28.61	6	-	-	-	-	-	-	9.69	-	1
Punjab	-	-	6	5.49	-	1	-	-	-	-	-	-
Rajasthan	22.31	5.90	3	6.13	40.13	15	6.61	45.43	21	14.20	6.94	4
Tamil Nadu	14.68	33.07	14	-	-	-	-	-	-	13.30	44.44	10
Telangana	6.39	42.13	-	-	-	-	-	-	-	11.51	3.66	2
Uttar Pradesh	5.52	38.19	15	4.59	36.02	26	6.68	44.76	4	6.43	4.40	2
Uttrakhand	12.54	45.26	2	6.34	-	1	-	-	-	-	-	-
West Bengal	14.73	26.43	7	6.98	25.36	6	7.14	38.18	10	-	-	-
International Reference Price	**11.10**			**17.94**			-			**11.06**		

Note: The table reports, for each state, the arithmetic average and coefficient of variation (CV) of the volatility estimates obtained from their respective *mandi*-level price series categorized by the four commodities under study. The number of series (n) included from each state are also reported respectively for each commodity.

Source: Author's calculations

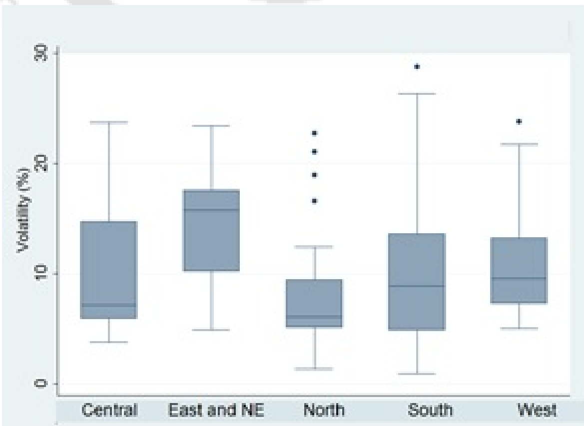
As expected, there is a lot of inter-state as well as intra-state variation in the estimates. Given the wide dispersions, findings for each commodity are examined separately in relation to the spatial variation observed in their *mandi*-level volatility estimates.

5.2.1 Paddy

The states differ substantially in the average volatility estimates as reported in Table 5.2. States reporting some of the highest averages (exceeding that of the international reference price) include Rajasthan (22.3%), NCT of Delhi (19%), Madhya Pradesh (17%), Assam (16.5%), Odisha (16%), West Bengal, Tamil Nadu (15% each), Uttarakhand (12.5%) and Jharkhand (12%). Since these range from almost all five geographical regions, we can conclude that instances of high volatility for paddy are not confined to any specific region. The intra-state dispersion of the estimates is quite noticeable from their respective CVs.

To give a visual picture, figures 5.2 and 5.3 present box plots of the spread of the estimates across regions and states respectively.

Figure 5.2: Distribution of volatility estimates across regions (2003-2016): Paddy



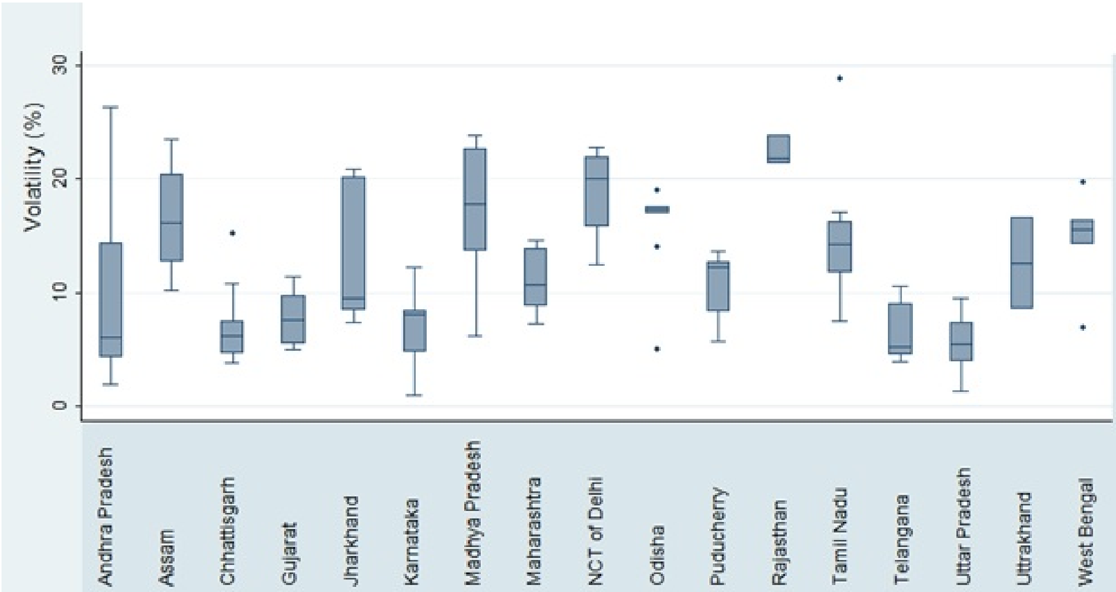
Note: The figure presents box-plots of the volatility estimates for *mandi*-level prices of the commodity Paddy categorized by region. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

Figure 5.2 presents box-plots of the volatility estimates for *mandi*-level prices of the commodity 'Paddy' categorized by region. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any. Averages and medians of the different regions are comparable as Levene's test indicates that the inter-regional dispersions of the estimates do not show any statistically significant difference at less than 5% level of significance (see Appendix A.4). Among the regions, while the Northern region reports the lowest average and median volatility, the Eastern region reports the highest. The outliers observed in the Northern region belong mostly to the NCT of Delhi. The region also reports a number of explosive volatility cases (as already presented in Table 4.3). The Southern region shows the widest apparent dispersion in the estimates. The outlier observed in this region belongs to Tamil Nadu. In addition, there are 10 instances of explosive volatility in the region (Table 4.3).

To give a state-level disaggregated picture, Figure 5.3 presents the distribution of volatility estimates for paddy across the individual states.

Figure 5.3: Distribution of volatility estimates across states (2003-2016): Paddy



Note: The figure presents box-plots of the volatility estimates for *mandi*-level prices of the commodity Paddy categorized by states. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

The figure shows that among states, Rajasthan reports the highest average volatility with quite low dispersion (5%). Uttar Pradesh, Telangana, Chhattisgarh and Gujarat report some of the lowest average and median volatility levels with considerably lower dispersion. However, except for Telangana, each of these states includes at least one *mandi* level series whose volatility estimate exceeds that of the international reference price. States that show the widest dispersion of estimates within them are: Andhra Pradesh (the estimates range from 2% to 26%; in addition there are 9 instances of explosive volatility), Madhya Pradesh ($6-24\%$; 1 instance of explosive volatility), Jharkhand ($7-21\%$), Uttrakhand ($8-16\%$; 3 instances of explosive volatility) and

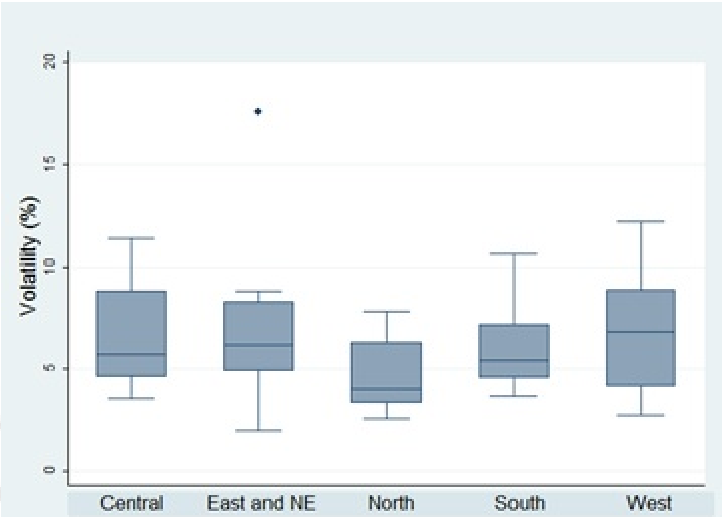
Assam ($10 - 23\%$).

The finding that, among all the five regions, the average volatility estimates for paddy is the highest for *mandis* belonging to states of the Eastern region raises great concerns. As per the Agricultural census of 2010-11, the proportions of operational landholdings belonging to 'small and marginal holding' category in states of the Eastern region are very high: West Bengal- 96%, Odisha- 92%, Assam-86% and Jharkhand-84% (Government of India, 2015). Further, the commodity paddy is very widely cultivated in this region and it accounts for the largest share of area under paddy cultivation in India (*i.e.* 38% of the total area under paddy). In addition, procurement of paddy is very low in the East, which means that farmers in this region are not insulated from sharp price drops beyond the stipulated floor price (MSP). Consequently, for a very large section of cultivators in this region, the instability in market price will not only affect their returns from agriculture but also impacts their livelihood sustainability.

5.2.2 Wheat

Among the four commodities considered in this dissertation, wheat shows relatively lower variation in the estimates of volatility among the major producing states (Table 5.2). The spread of the estimates within the respective regions and states are presented in Figures 5.4 and 5.5 through box plots. These figures give a disaggregated picture of the dispersion of volatility levels across location.

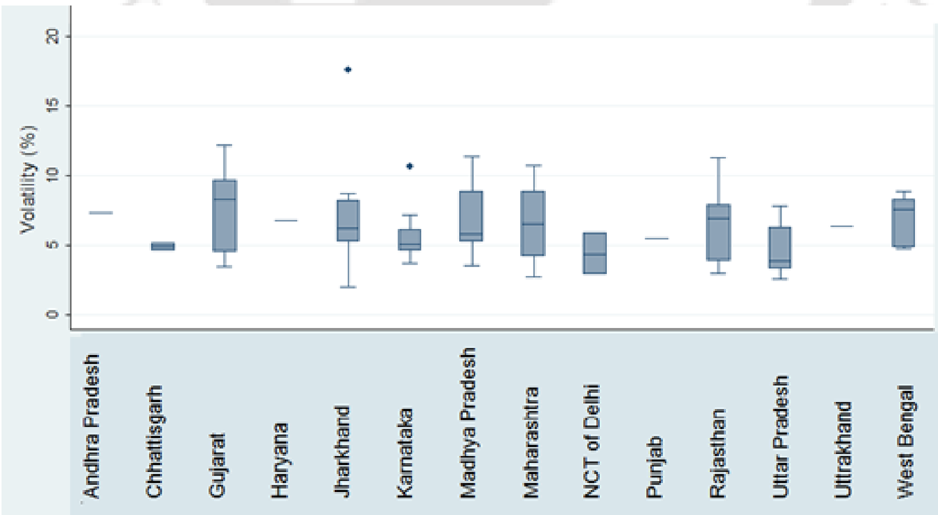
Figure 5.4: Distribution of volatility estimates across regions (2003-2016): Wheat



Note: The figure presents box-plots of the volatility estimates for *mandi*-level prices of the commodity Wheat categorized by region. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

Figure 5.5: Distribution of volatility estimates across states (2003-2016): Wheat



Note: The figure presents box-plots of the volatility estimates for *mandi*-level prices of the commodity Wheat categorized by states. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

In both the figures, the horizontal bars across the boxes represent the medians of each distribution. The results of Levene's test (Appendix A.4.1) for eqaulity of variance across the different regions indicate that the inter-regional dispersions of these estimates do not show any statistically significant difference (at less than 5% level of significance). Therefore, the averages and medians are comparable. While the Western and Eastern regions report the highest average and median volatilities, the Northern region reports the lowest.

The averages of the estimates for all states range from 4% to 7% and are much below the estimate for the international reference price of wheat (17%). However, there are some noticeable intra-state differences. It is mostly the states belonging to Eastern, Central and Western regions, which report some of the highest *mandi* level volatility estimates including five instances of explosive volatility. The prominent cases from East India include Gumla *mandi* (17.5%) and Deoghar *mandi* (explosive) of Jharkhand. Those from Central India, belong to Madhya Pradesh- Akodia (11.5%), Harda (explosive) and Jabalpur (explosive) *mandis*. Again, instances of markedly high volatility from the Western region of India belong to the state of Gujarat and include the *mandis* Amreli (12%) and Dhrol (11.5%). Apart from these, instances of explosive volatility are found in Karnataka in the South and Haryana in the

North.

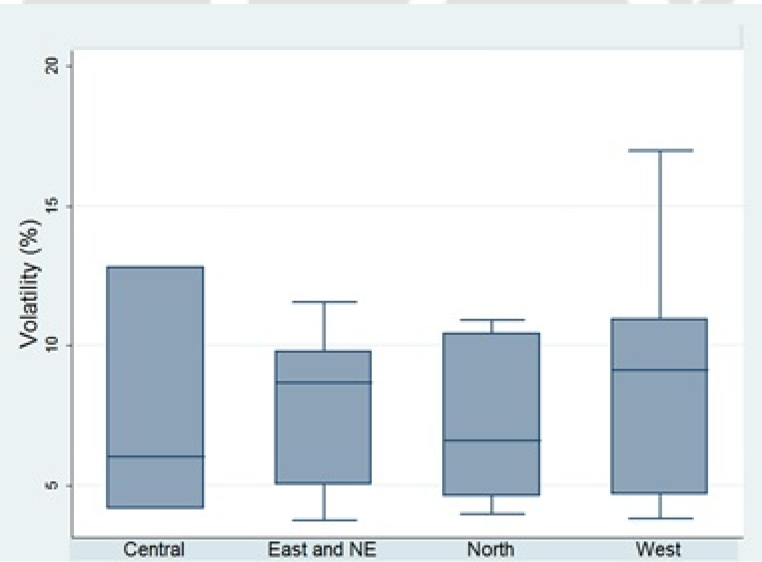
Among the rest of the states, the lowest intra-state variation in volatility estimates is seen in Chhattisgarh, which also has one of the lowest average volatility. States that show the widest dispersion of estimates within them are: Gujarat (the estimates range from 3.5% to 12%, in addition there are 9 instances of explosive volatility), Jharkhand ($2-17\%$; 1 instance of explosive volatility), Madhya Pradesh ($3-11\%$; 2 instances of explosive volatility), Rajasthan ($3-11\%$), and Maharashtra ($3-11\%$). Among all estimates, the most marked outlier is from the state of Jharkhand (Figure 3.11) and belongs to Gumla *mandi*. This is the same outlier observed in the Eastern region in Figure 3.10. The volatility in wheat prices reported at Gumla *mandi* do not show any significant evidence of being time-varying and the estimate is therefore calculated as their standard deviation. Jharkhand also reports an instance of explosive volatility as already highlighted.

A close look at individual estimates from the *mandis* of the Western regions brings up an interesting observation. Within the region, the states which report relatively higher averages of *mandi* level volatility are Gujarat, Rajasthan and Maharashtra. These states have relatively higher proportions of smallholders as compared to the rest of the states in the region (Government of India, 2019). As per the Agricultural Census of 2010-11, more than half the total operational landholdings in these states belong to 'small and marginal holding' category: Maharashtra (78.6%), Gujarat (66.5%) and Rajasthan (58.5%) (Government of India, 2015). As most farmers in these states are expected to have low risk-bearing capacity, the presence of high volatility in returns can affect their livelihood security and raise concerns of aggravating existing inequality.

5.2.3 Mustard

Table 5.2 shows that the states reporting some of the highest averages of *mandi* level volatility estimate for mustard include Chhattisgarh (13%), Maharashtra (12%) and Assam (11.3%). Again, Madhya Pradesh reports one of the lowest average volatility with relatively low dispersion. To give a visual picture of the spatial dispersions in the estimates, figures 5.6 and 5.7 present box plots of their spread across regions and states respectively.

Figure 5.6: Distribution of volatility estimates across regions (2003-2016): Mustard



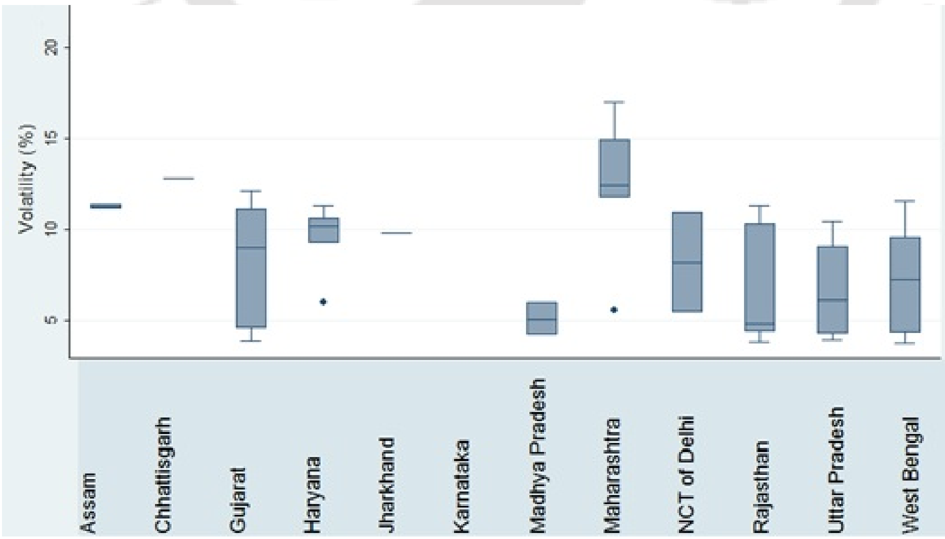
Note: The figure presents box-plots of the volatility estimates for *mandi*-level prices of the commodity Mustard categorized by region. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

The inter and intra-regional dispersions of the estimates are apparent in Figure 5.6. Levene's test results for indicate that for Mustard the inter-regional dispersions of the estimates do not show any statistically significant difference at less than 5% level of significance (see Appendix A.4.1). Therefore, the inter-regional differences in mean and median levels are comparable. Among the regions, the lowest median volatility is found for estimates belonging to *mandis* of Central region, followed by North. Similarly, the highest median is reported from West, followed by East.

Next, Figure 5.7 presents the state-level dispersions inthe estimates of volatility.

Figure 5.7: Distribution of volatility estimates across states (2003-2016): Mustard



Note: The figure presents box-plots of the volatility estimates for *mandi*-level prices of the commodity Mustard categorized by states. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

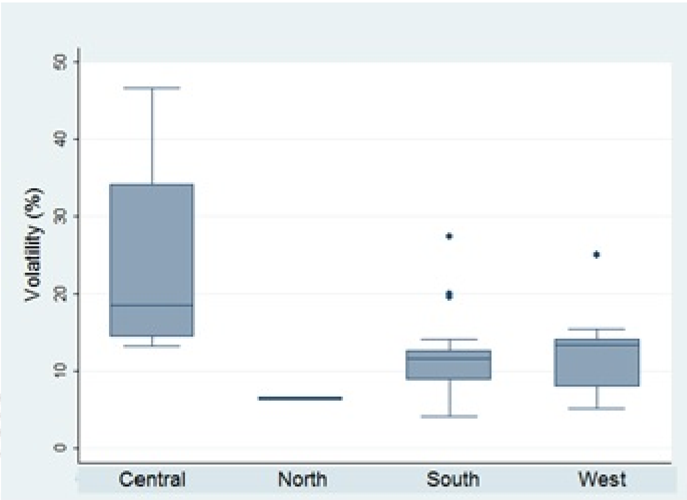
From Figure 5.7, some of the most noticeable intra-state dispersion of the estimates is seen in Gujarat and Rajasthan in the West, in West Bengal in the East as well as in Uttar Pradesh and NCT of Delhi in the North. As the Levene's test results for equality of variance across states remains inconclusive for Mustard (see Appendix A.4.2), we cannot directly compare the inter-state median and mean differences in the magnitude of volatility.

5.2.4 Groundnut

In most of the major producing states of groundnut, the average of the estimated volatility levels are higher than that of the international reference price (Table 5.2). Thus, groundnut prices are found to be highly volatile across India. While Uttar Pradesh and Maharashtra have relatively lower average values at 6.5% and 7.5% respectively, the average of volatility estimates in several other states is higher than that in the international reference price. These include Madhya Pradesh (24%), Rajasthan (14%), Tamil Nadu, Haryana and Karnataka (13% each).

To give a visual idea about the dispersion of estimated volatility levels, Figures 5.8 and 5.9 present box plots of the spread of the estimates across regions and states respectively.

Figure 5.8: Distribution of volatility estimates across regions (2003-2016): Groundnut



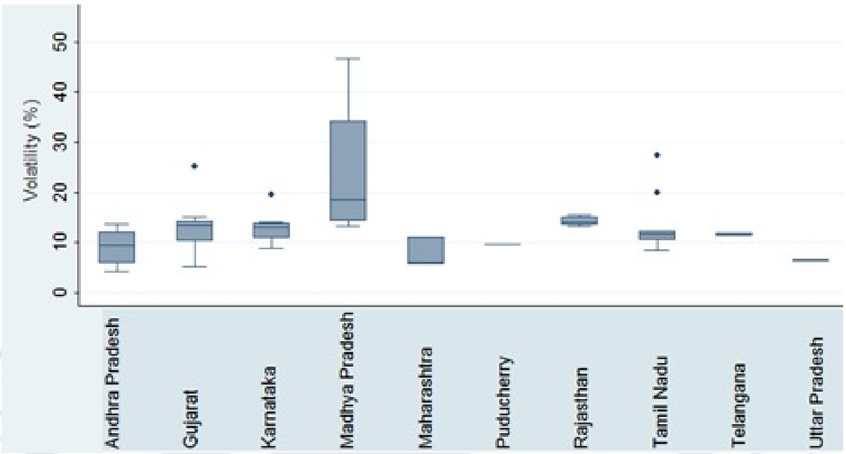
Note: The figure presents box-plots of the volatility estimates for *mandi*-level prices of the commodity Groundnut categorized by region. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

In the figure, the wide dispersion in the Central region clearly stands out from that of the rest and Levene's test for equality of variance across regions (A.4.1) rejects the null hypothesis of equal variation across regions at less than 5% level of significance. The Northern region reports the lowest median and mean volatility with the lowest spread. However, the latter observation may be due to the low representation of *mandis* in the Northern region for groundnut.

The inter and intra-state dispersions become clear from Figure 5.9.

Figure 5.9: Distribution of volatility estimates across states (2003-2016): Groundnut



Note: The figure presents box-plots of the volatility estimates for *mandi*-level prices of the commodity Groundnut categorized by states. The horizontal bars across the boxes represent the medians of each distribution. The dots above the plots represent the outliers, if any.

Source: Author's calculations

From the figure, the most noticeable intra-state dispersion is seen in Madhya Pradesh (MP), which belongs to the Central region. Within MP, the highest estimate for volatility is from Shivpuri *mandi* (45%) and Karena *mandi*, both of which belong to the same district (Shivpuri). It is also noteworthy that lowest estimate from MP is at 13.3% (Neemuch *mandi*), which itself is higher than the volatility estimated for the international reference price.

In sum, the findings show that high price volatility levels are neither confined to a single crop nor to a single region. In general, it is the Eastern region where average volatility levels are found mostly to be high in *mandis*. In the Southern region, although the median (and mean) of the volatility estimates is high, the dispersion in the estimates is also wide. For instance, among the states in this region, the estimates from Andhra Pradesh and Tamil Nadu show the highest dispersion and most of the high volatility *mandi*-level series of the region also belong to either of them. These two states have a higher proportion of smallholders relative to the state of Karnataka in the same region. The Agriculture Census 2010-11 data shows that the latter state accounts for a relatively higher proportion of medium and large farmers within the Southern region. In the two former states, the *mandis* that report the highest volatility estimates belong to districts where $80-90\%$ of the total operational holdings fall in the SMF category, *viz.* Guntur (90%), Krishna (90%), Prakasam (82%) in Andhra Pradesh as well as Villupuram (94%), Tuticorin (84%), Madurai (95%) and Virudhunagar (90%) in Tamil Nadu. The work of Chand and Raju (2008), which examines pre and post reform prices of different agricultural commodities in Andhra Pradesh finds strong evidences of increasing instability in the prices received by farmers in several districts of the state in the post reform period (1993 to 2004). They stress on the finding that while the state level data shows no change in price volatility over time, the instability in gross returns to farmers to have increased in almost half of the total districts in the state for groundnut, and in more than one-fourth of the districts for paddy. The findings of this dissertation add to their analysis and show that there is not just inter-district variability in price volatility, but intra-district dispersion as well.

Further, in the Central region, Madhya Pradesh (MP) presents an interesting case. For groundnut and paddy, the *mandi* level series belonging to MP show much higher estimates compared to the rest of the price series under study.

However, for mustard, the volatility estimates for the series from MP are lower relative to those estimated for *mandis* belonging to the rest of the states. This issue may be taken up in future research by covering more *mandis* from the state and conducting primary survey, if needed. A point to note here is that in the recent decades, MP has performed very well in terms of productivity due to improved irrigation cover, procurement and infrastructure development. Notwithstanding this, violent farmer protests have erupted in the state at the same time (Gulati et al., 2017; Kannan, 2017; Gulati et al., 2018). Studies have explained this by pointing out the inequity in opportunities prevalent across rural MP. Highlighting the inequity faced by different classes of farmers in the state, Gulati et al. (2018) discuss how the nature of *mandi* practices are such that the access to market facilities and state procurement is unequal and favours the relatively larger farmers. Even the much talked about Bhavantar Bhuktan Yojana (BBY scheme) is found to be prone to manipulations by traders and mandi level functionaries. The BBY is a price deficiency payment scheme introduced by the government of MP in September 2017. As per the scheme, the farmer selling his produce in the notified APMC yard will be directly paid the difference between the MSP and the average sale price (ASP) for eight Kharif crops. The ASP is the average of the prevailing modal *mandi* prices in MP and two other states. Gulati et al. (2018) show that in Kharif 2017-18, the scheme benefited less than one-fourth of the production. Further, Kannan (2017) shows that the inequity in agricultural development is prominent in tribal dominated regions of the state, *i.e.* in regions with higher Scheduled Tribe (ST) population, both irrigation development and land productivity are considerably lower. These findings take us back to the inference of Harriss-White and Janakarajan (1997) that programmes aimed to bring about institutional changes to improve social and economic efficiency in agricultural production do not provide satisfactory results because government interventions lack adequate recognition of existing social relations with agricultural production at the level of implementation.

Having highlighted the dispersion in price volatility across India, the next section seeks to obtain more information on the implications of this dispersion for farmers. The section investigates how the estimated volatility levels vary across locations having different socio-economic conditions.

5.3 Volatility, seasonal gaps and smallholders across India: Implications

The impact of price volatility on cultivating households will differ in accordance to the households' risk-bearing capacity. Smallholders with limited economic means are, often, not in a position to sustain frequent shocks to their revenue stream. They are, therefore, expected to be risk-averse (Kahlon and Singh, 1980; Morduch, 1995; Senapati, 2020). Consequently, the incidence of high volatility raises greater welfare concerns in those locations which have a large proportion of small and marginal farmers (SMF). The risk-bearing ability will be even lower if the pressure on the resource base of these farmer-households is high (Kahlon and Singh, 1980; Rosenzweig and Stark, 1989; Rosenzweig and Wolpin, 1993; Senapati, 2020). Further, if the price received by farmers is in itself low (resulting in low returns from harvest), high volatility in prices may increase the vulnerability of smallholders. The findings presented in Chapter 3 imply that the incidence of wide seasonal gaps are an indication that most farmers in those locations are 'selling-low', which may, in turn, be leading to non-remunerative price realisations for them. As the majority of farmers in such locations are already distressed, high volatility in the returns from harvest can adversely affect their livelihood sustainability and increase their vulnerability. This means that the adverse impact of price volatility on resource-poor farmers will be compounded in those locations which are prone to wide seasonal gaps.

Given this backdrop, it becomes important to assess the locations exhibiting high price-volatility in light of the socio-economic conditions prevailing there. Therefore, using its finding, this dissertation seeks answers to a more general empirical question: *Are locations with a large number of resource-poor smallholders facing high price volatility in India?*

One way of investigating this research question is to conduct an Analysis of Variance (ANOVA). However, the results of an ANOVA may not be valid when the variance among the different groups under examination are not equal. The Levene's test results reported in sections 4.2.2 and 5.2 show that, in most cases, the tests for equality of inter-commodity and inter-locational variances either remain inconclusive or reject the null. Therefore, this thesis takes up an alternate approach to investigate the spatial differences in volatility levels: it runs an OLS regression on the volatility estimates by taking a number of location-specific measurable indicators of socio-economic conditions as regressors. This enables carrying out of the spatial difference examination at a lower level of aggregation than that of the 'state'. As the preceding discussion has shown noticeable intra-state dispersion in several states (section 5.2), this approach takes us a little closer towards deciphering the ground-level picture .

Kindly note, here the intent of using an OLS regression is not to draw any 'causal inference' between the regressors and the volatility estimate. Instead, here regression is used as a purely empirical statistical tool to understand the spatial variation in the estimates. The intuition behind using this comes from the very fact that regression does not imply causation. Rather, each coefficient in a multiple linear regression gives us the degree of correlation between a respective regressor (explanatory variable) and the regressand (explained variable), which is called its *net effect*. In other words, each coefficient represents the changes in the explained variable associated with a change in the value of a given regressor variable for fixed values of the other regressors specified in the model. Thus, OLS regression comes as a handy tool to investigate the spread of the empirical estimates of volatility across locations for the period of reference of the study. A similar approach has also been used in Chatterjee (2019).

In general, a stronger resource base (landholding size, asset value, net worth) is expected to result in a higher risk-bearing capacity and vice versa. Therefore, a set of variables are incorporated to represent the prevailing socio-economic conditions among farmers selling their produce in a particular *mandi*. These include the proportion of smallholder cultivators, asset ownership and indebtedness. Now, as pointed out in Chapter 3, there is an absence of clarity on the specific set of villages that are allowed to sell in a particular *mandi*. Therefore, like in that chapter, district level characteristics are taken as an approximation of the indicators of socio-economic conditions prevailing for cultivators selling in each *mandi*.

Landholding size is an important indicator of the asset base of farmers. If very large proportions of farmer-sellers belong the small and marginal farmer (SMF) categories, the risk bearing capacity of the average farmer-sellers will be low in that location. Two continuous variables (SMF_a and SMF_b) are taken to represent the proportions of operational holdings belonging to the size classes 0.5 to 1.00 Ha and 1.00 to 2.00 Ha respectively within the district to which a particular *mandi* belongs. Data on these parameters are obtained from the Agricultural Census of India 2010-11 (Government of India, 2015). Although there are three sub-categories of SMF, severe multi-collinearity issues arise if all three are included in the model. Therefore, one of the size classes ('less than 0.5 Hectares' category) is dropped from the estimation. The assumption is that farmers cultivating on such small-sized holdings will be cultivating for subsistence and not for marketing. Thus, their incomes may not be directly affected by price volatility in the market.

Ownership of household assets is another indicator of the resource base (and risk bearing capacity) of farmers. The average value of assets (AoA) of households in a district is taken to represent this indicator. The larger the AoA, the higher is the expected risk bearing capacity of an average farmer in the location and *vice versa*. Similarly, the net-worth of farmer is another crucial indicator of the risk-bearing capacity. Here, the average debt-asset ratio (DAR) of households in a district is taken to account for the net worth. The higher the DAR, lower will be the net-worth and risk bearing capacity. Data on both these variables are available from NSSO (2014a).

A description of the included variables is presented in Table 5.3 and their descriptive statistics are presented in Table 5.4.

Table 5.3: Regression on volatility estimates: Description of included variables

Variables	Description of variable	Type of variable
(1)	(2)	(3)
$V_{x,y}$	Volatility estimate (for crop x in $mandi_y$)	Continuous
d_crop_1	Wheat	Dummy
d_crop_2	Mustard	Dummy
d_crop_3	Groundnut	Dummy
SMF_a	Prop. of 0.5 – 1.00 Ha holdings	Continuous
SMF_b	Prop. of 1.00 – 2.00 Ha holdings	Continuous
$SG_{x,y}$	Seasonal gap estimate	Continuous
	(for crop x in $mandi_y$)	Continuous
AoA_y	Average value of assets per household	Continuous
DAR	Debt-Asset Ratio	Continuous
d_region_1	North region	Dummy
d_region_1	West region	Dummy
d_region_1	East region	Dummy
d_region_1	Central region	Dummy

Note: The table presents a list of measurable variables that are included in an OLS regression on the volatility estimates. The variable name and its description are provided in Columns (1) and (2) resp. Column (3) describes the type of the variable (discrete, continuous, binary/dummy).

Table 5.4: Regression on volatility estimates: Descriptive statistics of variables

Variables	n	Mean	SD	Min	Max
$\text{Vol}_{x,y}$	395	9.13	5.37	0.93	46.68
$\text{SG}_{x,y}$	390	10.63	8.21	1.37	80.81
SMF_a	393	0.22	0.05	0.01	0.34
SMF_b	393	0.22	0.08	0.05	0.41
DAR	371	3.54	4.01	0.03	14.31
AoA	371	5169353.00	14100000.00	677035.00	100000000

Note: Only the continuous variables are included

Source: Author's calculations based on data obtained from DMI, MoA&FW, Govt. of India, Government of India (2015), NSSO (2014a)

Equation 5.1 defines the regression model in terms of the location-specific variables examined. Dummies are also included to capture region and crop specific differences.

$$V_{x,y} = B_0 + \sum_{i=1}^{3} B_{1,i} d\_crop_i + B_2 SMFa_y + B_3 SMFb_y + B_4 SG_{x,y} + B_5 AoA_y + B_6 DAR_y + \sum_{r=1}^{4} B_{7,r} d\_region_r + \varepsilon_{x,y} \tag{5.1}$$

On the left-hand-side of the equation, V represents the volatility estimate for commodity x in *mandi* y. On the right-hand-side, d_crop_i and d_region_r are the crop and region dummies respectively. The former is a set of three dummies that take the value of one (1) if $i = x$ and zero (0) otherwise. Paddy is taken as the base category. Similarly, the region dummies are a set of four dummies with South being the base category. The seasonal gap estimated for the crop x in the *mandi* y is also included as a regressor. Smallholder-farmers in locations prone to wide seasonal gaps may already be under severe revenue strain and therefore, it is important to examine whether prices in these markets also exhibit high instability. If yes, there may be serious welfare concerns. The rest of the variables are as defined in Table 5.3.

The model uses robust standard errors as otherwise a problem of heteroscedasticity is encountered. The model diagnostic statistics are reported in the Tables 5.5 and 5.6.

Table 5.5: Variance Inflationary Factor and Tolerance of explanatory variables: Regression on volatility estimates

Variable	VIF	1/VIF
West region (dummy)	4.55	0.220006
East region (dummy)	4.48	0.222973
North region (dummy)	3.74	0.267582
Debt-to-asset ratio	3.73	0.268231
Central region (dummy)	2.74	0.364352
Prop. of 1.00 - 2.00 Ha holdings in district	2.03	0.492466
Average value of Assets	1.73	0.578025
Groundnut (dummy)	1.6	0.624202
Wheat (dummy)	1.52	0.658078
Mustard (dummy)	1.5	0.668656
Prop. of 0.5-1.00 Ha holdings in district	1.33	0.7516
Seasonal gap	1.23	0.813921
Mean VIF	2.51	

Source: Author's calculations

Table 5.6: Breusch-Pagan/Cook-Weisberg test for heteroskedasticity: Regression on volatility estimates

Dependent variable: Volatility estimates
H_0: Constant variance
$chi^2(1) = 83.27$ Prob $> chi^2 = 0.0000$

Source: Author's calculations

The results of the regression on the estimated *mandi*-level volatility estimates are reported in table 5.7. In the table, the regression coefficients of the various factors including crop type and region in addition to average socio-economic conditions prevailing in district are presented in the second column.

Table 5.7: Regression results: Volatility level, crop type and location-specific characteristics

Explanatory Variables	Coef.	Robust Std. Err.	$p > t$	
(1)	(2)	(3)	(4)	
Wheat (Dummy)	-5.03	0.55	0.000	***
Mustard (Dummy)	-4.36	0.74	0.000	***
Groundnut (Dummy)	0.37	0.93	0.691	
SMFa_y	-4.70	4.56	0.304	
SMFb_y	12.40	3.84	0.001	***
SG$_{x,y}$	0.20	0.07	0.004	***
AoA$_y$	0.00	0.00	0.055	*
DAR$_y$	0.21	0.11	0.068	*
North region (Dummy)	2.84	1.19	0.017	**
West region (Dummy)	3.49	0.92	0.000	***
East region (Dummy)	6.72	1.29	0.000	***
Central region (Dummy)	3.64	1.13	0.001	***
Constant	3.15	1.70	0.065	*
n	364			
F(12, 351)	17.58	***		
R^2	0.4			
Root MSE	4.1358			

Note: The table presents the results of the regression on the estimated *mandi*-level volatility estimates on various factors including crop type and region in addition to district characteristics (socio-economic conditions and proportion of smallholders). The stars represent the level of significance: $^{***}p < 0.01$, $^{**}0.05 > p > 0.01$, $^{*}p < 0.10$.

Source: Author's calculations

Table 5.7 shows that the fitted model as a whole is highly statistically significant with the F-statistic reporting a p-value of less than 0.001. The goodness of fit measure (R^2) is 0.4, which is a fairly acceptable model fit for cross-section analysis. The regression results provide evidence in favour of the crop-specific inferences drawn in the previous section. The crop dummies are negative and highly significant for wheat and mustard, indicating that, in general, wholesale prices of these two crops exhibit relatively lower volatility. Furthermore, all the locations dummies are positive and significant. This indicates that, in most cases, the *mandis* belonging to the base region (South) have relatively lower volatility levels relative to *mandis* in the rest of the country. Among the region dummies, the size of the estimated coefficient is the highest for 'East'. This indicates that most *mandis* belonging to this region report volatility levels that are higher than the rest of the country.

Moving to the core variables, the results indicate that volatility levels are significantly and substantially high in those locations where the proportion of smallholders is high. The variable $SMFb_y$, which represents, small farmers (owning operational holdings sized between 1 and 2 Ha) has a highly significant positive coefficient of 12.5. This indicates that locations with large proportions of smallholders have faced high volatility during the studied period in India. Further, the value of the coefficient estimate tells us that, during the studied period, on an average, the degree of price volatility has been higher by as much as 12% in a location having just 1% higher percentage of small farmers compared to another location. This empirical finding has adverse welfare implications for the population dependent on agriculture in India.

The average value of assets (AoA) and debt asset ratio (DAR) too show some associations at less than 10 percent level of significance. While a higher AoA indicates better risk bearing capacity, a high DAR indicates additional pressure of indebtedness on household resources. However, since the size of the coefficient for the former variable is very small (nearer to zero), we are not in a position to infer whether, on an average, locations with low AoA of households are facing higher volatility levels. The coefficient of DAR is positive, which indicates that high volatility levels are being faced in districts where households have higher debt amounts relative to the value of their assets. Since the pressure on existing resources is high for such households, they too may not be in a position to sustain risks to their revenue stream. The final variable of interest is the seasonal gap (SG), which is found to have a positive and highly significant coefficient. Thus, markets that are prone to large post-harvest price drops have also been facing higher price volatility in India. This, in turn, indicates that the smaller farmers are not only"selling-low", but they are also selling at highly uncertain prices.

Now, the coefficient of the variable representing marginal farmers ($SMFa_y$), is not significant. However, as a majority of such farmers cultivate for subsistence (and not for sale), price volatility in the commodities they cultivate may not directly affect their revenue to a large extent.

The results, taken together, indicate that, since the early 2000s, locations with a high proportion of distressed farmers are also facing high price volatility (unpredictability). Such volatility translates into revenue stream uncertainty for those households that are primarily dependent on agriculture for their livelihood. While, *prima facie*, both the Eastern and the Southern regions show relatively higher median volatilities, more rigorous investigation shows that if we control for differences in socio-economic factors like the proportion of smallholders, average value of household assets, indebtedness et cetera, it is only the East that emerges as a region with significantly higher volatility relative to rest of India. This raises concern as over 90 percent of farmers in most of the states of this region are smallholders (Government of India, 2015) whose risk-bearing capacity is expected to be low.

These findings also intrigues us to revisit the arguments of Mitra (1977) and Kalecki (1971). They discuss how class relations can affect agricultural terms of trade and investigate the possibility that large landed farmers in regions which have a highly skewed distribution of land ownership may be able to exercise monopolistic power, leading to favourable outcomes for them. Mitra (1977) asserts that interregional disparities in India are an outcome of "political arrangements having their roots in the antithesis of class". His work shows that the way the policy of administered prices (MSP) was executed in India, it has not just led to inter-regional price disparities, but also to inter-crop discriminations favouring the crops which are more widely cultivated by the larger landed farmers (wheat and cotton). While the above arguments were raised in the 1970s, the findings of this dissertation opens up the possibility to investigate further along the lines of Mitra (1977). If the influence of class inequalities in shaping agricultural market outcomes has not weakened over time, it would raise doubts on the efficacy of prevailing agricultural policies in reducing inequalities in a country where small and marginal farmers are growing every year.

5.4 Conclusion

This chapter has carried forward the analysis from the preceding chapter by examining the diversity observed in the estimates of volatility in the time-series behaviour of some major agricultural commodity prices across India. A look at the broad regional patterns shows clear differences in not just the averages of the volatility estimates, but also in their spread. The most crucial finding of this analysis is that farmers in economically distressed locations of rural India are also facing high-price volatility, *i.e.* locations where a majority of cultivators are not in a position to economically sustain frequent shocks to their revenue stream have faced high price volatility during the period of reference of the study. Irrespective of region and crop type, prices in *mandis* of districts having very large proportions of resource-poor small farmers have been found to have exhibited high volatility. Given their weak resource base, high volatility in the returns from their harvest increases the vulnerability of such farmer-households. This is an important finding and calls for policy-makers' urgent attention. The existing inter-regional inequalities as well as class-inequalities in rural regions may aggravate over time if the current trends continue. Given the differences in price behaviour across the country, this study emphasizes on the need for location-specific policy approaches. Moreover, timely intervention is crucial because the findings of Chapter 4 show that, in most cases, future movements of price are dependent on its past and present realisations. Unless appropriate measures are taken to either manage the high volatility, or to mitigate the effects of such high volatility in the most distressed locations, there will be serious consequences for poverty and inequality across rural India. These will, in turn, lead to adverse welfare outcomes.

6 | Conclusion and policy recommendations

Rural India has been struggling with an agrarian crisis for decades now. Faced with non-remunerative returns, a majority of farmers have expressed a desire to quit farming NSSO, 2014b. With an aim to contribute towards the understanding of this crisis, the present dissertation has taken up a detailed analysis of one aspect of this crisis, which has associations with several of the others, *viz.* agricultural commodity prices. Specifically, it has examined the prices received by farmers across India in the primary wholesale commodity markets (*'mandis'*), which are the first state-mandated points of sale for farm-produce in India. The primary focus has been on understanding the extent and nature of predictable (seasonal) and irregular (volatile) price fluctuations in these markets.

This is the final chapter of my thesis and it summarises the major inferences drawn from the findings of the study as well as presents the conclusions drawn. The chapter is divided into four sections. The first section begins with a recap of the major findings of this dissertation, which are under presented under different heads, *viz.* seasonal behaviour, price volatility and their spatial pattern respectively. The second section is titled 'Conclusion' and it concludes the entire thesis. Specifically, it highlights the major implications of all the findings taken in their totality. The third section of this chapter presents the policy implications arising in light of the findings of this study. Finally, the fourth section points out the ways in which the study can be improved. It also touches upon the scope for further research along the lines of this thesis.

6.1 Principal findings and their implications: A summary

6.1.1 Seasonal behaviour of prices

Although farmers are rational economic agents, certain barriers may constrain a majority of them in developing countries from engaging in optimum selling behaviour. Market failure, limited resources, the need for cash are some of the responsible factors that have been identified by the various studies discussed in chapters 2 and 3 of this dissertation. These factors interact with each other and often result in farmers selling their harvest immediately after harvest, leading to a post-harvest glut even for storable commodities. As a result, agricultural commodity markets of developing countries are often prone to wide seasonal gaps.

In this context, research objective (1) of this dissertation has been to examine the seasonal behaviour of *mandi* prices of the selected commodities over the period from 2003 to 2016 across India. The major findings in relation to the seasonal behaviour of prices are:

- For all the four commodities, statistically significant evidences are found in favour of the presence of seasonal patterns in most of the wholesale price series under study: paddy (75%), wheat (91%), mustard (86%) and groundnut (74%). This indicates that the prices of some of the most widely cultivated commodities across India tend to experience periodic drops in specific months of a calendar year.

- The most common seasonal pattern across India is an asymmetric structure: the prices reach a peak just before the harvest month and then drop sharply for a month or two, after which prices rise gradually until the next harvest month. This pattern of seasonality is formally termed as the 'sawtooth pattern'.

- Among the commodities, on an average, both the oilseeds exhibit relatively higher magnitudes of seasonal gap compared to the two cereals. While the respective averages of the estimated seasonal gaps are 11% for mustard and 13% groundnut, those for both the cereals are a little less than 9%. As the oilseeds are mostly cultivated as commercial crops, the incurrence of loss can adversely affect income-streams of producers. While those selling at the peak price would benefit, the ones selling at (or near) the trough price receive disproportionately lower returns on their harvest and, therefore, may be incurring substantial losses depending on how low the trough price is.

- Except for wheat, the distributions of the *mandi*-level seasonal gap estimates are positively skewed for all the three commodities. Thus, several commodity prices in several *mandis* report seasonal gap estimates that are much higher than the average value. In case of wheat, however, the distribution of the estimated seasonal gaps approximates a normal distribution and they stay mostly around the mean value.

- The estimates show wide dispersion. Among the four commodities, paddy and groundnut show the widest dispersions.

- In comparison to international prices, the dissertation finds that the averages of the seasonal gap estimates obtained for the domestic wholesale prices are lower relatively. However, there exist quite a number of cases where the *mandi*-level seasonal gap is higher by a substantial margin relative to the seasonal gap in the international price.

In sum, the dissertation shows that while seasonality in prices is common across India, there is a marked dispersion in both the nature of the seasonal behaviour as well as in the magnitude of the seasonal price drops across the country.

6.1.2 Volatility in prices

Increased food price volatility has raised concerns all across the globe in the recent decades. As markets around the world have become more integrated, smaller farmers in developing countries are now exposed to a wide variety of risks. Given the poor resource base of majority of farmers in developing countries, most of them are expected to be risk-averse.

In this context, research objective (2) has been to examine the volatility in *mandi* prices of the selected commodities over the period from 2003 to 2016 across India. The findings presented in Chapter 4 show that the studied prices are not only volatile, but this volatility is, very often, time-varying. The major findings of this chapter are:

- Both the nature and magnitude of price volatility varies widely across individual markets.
- Time-varying volatility is common across India and around half of the total price series studied here show statistically significant evidence of autoregressive conditional heteroscedasticity. Thus, the effect of a price shock in one period is carried over to the future period(s) in most markets.
- The presence of volatility clustering and persistence in *mandi*-level prices implies that past volatility is an important determinant of future volatility in several wholesale markets of India. In a sizable number of markets, any increase in the volatility level is found to persist for several months before returning to its long-term average level.
- The average time taken by volatility levels to revert back to their mean levels is longer in case of the cereals (paddy and wheat) compared to the oilseeds under study. Here, it is interesting to note that while the

oilseeds have been more freely traded in the commodity derivatives markets of India since 2003, futures-trading in the two cereals has been relatively restricted and it has faced several bans, especially since 2007. Thus, it may the case that the futures trading in the oilseeds could be playing a stabilising role, leading to shorter half-lives of volatility. However, the academic literature on this subject is inconclusive. Therefore, this dissertation refrains from making any comment on the role of futures trading in lowering persistence of volatility.

- The estimates of volatility differ widely across individual markets. While the averages of the estimated figures are quite close to international levels for two commodities- paddy (a foodgrain) and groundnut (an oilseed), several individual markets exhibit volatility levels that are much higher than this.

- Volatility shows a tendency to be non-stationary (or explosive) in a number of cases. In these price series, an increase (or decrease) in volatility is sustained over time and the volatility level never returns to any long-run average. This finding can be related to the emerging literature on trending volatility (Gilbert and Morgan, 2010; Minot, 2014).

- The highest number of cases of explosive volatility is found to be exhibited by the commodity paddy, which is very widely cultivated across India.

- The findings regarding the nature of volatility strengthen the inferences made by Conforti (2004) that, despite being deeply regulated by public intervention, agricultural prices tend to show considerable degree of linkage with international price movements in countries like India.

- Among the four commodities being studied in this dissertation, wheat reports relatively lower price volatility as well as much lower dispersion in the individual estimates. This finding is in line with previous studies (Bathla, 2012; Tripathi, 2014). Bathla (2012) attributes the relative stability in wheat prices to policy measures like price support, procurement and trade regulation. While the policy measures existing for paddy are similar to those for wheat, this dissertation finds that such policies are not able to insulate paddy prices from exhibiting volatility levels that are as high as seen in the international market.

- Wheat is more widely cultivated in states of the Western and Northern region of India, which have relatively greater proportions of larger operational landholdings. Historically, these regions have also performed well in terms of agricultural productivity and states like Punjab and Haryana have seen the emergence of a class of commercial farmers. With relatively stronger resource bases, such farmers may be in a position to control large portions of the supply in wholesale markets and thus smoothen price shocks through optimal trading strategies.

Taken together, the results of the price volatility analysis show that volatility estimates for individual price series differ quite a lot in their magnitudes. In addition to the inter-crop differences, there is substantial intra-crop variation in volatility levels as well.

6.1.3 Price behaviour across space

Given the vastness and diversity across India, country-wide averages carry very little meaning. Therefore, this dissertation has conducted all analysis at a highly disaggregated level, *i.e.* at the level of the *mandi* or wholesale market.

Specifically, research objective (3) has been to examine the spatial variation in price behaviour and its implications for cultivating households across India. The examination of seasonality and volatility in the prices of the selected commodities brings attention to the wide-spread differences in the individual estimates. The findings also show that there are associations of price behaviour to differences in socio-economic factors prevailing in various locations. The major findings from examining the spatial dispersion in *mandi*-level estimates of seasonal gaps and volatility across India are:

- There is a wide diversity in the influence of seasonal factors and the magnitude of seasonal gaps across location and commodity. The estimates of seasonal gaps do not just differ across states. In several cases, the dispersion of the estimates within specific states is quite high.

- The study finds that seasonal price drops are significantly high in districts where resource-constrained smallholders are larger in number. As they are unable to hold on to stocks and sell soon after the harvest, they are the ones who receive the lowest price for their produce. Given their high economic vulnerability, negative shocks to income-streams of smallholder cultivators can threaten their livelihood sustainability. Furthermore, as the relatively larger farmers have the means to hold on to stocks, they may be selling when prices are nearer to the peak price. Thus, large seasonal gaps could indicate that the more vulnerable lose out, while the relatively better off are able to gain disproportionately.

- The volatility estimates also show substantial variation across space. Furthermore, there is both inter-state and intra-state dispersion in the estimates.

- The Eastern region of India emerges as a region exhibiting significantly higher volatility relative to rest of India. This is true even after controlling for differences in socio-economic factors like the proportion of smallholders, average value of household assets and indebtedness. As the proportions of smallholders among cultivators are very high (above 80%) in the states of this region, this finding raises livelihood sustainability concerns in this region.

- Within the Western region, the states reporting relatively higher averages of *mandi* level volatility (Gujarat, Rajasthan and Maharashtra) also have relatively higher proportions of smallholders within the region.

- In the South, after controlling for differences in socio-economic factors, the dissertation finds that that the region accounts for lower volatility compared to the other regions. This indicates that within the South region, while *mandis* in the more distressed locations exhibit higher volatility estimates, those in the rest of the locations exhibit much lower price volatility.

- In the Central region, Madhya Pradesh (MP) presents an interesting case: while groundnut and paddy are found to exhibit very high volatility, the estimates for mustard are much lower relative to the other states of the country. There is also a wide dispersion in the seasonal gaps estimates in the state for all the commodities. There are studies that discuss the inequity in MP's agricultural development story. Gulati et al. (2018) find that *mandi* practices are prone to manipulations by traders and other *mandi* functionaries such that they favour the relatively larger farmers in terms of the access to market facilities and state procurement. Kannan (2017) shows that both irrigation development and land productivity are considerably lower in the tribal dominated regions of the state. These findings take us to the inference of Harriss-White and Janakarajan (1997) that programmes aimed to bring about institutional changes to improve social and economic efficiency in agricultural production do not provide satisfactory results because government interventions lack adequate recognition of existing social relations with agricultural production at the level of implementation.

- A crucial finding is that, irrespective of region and crop type, volatility is higher in *mandis* of those districts that have larger proportions of resource-poor small farmers. Given their weak resource base, high volatility in the returns from their harvest increases the vulnerability of such farmers.

6.2 Conclusion

This thesis has conducted a disaggregated analysis on the behaviour of wholesale prices of four major agricultural commodities widely produced and traded across the country. Specifically, it has analysed two important time-series components, *viz.* seasonal variations and irregular fluctuations (or volatility). The findings of the study have highlighted the diversity in the behaviour of agricultural commodity prices.

India is a vast and diverse country and over the years, socio-economic inequalities have become more and more pronounced in the country. While some regions of rural India have progressed well, others have continued to remain less developed. Even within regions, there is marked socio-economic inequality among the different classes of farmers. Therefore, in this concluding section of my thesis, I analyse the implications of its findings with respect to the state of inequalities in rural India.

The first research objective of this dissertation has been to examine the seasonal behaviour of *mandi* prices of four widely cultivated agricultural commodities (paddy, wheat, mustard and groundnut) over the period from 2003 to 2016 across India. Chapter 3 pursues this objective and the null hypothesis being tested in this regard is that 'there is no statistically significant seasonal pattern in the price behaviour of the studied commodities.' However, the study finds that this null hypothesis can be rejected for most markets across India. In the light of earlier works on India that established the presence of seasonality in the previous decades (Sarkar, 1993; Sharma & Kumar, 2001; Kumar & Sharma, 2006), the present study shows that seasonal factors have continued to affect prices across India in the recent periods as well. Since the commodities being studied are widely cultivated and traded across the country, the presence of a pronounced seasonal pattern implies that farmers selling at different points of time in the year get different prices (or returns) on their produce.

Chapter 4 takes up the second research objective of this dissertation, which relates to the examination of volatility in commodity prices. Two null hypotheses have been tested to pursue this objective. The first relates to the degree of volatility and states that 'there is no idiosyncratic variation in prices'. This is rejected for all series. The second null hypothesis relates to the nature of volatility. It states that 'the studied prices are homoskedatic', *i.e.* the variance of the disturbances remain constant over time. This null hypothesis is rejected in about half of the studied cases. Thus, the findings not only present evidences in favour of substantial idiosyncratic variations in the prices of the examined commodities, they also show that in several cases, the degree of this variation itself may be time-varying. Further, volatility is found to be persistent in several cases, which implies that shocks take a long time to die down in quite a number of markets. Such volatility in prices (and, therefore, in returns from farming) may adversely affect the livelihood-sustainability of risk-averse resource-poor farmers who form the majority of our cultivators.

The final research objective of this dissertation has been to probe the ground-level picture through a detailed and disaggregated examination of the spatial variations in price behaviour. The first hypothesis being tested to meet this objective is that 'the nature of price behaviour is uniform across the country.' This hypothesis is rejected as the findings in both Chapters 3 and 5 highlight the spatial diversity of price seasonality and volatility respectively. The second hypothesis being tested states that 'there is no association of price behaviour to differences in socio-economic factors prevailing in various locations.' This hypothesis, too, is rejected for both price seasonality and volatility.

In case of seasonality, the findings show statistically significant associations between the magnitude of seasonal price drops and the differences in socio-economic conditions prevailing among farmers in various locations. The results show that the seasonal gaps in prices are substantially wider in locations which have a higher proportion of resource-poor farmers. This is in agreement with the thesis' conceptual framework (Section 3.1) that it is indeed the resource-constrained smaller farmers who are opting for the sub-optimal trading strategy of "sell-low" and causing a post-harvest glut in the market. These findings have adverse implications for inequality. The evidences presented indicate that it is the relatively smaller farmers in less-well-to-do regions who are receiving disproportionately lower returns on their harvest. Unless these farmers are extended some effective support mechanisms to be able to switch their behaviour to an optimal strategy, the state of inequalities will worsen in our rural regions. Most importantly, even the intra-regional inequalities will widen.

The same null hypothesis also gets rejected for the price volatility estimates. The larger intention of testing the associations between socio-economic conditions and price instability has been to investigate whether the most distressed locations of the country have faced high volatilities in the prices of the studied commodities during the period of reference of this study. The null hypothesis states that 'locations having a high proportion of resource-poor farmers are not facing high volatility in the prices of the commodities they commonly sell'. The findings presented in Chapter 5 provide evidences against this hypothesis.

This thesis repeatedly shows that, across India, it the least-well-to-do farmers who are facing highly unpredictable prices (*i.e.* high risk) as well as attaining the lowest prices in the market. The incidence of large seasonal gaps indicate that in several locations the larger farmers are able to sell at prices much higher than the smallholders. It also indicates that smaller farmers in most locations face constraints that prevent them from adopting rational trading strategies. Further, the results from the volatility analysis show that, since the turn of the millennium, resource-poor farmers in several locations across India have stayed exposed to high levels of price volatility. As they have low risk-bearing capacity, in the absence of state intervention, their vulnerability status may have gone up considerably.

In sum, the findings of this dissertation indicate that existing inter-regional inequalities as well as class-inequalities in rural regions may aggravate over time if the current trends continue. Now, let us come to the policy responses to the agrarian crisis taken by the government in the country. For a long time, the most publicised policy responses to the agrarian crisis have been the raising of support prices (MSP) and the issuing of farm loan-waivers. The former of these has failed to safeguard the interests of the most distressed of farmers in several parts of the country. This has been brought to light multiple times by reports and studies showing how most farmers do not have access to MSP and that the realised prices in several wholesale markets are way below the MSP (Chand, 2012; NSSO, 2014b; Chatterjee and Kapur, 2016; Chatterjee, 2019). This dissertation adds to these findings by showing that it is the resource-poor smallholders who receive the lowest prices in the market. Further, the other major policy response, *i.e* providing farm loan-waivers, is also not a solution. Such waivers only provide temporary relief to farmers. In the long-run, they would go nowhere near addressing the issues raised by this dissertation.

The newly passed Farm Bills of 2020 have not been discussed here. As their scopes are quite wide, they necessitate detailed study before any comment can be made on their efficacy.

The most important contribution of this thesis is that it highlights the diversity in agricultural commodity price behaviour across the country. Unless agricultural policies become more conscious of the location-specific differences in price movements and land-ownership patterns, they may end up pushing worsening existing inequalities. Furthermore, the prolonged adverse impact on the livelihood security of farmers may culminate into social unrest and political instability. The recent years have, in fact, seen a number of mass farmer movements and protests in India. Thus, in the absence of well-directed policy, the associated welfare costs to the nation may turn out to be severe.

6.3 Policy Implications of the major findings

This study brings out a disaggregated picture of the nature of price variations across India. It shows that certain locations are in greater need of state intervention. Unless corrective measures are taken, there will be serious consequences for the long-run distribution of income, which will lead to highly unequal economic outcomes. Moreover, timely intervention is crucial because the study finds that, in most cases, future movements of price are dependent on its past and present realisations.

The discussions carried out in this dissertation show how both seasonal variations and volatile fluctuations affect smallholders disproportionately. Therefore, agricultural crisis mitigation policies in smallholder-dominated developing countries like India will be more meaningful if they are directed towards addressing the constraints faced by the smallholders. Keeping this in mind, most of the policy suggestions coming out of my findings lay focus on facilitating the resource-poor smallholders to be able to become more competitive.

- There is a need to ensure easier access to credit for smallholders so that they may not engage in 'distress sale' immediately after harvest due to cash constraints.

- As storage plays an important role in aiding farmers to opt for optimal trading strategies, there is a need to improve the access to storage facilities in *mandis*. Proper storage facilities need to be built in those *mandis* where they are currently unavailable. The existing storage facilities need to be made accessible to small farmers by either creating provisions for allowing storage of smaller lot sizes, or by allowing shared storage.

- The seasonal gaps may be made narrower if there is an effective 'price floor' support to the price, which can prevent the market price from falling too low at time of excess supply. As concerns have been raised about the prevailing price support measures (Bathla, 2012; NSSO (2014b); Chatterjee and Kapur, 2016), therefore, the access to procurement (and, therefore, MSP) also needs to be made more equitable.

Although these measures are long-run measures and will take some time to show their effect, adopting each of these measures can have concrete benefits for the farmers. These measures will not only address some of the major disadvantages that force small farmers to adopt sub-optimal trading practices (leading to large post-harvest price drops), they may also provide small-holders some resource-buffer to be able to sustain (and even profit from) price volatility.

Given the differences observed in price behaviour across the country, this study also emphasizes on the need for location-specific policy approaches. Priority has to be given to those locations, which show high price volatility and are prone to wide seasonal gaps. The finding that price volatility is higher in locations where a large proportion of farmers are resource-poor calls for urgent attention. While market outcomes are dependent on several factors, the state can help reduce the vulnerability of cultivators to price shocks in such locations.

Some short-term policy recommendations in that direction include:

- active monitoring of volatility in APMC prices (through AGMARKNET) in those locations which have high proportions of resource-poor small-holder farmer-sellers. Some automatic indexes may be devised in the portal, which can signal the need for intervention in these locations on a real-time basis.
- directing relief measures (like credit-waivers or cash-transfers) to small-holders in more distressed locations, i.e. locations having high volatility and/or wide seasonal gaps.

Further, there is a need for strong long-term policy measures to address this issue. Some suggestions are:

- providing alternative avenues for income generation so that resource-poor households are not solely dependent on returns from agriculture;
- promoting diversification in enterprises so that the risk-bearing capacity of farmer households strengthens;
- reducing the imperfections in the credit market for better access to credit, which becomes crucial at times of increased price instability.

6.4 Scope for improvement and future research

- Although the study has tried to cover as many *mandis* as possible, the representation from certain states is low due to non-availability of consistent data.
- While care has been taken to ensure that the four commodities studied in this thesis represent a large share of an average Indian farmer's traded basket, it falls short of capturing recent changes in cropping patterns observed in many parts of the country. Specifically, there has been a shift towards high-valued crops and livestock in several regions of India (Rao et al., 2006; NSSO, 2014b). Thus, extending the analysis to include a more diverse commodity basket can give even richer region-specific insights.
- This study highlights the diversity in price behaviour across the country. Future studies using primary data can substantiate its findings

and bring out more location specific ground realities.

- If farm harvest prices can be obtained (with reasonable consistency), they will give a better picture of the actual prices received by farmers.
- While investigating the sources of dispersion in the seasonal gaps, there is a scope to include additional relevant variables like access to storage, road connectivity and so on.
- Price behaviour in Madhya Pradesh throws up several questions which merit more rigorous study: *Why do seasonal gaps for all the major commodities show such wide dispersions within the state? Why are prices of commodities like paddy and groundnut highly unstable in the state, while those for mustard are relatively stable?* These issues may be taken up in future research by covering more *mandis* from the state and conducting primary survey, if needed.
- Future studies can also examine some other related issues at disaggregated levels like the trend in real prices across space, the drivers of price movement, volatility spillovers, and international transmissions.

Conferences, workshops and publications

6.5 Conferences and Workshops

1. December 2015: ICSSR sponsored *Research Methodology Course for Ph.D. Students*
   Workshop organised by the Department of Economics, Manipur University, Imphal from 1-11 December, 2015.
2. December 2016: 18^{th} Annual Conference of the *North Eastern Economic Association*
   Conference organised by Department of Economics, Guwahati, Assam from 15^{th} to 17^{th} of December, 2016.
3. November, 2017: *Conversations on Research (CoRe): IGIDR PhD Colloquium*
   Colloquim organised by IGIDR, Mumbai from 7^{th} to 10^{th} of November, 2017.
4. November, 2017: *The Economy as a Complex Sysyem IV: Can Economics be a Physical Science*
   International Workshop organised by IMSc, Chennai from 13-14 November, 2017.
5. February, 2018: *Agrarian Crisi, Rural Credit and Employment in the North East*
   National seminar organised by NEHU, Shillong from 23^{rd} to 24^{th} February, 2018.

6. March, 2018: *Research Conclave 2018*
   Conclave organised by IIT Guwahati, India from 8^{th} to 11^{th} March, 2018.
7. March, 2018: *Innovations in Ensuring Remunerative Prices (MSP) to Farmers*
   Policy Dialogue organised by NASC, Pusa, New Delhi
8. January 2019: *Second International Conference on Business, Economics & Sustainable Development (ICBESD 2019).*
   International Conference organised by TERI School of Advanced Studies, in collaboration with the Government of India Rooftop Solar Technical Assistance Program supported by the World Bank.
9. March 2019: *SAP Seminar 2018-19*
   Seminar organised by- The Department of Economics, Gauhati University under DRS SAP-II of the UGC from 29^{th} to 30^{th} March, 2019.
10. January 2020: 56^{th} *Annual Conference of the Indian Econometric Society (TIES)*
    Conference organised by TIES in collaboration with Madurai Kamraj University from 8-10 January (2020).
11. January 2020: *Pre-Conference Workshop on Time-series Econometrics.*
    Workshop organised by TIES from 5-7 January (2020) held at the Madurai Kamraj University, Madurai
12. April 2020: 94^{th} *Annual Conference of the Agricultural Economics Society (AES)*
    (CANCELLED due to the COVID19 pandemic)
    This international conference organised by AES was scheduled to be held at MTC1 Maria-Theresiacollege, Leuven, Belgium from 15-17 April (2020). However, the organisers have indexed the submitted paper in the AgEcon Search database.

6.6 Publications

1. Baruah, P. (2017). Level of Competition in Direct Farmers' Markets Model in India: A Critical Evaluation. In Ratul Mahanta & Nissar A Barua (eds) *Agriculture in North-East India: Present Status and the Scenario Ahead*, 209-228. Kamrup: Maliyata Offset Press

2. Baruah, P. (2018). Understanding the Movements of Agricultural Price: An Examination of Theory and Empirical Evidences. *Assam Economic Review, 11*, 279-296.

3. Baruah. P. (2020). Impact of Green Revolution on Price Sensitivity of Agriculture in India, in Datta M., Mahajan R. & Bose M. (eds.) *Business, Economics & Sustainable Development: The emerging Issues*, 156- 173. New Delhi: Bloomsbury.

6.6.1 Paper indexed in AgEcon Search database

4. Baruah, P. (2020). Seasonality in commodity prices across India: Extent and implications, No 303694, 94^{th} *Annual Conference*, April 15-17, 2020, K U Leuven, Belgium (Cancelled), *Agricultural Economics Society - AES*, https://EconPapers.repec.org/RePEc:ags:aesc20:303694.

A Appendices

A.1 The commodities chosen for study: Geographical spread and marketed surplus

A.1.1 Volume of production under some major crop categories in India (Average of 2013-14 to 2017-18)

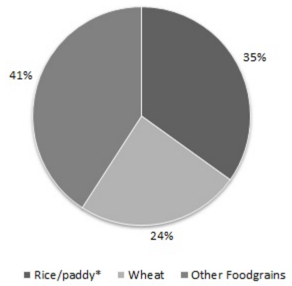
Crop category	Crop	Production	
		(in mn ha)	(% share within crop category)
Food grain	Rice/paddy*	107.80	40.56
	Wheat	94.61	35.60
	Total Foodgrains	265.75	
Oilseed#	Mustard and rapeseed	7.46	25.16
	Groundnut	8.11	27.35
	Total nine Oilseeds	29.65	

Note: *Area for rice is the total of both Kharif and Rabi seasons; # Although, among the oilseeds, area under Soyabean in high (11.15 mn Ha) it is not included due to its limited geographical spread compared to Groundnut or Rapeseed and Mustard. In fact, over 80% of the total area under cultivation (and production) of soyabean is from two states only, *viz.* Madhya Pradesh and Maharashtra (GoI, 2019).

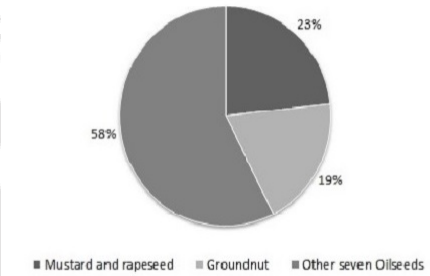
Source: Directorate of Economics & Statistics, DAC&FW, GoI

A.1.2 Area under cultivation for some major crop categories in India (Average of 2013-14 to 2017-18)

Figure A.1: Break-up of area under cultivation



(a) Foodgrains



(b) Oilseeds

Source: Directorate of Economics & Statistics, DAC&FW, GoI

A.1.3 Major producing states of the commodities under study

Crop	Major producing states	Share of total area (%)
(1)	(2)	(3)
Rice/paddy	Andhra Pradesh, Assam, Bihar, Chhattisgarh, Haryana, Madhya Pradesh, Odisha, Punjab, Tamil Nadu, Telangana, Uttar Pradesh, West Bengal	83.66
Wheat	Bihar, Gujarat, Haryana, Himachal Pradesh, Madhya Pradesh, Maharashtra, Punjab, Rajasthan, Uttar Pradesh, Uttarakhand	97.00
Mustard and rapeseed	Gujarat, Haryana, Madhya Pradesh, Rajasthan, Uttar Pradesh, West Bengal	95.69
Groundnut	Andhra Pradesh, Gujarat, Karnataka, Maharashtra	95.65

Note: The table presents the major producing states in terms of area under cultivation for the four commodities under study. The last column reports the percentage share of the area under cultivation accounted for by the listed states out of the total area under cultivation for each crop in India. The figures are averages for the period from 2013-14 to 2017-18.

Source: Directorate of Economics & Statistics, DAC&FW, GoI

A.1.4 Marketed Surplus Ratio (MSR)

Crop	2012-13	2013-14	2014-15
Rice/paddy	81.51	82	84.35
Wheat	77.49	73.11	73.78
Mustard and rapeseed	90.41	94.49	90.94
Groundnut	93.54	95.20	91.63

Note: These are the latest estimates available from the DES, GoI based on Comprehensive Scheme for Studying Cost of Cultivation of Principal Crops in India.

Source: Directorate of Economics & Statistics, DAC&FW, GoI

A.2 Data

A.2.1 About the dataset

The data on *mandi* level prices of the selected commodities is the most important dataset of this study. The dataset used is compiled from the agriculture e-governance portal (AGMARKNET) developed by the Ministry of Agriculture (MoA), Government of India, which covers about 7000 *mandis* of India. This portal was formulated by the DMI under the Agricultural Research and Marketing Information Network (a Central Sector Scheme) for linking all regulated markets, State Agriculture Marketing Boards/Directorates and DMI headquarters. It provides daily price and arrival information on a market-wise, commodity–wise and variety-wise basis from 2003. The coverage of markets became complete only after 2005. To ensure reliability of the reported data, the portal has several checks in place. Before being posted online, the daily prices are hosted on the intranet of DMI and examined for deviations in range. All doubtful entries are segregated and cross-verified.

A.2.2 Inclusion of *mandi*-level price series

Although the chosen data-source provides data at a highly disaggregated level and has a very good coverage of markets, after obtaining the data, it is found that the data has a lot of missing observations or unreported data points. One reason for such missing data is the fact that the coverage of *mandis* in the dataset was expanded gradually and so not all markets have prices reported from 2003 onwards. This issue is dealt with by taking different start years for individual *mandis* depending on the availability of data. Furthermore, it is found that there are gaps in the data within the series as well. These may either be a result of non-reporting of data, or due to absence of trade in certain *mandis* on particular days/months. The gaps remain in the data even after we aggregate the daily prices to monthly frequency. Now, the application of econometric tools requires fairly consistent series and, therefore, it is not possible to include those series that have far too many missing observations within them. Recent studies facing similar issues have allowed for about $30-50\%$ gaps in individual series (Gilbert, et. al, 2017; Kaminski et. al, 2016). Following them, this dissertation has only considered those *mandi*-level series for which at least more than 50% of observations are reported (i.e. are not missing) during their respective reference periods.

The numbers of *mandis* that qualify for analysis under each commodity are: Paddy-167, Wheat-126, Mustard-69 and Groundnut-65.[1] The details on the number of series included for each commodity are reported in the Tables below.

[1]Unfortunately, because of the presence of large data gaps, most of the *mandis* from two important agricultural states (Punjab and Haryana) do not qualify for analysis of time-series components in price. From Haryana, although seven price series qualify for mustard, only two qualify for wheat, while from Punjab only one *mandi* qualifies for wheat. Towards the end of the dissertation, some comparisons are made on a limited basis by analyzing the available data for *mandis* of these states.

A.2.2.1 Paddy

State	No. of wholesale price included from State						Gap (%)
	2003-2016	2004-2016	2005-2016	2006-16	2007-16	Total	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Andhra Pradesh	6	0	19	8	3	36	10.08
Assam	3	0	0	0	1	4	43.59
Chhattisgarh	6	1	0	2	2	11	6.29
Gujarat	0	5	4	0	1	10	8.47
Jharkhand	0	0	1	5	1	7	22.84
Karnataka	11	0	0	0	0	11	8.28
Maharashtra	2	2	3	2	0	9	24.63
Madhya Pradesh	2	0	1	4	0	7	27.88
NCT of Delhi	1	2	1	0	1	5	20.30
Orissa	6	0	2	1	1	10	15.12
Pondicherry	6	0	0	0	0	6	17.16
Rajasthan	3	0	0	0	0	3	28.57
Tamil Nadu	0	8	0	4	2	14	17.56
Telangana	1	0	0	5	0	6	10.63
Uttar Pradesh	9	0	1	2	4	16	15.33
Uttarakhand	3	1	0	0	1	5	37.56
West Bengal	5	0	1	1	0	7	12.28
Total	64	19	33	34	17	167	15.76

Note: The columns 2 to 6 present the no. of *mandi*-level series in accordance to their coverage time period. Column 7 presents the total number of price series included from the respective states. While the end year of each series is same (2016), they differ in terms of the start year. The final column reports the average percentage of gaps in the price series from each state.

A.2.2.2 Wheat

State	No. of wholesale price included from State						Gap (%)
	2003-2016	2004-2016	2005-2016	2006-16	2007-16	Total	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Andhra Pradesh	1			1			15.97
Chhattisgarh	2	2					5.36
Gujarat	14	7	1	4		2	8.90
Haryana	2			2			28.82
Jharkhand	14	6	1	1	2	4	19.51
Karnataka	10	9	1				10.06
Madhya Pradesh	15	6	2	2	4	1	25.79
Maharashtra	17	8	9				13.31
NCT of Delhi	2	1			1		4.98
Punjab	1	1					25.59
Rajasthan	15	10		3		2	10.87
Uttar Pradesh	26	24		2			8.92
Uttarakhand	1	1					43.45
West Bengal	6	3		1		2	22.92
Total	78	14	16	7	11	126	14.34

Note: The columns 2 to 6 present the no. of *mandi*-level series in accordance to their coverage time period. Column 7 presents the total number of price series included from the respective states. While the end year of each series is same (2016), they differ in terms of the start year. The final column reports the average percentage of gaps in the price series from each state.

A.2.2.3 Mustard

State	No. of wholesale price included from State						Gap (%)
	2003-2016	2004-2016	2005-2016	2006-16	2007-16	Total	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Assam	1	1				2	38.00
Chhattisgarh	1		1			2	17.16
Gujarat	7	1	2	1	1	12	8.54
Haryana	2		4	1		7	27.05
Jharkhand	1					1	26.19
Karnataka	1					1	25.00
Madhya Pradesh	2					2	17.56
Maharashtra		2	2	1		5	35.49
NCT of Delhi	2					2	2.38
Rajasthan	14		5	1	1	21	10.59
Uttar Pradesh	4					4	1.79
West Bengal	1			2	7	10	27.65
Total	36	4	14	6	9	69	16.93

Note: The columns 2 to 6 present the no. of *mandi*-level series in accordance to their coverage time period. Column 7 presents the total number of price series included from the respective states. While the end year of each series is same (2016), they differ in terms of the start year. The final column reports the average percentage of gaps in the price series from each state.

A.2.2.4 Groundnut

State	No. of wholesale price included from State					Gap (%)
	2003-2016	2004-2016	2005-2016	2006-16	Total	
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Andhra Pradesh	4	2	10		16	18.35
Gujarat	8	1	4		13	17.61
Karnataka	9				9	12.83
Madhya Pradesh	2		1	1	4	37.64
Maharashtra	1	1		1	3	26.21
Pondicherry	1				1	19.64
Rajasthan	1		2	1	4	29.06
Tamil Nadu	8		1	2	11	24.28
Telangana		1		1	2	42.19
Uttar Pradesh	1			1	2	38.37
Total	35	5	18	7	65	22.02

Note: The columns 2 to 5 present the no. of *mandi*-level series in accordance to their coverage time period. Column 6 presents the total number of price series included from the respective states. While the end year of each series is same (2016), they differ in terms of the start year. The final column reports the average percentage of gaps in the price series from each state.

A.3 Seasonality Estimation

A.3.1 The three specifications of seasonality

This dissertation uses three alternative functional specifications of the seasonal pattern: dummy variable, trigonometric and sawtooth. The latter two are inspired by typical harvest-patterns and are restricted forms of the general dummy variable specification. All the three are run on each series and tested against each other using F-tests. The aim is to see if either of the two harvest-pattern inspired specifications can be preferred over the unrestricted dummy specification.

A.3.1.1 Dummy variable specification

In this specification, the seasonal gap of a price series is the difference between its highest and lowest seasonal factor as illustrated in Figure A.2.

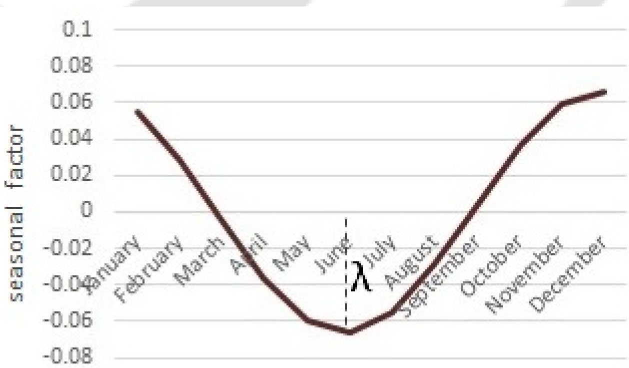
Figure A.2: An illustration of estimated seasonal pattern and seasonal gap using seasonal factors

Limitations of dummy-variable approach: In this approach, there is a chance of overestimation bias in the seasonal gap due to three factors that interact with each other: peak and trough months may be incorrectly identified from data; the estimated gap may be a non-linear function of the dummy variable coefficients; and the number of observations used to estimate the coefficients of the peak and trough month dummy variables is usually very small in short samples. illustrate through Monte-Carlo experiments that if samples are not too long (5-15 years) there is an upward bias observed in seasonal gap estimates obtained using a dummy variable specification.

A.3.1.2 Trigonometric specification

This defines the seasonal pattern as a pure sine wave. Figure A.3 represents an illustrative pattern. This specification is, however, restrictive in the assumption that the post-harvest price decline is symmetric with respect to the pre-harvest price rise.

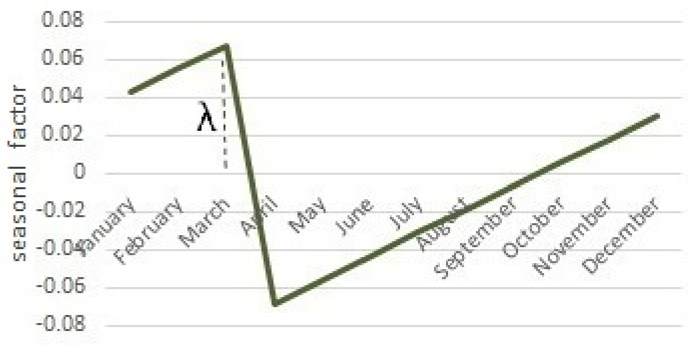
Figure A.3: An illustrative trigonometric seasonal pattern



A.3.1.3 Saw-tooth specification

This one is based on the assumption that the peak price occurs in the month prior to the harvest and then prices drop sharply in the month of harvest and the next, after which prices gradually rise over the remainder of the year. Figure A.4 represents an illustrative pattern. This specification is closer to the theoretical expectation of seasonal behaviour compared to the former.

Figure A.4: An illustrative saw-tooth seasonal pattern



A.4 Commodity specific Levene's Test Results

A.4.1 Test statistics for Equality of Variance in Volatility Estimates across Regions for all commodities

Crop	(W_0)	(W_{50})	W_{10})	Degrees of freedom (k-1,n-k)
(1)	(2)	(3)	(4)	(5)
Paddy	0.82	0.38	0.51	df(4, 144)
	(0.513)	(0.820)	(0.562)	
Wheat	2.04	1.98	2.01	df(4,116)
	(0.092)	(0.119)	(0.097)	
Mustard	1.44	0.73	1.49	df(3,62)
	(0.239)	(0.539)	(0.225)	
Groundnut	6.54	3.55	6.75	df(3,55)
	(0.001)	(0.020)	(0.001)	

Note: The table reports the Levene's robust test statistic (W_0), Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the groups (regions). The figures in parenthesis are the respective p-values. The final column reports the respective degrees of freedom $(k-1,\ n-k)$, where k is the number of groups and n is the number of observations in the group.

Source: Author's calculations

A.4.2 Test statistics for Equality of Variance in Volatility Estimates across States for all commodities

Crop	(W_0)	(W_{50})	$W_{10})$	Degrees of freedom (k-1,n-k)
(1)	(2)	(3)	(4)	(5)
Paddy	0.82	0.38	0.51	df(4, 144)
	(0.513)	(0.820)	(0.562)	
Wheat	2.04	1.98	2.01	df(4,116)
	(0.092)	(0.119)	(0.097)	
Mustard	1.44	0.73	1.49	df(3,62)
	(0.239)	(0.539)	(0.225)	
Groundnut	6.54	3.55	6.75	df(3,55)
	(0.001)	(0.020)	(0.001)	

Note: The table reports the Levene's robust test statistic (W_0), Brown's (W_{50}) and Forsythe's (W_{10}) statistics for the equality of variances between the groups (states). The figures in parenthesis are the respective p-values. The final column reports the respective degrees of freedom $(k-1,\ n-k)$, where k is the number of groups and n is the number of observations in the group.

Source: Author's calculations

B | Notes

Chapter 1

1. (page 17) This clubbing is also justified as the nature of land relations and agricultural practices in Assam resemble that of the other states in East region.
2. (page 18) Available at $pubdocs.worldbank.org/en/561011486076393416/CMO–Historical–Data–Monthly.xlsx$

Chapter 3

1. (page 69) Using differenced dummies (ΔZ_{mj})instead of using differenced coefficients for the dummies) adds to the ease of interpreting the estimated coefficients
2. (page 107) Bangladesh has over 40% of its labour force dependent on agriculture. Paddy is the most widely cultivated crop (it constitutes over 87% of total foodgrain production in 2017-18. Wheat and maize are the other important food-grains in terms of volume of production constituting around 2.5% and 9% of total production respectively in 2017-18 (Government of the People's Republic of Bangladesh, 2019).
3. (page 109) The exact magnitudes of the estimates by Kumar and Sharma (2006) are not comparable to this study's estimates due to certain technical differences in the functional specifications of seasonality. However, the basic approach taken up to estimate seasonality and the seasonal gap is similar to the one taken up in this dissertation.

Chapter 4

1. (page 118) An ARCH model can be expressed as an AR model of squared residuals.

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