ISSN 0971-3441
Online ISSN 0974-0279

July-
December
2022
Volume 35
Number 2

Agricultural Economics Research Review

Agricultural Economics Research Association (India)

AGRICULTURAL ECONOMICS RESEARCH REVIEW

ISSN 0971-3441
Online ISSN 0974-0279

Agricultural Economics Research Review

Agricultural Economics Research Association (India)
National Agricultural Science Centre Complex
Dev Prakash Shastri Marg, Pusa
New Delhi - 110 012

Agricultural Economics Research Review
Vol. 35 (No.2) 2022

Financial support from:
Indian Council of Agricultural Research (ICAR), New Delhi

Published by:
Dr Suresh Pal, Secretary, AERA on behalf of Agricultural Economics Research Association (India)

Printed at:
Cambridge Printing Works, B-85, Phase II, Naraina Industrial Area, New Delhi 110 028

ISSN 0971-3441

Agricultural Economics Research Review

[Journal of Agricultural Economics Research Association (India)]

Volume 35 **Number 2** **July-December 2022**

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Agricultural Economics Research Review 2022, 35 (2), 1-25
DOI: 10.5958/0974-0279.2022.00028.3

Indian sugar policies: connecting production, consumption, and health

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Abstract Sugar is one of the most regulated agricultural commodities in India. Every stage of its value addition has some mechanism of government support. Sugar emerges to be an interesting case study which shows how one market distortion triggers a spate of distortionary policies resulting in a highly distorted domestic sugar market, which at many times stands alienated from its global reference prices. The observed and estimated costs (actual and implied) of policy interventions by the government in the cane and sugar industry are high and have been rising overtime. Combining them with the high environmental and social costs, there emerges a need for a course correction in policies.

Keywords sugar, India, diets, nutrition, obesity, sugar exports, subsidies

JEL codes H25, I18, Q17, Q18

Sugar is one of the most tightly regulated agricultural commodities in India. It is also one in which almost every stage of its value addition has some mechanism of governmental support. It is one sector where not just the cane farmers, but also the cane millers get significant support from the government. Besides, in providing support to the processors/millers, the governmental policies are also effectively 'taxing' sugar consumers in the country.

In 2021-22, India was the second largest producer of sugarcane in the world. Despite growing diversion to ethanol, rising consumption both by industries and individual consumers, the country has been able to generate large sugar surpluses. These surpluses have supported in strengthening India's position as a global sugar exporter. However, not just is sugarcane a water guzzler and thus has obvious environmental costs, its higher consumption has been increasingly associated with deteriorating health outcomes. In this paper, the sugarcane policy environment in the country is outlined and is used to showcase how one distortion in policy snowballs into an intricate web of distortions leading to sometimes, inefficient outcomes.

The report is organized in nine sub-sections. The Indian sugar and cane production and consumption trends are profiled in first two sections, followed by India's sugar trade trends. An analysis of key health metrics concerned with sugar are presented in the next section. The structure of the Indian sugar value-chain is explained in the next, followed by a listing of the key governmental programs and schemes for cane and sugar. An analysis of the level of fiscal (or budgetary) support given to the cane and sugar industry is presented next followed by the qualitative insights on sugar costs and benefits. The paper ends with policy recommendations.

Production of cane and sugar

Sugarcane is one of the most important crops globally as it provides raw material, both for food and fuel. More than 100 million individuals around the world depend on sugarcane cultivation and processing for livelihoods (IISD 2019). Since 1961, global sugarcane production

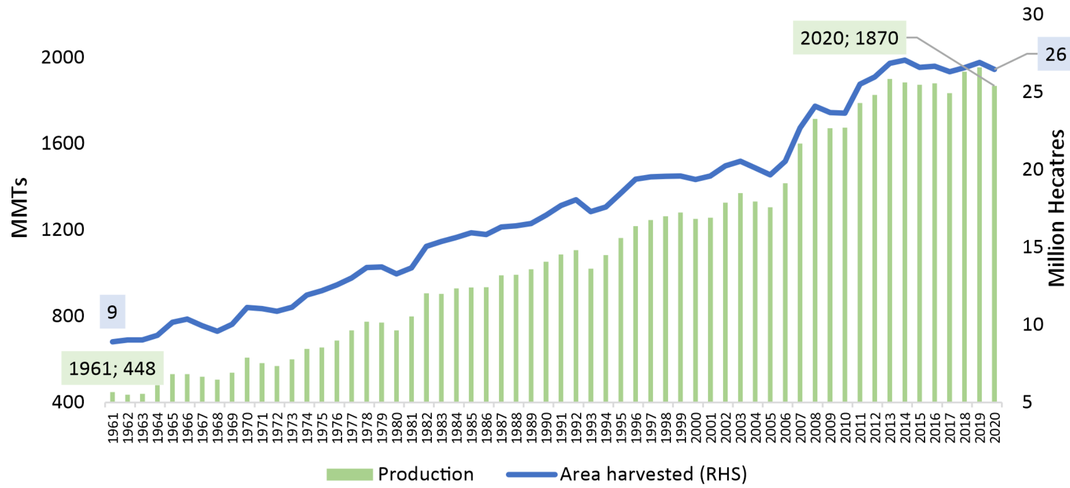

Figure 1 Global sugarcane since 1960: area (Mn Ha) and production (MMTs)
Source FAO

has increased fourfold, from 448 million metric tons (MMTs) to 1870 MMTs in 2020. In the same period, area under sugarcane increased about 3 times, from about 9 million hectares to 26 million hectares (Figure 1).

Globally, about 77 per cent of the cane comes from four countries: Brazil (39 per cent), India (20 per cent), China (12 per cent) and Thailand (6 per cent).

Cane is mostly used as raw material for the production of sugar. A small quantity of sugar is also produced from sugar beet (FAO 2022). Globally, 80 per cent of sugar is derived from sugarcane (ISO 2022). In India, production of sugar is almost solely from sugarcane (Mall et al. 2021).

The sugar content of cane ranges approximately between 8 to 15 per cent. (FAO 2022 and ICAR 2022). For triennium ending (TE) 2021, 170 MMTs of sugar (from cane and beet) was produced globally (ISMA). Eight countries produced about 70 per cent of this: Brazil (18 per cent), India (18 per cent), European Union (10 per cent), Thailand (7 per cent), China (6 per cent) and US, Russia and Mexico about 4 per cent each (USDA) (Figure 2).

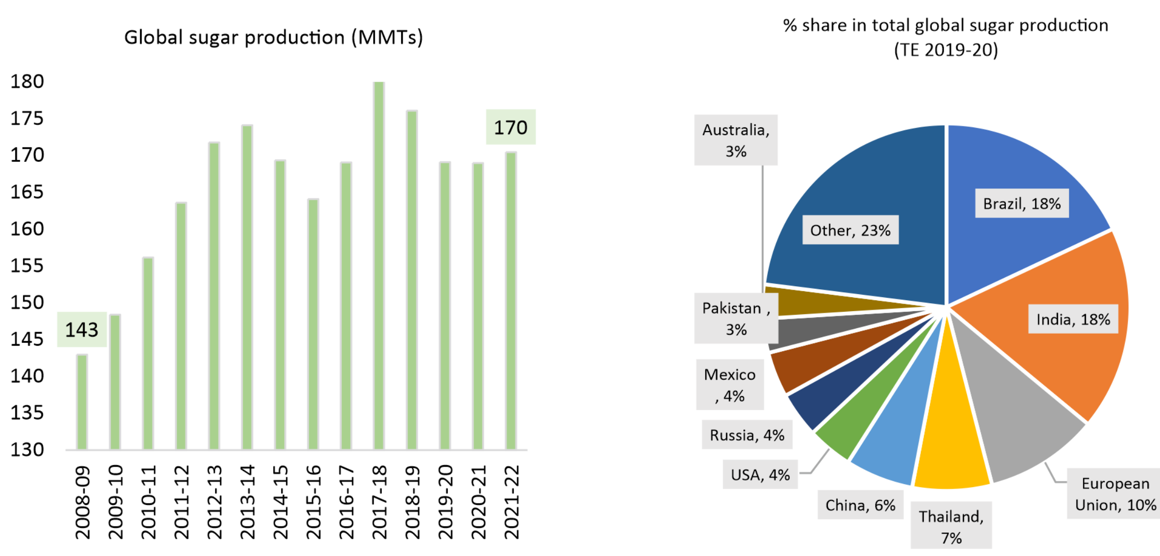

Figure 2 Global sugar production (MMTs) and its Geography (% global production)
Source ISMA and USDA
Note Reported number is sugar produced from both cane and beet

Indian cane and sugar

India is the second largest producer of sugarcane in the world. In TE 2020-21, 4.8 million hectares was under sugarcane cultivation in the country, producing on average 394 MMTs of sugarcane. On average, about 75 per cent of sugacane in India is used to produce white sugar, 13 per cent to produce *gur* (Jaggery) and the rest 12 per cent for seed/feed production (ISMA 2021). Production of sugar is largely dependent on the recovery rate[1] of sugar from sugarcane. In recent years, the recovery rate has gone up, mainly due to varietal improvement of sugarcane. In TE 2020-21, 31 MMTs of sugar was produced in the country (ISMA 2021).

Geographically, both cane and sugar production is highly concentrated in a few states in the country. In case of cane, three states account for about 77 per cent of all-India production (Figure 3): Uttar Pradesh (47 per cent), Maharashtra (21 per cent) and Karnataka (9 per cent) (TE 2019-20). Out of the 461 operational sugar factories in India in 2019, 26 per cent were in Uttar Pradesh, 31 per cent were in Maharashtra and 14 per cent were in Karnataka (ISMA 2020).

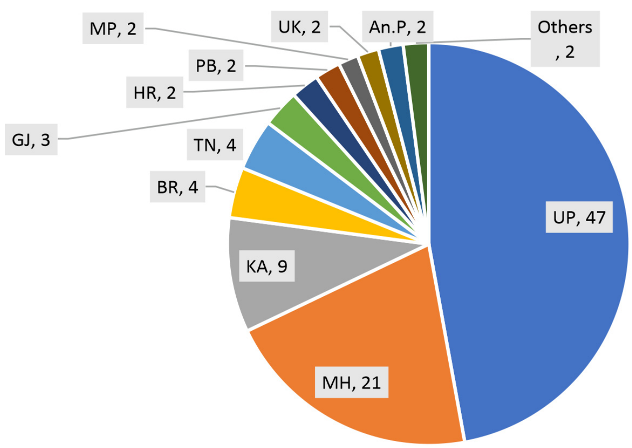

Figure 3 State-wise share in cane production (TE 2019-20)
Source Ministry of Agriculture & Farmers' Welfare (GoI)
Note UP is Uttar Pradesh, MH is Maharashtra, KA is Karnataka, BR is Bihar, TN is Tamil Nadu, GJ is Gujarat, HR is Haryana, PB is Punjab, MP is Madhya Pradesh UK is Uttarakhand, An.P is Andhra Pradesh

Consumption of sugar in India

India emerges to be the largest consumer of sugar in the world (ISMA 2021). In TE 2019-20, almost 50 per cent of global sugar production was consumed in five countries: India (16 per cent), European Union (11 per cent), China (9 per cent), USA (6 per cent) and Brazil (6 per cent) (Figure 4).

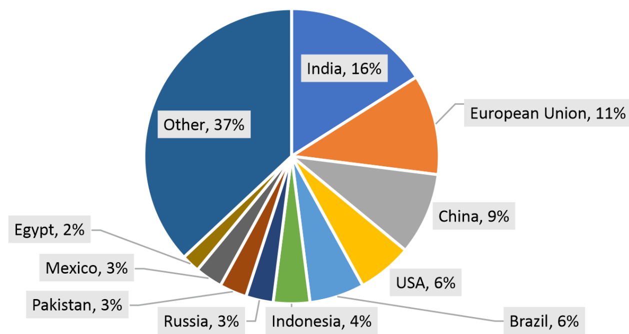

Figure 4 Global consumption of sugar: share of countries (TE 2019-20)
Source USDA

Despite the large value of consumption and production, per capita sugar availability in India is much lower than the global average. The estimate of per capita availability of sugar in India comes out to be about 19.3 kg per person per year, whereas the global average is of about 22.1 kg per person per year. (ISO 2019 and ISMA 2021).

Trends in sugar consumption

To estimate the level of per capita sugar consumption, we used the household-level data from Government of India's (GOI) consumer expenditure surveys. The latest data is available for 2011-12 as the 2017-18 Consumption Expenditure Survey was retracted by GOI "*in view of the data quality issues*" (PIB 2019).

Among other things, as part of the survey by National Sample Survey Office (NSSO), the respondents were asked about their consumption of the raw sugar consumption (sourced from Public Distribution System- PDS and other sources), consumption of fruit juices and shakes, prepared sweets, cake & pastry, biscuits & chocolates, and sauce, jams, and jellies. A snapshot of the estimates of per capita consumption for the following commodities is given in Table 1.

For this study, we have only looked at raw sugar consumed from PDS and 'other' sources which excludes sugars naturally present in fruits, honey,

[1]Recovery rate is the amount of sugar extracted from sugarcane. Higher the recovery rate, more expensive is the cane in India.

Table 1 Consumption of various raw and processed sugars (per capita per month)

Commodity name	Unit	All India per capita consumption	
		2011-12	2004-05
Sugar-PDS	Kilograms	0.10	0.06
Sugar-Other	Kilograms	0.64	0.63
Fruit juice and shake	Litre	0.01	0.01
Prepared sweets, cake, pastry	Number	0.00	0.01
Biscuits, chocolates, etc.	Number	0.00	0.20
Sauce, jam, jelly	Grams	1.85	0.75

Source Estimated by authors using unit level data from NSSO: 2004-05 and 2011-12.
The data is for year July-June.

sweeteners, etc. Also, we have not included sugar intake via processed commodities such as biscuits, chocolates, jams, and other processed food.

As per NSSO data, India has seen increasing sugar consumption over the years. In 2011-12, average per capita raw sugar consumption in India was about 23.9 grams per day in rural areas and 27.4 grams per day in urban areas. The corresponding numbers in 2004-05 were 21.6 and 27.3 respectively. Consumption clearly has grown in both areas; however, the cumulative annual growth rate (CAGR) is higher for rural areas (1.46 per cent) compared to urban areas (0.05 per cent) (Figure 5).

Despite the rise, Indian sugar consumption levels on average have been below or close to the recommended threshold levels of sugar. As per Indian Council of Medical Research (ICMR), the recommended threshold level of sugar consumption is about 30 gm per person per day and as per the WHO, recommended threshold intake is about 25 grams per day. Both the thresholds have been plotted as dotted lines in Figure 5.

As the NSSO's 2011-12 data is dated, we use alternate methods to extrapolate more recent values of sugar consumption in the country. For this we use data on per capita income from GOI and data on income-demand elasticities from Kumar (2017). By adjusting

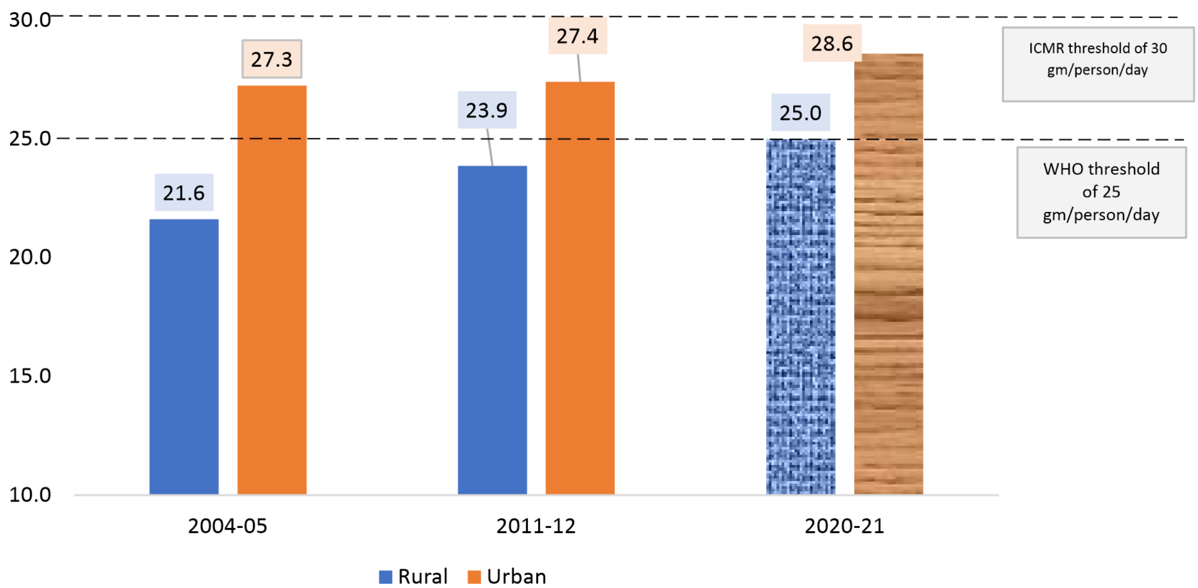

Figure 5 Indian Sugar Consumption (grams/person/day) for 2004-05 and 2011-12
Source Unit level NSSO 68th round consumption data, MOSPI, Kumar 2017

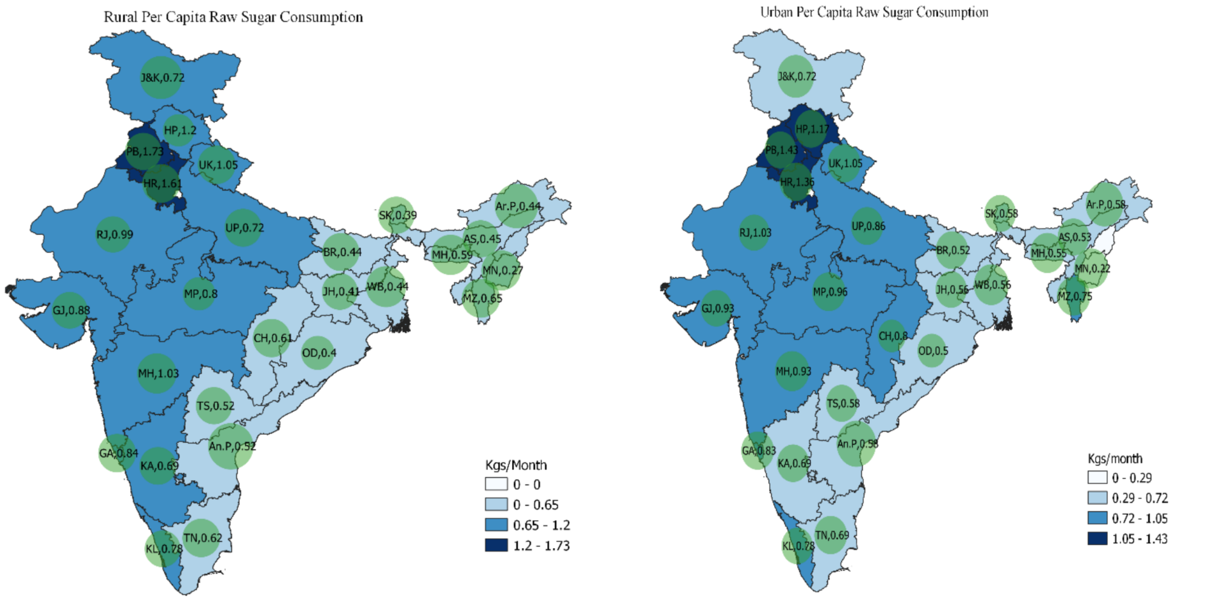

Figure 6 Per capita consumption of raw sugar (kg/month) 2011-12

Source Maps prepared by authors based on estimates from unit level NSSO 68th round consumption data.

Notes Sugar consumption is summation of sugar consumed from PDS and other sources. Union Territories not considered for this analysis.Do rich Indians consume more sugar?

the 2011-12 sugar consumption levels using income demand elasticities and annual change in overall per capita income in the country, ceteris paribus, we estimate sugar consumption levels for year 2020-21. As per the estimates, about 25 and 28.6 grams per person per day of sugar was consumed in rural and urban areas respectively in 2020-21. We plot these estimates in Figure 5.

Within India, there is a disparity between states based on the levels of sugar consumption. While several states such as Gujarat, Haryana, Himachal Pradesh, Madhya Pradesh, Maharashtra, Punjab, Rajasthan, Uttarakhand, and Uttar Pradesh observed above average sugar consumption levels, there were others like Telangana, Tamil Nadu, Andhra Pradesh, Odisha, Jharkhand, Bihar, West Bengal, Sikkim and the North-Eastern states where sugar consupmption fell short of national average in both urban and rural areas (Figure 6).

Using the 2011-12 NSSO unit-level data, surveyed households were bifurcated into five expenditure (*proxy for income*) classes based on their level of monthly per capita expenditures (MPCE). It is found that sugar consumption increased with higher income/expenditure levels, in both rural and urban areas (Figure 7).

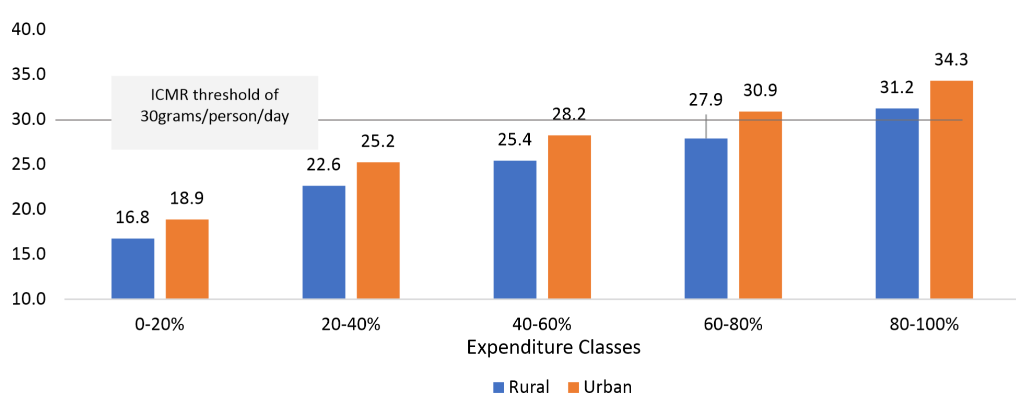

Figure 7 Expenditure class wise per capita sugar intake (2011-12)

Source Estimated by authors using unit level NSSO 68th round consumption data

It emerges that about 60 per cent households in rural areas and about 54 per cent households in urban areas consumed below ICMR's threshold of 30 grams per day threshold. Benchmarking against WHO's threshold, about 16 per cent population in rural areas and 15 per cent population in urban areas was consuming below 25 grams per day.

It is important to note that compared to other foods such dairy, meat, beverages, spices, etc., the income elasticity of sugar demand is low (Kumar. P 2017). It means that with increases in incomes, demand for other commodities is likely to grow much faster than sugar. However, the expenditure elasticity for sugar may differ across different expenditure groups.

Consumption of subsidized sugar from PDS

As per NSSO data, Indian consumers consume raw sugar sourced either from 'other sources' (i.e., the open market) or through GOI's Public Distribution System (PDS) (subsidized sugar). Under India's PDS, AAY families (or Antyodaya families which are categorized as *poorest of poor*) are provided 1 kg of sugar per family (DFPD). As per our calculations from NSSO 2011-12 data, per month consumption of sugar for a family of five[2] was 3.58 kgs in rural areas and 4.11 kgs in urban areas. Intuitively, in 2011-12, the percent of 1 kg PDS sugar supplied by sugar in total consumed sugar should be 28 percent and 24 percent for rural and urban areas respectively.

However, calculations from 2011 NSSO survey data, show that at all-India level, in rural areas, 15 per cent of the total sugar consumption by individuals was from sugar sourced through PDS. For urban areas, this was lower, with only 10 per cent of sugar sourced from PDS for consumption. NSSO data also show that for states, the share of PDS sugar in total sugar consumption varies.

In rural areas, states such as Himachal Pradesh (54 per cent), Assam (67 per cent), Jammu & Kashmir (68 per cent), Tamil Nadu (70 per cent), Sikkim (70 per cent), Mizoram (71 per cent) and Tripura (89 per cent), depended on PDS for more than 50 per cent of sugar intake. In urban areas, overall, there was less dependence on PDS. Sikkim (62 per cent), Tamil Nadu (63 per cent), Jammu & Kashmir (64 per cent), Mizoram (65 per cent) and Tripura (83 per cent) depended on PDS for more than 50 per cent of sugar intake (Table 2).

Global trade of Indian sugar

India is not a regular exporter of sugar. Global trade is a function of, inter alia, domestic surpluses. Besides, as explained later, Indian sugar is not globally price competitive and therefore its exports have historically

Table 2 Proportion of PDS sugar in total consumed sugar (NSSO 2011-12)

Share	Rural	Urban
0-25%	Andhra Pradesh (24%), Karnataka (21%), Madhya Pradesh (17%), Kerala (14%), Gujarat (13%), Uttar Pradesh (11%), West Bengal (10%), Manipur (9%), Maharashtra (7%), Haryana (4%), Goa (3%), Rajasthan (2%), Bihar (2%), Nagaland (1%), Punjab (1%), Jharkhand (0.3%)	Chhattisgarh (11%), Karnataka (11%), Odisha (10%), Andhra Pradesh (10%), Kerala (9%), Madhya Pradesh (8%), West Bengal (6%), Manipur (5%), Uttar Pradesh (3%), Bihar (2%), Haryana (2%), Maharashtra (2%), Gujarat 2%), Rajasthan (2%), Jharkhand (1%), Goa (1%), Punjab (0.4%), Nagaland (0.3%)
25% to 50%	Arunachal Pradesh (40%), Uttarakhand (40%), Meghalaya (36%), Chhattisgarh (27%), Odisha (26%)	Arunachal Pradesh (38%), Assam (38%), Himachal Pradesh (35%), Uttarakhand (29%), Meghalaya (25%)
>50%	Tripura (89%), Mizoram (71%), Sikkim (70%), Tamil Nadu (70%), Jammu &Kashmir (68%), Assam (67%), Himachal Pradesh (54%)	Tripura (83%), Mizoram (65%), Jammu & Kashmir (64%), Tamil Nadu (63%), Sikkim (62%)

Source Unit level NSSO 68th round consumption data
Notes Number in parenthesis is the per cent share of PDS sugar in total sugar consumption

[2]As per Census 2011, average family size in India is five

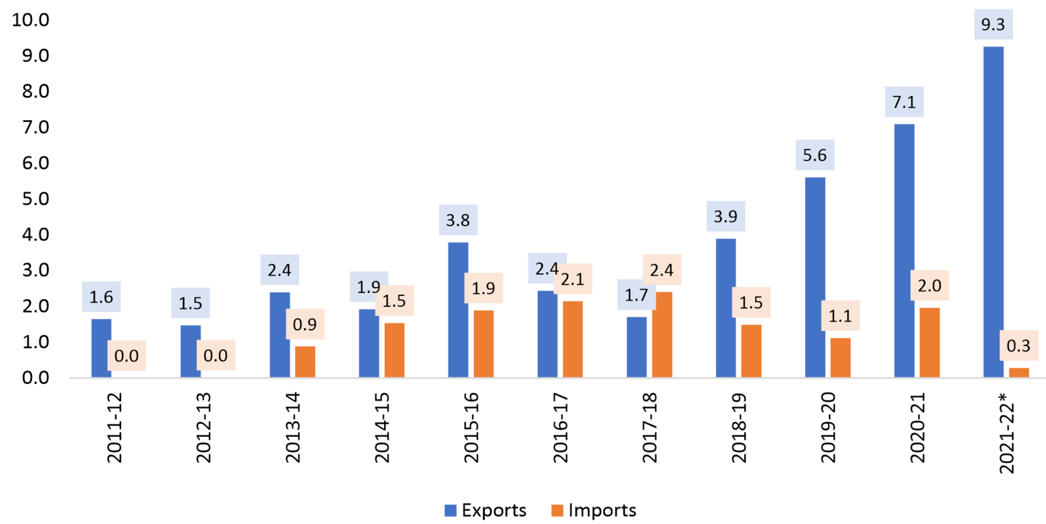

Figure 8 Sugar exports and imports from India (MMTs)
Source Ministry of Commerce and Industry
Notes Data is reported for both raw and refined sugar. *from April to February. The data here is for finanicial year.

been few and scattered. However, trends have changed around 2018-19. In TE 2019-20, India became the third largest sugar exporter and accounted for 7.3 per cent of global sugar exports following Brazil (38.2 per cent) and Thailand (16.3 per cent) (USDA 2022). A time series plot of Indian sugar exports and imports is given in Figure 8. India's major export destinations include Afganistan, Bangladesh, Djibouti, Iran, Indonesia, Jordan, Myanmar, Malayasia, Nepal, Qatar, Saudi Arab, Sri Lanka, Somalia, Sudan and UAE.

The good performance of Indian sugar exports since 2017-18 has largely been a function of growing support provided to sugar mills given by the government(s) (we explain this in later sections). The situtation in 2022 was, however, different. The Russian war on Ukraine resulted in huge spike in global prices of agricultural commodities, including that of sugar, which increased global competitiveness of Indian sugar. This led to a surge in Indian exports in 2021-22. However, fears of high domestic food inflation led GOI to cap sugar export at 10 MMTs for the year 2021-22 (GOI 2022). This was despite the country having a bumper sugar production of 35.5 MMT in 2021-22. This reflects the rather unpredictable character of Indian sugar trade policy. In terms of imports, there have been significant imports in 2016-17 (2.1 MMTS) and 2017-18 (2.4 MMTs). These were years of drought that impacted domestic production of sugarcane.

In the recent years, to meet the twin objectives of (i) helping financially unviable Indian sugar mills; and (ii) for promoting ethanol blending for fuel purposes, Indian government has been promoting diversion of cane towards ethanol production (we explain this in later sections). In 2019-20, 0.9 MMTs and in 2020-21, 2.2 MMTs of sugarcane was diverted towards ethanol production in the country (DFPD 2021).

Key health metrics of Indian population

Non-communicable diseases (NCDs) account for 61.8 per cent of the total deaths in India (Global Burden of Disease in Indian States 2016). The share of various causes of death under NCDs is given in Figure 9.

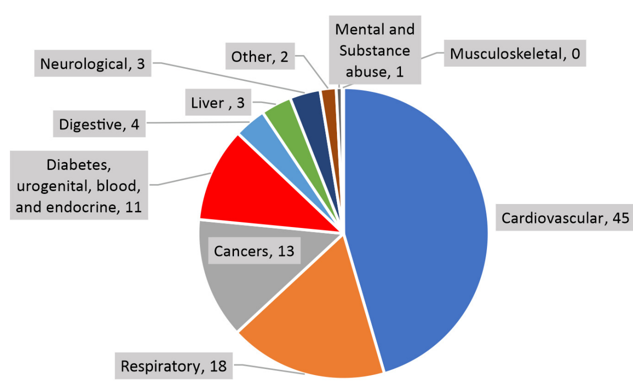

Figure 9 Death caused due to NCDs (2016)
Source Global Burden of Disease in Indian States 2016

Table 3 Health metrics of Indian population

Year	% Population with high blood sugar (>140 mg/dl)		% Population obese/overweight (BMI ≥ 25.0 kg/m)		% Population with diabetes	
	Women	Men	Women	Men	Women	Men
2005-06	NA	NA	12.6	9	2.7	2.9
2015-16	5.8	8	20.6	18.9	4.6	4.8
2019-20	6.1	7.3	24	22.9	NA	NA

Source National Family Health Survey (NFHS) (various years)

Diabetes, urogenital, blood and endocrine diseases accounted for 11 per cent of the total deaths due to NCDs.

Diabetes is a chronic condition marked by high concentration of glucose (sugar) in the blood (IDF 2021). Globally, 537 million people were diabetic in 2021. Out of this, India was home to 74.2 million diabetic people (about 14 per cent)[3]. It is estimated that by 2045, the incidence of diabetes in India is likely to go up to about 124.9 million (IDF 2021). It is important to note that consumption of added sugars is not directly related to incidence of diabetes. However, being overweight/obese increases the chances of a person becoming diabetic.

There are two types of diabetes, Type I and Type II. The Type I diabetes is not caused by sugar or lifestyle choices. However, overweight/obese people consuming more sugar are prone to Type II diabetes (IDF 2021). Consuming natural sugars under recommended thresholds is okay. However, consumption of added sugars, particularly when in excess, can cause health problems such as high blood pressure, inflammation, weight gain, diabetes, etc. (HMS 2022). Therefore, the Food Safety and Standards Authority of India (FSSAI) promotes intake of natural sugar present in fruits and vegetable and discourages consumption of simple sugars from sugar sweetened beverages (SSBs) and processed snacks with high added sugar contents (FSSAI 2017).

The Comprehensive National Nutritional Survey (CNNS 2019) finds that at all India level 1.3 per cent of children between 5 to 9 years and 1.1 per cent adolescents between 10 to 19 years were obese. CNNS is a national representative survey conducted between 2016 and 2018 covering preschoolers, school-age children, and adolescents in both rural and urban areas of the country. The survey also found that the prevalence of diabetes is increasing in the country across age and social groups and diabetes is being increasingly diagnosed in children, adolescents, and younger adults. Reduced physical activity, obesity and poor diet are causing increase in diabetes (CNNS 2019).

National Family Health Survey (NFHS) 2019-21 data also suggests that both overweight/obesity and diabetes are increasing in India (Table 3). In 2005-06, 12.6 per cent women and 9 per cent men were overweight/obese. This increased to 20.6 per cent and 18.9 per cent in 2015-16 for women and men respectively. In 2019-21, it again increased, with 24 per cent women and 22.9 per cent being overweight/obese. Also, between 2005-06 and 2015-16, incidence of diabetes increased from 2.7 per cent to 4.6 per cent for women and 2.9 per cent to 4.8 per cent for men.

State-wise incidence of obesity/overweight

Using the NFHS state-level data, we map obesity/overweight for men and women in rural areas in Figure 10 and Figure 11. It appears, that obesity in women is highest in Punjab, Chandigarh in north and Kerala and Tamil Nadu in the south. In case of men, Tamil Nadu, Telangana and Jammu & Kashmir top the rank.

Overall, it appears that the southern state of Tamil Nadu has among the highest rates of obesity across gender and geography. Not surprisingly, poorer Indian states of Madhya Pradesh, Chhattisgarh, Jharkhand, Bihar rank lower on obesity.

[3]Estimates for adults between 20 and 79 years of age

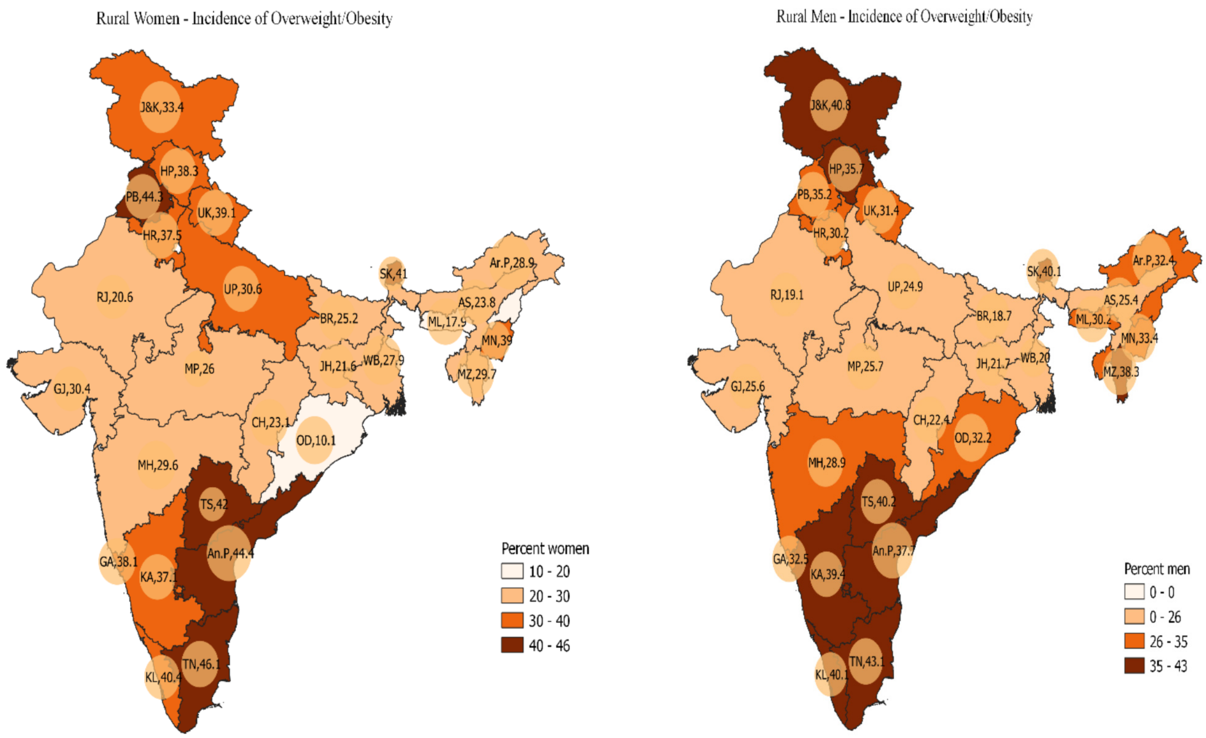

Figure 10 Incidence of overweight/obesity- Percent Women and Men (Rural 2019-21)
Source Maps created by authors based on NFHS 2019-21 data

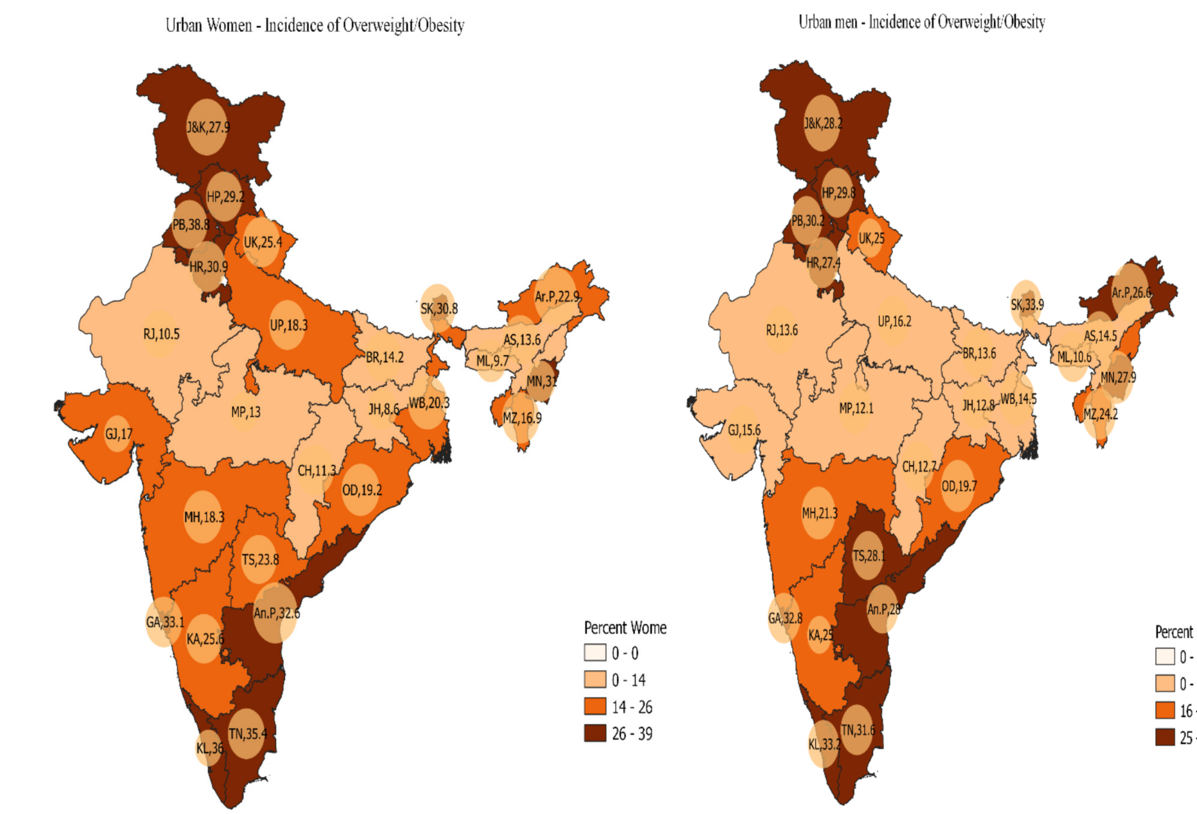

Figure 11 Incidence of overweight/obesity- Percent Women and Men (Urban 2019-21)
Source Maps created by authors based on NFHS 2019-21 data

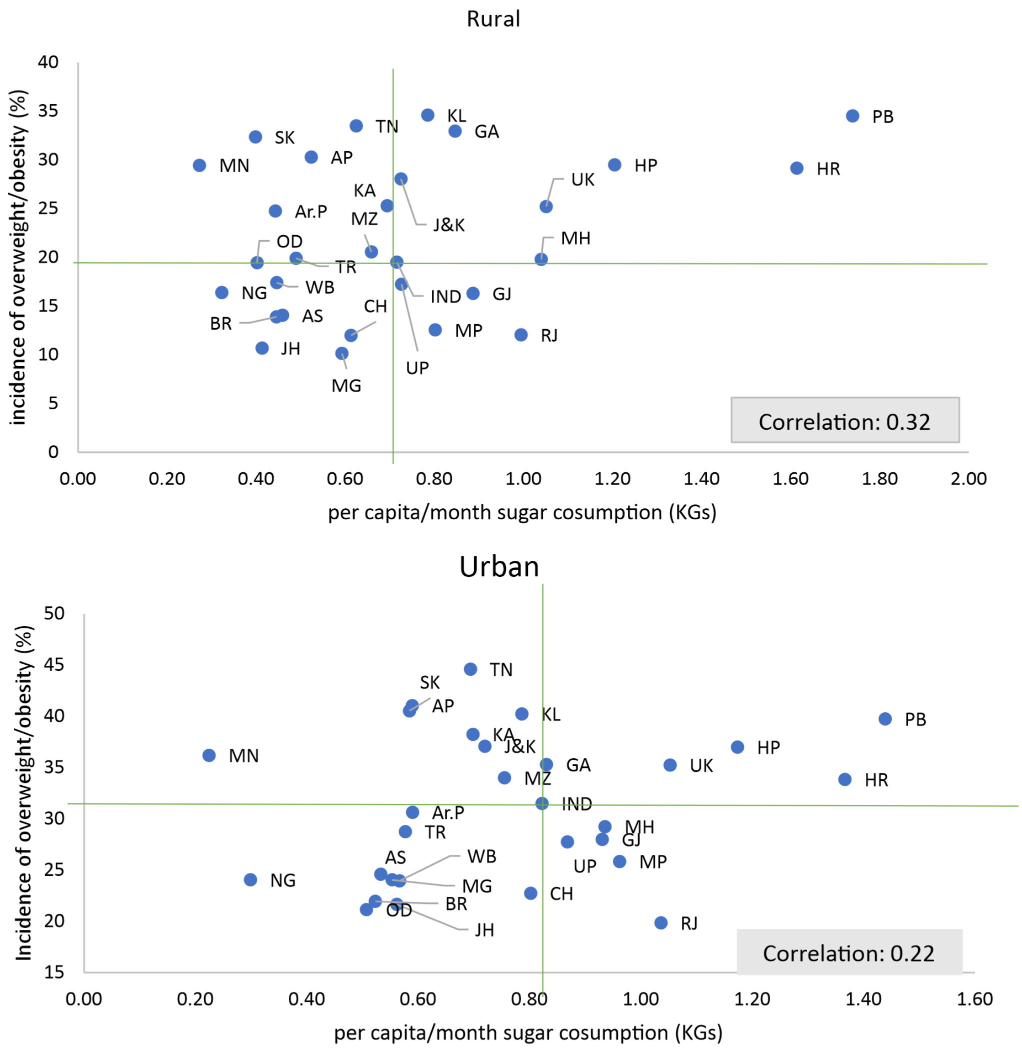

Figure 12 Per capita sugar consumption (kg/ month) and incidence of overweight/obesity (% population)
Source NSSO (2011-12) and NFHS (2019-21)

Mapping obesity with sugar consumption

Using the data on consumption of sugar from NSSO and obesity from NHFS, we find that both, per capita sugar consumption and incidence of overweight/ obesity were higher in the northern and southern states. But is that a pattern? We check it via correlation charts (Figure 12).

In case of rural and urban areas, correlation between the level of per capita consumption and incidence of obesity is 0.32 and 0.22, respectively. This is not very high. Intuitively, this may be because of the high level of heterogeneity in consumption and health outcomes for groups within a specific state. Therefore, a more granular analysis is required. However, as stated before, there is evidence suggesting that increased sugar consumption causes deterioration in health outcomes.

Stakeholders in Indian sugar value chain

The value chain of sugar is small and involves farmers, sugar mills and consumers (Figure 13). Most of the functions related to production, processing and marketing are regulated by the Government. All stakeholders are regulated in some way by either the central or the state governments, and some by both.

Farmers produce sugarcane which is used as raw material by the sugar mills for production of sugar. They receive support for producing cane in the form of various incentives and subsidies. There are multiple

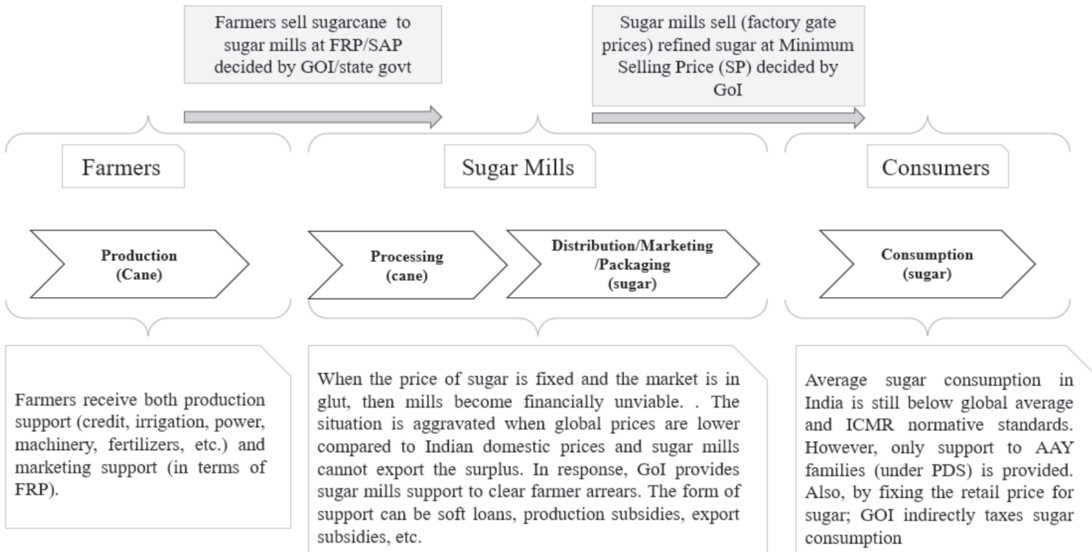

Figure 13 Life cycle of sugar in India
Source Compiled by authors

schemes of the Union and state governments that allow farmers to access subsidized inputs like credit, insurance, micro irrigation facilities, fertilizers, and machinery. In addition, farmers also receive price support for their cane in the form of Fair and Remunerative Prices (FRP). To increase support to cane farmers, some states declare a bonus over and above the FRP and declare a state advised price (SAP) that is generally higher than the FRP. To nudge farmers to produce, these prices are declared before the onset of the cropping season of the cane.

Sugar mills purchase cane from the farmers and pay them FRP (or SAP). Unlike the usual procurement process of grains under the minimum support price (MSP) regime, where government agencies physically procure and pay the farmers, for cane, the sugar mills procure and pay the price to farmer. Governments do not pay the FRP/SAP to the farmers. Mills undertake processing of cane and produce sugar, ethanol, and other by-products. As cost of input (cane) is fixed (as FRP or SAP), mills suffer when prices of its main product i.e., sugar fall. They need help from governments to tide-over financial stress. As one effort, GOI has started to peg ex-mill price of sugar to support the mills. The sugar from here is either consumed by individual or by industries for further value addition. There are several more aspects of policies influencing these stakeholders. These are detailed below.

Cane and sugar policy environment

Production related policies

Indian sugar industry is highly regulated with regulations ranging from cultivation of sugarcane to production of sugar and its by-products such as molasses and ethanol. These regulations are in the form of area reserved for sugarcane cultivation, minimum distance between sugar mills, price fixation, buffer stocking, sale of sugar by mills and trade policy of sugar for regulation of tariffs. Regulatory powers are exercised by both central and state governments.

The rationale behind regulating the Indian sugar industry is to ensure welfare of farmers, ensure return to the sugar industry and maintain adequate supply of sugar at a reasonable price to the consumer (NITI 2018, FAO 1997). In India, both cane and sugar are considered essential commodities under the Essential Commodity Act 1955 (ECA). ECA was enacted to ensure supply of essential commodities which are prone to hoarding and black marketing. This act gives powers to GOI to regulate production, supply/distribution, trade, and commerce of listed commodities (GOI 1955).

Exercising powers under the ECA, GOI notified the Sugar (Cane) Control Order (SCO) in 1966. SCO gives GOI the powers to regulate production of sugar, put restrictions on sale of sugarcane by farmers, issue directions to producers and dealers, regulate movement of sugarcane, fix sugarcane prices and allot quotas for marketing of sugar, and provide directions to supply sugar etc. (GOI 1966). With amendments to SCO in 2009, 2016 and twice in 2018 and 2019, GOI now regulates production of molasses as well as the ethanol produced from cane juice and sugar.

In the section below, we list major policies in this regard.

Pricing of sugarcane

To deliver remunerative prices to cane farmers, GOI declares minimum price for sugarcane. Before 2009, these prices were referred to as statutory minimum prices (SMP). Post 2009, GOI replaced SMP with the Fair and Remunerative Prices (FRP). In case of wheat and paddy, the Government not only declares the MSP, but also procures the same for distribution under the PDS. In case of cane, the GOI only declares the FRP and does not undertake any physical procurement. The FRP is to be paid by the sugar mills to the farmers.

FRP is decided by the central government based on recommendations of the Commission of Agricultural Cost and Prices (CACP). It is calculated based on factors like the cost of production, return to producers from alternate crops, availability of sugar to consumer at fair prices, selling prices, recovery rates of sugarcane, and margins of producers after accounting for risks (DFPD). Sugar mills are mandated to pay at least this price to sugarcane growers. These payments have to be made to farmers within 14 days of purchasing cane by sugar mills.

There are three important aspects about cane support prices:

i. Effective FRP differs from FRP: Sugar recovery rates from cane differ between states and sometimes even within sates. Consequently, FRP payments, which are linked to recovery rates of sugar from sugarcane, differ. Usually, FRP is declared based on an average recovery rate and there is a rate of adjustment provided for estimating FRP for varying rates. For example, before 2018-19, FRP was linked to an average recovery rate of 9.5 percent. However, due to improved yields and quality of cane, the average recovery rate has increased to 10 per cent since 2018-19. For 2021-22 season, for every 0.1 percentage point increase in recovery rates, there is an addition of Rs. 2.90 per quintal to the FRP. The adjusted FRP amount is referred to as the effective FRP.

ii. Some state governments announce State Advisory prices (SAP) which are higher than FRP. In 2022, Punjab, Haryana, Uttarakhand, and Uttar Pradesh declared SAP which was higher than FRP. Details of SAP notified by states are given in Figure 14. Among the states declaring SAP, highest SAP is reported by Haryana (in 2019-20, Rs 340, Rs 335 and Rs 335 per quintal for early, mid, and late varieties of sugarcane respectively). In 2019-20, the highest gap between FRP and SAP for early variety was in Haryana (Rs. 65 per quintal), followed by Uttar Pradesh (Rs. 50 per quintal). Two major sugar producing states, Maharashtra,

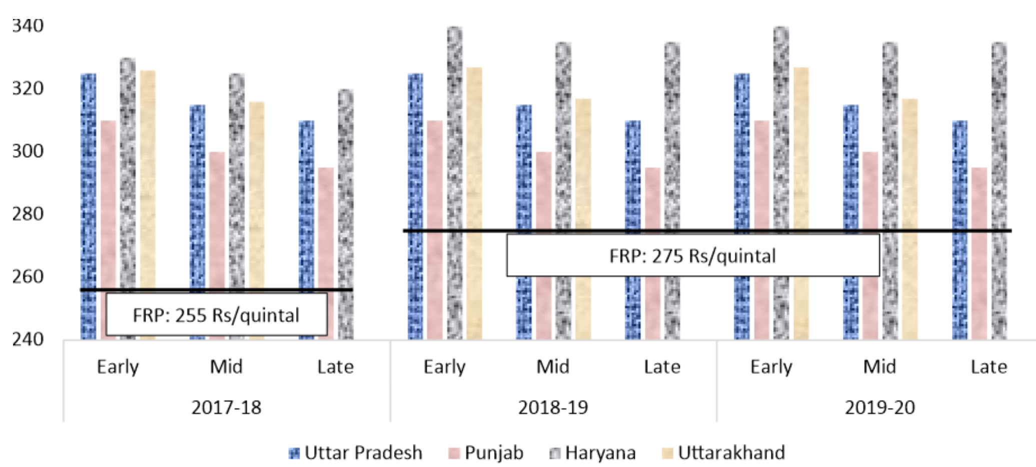

Figure 14 State Advised Prices (SAP) for different varieties
Source Commission on Agricultural Costs and Prices (CACP)

and Karnataka, do not declare SAPs. It is important to note that the SAP is not liked to recovery rates of sugar from sugarcane, and it is paid to farmers irrespective of recovery rate of sugar from sugarcane.

iii. Early variety of cane gets the highest SAP: In UP, the SAP is notified for three sugarcane varieties, i.e., early variety, mid variety, and late variety. Highest SAP is issued for the early variety.

Cane reservation area

As per SCO 1966, the GOI reserves the area from which the sugar mills can purchase sugarcane. It means that the mills are mandated to purchase sugarcane from farmers growing in the cane reservation area only and the farmers are obligated to sell to the mills in the reserved area. The rationale behind this policy is to ensure adequate supply of sugarcane to the sugar mills. Another objective is to reduce the purchase cost of sugarcane (by minimizing transportation cost) so that the farmers are ensured remunerative price for sugarcane.

Minimum distance criteria

As per SCO, the minimum distance between two mills is fixed at 15 kilometers. Following on the cane reservation policy, this regulation is to ensure ample availability for sugarcane to sugar mills. While all the above policies were meant for cane producers and mills, we next list policies/programs which affect sugar.

Minimum selling price (SP) of sugar

India has been producing surplus sugar for the last five years since 2017-18. To help the sugar industry/mills fight depressed prices due to this surplus production and to protect the interest of the farmers whom the mills had to pay, the GOI in 2018 amended the SCO. It introduced the concept of minimum Sale Price (SP) of sugar (CACP). SP was derived from FRP, and the minimum conversion cost incurred by the mills to produce sugar. In June 2018, the government fixed the prices of white/refined sugar at Rs 29 per kg. This was increased Rs 31 per kg in February 2019. The SP has not been changed since then and it continues to be at Rs. 31 per kg. In 2022 sugar retail prices were above the SP.

Buffer stocks of sugar

In addition to setting a minimum price for sugar, GOI has supported the cane farmers and the sugar mills via its buffer stock scheme. In years of surplus and depressed sugar prices, mills are unable to sell sugar in the open market at viable prices and thus pay the cane farmers. In such years, sugar mills are advised to maintain buffer stock of sugar on behalf of GOI, which in turn reimburses the cost of maintenance of these stocks. The reimbursement is called the 'buffer subsidy' which is paid quarterly, directly to the farmers relative to their cane dues and the rest is credited the sugar mills (DFPD).

Trade policy for sugar

Export and import of sugar is regulated by customs duties, export quotas and export subsidies (DFPD). In years of larges surplus of sugar, GOI fixes export targets for liquidating excess sugar in export markets. These quotas are called MIEQ i.e., Minimum Indicative Export Quotas. MIEQs are based on average sugar production in last two seasons and the current season (DFPD). In 2017-18, 2018-19, GOI announced MIEQ of 2 MMTs and 5 MMTs respectively (DFPD).

GOI has also announced export subsidies to facilitate export of sugar. These subsidies are in form of marketing assistance, including freight charges, upgrading and other processing costs, etc. In 2019-20 season, under the export subsidy scheme GOI announced a Maximum Admissible Export Quota (MAEQ) of 6 MMTs for sugar mills. To receive assistance under the subsidy scheme, mills had to at least export 50 percent of MAEQ allocations (GOI 2019).

These quotas are fixed in order to ensure liquidity of the sugar mills, ensuring timely cane price payments and ensuring domestic availability of sugar in the country (Niti Aayog 2021).

In year 2021-22, GOI has put restrictions on sugar export. This, as mentioned before, is motivated to curtail any domestic price pressures building up in sugar. Despite a bumper sugar production of 35.5 MMTs in the current year, GOI capped export of sugar.

Ethanol and other by products

The government in 2003 initiated the ethanol blending programme (EBP). Under the scheme, the government supports production and marketing of ethanol in the country. Exercising powers under the sugar control order, the government can control the production of ethanol from sugarcane, sugar, and sugar syrups. GOI also regulates and fixes the price for ethanol derived from sugar and its by-products. For 2021-22 season, the ex-mill prices fixed by the GOI range between Rs. 46.66 per liter to Rs. 59.08 per liter for ethanol derived from C-heavy and B-heavy molasses, respectively. The ex-mill price for ethanol derived from 100 percent sugarcane juice/sugar/sugar syrup is Rs. 63.45 per liter (DFPD). In addition, the government also provides support (in terms of soft loans and assistance) to sugar mills and distilleries for increasing capacity of ethanol production in the country with, among other things, to support timely cane payment to farmers (DFPD).

As per MOPNG, 84 per cent of the ethanol used for blending with fuel in India for in the ethanol supply year 2021-22 came from sugarcane and its by-products. By 2025-26, the target is that 55 per cent of total ethanol demand for fuel blending would be fulfilled by the sugar industry (NITI Aayog 2021).

Consumption related policies

Distribution of sugar under PDS to AAY families

To support the sugar consumption needs of the poorest-of-poor families (referred to as the Antyodaya households), GOI provides them with subsidized sugar under the Public Distribution System (PDS). As per the National Food Security Act (NFSA) 2013, AAY families are provided 1 kg per month per household. The central government provides a fixed subsidy of Rs. 18.5/kg to states for open market procurement of sugar.

FSSAI regulations related to processing, packaging/ labelling regulations

i. Food Safety and Standards (Food Products Standards and Food Additives) Regulations, 2011: specify the quality standards for various products such as milk & related products, drinking water, meat and its products.

ii. Food Safety and Standards (Packaging and Labelling) Regulations, 2011: provide guidelines for product packaging and labelling including sugar. After these regulations, it is mandatory to display nutritional information (including added sugars) on the packaging of processed products.

iii. Food Safety and Standards (Advertising and Claims) Regulations, 2018: the regulations make businesses accountable for the claims that they may be advertising for certain food products. These claims are categorized under various heads such as 'nutritional claims', 'non-addition claims', claims related to dietary guidelines, etc.

iv. Food Safety and Standards (Safe food and balanced diets for children in school) Regulations, 2020: The regulation make way for clear bifurcation on health and non-healthy foods for school children.

Health related policies

To address the issue of increasing overweight/obesity and diabetes in the country, GOI has initiated various measures.

National Programme for Prevention and Control of Cancer, Diabetes, Cardiovascular Diseases and Stroke (NPCDCS)

In 2010, in order to prevent and control NCDs, GOI initiated NPCDCS. The objective of this programme is to create infrastructure, develops human resource, promote health and early diagnosis and support management NCDs. NPCDCS follows a strategy of early diagnosis, treatment and follow-up through NCD clinics. Under the National Health Policy 2017, a target of 25 per cent decrease in premature deaths by 2025 due to cardiovascular diseases, cancer, diabetes and chronic respiratory diseases has been set (NHP 2017).

Rashtriya Kishore Swasthaya Karyakram (RKSK)

In 2014, the GOI launched RKSK for adolescents between 10 to 19 years. Under the scheme, a national adolescent health strategy has been made with the objective to improve nutrition, sexual & reproductive health, mental health and prevent injuries and substance misuse of the 234 million adolescents in the country (National Health Portal).

Working group to address consumption of food high in fat, salt and sugar

To address the increasing risk of NCDs among children due to increasing incidence of obesity/overweight, the

Ministry of Women and Child Development has set up a working group to address the high fat, salt, and sugar (FSS) diets of the children in 2015. The recommendation of the group ranges from a ban on HFSS sale in school canteens, setting up of School Canteen Management Committees, ensuring labelling of readable sizes, incorporation of warning for specific diseases for infants, children, and pregnant women, among others. (WCD 2015).

Ongoing policy dialogues

Various committees/institutions have recommended (Rangarajan committee, CACP, NITI Aayog) the deregulation of the sugar sector. This includes removing the cane reservation area, minimum distance criteria for sugar mills, levy sugar, regulated release mechanism. Only levy sugar has been dispensed with. The rest have not yet been adopted by most of the state governments (NITI Aayog 2021). CACP and NITI Aayog are also advocating discontinuation of State Advised Prices of sugarcane.

To tackle the increasing incidence of overweight and obesity in India, the Government is looking at country specific evidence to understand the type of policy interventions that can be opted. NITI Aayog has suggested front-of-pack labelling, marketing and advertising of High-FSS foods and taxation of foods with high FSS contents.

Level of support to cane and sugar industry

After highlighting the policies which are used to support the cane farmers and sugar mills, we move to an analysis of the union/state (in this case Uttar Pradesh) budgets to understand ways in which the governments support these two stakeholders. Using the annual budget statements of the union/state government, we present an analysis for seven years, 2015-16 through 2022-23.

Union Government's support to sugar industry

Budgetary allocations to the sugar industry are made under GOI's Ministry of Consumer Affairs and Food and Department of Food and Public Distribution (DFPD). Since 2015-16, the total departmental allocations and the share of sugar in total allocations are given in Figure 15.

GOI uses multiple conduits for providing support to the sugar industry. Based on the objective of the budgetary provision, the support to the sector can be broadly segregated under two heads:

i. Budgetary support for development of infrastructure, increasing capacity of sugar mills and distilleries, co-generation plants, fulfilling administrative expenses of loss-making sugar mills, etc. Schemes financed from the Sugar Development Fund (SDF), schemes for the

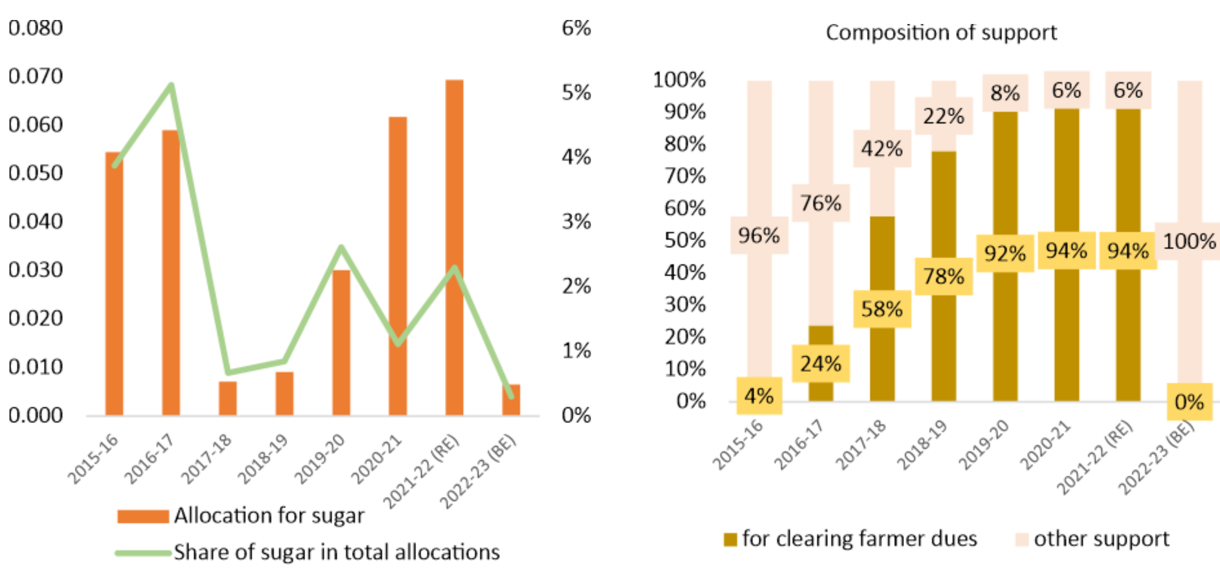

Figure 15 Allocations to sugar industry and composition of support
Source GOI budget documents

development of sugar industries, financial assistance for ethanol production are under this set of budgetary support; and

ii. Budgetary support provided to support cane price payments by sugar mills to the farmers. This includes schemes providing assistance, or soft loans to sugar mills and export subsidies are under these set of budgetary support.

Sometimes, there is an overlap between these two, otherwise distinct sets of objectives. For example, in the case of ethanol, the GOI supports sugar mills for producing ethanol, but sometimes, this would be done to provide an additional source of revenue for the mills, so they can pay the arrears of sugar cane to the farmers. From right panel in Figure 15, it emerges that within the overall budget allocated for sugar, more than 90 per cent (since 2019-20) has gone as loans/ assistance to mills for clearing arrears of the farmers. The situation is more vivid since 2017-18. However, in two years prior to that, most of the sugar budget went towards betterment of the sugar industry, paying for sugar under the public distribution system (PDS) and the Sugar Development Fund (SDF). While allocations under SDF, schemes for development of sugar industries and the PDS have been falling, that of assistance for settling farmer arrears have been rising.

In 2022-23, the budget for sugar industries is exceptionally low, due to the high global prices which have been used by sugar mills to export sugar.

Uttar Pradesh Government support to sugar industry

Uttar Pradesh (UP) is an important sugar producing Indian state. To support cane farmers, it declares SAP that the sugar mills have to pay the farmers. SAP is higher than FRP. While FRP varies with the yield and sugar conversion power of cane, SAP is fixed. In Uttar Pradesh, SAP remained constant between 2017-18 and 2020-21. Due to this, the gap between effective FRP and SAP has been falling and the effective FRP was higher than the SAP in 2019-20 and 2020-21. It means that that if the UP did not have an SAP policy, the cane farmers could have realized better prices under GOI's FRP mechanism. (Figure 16).

In UP, budgetary allocations to sugar industry are made to two departments. These are mentioned below.

i. Sugarcane Development Department (Sugar Industry) (CDD-SI): under this head, budgetary allocations are made to sugar industry for a variety of purposes ranging from allocation for capital investments crop farming, research & development, loans to mills for increasing ethanol capacity and loans/assistance to mills for clearing farmer dues.

ii. Sugarcane Development Department (Sugarcane) (CDD-S): under this head, all the administrative expenses are budgeted.

Majority of the allocations for sugar industry are made under the CDD-SI department (Figure 17). Going forward we look at CDD-SI department for support provided to the sugar industry in the state.

The budgetary allocation and composition of those allocation are mentioned in the Figure 18 below. Between 2016-17 and 2022-23, on average the total budget of the department is Rs. 1641 crores. However, the budget allocation drastically increased in FY 2018-

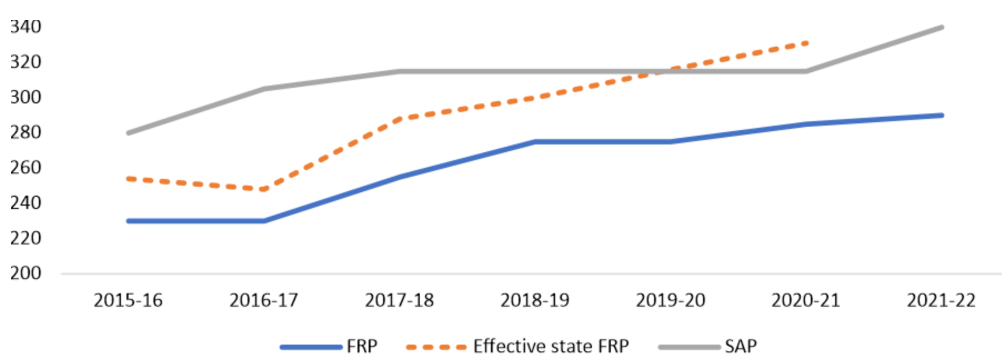

Figure 16 Effective FRP, FRP and SAP: Uttar Pradesh (Rs. /quintal)

Source CACP

Note SAP for common variety. Effective FRP for 2019-20 and 2020-21 has been taken from ISMA and is based on recovery rates which include the sugar equivalent diverted to sugarcane juice, syrup, sugar, or B-heavy molasses.

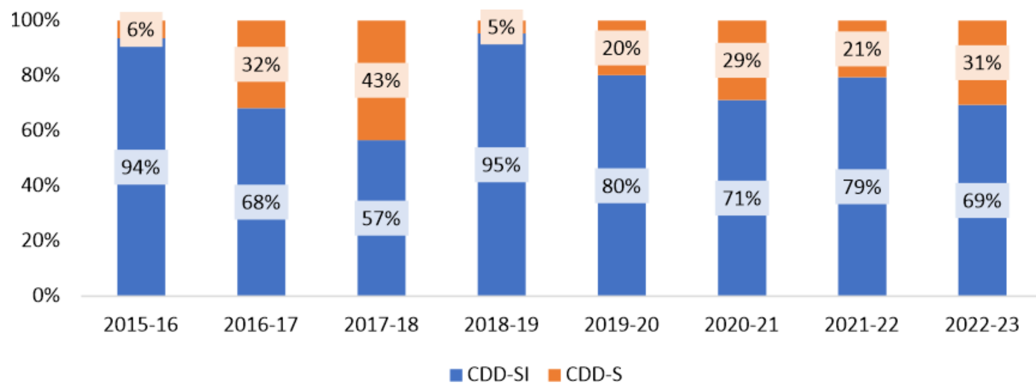

Figure 17 Share of budgetary allocation for CDD-S and CDD-SI
Source UP budget documents

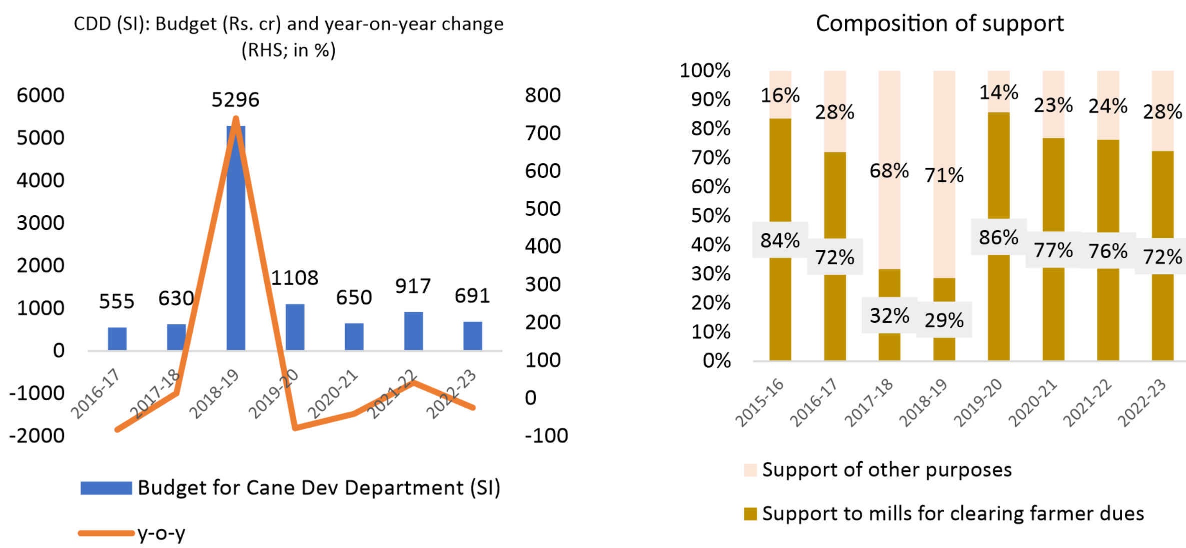

Figure 18 CDD-SI: Budget and composition of support
Source UP budget documents

19 to about Rs. 5,296 crores. The allocation under the department peaked in 2018-19 and 2019-20 and has been decreasing since then. When looked at the composition of this budgetary allocation, it is observed that on average, above 60 per cent of the budgetary allocations are in form of loans and assistance/subsidies for paying the cane dues of farmers. In 2015-16, 84 per cent of the total budget allocation was given as support to sugar mills for clearing farmer dues. In this year Rs. 2130 crore assistance and Rs. 617 crores of loans were provided to sugar mills. The share of budget for clearing farmer due decreased to 29 per cent in 2018-19 (though the absolute allocation for clearing farmer dues increased, the effect of which wasn't seen as the total budget of the department increased too). It then again increased to 86 per cent in 2019-20 and is currently at 72 per cent in FY 2022-23. In majority of the years since 2015-16, budgetary support to mills was provided as loans.

On the other hand, on average 34 per cent of the allocations to CDD-SI are made for R&D, capital investments purposes. The share increased to 68 per cent and 71 per cent in FY 2017-18 and FY 2018-19 respectively and has decrease to pre-2017-18 levels since then.

We also found that budgetary support for clearing farmer dues is correlated with price of sugar in global markets. We explore this in the section below.

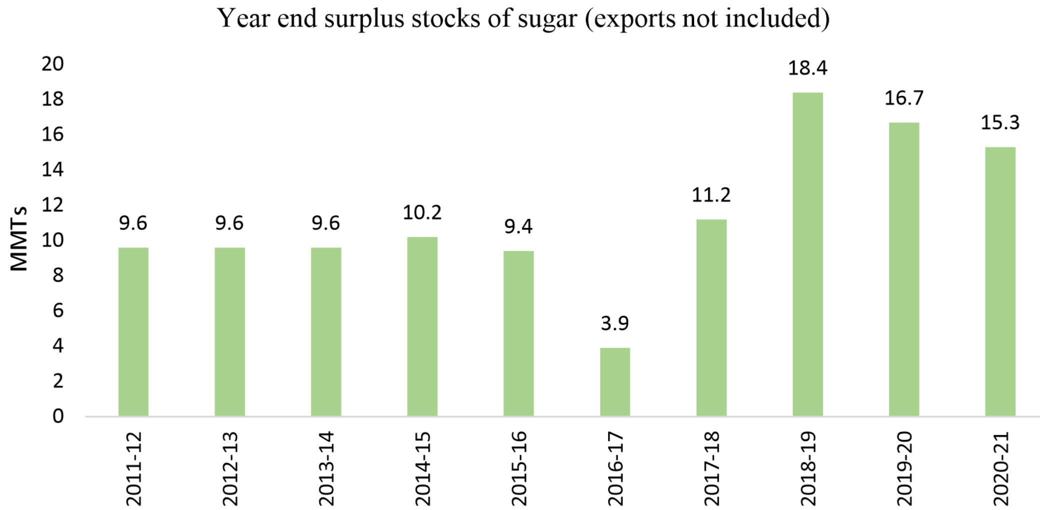

Figure 19 Domestic surplus of sugar
Source ISMA

Connecting the dots

Is it true that Indian exports are a function of domestic surpluses? And despite high and rising domestic prices of sugar, how could Indian mills export large quantities of sugar? We explore answers to these questions below.

Detailed below is the change in sugar surplus in India since 2011-12 (Figure 19). Surplus/deficit are summation of opening stocks, production, and imports net of domestic consumption. Data is sourced from ISMA. It is evident that surplus of sugar has been rising in India, especially in 2018-19, 2019-20 and 2020-21. In addition, as per data on level of consumption and production of sugar in India from OECD, in 2019 and 2020, India produced 8.6 MMTs and 1.6 MMTs of sugar above the estimated level of consumption in the country. OECD data states that between 2011 and 2020, in most years, India reported surplus production of sugar.

As we see below, in the years of high surpluses, exports are high too (Figure 20).

Interestingly, between 2017-18 and 2020-21, Indian sugar prices (ex-mill prices) were much higher than global counterpart prices (EU refined sugar fob prices proxied by their unit value of exports) (Figure 21).

The data suggests that Indian ex-mill prices were lower than EU-28 export prices between FY 2011-12 and

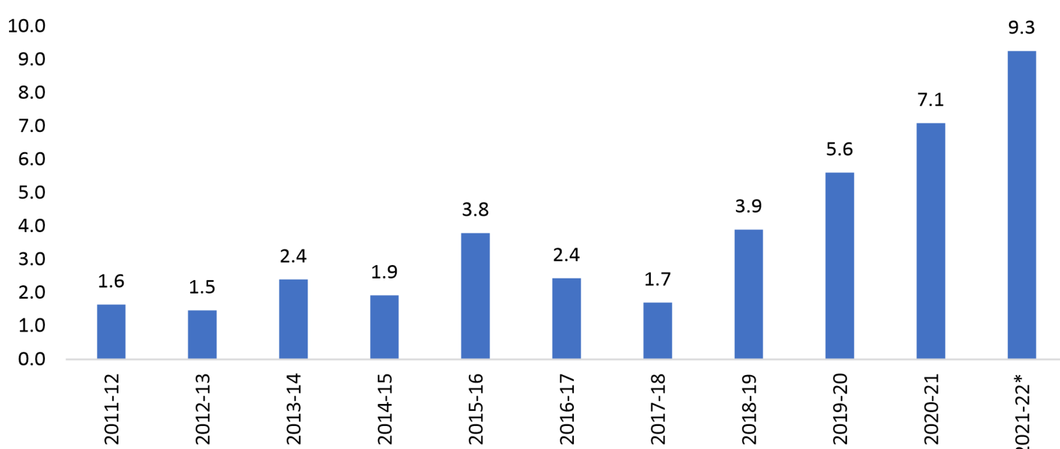

Figure 20 Export of Indian sugar (Refined sugar) (MMTs)
Source Ministry of Commerce and Industry (GOI)
Note *from April to Feb

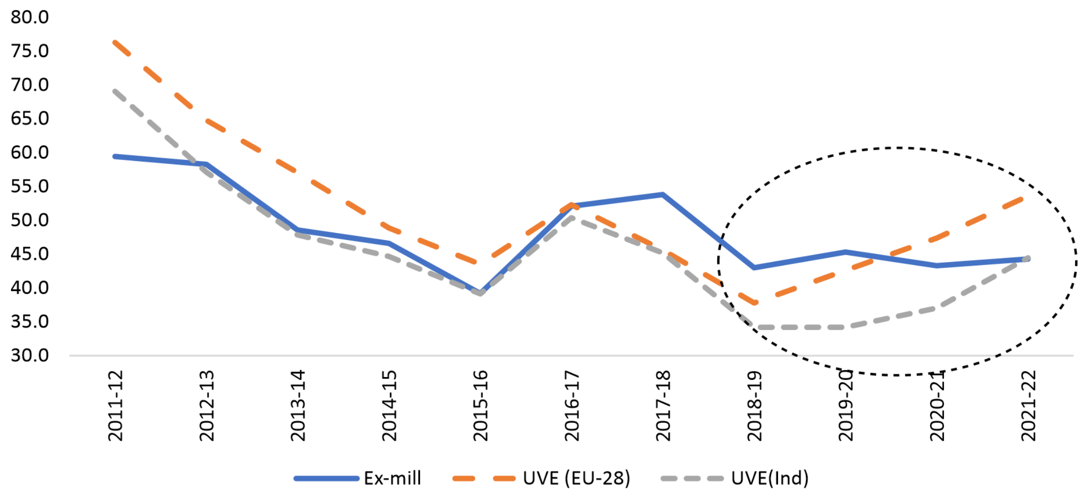

Figure 21 Trends in sugar prices ($ per quintal)
Source ISMA, Ministry of Commerce and Industry, Department of Consumer Affairs (GOI), UN-Comtrade. Note: EU-28 export prices are not adjusted for domestic transportation and marketing costs of sugar and hence represent FOB EU prices.

2016-17. Between 2017-18 and 2019-20, Indian ex-mill prices were higher than global prices. This means, that in these years, Indian sugar was not price competitive in global markets. When Indian export prices (unit value of exports) are considered, we find that till 2016-17, Indian export prices were largely in sync with ex-mill prices. However, since 2017-18 (till 2021-22), Indian exports prices were lower despite relatively high domestic ex-mill prices.

Mapping these years with budgetary support (focusing on the time period between 2015-16 and 2021-22) provides interesting insights (Figure 22). It appears that the quantum of total budgetary support to sugar and cane industry increased post 2018-19 till 2021-22. Intuitively, it appears that Indian sugar exports have been increasing despite the mismatch in ex-mill (domestic) and Indian sugar export prices due to assistance from GOI.

Benefits and costs associated with cane and sugar industry

Till now, we have found that a) the country is producing more sugar than is required to meet its current consumption requirements; b) average Indian consumption of sugar is below the global averages; and c) the industry is regulated heavily on both

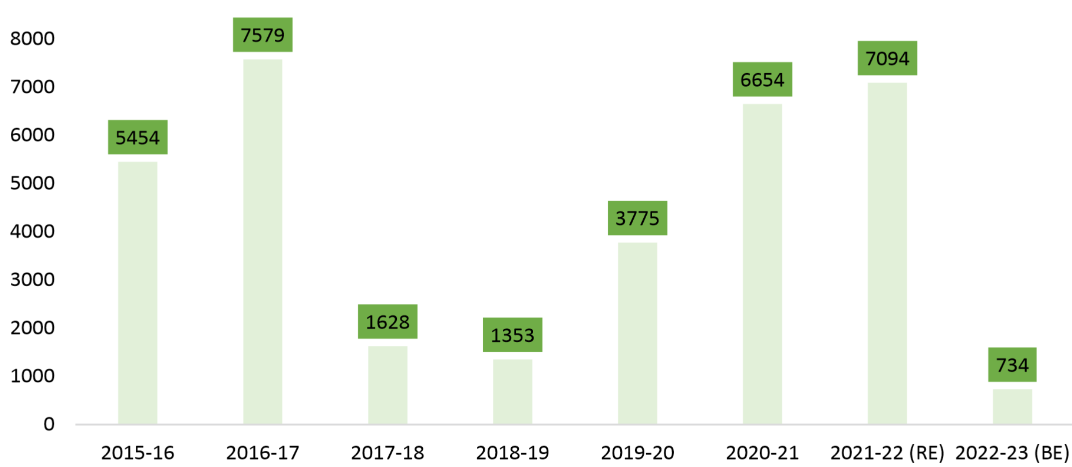

Figure 22 Budgetary support to cane and sugar industry (Rs. crore)
Source GOI budget documents

production and marketing sides of the value chains, which have distortionary impacts on the sugar markets.

Building on these results, in this section we quantify benefits of production of cane and sugar. This is followed by an examination of the associated costs of cane and sugar production and consumption on health, environment and people involved in the sugar value chains.

We identify the following benefits and costs.

Benefits

i. High value of output for cane and sugar and employment opportunities

   Ministry of Statistics and Programme Implementation (MoSPI) provides estimates for the value of output generated from various agricultural commodities. Data in this regard is available till 2017-18. Data averaged for the triennium ending 2017-18, suggest that cane production in the country was valued at Rs. 82,022 crores (approximately $12.7 billion). This was about 0.17 percent of the total gross domestic product (GDP) of the country. With regards to the value of production for raw sugar[4], it was found that sugar production was valued at Rs. 1,02,933 crores (approximately $15.9 billion[5]).

   In addition to this, sugarcane and sugar industry provides employment to a large proportion of country's workforce. Data from CACP for year 2020-21 suggests that 50.5 million individuals are employed either in cane or sugar production. Out of these, 50 million are farmers and the rest 0.5 million are directly employed by the sugar mills. When mapped with the total workforce as per Census, 2011 comes out to be 10.64 per cent of the total workforce, suggesting that a big chunk of people working in the economy are dependent on the sugar industry.

ii. High profit margins for cane producers

   Department of Economics and Statistics (DES), GOI provides data on cost of cultivation (CoC) and value of the produce. This helps us calculate the profitability of for major crops. Latest data in this regard is available till 2018-19. DES provides CoC estimates using various methods. These are:

   a. A2 cost includes the actual paid out cost incurred by cultivators on inputs, hired labor, etc.

   b. A2 cost + Family labor (FL): A2 cost added with the imputed cost of unpaid family labor. CACP uses this cost, among other things to calculate the minimum level of price support to identified commodities. We make use of this for further analysis.

   c. C2 cost: costs including imputed rent and interest on owned land and capital.

   For calculating profitability, we look at A2+FL cost. A2 cost looks at the paid-out cost by the farmers. As the cultivation of sugarcane and other considered crops (wheat and rice) for the analysis are labor intensive, we also look at the imputed value of family labor in the total cost of cultivation. The top four sugarcane producing states, i.e., Uttar Pradesh (UP), Maharashtra (MH), Karnataka (KA) and Bihar (BR) are considered for this analysis. We find that sugarcane profitability is higher than paddy and wheat profitability (Figure 23). Profitability is revenue divided by CoC expressed in percentage terms. For sugarcane, profitability ranged between 74 per cent to 302 per cent for the selected states. The highest profitability was observed in Karnataka (302 per cent), followed by Uttar Pradesh (199 per cent), Bihar (167 per cent) and Maharashtra (74 per cent). In all the four states, profitability of paddy and wheat was way lower when compared to sugarcane.

iii. Benefits of the by-products: Apart from the regular use of cane by-products in making bio-gas, paper pulp etc., it is ethanol that is delivering benefits to all in the value chain. From reducing, *albeit* marginally, country's crude oil dependence, using ethanol in fuel is also reducing vehicular emissions. But is cane production and diversion to ethanol net carbon-reducing? Is the net carbon footprint of cane negative? It needs deeper research.

[4]Value of output for raw sugar is calculated by multiplying total production with domestic wholesale prices

[5]Monthly exchange rate from April, 2015 to March, 2018 was simple averaged

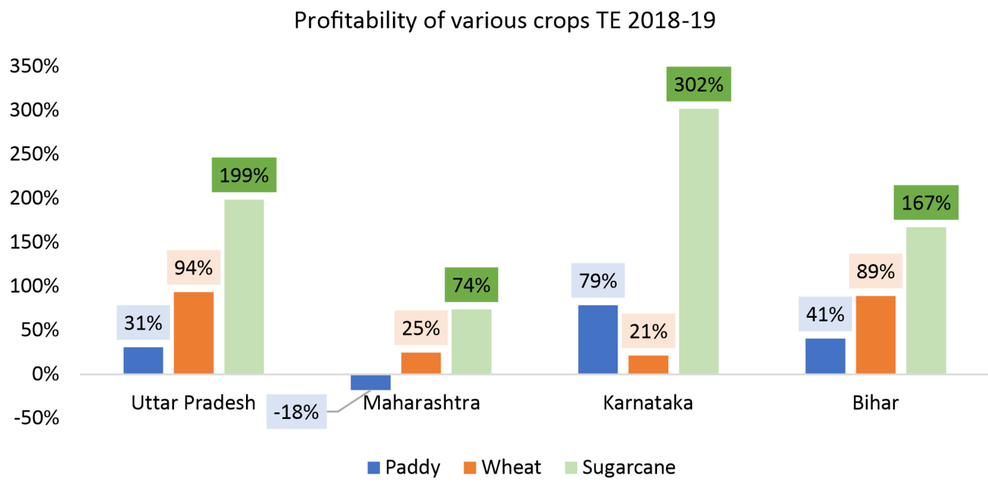

Figure 23 Profitability of major crops
Source Department of Economics and Statistics (GOI)

Costs

i. **High cost of cultivation (COC)**

Data averaged for triennium ending (TE) 2018-19 suggests that A2+FL CoC for sugarcane is higher in all the four states. Maharashtra had the highest COC (Rs. 1,35,216/ha), followed by Bihar (Rs. 71,013/ha), Uttar Pradesh (Rs. 66,162/ha) and Karnataka (Rs. 58,760/ha). Whereas CoC for wheat and paddy were relatively lower. It is interesting to note that, in Maharashtra and Bihar, combined CoC for paddy and wheat was lower than CoC for sugarcane (Figure 24).

If economic costs associated with of excessive water use is added, this CoC will be even higher. The annual per capita availability of water has been decreasing constantly in India. It decreased from 5177 cubic meters in 1955 to 1544 cubic meters in 2011 (CWC 2015). Also, 78 per cent of all water resources in India are used by agriculture. (CWC 2014). Sugarcane cultivation is highly water intensive. For instance, in Maharashtra, only 4 per cent area is under sugarcane cultivation but it uses 64 per cent of the total irrigation water available (Gulati and Mohan 2018).

A measure of water use is the Physical Water Productivity (PWP). PWP is calculated using Total Consumptive Water Use (TCWU) and total production and expressed as the ratio of agriculture output to amount of water used. The global average

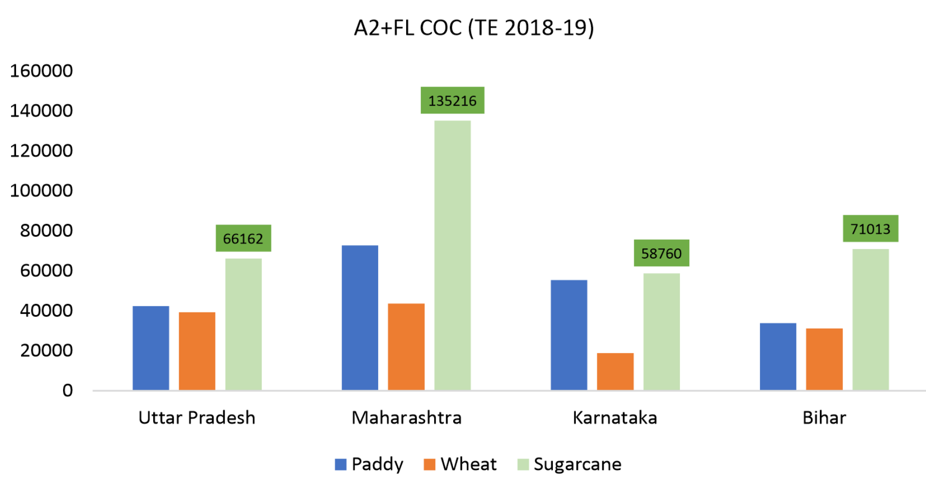

Figure 24 Cost of Cultivation for major crops (Rs. per hectare)
Source Department of Economics and Statistics (GOI)

PWP for sugarcane was found to be 5.8 kg per cubic meter (Sharma et al. 2018). This means that 5.8 kg of sugarcane can be grown with 1 cubic meter of water. In India, PWP was estimated to be 5.2 kg per cubic meter. PWP varied between 0.6 to 22.4 kg per cubic meter in India (Sharma et.al 2018). Land productivity and water productivity was also not in sync for several states such as Tamil Nadu, Haryana, Andhra Pradesh, Madhya Pradesh, etc. Meaning higher water use followed by low productivity. Efforts need to be made to increase water efficiency by adjusting price of power and irrigation water. Also, aligning cropping patterns with water endowments of the regions is crucial (Sharma et.al. 2018).

ii. **Costs associated with deteriorating public health**

As seen in the sections above, incidence of obesity/overweight is rising in the country. Even though sugar is not directly connected to diabetes, obesity/overweight can increase the chances of being Type II diabetic. It is estimated that in India, economic cost of overweight and obesity was $23 billion, which is expected to increase to $479 billion in 2060 (WOF 2021). Non-communicable diseases account for 61.8 percent of the total deaths in India (GBD 2021). Where diabetes (part of NCDs) ranked seventh in causes of deaths with a rate of 23 deaths per 100000 individuals (IHNS 2016). Diabetes accounted for DALYs (836/100000) with mean Out of Pocket Expenditure (OOPE) for hospitalization Rs. 18,091 ($235).

iii. **Transfer of benefits from consumers and taxpayers to sugar producers**

Support for a single commodity is referred as the Single Commodity Transfer (SCT) as per OECD's Producer Support Estimate (PSE) manual. SCT measure the annual monetary transfers from consumers and taxpayers to agricultural producers of a commodity. A positive SCT implies positive support to the sugarcane farmers. The OECD provides estimates of SCT for various commodities. For India, SCT data is available from 2000 to 2020 (Figure 25). The sugar SCT is positive for majority of the years. The SCT support has increased post 2016 indicating to higher support reaching cane farmers. This is in line with our observations made on the increase in support following increase in domestic surpluses in previous section.

iv. **Water pollution by mills**

All major divisions of the sugar mill such as processing plants, cooling towers, sugar manufacturing plant produce waste. The waste materials include solid wastes, depleted water oxygen level contents, molasses, etc. (Ranjan et.al 2021). Also sugar industries are one of the biggest polluters of fresh water. In India, sugar industry produces about 1000 litres of wastewater for every kilogram of crushed sugarcane (Sahu and Chaudhuri 2015). Effluents discharged from sugar

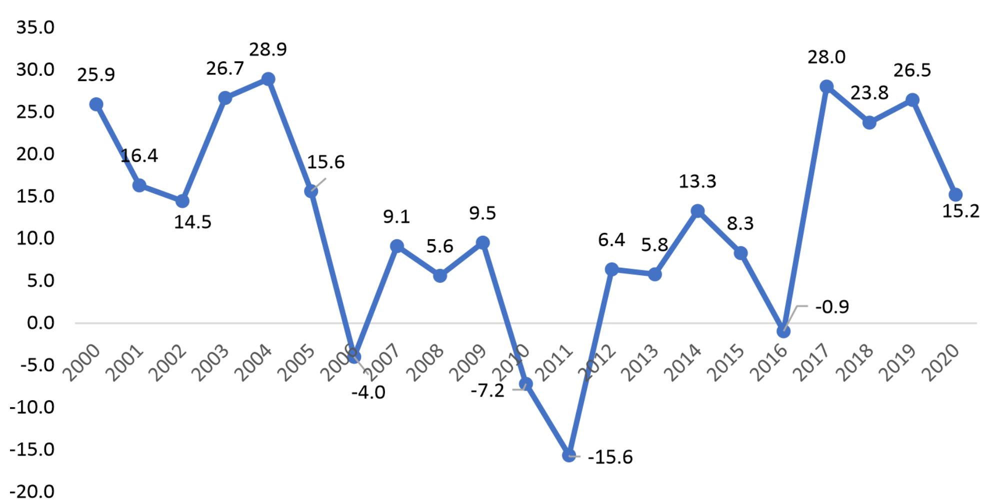

Figure 25 SCT for Indian refined sugar (percent)
Source OECD

industry have high amount of biochemical oxygen demand (BOD) load, chemical oxygen demand (COD), total suspended solids (TSS), sulphate (Ranjan et.al 2021). These pollutants can cause damage to water resources in the nearby areas if not discharged properly. Most the cases of pollution are observed in UP where there are cases of pollutants being discharged in river Ganga without being treated. Several legal cases have also been made against the sugar mills in the areas. To address these problems, Central Pollution Control Board (CPCB) introduced a charter to effectively regulate discharge of wastes into freshwater. In addition, a compensation plan was also designed and implemented under the charter for sugar industries situated in and around river Ganga.

v. **Impact on well-being of people employed in the industry**

Individuals employed in the sugar industry face costs related to socio-economic factors such as poor working conditions for on farm and sugar mills. In addition, special mention is to be made for women workers on the farm who are forced to undertake hysterectomies to avoid absence from fields in Maharashtra. Over 13,000 females in Beed district of Maharashtra have undergone hysterectomies to avoid daily wage losses (Mulye 2019). Maharashtra State Commission for Women ordered to set up a committee to look at the grave problem in 2019 (The Wire 2019). The committee reported that migrant women workers are promised Rs. 1,50,000 as annual wages but must work 12 hours daily. As per Oxfam 2020, these labourers took advances on wages from contractors for the procedures. These women also experienced grave sexual and reproductive health issues.

Conclusions and policy implications

Sugar is one of the most tightly regulated agricultural commodities in India. It is also one in which mostly every stage of value addition has some mechanism of government support. Starting from FRP (or SAP) for cane farmers, to soft loans for mills to fixing sugar ex-mill prices to setting quotas for releasing sugar from the mills, to providing support to the mills for producing ethanol or exporting sugar, GOI has a mechanism of support. This results in distortion, inefficiency, and excessive production of sugarcane.

Overall, it appears to be a classic case of how one distortion snowballs into an intricate web of distortions. Based on our analysis, we propose the following policy recommendations.

Pricing of sugarcane

i. Remove State Advised Prices (SAP): The SAPs are declared over and above the FRP declared by the GoI. There is a need for state governments to accept recommendations of the Rangarajan Committee Report and not declare SAPs going forward.

ii. Rationalize increases in FRP: The FRP should be made a function of domestic demand and production costs in addition to global demand, supply, and prices of sugar. This may require only moderate increase in FRP of sugarcane.

iii. Bring inter-crop price parity: Higher FRP of sugarcane needs to be moderated in the interest of inter-crop parity, ecological sustainability, and long-term health of sugar sector as a whole.

Market for by-product of sugar

i. Ethanol: The national bio-fuel policy of Government of India (2018) had recommended a target of 10 percent blending of ethanol in petrol by 2021-22 and 20 percent by 2030. By 2021-22, India has already reached 9.3 percent blending (target was 10 percent) (USDA 2022). Encouraged by its performance and to build on its momentum, in 2022, GOI revised the national bio-fuel policy and advanced the target of 20 percent blending to 2025-26 (NBP 2022). Recommendations in this regard are:

a. Bring dynamism to ethanol pricing- Instead of fixing the price of ethanol, a more transparent and scientific mechanism for determining ethanol prices may be introduced.

b. Diversion of cane to ethanol: With ambitious ethanol targets in the coming years, increased acreages in the country will move to cane thus requiring greater investments by both the public and private sector in making cane production more water- and fertilizer-use efficient.

ii. Molasses: It is an important by-product of sugar industry, but it is tightly controlled in largest sugar producing state of Uttar Pradesh. The sugar mills are not free to sell entire production of molasses in the open market and a certain percentage, about 18-20 percent, is reserved for supply to manufacturers of country liquor. This fetches them lower price as compared to the open market price of molasses. Not only that, but the sugar mills are also required to maintain a certain ratio of monthly sale between reserved molasses and free molasses. This has an impact on profitability of sugar mills. There should be no restriction on movement of molasses from one state to another; and

iii. To use the excessive production of sugarcane, the government may promote marketing of jaggery. The nutritional benefits of jaggery are not well known even to the educated sections of society. With the increasing incidence of Type 2 diabetes there is a need to better communicate the nutritional benefits of jaggery. The possibility of exporting jaggery from India should also be explored. The global market of NRIs and people of Indian origin should also be targeted for consumption of jaggery.

Processed sugar products

With a positive income elasticity of sugar of 0.06, we expect that with the growth of per capita income of the average Indian, the consumption of sugar will also increase. For ensuring safe consumption of sugar:

1. New labelling norms must be implemented: FSSAI is in the process of implementing a system of front of pack labelling under which packaged food items will have to carry health-stars. This system must be implemented in its true sprit across packaged food category. Under this system, based on Australia's experience, stars are assigned to a product for sugar, sodium, and saturated fat. However, they are offset for any positive components like (fibre, fruit, legume, nut, protein, and vegetable content. Awareness and education campaigns need to be designed for educating consumers about the star-rating system.

2. Unpackaged food: As there are no regulations for the products which are not sold in the packaged form, consumers must be made aware about the health effects of excess sugar and fat.

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Received 5 September 2022 Accepted 13 November 2022

Agricultural Economics Research Review 2022, 35 (2), 27-42
DOI: 10.5958/0974-0279.2022.00029.5

Investigating the impact of information on the efficiency of smallholder dairy production systems in India and the lessons for livestock extension policy

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Abstract Using data from a nationally representative farm survey and applying the instrumental variable method, this study has assessed the impact of information on the efficiency of smallholder dairy farming in India. There are four key highlights of this study. One, using information in farm decisions leads to an improvement in dairy productivity by about 15%. Two, different types of information have differential impacts — information on livestock management has a more significant effect than on health, breeding, and nutrition. Three, the payoff is larger for joint use of information than to any kind of information used in isolation. Four, there is also an information source effect — public extension system has a larger effect than any other information source.

Keywords Information, efficiency, dairying, India

JEL codes Q12, Q16

In developing countries, which are dominated by resource-poor small landholders, livestock are not only a source of nutritious foods for humans, draught power, and organic manure for agriculture, they also act as a financial institution—a bank deposit with offspring as interest and self-insurance during income shocks—and as an instrument for reducing socio-economic inequality (Delgado et al. 1999; Birthal et al. 2014) and rural poverty (Heffernan 2004; Upton 2004; Birthal and Taneja 2012; Birthal and Negi 2012; Bijla 2018). Using data from a large-scale survey of farm households in India, Birthal and Negi (2012) have empirically demonstrated that compared to the income from crop farming, the income from animal farming is more equally distributed and has 1.4 times larger poverty reduction potential. Using a panel dataset on rural households, Bijla (2018) too has shown that livestock help households escape poverty and prevent them from falling into poverty.

India's livestock production system has experienced a significant demand-driven growth over the past five decades. Milk production, which had rarely exceeded 25 million tons during the 1960s and 1970s, crossed 210 million tons in 2020–21 (GoI 2022). Similarly, the production of eggs increased from 10.1 billion in 1980–81 to 114.4 billion in 2019–20. Overall, the economic contribution of livestock has grown faster than that of crops, making it an engine of agricultural growth. Its share in agricultural growth increased from 32% in the 1990s to 36% in the 2000s (Birthal and Negi 2012) and further to over 50% in the 2010s (Birthal and Mishra 2021). In 2019–20, livestock contributed 4.5% to the overall gross domestic product (GDP) and 29.7% to the agricultural GDP.

Nevertheless, the need for a sustainable growth in livestock production remains as urgent as in the past. The growing population, urbanization, and increasing per capita income have been fuelling rapid changes in food consumption patterns in favour of animal-source foods (Hamshere et al. 2014). The trends in these factors have been quite robust, and these are unlikely to subside soon, implying a faster increase in the demand for animal-source foods. By 2050, in a business-as-usual scenario, the demand for most animal-source foods is projected to be more than double that in 2009 (Hamshere et al. 2014).

India has a large population of diverse livestock species; yet, fulfilling the future demand for animal-source foods from the domestic production would be challenging. The current productivity levels of most livestock species are low. For instance, the annual milk yield of a cow in India is about 1,700 kilograms, which is just 16% that in North America and 25% that in Europe.

Further, resource-poor smallholders—or households cultivating plots of land as small as one hectare or even smaller, with an average herd size that hardly exceeds two animals—dominate India's livestock production systems (Birthal and Mishra 2021). Smallholder farmers face several constraints, including the scarcity of feed and fodder, and poor access to animal breeding and health services, credit, and markets, in improving livestock productivity.

Information can catalyse a transformation in smallholder production systems. Farmers' access to and use of information influence their decision to adopt improved technologies and practices and, consequently, farm outcomes (Mwabu 2001; Liu 2013; Bandierra and Rasul 2006; Conley and Udry 2010; Birthal et al. 2015). However, most of these studies have analysed the impact of information on returns from crop farming, and crop prices. Our understanding of the impact of information on the performance of other agricultural activities, including animal husbandry, and fisheries, is extremely limited.

On the other hand, with the increasing biotic and abiotic pressures on animal production, the demand for information is expected to increase exponentially. Furthermore, the inherent potential of ruminants' greenhouse gas (GHG) emissions, and the zoonotic nature of several animal diseases, would compel farmers to adjust their production practices to protect the environment, conserve natural resources, and ensure food safety and hygiene.

Farmers' information needs are diverse. They need information on animal breeds and breeding practices, feeds and feeding practices, disease prevention and control, animal housing, clean production practices, food safety standards, credit, insurance, markets, prices, and trade. A single agency is unlikely to cater to all sorts of information; for their information needs, therefore, farmers rely on multiple sources, including traditional and modern, public and private, formal and informal. These sources likely differ in the quality of information and the method of its delivery and, hence, in their impact on farm outcomes.

This paper assesses the impact of information on the efficiency of dairy farming in India by its type and source. The study uses data from a nationally representative survey of farm households conducted by the National Sample Survey Office (NSSO) of the Government of India. This survey contains data on the subject and sources of information along with several farm and household characteristics, which allow us to estimate the impact of different types and sources of information on farm outcomes, controlling for several covariates that can potentially influence the farm outcomes.

Nevertheless, establishing a causal relationship between the information and farm outcomes is challenging. Several observable and unobservable factors may simultaneously influence the uptake of information and the farm outcomes, leading to bias in its impact (Aker 2011; Birthal et al. 2015). This study employs the instrumental variable (IV) method to estimate the true effect of information, therefore.

To the best of our knowledge, there is hardly any empirical evidence on the impact of information on livestock productivity. Ours is perhaps the first study that analyses the relationship between the information and livestock productivity. Four key findings have emerged from this study.

Controlling for several observable and unobservable covariates, using information in farm decisions results in 15% higher milk yield.

Information has a source effect on productivity — information acquired from public sources impacts productivity greater than information sourced from social networks, mass media, private service providers, and input dealers.

The impact of information differs by its content—livestock management information is more effective than information on animal breeding, feeding, and health.

The payoff from using different sorts of information in combination is higher than from using any type of information in isolation.

Our findings have some important implications for developing countries, where governments rarely accord priority to livestock extension systems (Morton and Matthewman, 1996). In India, for instance, investment on extension accounts for hardly 2% of the total public spending on livestock sector (Birthal and Mishra 2021). Only about 25% of livestock farmers have access to information, mainly from non-governmental sources. The outreach of the public extension system is limited to 14% of information users.

Our findings indicate that a comprehensive livestock extension strategy needs to be designed to empower farmers to cope with the challenges in the process of the transformation of the livestock production systems.

Data and descriptive statistics

This study uses data from a nationally representative survey of farm households conducted by the National Sample Survey Office of the Ministry of Statistics and Programme Implementation, Government of India, for the agricultural year 2018–19 (NSSO 2021). This survey is a sequel to the surveys conducted in 2002–03 (NSSO 2005) and 2012–13 (NSSO 2014).

This survey aims to track the changes in the status of farming and farm households and the factors underlying these dynamics. The survey followed a multistage stratified random sampling procedure (see NSSO (2021) for sampling details) and collected data from 50,840 farm households spread over 5,885 villages across all the states of India. Compared to the previous farm surveys, this survey is extensive in its coverage of several characteristics of farming and farm households.

The survey provides data on the subsectors of agriculture (crops, livestock, and fisheries) and on the subject and channel of information dissemination for each subsector. It contains data on the production and value of crops, livestock, and fisheries outputs, and on farm and household variables (land and livestock holdings; irrigation coverage; income sources; access to credit; disposal of farm produce; and age, gender, education, social status (caste and religion) of household heads, and their affiliation with formal or informal farmer organizations). Yet, a key limitation is that the dataset provides production cost data not by individual farm commodity but by subsector.

Characteristics of information users and non-users

Dairying has a 20% share in the value of agricultural output. It is the largest agricultural activity. Therefore, this study focuses on examining the impact of information on dairy productivity.

The survey data shows that over 50% of the farm households in India own one or the other livestock species and 63% of them are engaged in dairying (in-milk cows and buffaloes). Farm households' informational constraints are acute: only 25% have access to information on livestock production and management. Notably, most information seekers (92%) utilize it in their decision-making. Hence, our analysis is based on the use of information and not access to it.

Farmers' access to, and use of, information is influenced by demographic characteristics (age, education, and gender of the household head or decision-maker); availability of labour (family size); socio-economic status (religion, caste, assets, and income); landholding size; irrigation status; number and type of livestock owned; input use in livestock production; and access to credit, market and support services (Ali 2012; Alvarez and Nuthall 2006; Babu et al. 2011; Carter and Batte 1993; Okwu and Dauda 2011; Solano et al. 2003).

Table 1 compares the key characteristics of non-users and users of information. Regarding demographic characteristics, the heads of information-using households are older and have a slightly higher level of schooling. The number of households reporting formal training in agriculture and allied activities and affiliation with farmer organizations is extremely small, but their proportion is higher among information users.

The information-using households have smaller families but a more diversified income portfolio (non-farm business activities, wages, salaries, and remittances). Interestingly, there is no gender bias in accessing and using information—the proportion of

Table 1. Means and standard deviations of characteristics of users and non-users of information

	Non–users		Users		Difference in means and proportions (t–statistics)
Milk yield (litre/in–milk animal/annum)	1716.835	(1498.28)	2467.963	(1873.30)	–26.7***
Household characteristics					
Family size (No.)	5.51	(2.58)	5.07	(2.45)	9.8***
Age of the household heads (years)	51.94	(13.21)	52.56	(13.04)	–2.65**
Female–headed household (%)	7.07	(0.26)	6.82	(0.25)	0.6
Education level (% household heads)		–		–	
Illiterate	34.79	(0.48)	31.71	(0.47)	3.65***
Below primary	8.96	(0.29)	10.62	(0.31)	–3.2**
Primary	14.65	(0.35)	16.10	(0.37)	–2.3**
Middle	16.03	(0.37)	15.64	(0.36)	0.6
Secondary	12.88	(0.33)	14.76	(0.35)	–3.15**
Higher secondary	7.01	(0.26)	6.29	(0.24)	1.6*
Graduate and above	5.68	(0.23)	4.88	(0.22)	2**
Caste (% households)		–		–	
Scheduled caste	11.31	(0.32)	7.68	(0.27)	6.75***
Scheduled tribe	13.56	(0.34)	11.05	(0.31)	4.25***
Other backward caste	45.68	(0.50)	52.19	(0.50)	–7.4***
Upper or other caste	29.45	(0.46)	29.08	(0.45)	0.45
Net assets (Rs/person)	1699.05	(19173.66)	3468.42	(48848.71)	–1769.375***
Formal training in agriculture (% households)	1.81	(0.13)	3.23	(0.18)	–5.55***
Non–farm business income (% households)	7.84	(0.27)	8.97	(0.29)	–2.35**
Wages, salary and remittance (% households)	46.89	(0.50)	53.07	(0.50)	–7***
Farm characteristics					
Landholding size (ha/household)	1.04	(1.41)	1.05	(1.76)	–0.5
Area irrigated (%)	63.14	(0.44)	52.87	(0.47)	12.9***
Herd size (No. of in–milk animals/household)	1.54	(1.15)	1.92	(2.50)	–13.9***
Proportion of buffaloes in herd	22.04	(0.71)	25.63	(0.80)	–2.8**
Breeding charges (Rs/animal)	123.64	(1,088.06)	306.18	(3,475.02)	–5.35***
Feed cost (Rs/animal)	3507.37	(3,873.81)	5021.27	(5,584.56)	–19.8***
Veterinary charges (Rs/animal)	90.91	(465.97)	250.67	(659.06)	–17.5***
Membership of farmer organizations (% households)	0.34	(0.06)	2.42	(0.18)	–11.3***

Note Standard deviations are in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

female-headed households is almost identical in both categories.

The social status of households can differentiate them in their access to, and use of, information and its outcomes (Batte and Arnholt 2003; Ali 2012; Birthal et al. 2015). Caste is an important social identity in rural India, and households at the bottom of the caste hierarchy (Scheduled Castes and Scheduled Tribes) have lower access to information (Birthal et al. 2015). A look at the distribution of non-users and users of information by caste confirms this—the proportion of lower-caste households among information-using households is low (Table 2 in the Appendix).

In terms of farm characteristics, information non-users and users have an identical landholding size on average, but users' access to irrigation is lower. On the other hand, information users have a larger herd size (in-milk cows and buffaloes). Notably, the availability of information facilitates households to expend more on feeds, animal health, and breeding.

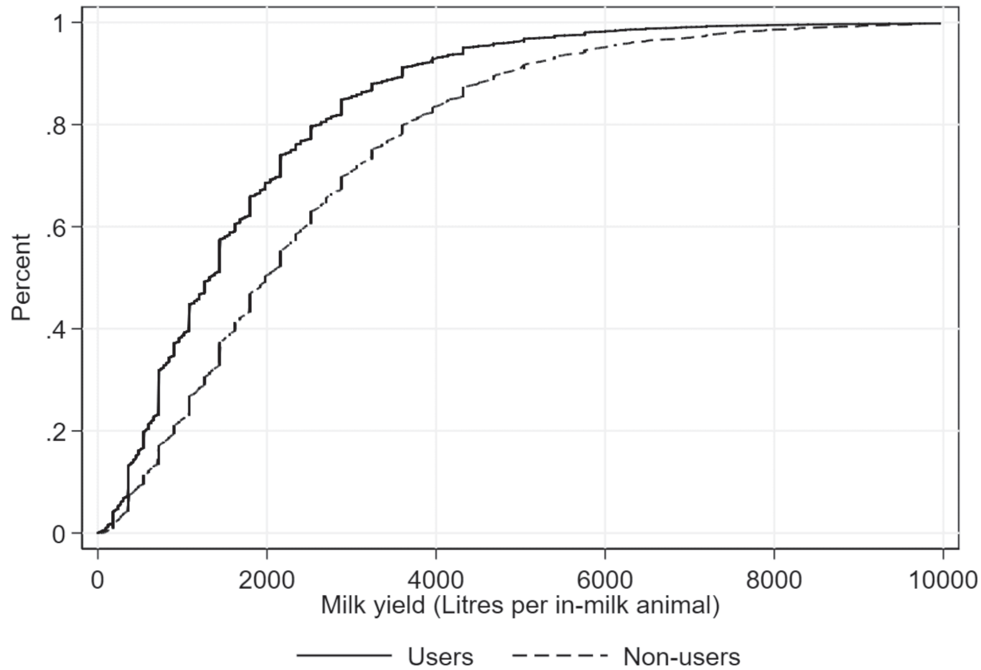

Figure 1. Cumulative distribution functions of milk yield for non-users and users of information

Information users realize almost 1.5 times the milk yield as non-users (Table 1). The difference in the cumulative distribution functions of milk yield for information non users and users is significant (Figure 1), and it is confirmed by the Kolmogorov-Smirnov test (K-S =0.21, p=0.0).

Heterogeneity in information and its sources

Livestock farmers' information needs are diverse, ranging from information on breeds and breeding practices, feed and nutrition, diseases and their management, animal hygiene and shed management, food safety standards, markets, prices, and trade. Farmers acquire such information from several sources, including public and private, formal and informal, traditional and modern. The public information system comprises government institutions, including veterinary hospitals, dispensaries, artificial insemination centres, research institutions, Krishi Vigyan Kendras (agriculture science centres), agricultural universities /colleges, dairy cooperatives, and government extension agents, and farmer producer organizations.

Following Anderson and Feder (2007) and Aker (2011), the rest of the information channels is aggregated into private information channels, mass media, input dealers, and progressive farmers. Private information sources are private clinics, nongovernmental organizations, and private commercial agents (including contract farming sponsors and companies) and commodity traders and processors. Mass media comprises telephones, mobile phones, radio, print, and the internet and other electronic media.

Farmers' information needs are diverse, and they seek these from multiple sources; hence, information sources are not mutually exclusive. The information on a subject can be accessed from various sources, or a single source can provide all sorts of information, and farmers seek information from multiple sources. About 73% seek only one type of information, and 60% of them acquire it from two or more sources; the rest acquire more than one type of information and mostly from more than one source (Table 1 in the Appendix).

A two-way frequency distribution of farmers by subject and information source shows that private service providers appear to be the dominant source of information (Table 2). Overall, 39% of dairy farmers have acquired information from private sources. The outreach of other information sources, including the public extension system, is almost equal, catering to the information needs of around 15% of the farmers.

Information on animal health is the most sought after; and over 50% of farmers acquire it from private

Table 2 Frequency distribution of information by its subject and source

	Breeding	Feeding	Health	Management	All
Progressive farmers	19.83	26.99	43.85	9.33	100
	16.48	23.38	14.92	21.12	17.43
	[440]	[599]	[973]	[207]	[2219]
Input dealers	21.15	20.97	45.56	12.32	100
	13.37	13.82	11.79	21.22	13.26
	[357]	[354]	[769]	[208]	[1688]
Mass media	22.60	18.87	50.73	7.80	100
	17.90	15.57	16.45	16.84	16.61
	[478]	[399]	[1073]	[165]	[2115]
Government	21.22	20.49	51.62	6.66	100
	14.19	14.29	14.14	12.14	14.03
	[379]	[366]	[922]	[119]	[1786]
Private	20.63	17.14	56.53	5.71	100
	38.05	32.94	42.69	28.67	38.68
	[1016]	[844]	[2784]	[281]	[4925]
All	20.97	20.12	51.21	7.70	100
	100	100	100	100	100
	[2670]	[2562]	[6521]	[980]	[12733]

Note

The figures in the upper row against an information source are the percentage of households seeking different kinds of information from that source.

The figures in the lower row are the percentage of households seeking information from different sources.

The square brackets contain the number of households seeking information from a particular source.

sources. Private sources are important also for information on animal breeding (38%) and feed and nutrition (33%). Mass media and social networks (farmer-to-farmer exchange) are used by around 17% of the farmers. The outreach of the public extension system is limited to only 14% of the farmers, irrespective of the subject of the information.

The possibility that the content and source of information affect the productivity cannot be ruled out. The kernel density functions of milk yield by type of information (Panel A) and also by source of information (Panel B) differ (Figure 2), providing preliminary evidence of their differentiated impact on dairy productivity.

Empirical strategy

To assess the impact of information on productivity, we begin with estimating the following linear specification:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \eta_i \qquad (1)$$

where,

Y_i denotes milk yield realized by the ith farm household;

X_i is a vector of demographic, farm, and institutional characteristics;

D_i is a categorical variable, taking the value of 1 if the household uses information in decision-making, and 0 otherwise; and

η_i is an independent and normally distributed error term.

If X_i includes all the variables that influence the use of information, and it is simultaneously uncorrelated with the error term (η_i), then an ordinary least squares (OLS) estimate of β in Equation 1 is consistent, that is, it provides the true effect of information on Y_i.

However, it is possible that X_i does not include the variables that influence the use of information, such as farmers' inherent abilities, skills, risk preferences,

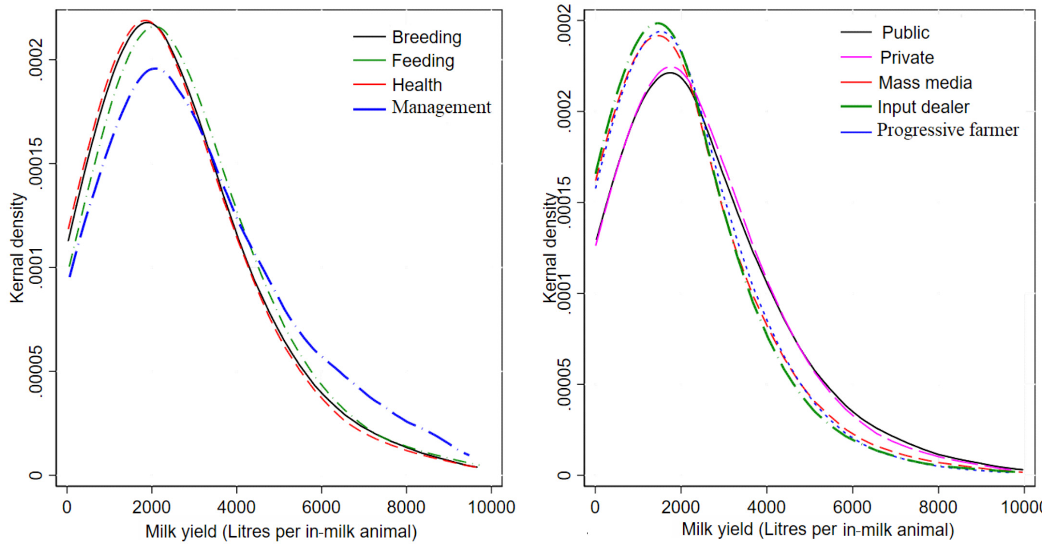

Figure 2. Kernel density functions of milk yield by type and source of information

and social ties. Such unobserved factors cannot be controlled for and may lead to omitted variable bias.

To deal with such potential biases, we employ the instrumental variable (IV) approach. An ideal instrument is correlated with the use of information (I_i has a direct effect on D_i) but not with the outcome (I_i does not have a direct effect on Y_i). Being correlated with the use of information and uncorrelated with the outcome, the instrument effectively randomizes households across treatments and achieves equal distribution of both the characteristics and the pre-treatment outcomes. Additionally, the IV method addresses both overt and unobserved biases in estimating the average treatment effect.

To construct an instrumental variable, we exploit the role of local social networks in information transmission (Evenson and Mwabu 2001; Bandierra and Rasul 2006; Conley and Udry 2010; Liu 2013). The rationale is that if a larger proportion of the farmers in the network are informed, the likelihood of a particular farmer being informed would be greater (the first condition of IV is likely to be satisfied). In addition, the proportion of informed farmers in the network should not directly affect the productivity on a particular farm (the second condition of IV is satisfied).

The literature does not provide a uniform definition for "social network", so here we consider it to be composed of the individuals whose mean outcome and characteristics influence an individual's outcome and characteristics (Bandiera and Rasul 2006; Conley and Udry 2010). The reference groups for a farmer in rural India need not be geographically most proximate but of the same caste, religion, or ethnic group (Fontaine and Yamada 2011). Hence, we define a social network for each farmer based on geographical proximity (residing in the same village) and social identity (belonging to the same caste). Table A2 shows farm households' use of information from different sources by their caste group.

With these conditions in mind, we define our instrument as the proportion of informed farmers in a network; to determine whether a farmer uses information, we specify the equation

$$D_i = \delta + \theta I_i + u_i \tag{2}$$

Combining Equations 1 and 2

$$Y_i = \vartheta + \tau I_i + \gamma X_i + \eta_i \tag{3}$$

where,

$\vartheta = \alpha + \beta\delta$, and

$\tau = \beta\theta$.

Hence, the estimate $\hat{\beta}$ can be obtained as $\hat{\tau}/\theta$. The instrumental variable estimator is an unbiased and consistent estimator of β in large samples.

The farm survey randomly selects households in a village. The actual proportion of households using the information within a social group in a village may not equal the proportion estimated from the sample, i.e. I_i

$= I_i^* + \omega i$. This can lead to the attenuation bias in θ, due to which the analysis may provide the lower bound of θ. However, the estimated treatment effect is unbiased as long as ω_i is uncorrelated with D_i and η_i.

Equation 1 includes a dummy variable for any information, that is, whether a farmer has used any sort of information. However, farmers' information needs are diverse, as are the sources dispensing these, and it is likely that the type of information type its source may impact productivity differentially. To capture the heterogeneity in their impacts, Equation 1 is augmented by including information on breeding, feeding, health, and management or the sources of information (public, private, mass media, progressive farmer and input dealer), and their corresponding instrumental variables, as in Equation 3.

$$Y_i = \vartheta + \tau_B I_{Bi}^k + \tau_F I_{Fi}^k + \tau_H I_{Hi}^k + \tau_M I_{Mi}^k + \gamma X_i + \eta_i \quad (4)$$

Where, I_{Bi}^k, I_{Fi}^k, I_{Hi}^k and I_{Mi}^k represent the instruments for the information on breeding, feeding, health, and management.

Similarly, we include information sources:

$$Y_i = \vartheta + \tau_G I_{Gi}^s + \tau_{MM} I_{MMi}^s + \tau_{PF} I_{PFi}^s + \tau_I I_{Ii}^s + \tau_P I_{Pi}^s + \gamma X_i + \eta_i \quad (5)$$

Where, I_{Gi}^s, I_{MMi}^s, I_{PFi}^s, I_{Ii}^s, and I_{Pi}^s represent the instruments for the public, mass media, progressive farmer, and input dealer, and private information sources.

To account for the heteroscedasticity and autocorrelation, we estimate linear regressions using robust (heteroskedastic-consistent) and cluster-robust variance estimates.

Impact of information on productivity

Validity tests for instrumental variables

Table 3 presents the validity tests for instrumental variables. First, we look at the results of the under-identification tests. The p-values are highly significant, rejecting the null hypotheses that the instruments are irrelevant and the model is under-identified. Further, we look at the Hansen J-statistic that tests the null hypothesis that the instruments are valid and uncorrelated with the error term. The higher p-values provide strong evidence that the instruments are valid.

We also test for the failure of the relevance condition and weak instruments. Both the Cragg-Donald Wald F-statistic (preferred in the case of no heterogeneity) and Kleibergen-Paap Wald rk F-statistic (preferred in the case of heterogeneity) are more than the Stock-Yogo critical value, rejecting the null hypothesis that instruments are weak. These test statistics enable us to conclude that the application of the IV method is necessary in our case and the proposed IVs are valid.

Impact of different types of information

First, look at the OLS estimates corresponding to Equation 1 (Table 4). Dairy productivity is positively and significantly influenced by the age and education of household heads. The effect, however, differs across

Table 3 Instrumental variable tests

	Eq. (3) [1]	Eq. (4) [2]	Eq. (5) [3]
Under-identification test (F test of excluded instruments)	33911.48	71.20	3239.36
H0: instruments are jointly irrelevant in the first stage	0.0000	0.0000	0.0000
Under-identification test (Kleibergen-Paap rk LM Statistic)	5975.22	224.70	3303.96
H0: model is under-identified, instruments are not good	0.0000	0.0000	0.0000
Over-identification test (Hansen J-statistic)	0.8789	0.8056	0.8465
H0: exclusion restrictions of instruments are valid	0.8752	0.6533	0.6256
Weak identification test (Cragg-Donald Wald F-statistic)	12000	4991.80	12000
Weak identification test (Kleibergen-Paap Wald F-statistic)	34000	36.92	765.62
H0: weakly identified system (Stock-Yogo critical value 10 %)	16.38	10.27	10.83

Note

The tests in Columns 1, 2, and 3 are based on the estimation of, respectively, Equations 3, 4, and 5.

The results of the full models for Equations 3, 4, and 5 are presented in, respectively, Column 2 of Table 5, Column 3 of Table 5, and Column 3 of Table 6.

Table 4 Estimates of OLS regression

Dependent variable: Ln milk yield	Any type of information [1]		Differentiated by type of information [2]	
Household characteristics				
Family size	0.0536***	(0.0131)	0.0548***	(0.0131)
Age	0.0305	(0.0218)	0.0283	(0.0218)
Gender	0.0025	(0.0227)	0.0006	(0.0227)
Education level				
Below primary	0.0301	(0.0207)	0.028	(0.0207)
Primary	0.0334	(0.0177)	0.0333	(0.0176)
Middle	0.0266	(0.0178)	0.026	(0.0178)
Secondary	0.1123***	(0.0177)	0.1071***	(0.0176)
Higher secondary	0.0966***	(0.0223)	0.0976***	(0.0223)
Graduate and above	0.1525***	(0.0248)	0.1531***	(0.0247)
Caste				
Scheduled caste	-0.1833***	(0.0223)	-0.1867***	(0.0222)
Scheduled tribe	-0.0588**	(0.0194)	-0.0580**	(0.0194)
Other backward caste	0.0413**	(0.0131)	0.0410**	(0.0131)
Net assets	-0.0127***	(0.0018)	-0.0128***	(0.0018)
Formal training in agriculture	0.0285	(0.0421)	0.0223	(0.0420)
Non-farm business income	-0.0481*	(0.0207)	-0.0490*	(0.0207)
Wages, salary, and remittance	-0.0971***	(0.0122)	-0.0975***	(0.0122)
Farm characteristics				
Landholding size	-0.0276***	(0.0039)	-0.0255***	(0.0039)
Area irrigated	0.0940***	(0.0143)	0.0965***	(0.0143)
Herd size	0.0101	(0.0148)	-0.0006	(0.0148)
Proportion of buffaloes in herd	0.0043	(0.0083)	0.0058	(0.0082)
Breeding charges	0.0404***	(0.0035)	0.0389***	(0.0035)
Feed cost	0.4668***	(0.0127)	0.4640***	(0.0127)
Veterinary charges	0.0248***	(0.0025)	0.0241***	(0.0024)
Member of farmer organizations	-0.0535	(0.0671)	-0.1055	(0.0654)
Information type				
Any information	0.1386***	(0.0144)		
Breeding			0.1028***	(0.0220)
Feeding			0.1704***	(0.0225)
Health			0.0820***	(0.0159)
Management			0.2618***	(0.0413)
Constant	3.1461***	(0.1397)	3.1804***	(0.1395)

Note District dummies are included in the regressions. Figures in parentheses are village-clustered standard errors. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

social groups—it is lower for the lower-caste households than for the upper-caste households. It is also negatively associated with land size, assets, and access to non-farm income sources. The effect of herd size, however, is insignificant.

Further, as expected, productivity is positively and significantly associated with expenditure on animal breeding, feeding, and health. These findings indicate that small farmers with limited assets and non-farm income expend more on productivity-enhancing inputs to compensate for the scale effect on farm income.

Information has a significantly positive impact on the efficiency of dairy farming. It raises milk yield by 14%. The impact, however, differs by the content or subject

Table 5 Estimates of IV regressions

Dependent variable: Ln milk yield	Any type of information [1]		Differentiated by type of information [2]	
Household characteristics				
Family size	0.0543***	(0.0131)	0.0559***	(0.0131)
Age	0.0297	(0.0218)	0.0266	(0.0217)
Gender	0.0028	(0.0227)	0.0005	(0.0226)
Education level				
Below primary	0.0297	(0.0206)	0.0266	(0.0206)
Primary	0.033	(0.0176)	0.0325	(0.0176)
Middle	0.0264	(0.0178)	0.0253	(0.0178)
Secondary	0.1119***	(0.0176)	0.1053***	(0.0176)
Higher secondary	0.0966***	(0.0223)	0.0973***	(0.0223)
Graduate and above	0.1525***	(0.0247)	0.1528***	(0.0246)
Caste				
Scheduled caste	–0.1833***	(0.0222)	–0.1868***	(0.0221)
Scheduled tribe	–0.0585**	(0.0194)	–0.0575**	(0.0193)
Other backward caste	0.0408**	(0.0131)	0.0402**	(0.0130)
Net assets	–0.0128***	(0.0018)	–0.0130***	(0.0018)
Formal training in agriculture	0.0277	(0.0420)	0.0201	(0.0419)
Non”farm business income	–0.0481*	(0.0206)	–0.0490*	(0.0207)
Wages, salary, and remittance	–0.0977***	(0.0122)	–0.0983***	(0.0121)
Farm characteristics				
Landholding size	–0.0271***	(0.0039)	–0.0245***	(0.0039)
Area irrigated	0.0948***	(0.0143)	0.0979***	(0.0142)
Herd size	0.0083	(0.0147)	–0.0049	(0.0149)
Proportion of buffaloes in herd	0.0046	(0.0082)	0.0066	(0.0082)
Breeding charges	0.0403***	(0.0035)	0.0383***	(0.0035)
Feed cost	0.4659***	(0.0127)	0.4621***	(0.0127)
Veterinary charges	0.0244***	(0.0024)	0.0234***	(0.0024)
Member of farmer organizations	–0.0574	(0.0669)	–0.1221	(0.0645)
Information type	–	–	–	–
Any information	0.1521***	(0.0150)		
Breeding			0.1332***	(0.0242)
Feeding			0.1719***	(0.0249)
Health			0.0951***	(0.0170)
Management			0.3315***	(0.0434)
Constant	3.1546***	(0.1394)	3.1978***	(0.1391)

Note District dummies are included in the regressions.
Figures in parentheses are village-clustered standard errors.
***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

of information—the information on management raises productivity the most (26%), followed by the information on feed and nutrition (17%), animal breeding (10%), and health (8%).

The OLS estimates, however, could be biased. The bias corrected estimates from IV regressions are presented in Table 5. Controlling for the influence of several observable and unobservable factors, the impact of information now increases marginally to 15%. This is true for all sorts of information, especially the information on management and breeding. The estimated productivity effect of the management and breeding information is now higher. These results imply that correction for selection and omitted variable bias was important in our study.

A glance at Table 1 in the Appendix shows that most farm households (73%) use the information on a single subject and only 5% on more than one information (three or more). This motivates us to probe whether a combination of information is more effective at raising productivity than any information used in isolation.

To know this, we estimate IV regressions for sub-samples of households using (1) only one type of information, (2) two types of information, and (3) three or more types of information. Notably, the impact of using three or more types of information is more than four times larger than the isolated use of any type of information (Table 3 in the Appendix).

These findings indicate a pecking order in the effect of different types of information. It is linked to the complexity of the problem and the technical expertise required for its remedy. In general, the more specialized or complex the information, the less is the impact on

Table 6 OLS and IV regressions for source effect

Dependent variable: Ln Milk yield	OLS regression [1]		IV regression [2]	
Household characteristics				
Family size	0.0528***	(0.0131)	0.0538***	(0.0131)
Age	0.0285	(0.0218)	0.0276	(0.0217)
Gender	–0.0035	(0.0227)	–0.0026	(0.0227)
Education level				
Below primary	0.0347	(0.0207)	0.0342	(0.0206)
Primary	0.0344	(0.0176)	0.0343	(0.0176)
Middle	0.0264	(0.0179)	0.0264	(0.0178)
Secondary	0.1098***	(0.0177)	0.1098***	(0.0176)
Higher secondary	0.0945***	(0.0223)	0.0954***	(0.0223)
Graduate and above	0.1492***	(0.0247)	0.1498***	(0.0247)
Caste				
Scheduled caste	–0.1902***	(0.0223)	–0.1894***	(0.0223)
Scheduled tribe	–0.0620**	(0.0195)	–0.0618**	(0.0194)
Other backward caste	0.0416**	(0.0131)	0.0410**	(0.0130)
Net assets	–0.0113***	(0.0018)	–0.0115***	(0.0018)
Formal training in agriculture	0.0128	(0.0426)	0.0101	(0.0425)
Non”farm business income	–0.0479*	(0.0207)	–0.0487*	(0.0206)
Wages, salary, and remittance	–0.0943***	(0.0122)	–0.0950***	(0.0122)
Farm characteristics				
Landholding size	–0.0290***	(0.0039)	–0.0294***	(0.0039)
Area irrigated	0.1016***	(0.0144)	0.1001***	(0.0144)
Herd size	0.0123	(0.0147)	0.0109	(0.0147)
Proportion of buffaloes in herd	0.0048	(0.0081)	0.005	(0.0081)
Breeding charges	0.0404***	(0.0035)	0.0403***	(0.0035)
Feed cost	0.4710***	(0.0128)	0.4696***	(0.0128)
Veterinary charges	0.0268***	(0.0024)	0.0264***	(0.0024)
Member of farmer organizations	–0.037	(0.0678)	–0.0426	(0.0678)
Information source				
Government	0.1207***	(0.0171)	0.1355***	(0.0175)
Mass media	–0.0173	(0.0158)	–0.0327	(0.0173)
Progressive farmer	0.0091	(0.0129)	0.021	(0.0139)
Input dealer	–0.1128***	(0.0137)	–0.1041***	(0.0148)
Private	0.0654***	(0.0146)	0.0769***	(0.0155)
Constant	3.1390***	(0.1398)	3.1447***	(0.1394)

District dummies are included in the regressions. Figures in parentheses are village-clustered standard errors. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

productivity. Disease diagnosis and management and animal breeding require significant knowledge and technical skills. On the other hand, the information on feed and feeding practices, financing, markets, and post production management does not involve much technical expertise and skills.

Impact of information sources

The literature indicates differential impact of different information sources on farm outcomes (Birol et al. 2015; Glaeser et al. 2002; Putnam 2001; Feder and Slade, 1986; Foster and Rosenzweig, 1995; Singh et al. 2003; Bhagat et al. 2004). Nonetheless, most studies have analysed the impact of a single information node at a time, while farmers depend on multiple sources for their information needs.

Table 6 provides the IV estimates of the impact of information sources on dairy productivity. The results indicate significant differences in the impact of information sources. The information sourced from the public extension system has the highest positive impact (13.6%), almost twice that of the private information sources. Mass media and social networks do not impact productivity significantly. The impact of information sourced from the input dealers is negative and significant.

The heterogeneity in the impact of information sources could be attributed to the differences in the quality of information and the human resources and methods deployed to deliver the information. The public extension system is more effective in improving productivity because it engages highly trained human resources capable of diagnosing the remedies and providing effective solutions. Note that an overwhelming majority of veterinarians (over 95%) in India are employed in the public sector, leaving little trained human resources for the private sector.

Studies have shown a positive and significant impact of information from social networks and mass media on the returns from crop farming (Feder and Slade 1986; Foster and Rosenzweig 1995; Birol et al. 2015). Our findings, however, show no significant effect of these sources on dairy productivity. This can be expected. Animals have a complex biological system, understanding of which is essential for the diagnosis of an ailment or disorder. Only a qualified veterinarian can, upon physical examination of the animal, diagnose the ailment and suggest remedial measures. Further, social networks and mass media often acquire information from public extension system; hence, the probability of loss of information and miscommunication in dissemination is high.

Conclusion and implications

Utilizing data from a nationally representative farm survey and applying the instrumental variable method, this study assesses the impact of information on the efficiency of dairy farming in India. A few important conclusions emerge.

Using the information in farming decisions can enhance the production potential of dairy animals by around 15%. Farmers' information needs are diverse; hence, the impact on dairy productivity differs by information type—the information on livestock management has a larger effect than the information on feeding, breeding, and health.

The payoff of using different types of information in combination is larger than of using any one type of information in isolation. The impact of information is differentiated also by the source dispensing it—information from public sources has a significantly larger impact than from private sources, social networks, mass media, and input dealers.

In the past few decades, there has been increasing recognition of livestock's contribution toward sustaining agricultural growth, reducing income inequality, poverty and malnutrition, and empowering rural women. Yet, the livestock sector is under-appreciated and inappropriately funded when public resources are allocated. The livestock sector shares approximately 10% of the total public spending on agriculture and allied activities (Birthal and Mishra 2021). The delivery of livestock services, including extension services, is grossly lacking, despite the country having an extensive veterinary infrastructure (hospitals, polyclinics, and dispensaries) engaging over 80,000 trained veterinarians. The findings of this study reveal that the government extension or service delivery system reaches only 14% of livestock farmers. A few important implications emerge.

Animals have a complex biological system; hence social networks, mass media, and input dealers need not be relied upon for disseminating complex information, especially related to animal health and breeding.

Should the government create a new institution to deliver livestock extension services or utilize the existing infrastructure and human resources? The impact of the public extension system is high, and the public sector employs most veterinarians, but its reach to livestock farmers is limited. The service functions of veterinarians need to be reconsidered, therefore, and their expertise used to provide livestock extension services.

The network of dairy cooperatives that links dairy farmers to markets is strong: 193,195 village dairy cooperatives procured 17.5 million tons of milk (9% of the total production) from 17.2 million farmers in 2020–21 (NDDB 2021). Private dairy processors procured as much. India needs to strengthen this network and use it to disseminate information, especially on livestock management, feed and feeding practices, animal hygiene, food safety, and waste management.

The livestock population is large and diverse, as are the production systems. Therefore, certain livestock services need to be privatized and the capacities of private livestock service providers built through regular interaction with the public extension system.

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Received 13 January 2022 Accepted 26 June 2022

Appendix

Table 1 Frequency distribution of households by number of information and information sources used

No. of Information	Number of information sources One	Two	Three	Four	Five	Total
One type	1225	957	665	168	24	3039
Two types	118	382	274	121	33	928
Three types	4	54	79	37	26	200
Four types	0	0	6	3	5	14
All	1347	1393	1024	329	88	4181

Note Different kinds of information include information on breeding, feeding, health, and management. The different sources of information include government, private, progressive farmer, mass media, and input dealer.

Table 2 Sources of information by caste of information users

Category / Source	Scheduled Caste	Scheduled Tribe	Other Backward Caste	Upper or Other Caste	Total
Progressive farmer	9.28	9.54	48.33	32.85	100
	14.60	10.69	11.73	12.25	12.01
	[211]	[217]	[1099]	[747]	[2274]
Input dealer	8.22	9.13	46.94	35.72	100
	14.95	11.82	13.17	15.40	13.88
	[216]	[240]	[1234]	[939]	[2629]
Mass media	7.30	10.99	50.43	31.29	100
	26.57	28.47	28.32	26.99	27.77
	[384]	[578]	[2653]	[1646]	[5261]
Government	7.30	11.10	48.56	33.04	100
	22.77	24.63	23.34	24.40	23.78
	[329]	[500]	[2187]	[1488]	[4504]
Private	7.14	11.58	51.38	29.90	100
	21.11	24.38	23.44	20.96	22.56
	[305]	[495]	[2196]	[1278]	[4274]
All	7.63	10.72	49.46	32.19	100
	100	100	100	100	100
	[1445]	[2030]	[9369]	[6098]	[18942]

Note The upper rows contain the row percentage, the lower rows contain column percentage, and frequencies are shown in square brackets.

Table 3 IV regressions for number of information used

Dependent variable: Ln milk yield	One type of information [1]		Two types of information [2]		Three or more types of information[3]	
Household characteristics						
Family size	0.0586***	(0.0136)	0.0624***	–0.0145	0.0552***	(0.0149)
Age	0.026	(0.0225)	0.0223	–0.0241	0.0296	(0.0250)
Gender	0.0005	(0.0239)	0.005	–0.0245	0.0036	(0.0260)
Education level						
Below primary	0.0279	(0.0216)	0.0111	–0.0228	–0.0013	(0.0240)
Primary	0.0255	(0.0183)	0.0214	–0.0197	0.0251	(0.0206)
Middle	0.0247	(0.0184)	0.0126	–0.0197	0.0158	(0.0205)
Secondary	0.1028***	(0.0184)	0.0926***	–0.0196	0.0886***	(0.0205)
Higher Secondary	0.0987***	(0.0230)	0.0776**	–0.0245	0.0807**	(0.0251)
Graduate and above	0.1521***	(0.0255)	0.1531***	–0.0273	0.1421***	(0.0281)
Caste						
Scheduled caste	–0.1947***	(0.0228)	–0.2151***	–0.0241	–0.2164***	(0.0241)
Scheduled tribe	–0.0652**	(0.0200)	–0.0604**	–0.0212	–0.0697**	(0.0217)
Other backward caste	0.0435**	(0.0136)	0.0339*	–0.0145	0.0372*	(0.0149)
Net assets	–0.0121***	(0.0019)	–0.0120***	–0.0021	–0.0128***	(0.0021)
Formal training in agriculture	0.0389	(0.0464)	0.0431	–0.0493	0.0813	(0.0522)
Non-farm business income	–0.0368	(0.0215)	–0.0486*	–0.0234	–0.0431	(0.0243)
Wages, salary, and remittance	–0.1040***	(0.0127)	–0.0882***	–0.0135	–0.0838***	(0.0139)
Farm characteristics						
Landholding size	–0.0263***	(0.0042)	–0.0202***	–0.0046	–0.0177***	(0.0050)
Area irrigated	0.0956***	(0.0148)	0.0783***	–0.0157	0.0704***	(0.0161)
Herd size	0.0016	(0.0159)	–0.0164	–0.017	–0.0219	(0.0179)
Proportion of buffaloes in herd	0.0098	(0.0087)	0.0191*	–0.0088	0.0230*	(0.0094)
Breeding charges	0.0395***	(0.0038)	0.0430***	–0.0038	0.0475***	(0.0041)
Feed cost	0.4612***	(0.0131)	0.4544***	–0.0137	0.4551***	(0.0139)
Veterinary charges	0.0251***	(0.0026)	0.0235***	–0.0029	0.0268***	(0.0031)
Member of farmer organizations	–0.1694	(0.1018)	–0.1114	–0.0955	–0.0113	(0.1146)
Information						
Any information	0.0974***	(0.0165)	0.2769***	–0.0246	0.4572***	(0.0505)
Constant	3.2321***	(0.1442)	3.3106***	–0.1526	3.3257***	(0.1527)

Notes District dummies are included. The figures in parentheses are village-clustered standard errors. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively

Agricultural Economics Research Review 2022, 35 (2), 43-58
DOI: 10.5958/0974-0279.2022.00030.1

Farm households that adopt ICT change production decisions: evidence from India

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Abstract Farm households in India use information and communication technology (ICT) and ICT devices in making production related decisions. I explore the impact of ICT ownership and use on agricultural diversification and commercialization. Households that adopt ICT opt for higher commercialization, diversify towards high-value crops, invest in modern inputs, and hire more agricultural labour. Villages that adopted mobile technology early and households in those villages drove the impact of ICT adoption on farm diversification. The adoption of ICT leads to diversification by improving awareness and by facilitating access to the credit market, social interaction, and mass media.

Keywords ICT adoption, high value commodities, farm diversification, commercialization, market access

JEL codes Q12, Q19

Agriculture is the primary source of livelihood for over half the population of India, and over four-fifths of that population are small and marginal farmers. Farmers choose to produce fruits and vegetables if their landholding size and the urbanization-led demand is large enough and if they can access markets, roads, credit, irrigation, mass media, and the household size of labour endowments (Joshi et al. 2004; Birthal et al. 2013). Agriculture policy has always been biased towards cereals: since the green revolution, a focus on food security, and policies that ensured the procurement of rice and wheat at the minimum support price (MSP) at a few locations in the country, have ensured that cereals dominate (procurement of other crops, like pulses and oilseeds, started only recently). The cereal centred policy has led to the over extraction of groundwater, depletion of the water table, and reduction of soil fertility, however, and it has favoured large farmers in a few states. And a cereal centric diet low on minerals and vitamins causes malnutrition and poor health and it is a primary reason for India's ranking 94 on the Global Hunger Index out of 107 countries in 2020.

Policymakers and the government have been moving away from cereals and focusing on agricultural diversification because it can restrict the unsustainable use of soil and water resources; augment farm income, profitability, alleviate poverty, and food security; stabilize income across seasons; and promote exports (Ali and Abedullah 2002: Barghouti et al. 2004: Joshi et al. 2004: Weinberger and Lumpkin 2007: Birthal et al. 2013; Birthal et al. 2015a). And farm households have been adopting information and communication technology (ICT) in making production-related decisions and diversifying production towards high-value agricultural commodities. My definition of ICT is broad; it is a proxy for enhanced connectivity among households because of ICT devices; it is not restricted to agriculture-related interventions or extension services through SMS or email; and ICT adoption has two aspects: ownership and use. Diversification needs infrastructure, like roads, and it requires farmers to adopt and use new technologies such as ICT, but information is a constraint, as in the adoption of hybrid seeds (Foster and Rosenzweig 2010). For farm production decisions, timely and correct information is critical; information requirements range from forecasts related to rainfall and other weather conditions, and the latest government welfare schemes and agricultural technologies and practices, to the availability and prices of agricultural inputs, the best prices for outputs, pest management, and markets (Aker 2011).

Mobile phone and internet connectivity has surged rapidly in the past two decades in low-income and developing countries, including in India. The gain in momentum can be judged from the high tele density in October 2020: 86.37% in urban areas, and 58.85% in rural India (BS, 2021),up from 92.18 million in 2014 to 302.35 million in 2020 (HBS, 2021). Connectivity may be seen as an input in the agricultural production process that reduces friction in information dissemination and transaction cost, especially in remote areas. Social learning helps to diffuse new technologies (Munshi 2004). The use of mobile phones and/or computers could connect households and make them communicate more, share information, become more aware of developments, and induce behavioural changes if government extension officers use ICT, mobile phones, and/or computers, effectively to disseminate this information to farmers timely, efficiently, and affordably and to make it cheaper and faster for them to hire labour, buy inputs, and sell their output.

Technology adoption is low in sub-Saharan Africa and in the eastern states of India because access to information is poor (De Janvry et al. 2016). In India, the net return per hectare is 12% more for farmers who use information than those who do not (Birthal et al. 2015b). Mobile-based price-related information reduced price dispersion in fisheries in Kerala; in Madhya Pradesh, it helped fishermen and soybean farmers realize higher prices (Jensen 2007; Goyal 2010). But providing SMS-based agricultural information to farmers in Maharashtra did not significantly affect cultivation practices or yields (Fafchamps and Minten 2012). Farmers in Gujarat had access to agricultural advice on the phone; the access impacted agricultural practices significantly but not yield (Cole and Fernando 2016). The adoption of high-yield variety (HYV) seeds and chemical fertilizers was higher in areas with mobile phone coverage; the uptake of agricultural credit was also higher in these areas (Gupta et al. 2019). The diffusion of ICT in India can ensure connectivity and the timely dissemination of information at a reasonable cost,[1] and its impact has been studied and found not to have been universal. All these studies focus on some specific type of ICT intervention, however, and most, except Gupta et al. (2019), have a small geographic focus.

This study explores whether the adoption of ICT impacts agricultural production decisions, the commercialization of farm output, and input use, and whether ICT adoption has led to an increase in the cultivation of high value crops in India. As in the literature, I define high value crops as comprising spices, oilseeds, fruits and vegetables, and others. I also explore the channels through which ICT adoption could possibly encourage the production of high value crops. To the best of my knowledge, this is the first study that uses a nationally representative dataset—the Indian Human Development Survey 1 (IHDS 1), conducted in 2004–05—and an instrumental variable estimation strategy to explore if ICT adoption drives decisions related to farm production, diversification towards high-value crops, input investments, and market participation.

Data

The IHDS 1 is a nationally representative survey conducted by the University of Maryland and the National Council of Applied Economic Research (NCAER) in 2004–05. The IHDS 2, conducted in 2011–12, and the Situation Assessment Survey, conducted by the National Sample Survey Office (NSSO) in 2013–14, are more recent, but the IHDS 2 has not made the data on crop production publicly available yet, and the Situation Assessment Survey does not provide details on the ownership, use, or expenditure on ICT devices (mobile phones or computers). Therefore, I use the IHDS. It covers all the states and (except for the union territories of Andaman and Nicobar Islands and for Lakshadweep)

[1]https://www.bbc.com/news/world-asia-india-47537201

all the union territories. The IHDS covers 41,554 households across 382 districts. My dataset comprises households that report agriculture as their primary source of income and provide information on crops cultivated by them in the 12 months preceding the survey.

For the analysis, I use information on the crops grown in each season (kharif, rabi, and summer) by plot, the area planted under a crop, total production, and its price. The other inputs are labour (person-days), farm equipment, water, seeds, fertilizers, manures, pesticides, and repayment of agricultural loans. Further, I use the data on the usage of these inputs in household level farm production in the previous 12 months for the entire agricultural year. From the total household expenditure, From the total household expenditure, I calcuate the expenditure on ICT over the 30-day period preceding the date of the interview.

Outcome variables

The main outcome variables relate to the production of high-value crops. I use two outcome variables. One is a dummy indicator variable, equal to 1 if the household had produced a high-value crop in the previous 12 months. The other is the share of the total area under high-value crops in both the seasons (Rabi and Kharif).

Channels

The adoption of ICT could be driving decisions on agricultural production by disseminating information through formal channels of mass media (television, radio, and newspapers) and through informal social networks; insuring households through other channels and therefore raising their risk appetite; improving access to credit markets.

Disseminating information through mass media

Farmers need correct information timely. Using ICT can efficiently disseminate correct and timely information. The coverage of relatively cheap internet and mobile connectivity is expanding. If farmers adopt ICT, their access to correct and timely information would improve, as information can be disseminated through formal mass media (television, radio, and newspapers) or informal social networks. Such access would drive diversification towards high-value crops and improve the commercialization of agricultural production.

Compared to farm households that do not use ICT, farm households that do are likelier to be part of a bigger social circle—such as their social peers and the influential people in their village and informal and formal groups in their village and neighbouring villages—and to access mass media and, therefore, be more aware of consumer demand, prices, new developments, best practices, and input and output markets (Table 1). Farm households that use ICT would be better informed of crops that could yield higher returns. Therefore, they are more likely to plant and sell those crops and make a higher income and profit.

Insuring households

The use of ICT can determine agricultural diversification by insuring households and therefore raising their risk appetite. Compared to households that do not adopt ICT, households that do are likelier to have ration and job cards and be aware of government welfare schemes and benefit from them. They are more likely to be aware of alternative income sources and to diversify their income sources (Table 1). High-value crops are considered to be riskier than cereals; and households that have diversified their sources of income and are relatively insured from production, health, and other risks could be more likely to diversify their production basket.

Adopting ICT improves access to credit markets

The use of ICT improves farm households' awareness of credit programmes, government agricultural loans, and interest subsidy announcements, and it could improve financial security which, in turn, could improve their risk appetite and ability to overcome financial constraints and enable them to cultivate high-value crops—more risky, and also more profitable. Compared to households that do not adopt ICT, households that do are likelier to access formal credit markets and take agriculture and business loans (Table 1).

Heading Outcome variables to explore the channels

This paper explores whether the adoption (use and ownership) of ICT drives these channels and, in turn,

Table 1 ICT adoption and broad pathways

	(1) Mean- No ICT use	(2) Mean- ICT use	(3) Difference	Mean-No ICT ownership	Mean- ICT ownership	Difference
			Formal information source			
Mass media access(1/0)	.329	.649	-.321***	.367	.81	-.443***
News(1/0)	.076	.244	-.169***	.095	.341	-.247***
			Informal source of information			
Membership(1/0)	.353	.461	-.107***	.372	.476	-.104***
Knowpeople(1/0)	.486	.735	-.248***	.526	.795	-.269***
			Diversified income source			
No of income source	2.047	2.034	.014	2.039	2.067	-.028
card (1/0)	.883	.933	-.051***	.888	.966	-.077***
			Access to credit			
loan (1/0)	.486	.541	-.055***	.208	.363	-.155***
Agri/business loan (1/0)	.228	.29	-.063***	.244	.263	-.018*
Formal source of loan(1/0)	.192	.313	-.121***	.208	.363	-.155***
No. of obs.	9927	4418				

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Source Author's calculations using data from IHDS1

the adoption of high-value crops, although I cannot rigorously identify causal pathways, and exogenous factors likely drive these pathways. I use several outcome variables to explore the three channels.

For the first channel, I use access to mass media (television, radio, or newspapers); whether the household members watch the news; and whether the household is a member of a social group and is acquainted with influential people in the village.

For the second channel, related to risk-taking ability, I use a household's income sources and whether a household has ration and job cards, Kisan Credit Card, and and Life Insurance policies

For the third channel, I use loans as the indicator variable (if the household took at least one loan in the preceding five years, the value of *loans* is 1; otherwise, it is 0). I consider whether the household took the largest loan for agricultural or other business. If the household took the largest loan from a formal source, the value of *formal loan* is 1; otherwise, it is zero. Finally, I consider the interest rate that the household paid for its largest loan in the preceding five years.

Other impacts of ICT

The other outcome variables I use to estimate the additional impacts of adopting ICT relate to input use and commercialization. The outcome variables related to input expenditure are the share of hired labour in total labour used for agricultural production by a household in the preceding 12 months, and the log of expenditure on seeds purchased from the market, pesticides, fertilizers, hired equipments, and the repayment of agricultural loans.

The outcome variables related to the commercialization of agriculture are sales, a dummy indicator variable equal to 1 if the household sells their produce and 0 if they do not; sales of high-value crops, a dummy indicator variable which is equal to 1 if a household sells high-value crops and 0 if they do not; and the impact of ICT adoption on income and profit from farm production.

I calculate the profit by deducting the total production expenditure from the total household farm income.

ICT-related variables

Our main variable of interest is the adoption of ICT, measured using two variables: the use of ICT and the ownership of ICT. Both are binary variables with values equal to 0 or 1. The use of ICT takes the value of 1 if the members of the household either spends on telephone, cable, or internet, and zero if not. Ownership equals 1 if the household owns either mobile phones, telephones or computer and 0 if they do not.

Other controls

The household-specific characteristics included in the estimated models are household size, total land cultivated by the household, number of years of education completed by the head of the household, square of education, age of the head of the household, square of age, if household head is married, whether the household belongs to scheduled castes, scheduled tribe and other backward caste social categories and district fixed effects to control for unobservable district specific characteristics (Appendix Table A 1).

Given the heterogeneity among farm households in India, the impact of ICT adoption is unlikely to be the same across all households. It is plausible that farm diversification is dependent on infrastructure availability and therefore farm households residing in villages which are more connected, with well-developed infrastructural support would benefit from ICT use and ownership. However, if ICT impacts remotely located villages and small farmers, it can become a critical policy tool in making agricultural more profitable for farmers. Given that most farmers are small or marginal, and villages have poorly developed infrastructure support, it is interesting to explore heterogeneity in these aspects.

In this paper, I explore heterogeneity in impact because of all-weather or pucca roads and because of late/early adoption of mobile technology. Given that ICT is relatively new in India, especially among rural farming communities, some gestation period is likely required for ICT to work as an efficient tool of interaction and, hence, information dissemination.

Empirical strategy

I estimate the impact of ICT adoption on farm diversification as

$$Y_i = \beta_0 + \beta_1 \, ICT_i + \beta_2 X_i + \beta_3 d_i + \varepsilon_i \qquad (1)$$

Our main outcome variables, to explain the extent of high-value crop cultivation, are a dummy indicator variable for high-value crops and the share of area under cultivation. The other outcome variables are related to input use and commercialization of agriculture.

X_i are other household specific factors which are likely to drive the outcome variables, d_i are district fixed effects and standard errors are clustered at the district level. Our goal is to estimate the impact of ICT adoption on our outcome variables, or β_1.

However, using ordinary least square (OLS) to estimate Equation 1 can be erroneous and coefficient-biased, since it is possible that *Corr*(*Outcome variable$_i$*, ε_i) ≠ 0, because of unobserved household-specific characteristics—like ability, skill ,or motivation—that cannot be controlled for. To correct for that I use an instrumental variable strategy to estimate the impact among households of adopting ICT on the cultivation of high-value crops.

Choice of instrument

In specifying an instrumental variable I need an instrument that is correlated with the measure of a household's adoption of ICT and that does not directly affect our outcome variables. I appeal to the role of network and peer effects in the adoption of ICT (or any new technology, for that matter) and I use the adoption of ICT by a household's peer group, composed of households in geographic and social proximity, as our instrument. Given the Indian rural setting, I define a household's peer group as comprising households of the same social caste and religion and that reside in the same village. I calculate the share of households in a particular household's peer group who adopt ICT related devices. For each household, the instrument is derived after excluding that household's ICT adoption (Appendix Table A2). Other studies (Fontaine and Yamada 2011; Birthal et al. 2015a; Birthal et al. 2015b; Deng et al. 2019) use instruments based on peer group behaviour, and Songsermsawas et al. (2016) and Di Falco et al. (2020) use the average characteristics of friends of friends as an instrument for friends' characteristics.

Results

To indicate the extent of diversification, I use two measures of agricultural diversification: dummy indicator variable of high-value crops and share of area under high value crops, and I find a statistically significant positive association between ICT adoption (use and ownership) and agricultural diversification (Table 2). The coefficients estimated are likely biased and misleading, however, and I estimate the instrumental variable and report the coefficients of interest (Table 3) and the impact of, respectively, ICT use and ownership on the likelihood of cultivating each crop group type (Table 4). I present the first stage regression estimates (Appendix Table 2) and the entire regression output with other controls (Appendix Table 3). I find that ICT use and ownership cause a statistically significant increase in the likelihood of cultivating high-value crops and in the area under cultivation. The use of ICT increases the probability of cultivation by 12.8%[2] and ownership by 7.9%. That use impacts agricultural diversification more than ownership is expected as it is obvious that mere ownership of devices would not have the same impact as actual use of ICT.

The impact of ICT adoption on the production of spices and other high-value crops is positive and statistically significant; it is statistically and significantly negative on the production of pulses and not statistically significant on the production of cereals. Our result is

Table 2 OLS regressions

	(1) HVC	(2) HVC	(3) HVCshare	(4) HVCshare
ICT use	0.0373***		0.0183**	
	(0.0122)		(0.00736)	
ICT own		0.0483***		0.0365***
		(0.0150)		(0.0108)
Other controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
_cons	0.0983**	0.0965**	0.0926***	0.0953***
	(0.0465)	(0.0470)	(0.0271)	(0.0274)
N	14275	14275	14275	14275

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Outcome variable in column 1 and 2 are dummy indicator variable which equals 1 if household cultivates HVC and 0 if not. Outcome variable for column 3 and 4 are share of total land under HVC cultivation.

Table 3 Instrumental variable regression

	(1) HVC	(2) HVC	(3) HVCshare	(4) HVCshare
ICTuse	0.121*		0.0875**	
	(0.0662)		(0.0408)	
ICTown		0.0757*		0.0546**
		(0.0406)		(0.0252)
_cons	0.133**	0.105**	0.122***	0.101***
	(0.0528)	(0.0471)	(0.0307)	(0.0273)
N	14272	14272	14272	14272

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Outcome variable in column 1 and 2 are dummy indicator variable which equals 1 if household cultivates HVC and 0 if not. Outcome variable for column 3 and 4 are share of total land under HVC cultivation.

[2]The treatment effect in the percentage terms is calculated as: $(e^{\hat{\delta}}$-1)*100), where $\hat{\delta}$ is the estimated coefficient.

Table 4 Instrumental variable regression- food group dummy indicator outcome variable

	(1) cereals	(2) pulses	(3) spices	(4) oilseeds	(5) vegfruits	(6) others
			ICT use			
ICT use	0.00587	-0.103**	0.0897***	0.0546	0.0591	0.0618*
	(0.0392)	(0.0402)	(0.0285)	(0.0465)	(0.0570)	(0.0345)
_cons	0.873***	0.0505	-0.0372	0.0284	0.213***	-0.100***
	(0.0290)	(0.0386)	(0.0234)	(0.0441)	(0.0357)	(0.0288)
N	14272	14272	14272	14272	14272	14272
			ICT ownership			
ICT own	0.00367	-0.0644**	0.0560***	0.0341	0.0369	0.0386*
	(0.0244)	(0.0252)	(0.0176)	(0.0288)	(0.0352)	(0.0212)
_cons	0.872***	0.0747**	-0.0582***	0.0155	0.200***	-0.115***
	(0.0270)	(0.0367)	(0.0222)	(0.0406)	(0.0286)	(0.0256)
N	14272	14272	14272	14272	14272	14272

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Outcome variable in column 1 to 6 are respectively dummy indicator variables for each of the crop groups which equal 1 if household cultivates the same and 0 otherwise.

in line with Birthal et al. (2015a), which finds that households produce both cereals and high-value crops; they rarely switch completely from cereals to high-value crops. The impact of ICT use is greater than that of ownership.

Heterogeneity

The late or early adoption of mobile phones, and the remoteness of a village (pucca road or all-weather), determines the impact of adopting ICT. I define "early adopters of mobile technology" as villages that had mobile telephone services earlier than the median number of years when villages had first mobile telephone service. The IHDS 1 provides data on the number of years that households in a village had mobile telephone services. Early adopters drive the likelihood and extent of cultivating high-value crops; however, ICT related devices start impacting farm households only after a gestation period (Table 5- Panel A).

Heterogeneity based on early and late adopting villages and presence or absence of pucca (all-weather road)

Households in villages that do not have pucca roads (Table 5, Panel B, Columns 1, 2, 5 and 6) are likelier to adopt ICT than households in villages with pucca roads (Table 5, Panel B, Columns 3, 4, 7 and 8) The impact of ICT adoption is positive and statistically significant for villages with no pucca road; the impact for villages with pucca roads is not statistically significant. The result suggests that households that adopt ICT overcome the bottleneck of poor connectivity. The impact of ICT adoption was driven by early adopters of ICT that had no pucca roads.

The Pradhan Mantri Gram Sadak Yojana (PMGSY) aimed to build by 2003 pucca roads for all villages with a population of at least 1000 and by 2007[3] for all villages with a population of at least 500. Investments started in 2000. Higher populated villages were prioritized first. The data used for this analysis was collected in 2004–05, and only a few villages would have been covered by then, but late adopters were fewer in villages with pucca roads (1,149) than without (5,685). Interventions supporting investment in ICT adoption clearly did not correlate with investments to connect villages with pucca roads and the rate of ICT diffusion was much higher than of road connectivity. Policy must be formulated, and implemented, to improve the penetration of ICT in remote, poorly connected villages.

[3]https://web.archive.org/web/20121221150318/https://pmgsy.nic.in/pmg31.asp#2

Table 5 Heterogeneity based on early and late adopting villages and presence or absence of pucca (all-weather road)

Panel A-Early and late adopting villages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HVC early	HVC late	HVC early	HVC late	HVC share early	HVC share late	HVC share early	HVC share late
ictexp	0.126*	-0.0286			0.120**	-0.104		
	(0.0694)	(0.371)			(0.0475)	(0.192)		
ictown			0.0821*	-0.0131			0.0784**	-0.0474
			(0.044)	(0.168)			(0.031)	(0.081)
_cons	0.0570	0.772***	0.0255	0.776***	0.101***	0.914***	0.0714**	0.929***
	(0.065)	(0.107)	(0.059)	(0.090)	(0.039)	(0.055)	(0.035)	(0.053)
N	9209	1149	9209	1149	9209	1149	9209	1149

Panel B-Heterogeneity on the basis of presence or absence of Pucca (all-weather) roads								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HVC No Pucca road	HVC Pucca road	HVC No Pucca road	HVC Pucca road	share No Pucca road	share Pucca road	share No Pucca road	share Pucca road
ICTuse	0.262**		0.0464		0.119*		0.0510	
	(0.105)		(0.0732)		(0.0654)		(0.0473)	
ICTown		0.193***		0.0267		0.0874*		0.0293
		(0.0749)		(0.0421)		(0.0468)		(0.0273)
_cons	0.161**	0.134**	0.169**	0.155**	0.0869***	0.0749**	0.171***	0.156***
	(0.0703)	(0.0680)	(0.0688)	(0.0608)	(0.0308)	(0.0293)	(0.0445)	(0.0401)
N	5685	5685	8587	8587	5685	5685	8587	8587

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Outcome variable in column 1,2,3 and 4 are dummy indicator variable which equals 1 if household cultivates HVC and 0 if not. Outcome variable for column 5 ,6, 7 and 8 are share of total land under HVC cultivation. In Panel A, Columns 1, 3, 5 and 7 pertain to early adopters subsample while 2, 4, 6 and 8 pertain to late adopters subsample. In Panel B, Columns 1, 3, 5 and 7 pertain to no-pucca roads subsample while 2, 4, 6 and 8 pertain to villages with pucca roads subsample.

Channels

The adoption of ICT impacts farm production and the diversification towards high-value crops by improving farmers' access to credit markets, formal sources of information (Table 6- Panel A) and informal social networks (Table 6- Panel B), and enabling them to diversify their sources of income—although I am not able to identify causal pathways, and these channels could be driven by other, exogenous factors. Mass media makes it easier for government and policymakers to reach farm households. and mass media can raise their awareness of daily market prices, the availability and prices of inputs, and farmer support initiatives taken by the government.

The adoption and use of ICT connects farmers to each other. To capture the impact of ICT adoption on social informal networks, I use two measures: membership in social groups and acquaintance with influential people. The indicator for membership in social groups equals 1 if any household member is a member of a trade union, caste association, or a women's, self-help, or religious group. People may be influential in society owing to their role as medical professionals, schoolteachers, or as employee of the central

Table 6 Channels- education, mass media and news

	Panel A: education, mass media and news			
	(1)	(2)	(3)	(4)
	Mass-media	Mass-media	News	News
ICTuse	0.431***		0.323***	
	(0.0478)		(0.0469)	
ICTown		0.269***		0.202***
		(0.0294)		(0.0278)
_cons	0.318***	0.217***	-0.0384	-0.114***
	(0.0534)	(0.0495)	(0.0330)	(0.0311)
N	14272	14272	14272	14272

	Panel B: Membership and information			
	membership	membership	knowpeople	knowpeople
ICTuse	0.0496		0.273***	
	(0.0610)		(0.0537)	
ICTown		0.0310		0.170***
		(0.0381)		(0.0323)
_cons	-0.171***	-0.183***	0.546***	0.482***
	(0.0489)	(0.0443)	(0.0483)	(0.0433)
N	14272	14272	14272	14272

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ In Panel A, Outcome variable in column 1 and 2 are dummy indicator variable which equals 1 if household has access to mass media and 0 if not and Outcome variable for column 3 and 4 are dummy indicator variable which equals 1 if household watches news and 0 if not. In Panel B, outcome variable in column 1 and 2 are dummy indicator variable which equals 1 if household is a member of some social group and 0 if not and outcome variable for column 3 and 4 are dummy indicator variable which equals 1 if household has acquaintance with some influential person.

government or state governments. I find that ICT adoption does not have a statistically significant impact on membership of any group but it does have a positive, statistically significant impact on acquaintance with influential people. Households that adopt ICT are possibly more informed than those that do not because they are more connected with others and more aware of new agricultural developments, good practices, input and output markets, and therefore more likely to commercialize and diversify production.

Farm households diversify into cultivating high-value crops that are riskier if they have access to credit markets that lets them hedge risk (Table 7). And they can take new initiatives and adopt new technology if they have food and financial security through insurance, several sources of income, a ration card, and a Kisan Credit Card. The adoption of ICT might help farmers access the benefits of government social welfare schemes and diversify their portfolio by working in more than occupation. I find that ICT adoption has a positive and significant impact on the number of income sources of farm households but I do not find any statistically significant impact of benefits from social welfare schemes or a Kisan Credit Card.

Next, I explore whether farm households that adopt ICT enjoy differential access to credit markets than households that do not. I consider the likelihood of taking a loan in the previous five years, purpose of the largest loan, source of the largest loan, and the monthly interest rate on the largest loan.[4] I use indicator variables

[4]Survey provides detail only on the largest loan taken by the household and therefore I explore impact of ICT on the largest loan

Table 7 Channels-more sources of income

	(1) sumdivincsource	(2) sumdivincsource	(3) card	(4) card	(5) kcc	(6) kcc
ICTuse	0.213***		0.0146		0.0405	
	(0.0815)		(0.0217)		(0.0423)	
ICTown		0.133**		0.00913		0.0253
		(0.0517)		(0.0135)		(0.0258)
_cons	1.868***	1.818***	0.501***	0.497***	-0.161***	-0.171***
	(0.0775)	(0.0740)	(0.0417)	(0.0410)	(0.0329)	(0.0289)
N	14272	14272	14272	14272	14272	14272

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Outcome variable in column 1 and 2 are sum to total income sources for households. Outcome variable for column 3 and 4 are dummy indicator variable which equals 1 if household some card and 0 if not. Outcome variable for columns 5 and 6 are dummy indicator variable which equals 1 if household has kcc card and zero otherwise.

Table 8 Channels- credit market access

	(1) loan	(2) loan	(3) agriloan	(4) agriloan	(5) formalloan	(6) formalloan	(7) loginterest	(8) loginterest
ictexp	0.00918		0.0642		0.202***		-0.152**	
	(0.0541)		(0.0405)		(0.0446)		(0.0671)	
ictown		0.00573		0.0401		0.126***		-0.0910**
		(0.0338)		(0.0250)		(0.0270)		(0.0396)
_cons	-0.150***	-0.152***	-0.0845*	-0.0996**	-0.163***	-0.210***	0.845***	0.861***
	(0.0494)	(0.0466)	(0.0486)	(0.0463)	(0.0488)	(0.0452)	(0.0644)	(0.0642)
N	14272	14272	14272	14272	14272	14272	7191	7191

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Outcome variable in column 1 and 2 are dummy indicator variable which equals 1 if household has taken atleast one loan in the last five years and 0 if not. Outcome variable for column 3 and 4 are dummy indicator variable which equals 1 if household's largest loan was an agri or business loan, columns 5 and 6 are dummy indicator variables which equals 1 if household's largest loan in the last five years was from a formal source and columns 7 and 8 are log of interest rate at which the household took the largest loan in the last five years.

for loan, agri/business loan, formal loan and use log of monthly interest rate as the final outcome variable. I find that ICT adoption has no statistically significant impact on the probability of taking a loan in the previous five years or on the purpose of the largest loan, but it increases the likelihood of borrowing from a formal source (Column 5 and 6), and those who adopted ICT pay statistically and significantly lower interest rates for the largest loan they took in the previous five years (Table 10). Households that use ICT have better awareness then those who do not, and it is plausible that this awareness led to cheaper loans from formal sources.

Other impacts of ICT adoption

I explore the impact of ICT adoption on two aspects of agricultural production: farm commercialization and investment in inputs. I measure market activity using four indicators: the log of income profit from agricultural production; the log of profit from agricultural production; an indicator variable, market sale (mktsale), which equals 1 if the household sells any of its agricultural output; and another indicator variable, HVC market sale (HVCmktsale), which equals 1 if a household sells high-value crops.[5] I find no statistically significant impact of ICT on overall

[5]I also explored impact of ICT adoption on prices received by farm households on sale of their produce. I do not find any statistically significant impact of ICT adoption on prices.

Table 9 Instrumental variable regressions- farm commercialization

	(1) mktsale	(2) mktsale	(3) HVCmktsale	(4) HVCmktsale	(5) loginc	(6) loginc	(7) logprofit	(8) logprofit
ICTuse	0.0487		0.146^{**}		0.627^{***}		0.543^{**}	
	(0.0570)		(0.0652)		(0.203)		(0.272)	
ICTown		0.0304		0.0913^{**}		0.400^{***}		0.345^{**}
		(0.0353)		(0.0394)		(0.124)		(0.165)
_cons	0.0963^{*}	0.0848^{*}	0.0561	0.0217	7.011^{***}	6.860^{***}	6.811^{***}	6.706^{***}
	(0.0497)	(0.0459)	(0.0506)	(0.0467)	(0.164)	(0.149)	(0.214)	(0.202)
N	14272	14272	14272	14272	12852	12852	9450	9450

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Outcome variable in column 1 and 2 are dummy indicator variable which equals 1 if household has sells his production in the market and 0 if not. Outcome variable for column 3 and 4 are dummy indicator variable which equals 1 if household sells HVCs it cultivates in the market, columns 5 and 6 are log of income earned from farm production, and columns 7 and 8 are log of profit gained from farm cultivation.

Table 10 Instrumental variable regression- input expenditure

	(1) hiredlabratio	(2) logseedsmkt	(3) logfertilizer	(4) logpesticide	(5) loghiredequip	(6) logagriloanrepayment
ICTuse	0.144^{***}	0.427^{**}	0.876^{***}	1.283^{***}	0.377	0.954^{***}
	(0.0285)	(0.188)	(0.290)	(0.437)	(0.409)	(0.360)
_cons	0.0935^{***}	4.522^{***}	5.145^{***}	3.192^{***}	6.224^{***}	-0.919^{***}
	(0.0265)	(0.144)	(0.213)	(0.299)	(0.361)	(0.296)
N	10892	14146	13950	13253	13557	12494
ICT own	0.0934^{***}	0.266^{**}	0.544^{***}	0.794^{***}	0.233	0.590^{***}
	(0.0164)	(0.114)	(0.170)	(0.256)	(0.255)	(0.214)
_cons	0.0618^{**}	4.422^{***}	4.941^{***}	2.908^{***}	6.134^{***}	-1.134^{***}
	(0.0250)	(0.134)	(0.190)	(0.267)	(0.338)	(0.272)
N	10892	14146	13950	13253	13557	12494

Source authors' computation using IHDS-1 data. Robust Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Outcome variable in column 1 is ratio of hired labour to total labour employed by the household in cultivation, column 2 is log of expenditure on seeds from the market, column 3 is log of expenditure on pesticide, column 4 is log of expenditure on pesticide, column 6 is log of expenditure on hired equipments and column 7 is log of expenditure on repayment of loan taken for purpose of investing on agriculture.

market sale. However, ICT adoption has a positive and statistically significant impact on likelihood of HVC market sale, and households that use or own ICT earned statistically significant and higher agricultural incomes and profit (Table 9). As with all other results, impact of ICT use is higher than ICT ownership. These results point towards overall commercialization of agriculture for households which have adopted ICT.

Agricultural inputs are measured using the ratio of hired labour to total farm labour, log of total expenditure on purchased seeds from the market, log of fertilizer expenditure, log of total pesticide expenditure, log of expenditure on irrigation, hired equipments and log of expenditure incurred on agricultural loan repayment. I find that ICT adoption has a statistically significant and positive impact on ratio of hired labour, seeds purchased, fertilizer and pesticide purchased from the market and expenditure incurred on repayment of agricultural loans (Table 10). Given that inputs, specifically productivity enhancing technologies, complement each another (Foster and Rosenzweig, 2010; Suri, 2011), these findings on an increase in expenditure for these inputs are not surprising.

Conclusions

Agriculture is the main source of livelihood for more than 50% of the population. And the increasing penetration of cheap mobile phones and internet connectivity over the past two decades makes India an interesting case study for estimating the impact of ICT as a means of effective communication on farm decisions. This study uses the IHDS-1 dataset and an instrumental variable strategy to explore the impact of ICT ownership and use on agricultural diversification, farm commercialization, and investment in new technology; it does not evaluate ICT related interventions (like agri-extension through SMS/internet or weather or any other information dissemination through SMS/internet).

Villages that adopted mobile technology early reaped the benefits of ICT best. The adoption of ICT facilitates farm diversification but the benefits depend on whether a village was early or late to adopt it, implying that ICT adoption and use has a gestation period before it can serve as an efficient means of communication among farmers.

The benefits of ICT adoption are driven by villages that do not have an all-weather (pucca) road, suggesting that ICT can reach the remotest villages.

We hypothesized that the adoption of ICT drives farm diversification through awareness, information (formal and informal sources), risk bearing capacity, and access to credit markets. Our findings confirm the hypothesis.

Households that adopt ICT are likelier to spend on agricultural inputs and technologies, hire labour for farm work, sell their output in the market, earn higher income and profits, and commercialize farms. The adoption of ICT has a positive and significant impact on agricultural diversification towards high-value commodities. In India most farmers are small or marginal and villages poorly connected, and ICT holds promise and potential in promoting diversification and commercialization.

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Received 18 February 2022 Accepted 7 June 2022

Annexure

Table A1 Descriptive statistics- outcome variables and controls in the regression

Variable	Obs	Mean	Std. Dev.
High Value Commodities related			
High Value Commodities (1/0)	14345	.403	.491
High Value Commodities (share area)	14345	.193	.305
ICT related			
ICT use (1/0)	14345	.308	.462
ICT own (1/0)	14345	.135	.342
Inputs in cultivation			
Hired labour ratio	10938	.161	.203
Seed expenditure (Rs)	14217	1824.626	4113.153
Fertilizer and manure expenditure (Rs)	14018	2571.936	8103.267
Pesticides and herbicides expenditure (Rs)	13306	1051.552	4538.92
Irrigation expenditure (Rs)	13060	517.964	1871.472
Tractor and equipment expenditure (Rs)	13614	1388.369	3024.445
Agriculture loan repayment expenditure (Rs)	12545	1297.519	9180.913
Income & profit from production			
Income for farm (Rs)	14345	22594.414	77758.795
Profit from farm (Rs)	14205	10715.275	72036.444
Household characteristics			
Head age (in years)	14345	49.026	13.438
Head edu (in years)	14275	4.477	4.437
Head married (1/0)	14345	.885	.319
Caste SC(1/0)	14345	.158	.364
Caste ST (1/0)	14345	.118	.323
Caste OBC (1/0)	14345	.416	.493
Household size (no)	14345	5.89	2.84
Total land (acre)	14320	4.51	8.035

Source Author's calculations using data from IHDS1

Table A2 Instrumental variable regression- first stage

	(1) ictexp	(2) ictown	(3) ictexp	(4) ictown
instictown	0.495***	0.792***	0.495***	0.792***
	(0.0272)	(0.0108)	(0.0272)	(0.0108)
headage	0.00584***	0.00231**	0.00584***	0.00231**
	(0.00148)	(0.000916)	(0.00148)	(0.000916)
agesq	-0.0000320**	-0.00000215	-0.0000320**	-0.00000215
	(0.0000141)	(0.00000893)	(0.0000141)	(0.00000893)
headedu	0.00789***	-0.00227	0.00789***	-0.00227
	(0.00241)	(0.00167)	(0.00241)	(0.00167)
edusq	0.000831***	0.00124***	0.000831***	0.00124***
	(0.000210)	(0.000159)	(0.000210)	(0.000159)
headmarried	-0.0324***	-0.0147*	-0.0324***	-0.0147*
	(0.0120)	(0.00830)	(0.0120)	(0.00830)
castesc	-0.0343***	0.00593	-0.0343***	0.00593
	(0.0132)	(0.00375)	(0.0132)	(0.00375)
castest	-0.0603***	0.00937**	-0.0603***	0.00937**
	(0.0175)	(0.00401)	(0.0175)	(0.00401)
casteobc	-0.0249**	0.00104	-0.0249**	0.00104
	(0.0111)	(0.00361)	(0.0111)	(0.00361)
loghhsize	0.0771***	0.0457***	0.0771***	0.0457***
	(0.00864)	(0.00630)	(0.00864)	(0.00630)
totalland	-0.0000116***	-0.00000629*	-0.0000116***	-0.00000629*
	(0.00000316)	(0.00000350)	(0.00000316)	(0.00000350)
District FE	Yes	Yes	Yes	Yes
_cons	-0.385***	-0.240***	-0.385***	-0.240***
	(0.0415)	(0.0291)	(0.0415)	(0.0291)
F test of excluded instruments:				
Sanderson-Windmeijer test	330.01***	5403.90***	330.01***	5403.90***
Under identification test				
Kleibergen-Paap rk LM statistic	72.64***	112.06***	72.64***	112.06***
Weak identification test				
Cragg-Donald Wald F statistic	758.56	4412.05	758.56	4412.05
10% maximum IV value	16.38	16.38	16.38	16.38
N	14272	14272	14272	14272

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3 Instrumental variable regression- main results- all controls

	(1) hyv	(2) hyv	(3) hyvshare	(4) hyvshare
ictexp	0.121*		0.0875**	
	(0.0662)		(0.0408)	
ictown		0.0757*		0.0546**
		(0.0406)		(0.0252)
headage	0.00258	0.00311*	0.00114	0.00152
	(0.00173)	(0.00170)	(0.00107)	(0.00104)
agesq	-0.00000319	-0.00000691	-0.00000683	-0.00000951
	(0.0000164)	(0.0000164)	(0.0000102)	(0.0000101)
headedu	0.00795***	0.00908***	0.00239	0.00321**
	(0.00262)	(0.00258)	(0.00164)	(0.00159)
edusq	0.0000315	0.0000385	0.0000599	0.0000650
	(0.000224)	(0.000222)	(0.000135)	(0.000133)
headmarried	0.0227**	0.0199*	0.0105	0.00845
	(0.0113)	(0.0110)	(0.00695)	(0.00670)
castesc	-0.0947***	-0.0993***	-0.0188*	-0.0221**
	(0.0198)	(0.0191)	(0.0105)	(0.0103)
castest	-0.0708**	-0.0788***	-0.0403**	-0.0461***
	(0.0302)	(0.0291)	(0.0160)	(0.0152)
casteobc	-0.00498	-0.00808	-0.00233	-0.00457
	(0.0160)	(0.0156)	(0.0108)	(0.0104)
loghhsize	0.0495***	0.0554***	-0.00354	0.000702
	(0.0114)	(0.00968)	(0.00701)	(0.00595)
totalland	0.00000113	0.000000199	-0.00000889**	-0.00000956**
	(0.00000707)	(0.00000717)	(0.00000446)	(0.00000444)
District FE	Yes	Yes	Yes	Yes
_cons	0.133**	0.105**	0.122***	0.101***
	(0.0528)	(0.0471)	(0.0307)	(0.0273)
N	14272	14272	14272	14272

Standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Agricultural Economics Research Review 2022, 35 (2), 59-77
DOI: 10.5958/0974-0279.2022.00031.3

Implications of appropriate technology and farm inputs in the agricultural sector of Gujarat: empirical analysis based on primary data

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Abstract This study examines the usages, benefits, and obstacles in the applications of various technologies, and the impact of appropriate technologies, on agricultural productivity in Gujarat, India. Most farmers are aware of the economic, social, and environmental viability of appropriate technologies and they use these for a variety of purposes. The results imply that agricultural productivity is influenced by many factors, including technology cost, technological development, total arable land, cropping intensity, irrigated area, use of fertilizer and agricultural labour, annual income of farmers, practice of appropriate technologies in cultivation, financial support from government, agricultural co-operative societies, and agricultural extension offices.

JEL codes C21, C31, O14, Q10, Q12, Q16, Q18

Keywords Agricultural productivity, appropriate technology, farm management practices, technological development, sustainable agricultural development

In the 1970s Schumacher introduced the concept of "appropriate technology" (Zhou, Jiao, and Li 2017; Lee et al. 2018; Patnaik and Bhowmick 2018), defined as technology that meets the ecological, cultural, and economic requirements of society (Musunuri 2014). Appropriate technologies are new, small-scale technologies, or ideas or knowledge or knowledge-know-how, that are useful in reducing the negative impact of production activities on economic, social, and environmental sustainability (Moon and Hwang 2018) and that are discovered or invented to meet the basic requirements of a community (Patnaik and Bhowmick 2018).

Being labour-intensive technologies that are useful in creating jobs and improving livelihood security (Lissenden, Maley, and Mehta 2015), appropriate technologies provide for the use of alternative, renewable resources in production activities (Beder 2000) and assist in improving the efficiency of socio-economic and human activities, and energy and material resources, at the micro level (Garniati et al. 2014). Appropriate technologies have brought several benefits to food production, energy, health, sanitation, water, education, service, agriculture, and industry (Dunn 1978; Rohatgi and Rohatgi 1979; Shanthy 2011); for instance, digital technologies and digitalization may be used as an appropriate technology in farming (Mondejar et al. 2021). Appropriate technologies would help in improving the productivity and efficiency of inputs (labour, water, land, human, energy, and finance) without degrading the quality of ecosystem services (Costanza et al. 2012; Garniati et al. 2014; Singh, Narayanan, and Sharma 2019).

High population growth worldwide is increasing the pressure on ecosystem services and the agriculture sector to meet the growing food demand (Singh and Issac 2018; Calicioglu et al. 2019). The world population, now 7.3 billion, would be around 10 billion by 2050 (Talaviya et al. 2020), and providing them all food security will be difficult (Kumar, Ahmad, and Sharma 2017). Developing economies will face several obstacles in creating jobs and in providing food security, social security, and health security; sustaining the environment; and in reducing poverty and income inequality (Kumar 2015; Calicioglu et al. 2019). And these obstacles can be surmounted only with the applications of technological development, such as digital, and appropriate technologies in cultivation, to achieve sustainable agricultural development (Pasa 2017; Talaviya et al. 2020; Mondejar et al. 2021; Ashraf and Singh 2021).

Appropriate technologies would be effective in improving land and cropping patterns; farm management practices and techniques; seed quality, germination, and marketing; and soil quality and fertility (Abdullahi, Mahieddine, and Sheriff 2015; Talaviya et al. 2020). The use of appropriate technologies would help to increase the production of food grains and cash crops, create employment (Talaviya et al. 2020), and contribute to increasing the production of animals, meat, and milk. The application of appropriate technologies will create development opportunities for agriculture, industry, and the livestock rearing, and dairy, services, and energy sectors in countries (Mondejar et al. 2021) and contribute to improving the well-being and livelihood security of farmers and citizens worldwide.

Appropriate technologies have multidimensional aspects, including technology and knowledge transfer, technology mechanisms, and capacity-building across sectors (Lee et al. 2018). Subsequently, technology transfers create entrepreneurship ecosystems, improve access to markets, and commercialize existing technologies (Pearce 2019). Appropriate technologies are a crucial determinant of innovation and technological development (Singh and Bhowmick 2015; Singh et al. 2022). Also, the usage of appropriate technologies in agriculture will create jobs and improve crop productivity and the sustainability of ecosystem services.

The practices of appropriate technologies have brought several alternatives to improving food production and the economic condition of farmers (Dunn 1978; Dhehibi et al. 2020). Appropriate technologies help to improve agricultural productivity, efficiency, and profitability. Using appropriate technologies helps to maintain crop quality and durability and reduce bacteria in agricultural products. In India, for instance, using biotechnology in cultivating cotton increased farmers' profit and reduced the application of chemical fertilizer (Kapur 2018). In largely agrarian economies, technological development may help to improve production, yield, cropped area, and farmers' income (Ashraf and Singh 2021; Kapur 2018).

Science and technology, and technological development, have had a positive impact on the agricultural sector in India (Rohatgi and Rohatgi 1979; Parayil 1992; Desai 1994; Gandhi 1997; Parthasarathy 2002; Larson et al. 2004; Birthal and Kumar 2004; Shanthy 2011; Joshi 2012; Yadav and Goyal 2015; Swain 2016; Shabbir and Yaqoob 2019; Ashraf and Singh 2021).

Applying green revolution technologies, technological development, biotechnologies, irrigation technologies, and farm management practices would help India to improve the production and productivity of food grains and cash crops (Birthal and Kumar 2004; Ashraf and Singh 2021). India needs to use appropriate technologies to improve crop productivity and sustainability in ecosystem services and, therefore, sustainable agricultural development, which will bring about food security and maintain food quality, increase the yield of food grains and cash crops, create jobs, increase profits of farmers, and reduce poverty and income inequality (Saiz-Rubio and Rovira-Mαs 2020; Singh et al. 2022) so that it can feed its population in the near future (Singh, Kumar, and Jyoti 2022).

Several studies conceptually identify the importance of appropriate technologies and technological development in agricultural production activities (Dunn 1978; Birthal and Kumar 2004; Shanthy 2011; Calicioglu et al. 2019; Dhehibi et al. 2020), but no empirical model has been developed to assess the impact of appropriate technologies and other inputs on agricultural productivity in India. This study aims to identify the usages, benefits, and obstacles in the applications of technologies in the agricultural sector; observe farmers' perceptions of appropriate technologies and their components; and examine the impact of appropriate technologies, technological development, agricultural development institutions, and other inputs on agricultural productivity by addressing four research questions.

1. What are the usages, benefits, and obstacles of technological development in the agricultural sector?
2. Do farmers understand the appropriate technologies and their applications?
3. How do appropriate technologies and technological development have a positive impact on agricultural productivity?
4. How can local stakeholders, financial institutions, and agricultural cooperative societies, extension offices, universities, and industries help improve farmers' awareness of appropriate technologies and their practices?

This study uses actual information on the applications of technologies in the agricultural sector to assess the role of appropriate technologies, technological development, and other inputs in the agricultural sector of Gujarat, and it is thus a significant contribution to the existing literature.

The study has several limitations, however: it could not evaluate the role of industry in improving the uptake of appropriate technologies in agriculture, or suggest appropriate ways to apply these, or consider factors such as climatic conditions, geographical location, soil and seed quality, sowing time of seed, irrigation methods, farmer's experience, appropriate marketing, appropriate price of production, government policies and agricultural research and development (R&D)—all of which have a significant impact on agricultural productivity.

Materials and methods

Study area

Gujarat is a highly industrialized state, and it has the lion's share of India's industrial growth. Despite that, around 49% of its workforce is engaged in the agricultural sector (Gulati, Roy, and Hussain 2021). Also, most farming households earn their livelihood from the agricultural and allied sector.

Agricultural growth was high from 2001–02 to 2014–15 (Gulati, Roy, and Hussain 2021). The state has a dominant position in food grains (wheat, maize, bajra, rice, sorghum) and cash crops (sugarcane, groundnut, castor, cotton, rapeseed, mustard, soyabean). The growth of cropped area, production. and yield of food grain and cash crops were observed to be positive due to technological development (Ashraf and Singh 2021). It is expected that the growth of Gujarat's agricultural sector will be positive in future due to the applications of various technologies in farming.

For this study, we selected eight districts—Anand, Banas Kantha, Bharuch, Bhavnagar, Junagadh, Kheda, Surat, and Vadodara—because these contribute around 46% of the agricultural labour, 36% of the agricultural district domestic product, 36.6% of the gross cropped area, 31% of the net area sown, and 44% of the gross irrigated area. These eight districts occupy a significant share of the cropped area of food grains and cash crops and contribute significantly to production: around 35% of wheat, 40% of rice, 41% of jowar, 39% of maize, 65% of bajra, 30% of moong, 58% of arhar, 57% of rapeseed and mustard, 39% of groundnut, 70% of sugarcane, and 63% of potato.

Data collection technique

Two blocks from each district were selected randomly. Thereafter, one village from each block was chosen purposively. Accordingly, 16 villages were identified, and 15 farmers from each village considered for personal face-to-face interviews; therefore, a total of 240 farmers were chosen to collect the desired information.

We conducted the interviews in 2019 from 1 October to 31 December using a well-structured questionnaire. The questionnaire included questions on socio-economic structure, educational profile, physical assets, schooling, physical resources, income-generating occupations, use of technologies in farming, barriers in the applications of appropriate technologies, and the involvement of agricultural development and financial institutions in the agricultural sector.

Dependent and independent variables

Agricultural productivity (ap)

We used farm harvest prices to estimate the economic value of each crop and, accordingly, agricultural productivity, and we used agricultural productivity as the dependent variable in the regression analysis (Kumar, Sharma, and Joshi 2016; Ashraf and Singh 2021).

Age of respondent (ar) and family size of respondent (fs)

Farm management practices, which have a positive impact on agricultural production, improve as the age of a farmer increases (Jamal et al. 2021). Family members also have a positive impact on farming activities.

Education level of respondents (el)

Literate farmers understand appropriate technologies and practices and other agricultural inputs (Kumar, Sharma, and Joshi 2016; Jamal et al. 2021).

Gender of respondents (gr)

Male farmers can be associated with various stakeholders and be members of agricultural development institutions. Thus, the gender of respondents has a crucial contribution in the agricultural sector (Singh and Singh 2019).

Annual income of respondent (ai)

Agricultural production is expected to increase as farmer income increases. High-income farming households can use inputs and technologies to improve returns (Jamal et al. 2021). Hence, annual income has a positive impact on agricultural production.

Total agricultural land (tal)

Agricultural production is not possible without arable land. Hence, total agricultural land was used as an independent variable (Chandio et al. 2021).

Irrigated area (ia) and non-irrigated area (nia)

Irrigated land has a higher yielding capacity than non irrigated land (Kumar, Sharma, and Joshi 2016; Msomba, Ndaki, and Nassary 2021).

Use of agricultural labour (ual)

Human resources are crucial in the agricultural sector, and labour force and agricultural labour have been used to capture its impact (Kumar, Sharma, and Joshi 2016; Chandio et al. 2021).

Use of fertilizer (ugf)

Fertilizers help to maintain soil fertility and quality (Msomba, Ndaki, and Nassary 2021); as the use of fertilizer increases, crop productivity increases.

Number of crops cultivated (cropping intensity) (ci)

Cropping intensity is the ratio of gross cropped area to net sown area, or the efficiency of a specific arable area, or its ability to cultivate several crops in a year; for instance, maize, sorghum, and rice grow in the kharif season and wheat, mustard, and gram grow in the rabi season on the same land. We used the number of crops cultivated during the survey year as an independent variable to capture the impact of cropping intensity on agricultural productivity.

Technological cost (ttc)

We used the cost of technology per hectare as an independent variable to capture the impact of technological development on agricultural productivity (Singh et al. 2022).

Economic viability of technology (evt), social viability of technology (svt), environmental viability of technology (envt), and appropriateness of technology (at)

Appropriate technologies have three aspects: economic, social, and environmental (Musunuri 2014; Lee et al. 2018; Moon and Hwang 2018; Siddick 2019; Bhattacharjya, Kakoty, and Singha 2019; Maynard et al. 2020; Singh et al. 2022). Economic viability can be measured by net present value. A technology has social viability when it does not pose users any risk. Technologies are environmentally viable if they can improve the quality of soil, water, and air, soil fertility, water conservation, energy saving and energy use efficiency, natural biological processes, and biodiversity (Kriesemer, Vichow, and Weinberger 2016). Technical, economic, environmental, and sociopolitical sustainability are also components of appropriate technologies (Kriesemer, Vichow, and Weinberger 2016). We can use the components' indicators to check the viability of appropriate technologies. It is difficult to examine the impact of appropriate technologies (Singh et al. 2022), and so we considered farmers' views on the social, economic, and environmental viability of appropriate technologies to capture their influence on agricultural productivity.

Financial problem (fp) and financial support for government (fsg)

Poor and small farmers cannot afford the high cost of agricultural inputs and technologies. Therefore, small landholders cannot improve productivity. Financial support from the government and credit facilities from the banking sector would help them buy seeds, fertilizers, pesticides, technologies, and other inputs (Msomba, Ndaki, and Nassary 2021) and improve productivity.

Farmers' collaboration with different stakeholders (fas)

Agricultural entrepreneurs, universities, extension offices, cooperative societies, and industry provide farmers skilled and technical support (Jamal et al. 2021). Hence, agricultural developmental institutions are crucial in making agricultural development sustainable (Syan et al. 2019).

Skills and technical support from technology developers or sellers (stsf)

Technology developers also train farmers to operate new technologies in the agricultural sector (Singh et al. 2022). Thus, their involvement would help improve productivity.

Empirical analysis

The primary aim of this study is to estimate the impact of appropriate technologies on agricultural productivity in Gujarat. Thus, the study estimates the economic value of all crops at farm harvest prices cultivated by farmers in a survey year; divides the aggregate economic value of all crops by the gross cropped area to measure agricultural productivity; and uses agricultural productivity as the dependent variable in the regression model.

Earlier studies used different factors to estimate the impact of technological development and change on agricultural production (Hayami and Ruttan 1970; Deb, Mandal, and Dey 1991; Ziberman, Khanna, and Lipper 1997; Grabowski and Self 2006; Kumar, Sharma, and Ambrammal 2015; Gebeyehu 2016; Ali et al. 2017; Singh, Narayanan, and Sharma 2017; Siddick 2019; Jyoti and Singh 2020; Ashraf and Singh 2021).

Agricultural productivity is impacted by respondent gender and age; family size; farmers' annual income and education level; gross cropped area; irrigated and non-irrigated area; agricultural labour; fertilizer and cropping intensity (Deb, Mandal, and Dey 1991; Kumar 2015; Swain 2016; Lee et al. 2018; Siddick 2019; Dhehibi et al. 2020); and financial support from government and agricultural developmental institutions. The empirical investigation considers these factors as explanatory variables.

This study uses the cost of technologies to cultivate all crops as an independent variable, and farmers' opinions on appropriate technologies and their components in binary forms, to examine the impact of each on agricultural productivity. We employed the linear, nonlinear, and log linear regression models to assess the effect of appropriate technologies and other inputs on agricultural productivity. Similar empirical models have been used to examine the impact of climatic factors and agricultural inputs on agricultural productivity in India (Kumar, Ahmad, and Sharma 2017; Jyoti and Singh 2020; Ashraf and Singh 2021; Singh et al. 2022). Our study assumes that agricultural productivity is a function of the cost of technology, appropriate technologies, and other inputs.

$$(ap) = f(ttc, tal, ci, ia, nia, ugf, ual, el, ai, fs, ar, evt, svt, envt, at, fp, fsg, fas, stsf, gr) \quad \ldots(1)$$

where,

ap is agricultural productivity;

ttc is cost of technology,

tal is agricultural land,

ci is cropping intensity,

ia is irrigated area,

nia is non-irrigated area,

ugf is use of fertilizer,

ual is use of agricultural labour,

el is educational level,

ai is annual income,

fs is family size,

ar is age of farmers,

evt is economic viability of technology,

svt is social viability of technology,

envt is environmental viability of technology,

at is appropriateness of technology,

fp is financial problem,

fsg is financial support from government,

fas is farmer's collaboration with various stakeholders,

stsf is skilled and technical support from technology developers, and

gr is gender of farmers in Equation 1 (Table 1).

Table 1 Dependent and independent variables

Variables	Symbol	Units
Agricultural productivity	*ap*	Rs.
Technological cost to cultivate all crops	*ttc*	Number
Total agricultural land	*tal*	Ha.
Number of crops cultivated (cropping intensity)	*ci*	Number
Irrigated area	*ia*	Ha.
Non-irrigated area	*nia*	Ha.
Use of fertilizer	*ugf*	Kg.
Use of agricultural labour	*ual*	Number
Educational level of respondent	*el*	Years
Annual income of respondent	*ai*	Rs.
Family size of respondent	*fs*	Number
Age of respondent	*ar*	Years
Economic viability of technology (1 = Yes and 0 = No)	*evt*	Number
Social viability of technology (1 = Yes and 0 = No)	*svt*	Number
Environmental viability of technology (1 = Yes and 0 = No)	*envt*	Number
Appropriateness of technology (1 = Yes and 0 = No)	*at*	Number
Financial problem (1 = Yes and 0 = No)	*fp*	Number
Financial support from government (1 = Yes and 0 = No)	*fsg*	Number
Farmer's collaboration with different stakeholders (Agri-entrepreneurs, agricultural universities, agricultural extension offices or Krishi Vigyan Kendras (KVKs), co-operative societies, ago-industries) (1 = Yes and 0 = No)	*fas*	Number
Skills & technical support from technology developers or sellers (1 = Yes and 0 = No)	*stsf*	Number
Gender of respondents (1 = Male and 0 = Female)	*gr*	Number

The linear regression model is

$$(ap)_i = \alpha_0 + \alpha_1 (ttc)_i + \alpha_2 (tal)_i + \alpha_3 (ci)_i + \alpha_4 (ia)_i + \alpha_5 (nia)_i + \alpha_6 (ugf)_i + \alpha_7 (ual)_i + \alpha_8 (el)_i + \alpha_9 (ai)_i + \alpha_{10} (fs)_i + \alpha_{11} (ar)_i + \alpha_{12} (evt)_i + \alpha_{13} (svt)_i + \alpha_{14} (envt)_i + \alpha_{15} (at)_i + \alpha_{16} (fp)_i + \alpha_{17} (fsg)_i + \alpha_{18} (fas)_i + \alpha_{19} (stsf)_i + \alpha_{20} (gr)_i + u_i \quad \ldots(2)$$

where,

α_0 is the constant coefficient,

$\alpha_1, \alpha_2, \ldots, \alpha_{20}$ are the regression coefficients of independent variables, and

u_i is the error term in Equation 2.

The log linear regression model is

$$ln\,(ap)_i = \beta_0 + \beta_1\, ln\,(ttc)_i + \beta_2\, ln\,(tal)_i + \beta_3\, ln\,(ci)_i + \beta_4\, ln\,(ia)_i + \beta_5\, ln\,(nia)_i + \beta_6\, ln\,(ugf)_i + \beta_7\, ln\,(ual)_i + \beta_8\, ln\,(el)_i + \beta_9\, ln\,(ai)_i + \beta_{10}\, ln\,(fs)_i + \beta_{11}\, ln\,(ar)_i + \beta_{12} (evt)_i + \beta_{13} (svt)_i + \beta_{14} (envt)_i + \beta_{15} (at)_i + \beta_{16} (fp)_i + \beta_{17} (fsg)_i + \beta_{18} (fas)_i + \beta_{19} (stsf)_i + \beta_{20} (gr)_i + v_i \quad \ldots(3)$$

where,

ln is the natural logarithm of respective variables (except binary variables),

β_0 is constant coefficient;

$\beta_1, \beta_1, \ldots, \beta_{21}$ are the regression coefficient of associated variables; and

v_i is the error term in Equation 3.

The nonlinear regression model is

$$(ap)_i = \gamma_0 + \gamma_1 (ttc)_i + \gamma_2 (Sq\ ttc)_i + \gamma_3 (tal)_i + \gamma_4 (Sq\ tal)_i + \gamma_5 (ci)_i + \gamma_6 (Sq\ ci)_i + \gamma_7 (ia)_i + \gamma_8 (Sq\ ia)_i + \gamma_9 (nia)_i + \gamma_{10} (Sq\ nia)_i + \gamma_{11} (ugf)_i + \gamma_{12} (Sq\ ugf)_i + \gamma_{13} (ual)_i + \gamma_{14} (Sq\ ual)_i + \gamma_{15} (el)_i + \gamma_{16} (Sq\ el)_i + \gamma_{17} (ai)_i + \gamma_{18} (Sq\ ai)_i + \gamma_{19} (fs)_i + \gamma_{20} (Sq\ fs)_i + \gamma_{21} (ar)_i + \gamma_{22} (Sq\ ar)_i + \gamma_{23} (evt)_i + \gamma_{24} (svt)_i + \gamma_{25} (envt)_i + \gamma_{26} (at)_i + \gamma_{27} (fp)_i + \gamma_{28} (fsg)_i + \gamma_{29} (fas)_i + \gamma_{30} (stsf)_i + \gamma_{31} (gr)_i + \bullet_i \quad \ldots(4)$$

Here, *Sq* is the square term of corresponding variables (except binary data); γ_0 is the constant coefficient; γ_1,

$\gamma_2, \ldots, \gamma_{31}$ are the regression coefficients of associated explanatory variables; and $\bullet_i$ is the error term in equation (4).

Selecting the appropriate model

We used the Cronbach α statistical test to check the validity of the collected variables (Syan et al. 2019). Moreover, if a variable has a high variation, it may not be in a normal form (Singh et al. 2022); if the values of skewness and kurtosis for a variable lie between "1 and 1, the variable may be considered to be in a normal form.

As we used the linear, nonlinear, and log linear regression models to assess the impact of appropriate technologies and other inputs on agricultural productivity, we used the Ramsay RESET test to check the appropriate functional form of the proposed models (Singh et al. 2022). We estimated the values of the Akaike Information Criterion (AIC) and Bayesian information criterion (BIC) to check the consistency of the regression coefficients (Singh et al. 2022).

Multi-correlation measures the existence of a linear and exact relationship among the explanatory variables (Singh et al. 2022), so we estimated the value of the variance inflation factor (VIF) to assess the presence of multi-correlation between the explanatory variables in the proposed models (Jyoti and Singh 2020). A specific group of variables that have a mean value of VIF less than 10 were considered in the empirical investigation.

Heteroscedasticity measures the non-constant variance that may be caused to increase non-normality in one or more variables in the model. We applied the Cameron and Trivedi decomposition of the IM test and the Breusch-Pagan/Cook-Weisberg test to recognize the incidence of heteroskedasticity (Jyoti and Singh 2020). SPSS and STATA statistical software were used for the regression analysis.

Discussion

Socio-economic background of farmers

Table 2 provides the socio-economic background (age, family size, educational level, and gender) of the respondents and shows the diversity of the social-economic structure of the respondents in the sample.

Practices of various technologies in the agricultural sector

Farmers were using 63 separate technologies to cultivate food grains and commercial crops (Figure 1). The women friendly fertilizer broadcaster technology has applications in the cultivation of 20 crops.

Several technologies have various usages in the cultivation of 19 crops. Some of these technologies are animal-drawn three-row seed-cum-fertilizer drill; tractor-drawn cultivator tines; zero-till seed-cum-fertilizer drill, and tractor-drawn hydraulic platform for harvesting, pruning, and spraying.

Some of the technologies deemed suitable for the cultivation of 18 crops are animal-drawn bhoram deo seed drill, animal-drawn improved blade harrow, and tractor-operated six-row pneumatic planter and rotary weeder.

Some of the technologies used to grow 14 crops are the animal-drawn IGKV biasi plough, seed-cum-ferti-drill, and three-row inclined plate planter and the motor operated rotary dibber and vacuum seeder.

Table 2 Socio-economic background of respondents

Age (in years)		Family size		Education level		Gender	
Group	Number	Group	Number	Group	Number	Sex	Number
20–29	44	0–3	18	8th Passed	43	Male	234
30–39	82	4– 5	124	10th Passed	41	Female	6
40–49	65	6–8	79	12th Passed	46	-	-
50–59	35	9–10	12	Graduate	71	-	-
60 and above	14	11 and above	7	Postgraduate	39	-	-
Total	240		240		240		240

Source Based on field survey

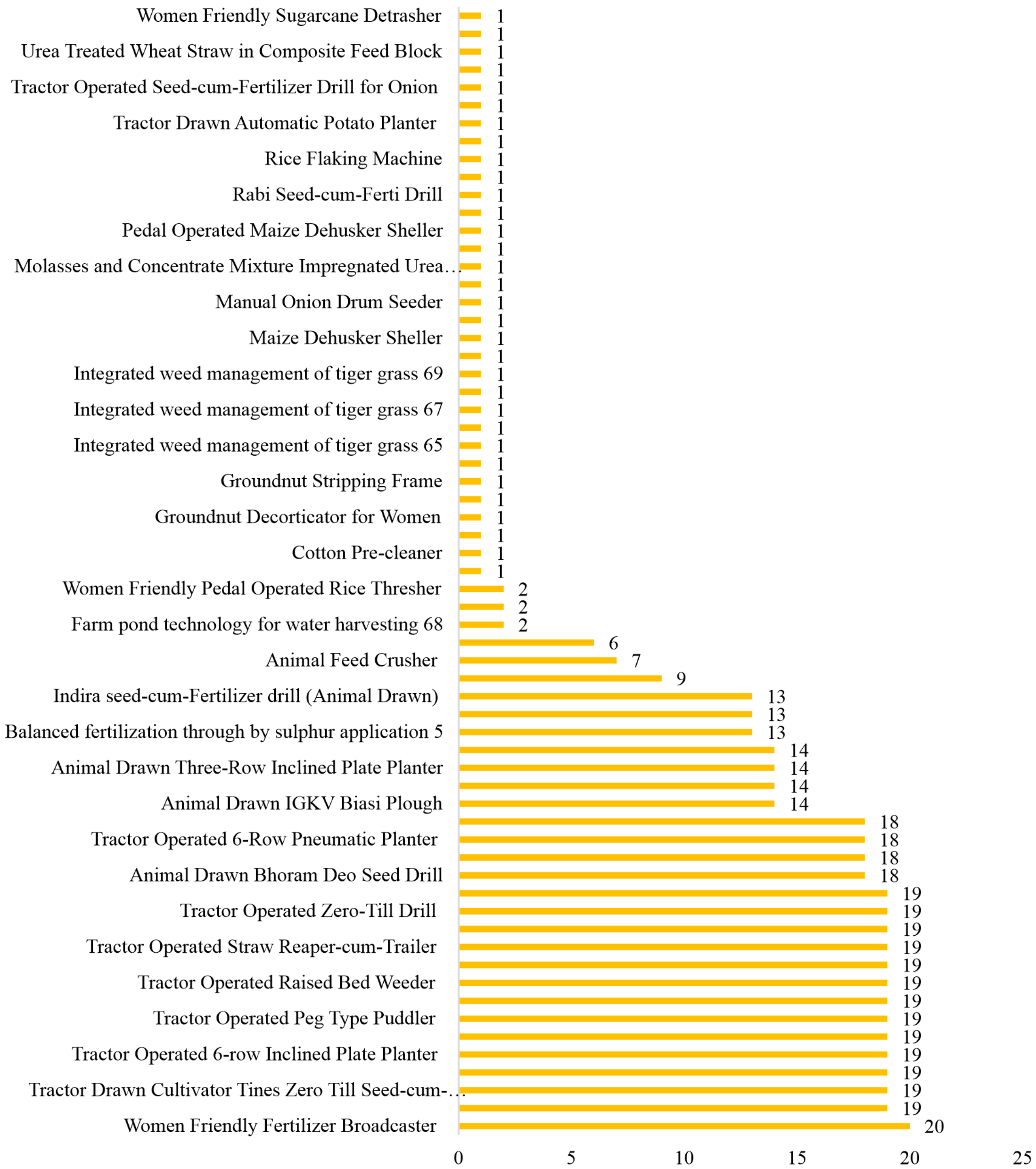

Figure 1 Applications of a specific technology in cultivation of crops (number)

Source Based on field survey

Some of the technologies deemed suitable for the cultivation of 13 crops are balanced fertilization through the application of sulphur and the use of high-capacity multi-crop thresher and Indira seed-cum-fertilizer drill.

Some technologies were applicable for a particular crop only; for instance, gender-friendly rice weeder technology for rice, woman-friendly decorticator for groundnut, dehusker sheller for maize, multi-row manual seed drill for jute, manual drum seeder for onion, comb cutter for banana, pre-cleaner for cotton, and tractor-drawn automatic planter for potato.

Some technologies can be used to cultivate several crops (Figure 2): for instance, 30 technologies can be used for rice; 28 technologies for bajra, cotton, maize, and wheat; 26 for gram, castor seed, groundnut, and moong; 24 for arhar, jowar, math, rapeseed, mustard, and sesamum; 23 for onion; 22 for guar seed, potato,

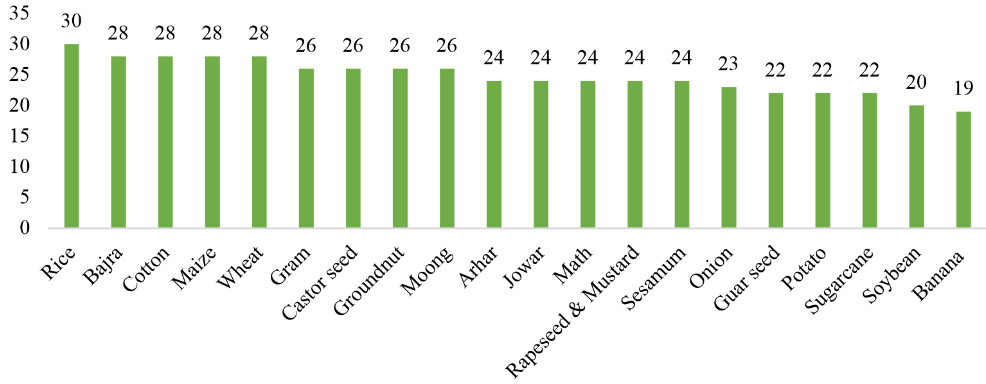

Figure 2 Number of technologies for a particular crop
Source Based on field survey

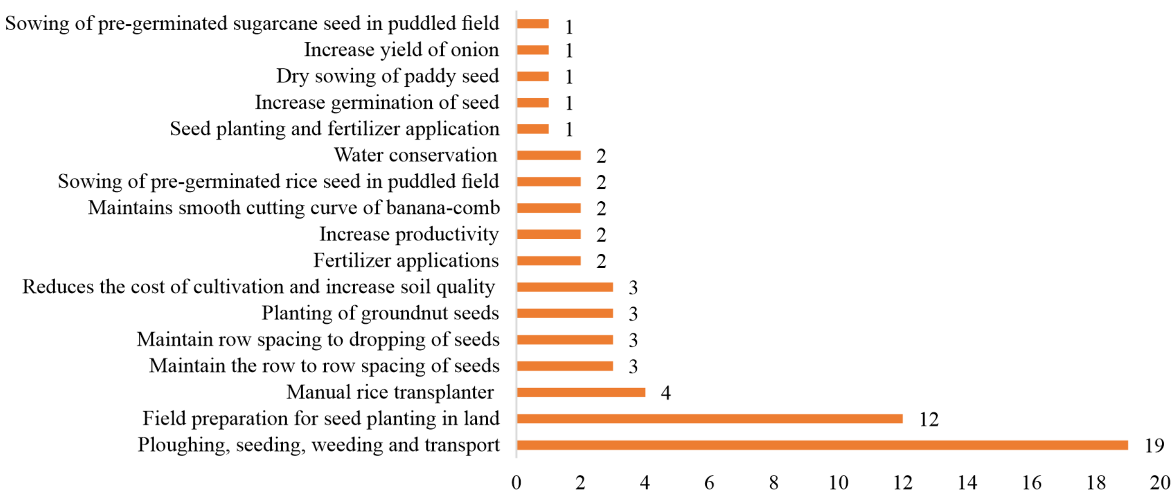

Figure 3 Various usage of technologies in cultivation
Source Based on field survey

and sugarcane; 20 for soyabean; and 19 for banana. These 63 technologies have 494 separate applications in farming food grains and cash crops.

These technologies were grouped into 18 by usage in cultivation (Figure 3): 19 technologies were related to ploughing, seeding, weeding, and transport; 12 to field preparation for seed planning; and 4 technologies to rice cultivation. These technologies were used also for other purposes: manual rice transplanter; maintain the row to row spacing of seeds; maintain row spacing to dropping of seeds; planting of groundnut seeds; and reduce cost of cultivation and increase soil quality.

Benefits of technologies in the agricultural sector

Around 18.33% of the farmers claimed that applying appropriate technologies helped to save water and human effort; 10.83% accepted that technological applications were conducive to preparing the land for seed planting; and 8.3% were unable to provide any answer on the benefits of technologies in cultivation (Figure 4).

Agricultural technologies are understood to have 22 benefits, including a reduction in cultivation cost, water and fertilizer use, labour, and waste material; an improvement in seed germination, yield, marketing, and easy transportation; and the maintenance of farm operations, soil quality and fertility, and soil conservation.

Farmers' problems in applying cultivation technologies

Farmers face several problems in using cultivation technologies (Figure 5).

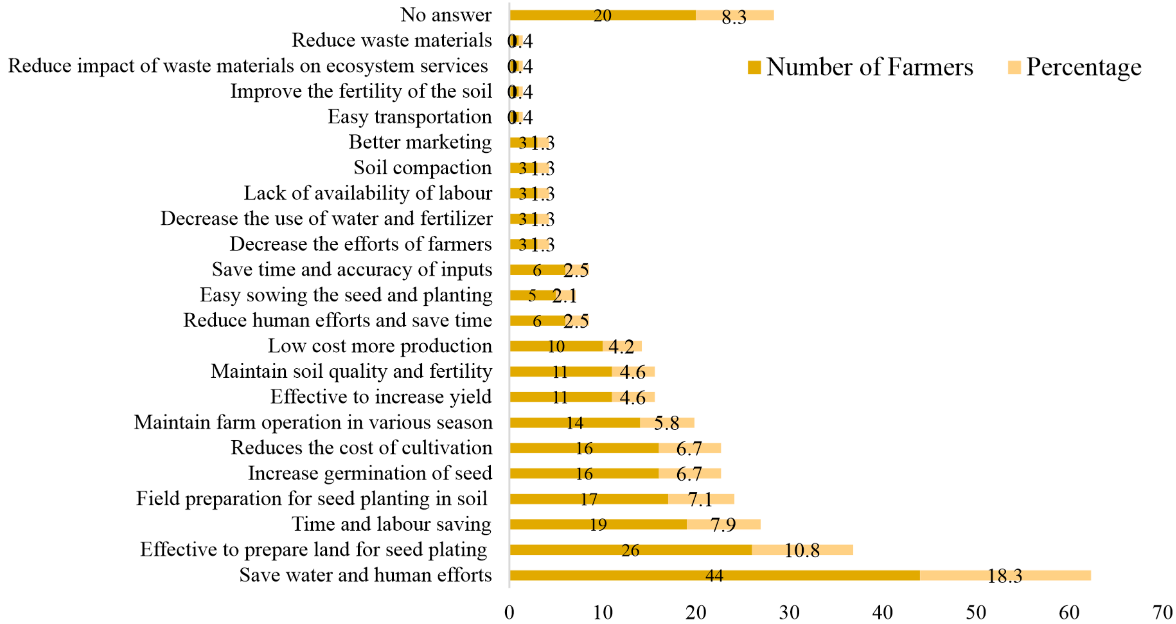

Figure 4 Various advantage of application of technologies in cultivation

Source Based on field survey

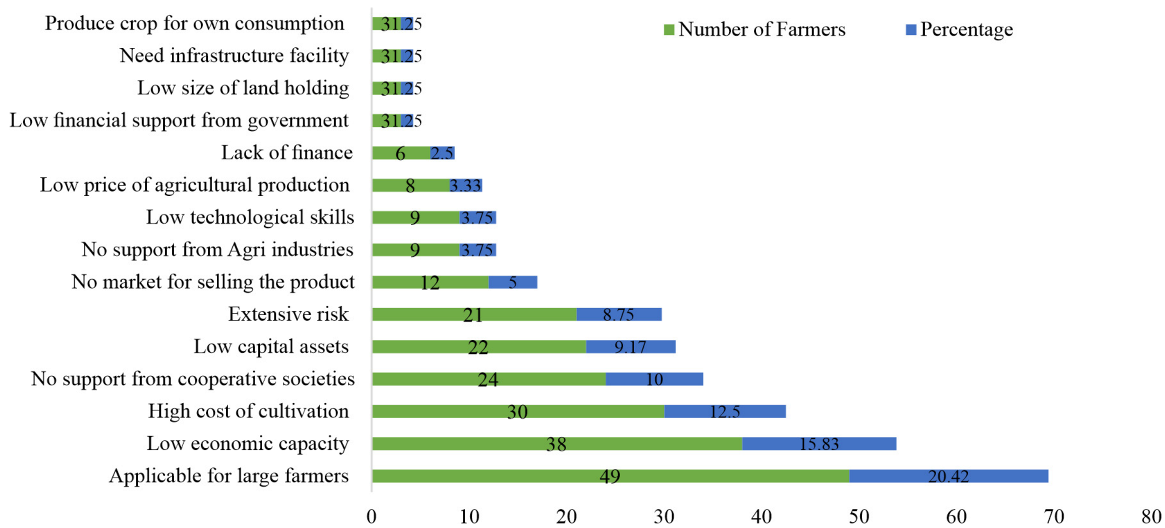

Figure 5 Farmers' limitations in using cultivation technologies

Source Based on field survey

About 20.42% farmers agreed that technologies are effective on large landholdings; therefore, small-size landholdings constitute a prime barrier. Small-scale landholders cannot afford new technologies; 15.83% of the farmers could not apply cultivation technologies. Using these technologies raised their cultivation cost, reported 12.50% of the farmers, and about 10% claimed that the support from agricultural cooperative societies and industry is not significant.

Several other barriers exist: capital assets are low; the risk involved in technologies is significant; markets are not available; the price of produce is low; farmers lack access to finance; financial support from government is low; farmers' skills are poor; and the infrastructure is inappropriate. Approximately 5% of the farmers grow food grains for their own consumption and they do not want to use cultivation technologies.

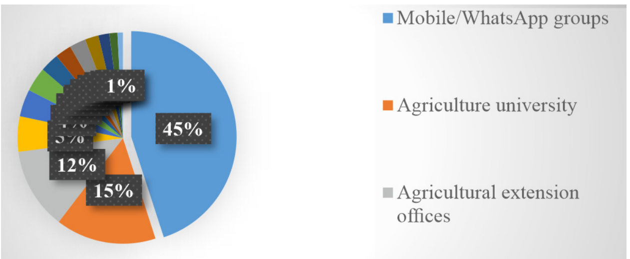

Figure 6 Agricultural input- and technology-related information providers for farmers
Source Based on field survey

Agricultural input–related information providers for farmers

Around 45% of the farmers obtain information on agricultural inputs (new technologies and varieties of seed, fertilizer, and pesticide) through mobile and WhatsApp groups (Figure 6). Therefore, social media must be used extensively to improve awareness of new technologies and other inputs.

Information and communication technologies (ICT), video, and mobile help to make agriculture cost effective (Dhehibi et al. 2020). Around 15.42% of the farmers received information on inputs from agricultural universities and 12.50% from agricultural extension offices or Krishi Vigyan Kendras (KVK). Thus, both universities and KVKs can improve farmers' awareness of various inputs. Television, local stakeholders and markets, newspapers, large landholders, relatives, and the agricultural and agri-product machine manufacturing industry were also deemed helpful in disseminating information on agricultural inputs among farmers.

Agricultural co-operative societies and KVKs created the WhatsApp groups; therefore, 65.42% of the farmers receive information from them. Most districts of Gujarat have established KVKs to provide various information to the farmers regularly. Agricultural universities also organize seminars and train farmers; therefore, around 19.17% of the farmers received information from them.

The agricultural industry and agricultural technology development industry also train farmers, but only 3.33% of farmers are beneficiaries. Shopkeepers at local markets also convey information on the latest technologies, inputs, and seeds to farmers. Relatives, large landholders, and daily newspapers were the major information providers for small farmers.

Farmers' perception of appropriate technologies and their components

It is difficult to recognize whether a technology is appropriate; therefore, this study considered farmers' opinions. About 64.17% of farmers are aware of the economic viability of technologies, 89.17% of their social viability, and 63.33% of their environmental viability, and 72% farmers know about appropriate technologies (Figure 7). The scope of using appropriate technologies in Gujarat is enormous, therefore, and agricultural development institutions should train farmers to achieve sustainable agricultural development.

Discussion on empirical results

Statistical summary of the variables

Table 3 provides the statistical summary of dependent and explanatory variables. The statistical summary includes the minimum, maximum, mean, standard

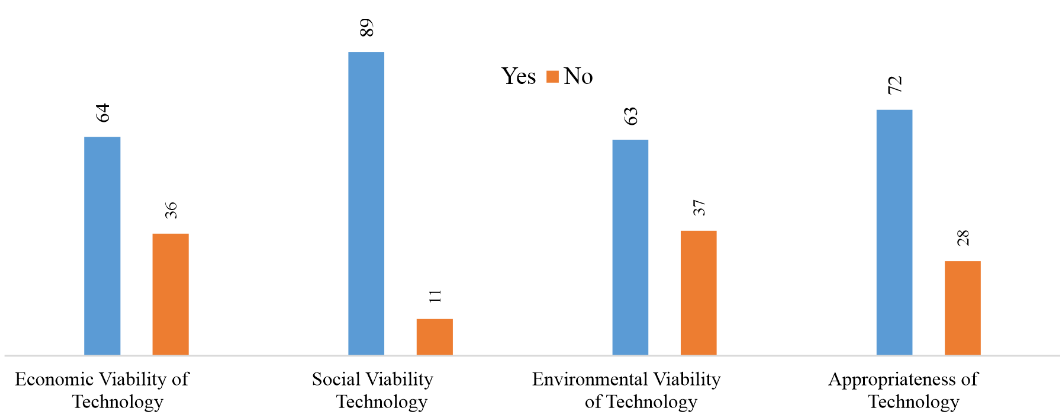

Figure 7 Farmers' awareness of appropriate technologies and their components
Source Based on field survey

Table 3 Statistical summary of variables

Variables	Min	Max	Mean	Sta. Dev.	Skewness	Kurtosis
ap	699.25	83910.56	8739.23	10097.64	3.76	23.61
ttc	250.00	2890.00	2198.55	388.89	–1.10	6.62
tal	1.00	30.00	10.34	7.61	1.07	3.33
ci	3.00	8.00	6.16	1.29	–0.34	2.20
ia	0.50	25.00	7.06	5.67	1.33	4.23
ugf	132.80	16156.35	1700.92	1950.88	3.67	22.90
ual	51.00	86.00	65.47	5.48	0.38	4.07
el	8.00	17.00	12.61	3.14	–0.09	1.66
ai	50000	720000	299679	170182	0.52	2.05
fs	2.00	12.00	5.58	1.83	1.15	4.77
ar	20.00	65.00	39.81	10.83	0.29	2.20
at	0.00	1.00	0.72	0.30	–0.51	1.91
fp	0.00	1.00	0.69	0.46	–0.83	1.69
fsg	0.00	1.00	0.44	0.50	0.25	1.06
fas	0.00	1.00	0.51	0.50	–0.05	1.00
stsf	0.00	1.00	0.32	0.47	0.77	1.59

Source Authors' estimation

Table 4 Summary results of statistical tests

Statistical test/types of models	Linear regression	Log linear regression	Nonlinear regression
Scale reliability coefficients [*Cronbach's alpha* tests]	0.6876	0.7516	0.8201
Ramsey RESET test using powers of the fitted values of agricultural production [*Chi*^{2}]	19.06*	42.12*	79.07*
Ramsey RESET test using powers of the explanatory variables [*Chi*^{2}]	8.05*	15.69*	11.34*
Akaike information criterion (*AIC*)	- 4043.965	-456.7828	- 4035.157
Bayesian information criterion (*BIC*)	- 4099.655	-401.0926	- 4125.654
Mean *VIF* for multi-correlation	2.89	4.95	62.94
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity [*Chi*^{2}]	187.75*	80.19*	169.66*
Cameron & Trivedi's decomposition of IM-test for heteroskedasticity [*Chi*^{2}]	248.87*	264.78*	284.68*

Source Authors' estimation. ** regression coefficient is significant at the 0.01 level and * regression coefficient is significant at the 0.05 level.

deviation, skewness, and kurtosis values of the corresponding variables. The values of standard deviation were found greater than 1 for most variables (except binary variables). Also, the estimates indicate the values of *skewness* were between –1 to 1 for most variables. Thus, these variables were in normal form.

Summary of statistical tests

Table 4 provides a summary of the statistical tests we used to select the appropriate model. We applied the Cronbach's alpha test, which measures the internal consistency of variables (Singh et al. 2022), to examine the internal reliability of the group of independent variables. The scale reliability coefficients for all the models were between 0 and 1; therefore, the variables have internal consistency.

The chi^2 values under the Ramsay RESET test for the fitted values of agricultural productivity and the power of explanatory variables were observed to be statistically significant at the 1% significance level, meaning that the function forms of the linear, log linear, and nonlinear regression models were found suitable to estimate the coefficient of explanatory variables with agricultural productivity. The log linear regression model provides the lower values of AIC and BIC, however, and produces better results than the linear and nonlinear regression models. In the linear and log linear regression models, the mean VIF value was reported to be less than 10. But it was 62.94 in the nonlinear regression model because the multicollinearity between the original and square terms of the explanatory variables was high.

The estimates claimed that the set of explanatory variables in the linear and log linear regression models are not multi-correlated; irrigated area has a high correlation with non-irrigated area; the economic, social, and environmental viability of technologies have a high correlation with appropriateness of technology; and gender ratio has a high correlation with family size. Therefore, we dropped non-irrigated area; economic, social, and environmental viability of technology; and the gender ratio from the regression analysis. The chi^2 values estimated under the Breusch-Pagan/Cook-Weisberg and Cameron & Trivedi's decomposition of IM-tests were detected to be statistically significant; therefore, the cross-sectional data set was not heteroscedastic.

Interpretation of regression results

We used the linear, log linear, and nonlinear regression models to estimate the regression coefficients of the explanatory variables with agricultural productivity (Table 5). The linear regression model measures the linear relationship between dependent and independent variables. The nonlinear regression model provides the nonlinearity between the output and inputs. The log linear regression model produces the elasticity of inputs with respect to output (Kumar, Sharma, and Joshi 2016; Singh, Narayanan, and Sharma 2017); hence, it is noteworthy that in these models the regression coefficients of the explanatory variables with agricultural productivity were observed to be different in sign and magnitude.

Earlier studies selected a model by the lowest values of the AIC and BIC (Singh, Narayanan, and Sharma 2017; Singh et al. 2022). The log linear regression model in this study produces the lowest values of the AIC and BIC (Table 4) and, therefore, better results than the linear and nonlinear regression models.

The *F*-values were statistically significant for all models. The estimates imply that the explanatory variables have significant variation and that the overall impact of these variables on agricultural productivity was consistent. As per the R^2 values, 99% of the variation in agricultural productivity can be explained by the undertaken explanatory variables in the proposed models. Most essential variables that have a significant impact on agricultural productivity were included in the regression models. Therefore, it is obvious that all the models produce high values of R^2.

The regression coefficient of technology cost with agricultural productivity was reported to be positive and statistically significant at the 10% significance level. The result implies that agricultural productivity increases as the application of technology in cultivation increases. A similar positive impact of technology on agricultural productivity is noted in other studies (Pingali et al. 2019; Abdullahi, Mahieddine, and Sheriff 2015).

Arable land is a vital input for agricultural production systems. Thus, the regression coefficient of total arable land with agricultural productivity was positive and statistically significant at the 1% significance level. Previous studies observe a similar positive impact of arable land on agricultural production (Xie et al. 2018; Singh et al. 2022).

The regression coefficient of cropping intensity with agricultural productivity was positive and statistically significant at the 5% significance level. This estimate implies that agricultural productivity increases as cropping intensity increases. A similar positive impact has been observed earlier (Kumar, Ahmad, and Sharma 2017). Cropping intensity helps to improve the aggregate production of food grains and cash crops. Thus, agricultural productivity is likely to increase as cropping intensity increases.

Irrigated area has a higher yielding capacity than non-irrigated area (Kumar, Sharma, and Ambrammal 2015). The regression coefficient of irrigated area with agricultural productivity was found to be positive and statistically significant at the 10% significance level. Gujarat is drought-prone (Gulati, Roy, and Hussain 2021); thus, irrigated area will be useful to increase agricultural productivity.

Agricultural labour is an important input, and it has a positive impact on agricultural productivity, but the

Table 5 Association of agricultural productivity with explanatory variables

Models	Linear Regression			Log linear Regression			Non-linear Regression		
No. of Obs.	240			240			240		
F-Value	1408.59*			1522.16*			911.49*		
R^2	0.9895			0.9903			0.9907		
Adj. R^2	0.9888			0.9896			0.9896		
Variables	Reg. Coef.	Std. Err.	P>|t|	Reg. Coef.	Std. Err.	P>|t|	Reg. Coef.	Std. Err.	P>|t|
ttc	-0.1389	0.183	0.049	0.0006	0.024	0.079	-0.1850	0.891	0.036
(*ttc*)^2	-	-	-	-	-	-	0.0000	0.000	0.053
tal	-11.3411	31.39	0.018	0.1410	0.039	0.000	114.2049	90.640	0.009
(*tal*)^2	-	-	-	-	-	-	-0.8183	2.300	0.022
ci	35.4530	55.36	0.023	0.0097	0.027	0.019	-106.2816	487.400	0.028
(*ci*)^2	-	-	-	-	-	-	13.7723	40.649	0.035
ia	16.1951	39.05	0.079	0.0078	0.026	0.063	56.6456	106.381	0.095
(*ia*)^2	-	-	-	-	-	-	-0.5522	3.576	0.077
ugf	5.1340	0.054	0.000	0.8576	0.025	0.000	4.0947	0.212	0.000
(*ugf*)^2	-	-	-	-	-	-	0.0001	0.000	0.000
ual	13.2964	12.98	0.307	0.0760	0.072	0.095	-141.6507	182.698	0.099
(*ual*)^2	-	-	-	-	-	-	1.1509	1.368	0.001
el	-34.9454	41.4	0.009	-0.0150	0.040	0.006	86.3301	246.293	0.026
(*el*)^2	-	-	-	-	-	-	-5.4981	9.925	0.080
ai	0.0005	5E-04	0.071	0.0162	0.012	0.083	0.0017	0.002	0.063
(*ai*)^2	-	-	-	-	-	-	0.0000	0.000	0.019
fs	-10.2214	41.73	0.007	-0.0013	0.021	0.052	-5.2974	196.263	0.078
(*fs*)^2	-	-	-	-	-	-	0.8212	14.481	0.055
ar	-9.9742	7.461	0.083	-0.0279	0.025	0.026	-15.3228	48.032	0.075
(*ar*)^2	-	-	-	-	-	-	0.0679	0.574	0.006
at	-13.3409	399.1	0.073	0.0026	0.032	0.036	231.2919	415.464	0.078
fp	-121.2004	162.6	0.457	-0.0141	0.014	0.305	-95.9409	167.170	0.067
fsg	74.7096	163.0	0.047	0.0041	0.014	0.077	28.8213	164.137	0.061
fas	93.6934	144.2	0.517	-0.0058	0.012	0.636	98.1618	142.427	0.491
stsf	-50.2862	173.2	0.772	-0.0070	0.015	0.639	-24.6822	176.307	0.889
Con. Coef.	14.1298	1105	0.990	1.9486	0.409	0.000	4613.3020	6489.247	0.478

Source Authors' estimation.

law of diminishing returns may render the overuse of agricultural labour unproductive (Kumar, Sharma, and Ambrammal 2015).

The application of fertilizer in cultivation improves crop yield, and the regression coefficient of fertilizer with agricultural productivity was observed to be positive and statistically significant at the 1% significant level. Farmers in the high income group can use advanced inputs and technologies to raise crop productivity (Jamal et al. 2021). When their income increases, farmers can use farm management practices and new technologies, seed varieties, organic and green fertilizers, pesticides, and irrigation instruments. As the annual income of farmers increases, agricultural productivity will improve. Therefore, the regression coefficient of the annual income of farmers with agricultural productivity was found to be positive and statistically significant at the 10% significance level.

Family size also showed a positive impact on agricultural productivity. Educated farmers have an appropriate understanding on various inputs, technologies, and proper methods of cultivation. Hence, the regression coefficient of education level of farmer with agricultural productivity was seemed positive and statistically significant at 1% significance level.

The regression coefficient of appropriate technologies with agricultural productivity was found to be positive and statistically significant at the 1% significance level. Thus, the estimate indicates that appropriate technologies have a positive impact on agricultural productivity, consistent with previous studies (Kumar, Sharma, and Ambrammal 2015; Gebeyehu 2016; Ali et al. 2017; Singh, Narayanan, and Sharma 2017; Siddick 2019; Jyoti and Singh 2020; Ashraf and Singh 2021).

Farm management practices improve as the age of farmers increase. Hence, the regression coefficient of age of respondents with agricultural productivity was positive and statistically significant at the 5% significance level. Appropriate farm management practices make agricultural development sustainable (Singh, Kumar, and Jyoti 2022).

Financial support from the government improves the economic capacity of farmers and has a positive impact on agricultural productivity. A similar positive impact has been observed earlier (Kumar, Ahmad, and Sharma 2017). The regression coefficients of, on the one hand, the farmers' financial constraints and their collaboration with agricultural universities, extension offices, co-operative societies, and industry and of sellers' skilled and technical support with, on the other, agricultural productivity were found to be statistically significant. Farmers' association with various stakeholders and with skilled and technical support have a positive impact on agricultural productivity, as has been found earlier (Desai 1994; Syan et al. 2019; Msomba, Ndaki, and Nassary 2021; Jamal et al. 2021; Singh et al. 2022).

The empirical results based on the nonlinear regression model indicate that agricultural productivity has a nonlinear and linear association with the explanatory variables. Agricultural productivity has a nonlinear relationship with technology cost, arable land, cropping intensity, irrigated area, use of agricultural labour, education level, family size, and the age of a farmer.

Agricultural productivity has a hill-shape relationship with technological development, cropping intensity, use of agricultural labour, family size, and the age of a respondent. These factors may be effective in improving agricultural productivity only to a certain extent.

Agricultural productivity has a U-shaped association with arable land, irrigated area, and the education level of a respondent and a linear association with fertilizer use and annual income. Thus, agricultural productivity increases linearly as the contribution of these factors increases.

Conclusion and policy implications

As per the empirical results, the crucial determinants of agricultural productivity are technology cost, total arable land, cropping intensity, irrigated area, use of fertilizer and agricultural labour, annual income of farmers, the use of appropriate technologies in cultivation, and financial support from government.

The descriptive results indicate that to cultivate crops, farmers were using 63 technologies with usages such as ploughing, weeding, transport, field preparation of seed planting, fertilizer application, manual seed transplanter, and water conservation.

Technological development was useful in saving water and human effort; preparing the land for planting seeds; improving seed germination, crop yield, soil quality and fertility, and the marketing process; minimizing water and fertilizer use; and reducing cultivation cost, waste material, and the negative impact of activities on ecosystem services.

Agricultural cooperative societies and extension offices, and Krishi Vigyan Kendras, disseminate information on inputs and technologies among farmers through WhatsApp groups, so farmers were conscious of the viability of technologies: 64.17% of the economic viability, 89.17% of the social viability, and 63.33% of the environmental viability.

Agricultural development institutions in Gujarat may play a key role in improving farmers' understanding of appropriate technologies and their usage in cultivation to achieve sustainable agricultural development. Farmers with small landholdings do not have the infrastructure, capital assets, economic capacity, or support from agricultural cooperative societies, industry, or government and financial institutions to invest in and use expensive agricultural technologies. The government should support the farmers financially, and policymakers should consider these issues in formulating policy for sustainable agricultural development in Gujarat. Farmers should increase their collaboration with research institutions, agricultural universities, KVKs, and local stakeholders to increase their understanding on new technologies and most useful agricultural inputs.

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Received 29 December 2021 Accepted 9 May 2022

Agricultural Economics Research Review 2022, 35 (2), 79-94
DOI: 10.5958/0974-0279.2022.00032.5

COVID-19 and marine fishers in India: livelihood implications and coping strategies

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Abstract The paper examines the livelihood impacts of COVID-19 on marine capture fishers in India, the coping mechanisms adopted by them, and their correlates, by using primary data collected from fishers of Andhra Pradesh on the eastern coast and Kerala on the western coast. The fishers adopted several coping strategies, correlated with personal attributes, ownership of economic assets, social capital, and economic status. The study advocates the need to carefully evaluate the trade-off between restrictions to contain COVID-19 and loss of livelihood.

Keywords COVID-19, livelihood security, food security, coping strategies, small-scale fisheries, vulnerability, risk

JEL codes I38, O13, Q18, Q54, Q58

Ever since the new coronavirus (2019-nCoV) was first detected at Wuhan in China on December 2019 (WHO 2020a), it has quickly spread to almost all parts of the globe (Siche 2020). On 11 March 2020, WHO declared the highly contagious disease, popularly known as COVID-19, a global pandemic (Cucinotta and Vanelli 2020). As on 9 January 2020, COVID-19 had affected a cumulative number of 88.9 million persons globally, causing 1.9 million deaths (Johns Hopkins University 2021).

In the number of positive cases, India is placed second globally, with cumulative positive cases of 10.41 million and deaths of 0.15 million as on 7 January 2021 (GoI 2021). Since then, the second and third waves of COVID has spread all across the country, but it has subsided over time, although with significant causalities. In India, the first positive case was reported from Kerala on 27 January 2020, in a student returned from Wuhan (Andrews et al. 2020). The number of cases increased to 519 on 24 March 2020 (WHO 2021).

In a televised address to the nation, the prime minister of India announced a nationwide lockdown with effect from 25 March 2020, initially for a period of 21 days (PIB 2020). Subsequently, the national lockdown was extended to the end of May. The lockdown was envisaged to contain the spread of the disease by telling people to stay home but for unavoidable circumstances and by observing social distancing strictly. All transport services, educational institutions, hospitality services, tourism activities, social and religious functions and activities that attract gatherings were prohibited or suspended, with exemptions for designated essential services (PIB 2020; GoIb 2020). Subsequently, the national lockdown was relaxed in a phased manner.

However, economic activity continues to function only partially; it is limping back to normalcy. The pandemic and its containment methods focusing on social distancing have impacted the global economy to the level of a recession. Workers lost jobs, and an economic contraction was visible, particularly in the first and the second quarters of the year 2020; 400 million jobs (full time equivalent) were lost between April and June (McKeever 2020).

The pandemic affected the Indian economy as well. The growth in gross domestic product (GDP) fell from 3.9% for FY 2019–20 to –7.2% for FY 2020–21 (CSOa 2021), and from 3.0% for the January–March quarter of 2020 (CSOa 2021) to –22.8% during April–June and –7.0% during July–September 2020 (CSOb 2020; CSOc 2020).

Marine fisheries in India and the pandemic

With a production of 13.7 m tonnes of fish in 2019–20, India accounts for about 12% of the global fish production and contributes about 4.5% of the global marine capture fish production. Of this, marine fish accounts for about 4.8 million tonnes, from a coastline of 8,129 km. Also, marine products are the largest exported commodity group within the agricultural sector. Exports grew at 10.8% per annum over the past decade to reach a revenue of US$ 6.7 billion in 2019–20.

About three-fourths of total marine fish produced in India is marketed domestically. India has about 3.78 million fisherfolk, of which 92% belong to the traditional and small-scale category. About 4 million people depend directly on marine fishing and allied activities for their livelihood.

The pandemic has disrupted the supply chain of aquatic commodities in India. The restriction on the movement of persons, vehicles, and mass gatherings have affected fishing operations and working of harbours and landing centres. Organized fish marketing was closed as a measure to maintain social distancing during the lockdown. Fish processing activities were also closed. This is in line with the global experience. Restrictions on operation of flights and other logistics, and restriction on trade is found to have impacted exports and market access during COVID-19 globally (FAO 2020; Ivanov 2020; IFPRI 2020).

In this backdrop, this article examines the impact of COVID-19 on livelihood of marine fishers in India during its first wave, the coping strategies adopted by them and the correlates of the adopted coping strategies. Based on the insights from the study, it identifies important considerations while preparing strategies for managing COVID-19 and similar situations beyond.

Review of studies on impact of COVID-19 on fisheries

In this section we review the impact of COVID-19 on fisheries in India and in other countries during the first wave. The pandemic affected the value chain of marine and aquatic products. The disruption of the value chain has increased financial risks in terms of reduced cash flow, reduced repayment capacity, risk-bearing ability, and capability to meet financial obligations. In USA, prior to the pandemic, restaurants made about 68% of seafood purchases (Tiernan 2020), but since COVID-19, sales declined 95% (Sorenson et al. 2020). Relative to the previous year, the fresh seafood catch declined 40%, imports 37%, and exports 43% (White et al. 2020).

The COVID-19 crisis has severely affected the income and livelihood of fishers in Cyprus. (Elias et al. 2020). The average gross margin during the lockdown month was lower by 4 times that for the previous winter period (December 2019–February 2020) and 2.5 times lower than that of 2019.

The negative impacts have fallen disproportionately and heavily on small-scale fisheries, which employ more than 90% of the world's fishers (FAO 2019). COVID-19 has accentuated the vulnerability of such marginalized groups (Bennet et al. 2020; Sorenson et al. 2020). The impact has been severer on small-scale fisheries (America et al. 2020) that depended on global markets, as in the case of South-East Asia (Kaewnuratchadsorn et al. 2020). Export-oriented small-scale fisheries with low level of geographical diversification are shown to be highly vulnerable to the pandemic and to other global disruptions like recessions, trade wars, and natural disasters (Knight et al. 2020).

COVID-19 impacted the efforts to ensure the health and safety of fishers working on board vessels. The pandemic has cut short the opportunities for training on safety measures to be followed while fishing because it is difficult to provide training while maintaining safety protocols (Sorenson et al. 2020). Migrant industrial fishing workers are vulnerable to poor health and safety conditions, poor remuneration, exploitative working conditions, and unreasonable deductions in payments (EJF 2019; Greenpeace East Asia 2020), which has intensified during the COVID period (Marschke et al. 2020). The impact of the pandemic has transcended the marine fisheries sector, and it is set to affect the blue economy, including maritime transport, coastal tourism, and port and harbour activities, as noted in the case of the EU (Kolesnikova 2020; Gamlen 2020).

The pandemic has had a few positive outcomes, however, such as in enhancing sustainable fisheries and increasing social cohesiveness (Bennet et al. 2020; Kemp et al. 2020). COVID-19 has effected a global slowdown of commercial fishing, reducing pressure on some threatened stocks and thereby helping to build up stocks. This would give a unique opportunity to further build up stocks and move to sustainable fisheries, provided it is followed with supportive policies of fish resource management (Kemp et al. 2020).

Studies in India

The lockdown and the supply chain disruption has affected almost 14.5 million people associated with the sector. It has impacted multiple dimensions of the fisheries sector, including production distribution and marketing of inland fisheries, marine capture fisheries, seed supply, and seafood export (Purkait et al. 2020).

The economic loss of COVID-19 on shrimp aquaculture during 2020–21 was about USD 1.50 billion (Kumaran et al. 2021). An analysis carried out using primary data showed that the major constraints were associated with shrimp seed production and supply, logistics and the supply chain, processing activities, marketing, and loss of employment and income for workers. In the case of marine fisheries, disruptions in the supply chain of both inputs and outputs were reported (Suresh and Sajesh 2020). In the initial months of the lockdown, only a few traditional fishers were venturing out into the seas. The Central Institute of Fisheries Technology (ICAR-CIFT) estimated the daily loss at about INR 2.24 billion (Businessline 2020). Several media reports suggested all the stakeholders in the value chain lost their livelihood. Women, who constitute 75% of the workforce in processing units (Jeyanti et al. 2015) and 72% of the casual labour force, also became jobless.

Materials and methods

The study primarily utilizes data collected from fishers of two maritime states. A total of nine major maritime states in India are spread along the eastern and western coasts. Out of the nine states, one state from each of the coasts, Andhra Pradesh from the eastern coast and Kerala from the western coast, was selected purposively based on the convenience of conducting the primary survey. From each state, fishers operating in one major fishing ground was selected purposively, based on the quantity of fish landed. Accordingly, Vizag in Vishakhapatnam district of Andhra Pradesh and Kochi (also known as Cochin), in Ernakulam district of Kerala state, were selected.

Description of study location

Vizag / Visakhapatnam in Andhra Pradesh

The Visakhapatnam district of Andhra Pradesh has a coastline of 136 km dotted with 43 fish landing centres. The district has a fisher population of more than 0.11 million. There are 4,408 marine fishing vessels in the district. Fishing operations consist mainly of small-scale traditional (artisanal fishing), motorized, and mechanized fishing, in fishing vessels of (less than 24 m overall length. Mechanized fishing consists of mainly trawling, gillnetting, and longlining. Dwindling trawl catches in recent years have brought combination fishing practices like trawling and long lining into vogue.

Visakhapatnam is a major centre of exports of marine products along the east coast, particularly shrimp and marine capture fishes. The domestic fish market is not well developed. The local marketing system mainly survives on freshwater fishes, with little contribution from marine capture fisheries. Most of the fish catch is either transported to other states and/or exported.

Ernakulam in Kerala

Kochi, in Ernakulam district, is the most important marine fish landing centre in Kerala. Kerala has 9 maritime districts (out of a total of 14), with a total coastline of 590 km. The total marine fish production is about 610,000 tonnes in the year 2019, of which 11.1% is contributed by Ernakulam district. (GoK 2020). Ernakulam has a coastal length of 46 km, with an estimated marine fisherfolk population of over 73,000 in 2019–20, accounting for 9.2% of the total marine fisherfolk population of the state.

Fishing operations in Ernakulam are mainly small-scale traditional (artisanal fishing), motorized, and mechanized. Trawl fishing, mini purse seining (also known as ring seine), gillnetting, and long lining are other major fishing practices. Ernakulam is a major centre of exports of marine products from India, particularly marine capture fishes. Further, more than 90% of the population in Kerala state and Ernakulam district consume fish regularly. Therefore, there is always a thriving local demand for marine fish and fish products in Ernakulam. The district caters to demands for marine fishes from other districts of the state as well. The survey locations are shown in Figure 1.

Data

The study is mainly based on primary data collected from fishers of Vizag and Ernakulam (Kochi). The primary data was collected following the snowball sampling method (a non-probability sampling method). Initially, some known fishers who operate in major harbours or landing centres were contacted, and the telephone or mobile number of other fishers were gathered from them. Information was collected from fishers who are engaged in fishing operations. Data was collected from 181 fishers from Andhra Pradesh and 169 fishers from Kerala.

The data was collected using a structured interview schedule (questionnaire), which was prepared based on consultations with fishers, academics, and

Figure 1 Map showing the study locations
Source https://www.istockphoto.com/vector/kochi-india-map-with-city-labels-gm878970092-245066615

development personnel engaged in the marine fisheries sector. The survey schedule was pretested with selected fishers and reformatted based on pretesting observations. The final questionnaire focused on social and economic background of fishers and their household; type of fishing assets owned and fishing operations undertaken; ownership of assets and access to facilities; perceived impact due to COVID-19 on fishing and other operations; impact on employment and income; perception of the constraints faced by the fishermen; and types of coping strategies followed.

The data collection set a reference period of six months, starting from 25 March 2020, when the country went into full lockdown. The period of six months was used as it was relatively easier for the fishers to avoid recall bias. The data was collected during November and December in 2020 using interviews over the telephone and in person. Face-to-face interviews were used in the later stages of data collection when the regulations were relaxed. The enumerators used all the prescribed measures like maintaining physical distance, face masks, frequent washing of hands, usage of sanitizer etc., as prescribed by the health department. The enumerators were allowed to choose the data collection method subject to government advisories. None of the enumerators or respondents contracted the disease due to the data collection process. The data was collected on a survey schedule.

Data analysis

The data, after cleaning, was subjected to statistical analysis. The descriptive statistics of fishermen, their family background, perception on COVID-19 impacts, and coping strategies followed were elicited through frequency analysis and percentages. The correlates of the coping strategies were analysed through the logit model (Gujarati et al. 2012). The dependent variables in this analysis are the adoption status of groups of coping strategies.

Four logit regressions were undertaken, each for a group of coping strategies—availing credit, liquidation of assets, food adaptation, and reduction in other expenditure. The dummy value of 1 was assigned if a coping strategy is adopted, and 0 otherwise.

The hypothesized correlates belonged to the farm and family characteristics of the fisherfolk (age of the decision maker, education of the decision maker, family size); economic status (asset position, number of sources of income, type of vessel, poverty status); and social capital (membership in various organizations).

The underlying hypothesis is that the resource-poor would tend to adopt these strategies, and that the younger the person, the more probable that they would avail credit as they would not have savings or alternative income sources to fall back upon. Higher family size is hypothesized to correlate positively as the family expenditure would be high. The status of BPL category, being workers in fisheries instead owners, and not having alternative employment in the household are hypothesized to correlate positively. The education status is anticipated to have a negative correlation as education provide prospects of having higher income.

The more the fisher is linked with social capital, the higher the probability that they would avail credit, as there is higher chance of approval for loan from formal agencies and money lenders. Therefore, a positive relation was hypothesized.

Results and discussion

General information

In general, the fishermen are middle-aged (43 years in Andhra Pradesh and 50 years in Kerala) (Table 1). Both Andhra Pradesh and Kerala have progressed in per capita income and in several developmental indicators.

Despite a lower per capita income, Kerala ranks the highest on the Human Development Index (HDI); its literacy rate is 94%, compared to 74% at the national level (Census of India 2011); the average life expectancy at birth is 75.2 years compared to 69 at the national level (MoHFW 2020); the infant mortality rate is 10 for 1000 children at age 1 compared to 33 at the national level (Office of the Registrar General 2019). However, Kerala's per capita income for 2018–19 was INR 184,000, compared to INR 135,050 at the national level, ranking it 11th among the major states of India (JagaranJosh 2020). Fisheries in Kerala is said to be an outlier in the overall developmental saga of the state (Kurian 1995), and it is reflected in the social development of fishers.

Andhra Pradesh has a per capita income of INR 106,425, and its developmental parameters are improving fast. The average literacy rate is 67.7%, life

Table 1 Basic information regarding households in Andhra Pradesh and Kerala

Characteristic	Andhra Pradesh	Kerala
Age of the decision maker of the household (years)	43.0	50.4
Mean family size	4.0	3.9
No. of females (mean)	2.1	1.9
No. of males (mean)	1.9	2.0
Total number of earning members in the family (mean)	1.6	1.3
No. of earning males (mean)	1.5	1.2
No. of earning females(mean)	0.2	0.38
Dependency ratio (number of total earning members to total number of family members)	40.7	33.1
N	169	181

expectancy 69.7 years, and infant mortality rate 32 per 1000 births.

The family composition of fishers shows that households are highly vulnerable to shocks in income and employment in fishing activities, as the families in general are nuclear (family size 4), and the dependency ratio in both states is high. The number of earning members is relatively low (1.6 in Andhra Pradesh and 1.3 in Kerala), and the ratio of earning members to family size is 41% in Andhra Pradesh and 33% in Kerala. One key feature is the poor participation of women in work; they participate mainly in marketing and processing activities.

Education is a critical factor that could affect the ability to enhance income and reduce vulnerability (Muttarak and Lutz 2014). While about 84% of the sampled fishers in Andhra Pradesh were illiterate, that percentage was only 1% in Kerala (Figure 2). About 57% of the fishers in Kerala are educated up to the high school level.

Status of ownership of fishing vessels and types of fishing operations performed

Based on vessel ownership and operations undertaken, fishers are grouped into (1) those who are owners of vessels (either full or a share) and participate in fishing, (2) those who own vessels but do not participate in fishing, and (3) those who do not own vessels and only work on them. The difference between these two states in ownership and operations of fishing vessels is perceptible (Table 2).

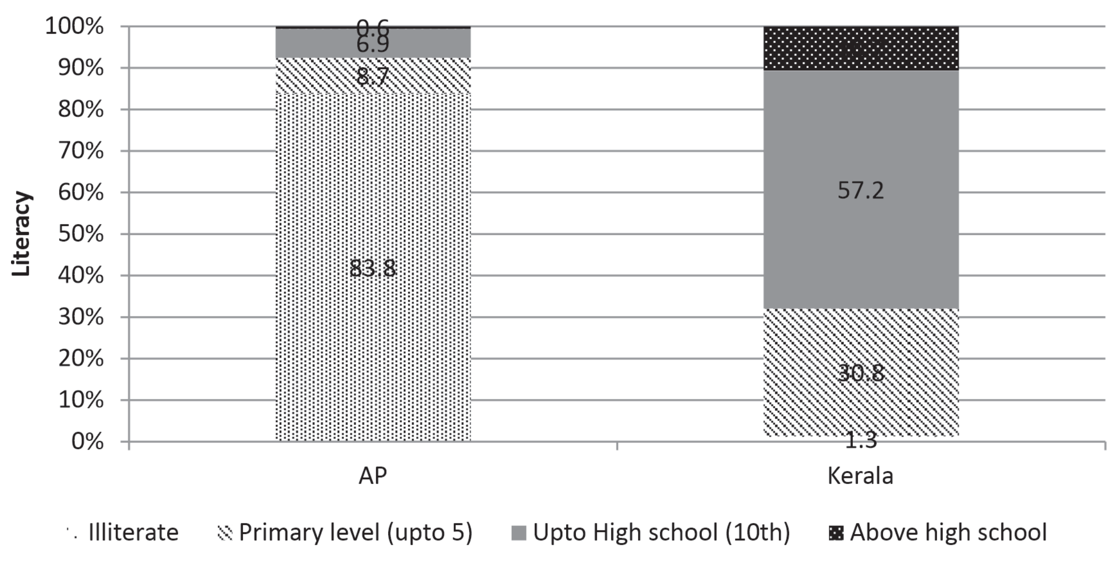

Figure 2 Distribution of education status of the head of the households

Table 2 Distribution of respondent by category (%)

Sl No	Category	Andhra Pradesh	Kerala
Distribution based on ownership of vessels and operational status			
1	Owner of vessel and a fish worker	9.4	55.7
2	Owner of vessel and not a fish worker	0.6	7.4
3	Non-owner, only worker	90.1	36.9
	Total	100	100
Type of vessels own/ has share / work with, Andhra Pradesh and Karnataka (%)			
1	Traditional	0	31.1
2	Motorized- Outboard	28.2	22.6
3	Motorized- Inboard	2.8	23.2
4	Mechanized traditional (ring seine)	59.7	5.5
5	Trawlers	0	14.0
6	Purse seine	0	0.6
7	Other	9.4	3.1
		100	100

Most fishers in Andhra Pradesh (90%) but only 37% in Kerala are non-owner workers. Fishers acting only as labourers generally receive a meagre share in the economic rent in marine fishing on a per capita basis.

The type of fishing operations undertaken by the sampled fishers varies widely (Table 2). Most of the sample fishers in Andhra Pradesh (60%) operate ring seines (small purse seines) followed by motorized outboard engines (28%), whereas that in Kerala consisted of traditional/ artisanal fishers (31%), inboard motors (23%), outboard motors (23%) and trawlers (14%).

Diversification is considered to reduce vulnerability and enhance household income by using labour power efficiently, but 98% of the respondents in Andhra Pradesh and 85% in Kerala reported fishing as their highest source of income, and only about 2% of the fishing households in Andhra Pradesh and 8% in Kerala participate in activities other than fishing. Occupational diversification and, gradually, the movement of fishers out of the primary sector activities is key to transforming the sector (Olale and Henson 2012).

Access to housing and other facilities

Only about 30% of fishing households in Andhra Pradesh owned their house, but that percentage in Kerala was as high as 98% (Table 3). While all the fishing households in Andhra Pradesh fall below the poverty line (BPL), based on income that is sufficient enough to purchase a basket of goods that yields 2,100 kilo calories per day, that percentage is about 80% in Kerala.

The Government of India and state governments provide foodgrains through the public distribution system (PDS) through designated outlets for the families targeted. During the COVID situation, foodgrains and other essential commodities were supplied through PDS shops under allocation from the central and state governments. The Government of Kerala has implemented a slew of measures to distribute kits containing essential commodities through the PDS shops, over and above those allocated by the central government (FAO 2020).

Fishermen's co-operatives facilitate the supply of inputs like credit and fishing gear and marketing (Table 3). Ownership of livestock as an income-yielding asset is relatively low. Kisan Credit Card (KCC) is a facility provided to avail short-term credit, at a very nominal interest rate, and thereby helps fishers to avoid non institutional sources of credit at least to a certain extent, but its penetration is quite low—only 12% fishers in Kerala.

Perceived impact of COVID-19

The pandemic has affected several dimensions of the activities of fisheries (Table 4). All the fishers in Andhra

Table 3 Status of ownership of assets, amenities, and membership in organizations (%)

Asset status	Andhra Pradesh	Kerala
Ownership of house (%)	30	98
Fishermen below poverty line (BPL) category (%)	100	80
Ownership of ration card (%)	100	99
Status of availing food through PDS (%)	100	96
Status of having regular drinking water supply (%)	88	78
Membership in cooperative society	94	78
Membership in any fishermen organizations (%)	93	69
Membership in political parties	2	21
Membership in women's groups/ self help groups	89	25
Status of ownership of livestock (%)	0	25
Status of having own transportation facility (%)	44	52
Possession of Kisan Credit Card (%)	0	12

Table 4 Perceived impact of COVID-19 (% of households)

Asset status	Andhra Pradesh	Kerala
Fishing and related activities are disrupted	100	97.6
Cost of fishing / expenditure of fishing has increased	100	61.3
Selling price of fish at harbour has increased	88.9	66.1
Income from fishing related activities were reduced	100	76
Household income reduced	100	71.4
Diet / food consumption pattern has changed adversely during COVID time	100	32.7
Some family member lost job/ returned back and rendered jobless	0.6	29.2

Pradesh reported a total disruption of fishing activities. The increase in cost and expenditure of fishing per trip is reported by 100% of the sample households of Andhra Pradesh and 61% of the sample households of Kerala.

Due to the restrictions in fishing by mechanized vessels, the competition for fish was relatively low in the seas. After the sector was opened gradually and fishing resumed, more fish was available than during the pre-COVID period (*The Hindu* 2020). The reduced supply of fish during the COVID period led to a price rise. The demand for fish in households in the coastal regions of India is thriving, and 89% of the respondents in Andhra Pradesh and 66% in Kerala report an increase in the selling price.

Reduction in income from fishing during the COVID period is also widely reported, mainly because of reduced catch. Though the price was higher, the fishermen did not have sufficient catch. There are regional differences in the perception regarding the impact.

The national lockdown prohibited restaurants from functioning and mass functions, including marriages and other social gatherings, that create demand for fish. However, there was latent household demand. Small scale fishing operations were partly allowed after a few weeks. Following central government norms, states issued guidelines to manage fishing operations. In Kerala, fish marketing was reorganized, disallowing auctioning to avoid mass gatherings. Alternatively, a fixed price system of fish marketing was brought in. This innovative fish marketing system envisaged a fixed price for fish depending upon the size and quality (Government of Kerala 2020).

Change in employment and income

To estimate the change in employment, the number of employment days during the COVID-19 period (six

Table 5 Level and change in employment during COVID and pre-COVID period, Andhra Pradesh, and Kerala

Variable	No. of labour days		% Change	
	Andhra Pradesh	Kerala		
Employment during pre-COVID period for men	123	87	61	38
Employment during COVID period for men	49	54		
Employment during pre-COVID period for women	19	17	92	42
Employment during COVID period for women	1	10		
Total employment during pre-COVID period	142	104	65	39
Total employment during COVID period	50	64		

months) and the six-month period prior to that (normal period) are elicited at the disaggregate level for both men and women of every respondent household (Table 5).

In a normal six-month period, an average fisher household works for 142 days in Andhra Pradesh and 104 days in Kerala. The extent of reduction in employment days is 65% for Andhra Pradesh (92 days) and 39% for Kerala (41 days).

One important dimension is the gender impact of COVID 19 on employment. During the pre-COVID period, women provided 19 labour-days in Andhra Pradesh and 17 labour days in Kerala on average, accounting for 13% of the total labour-days in Andhra Pradesh and 16% in Kerala, which fell to, respectively, 3% and 15% during the post-COVID period. The reduction in the total employment days for women is 92% in Andhra Pradesh and 42% in Kerala. Correspondingly, the extent of loss of employment-days for men was, respectively, 61% and 38%. Thus, the proportionate employment loss was severer for women compared to men. Women were mainly involved in fish processing activities, which were totally disrupted during COVID-19.

Change in income

The average reported income for a six-month period during pre-COVID and COVID period were elicited (Figure 3). The total income was INR 65,556 in Andhra Pradesh and INR 46,157 in Kerala during the pre-COVID period, which fell by, respectively, 74% and 14% during the COVID period. The reduction in the quantity of fish has outstripped the beneficial impact of the increase in fish prices in several cases.

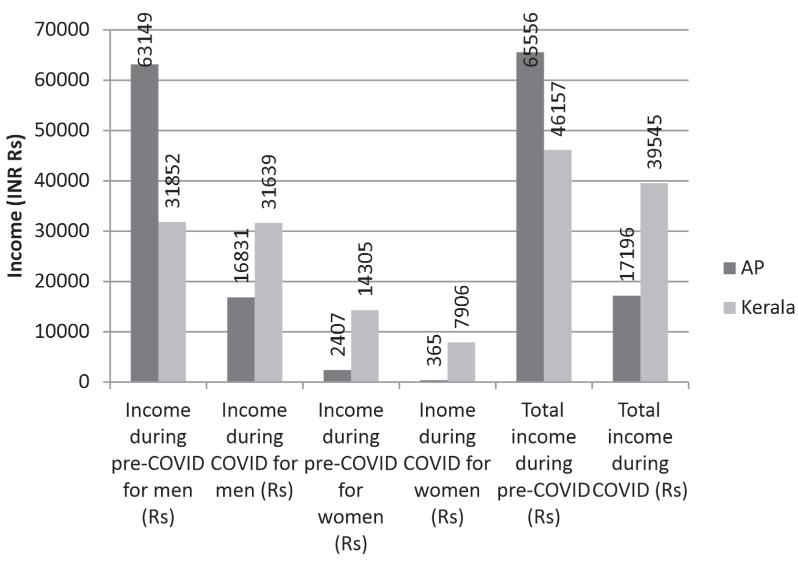

Figure 3 Level of income for six months during pre-COVID and COVID period, in Andhra Pradesh, and Kerala

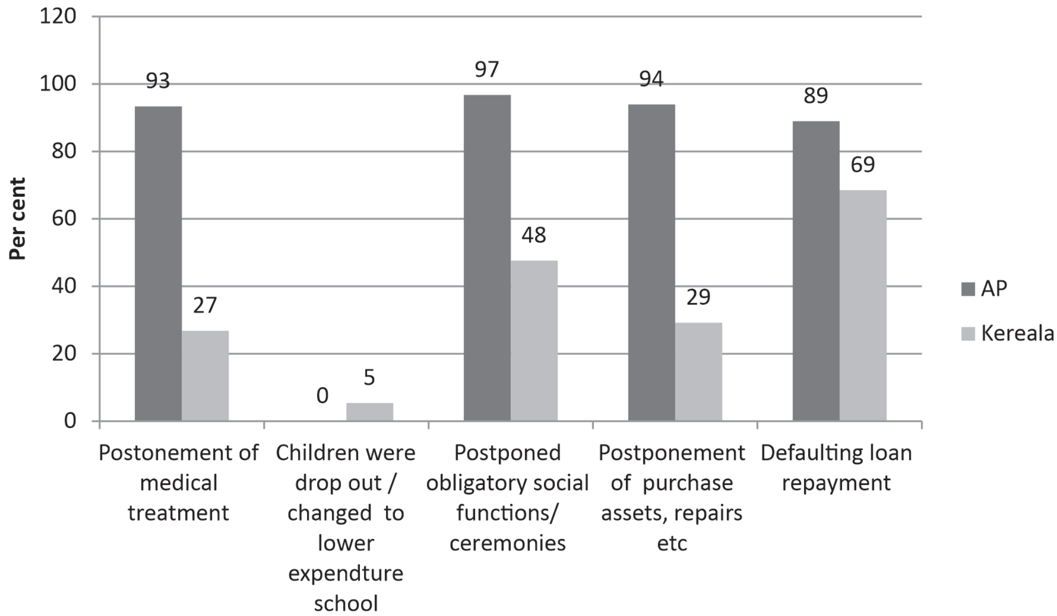

Figure 4. Impacts of COVID on households across Andhra Pradesh and Kerala

During the pre-COVID period, women provided 4–31% of the total household income (INR 2,406–14,305) from fisheries activities. During the COVID period, the income for women reduced by 85% for Andhra Pradesh and 45% for Kerala. The income of men did not change significantly in Kerala, mainly due to the high prices for fish in local markets.

Impact on other household activities

Depressed household income impacted several household necessities and activities, such as the medical treatment of members and education of children (Figure 4). The fear of COVID spreading from hospitals, high expenditure for private consultation, and the reduced availability of health services during COVID could have restricted access. Several households reduced educational expenditure (books, stationery, tuition, etc.), but about 5.4% of the households in Kerala shifted children to schools with lower expenditure. Households postponed social functions, obligations, ceremonies, the purchase of household durable assets like furniture and repairs of household items and defaulted on loan repayments.

The pandemic has impacted personal wellbeing in terms of interpersonal relationships (Figure 5). However, this information could be collected only from Kerala. Worsening of interpersonal relations in family is reported by 31% of respondents. This could also strain relations with society (26%). Psychological wellbeing is affected due to fear of loss of employment and income (82%). There were cases of anxiety (78%), and a sense of feeling isolation (46%). Income loss and the consequent strains within the family and society has lowered the prestige and self-esteem of people (13%).

Perceived reasons for the change in fishers' family income

An attempt is made to understand fishers' perception of the major reasons for the difficulties during COVID-19 (Table 6). One reason could be that some fisher families might have been affected by the first wave of COVID-19.

This information was not collected due to the sensitivities involved regarding data privacy. The restrictions imposed on movement, fishing, and fish marketing emerged as the most important reason (almost 100%), followed by reduced economic activity in general (72% in Andhra Pradesh and 50% in Kerala). Many migrant labourers work in marine fisheries in Kerala, and 51% of the households reported that labour was not available. When the national lockdown was relaxed, many migrant labourers left for home by buses and trains chartered for this purpose.

Another important reason suggested was loss of jobs for some family members. Spoilage of fish due to the

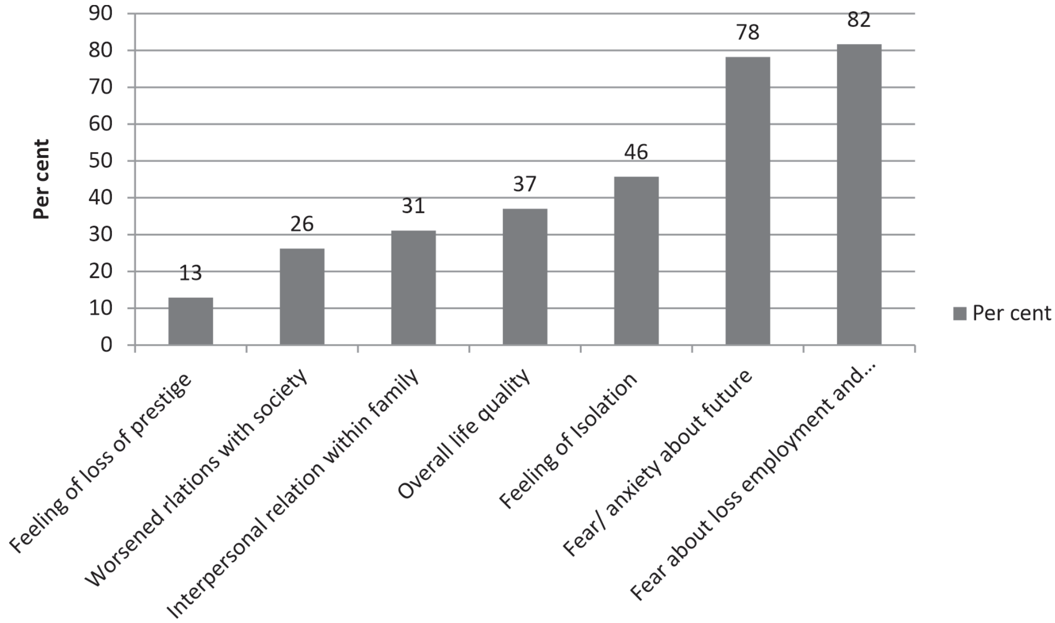

Figure 5. Perceived impact on personal and social wellbeing (% change), Kerala

Table 6 Reasons for change in income (% of respondents)

Sl No	Characteristic	Andhra Pradesh	Kerala
1	Movement was restricted (due to containment zone or any other reason)	100	97.6
2	Fishing was restricted	100	96.4
3	Fish marketing was regulated / restricted	100	97.6
4	Remittances reduced	9.94	76.2
5	Some family members lost job (including fishing)	10.49	36.4
6	Delayed payment of salary / wage for family member	1.10	44.6
7	Salary / wage reduction	0	23.8
8	Reduced economic activity	72	50.3
9	Loss due to fish wastage/ spoilage	11.05	14.6
10	Scarcity of labourers	11.05	51.47

lack of ice (11%) and marketing facilities were also reported (15%). Several multi-day fishing vessels that were in the sea when the national lockdown was announced discarded their catch before returning to shore. Other reasons identified were the reduction in remittances from family members and delays or reductions in the payment of salaries or wages.

Coping strategies adopted by fishers

Fishers adopted a multitude of coping strategies (Table 7). The major strategy was availing credit, either from non-institutional sources like moneylenders at a high rate of interest, or without interest from friends and relatives (the social network of fisherfolk emerged handy in this situation).

Another strategy was the liquidation of assets, mainly durable assets, reported by as high as 89% of fishers in Andhra Pradesh. Reduction of the household expenditure on food, education, and health care was another approach. Almost all the fishers in Andhra Pradesh reported a reduction in the quantity of food consumed and a compromise in the quality.

The quality compromise is in terms of the diversity and composition of food, reflected mostly in a reduction in the consumption of high-value food items like fruits

Table 7 Coping strategies adopted during COVID (% respondents)

Coping strategy	Andhra Pradesh	Kerala
Borrowed money /credit	100	54.2
Unconditional help from friends and relatives	100	41.9
Reduced the quantity of food taken at a time	100	13.1
Reduced the quality of food taken at a time (like non-veg, fruit, etc.)	100	32.3
Reduced the number of time food is taken	100	7.8
Reduced educational expenditure	100	12.6
Reduced medical expenditure	100	26.2
Started going for wage labour for more number of days / duration	11.05	25
Sale of livestock	0	8.3
Sale of household durable assets (furniture/ gadgets/ land/ jewellery)	88.95	9.5
Relied on ration from Government	100	84.3
Relied on social security support and income transfers from Govt	11.05	30.3
Participated in employment guarantee programme (MGNREGA)	0	15.2

and non-vegetarian products. In Kerala, while the reduction in food quantity was reported by only 13% respondents, about 32% compromised on food quality. A reduction in educational and medical expenditure were also reported.

One major avenue of income for the fisherfolk during this period was the guaranteed employment programme offered by the Government of India under the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA). About 11% of the fisher household in Andhra Pradesh and 30% in Kerala relied upon this social security programme offered by the local administration and government. During the COVID period, both the national and state governments operated subsidized food grains and other essential materials. Community kitchens were arranged in Kerala to serve food to the needy.

Correlates of coping strategies

The results show that the age of the fishers is significantly negatively correlated with all the four group of coping strategies, except asset liquidation (Table 8).

Table 8 Correlates of adaptation strategies analysed through logit regressions

Variable	Availing credit		Asset liquidation		Food adaptation		Expenditure reduction	
	b	Prob.	b	Prob.	b	Prob.	b	Prob.
Age of the fisher	-0.05	**0.02**	0.00	0.78	-0.07	**0.00**	-0.04	**0.03**
Family size	-0.07	0.68	0.31	**0.02**	0.09	0.50	-0.04	0.79
Education	-1.73	**0.00**	-0.75	**0.02**	-1.09	**0.00**	-2.08	**0.00**
Category								
a. Owner	-1.78	**0.03**	-0.61	0.60	-2.64	**0.03**	-0.42	0.66
b. Only worker	0.89	**0.05**	1.13	**0.00**	0.95	**0.01**	1.52	**0.00**
Type of vessel	1.03	0.07	-0.77	**0.06**	-0.36	0.40	0.37	0.42
House ownership status	-0.38	0.62	-3.54	**0.00**	-2.74	**0.00**	-3.15	**0.00**
Poverty status	0.12	0.81	-1.04	0.09	0.56	0.33	-0.77	0.17
Organizational participation	1.33	0.06	1.01	0.15	0.38	0.55	0.77	0.25
Number of income sources	-0.33	0.27	-0.97	**0.01**	-0.55	0.06	-0.30	0.34
Constant	3.19	0.08	3.88	0.01	6.67	0.00	5.70	0.00
Model chi square	79.86		186.62		151		190	
Pseudo R square	0.3		0.42		0.39		0.48	
N	326		326		326		326	

On the other hand, family size is correlated only with asset liquidation. The higher the education (categorized as those having less than high school level education and those above), the higher the probability that the fishers desist from these strategies, probably because education provides the capability to cushion income and livelihood loss.

Compared to those who are owners-cum-workers, those who are owners only are less probable to avail credit and worsen food consumption. On the other hand, the "only worker" category is positively and significantly correlated with all the four adaptation strategies. The workers get a proportionately lower share in the rent appropriated from marine capture fishing.

The type of vessel (categorized as 1 for mechanized and 0 otherwise) is only weakly correlated with coping strategies—positively with credit, negatively with asset liquidation, and not at all with other strategies. House ownership and access to alternative income reduces the probability of adopting most of these coping strategies. Interestingly, social capital enhanced the probability of availing credit, but did not influence other strategies. Having additional income sources also was correlated negatively with food adaptation and asset liquidation.

The cross-cutting observation is that while the status of "only worker" is positively correlated with all the coping strategies, education is negatively related. Therefore, being relatively poorly educated and functioning only as a worker enhances the probability that a fisher will adopt multiple strategies, including lowering food consumption.

Major constraints

The major constraints faced by fishers during the COVID-19 period were listed based on the discussion with the fisher population and other stakeholders, including academics and development workers. Fishers were asked to indicate whether they faced these constraints during the COVID-19 period. The central tendency, mode, of the responses were analysed to identify the severity of each constraint. The restriction of fishing activities, marketing, and movement of fish, reduced credit facilities, and depressed demand severely affected fishers (Table 9).

The fishers undertake their daily operations on credit basis, sourced mostly from informal sources, particularly from auctioneers and traders. Tied credit-market (product) relations are widely prevalent in the marine fisheries sector. Once the markets stopped functioning, credit flow was restricted. Credit servicing emerged as an issue that affected the operations of professional money lenders too, as they could not recover the outstanding credit from many fishers (private discussion with moneylenders in Kochi).

Fish spoilage and low demand for processed fish was reported as major constraints by fishers in Andhra Pradesh, but not in Kerala, probably because the fish marketing system has been reformed and marketing activities streamlined, and initiatives were taken in and around fish landing centres to for localized online fish sale (*The Hindu* 2000b), which could sell out fresh fish. Further, Andhra Pradesh has reported scarcity of ice as well, which could have contributed to the fish spoilage. Scarcity of labourers affected fishing

Table 9 Major constraints faced by fishermen households (mode)

Major constraint	Andhra Pradesh	Kerala
Fishing was restricted	5	5
Scarcity of labour	3	4
Marketing activities were restricted	5	5
Scarcity of ice	4	1
Scarcity for fishing net and other facilities	3	2
Spoilage of fish	5	1
Low demand for processed fish	5	4
Restrictions on movement of fish	5	5
Reduced credit facilities	5	5
Low demand for fish during COVID time	5	5

operations in Kerala (mode being 4), once it was resumed.

Summary and conclusions

One important conclusion is that the pandemic has disrupted the entire value chain of marine fisheries, employment, and income. The total employment has fallen 65% in Andhra Pradesh and 39% in Kerala and total family income, respectively, 74% and 14%.

Fish prices rose in several cases, but it could not offset the effect of a contraction in the fish catch. The COVID-19 crisis forced several fisher families to postpone medical treatment and obligatory social functions and compromise on the quality of education. The impact of COVID-19 has affected the psychological wellbeing of fishers, their interpersonal relationship within the family and the relationship with society. Feeling of isolation and a sense of loss of prestige is noted.

The fishers in both the state have low economic development compared to the general population, which accentuated their vulnerability to the economic impact of COVID-19. The pandemic has deteriorated the participation of women in the labour market to a proportionally higher level compared to their male counterparts. Low occupational diversification of the fisher households has worsened the economic crisis, when the harvest and post-harvest operations were disrupted.

The fishers varied in their capability to adapt coping strategies. The foremost coping strategies were availing credit and liquidating assets, compromising food consumption, reducing household expenditure and increasing labour market participation, and availing government support. Being less educated and functioning only as a worker worsens the fisher's welfare.

One key feature that emerged is the criticality of government during the crisis. For example, streamlining the fish market system of Kerala has helped non-mechanized fishers to avail better prices while maintaining the COVID protocol. Also, interventions to supply essential food items and food kits has helped to reduce the chances of reducing the quality and quantity of food intake.

The insights from the study have implications for developing responses during the continuing COVID-19 period and for reducing vulnerabilities during similar circumstances that could emerge in future, too.

First, the criticality of the livelihood loss on the welfare of the fishers, their interpersonal relations, and relationship with society is to be factored into policy formulation on the management of the pandemic and similar circumstances. The trade-off between income loss and the risk of contracting disease is to be carefully evaluated to prevent greater welfare loss due to income shocks.

Second, public policy has to respond to the income disruption through public support—transfer payments, and support in terms of food and other essentials, at least in limited manner, to avoid extreme destitution.

Third, the study points to the need to develop a targeted approach to address the more vulnerable sections of society. The proportionate reduction of income was severer for women.

Fourth, the immediate and most widely adopted coping strategy was to avail credit. Therefore, public policy needs to address household credit needs. Nudging credit institutions to respond to the financial needs of the fishers, and promoting fishers to approach formal credit institutions, could have far-reaching implications in addressing the shocks of income loss. Formal credit institutions need to develop credit products suitable to fishers taking into consideration their social context (low occupational diversification, in particular) and livelihood generation characterized by high risk in profession.

Fifth, in view of the greater vulnerability of marine fishers to natural calamities, weather hazards, and contagious diseases, it is relevant to factor in these risks while charting out development pathways for marine fisheries.

Acknowledgements

The authors thankfully acknowledge the services of Ms Tessy Francis, Ms Nimitha Paul, Mr Jos K.D., Mr Subhash Chandran Nair and Mr M. Baiju of Division of Extension, Information, and Statistics of ICAR-Central Institute of Fisheries Technology, Cochin Kerala; and Mr Swamy Kumar and Mr Chethan of Visakhapatnam Regional Station of ICAR-CIFT in collecting the primary data.

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Received 24 November 2021 Accepted 22 April 2022

Agricultural Economics Research Review 2022, 35 (2), 95-108
DOI: 10.5958/0974-0279.2022.00033.7

Performance analysis of electronic national agricultural markets: some evidence from Odisha

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Abstract This paper analyses the effect of electronic agricultural markets on commodity arrivals and price volatility. Compared to that in the period before the National Agricultural Market (eNAM), market arrivals of commodities declined later, average monthly prices increased, and farmers received lower prices on average. The paper also analyses the influences on farmers' decision to participate in electronic trading, and it finds that farmers' education, small landholding size, and age had a positive and significant effect on participation. The eNAM needs to include more markets, raise awareness about its features, and train farmers and traders to make their participation effective.

Keywords Agricultural markets, price volatility, market integration, eNAM

JEL codes Q02, Q13, Q18

Agricultural markets help to create forward and backward linkages in the economy that enhance growth in the farm and non-farm sectors (Acharya 1998; Vaswani et al. 2003). By balancing the demand and supply of agricultural products, agricultural markets protect producers and consumers from the adverse effects of price instability (Acharya et al. 2012). An increase in agricultural production does not necessarily improve returns to farmers, due to low income elasticity of demand and to depressed prices (because of high marketing cost, lengthy marketing channels, fragmented markets, and interlocked factor markets) (Planning Commission 2011; Chatterjee et al. 2020). Rather, the efficient functioning of agricultural markets improves price discovery, long-term investment by farmers, the welfare of both producers and consumers, and the proper allocation of resources for production and distribution activities (Chand 2012). An efficient agricultural marketing system requires adequate infrastructure facilities, transparency in transactions, and accountability of market officials, and it ensures higher market arrivals, efficient price discovery, and low price volatility (Acharya 2007).

However, agriculture markets are plagued by problems such as information asymmetry, collusion among traders, improper weighment, delays in payment, and poor infrastructure. Because the integration of markets is weak and the institutional arrangements poor, the prices of commodities traded are volatile and adversely affect farmers (Sekhar 2004; NIAM 2017). Farmers plan crops, credit requirement, and investment in farm activities based on the market information available, but smallholder producers lack timely access to market related information (Satapathy and Mishra 2020), and most sell their produce immediately after the harvest because they lack proper storage facilities, require cash to repay debts and pay labour wages, and need money for social ceremonies and their children's education (Sahu et al. 2009; Panda 2017).

To overcome some of these problems, electronic national agricultural markets conduct electronic auctions (e-auction), encompassing activities such as quality assessment, computerized lot allotment, public address mechanism, dissemination of market information, and conducting the e-auction in a designated hall. To create a “one nation, one market” system, the Government of India introduced the National Agricultural Market (eNAM) in April 2016. The nodal agency implementing the eNAM is the Small Farmers Agri-business Consortium (SFAC) under the aegis of the Ministry of Agriculture and Farmers’ Welfare, Government of India.

The Government of Karnataka introduced an electronic marketing system for paddy in the Mysore regulated market on a pilot basis in 2006–07. Later, in 2014, the state government launched the Rashtriya e-Marketing service in 105 markets in 27 districts. As Karnataka is the forerunner in introducing information technology (IT) in the trading of agricultural commodities, studies assessing the performance of eNAM were confined to this state (Chand 2016; Aggarwal et al. 2017; Pavithra et al. 2018; NABARD 2018) and focused on the process, conduct, and challenges of eNAM. A few studies found that the eNAM impacted commodity prices and market arrivals positively (Chengappa et al. 2012; Reddy 2018).

Research is needed on the performance of the eNAM in other regions of the country, too, however, and this paper critically assesses its performance in Odisha. Despite the structural transformation of the Odisha economy, agriculture continues to play an important role in its economic growth, contributing about 18.9% of the gross state value added (GSVA) and employing 48.9% of the total workforce (Government of Odisha 2019).

Agricultural marketing in Odisha

To improve the efficiency in marketing agricultural products and the price realization to farmers, the Government of Odisha introduced market regulations through the Orissa Agricultural Produce Markets Act, 1956, and many reforms to attract investment in setting up markets, improve infrastructure facilities, and decentralize the grain procurement system. Notwithstanding these reforms, only 50% of the marketable surplus of agricultural commodities is transacted through regulated markets; the rest is sold through other marketing channels such as village markets and cooperatives or procured directly by processors (NIAM 2017; Bisen and Kumar 2018; Chatterjee et al. 2020).

About 428 market yards work under the Odisha State Agricultural Marketing Board, Bhubaneswar. Each regulated market in the state serves 424 villages on average, more than the national average of 258 (Kathayat 2019). The open auction sale procedure cannot be used in many regulated markets in Odisha because of the small quantity of arrivals, lack of infrastructure, low trader participation, low production, transportation problems, weak regulatory mechanisms, and the lack of well-trained market staff (Gummagolmath et al. 2014; Purohit 2016; Krishnamurthy 2021).

The market fee collected from stakeholders is not uniform across the markets in the state. Most small and marginal farmers prefer to sell their produce in the periodic village markets because these are closer and the marketing cost is lower. But few periodic markets have the infrastructure to conduct transactions smoothly and ensure that farmers get a reasonable price for their produce (Gummagolmath et al. 2014).

To reap the advantages of the eNAM process, the Government of Odisha started integrating its regulated markets with the electronic platform. In the first phase (March 2017), 10 markets were integrated with the electronic platform, and 31 markets in the second phase (April–May 2020), but only 41 of 428 regulated markets in the state were linked (OSAMB 2021). About 1.6 lakh farmers, 4,981 traders, and 156 FPOs are registered to participate in the electronic markets located in different parts of Odisha (SFAC 2021). These statistics indicate that still many farmers and traders are not in eNAM-enabled markets despite the expansion of electronic agricultural markets over time.

Process flow of trade through the eNAM

To simplify the process of trade through eNAM and facilitate the transaction of commodities, the Government of India has developed the eNAM mobile app that farmers can use to trace real-time bidding of the crop produce (Chengappa et al. 2012; Shalendra and Jairath 2016; Pavithra et al. 2018). The app works in six different languages to simplify the process of trade through the eNAM. Trade takes place in six steps: gate entry, quality assessment, uploading produce information, declaration of the highest bid price, final weighing by market officials, and the generation of an exit gate pass.

Step 1 Gate entry

The market official generates a unique lot ID. The ID includes the farmer's name and address, commodity name, number of bags, and vehicle details.

Step 2 Quality assessment

Technicians assess the quality of the crop produce and weigh it.

Step 3 Upload produce information

The produce information, including the quality assessment certificate, is uploaded onto the eNAM website for e-auction by registered traders in the country. The auction process is shown on the display board.

Step 4 Declaration of the highest bid

After the auction, the highest bid for the farmer's produce is sent to their registered mobile number. If the farmer accepts the bid, the trading process moves to the next step.

Step 5 Final weighing

The market officials weigh the produce. The trader pays the market officials, who send it to the farmer's bank account. The transaction usually takes one or two working days.

Step 6 Exit gate pass

Once the trader has paid the farmer, the market official generates an exit gate pass and the trader takes away the consignment. Market officials supervise the entire trading process.

Data sources and methodology

The present study uses both primary and secondary data for analysis. A field survey was conducted with a reference period of 2018–19, covering 140 farmers, 40 traders, and 8 market officials. The primary data on the market participants was collected from two electronic agricultural markets—Kantabanji in Balangir district and Kunduli in Koraput district in Odisha during October–November 2019. These markets are located in different agroclimatic zones and trade a higher volume than other markets. About 4,317 tonnes of crop ouput was transacted through all the electronic markets in 2017 (Government of Odisha 2019); Kantabanji accounted for 51.49% of this volume and Kunduli for 17.56%. During the survey, we randomly selected farmers from the list provided by the market committees and interviewed traders and market officials when they were available. Table 1 in the Appendix lists the electronic agricultural markets and commodities traded.

We compiled the monthly data on market arrivals and price of commodities from March 2013 to February 2021 from the AGMARKNET portal to analyse the effect of the eNAM. We divided the study period into the pre-eNAM period (March 2013 to February 2017) and the post eNAM period (March 2017 to February 2021).

We also conducted a comparative analysis of eNAM enabled and non-eNAM enabled markets for select crops. We captured the effect of the eNAM through the price volatility of four major traded commodities—brinjal, tomato, maize, and cashew nut. We calculated the price volatility (PV) using the formula

PV = standard deviation of the log of (P_t/P_{t-1})

where,

P_t= price of crop produce in the current month and

P_{t-1}= price of crop produce in the previous month.

The binary logit regression model was used to analyse the factors influencing the farmers' decisions to participate in the eNAM enabled markets. The logit regression model can be written as

$$L_i = \ln (P_i/1-P_i) = x_i'\beta + u_i \qquad \ldots(1)$$

where,

L_i is the logit,

u_i is the stochastic error term,

P_i is the probability of farmers participating in trade through electronic platforms, and

x_i is the vector of independent variables.

The model is estimated by the maximum likelihood procedure. The likelihood can be obtained from a Bernoulli distribution with the probability of participation as $P(y_i=1) = F(x_i'\beta)$. The log likelihood function for the joint probability distribution is

$$lnL = \sum_{i=1}^{n} y_i \ln[F(x_i'\beta)] + (1 - y_i)\ln[F(x_i'\beta)] \quad \ldots(2)$$

where,

F(.) is the logistic cumulative distribution function.

Maximizing the log-likelihood function with respect to β provides the maximum likelihood estimators. The independent variables include the age of the farmer, age squared, years of schooling completed, computer literacy, distance from farm to market, and net operated area.

The marginal effect provides change in the probability of participaton of farmers in the eNAM due to one unit change in the explanatory variable. It is computed by taking partial derivative of the estimated function as

$$\frac{\partial P_i}{\partial x_i} = f(x_i'\beta).\beta_j,$$

where,

f (.) is the probability density function.

Market arrivals and price of major commodities

The consistent time series data on arrivals and price for brinjal and tomato are available from Bahadajhola electronic market, turmeric from Tikabali market, maize from Nabarangpur market, and cashew nut from Paralakhemundi market. The average quantity of arrivals of major commodities during pre and post-eNAM periods is given in Table 1 and Figures 1 to 3 in the Appendix.

Relative to the pre-eNAM period, the market arrival of all five commodities declined in the post-eNAM period. Brinjal fell 80%, from 1528.6 quintal per month to 308.1 quintal per month. Tomato also fell 80%, declining continually from March 2013 to February 2021. The market arrival of turmeric in Tikabali market declined 9%. Maize is a major crop grown in Nabarangpur market jurisdiction, but arrivals declined on average. The estimated t-test on market arrivals for turmeric, brinjal, tomato, and maize is not statistically significant. The arrival of cashew nut declined on average, with a higher degree of variability, and it is statistically significant at 1% level.

These patterns imply that farmers did not bring their produce to electronic markets because they do not know of the eNAM or how to use the electronic auction platform. The field survey evidence shows that 45.71% of the sample farmers were not aware about the e-auction process of trade through eNAM enabled markets or its benefits, and they prefer to sell their products through marketing channels like private traders, regulated markets, and weekly markets.

Table 2 provides the average quantity of arrivals of select commodities in markets both linked to and not linked to the e-NAM. The details of select crops and markets are given in Table 2 in the Appendix. The arrival of maize and cashew nut was higher on average in non-eNAM-enabled markets than in eNAM enabled markets.

In non-eNAM enabled markets, the arrival of maize averaged 8792.97 quintal per month, 7.84% higher than that in eNAM-linked markets; the arrival of cashew nut was 13.18% higher. But the arrival of perishable commodities such as tomato and brinjal was higher in eNAM linked markets. Farmers sell their produce in eNAM enabled markets because they can dispose of it quickly and traders pay them immediately. However, the estimated values of t-test statistic for the market arrival of all the select commodities are not statistically significant.

Table 1 Market arrivals (quintal)

Crop	Market	Pre–eNAM	Post–eNAM	Change in arrival (%)	t–test	P–value
Turmeric	Tikabali	176.27	160.43	–8.99	0.3958	0.3470
Maize	Nabarangpur	9956.22	8153.02	–18.11	1.1708	0.1237
Tomato	Bahadajhola	1310.96	260.03	–80.16	14.0098	1.0666
Brinjal	Bahadajhola	1528.65	308.13	–79.84	14.8161	1.2374
Cashew nut	Paralakhemundi	76.50	35.20	–53.99	3.6771***	0.0003

Note * p<0.1 and **p<0.05 and ***p<0.01
Source Computed based on AGMARKNET (2021)

Table 2 Market arrival in electronic and non-electronic agricultural markets (March 2017 to February 2021, quintal)

Crop	Electronic agricultural markets	Non-electronic agricultural markets	% change in arrival	t–test	P–value
Turmeric	160.43	NA	NA	NA	NA
Maize	8153.02	8792.97	7.84	–0.4635	0.3225
Tomato	260.03	123.00	–52.69	8.6973	1.1838
Brinjal	308.13	154.37	–49.90	9.7968	3.0925
Cashew nut	35.20	39.84	13.18	–1.1092	0.1364

Source Computed by authors based on AGMARKNET (2021)
Note "NA" represents not available

Table 3 shows that relative to the pre-eNAM period, the average market price of major commodities increased in the post-eNAM period: that of cashew nut the most, 30.8%, from INR 9,337 per quintal to INR 12,213 per quintal; brinjal by 16.3%; tomato from INR 2,112 per quintal to INR 2,304 per quintal; and maize by 7.5%.

The market arrival of all these commodities decreased, but their prices showed an increasing trend over time (Figures 4–6 in the Appendix). The stakeholders differ on the possible reasons. Most sample farmers felt that crop production had fallen, affecting market supply and raising commodity prices. Electronic market officials claimed that the introduction of the eNAM raised commodity prices, but the data does not support the claim.

Table 4 shows that from March 2017 to February 2021, the average market price of all the selected commodities except cashew nut was higher in non-eNAM-linked markets. The average market price of maize was INR

Table 3 Market price of commodities (before and after eNAM, INR per quintal)

Crop	Market	Pre-eNAM	Post-eNAM	Change in price (%)	t-test	P–value
Turmeric	Tikabali	5271.70	5457.77	3.53	–0.6715	0.2525
Maize	Nabarangpur	1316.90	1415.20	7.46	–4.4220	2.8766
Tomato	Bahadajhola	2112.42	2304.33	9.08	–1.1540	0.1271
Brinjal	Bahadajhola	1919.43	2232.20	16.29	–3.1217***	0.0015
Cashew nut	Paralakhemundi	9336.95	12213.08	30.80	–3.7522***	0.0002

Note * p<0.1 and **p<0.05 and ***p<0.01
Source Computed based on AGMARKNET (2021)

Table 4 Average market price of commodities in electronic agricultural markets and non-electronic agricultural markets during March 2017 – February 2021 (Rs./Quintal)

Crop	Electronic agricultural markets	Non-electronic agricultural markets	% change in price	t-test	P-value
Turmeric	5457.77	NA	NA	NA	NA
Maize	1415.20	1664.47	17.61	-2.0237**	0.0243
Tomato	2304.33	2346.79	1.84	-0.6873	0.2476
Brinjal	2232.20	2302.32	3.14	-2.4703***	0.0085
Cashew nut	12213.08	11367.09	-6.92	4.1137	7.7736

Note "NA" represents not available; * p<0.1 and **p<0.05 and ***p<0.01
Source Computed based on AGMARKNET (2021)

Table 5 Price volatility in electronic and non-electronic agricultural markets

Crop	Electronic agricultural markets		Non-electronic agricultural markets*
	Pre-eNAM	Post-eNAM	
Turmeric	0.0353	0.0559	NA
Maize	0.0168	0.0221	0.1405
Tomato	0.1840	0.1944	0.1716
Brinjal	0.1407	0.1788	0.1310
Cashew nut	0.0419	0.0277	0.0505

Note “NA” represents not available; Pre-eNAM period: March 2013 to February 2017; Post-eNAM period: (March 2017 to February 2021); * pertains to the period March 2017 to February 2021
Source Authors’ estimates.

1664.47 per quintal in non-eNAM-linked markets, 17.61% more than the INR 1415.20 per quintal in eNAM-linked markets, and it is statistically significant at 5% level.

Similarly, the average price of tomato and brinjal was slightly higher in non-eNAM-linked markets, and the price difference for brinjal was statistically significant at 1% level. The average price of cashew nut was slightly higher in eNAM-enabled markets, but it was not statistically significant. On average, farmers received higher prices in non-electronic agricultural markets.

Price volatility in eNAM-enabled and non-eNAM-enabled markets

Price volatility is an important indicator of the performance of agricultural markets. Table 5 shows the degree of volatility in the prices of major crops.

Relative to the pre-eNAM period, the volatility in the price of commodities other than cashew nut increased during the post-eNAM period: for turmeric, maize, and brinjal, price volatility was relatively high and for tomato, modest. In contrast, Sekhar and Bhat (2018) found little variation in the price of paddy, wheat, mustard, and cotton in the electronic agricultural markets of Haryana. For tomato and brinjal, price volatility was lower in non-eNAM linked markets; for maize and cashew nut, price volatility was lower in electronic agricultural markets.

Given the mixed evidence, the importance of electronic agricultural markets in reducing price volatility is not clear, and this also implies that market integration is not fully achieved. Perhaps the inclusion of more markets under the eNAM may help to stabilize the commodity prices across markets in the state.

Factors influencing farmers’ participation in electronic markets

We use the binary logit regression model to analyse the factors influencing farmers’ decision to participate in electronic agricultural markets. Table 6 provides the summary statistics of variables and Table 7 the results of the logit regression model.

Table 6 Summary statistics of variables

Variable	Mean	Std. Dev	Minimum	Maximum
Participation in eNAM (Yes/no)	0.50	0.5017	0	1
Age (year)	41.31	10.8779	18	77
Years of schooling completed	6.32	3.7728	0	15
Computer knowledge (Yes/No)	1.95	0.2187	1	2
Distance from farm to market (Km)	6.59	5.8004	0.5	30
Net operated area (acre)	4.02	3.4892	0.5	25

Source Field Survey

Table 7 Factor influencing farmers' decision to participate in eNAM

Explanatory variables	Odds Ratio	P>|z|	Marginal Effects (dy/dx)	P>|z|
Age	0.7679** (0.0903)	0.025	-0.0559** (0.0232)	0.016
Age square	1.0032** (0.0013)	0.022	0.0006** (0.0002)	0.013
Years of schooling completed	1.1044* (0.0663)	0.098	0.0211* (0.0122)	0.086
Computer knowledge	0.7251 (0.6680)	0.727	-0.0681 (0.1949)	0.727
Distance from farm to market	1.1425*** (0.0514)	0.003	0.0282*** (0.0084)	0.001
Operated area	0.8939* (0.0563)	0.075	-0.0237* (0.0128)	0.064
Constant	109.9573	0.167	-	
No. of observations = 140				
Log-Likelihood = - 85.4155				
LR chi2 (6) = 23.25, Prob>chi2=0.0007				
Pseudo R^2 = 0.1198				

Note Figures in parentheses are standard errors. * p<0.1 and **p<0.05 and ***p<0.01

About 50% of sample farmers participated in electronic agricultural markets. The average age of respondents was 41 years and they had reportedly completed six years of schooling. With a low level of education, only 2.0% of sample farmers had some knowledge of using computers for trading activities. Most sample farmers were small landholders; their net operated area averaged 4.0 acre. For the entire sample the average operated area ranged between 0.5 acre and 25 acre.

The dependent variable is a binary variable, which takes the value 1 if a farmer has participated in electronic trading and 0 otherwise. Among the factors, farmers' age and participation in electronic agricultural markets show a curvilinear relationship. Surprisingly, the likelihood of participation in eNAM-enabled markets decreases by 0.76 if the farmers are younger, which is statistically significant at 5% level. However, the odds ratio of farmer's age squared is greater than 1, and it is statistically significant, implying that the probability of participation in electronic markets is higher for older farmers than younger.

Education has a positive impact on participation. For every additional year of schooling, the odds of participation increases 1.10 times. In terms of the marginal effects of education, the probability of participation increases by 2.1%, and it is significant at 10% level; Chengappa et al. (2012) find a similar impact of education on participation. However, the effect of computer literacy was statistically insignificant.

Participation is not affected by location: the odds of participation increases with an increase in the distance from farm to market—5 km to regulated markets on average and 9 km to electronic markets, according to the field evidence. The size of electronic agricultural markets is larger, their facilities better, the probability that farmers would earn a reasonable price for their produce higher, and perhaps that is why farmers do not mind travelling the distance.

Farmers participate in markets that have better infrastructure (Manjunath and Kannan 2012; Shilpi and Umali-Deininger 2007; Khunt and Gajipara 2008).

Arrivals are higher in markets where facilities are better (Manjunath and Kannan 2012). New markets and modern amenities reduce wastage and earn farmers a reasonable price, and because modern facilities are price effective and efficient these attract bulk arrivals (Kerur et al. 2008). Farmers with a large marketable surplus would prefer to sell at distant markets because they would expect to sell larger quantities than at the farm gate and at a higher price (Fafchamps and Hill 2005).

The marginal effect of operated area on participation is negative and statistically significant at 10%, implying that small landholders participate in the eNAM to get a better deal than disposing their produce directly to intermediaries or traders within the village.

Farmers' perspectives on electronic agricultural markets

We analysed the qualitative response of the sample farmers on the aspects of electronic agricultural markets through the Likert scales. Over 50% of the sample farmers were either dissatisfied or highly dissatisfied (Figure 1), citing the lack of a cold storage facility as a major constraint, particularly for improving trade in perishable products like vegetables.

Only a few farmers and traders were provided training about the eNAM; most were unaware that electronic markets follow a process of trade that is different from the conventional trading process or that a mobile app is used for trading. The sample farmers mentioned that creating greater awareness about electronic markets and the trading process would improve participation and that marketing cost and time period for completion of trade have not declined after the introduction of the eNAM. The major crops grown within a market area are not included. All these issues constrain the successful implementation of the eNAM.

Traders' perspectives on electronic national agricultural markets

Traders link farmers and consumers, but only 15% of the sample traders were trained in trading through eNAM enabled markets. Many traders feel that price volatility, marketing cost, and the time required for marketing have not declined even after the introduction of the electronic marketing system. Although the average distance to eNAM-enabled markets is relatively high, traders prefer to transact their business activities through the eNAM because of the crop volume is large and transactions transparent (Figure 2).

Traders purchase agricultural produce based on the quality assessment report released by market officials—they have no direct contact with traders—but there are not enough market officials to assess quality. Only 25% of the sample traders were satisfied with the quality assessment reports by the market officials. And, like the farmers, traders were dissatisfied with the quality of the cold storage facilities in markets.

Electronic markets do not charge farmers a fee, but traders pay 1% of their total transaction as a charge. The sample traders consider this charge very high; lowering it would raise trader participation. Both traders and farmers reported that the fees collected in regulated markets are not uniform.

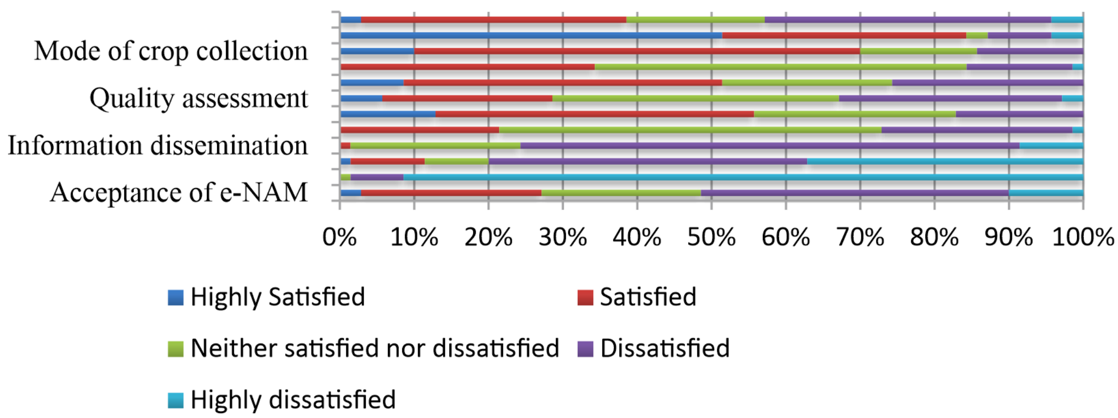

Figure 1 Rating of eNAM by sample farmers (%)
Source Field survey

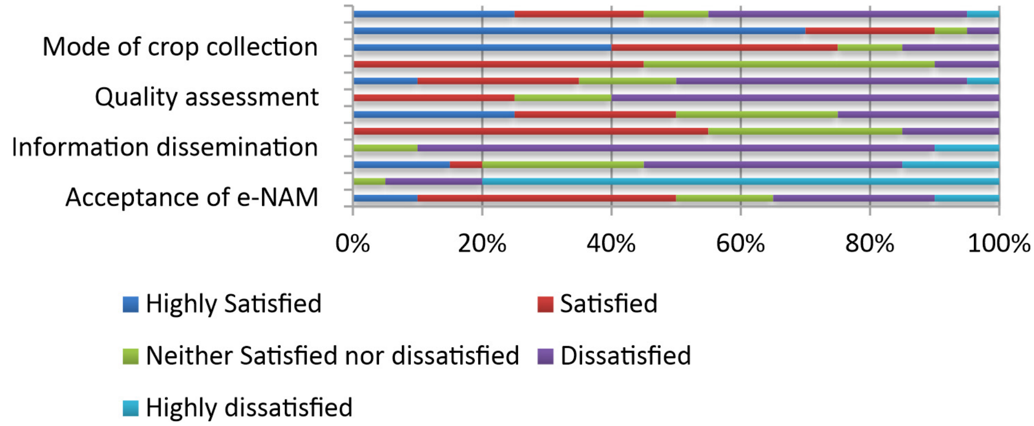

Figure 2 Traders rating of eNAM components (%)
Source Field survey

Conclusions and policy implications

This paper analyses the effect of the eNAM on price volatility, the factors influencing farmers' decision to participate, and the stakeholders' perspectives on how the eNAM functions.

Compared to that in the pre-eNAM period, the market arrivals of tomato, brinjal and cashew nut declined drastically in the post-eNAM period, but the price of these commodities increased over time and, in the post-eNAM period, the increase was volatile.

The increase was high for turmeric, maize, and brinjal, and modest for tomato. The rise in price volatility indicates that markets are not fully integrated and the inclusion of more markets under the eNAM may help to stabilize the prices to some extent.

Among the factors that influence participation, the effect of education and age squared was positive and statistically significant. Distance did not seem to affect the farmers' decision to sell their produce at eNAM enabled markets, as these were the large markets; nevertheless, proximity would reduce transportation and other related charges.

Compared to large landholders, small landholders participate more in electronic agricultural markets, but training farmers and traders in the training process of electronic market systems would help to improve participation considerably, as would the inclusion of the major agricultural crops grown within the market jurisdiction in eNAM-enabled markets.

The distribution of eNAMs by state is uneven: over 50% of the eNAMs are in Rajasthan, Gujarat, Maharashtra, and Uttar Pradesh (SFAC 2021). As on 28 February 2021, about 1,000 regulated agricultural markets in 21 states and union territories were integrated with the eNAM platform (SFAC 2021), and about 1.7 crore farmers, 1.57 lakh traders, and 88,000 commission agents—or only 14.4% of the 11.8 crore cultivators (Population Census 2011)—were registered. Interestingly, about 1,836 farmer producer organizations are registered in eNAM enabled markets; including them would create economies of scale and incentivize participation (Kumar et al. 2020).

Acknowledgements

Authors are thankful to the reviewer for useful comments. Authors also sincerely thank the Chief Editor for encouragement and motivation.

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Received 7 January 2022 Accepted 14 June 2022

Appendix

Table 1 List of e-NAM enabled markets and major commodities traded in Odisha

Market	District	Major commodities traded through e-NAM
Kantabanji	Balangir	Onion, cotton, sunflower seeds
Kendupatana	Cuttack	Moong (whole) (green gram)
Paralakhemundi	Gajapati	Cashew nut, maize
Tikabali	Kandhamal	Turmeric, green peas
Kunduli	Koraput	Ginger, jackfruit, leafy vegetables, potato, sweet potato
Nabarangpur	Nabarangpur	Maize
Bahadajhola	Nayagarh	Bitter guard, brinjal, cauliflower, cucumber, lady's fingers, moong (whole), tomato
Sakhigopal	Puri	Coconut
Rayagada	Rayagada	Cotton
Kuchinda	Sambalpur	Chillies, mahua flower

Source Odisha State Agricultural Marketing Board (OSDAMB), Bhubaneswar

Table 2 Select crops and markets

Crops	eNAM-enabled markets	Non-eNAM enabled markets	District
Turmeric	Tikabali	Not available	Kandhamal
Maize	Nabarangpur	Umerkote	Nabarangpur
Tomato	Bahadajhola	Sarankul	Nayagarh
Brinjal	Bahadajhola	Sarankul	Nayagarh
Cashew nut	Paralakhemundi	Kasinagar	Gajapati

Source AGMARKNET (2021)

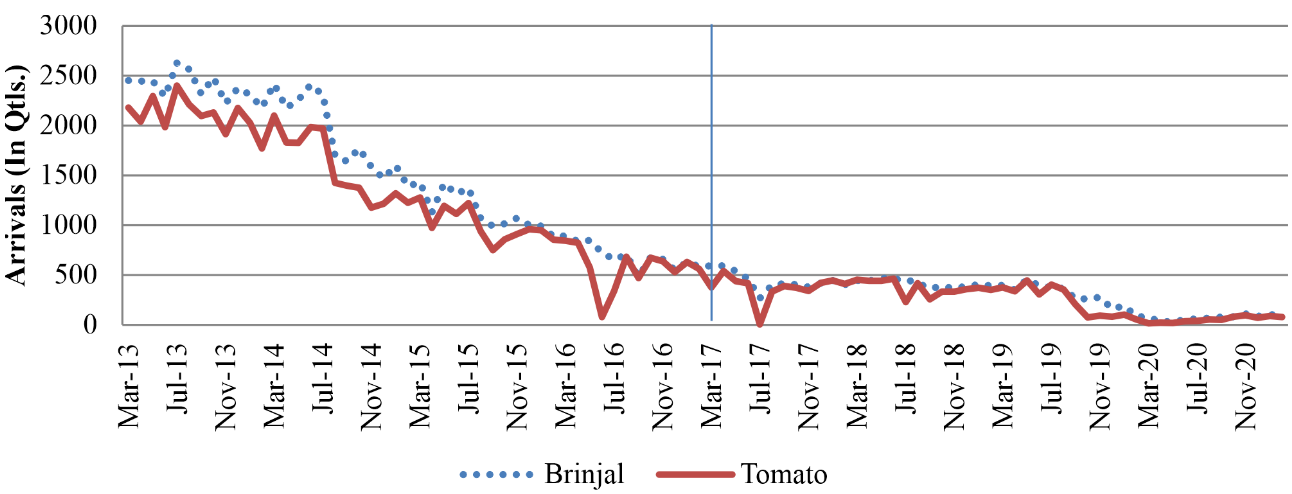

Figure 1 Trend of brinjal and tomato arrivals in Bahadajhola market
Note The vertical line distinguishes between the pre-eNAM and post-eNAM periods
Source AGMARKNET (2021)

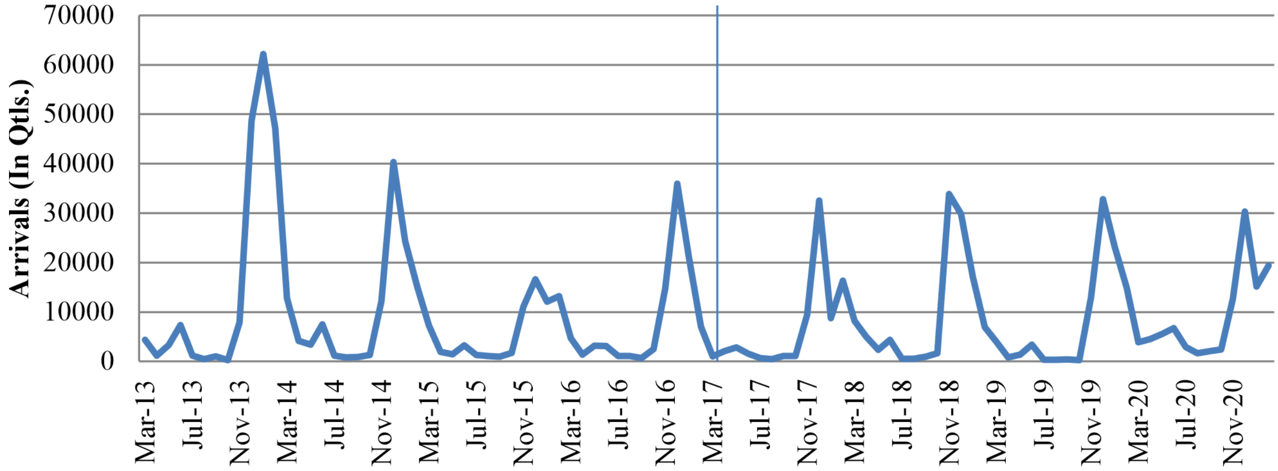

Figure 2 Trend in maize arrivals in Nabarangpur market
Note The vertical line distinguishes between the pre-eNAM and post-eNAM periods
Source AGMARKNET (2021)

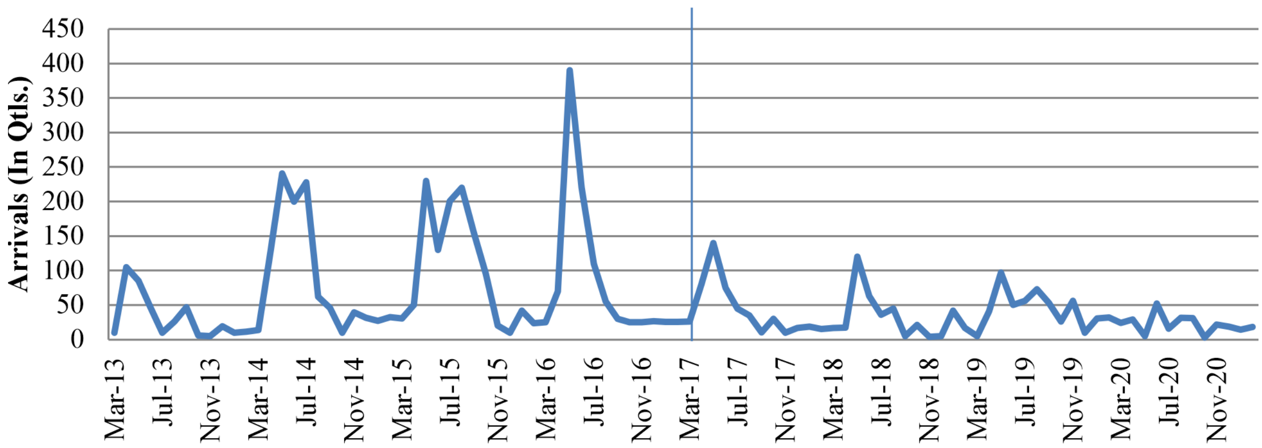

Figure 3 Trends in cashew nut arrivals in Paralakhemundi market
Note The vertical line distinguishes between the pre-eNAM and post-eNAM periods
Source AGMARKNET (2021)

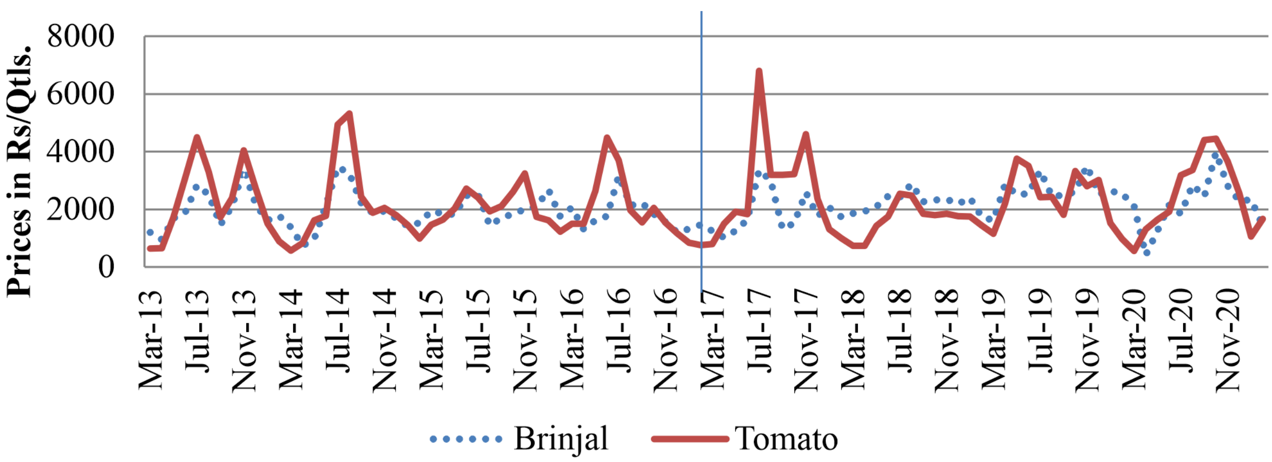

Figure 4 Trend in prices of crops in Bahadajhola market
Note The vertical line distinguishes between the pre-eNAM and post-eNAM periods
Source AGMARKNET (2021)

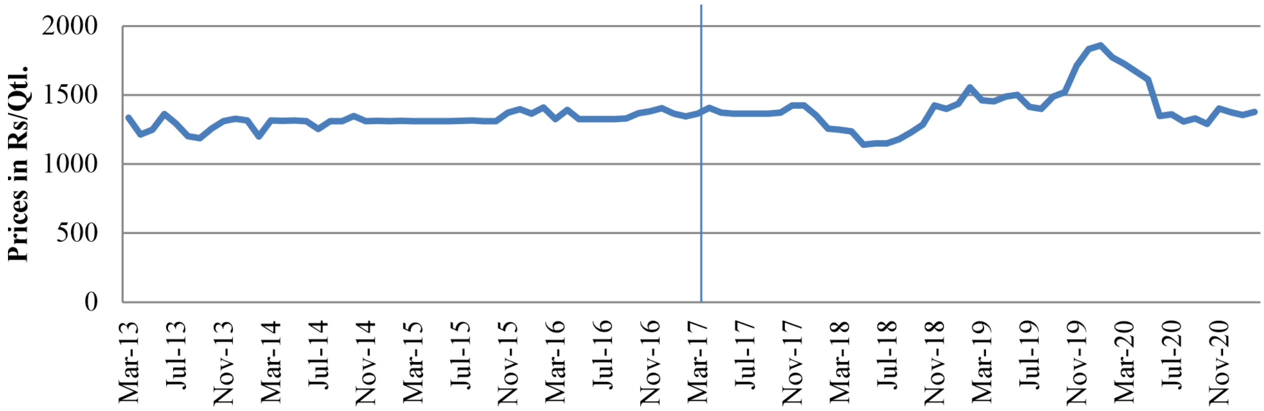

Figure 5 Trend in maize price in Nabarangpur market
Note The vertical line distinguishes between the pre-eNAM and post-eNAM periods
Source AGMARKNET (2021)

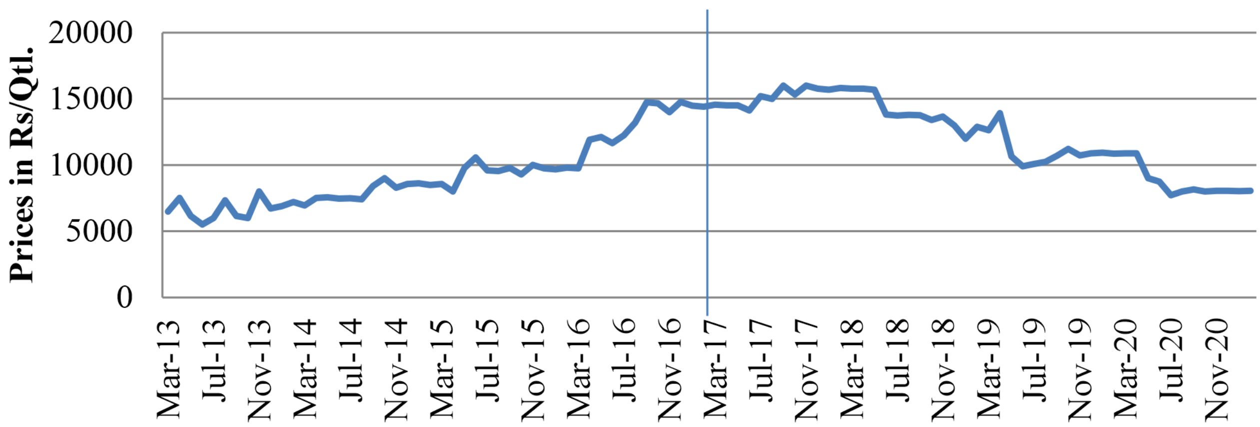

Figure 6 Trend in cashew nuts price in Paralakhemundi market
Note The vertical line distinguishes between the pre-eNAM and post-eNAM periods
Source AGMARKNET (2021)

Agricultural Economics Research Review 2022, 35 (2), 109-118
DOI: 10.5958/0974-0279.2022.00034.9

Price dynamics and market integration of tomato markets in India

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Abstract The current study uses the Johansen co-integration, Vector Error Correction model, and Granger causality test to investigate the level of market integration and price transmission in the key tomato markets in India. From January 2010 to March 2020, the study examined weekly average tomato pricing data (Rs/quintal) collected from specific markets in Kolar, Srinivaspur, Bangalore (production markets), Chennai, Kolkata, Pimpalgaon, and Delhi (consumption markets). The findings provided substantial evidence for the co-integration and interdependence of these market places in India. However, the rate of price adjustment was found to be moderate across all markets, and as a result, prices only correct a tiny portion of the market's disequilibrium, with external and internal forces accounting for the majority of the correction. Since there is unidirectional causality from Kolkata to Kolar markets, it makes it necessary for future research to examine the influence of internal and external factors like market infrastructure. It also calls for improving information technology to allow for the regular flow of market information to assist farmers in increasing their income.

Keywords Market integration, Agriculture, Indian markets, Granger causality

JEL codes Q11, Q13

No Indian kitchen is complete without tomato. Market integration is especially important because it promotes the efficient operation of well-integrated markets, which pay producers a fair price and enable consumers to purchase a commodity at a fair price. Price stability promotes high level of economic activity while preventing extended inflation or deflation. One of the signs of the existence of effective market functioning is the high degree of market integration. Because co-integrated markets are always competitive and efficient, market efficiency and competitiveness are positively correlated with co-integration of markets. Integration has an impact on how businesses behave in market places and how effectively they sell. Market integration is a requirement for maintaining regional price stability in both domestic and international markets (Mukim et al. 2009).

Data and methodology

Study area and data source: The present study has used secondary weekly wholesale average prices data from January 2010 to March 2020 from Kolar, Bangalore, Srinivaspur, Chennai, Kolkata, Delhi and Pimpalgaon markets. Kolar was taken as the central/ reference market.

In this study, ADF, KPSS and Zivot Andrews tests were employed to examine the unit root properties of data generating process (DGP). Prices of many agricultural products exhibit definite seasonal patterns which reflect the various marketing practices of farmers and market intermediaries as well as the natural biological lag processes that govern production.

Johansen's Co-integration test: Johansen's co-integration method serves as the foundation for the co-integration study. The Johansen's maximum likelihood approach was utilised to tackle the estimation of the co-integration vectors. Any p-dimensional vector autoregression can be expressed in the following "error correction" form, according to Johansen and Juselius (1990):

$$\Delta X_t = \sum_{t-1}^{k} \Delta X_{t-1} + \prod X_{t-k} + \mu + \varepsilon \tag{1}$$

Where;

X_t = p-dimensional vector of I (1) processes, μ = A constant, ε_t = A p-dimensional vector with zero mean (Δ is the variance– covariance matrix).

The Π matrix has a rank that is limited in the interval (0, r) and can be decomposed into components as follows; $\Pi = \alpha\beta'$ where; α, β p×r matrices, r: distinct co-integrating vectors. Johansen and Juselius Co-integration test procedure uses two tests to determine the number of co-integration vectors: The Maximum Eigen value test and the Trace test. The Maximum Eigen value statistic tests the null hypothesis of "r" co-integrating relations against the alternative of "r+1" co-integrating relations for r = 0, 1, 2…n-1.

Threshold model: Threshold models have been widely applied. Following the notation in Enders and Siklos (2001), the approach was employed in our study. This model permits a different speed of adjustment depending on the value of the error correction term (ECT). Popular specifications include the threshold autoregressive (TAR) and the momentum-TAR (M-TAR) models. Enders and Siklos (2001) discussed use of the Heaviside indicator produces; the threshold autoregressive model which can be expressed as

$$\Delta\mu_t = I_t\rho_1\mu_t + (1 - I_t)\rho_2\mu_{t-1} + \sum_{i=1}^{p} \gamma\Delta\mu_{t-1} + \omega_t \tag{2}$$

Where I_t is the Heaviside indicator function such that

$$I_t = \begin{cases} 1 \; if \; \mu_{t-1} \geq \tau \\ 0 \; if \; \mu_{t-1} \leq \tau \end{cases} \tag{3}$$

and τ is the value of the threshold, ω_t is a sequence of zero-mean, constant variance iid random variables, such that ω_t is independent of μ_t, J < t. The adjustment is symmetric if the speed of adjustment coefficients ρ_1 = ρ_2, and hence become a special case of Engle-Granger approach in equation $\Delta\mu_t = \rho\mu_t + s_t$. The lagged dependent variable was included to ensure the residuals were white noise and the lag length was selected using AIC or BIC. If the system is convergent then the long-run equilibrium value of the sequence is given by $\mu_t = \tau$. In such cases, adjustment is ρ_1 if μ_{t-1} is above its long-run equilibrium value and ρ_2 if μ_{t-1} below long-run equilibrium. If for instance $-1 < \rho_1 < \rho_2 < 0$, then the negative phase of the μ_t series will tend to be more persistent than the positive phase.

If the Heaviside indicator function depends on μ_{t-1} as in equation (3), then equation (4) is termed Threshold Autoregressive model (TAR). However, when the Heaviside indicator depends on the previous period's change in μ_{t-1}, *i.e.* Momentum Heaviside Indicator: then equation (4) is called Momentum-threshold autoregressive (M-TAR) model in that the $\rho_{5ØaÜ}$ series exhibit more "momentum" in one direction than the other. For M-TAR, if $|\rho_1| < |\rho_2|$, then the model exhibits little adjustment for positive but substantial decay for negative, thus, increases tend to persist but decreases tend to revert quickly to the attractor irrespective of where disequilibrium is relative to the attractor.

According to Enders and Granger (1998), M-TAR representation may capture sharp movements in a sequence while TAR is used to capture a deep-cycle process if, e.g. positive deviations are more prolonged than negative deviations. There is generally no presumption as whether to use TAR or M-TAR model, the recommendation is to select the adjustment process by a model selection criterion such as AIC or BIC.

The null hypothesis tested in the threshold model was no co-integration which is based on a nonstandard joint F-test of $\rho_1 = \rho_2 = 0$. The test statistic i (i = *TAR*, *MT*) was compared to critical values provided by Enders and Siklos (2001) when the point estimates of ρ_1 and ρ_2 imply convergence ($\rho_1 < 0$, $\rho_2 < 0$), alternatively the maximum t-statistic $t - max_i$, where i = *TAR*, *M-TAR* can be used. When the null hypothesis of no co-integration is rejected, then a standard F-test of symmetric adjustment can be performed by testing if $\rho_1 = \rho_2$. Rejection of both null hypotheses $\rho_1 = \rho_2 = 0$ and $\rho_1 = \rho_2$ imply the existence of threshold co-integration and asymmetric adjustment (thus price pairs exhibit nonlinear adjustment). The distribution of the test of the null of no co-integration is nonstandard and depends on the number of regressors included in the equation and the deterministic components.

According to Enders and Siklos (2001), τ is set to zero in most economic applications so that the cointegrating vector coincides with the attractor. However, in many applications, there is no a priori reason to expect the threshold to coincide with the attractor and therefore it becomes necessary to estimate the value of r along with the values of $\rho_1 = \rho_2$. Omitting the presence of threshold effects in the long-run equilibrium relationships will lead to misleading interpretations of equilibrium relationships because the co-integrating vector will not be consistently estimated (Gonzalo and Pitarakis, 2006).

In both the models, however, Chan's (1993) methodology which allows a grid search over potential thresholds that minimize the sum of squared errors from the fitted model to yield a super consistent estimate of the threshold was adopted. Thus, the estimated residuals were sorted in ascending order $\mu_1<\mu_2<\mu_3<\mu_4<\ldots\mu_t$ for TAR and $\Delta\mu_1< \Delta\mu_2<\Delta\mu_3< \Delta\mu_4<\ldots\Delta\mu_t$ for MTAR where T denotes the number of usable observations. The largest and smallest 15 percent of the values were eliminated and each of the remaining 70 percent of the series μ_t was considered as potential threshold.

Error Correction Method (ECM): The specification of standard VECM is given below

$$\Delta Y_t = \boldsymbol{\alpha_1} + \boldsymbol{\rho_1 e_1} + \sum_{i=0}^{n} \boldsymbol{\beta_1}\, \Delta Y_{t-i} + \sum_{i=0}^{n} \boldsymbol{\delta_1}\, \Delta X_{t-i} + \sum_{i=0}^{n} \boldsymbol{\gamma_1}\, \Delta Z_{t-i} \tag{4}$$

$$\Delta X_t = \boldsymbol{\alpha_1} + \rho_2 e_{i-1} + \sum_{i=0}^{n} \beta_i\, \Delta Y_{t-i} + \sum_{i=0}^{n} \delta_i\, \Delta X_{t-i} + \sum_{i=0}^{n} \gamma_i\, \Delta Z_{t-i} \tag{5}$$

The error correction representation sheds more light on the adjustment process in both short-run and long-run responsiveness to price changes which generally reflects arbitrage and market efficiency (Abunyuwah, 2007). The use of co-integration and error correction models help to explore further notions such as completeness, speed and asymmetry of price relationships as well as the direction of causality between two markets. The number of lags to be incorporated in the model before estimating the ECM will be determined using Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC).

Granger Causality Test: The presence and causality direction of long-run market price relationship can be assessed by using the Granger causality test directed within vector auto regressive (VAR) model. An autoregressive distributed lag (ADL) model for the Granger-causality test had been specified as below:

$$X_0 = \sum_{i=1}^{n} \alpha_i\, Y_{0-i} + \sum_{i=1}^{n} \beta_i\, X_{0-j} + \mu_1 \tag{6}$$

$$Y_0 = \sum_{i=1}^{n} \lambda_i\, Y_{0-i} + \sum_{i=1}^{n} \delta_i\, X_{0-j} + \mu_2 \tag{7}$$

Where,

μ_1 & μ_2 are error terms

t = time period,

X_0 & Y_0 are the price series of two different markets

To test the pattern of causality between two markets, F test was used.

The null hypothesis H_0: The lagged X_0 does not granger cause Y_0

The Alternative hypothesis H_1: The lagged X_0 granger cause Y_0

Here F statistic must be used in combination with the p value when deciding about the significance of the results.

If p value is less than the alpha level, individual p values are studied to find out which of the individual variables are statistically significant.

Results and discussion

Price instability

Prices of the agricultural commodities are influenced by many factors. The role of market intermediaries, domestic supply-demand mismatch due to the cob-web phenomenon in the market as well as the biological lags in the production process, weather and climatic factors influence the dynamic behavior in the agricultural price fluctuation. The higher growth of production with less instability would help in achieving sustainable growth. Analysis of fluctuations of prices

Table 1 Results of Cuddy Della Valle Index

Market	CV	Cuddy Della Valle
Kolar	72.54	70.59
Srinivaspur	76.15	74.92
Bangalore	76.16	74.93
Kolkata	54.43	51.65
Delhi	56.52	55.9
Chennai	67.84	65.86
Pimpalgaon	63.48	63.29

of commodities helps in knowing the nature of supply and demand conditions.

As per the results of Cuddy Della Valle Index value presented in Table 1, all the markets are considered to be highly unstable. Among the selected markets for study, Bangalore, Srinivaspur and Kolar markets (production markets) have highest instability with 74.93, 74.93 and 70.59 per cent, respectively. These values represent existence of very high instability in the prices of tomatoes in the markets considered. This may also lead to wholesale price inflation in the domestic markets, which, in turn, would reduce the consumption behavior of households. Further, the instability associated with the consumption markets (Kolkata, Delhi, Chennai and Pimpalgaon) is relatively less compared to production markets thereby indicating the scope for moving tomatoes from the production markets to distant consumption markets.

Correlation matrix

The results of the correlation matrix in Table 2 reveal that Chennai and Pimpalgaon markets were weakly correlated in prices. However, Kolar, Srinivaspur, and Bangalore markets were highly correlated in prices, due to the fact that these markets are located near to each other. Pimpalgaon market was weakly correlated with the other markets except with Delhi market, which is moderately correlated. Correlation coefficients however, are not a proof of market integration but rather are rough indicators of integration and efficiency. There have been criticisms against this approach by several authors such as Barrett (1996) and Negassa *et al.* (2003) who argued that testing of market integration based on correlation coefficients of local prices mask presence of other synchronous factors such as general price inflation, seasonality and population growth among others.

Unit root tests

The test of co-integration begins with the test of stationarity at different levels. Table 3 presents results of the evaluation of the univariate time series properties of the price series of the markets under study. Three different tests were conducted to verify the presence of a unit root in individual price series; an Augmented Dickey- Fuller (ADF) test, KPSS test and Zivot-Andrews test.

The test statistic rejected the null hypothesis of a unit root at level data for all the markets in the ADF, while KPSS test accepted (These tests have contradictory null hypothesis). To confirm the existence of a unit root in each price series with trend as deterministic part, the Augmented Dickey- Fuller (ADF) test was carried out. For all markets, the test statistic was unable to disprove the null hypothesis of a unit root in level data. As a result, it may be inferred that the markets are integrated into one another and have a similar long-run dynamic system.

Table 2 Zero Order Correlation Matrix for tomato prices

Markets	Kolar	Srinivaspur	Bengaluru	Kolkata	Delhi	Chennai	Pimpalgaon
Kolar	1						
Srinivaspur	0.878	1					
Bengaluru	0.797	0.836	1				
Kolkata	0.711	0.729	0.649	1			
Delhi	0.599	0.582	0.549	0.788	1		
Chennai	0.870	0.904	0.828	0.712	0.579	1	
Pimpalgaon	0.335	0.274	0.257	0.404	0.503	0.266	1

Note The correlation coefficients are significant at 0.01 level of probability

Table 3 Unit root tests for tomato markets

Market	ADF level	KPSS level
Kolar	-5.91[a]	0.82
Srinivaspur	-5.88[a]	0.42
Bangalore	-6.64[a]	0.44
Kolkata	-5.78[a]	0.92
Delhi	-5.99[a]	0.33
Chennai	-5.77[a]	0.73
Pimpalgaon	-6.11[a]	0.23

Note [a] denotes significance at 0.01 level of probability. The critical value for ADF at 1 is -3.98 for constant and trend specification.

The Zivot-Andrews unit root test, which allows for a single break point, was used to examine the structural break issue. Where t-Min is the minimum ADF test statistic and the probable break date is obtained, the break in intercept, trend, and both were taken into consideration. The test statistic was successful in rejecting the null hypothesis of unit root process when compared with the critical values (Table 4). All the tests for stationary/ unit root tests rejected the null hypothesis at level. This implies that the markets are integrated of the same order and share common long-run dynamics stochastic process. This test was used mainly to overcome the disadvantages of ADF test.

Co-integration

The approach for testing the integration of spatially separated markets is based on the fact that deviations from equilibrium conditions of two non-stationary variables should be stationary. This implies that, while price series may ramble extensively, market pairs should not diverge from one another in the long run (Abdulai, 2007).

Table 4 Zivot Andrews Unit Root test under Single Break Point

Market	Level	Potential break position	Date
Kolar	-5.7584[b]	359	17-Nov-17
Srinivaspur	-5.2426[b]	360	24-Nov-17
Bangalore	-8.3913[b]	360	24-Nov-17
Kolkata	-4.9683[b]	362	8-Dec-17
Delhi	-5.2908[b]	361	1-Dec-17
Chennai	-6.2738[b]	285	17-Jun-16
Pimpalgaon	-5.8263[b]	292	5-Aug-16

Note [b]denotes significance at 0.05 level of probability. The critical value for the test statistic at 95 per cent confidence level was -4.80.

Johansen Test of Co-integration

On the basis of the ADF test, the Johansen co-integration test frame work was employed to examine the long run equilibrium relationship among the selected markets of tomato and depicted in Table 5. The results were successful in rejecting the null hypothesis and confirming that there exists a co-integration between the markets. The results were found in accordance with the research conducted by Chandraprabha (2012), in which the author analysed the market co-integration between Kolar and Vaddahalli markets and found these markets to be co-integrated. From the results of Johansen co-integration test, it can be concluded that the selected markets exhibit long run co-integration between the market pairs.

Threshold and asymmetric transmission modeling

Here, test for possibilities of asymmetric adjustments and threshold Co-integration (non-linearity) other than assuming symmetric and linear relations as in the Johansen tests, were tested. In this regard, the Threshold Auto Regression (TAR) and its extension model called

Table 5 Johansen's co-integration test for selected tomato markets

Market pair	Null hypotheses	Trace statistic
Kolar-Srinivaspur	$r = 0$	69.6[a]
	$r \leq 1$	33.21[a]
Kolar-Bengaluru	$r = 0$	132.1[a]
	$r \leq 1$	33.47[a]
Kolar-Kolkata	$r = 0$	70.18[a]
	$r \leq 1$	30.14[a]
Kolar-Delhi	$r = 0$	91.58[a]
	$r \leq 1$	38.26[b]
Kolar-Chennai	$r = 0$	94.72[a]
	$r \leq 1$	32.45[b]
Kolar-Pimpalgaon	$r = 0$	94.6[b]
	$r \leq 1$	31.19[b]

Note [a] and [b] denote significance at 1 per cent and 5 per cent level of probability.

a "momentum" Threshold Auto Regression (M-TAR) with asymmetric adjustment as developed by Ender and Siklos (2001) was estimated to examine whether the prices of markets under study exhibit threshold co-integration and asymmetric adjustment. The null hypotheses were no co-integration ($\rho_1 = \rho_2 = 0$) and symmetric adjustment ($\rho_1 = \rho_2$).

The results of M-TAR model with zero thresholds (Table 6) revealed that all the markets considered for analysis exhibit a pair wise co-integration with the Kolar market, since Kolar is the second largest tomato market in the Asia. It is evident by rejection of null hypothesis of no co-integration ($\rho_1 = \rho_2 = 0$) at 1 per cent level of probability. The null hypothesis of symmetric price transmission ($\rho_1 = \rho_2$) was rejected in all market pairs with the reference market except with Srinivaspur. The Kolar market exhibited asymmetric price transmission mechanism with all other markets considered, except the Srinivaspur market which exhibited symmetric effect toward long-run equilibrium, due to the fact that these two markets are in the same locality with less distance between the markets. Here, the lags were selected based on the BIC since those estimates were more than AIC. The model considers the threshold value to be zero, in economic sense zero threshold would not exist, hence the consistent M-TAR model was run.

The results of the consistent M-TAR Model (CM-TAR) are presented in Table 7. The CM-TAR models revealed that all the variable pairs were co-integrated and have asymmetric price transmission, except Srinivaspur market. The TAR assumes zero as the threshold value, which is economically not true. Hence, CMTAR model is analysed. The point estimates of Kolar-Bangalore markets relationship were found to be $\rho_1 = -0.168$, and $\rho_2 = -0.684$, which indicates that 16.8 per cent of positive deviations and 68.4 per cent of negative deviations from the equilibrium were eliminated in one month. Since $|\rho_1|<|\rho_2|$, indicates markets players respond quickly and swiftly to the positive deviations than negative deviations. This may also be due to the market power, market agents react quickly and/ or more completely to shocks that squeeze their marketing margin than to corresponding shocks that stretches them (Amonde *et al*., 2009). All other market pairs such as Kolar-Kolkata, Kolar-Delhi, Kolar-Chennai and Kolar-Pimpalgaon had point estimates for positive deviations greater than negative deviations ($|\rho_1|>|\rho_2|$). These markets respond more to the positive deviations than the negative deviations. From Table 6 the obtained threshold values indicate that, if the transaction cost per quintal falls below the respective price then there won't be any price adjustments.

Asymmetric TVECM (Threshold Vector Error Correction Model)

By using a two-regime TVEC model, the price

Table 6 Results of M-TAR Model specification (null with Zero Threshold)

Variable	KS	KB	KK	KC	KD	KP
ρ_1	-0.123	-0.145	-0.049	-0.301	-0.137	-0.193
	(0.041)	(0.063)	(0.03)	(0.047)	(0.03)	(0.033)
ρ_2	-0.221	-0.4	-0.206	-0.175	-0.144	-0.169
	(0.039)	(0.064)	(0.033)	(0.053)	(0.04)	(0.04)
$\rho_1 = \rho_2 = 0$	19.884[a]	20.072[a]	20.942[a]	23.878[a]	17.16[a]	21.719[a]
$\rho_1 = \rho_2$	3.131[NS]	11.186[a]	12.3[a]	3.672[a]	0.019[a]	0.254[a]
Lags	1	4	1	2	1	7
LB(4)	0.647	0.971	0.809	0.938	0.994	0.992
LB(8)	0.653	0.978	0.551	0.716	0.784	0.999
LB(12)	0.583	0.946	0.58	0.701	0.733	0.985
AIC	6251	6748.14	6502.2	6459.6	6589.02	6639.38
BIC	6267.52	6769.18	6514.6	6474.31	6601.42	6657.13

Note 1. Figures in the parenthesis indicate standard errors.
2. [a] indicate significance at 0.01 level of probability; NS: Non Significant
3. KS: Kolar-Srinivaspur, KB: Kolar-Bangalore, KK: Kolar-Kolkata, KC: Kolar-Chennai, KD: Kolar-Delhi, KP: Kolar-Pimpalgaon
4. AIC- Akaike's Information Criteria, BIC- Bayesian Information Criteria, LB- Ljung-Box Q- statistic for residual autocorrelation

Table 7 Results of Consistent M-TAR Model Specification

Variable	KS	KB	KK	KD	KC	KP
Threshold value	98	209	335	541	183	246
ρ_1	-0.187 (0.052)	-0.168 (0.052)	-0.205 (0.053)	-0.209 (0.045)	-0.255 (0.041)	-0.353 (0.054)
ρ_2	-0.169 (0.034)	-0.684 (0.083)	-0.102 (0.025)	-0.112 (0.028)	-0.221 (0.071)	-0.142 (0.03)
$\rho_1 = \rho_2 = 0$	18.242[a]	34.368[a]	16.036[a]	18.887[a]	21.979[a]	28.999[a]
$\rho_1 = \rho_2$	0.087 [NS]	38.116[a]	3.061[a]	3.235[a]	3.202[b]	13.544[a]
Lags	1	4	1	2	1	7
LB(4)	0.591	0.952	0.753	0.992	0.945	0.989
LB(8)	0.668	0.966	0.731	0.803	0.615	0.998
LB(12)	0.581	0.897	0.532	0.665	0.619	0.978
AIC	6347.08	6777.9	6620.18	6691.81	6542.94	6639.42
BIC	6363.67	6805.97	6636.77	6708.4	6563.66	6680.76

Note 1. Figures in the parenthesis indicate standard errors.
2. [a] indicate significance at 0.01 level of probability, [b] indicate significance at 0.05 level of probability
3. AIC- Akaike's Information Criteria, BIC- Bayesian Information Criteria, LB- Ljung-Box Q- statistic for residual autocorrelation

transmission dynamics of the tomato market prices were investigated and presented in Table8. Two-regime when relative price discrepancies exceed a certain threshold of transaction costs, trade between the physically separated markets occurs. TVECM enables us to characterize this trading environment. When trade encourages market integration and causes price movements and responses between markets, it is known as atypical regime in this instance. Markets may co-integrate in this manner under this unusual regime. When transaction costs are lower than relative price disparities between market places, the usual regime prevails. In this scenario, there is no incentive to trade, therefore price changes within the transaction cost band and between markets will not be related.

Kolkata, Chennai and Delhi consumption markets were analyzed with respect to Kolar market. Kolkata and Delhi markets respond more to the negative price changes in Kolar market, whereas Chennai market is responsive to the positive price changes in the Kolar market. Kolkata market adjusts to eliminate 14.5 per cent of price changes from disequilibrium towards equilibrium as a result of perturbation of prices in the reference market. Distributed lag asymmetric effect was found for Kolar for its own price and asymmetric effect on Chennai and Delhi market. The cumulative asymmetric effect or in long run, the price change in Kolar market, not only affects Kolar, but also the other consumption markets. In the long run, the prices deviation in Kolar market are independent on price shocks from any of the distant consumption market, However, in short run there are adjustments for change in consumption market prices. The half-life time calculated for adjustments to equilibrium revealed that, Kolkata takes 3 days for adjustment towards equilibrium as a result of price shocks in the reference market whilst Chennai takes 5 days and Delhi takes approximately 3 days for complete adjustment towards equilibrium due to perturbation in the prices in the reference market (Table 8).

From Table 8, the results revealed that, Bangalore market responds to negative deviations of prices in Kolar market. In the short run, deviations in Kolar market were affected by its own prices and as well as the changes in prices of Bangalore market. The long run price dynamics of Kolar market is influenced by the price changes in the Bangalore market. The point estimates of the adjustment parameters imply that Bangalore prices adjusted to eliminate about 73.5 per cent of prices change above the threshold value for the negative deviations. The Bangalore market was likely to exhibit asymmetric path of adjustment to equilibrium in the long-run to price changes created by Kolar prices. The half-life time calculated proved that, Kolar takes two days to reach equilibrium by adjusting to the price changes of Bangalore, whereas Bangalore requires

Table 8 Results of Asymmetric Vector Correction model of tomato markets

Variables	Kolar	Kolkata	Kolar	Chennai	Kolar	Delhi	Kolar	Bangalore	Kolar	Pimpalgaon
Ect^{+}	-0.12	-0.079	-0.088[b]	0.268[a]	-0.11[a]	0.065[b]	-0.083	0.072	-0.356 [a]	0.048
Ect^{-}	-0.04	0.145[a]	-0.197[b]	0.128	0.033	0.11 [a]	-0.016	0.735[a]	-0.129[a]	0.076
$\alpha_1^+ = \alpha_1^-$	8.24[a]	2.837[b]	13.65[a]	10.77[a]	13.08[a]	3.02[b]	18.13[a]	2.722[b]	0.206	0.062
$\alpha_2^+ = \alpha_2^-$	0.28	0.651	0.553	0.455	0.701	1.039	0.22	1.056	0.88	3.393[b]
$\alpha_3^+ = \alpha_3^-$	-	-	-	-	-	-	0.001	0.202	0.008	1.575
$\alpha_4^+ = \alpha_4^-$	-	-	-	-	-	-	0.051	1.43	0.08	6.019[b]
$\alpha_5^+ = \alpha_5^-$	-	-	-	-	-	-	-	-	0.714	0.209
$\alpha_6^+ = \alpha_6^-$	-	-	-	-	-	-	-	-	0.001	6.973[a]
$\alpha_7^+ = \alpha_7^-$	-	-	-	-	-	-	-	-	0.234	10.859[a]
$\beta_1^+ = \beta_1^-$	0.56 [b]	4.993	1.509	2.123	0.02	0.18	8.687[a]	3.428[b]	0.532	9.861[a]
$\beta_2^+ = \beta_2^-$	1.5	1.39	1.6	1.46	2.23	7.82[a]	8.536[a]	1.389	0.075	2.832[b]
$\beta_3^+ = \beta_3^-$	-	-	-	-	-	-	1.495	0.019	0.713	2.02
$\beta_4^+ = \beta_4^-$	-	-	-	-	-	-	2.721	2.016	0.521	3.18[b]
$\beta_5^+ = \beta_5^-$	-	-	-	-	-	-	-	-	0.004	0.008
$\beta_6^+ = \beta_6^-$	-	-	-	-	-	-	-	-	0.007	6.057[a]
$\beta_7^+ = \beta_7^-$	-	-	-	-	-	-	-	-	1.187	2.37
$\sum_{i=1}^{7} \alpha_i^+ = \sum_{i=1}^{7} \alpha_i^-$	4.36[b]	4.14[b]	7.71[a]	11.11[a]	5.70[b]	0.38	0.579	5.68[b]	0.718	0.965[a]
$\sum_{i=1}^{7} \beta_i^+ = \sum_{i=1}^{7} \beta_i^-$	0.13	0.58	0.56	0.03	1.18	3.62[b]	11.93[a]	0.213	0.554	10.826
$\delta^+ = \delta^-$	0.845	5.081[b]	1.178	0.84	3.501[b]	0.47	0.363	10.008[a]	8.864[a]	0.095
Half Life time	0.39	0.46	0.55	0.74	0.36	0.4	0.299	0.415	0.957	0.332

Note [a] and [b] indicate significance at 0.01 level and 0.05 level of probability, respectively. Ect^{+} & Ect^{-} error correction term for positive and negative deviations, $\alpha^+_i = \alpha^-_i$ lagged symmetry/ short run deviations of price in reference market (Kolar market), $\beta^+_i = \beta^-_i$ short run deviations of Price in Bangalore or Pimpalgaon market

$\Sigma\alpha^+_i = \Sigma\alpha^-_i$, $\Sigma\beta^+_i = \Sigma\beta^-_i$ represents cumulative/ long term deviations of price in reference and other markets.

almost three days to adjust to price change equilibrium. In the case of Kolar-Pimpalgaon market, Kolar market responds to both positive and negative discrepancies in the price, it responds quickly to the positive deviations in the price than the negative deviations of its own price, as . The lagged symmetry of Pimpalgaon market was significant in short run as it responds to the price change of Kolar market and also to its own prices. In the long run, the Pimpalgaon market responds to the price changes of Kolar.

Granger causality test

The causality in tomato markets considered in the study was examined through Granger Causality technique. The results are depicted in Table 9 and Fig. 1. It is evident from the results that there is an existence of both unidirectional and bidirectional causality between tomato markets. Unidirectional causality was found between Kolkata-Kolar and Srinivaspur-Kolar. It means that a price formation in the former market in each pair granger cause the price changes in the latter market, whereas the price change in the latter market is not providing feed back to the price change in the former market.

Bidirectional causality exists between Bangalore-Kolar markets, Kolar-Delhi markets, Kolar-Chennai and Kolar-Pimpalgaon markets. In these cases, the former market in each pair granger causes the wholesale price formation in the latter market, which, in turn, provides the feedback to the former market as well. Results matched the estimates of Nandini *et al.* (2019), wherein the Granger causality test was employed to investigate the kind and direction of price transmission between market pairs, and it indicated that most markets had

Table 9 Results of Granger Causality Test

Null Hypothesis	F cal	p value
BANGALORE (x) does not Granger cause KOLAR	3.051[a]	0.002
KOLAR (y) does not Granger cause BANGALORE	4.75[a]	0.02
KOLKATA (x) does not Granger cause KOLAR	1.855[NS]	0.117
KOLAR (y) does not Granger cause KOLKATA	4.796[a]	0.001
DELHI (x) does not Granger cause KOLAR	8.832[a]	0.001
KOLAR (y) does not Granger cause DELHI	4.345[a]	0.002
PIMPALGAON (x) does not Granger cause KOLAR	5.445[a]	0
KOLAR (y) does not Granger cause PIMPALGAON	2.859[a]	0
SRINIVASPUR (x) does not Granger cause KOLAR	0.155 [NS]	0.856
KOLAR (y) does not Granger cause SRINIVASPUR	5.119[a]	0.006
CHENNAI (x) does not Granger Cause KOLAR	11.967[a]	0
KOLAR (y) does not Granger Cause CHENNAI	4.363[b]	0.013

Note [a] and [b] indicate significance at 0.01 level and 0.05 level of probability, respectively; NS: Non Significant

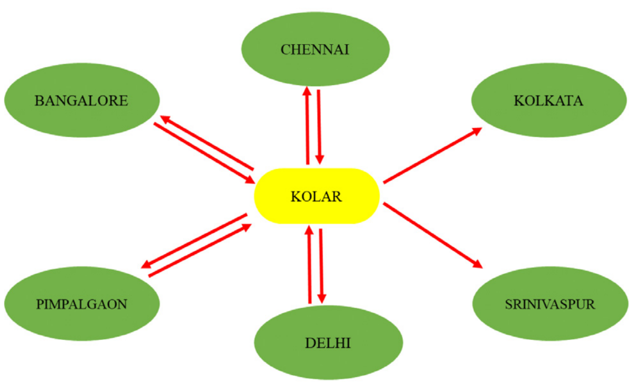

Figure 1 Granger causality directions between the tomato markets

bidirectional relationships whereas a small number of markets have unidirectional relationships in major vegetable markets in India. The discovered results show that the co-integration of the production and consumption markets hypothesis is accepted.

Conclusions

The study was conducted to assess the degree of the spatial market integration in distantly located three regional tomato markets in India, using co-integration and VECM model to the weekly wholesale prices from January, 2010 to March, 2020. According to the findings, the chosen markets—Kolar, Srinivaspur, Bangalore, Chennai, Kolkata, Pimpalgaon, and Delhi—are highly interconnected and have reached their long-term equilibrium. Between these market places, there are major differences in the rate of price transmission. The Granger Causality test findings showed that there is unidirectional causality from Kolkata to Kolar. This needs the attention of the policy makers to strengthen the use of information technology for flow of market information regularly and this will certainly help the farmers for increasing their income. On the whole, the study suggests that the regional markets for Tomato in India are strongly co-integrated and this encourages private traders' participation. Further, it was also observed that the distant consumption markets are less volatile in terms of prices compared to local production markets thereby suggesting that it is desirable to take advantage of the higher prices prevalent in the distant markets and increase the incomes.

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Received 13 November 2021 Accepted 19 March 2022

Agricultural Economics Research Review 2022, 35 (2), 119-134
DOI: 10.5958/0974-0279.2022.00035.0

Performance comparison of ARIMA and Time Delay Neural Network for forecasting of potato prices in India

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Abstract Accurate, timely and adequate forecasting of perishable crops have significant impact on the farmers' well-being in Indian agriculture. The time series data of these perishable commodities usually violate the assumptions of time-series datasets i.e., linearity and stationarity. In such conditions, the development and selection of the appropriate forecasting models for agricultural commodities plays an imperative role for various policy decisions. In this study, we are focused on comparison of ARIMA (linear) and TDNN (non-linear) models to accurately model the potato price. The inclusion of these non-linear model in this study handles nonstationary, nonlinear, and non-normal features of datasets simultaneously. The findings revealed that TDNN outperformed ARIMA, and it is regarded as the best fit model in terms of minimal RMSE and MAPE value. The identification of the best forecasting model and accurate forecasting of market prices would help all the stakeholders to take appropriate decisions.

Keywords Potato, Price, Forecasting, ARIMA, TDNN

JEL codes C53, Q02, Q11, Q12

Agricultural commodity prices are often volatile as these are heavily impacted by factors which are unpredictable (Kumar et al. 2022). Price volatility plays a crucial role in promulgating policies with dynamic political and economic contexts (Kalkuhl, Von, and Torero 2016). Price volatility is widely recognized to destabilize farm revenue and impede farmers from making optimal investments and resource utilization (Schnepf 1999). Higher volatility reduces overall welfare of the economy in the long term (Chavas, Hummels, and Wright 2014). Policymakers, as well as other stakeholders in agricultural commodity marketing chain require price modelling and forecasting (Lama et al. 2015). From a financial perspective, forecasting volatility of agriculture commodity futures helps to assess and hedge risks associated with the contracts and provides the policy makers with tools to evaluate different scenarios (Sharma 2015). A short-term market price forecasting has been a challenge for many decades because of too many factors which cannot be accurately predicted. (Li, Xu and Li 2010). Time series investigation has unavoidable application particularly in agriculture. One of the most important and widely used time series models is the autoregressive integrated moving average (ARIMA) model (Gupta, Patra, and Singh 2019). Lots of application of ARIMA model can be found in the literature (Paul, Alam, and Paul 2014; Paul, Gurung, and Paul 2015; Gupta, Rao, and Singh 2018; Gupta, Patra, and Singh 2019; Paul, Paul, and Bhar 2020). ARIMA model has gained much popularity in modeling linear dynamics but it fails to capture the nonlinearity present in the series. The real-world price data of agro-products and its underlying market changes are often nonlinear in nature, and therefore, linear models may not be suitable when market changes frequently. To overcome the restriction of the linear models and to account for certain nonlinear patterns observed in real problems, several classes of nonlinear models have been proposed in the literature (Paul and Garai 2021; Jha and Sinha 2013). Recently, the use of neural network models in forecasting agriculture phenomenon is getting more attention (Jha, Thulasiraman, and Thulasiram 2009; Paul and Sinha 2016; Zhang et al. 2020). Numerous comparative studies of traditional models and artificial neural networks (ANNs) have been conducted, for example, Hill, O'Connor, and Remus (1996), Chin and Arthur (1996), Elkateb, Solaiman, and Turki (1998) and Paul and Garai (2021) which proved artificial neural networks to be a superior method for forecasting.

The conspicuous element of numerous time series of different horticultural items, primarily the transitory ones, is the nearness of nonlinearity, non-normality and nonstationarity. Among those, potato exhibits high degree of price volatility (Singh, Pynbianglang, and Pandey 2017). Potato price in India is determined by free market conditions that depend on the supply which is highly affected by changes in area under cultivation, unexpected weather conditions, demand of the potato from the major cities etc. (Sreepriya and Sidhu 2020). In the current study, an attempt has been made to assess the forecasting performance of two methods, the ARIMA model, the TDNN model for forecasting the Potato price in the selected Indian markets.

Material and methods

The monthly wholesale price (INR per qtl) of potato in India traded in Azadpur (Delhi), Burdwan (West Bengal), Agra (Uttar Pradesh), Ahmadabad (Gujarat), Jalandhar (Punjab), Bangalore (Karnataka), and Mumbai (Maharashtra) markets was utilized in this study. These markets were chosen based on their percentage share of total potato market arrival. The data for each market was gathered from the AGMARKNET portal. The price series spanned a total of 120 months, from January 2012 to December 2021, with 80% (96 months) utilized as a training set and 20% (24 months) used as a testing set. For data analyses purpose R-statistical package was used.

Test for normality: Skewness, Kurtosis, and density plots were used to determine data normality. The *Shapiro–Wilk test* given by Shapiro and Wilk (1965) was used to provide evidence of normality or non-normality of the datasets.

Test for stationarity: The first stage in price series analysis is to look at the stationarity of each price series individually. A series is considered stationary if its statistical properties, such as mean and autocorrelation structures, remain constant over time. To determine the presence of a non-seasonal unit root in the price series, the Augmented Dickey Fuller (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron 1988) tests were used.

ARIMA model: Introduced by Box and Jenkins (1976), the ARIMA model has been one of the most popular approaches for forecasting. In an Auto-Regressive Integrated Moving Average (ARIMA) model, time series variable is assumed to be a linear function of previous actual values and random shocks. Since seasonal time series data is taken for this study. ARIMA model can be extended easily to handle seasonal aspects denoted as ARIMA(p,d,q)(P,D,Q)$_{[s]}$, where the small letter parentheses part (p,d,q) indicates the non-seasonal part of model while the capital letter part (P,D,Q)$_{[s]}$ indicates the seasonal part of model, s being the number of periods per season (Barathi et al. 2011; Gupta et al. 2019). The general seasonal autoregressive integrated moving average (SARIMA)is given in equation 1:

$$\Phi_P(B^s)\phi_p(B)\,{}_s^{D}{}^{d}\,Y_t = \theta_q(B)\Theta_Q(B^s)_t \qquad \ldots(1)$$

where,

$\Phi_P(B^s) = (1 - \Phi_1 B^s - \ldots - \Phi_P B^{sP})$ is the seasonal AR operator of order P;

$\phi_p(B) = (1 - \phi_1 B - \ldots - \phi_p B^p)$ is the regular AR operator of order p;

${}_s^D = (1 - B^s)^D$ represents the seasonal differences and ${}_s^D = (1 - B)^d$ the regular differences;

$\Theta_Q(B^s) = (1 - \Theta_1 B^s - \ldots - \Theta_Q B^{sQ})$ is the seasonal moving average operator of order Q;

$\theta_q(B) = (1 - \theta_1 B - \ldots - \theta_q B^q)$ is the regular moving average operator of order q;

τ is a white noise process.

In an ARIMA model, the estimated value of a variable is supposed to be a linear combination of the past values and the past errors. The agricultural commodities price data are inherently noisy in nature and are volatile too therefore ARIMA model will not be enough to deal with such series, as it is limited by assumptions of linearity and homoscedastic error variance.

Brock- Dechert-Scheinkman (BDS) test: The BDS test is a non-parametric technique of testing for nonlinear patterns in time series and developed in Brocket al. 1996. The null hypothesis states that data in a time series is distributed independently and identically. The test is unique in its ability to discover nonlinearities in data that are not dependent on linear relationships. The residuals of the best-fitting ARIMA model were used to test for nonlinearity in the data.

Time Delay Neural Networks (TDNN): This has been developed as a viable alternative to classic statistical models in order to overcome the constraint of non-linearity (Darbellay and Slama, 2000). TDNNs are a data-driven, non-linear, nonparametric self-adaptive approach with a few a priori assumptions about the data series (Zhang, Patuwo, and Hu 1998). It can be treated as one of the multivariate nonlinear nonparametric statistical methods (White, 1989; Cheng and Titterington, 1994). As a result, it's best for forecasting agricultural price series, which are typically noisy and nonlinear. Furthermore, ANNs are universal approximators since they can map any nonlinear connection as long as the structure is acceptable and sufficient training data is available.

The number of layers and total number of nodes in each layer of an ANN for a specific issue in time series prediction must be determined. Because there is no theoretical foundation for establishing these characteristics, it is normally discovered by experimentation. Given a sufficient number of nodes in the hidden layer and sufficient data points for training, neural networks with one hidden layer may approximate any non-linear function. We employed a neural network with one hidden layer in this research. The number of input nodes that are lagged observations of the same variable plays an important role in time series analysis since it aids in modelling the autocorrelation structure of the data. It is usually preferable to use a hidden layer model with fewer nodes, since this improves out-of-sample prediction accuracy and minimizes the issue of over-fitting. The general expression for the final output value y_{t-1} in a multi-layer feed forward time delay neural network is given by equation (2)

$$y_{t+1} = g[\textstyle\sum_{j=0}^{q} \alpha_j f(\sum_{i=1}^{p} \beta_{ij}\, y_{t-1})] \qquad ...(2)$$

where, f and g denote the activation function at the hidden and output layers, respectively; p is the number of input nodes (tapped delay); q is the number of hidden nodes; β_{ij} is the weight attached to the connection between i^{th} input node to the j^{th} node of hidden layer; α_j is the weight attached to the connection from the j^{th} hidden node to the output node; and y_{t-i} is the i^{th} input (lag) of the model. Each node in the hidden layer gets the weighted sum of all inputs, including a bias term whose value of the input variable is always one. Each hidden node then transforms the weighted sum of input variables using the activation function f, which is often a non-linear sigmoid function. Similarly, the output node gets the weighted total of all hidden node outputs and creates an output by converting the weighted sum with its activation function g. In time series analysis, the Logistic Sigmoid function (f) and the Identity function (g) are frequently used. The logarithmic function is written as an equation (3)

$$f(y) = \frac{1}{1+e^{-y}} \qquad ...(3)$$

For p tapped delay nodes, q hidden nodes, one output node and biases at both hidden and output layers, the total number of parameters (weights) in a three layer feed forward neural network is q(p + 2) + 1. For a univariate time series forecasting problem, the past observations of a given variable serves as input variables. The ANN model attempts to map the following function

$$y_{t+1} = f\left(y_t, y_{t-1,\ldots} y_{t-p+1}, w\right) + \varepsilon_{t+1} \qquad \ldots(4)$$

where, y_{t-1} pertains to the observation at time t+1, p is the number of lagged observation, w is the vector of network weights, and y_{t-1} is the error-term at time t+1.

Diebold–Mariano (DM) test: In order to assess whether the observed differences in forecasting power across models are statistically significant, the Diebold–Mariano (DM) test for predictive accuracy was performed among the models which present best forecasting power inside each class (Diebold and

Table 1 Descriptive statistics for the potato prices of major markets in India

Particulars	Agra	Ahmedabad	Bangalore	Burdwan	Jalandhar	Mumbai	Azadpur
Mean	938.35	1163.07	1463.65	1106.35	584.44	1336.00	1064.34
Median	872.06	1048.69	1375.24	1011.58	525.88	1228.33	947.67
Min	333.48	464.71	763.24	317.14	151.67	609.09	399.68
Max	2858.75	2847.06	3242.05	3625.24	2078.26	3254.00	2944.76
Range	2525.27	2382.35	2478.81	3308.10	1926.59	2644.91	2545.08
SE	43.31	43.61	38.37	51.45	32.39	39.98	48.50
SD	474.39	477.77	420.29	563.58	354.87	437.98	531.30
Skewness	1.34	1.00	1.19	1.44	1.52	1.31	1.26
Kurtosis	2.30	0.58	2.20	3.11	2.98	2.77	1.67
CV	50.56	41.08	28.72	50.94	60.72	32.78	49.92
CDVI	1.81	0.42	2.87	5.97	0.89	2.47	0.39

Mariano 1995). The DM test approach aims to test the null hypothesis of equality of accuracy against the alternative of significantly different accuracy. The best model was selected on the basis of significance of DM test.

Results and discussion

In Table 1, we compute the summary statistics of prices of potato in major markets of India. The descriptive statistics of potato prices in different wholesale markets indicated a clear-cut difference among different wholesale markets in India . The wholesale average prices of potato were the highest (INR 1464 per quintal) in the case of Bangalore market in Karnataka state with minimum of INR 763 per quintal and maximum of INR 3242 per quintal, indicating the lack of production in the market despite growing consumption demand for potato-based products in the state. Jalandhar market in Punjab received the lowest average prices (INR 584 per quintal) of Potato with minimum of INR 151.67 per quintal and maximum of INR 2078 per quintal. The average wholesale price varied between in range of INR 584 to 1463 per quintal in all the markets of India. The selected price series were positively skewed ranging from 1.01 to 1.52, indicating the distribution was long on the right side as compared to the left. Estimates of kurtosis showed that the pattern of prices among all the selected markets of the different states were non-stationary with upto-kurtic distribution, which implying a relatively peak curve than a normal distribution. The standard deviation in wholesale prices was more than 400 in unit among all the markets however, it was the highest in market Burdwan of the West Bengal state. Further, the skewness and kurtosis estimates imply that the monthly prices in the respective markets are widely spread around its mean.

In time series analysis, the first and foremost step is to plot the data. We have plotted all the price series of all the selected markets (Figure 3). From the time plot of the price series, almost a similar pattern has been observed for all the markets. However, we have replaced the outliers by using standard practices such as interpolation as these price spikes has been seen during month of November of the year 2012 and 2019. Another important property of the time series analysis is checking whether the price series is normally distributed or not. We have used the Shapiro-Wilk test (Shapiro and Wilk, 1965). The null hypothesis for this test is the price series of all the selected markets are normally distributed and results are depicted in Table 2, wherein our null hypothesis was rejected (alternative

Table 2 Shapiro-Wilk test to check the normality for the potato prices of major markets in India

Particulars	Agra	Ahmedabad	Bangalore	Burdwan	Jalandhar	Mumbai	Azadpur
Test-Statistics	0.895	0.921	0.928	0.895	0.869	0.916	0.892
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

hypothesis accepted). It depicts that the datasets of all the selected markets are non-normally distributed. This argument can be supported by the Kernel densities given in Figure 1, which shows highly positive skewness in all the selected markets.

Before proceeding to the subsequent step, it is pertinent to see the price series of the selected markets must be stationary. If not, then further statistical practices such as differencing has to be applied to make the price stationary because ARMA methodology can only be applied for the stationary series.

The "SEAS" test, a measure of seasonal growth strength was used to test the presence of seasonal unit root, where seasonal differencing is suggested if the seasonal strength exceeds 0.64 (Wang, Smith and Hyndman, 2006). The data were seasonally adjusted if the seasonal unit root were present. Augmented Dickey-Fuller test (Dickey and Fuller, 1979) and Phillips-Perron test (Phillips and Perron, 1992) have been applied to see the presence of non-seasonal unit root in the seasonally adjusted series. The results of ADF and PP test are illustrated in Table 3. Non-rejection of null hypothesis (presence of unit-root) of ADF and PP test at 5% level of significance indicates that differencing is required to make the price series stationary for the selected markets otherwise the data is stationary.

ARIMA

In this study, we exercised many ARIMA models while

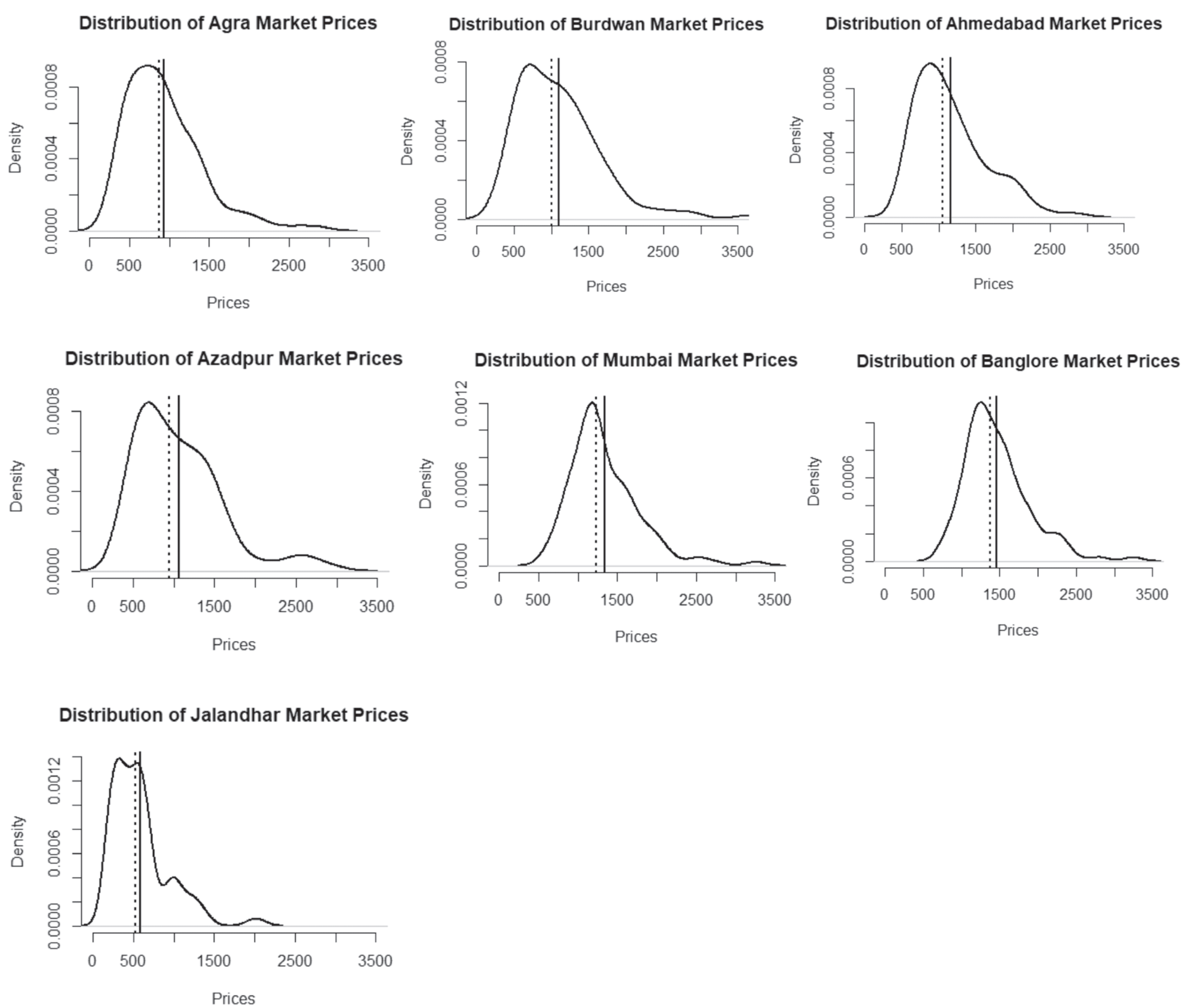


Figure 1 Kernel Density Plot for the potato prices of major markets in India

Table 3 Stationarity test for the potato prices of major markets in India

Particulars	Agra	Ahmedabad	Bangalore	Burdwan	Jalandhar	Mumbai	Azadpur
ADF	-3.998	-3.299	-3.354	-4.227	-3.279	-2.996	-3.916
	(0.012)	(0.075)	(0.065)	(0.010)	(0.072)	(0.163)	(0.016)
PP	-23.781	-22.710	-21.195	-28.980	-18.05	-21.025	-26.779
	(0.025)	(0.033)	(0.046)	(0.010)	(0.092)	(0.048)	(0.013)

Note The figures in parentheses are p-values of their respective figures

selecting best model for better forecasting in all the selected markets and results are shown in Annexure I. The performance of different models are evaluated on the basis of RMSE and MAPE. The various fitted ARIMA models are identified by above process and presented in Table 4. The evaluation criterion suggested that the best fit model for Agra market was {(1,0,1) (1,1,0)}$_{[12]}$ followed by Burdwan {(2,0,0) (2,1,1) $_{[12]}$}, Ahmedabad {(3,0,1) (1,1,1) $_{[12]}$}, Azadpur {(1,0,1) (1,1,0) $_{[12]}$}, Mumbai {(1,0,1) (0,1,1) $_{[12]}$}, Bangalore {(1,1,2) (0,0,0)$_{[12]}$} and Jalandhar {(2,0,1) (0,0,0)$_{[12]}$}. Additionally, among all the selected markets, the value of RMSE ranged between 232.76 to 571.98 among all the selected markets of India. However, the lowest value of RMSE recorded in Bangalore that suggest ARIMA {(1,1,2) (0,0,0)} $_{[12]}$ is the best price forecasting model among all the markets.

Non-linear test

Before proceeding with the TDNN, it is important to find whether the residuals of the best fitting ARIMA model of the selected markets are non-linear or not. If there is nonlinearity, then nonlinear models must be used to test for nonlinearity in the data. The study used BDS non-linearity model to test the residuals of the ARIMA model. The results of nonlinearity test presented in Table 5, reveal strong rejection of linearity in the case of residuals of the price series. In other words, the analysis has indicated the existence of some hidden structure left unaccounted in the residuals of

Table 4 Comparison of prediction performance of the selected models for the potato prices of selected markets of India

Market Name	ARIMA			Artificial Neural Network		
	Model	RMSE	MAPE	Layers	RMSE	MAPE
Agra	(1,0,1)	484.662	23.79	5:2s:11	303.16	16.27
	(1,1,0)$_{[12]}$	(129.221)	(11.47)		(68.47)	(5.74)
Burdwan	(2,0,0)	432.105	29.45	3:2s:11	299.73	20.14
	(2,1,1) $_{[12]}$	(119.072)	(6.93)		(82.74)	(5.63)
Ahmedabad	(3,0,1)	543.378	39.66	1:4s:11	216.49	12.49
	(1,1,1) $_{[12]}$	(136.013)	(9.52)		(61.96)	(4.03)
Azadpur	(1,0,1)	571.98	56.38	2:2s:11	265.99	24.15
	(1,1,0)$_{[12]}$	(142.26)	(7.28)		(103.76)	(6.49)
Mumbai	(1,0,1)	454.491	16.259	2:6s:11	242.56	11.54
	(0,1,1) $_{[12]}$	(131.52)	(8.289)		(77.14)	(4.86)
Bangalore	(1,1,2)	232.76	6.740	1:3s:11	213.47	5.93
	(0,0,0) $_{[12]}$	(164.91)	(7.316)		(72.53)	(2.99)
Jalandhar	(2,0,1)	334.484	40.55	2:3s:11	213.68	28.52
	(0,0,0) $_{[12]}$	(144.177)	(21.874)		(50.47)	(9.24)

Note The figures in parentheses are error measures of the training dataset

Table 5 Brock- Dechert-Scheinkman (BDS) test for nonlinearity for residuals

Markets	Epsilon=0.5		Epsilon=1		Epsilon=1.5		Epsilon=2	
	M=2	M=3	M=2	M=3	M=2	M=3	M=2	M=3
Agra	52.518	988.988	43.251	642.487	36.505	436.952	35.065	334.129
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Burdwan	37.657	665.255	31.026	388.723	25.729	284.006	23.176	237.714
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ahmedabad	56.453	1270.850	44.216	693.013	45.197	690.244	45.557	688.368
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Azadpur	42.159	770.840	34.339	466.604	34.588	453.985	36.154	452.599
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mumbai	56.71	1210.48	44.23	697.58	45.47	686.77	40.56	558.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bangalore	-4.85	-2.42	697.5	-31.21	206.35	-13.79	172.17	-19.75
	(0.00)	(0.015)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Jalandhar	-86.88	-38.64	-17.56	-7.64	-86.88	-38.64	-242.75	-108.34
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note The figures in parentheses are the respective p-value

linear model in selected potato markets. The test recommended the nonlinear model, i.e, Time Delay Neural Network (TDNN) for better price forecasting of potato.

Time delay Neural Network (TDNN)

The study has divided the datasets into two parts i.e., training set and testing set. The last 24 months of the monthly prices have been considered for testing purpose. Forecast models and its performance was tested using testing set. The summary of the fitted neural network model is given in Table 4. We have selected one hidden layer for best TDNN for this study. For this study, we have followed an iterative approach to select the hidden node, and we eventually chose one output node for better forecasting. We go through the different input nodes from 1 to 5 and the number of hidden nodes 2 to 6 for each selected market (Annexure II). TDNN model with one hidden layer is represented as I: Hs: Ol, where I is the number of nodes in the input layer, H is the number of nodes in the hidden layer, O is the number of nodes in the output layer, s denotes the logistic sigmoid transfer function, and l indicates the linear transfer function. The results of TDNN are summarized in Table 4 and Figure 2. We exercised different TDNN model at manual mode for each market, out of total 25 TDNN models that were tried, the best fit model for each market was identified based on the smallest value of RMSE and MAPE (Annexure II). The best fit TDNN model market was identified with 5 perceptron input layer and 2 perceptron hidden layer with one output (5:2s:1l) for Agra market of India. Likewise, the best TDNN for Burdwan market was 3:2s:1l followed by Ahmedabad (1:4s:1l), Azadpur (2:2s:1l), Mumbai (2:6s:1l), Bangalore (1:3s:1l) and Jalandhar (2:3s:1l). In all the selected markets, this network performed better than other competing networks for potato prices. Among all the markets, Bangalore market was performed best (with minimum value of RMSE 213) in India (Table 4 and Figure 2) with the selected Neural Network model. In Table 4, we have compared the results for the best in between ARIMA and TDNN models in terms of RMSE and MAPE for each market. We can see that for both the price series, the value of evaluation criterion (RMSE and MAPE) are comparatively lower in TDNN model than in ARIMA model. These lower value of RMSE and MAPE signifies that TDNN is better performing model. Nonetheless, in the study, we have used a variety of ARIMA models. However, all of the markets' pricing sets were nonlinear in character, which might be attributed to a nonlinear time series data set. In the nutshell, the results revealed that the TDNN model in general provided a better forecast

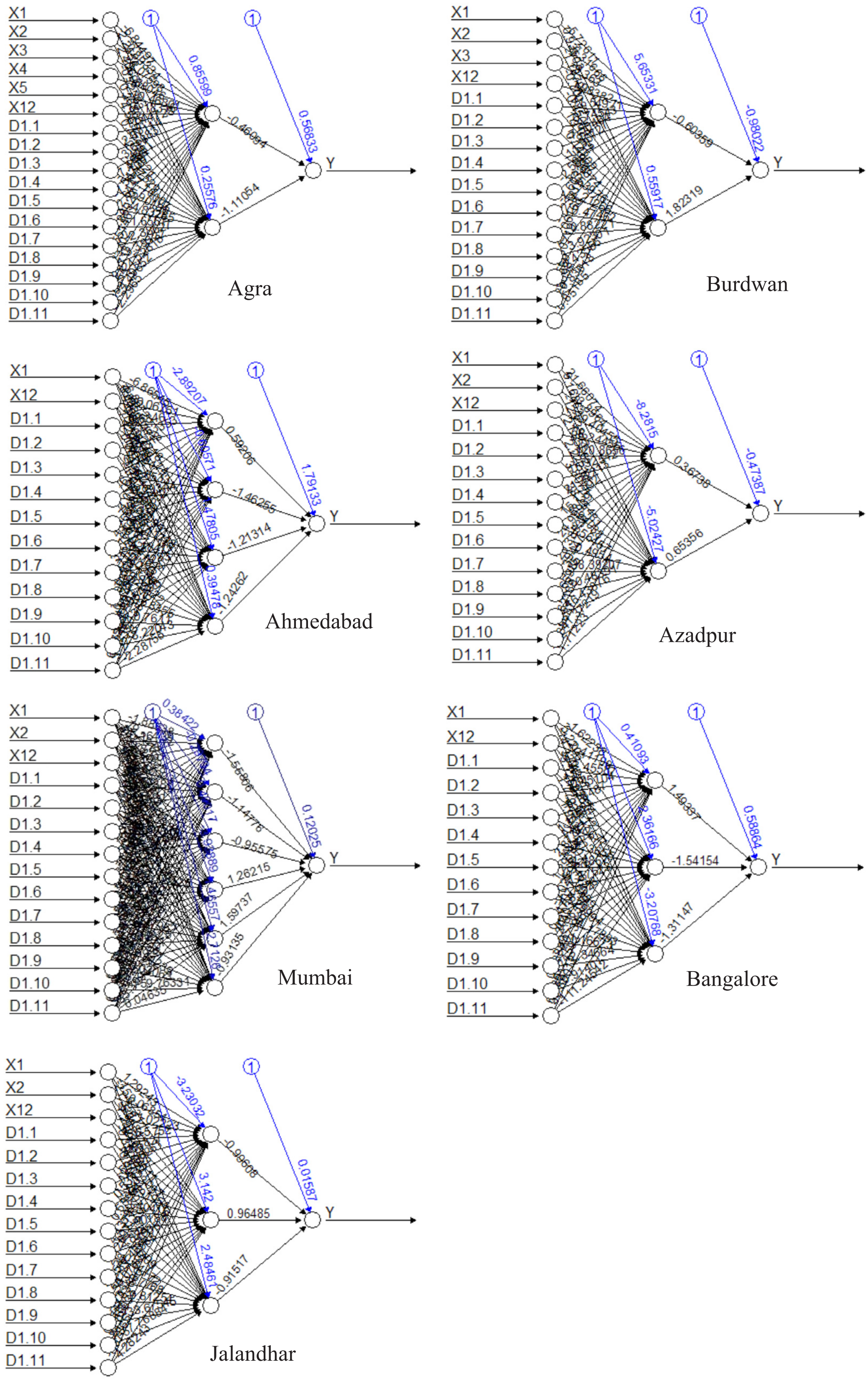
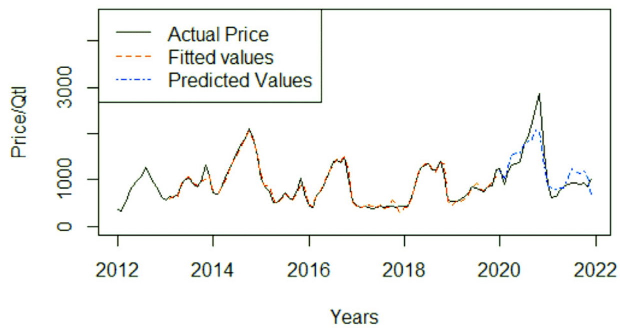
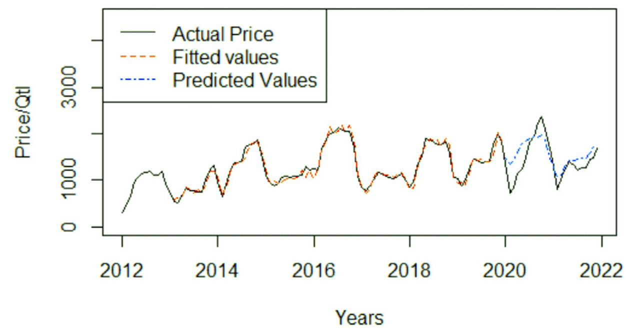


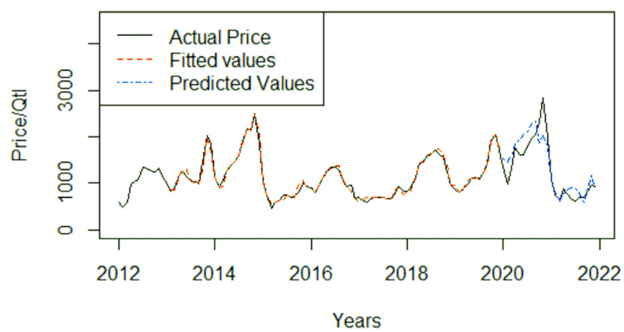
Figure 2 Artificial Neural Network layers for the potato prices of major markets in India



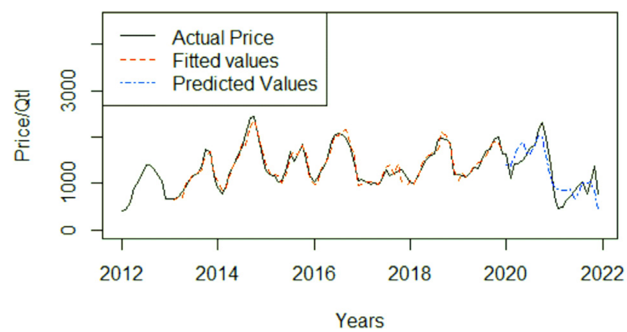
Agra



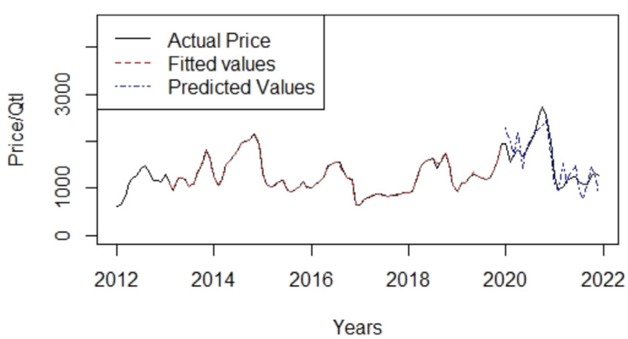
Burdwan



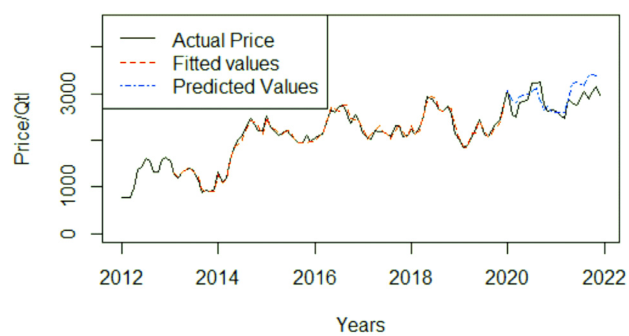
Ahmedabad



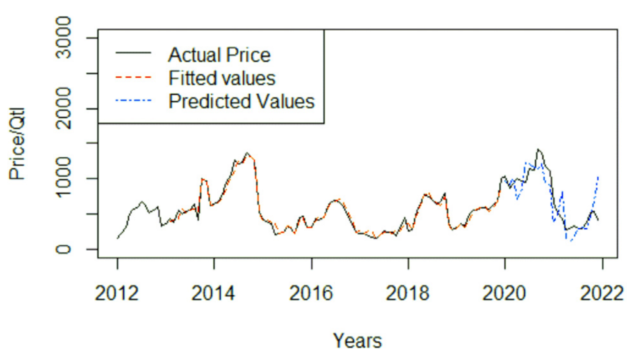
Azadpur



Mumbai



Bangalore



Jalandhar

Figure 3 Actual vs. fitted price series of selected markets of India by using ANN Model

Table 6 Diebold–Mariano (DM) test to see the forecasting power across models

Markets	Training set		Testing set	
	DM	p-value	DM	p-value
Agra	2.731	0.01	2.037	0.05
Burdwan	2.432	0.02	3.272	0.00
Ahmedabad	4.634	0.00	5.131	0.00
Azadpur	2.470	0.02	4.041	0.00
Mumbai	3.316	0.00	2.629	0.01
Bangalore	6.102	0.00	2.093	0.04
Jalandhar	3.068	0.00	3.752	0.00

accuracy in terms of RMSE and MAPE values as compared to the linear model, i.e., ARIMA (Figure 3).

To this end, Diebold–Mariano test (Diebold and Mariano, 1995) was applied for statistical comparison of forecasting performance among the ARIMA and TDNN models. It is found that the predictive accuracy of TDNN are significantly different than that of ARIMA models for all the selected markets (Table 6).

Conclusions

Timely and precise price forecasting of agricultural commodities have significance in the scenario of Indian agriculture, as this enables all the stakeholders associated with particularly perishable crops to take accurate decisions regarding the production and marketing. The agricultural time series datasets are asymmetric, meaning they are non-normal, nonlinear, and nonstationary. Pre-processing of the datasets is required for this purpose as our study compared two types of model, ARIMA and TDNN, as this exercise is demanding and getting popularity in this research area of agricultural marketing. In this study for empirical evaluation, forecasting of potato prices of all the selected markets across India have been carried out. Our results elucidate that potato price volatility is asymmetric in all of India’s chosen markets. Additionally, the study compared the ARIMA and TDNN models for forecasting potato prices and the results found that TDNN performed better than ARIMA, it is considered as the best fit model with respect to minimum RMSE and MAPE value. The study put forward that our efforts must be focused on machine learning techniques like neural network for designing market intelligence system, as these models handles the violation of traditional time series techniques assumptions. However, combination of statistical methods with these soft computing techniques and the local information to the farmers, traders and policymakers is still lacking. The synergy of these would help to provide accurate and timely price forecast.

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Received 4 October 2021 Accepted 17 March 2022

Annexure I

Parameters estimates and fitting performance of different models by using ARIMA for the Potato Prices of Major Markets

Model	AR_1	AR_2	AR_3	MA_1	MA_2	SAR_1	SAR_2	SMA_1	SMA_2	Mean	RMSE	MAPE
Agra												
Auto ARIMA	0.832**			0.589**				0.109	0.633**	880.887**	720.59	25.747
(1,0,1) (0,0,2)	(0.059)			(0.089)				(0.108)	(0.1573)	(185.187)	(125.506)	(11.476)
ARIMA	0.875**			0.539**		-0.767**					484.662	12.552
(1,0,1) (1,1,0)	(0.062)			(0.099)		(0.065)					(129.221)	(11.469)
ARIMA	1.33**	-0.436**				-0.794**		0.065			519.207	21.552
(2,0,0) (1,1,1)	(0.104)	(0.106)				(0.093)		(0.178)			(131.41)	(12.178)
ARIMA (1,0,1)	0.875**			0.54**		-0.767**		-0.004			484.774	23.762
(1,1,1)	(0.062)			(0.103)		(0.1)		(0.188)			(129.221)	(11.469)
ARIMA	1.335**	-0.441**				-0.768**					530.167	20.986
(2,0,0) (1,1,0)	(0.102)	(0.104)				(0.066)					(131.544)	(12.195)
Burdwan												
Auto ARIMA				0.38		0.135*	0.573**				721.412	52.7
(0,1,1) (2,0,0)				(0.103)		(0.076)	(0.089)				(129.396)	(8.216)
ARIMA	0.912**			0.379**		-0.782**	-0.084**				536.77	39.277
(1,0,1) (2,1,0)	(0.057)			(0.12)		(0.121)	(0.134)				(124.759)	(7.286)
ARIMA	1.443**	-0.517*		-0.147		-0.536**		-0.287			480.604	33.659
(2,0,1) (1,1,1)	(0.376)	(0.362)		(0.457)		(0.193)		(0.284)			(123.517)	(7.299)
ARIMA	0.918**			0.393**		-0.579**		-0.284			521.267	37.849
(1,0,1) (1,1,1)	(0.057)			(0.114)		(0.182)		(0.278)			(123.924)	(7.246)
ARIMA	1.289**	-0.355**				-0.003	0.402**	-0.896*			432.105	29.451
(2,0,0) (2,1,0)	(0.109)	(0.115)				(0.299)	(0.148)	(0.452)			(119.072)	(6.929)
Ahmedabad												
Auto ARIMA	0.508**	0.629**	-0.434**	0.971**		0.402**				1127.797**	709.802	32.388
(3,0,1) (1,0,0)	(0.102)	(0.117)	(0.102)	(0.04)		(0.099)				(162.892)	(158.2)	(11.018)
ARIMA	0.857**			0.536**		0.606**	-0.244**				603.39	54.337
(1,0,1) (2,1,0)	(0.062)			(0.097)		(0.118)	(0.128)				(164.972)	(11.478)
ARIMA (2,0,1)	1.364**	-0.511**		0.008		0.202		-1.00**			552.567	39.604
(1,1,1)	(0.209)	(0.196)		(0.249)		(0.13)		(0.325)			(140.938)	(10.002)
ARIMA	1.371**	-0.505**		-1.00**		0.227*	0.054	-0.999**			557.581	46.423
(2,1,1) (2,1,1)	(0.095)	(0.097)		(0.131)		(0.13)	(0.145)	(0.296)			(142.146)	(9.891)
ARIMA	0.478**	0.667**	-0.414**	1.00**		0.217**		-1.00**			543.378	39.657
(3,0,1) (1,1,1)	(0.103)	(0.099)	(0.106)	(0.09)		(0.128)		(0.387)			(136.013)	(9.52)

Contd...

Mumbai									
Auto ARIMA	0.793**		0.575**				1246.807**	733.119	25.28
(1,0,1) (0,0,0)	(0.071)		(0.088)				(109.592)	(147.088)	(9.421)
ARIMA (1,0,1)	0.834**		0.556**					618.332	36.16
(0,1,0)	(0.066)		(0.089)					(187.055)	(12.112)
ARIMA (1,1,1)	-0.096**		0.576**		0.954**	-0.885*		763.763	51.754
(1,0,1)	(0.195)		(0.155)		(0.336)	(0.508)		(148.839)	(9.078)
ARIMA (2,0,1)	0.838**	-0.011	0.527**			-0.999**		456.049	16.257
(0,1,1)	(0.209)	(0.207)	(0.177)			(0.24)		(131.514)	(8.294)
ARIMA (1,0,1)	0.828**		0.535**			-0.999**		454.491	16.259
(0,1,1)	(0.076)		(0.099)			(0.239)		(131.518)	(8.289)
Azadpur									
Auto ARIMA	0.835**		0.402**		-0.593**			151.232	7.302
(1,0,1) (1,1,0)	(0.068)		(0.127)		(0.086)			(142.255)	(7.28)
ARIMA (2,0,1)	0.375**	0.401**	0.877**					656.92	65.852
(0,1,0)	(0.196)	(0.189)	(0.136)					(175.242)	(9.368)
ARIMA (1,1,1)	-0.396*		0.731**		0.999**	0.959**		854.839	85.716
(1,0,1)	(0.231)		(0.177)		(0.004)	(0.096)		(134.323)	(8.204)
ARIMA (1,1,1)	-0.517**		0.799**		-0.104**	0.999**		863.603	86.038
(1,1,1)	(0.181)		(0.13)		(0.122)	(0.221)		(120.609)	(6.423)
ARIMA (1,1,0)	0.221**				-0.113	1.00**		883.67	88.318
(1,1,1)	(0.107)				(0.119)	(0.214)		(123.765)	(6.7)
Bangalore									
Auto ARIMA			0.341**					263.625	8.173
(0,1,1) (0,0,0)			(0.107)					(165.567)	(7.354)
ARIMA (1,0,1)	0.867**		0.418**					373.848	9.482
(0,1,0)	(0.059)		(0.122)					(203.116)	(7.737)
ARIMA (2,1,0)	0.296**	-0.168						233.989	6.713
(0,0,0)	(0.103)	(0.102)						(165.235)	(7.321)
ARIMA (1,1,2)	0.182		0.1255	-0.148				232.755	6.74
(0,0,0)	(0.955)		(0.947)	(0.324)				(164.912)	(7.316)
ARIMA (1,1,1)	-0.269		0.601**					785.389	23.895
(0,1,0)	(0.282)		(0.233)					(206.964)	(7.839)
Jalandhar									
Auto ARIMA	0.618**							577.134	98.314
(1,0,0) (0,0,0)	(0.083)							(169.072)	(218.076)
ARIMA (1,1,1)	0.897**		1.000**					467.996	93.176
(0,0,0)	(0.053)		(0.031)					(145.405)	(20.059)
ARIMA (1,0,1)	0.832**		0.142**				535.399**	338.594	40.286
(0,0,0)	(0.068)		(0.076)				(95.597)	(144.387)	(21.895)
ARIMA (1,0,1)	0.923**		-0.012		-0.69**			366.402	69.008
(1,1,0)	(0.05)		(0.127)		(0.077)			(134.617)	(21.605)
ARIMA (2,0,1)	0.406**	0.374**	-0.565**				53547**	334.484	40.554
(0,0,0)	(0.113)	(0.147)	(0.272)				(98.998)	(144.177)	(21.874)

Notes The figures in parentheses are the standard error of coefficients and error measures of the training group; ***p<0.01, *p<0.05, ·p<0.10.

Annexure II

Model Structure and fitting performance of different models by using TDNN for the Potato Prices of Major Markets

Model	Agra			Burdwan			Ahmedabad			Azadpur			Mumbai			Bangalore			Jalandhar		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
1:2s:11	369.72	571.92	22.92	520.04	420.01	44.56	329.41	251.06	21.26	460.92	405.5	46.19	779.24	636.03	49.81	338.29	252.43	8.55	247.5	575.94	147.37
	(95.03)	(66.02)	(9.38)	(97.84)	(71.81)	(7.02)	(102.32)	(71.7)	(7.3)	(105.41)	(84.97)	(6.71)	(99.44)	(68.77)	(6.32)	(100.76)	(81.62)	(4.71)	(79.07)	(55.46)	(15.14)
1:3s:11	399.74	348.08	87.02	326.99	282.9	22.99	304.68	233.63	18.35	395.44	335.95	29.86	493.69	430.03	32.87	213.47	166.77	5.93	259.29	220.06	83.4
	(55.95)	(39.93)	(5.54)	(85.58)	(59.07)	(5.64)	(77.84)	(54.29)	(5.41)	(77.63)	(60.38)	(4.78)	(70.77)	(45.31)	(4.16)	(72.53)	(52.43)	(2.99)	(60.02)	(42.64)	(11.53)
1:4s:11	358.2	297.01	22.23	389.05	314.43	23.84	216.49	151.92	12.49	447.82	395.15	43.61	348.35	305.01	20.31	233.06	212.15	7.43	242.41	154.64	19.34
	(35.89)	(23.94)	(3.28)	(73.39)	(46.44)	(4.34)	(61.96)	(40.42)	(4.03)	(49.42)	(35.38)	(2.92)	(47.56)	(27.47)	(2.49)	(44.2)	(29.77)	(1.67)	(47.37)	(28.02)	(7.88)
1:5s:11	395.89	315.33	26.71	552.93	275.1	23.02	443.17	367.13	42.28	338.57	302.93	31.13	382.58	697.44	19.14	322.87	269.88	9.52	278.14	222.69	30.58
	(21.71)	(14.1)	(2.02)	(56.39)	(30.61)	(2.7)	(48.41)	(27.87)	(2.82)	(31.62)	(20.28)	(1.74)	(32.6)	(17.37)	(1.54)	(23.92)	(13.64)	(0.74)	(44.58)	(24.66)	(6.94)
1:6s:11	448.77	331.07	25.11	529.93	455.79	37.93	474.35	565.11	62.45	367.42	393.44	40.85	451.86	393.71	28.26	259.25	210.97	7.32	250.44	215.6	38.53
	(15.36)	(9.07)	(1.31)	(43.9)	(18.8)	(1.51)	(36.99)	(19.05)	(1.87)	(25.6)	(14.89)	(1.29)	(24.9)	(13.03)	(1.14)	(9.99)	(4.9)	(0.27)	(40.78)	(19.84)	(5.54)
2:2s:11	333.86	244.59	20.03	394.97	331.77	27.95	346.77	291.07	27.22	265.99	231.77	24.15	409.58	381.04	27.95	227.39	181.95	9.99	218.01	145.94	22.79
	(91.37)	(61.25)	(8.37)	(95.25)	(68.31)	(6.71)	(95.65)	(68.92)	(7.01)	(103.76)	(81.01)	(6.49)	(84.31)	(57.64)	(5.48)	(74.19)	(56.49)	(3.06)	(78.14)	(54.85)	(15.81)
2:3s:11	357.52	289.45	25.64	364.9	306.56	23.21	499.17	337.96	58.82	487.06	440.8	44.19	326.14	209.08	10.58	324.6	241.63	5.31	213.68	162.71	28.52
	(47.96)	(32.03)	(4.38)	(76.34)	(48.72)	(4.64)	(66.37)	(44.94)	(4.59)	(67.31)	(48.22)	(3.89)	(58.59)	(36.25)	(3.48)	(46.45)	(33.23)	(1.82)	(50.47)	(35.06)	(9.24)
2:4s:11	562.65	477.81	47.52	517.86	459.95	33.27	539.29	455.67	43.25	416.24	341.49	35.2	444.38	362.31	23.15	331.47	264.1	9.28	311.69	258.29	43.89
	(28.19)	(17.25)	(2.37)	(55.53)	(30.54)	(2.73)	(45.04)	(28.43)	(3)	(45.83)	(29.44)	(2.48)	(30.73)	(16.89)	(1.62)	(23.19)	(14.8)	(0.81)	(37.59)	(23.58)	(6.28)
2:5s:11	673.98	587.99	59.01	562.65	426.41	27.22	562.76	484.15	30.98	475.7	427.79	41.77	307.4	243.77	15.14	423.25	317.44	11.61	238.5	187.72	29.09
	(18.26)	(10.25)	(1.33)	(44.66)	(21.23)	(1.77)	(33.08)	(19.03)	(1.97)	(27.18)	(15.07)	(1.31)	(17.22)	(8.38)	(0.77)	(7.39)	(4.65)	(0.26)	(22.28)	(13.84)	(3.91)
2:6s:11	528.82	371.82	30.71	444.71	341.18	26.42	567.57	411.58	33.53	392.78	264.37	34.83	323.51	261.67	19.89	323.49	286.54	10.05	279.78	234.55	45.02
	(14.66)	(7.55)	(0.99)	(36.89)	(14.94)	(1.14)	(24.03)	(11.3)	(1.19)	(21.34)	(9.4)	(0.82)	(15.38)	(6.39)	(0.57)	(4.45)	(2.33)	(0.13)	(18.09)	(9.52)	(2.79)
3:2s:11	387.89	312.1	27.21	299.73	252.85	20.14	380.18	282.68	24.64	502.34	382.77	49.66	242.56	194.88	11.54	287.97	245.31	8.83	434.98	332.71	82.89
	(77.62)	(52.64)	(6.99)	(82.74)	(59.55)	(5.63)	(85.56)	(62.15)	(6.34)	(97.6)	(77.72)	(6.12)	(77.14)	(52.5)	(4.86)	(74.67)	(58.27)	(3.21)	(74.74)	(50.17)	(14.09)
3:3s:11	429.67	340.03	31.74	395.04	361.37	26.98	446.96	392.77	34.33	354.24	293.61	32.1	586.52	509.59	37.53	247.99	200.7	7.12	290.97	211.46	42.41
	(43.73)	(27.62)	(3.66)	(57.45)	(36.93)	(3.45)	(45.56)	(33.22)	(3.48)	(54.23)	(37.65)	(2.9)	(48.79)	(30.89)	(2.88)	(37.74)	(28.05)	(1.55)	(41.19)	(29.68)	(7.28)
3:4s:11	633.71	496.75	45.12	434.79	392.82	29.07	477.43	379.01	35.63	362.33	308.65	30.35	454.21	379.28	27.81	392.26	325.79	11.04	398.23	310.02	73.4
	(23.03)	(13.95)	(1.87)	(40.54)	(21.63)	(1.83)	(27.04)	(18.42)	(1.92)	(27.73)	(18.64)	(1.48)	(29.37)	(16.67)	(1.53)	(16.47)	(10.68)	(0.58)	(21.93)	(15.34)	(3.89)
3:5s:11	598..31	510.49	44.37	771.38	467.73	33.57	438.07	353.48	30.66	360.63	315.09	32.06	509.88	426.98	29.76	514.28	431.1	15.03	792.02	686.68	133.76
	(12.67)	(6.94)	(0.86)	(28.76)	(11.98)	(0.92)	(16.12)	(10.54)	(1.12)	(13.34)	(8.22)	(0.69)	(16.5)	(7.81)	(0.69)	(6.01)	(3.55)	(0.2)	(14.47)	(9.76)	(2.42)
3:6s:11	514.08	371.4	26.95	934.19	774.05	57.73	584.04	433.78	47.49	626.32	534.08	50.84	517.08	466.25	31.73	431.59	345.01	12.01	359.01	263.08	46.61
	(9.54)	(4.68)	(0.61)	(26.42)	(9.07)	(0.69)	(15.42)	(10.02)	(1.07)	(8.74)	(5.01)	(0.43)	(12.95)	(5.05)	(0.44)	(4.98)	(2.13)	(0.12)	(11.74)	(7.07)	(1.72)
4:2s:11	402.26	312.76	26.79	393.81	337.57	33.49	564.66	448.88	32.33	735.9	393.11	75.28	273.97	255.64	17.34	291.42	236.03	8.33	483.54	415.84	95.44
	(78.8)	(54.07)	(7.37)	(76.65)	(54.68)	(5.31)	(84.07)	(64.87)	(6.55)	(86.13)	(63.64)	(5.05)	(71.86)	(49.5)	(4.6)	(70.69)	(55.89)	(3.04)	(64.37)	(43.61)	(11.43)
4:3s:11	473.05	356.23	31.72	347.29	251.77	16.14	527.36	386.19	28.35	358.64	311.5	32.07	310.64	244.64	15.7	370.8	322.35	11.77	486.58	377.62	89.81
	(37.07)	(22.69)	(2.87)	(47.89)	(30.83)	(2.89)	(43.82)	(33.42)	(3.52)	(53.64)	(38.18)	(3.04)	(39.92)	(25.08)	(2.33)	(27.71)	(19.61)	(1.07)	(42.41)	(27.52)	(7.34)
4:4s:11	379.98	313.45	28.94	634.69	510.26	96.66	668.98	415.27	38.49	417.66	338.23	39.31	441.12	293.46	15.47	342.42	276.87	5.75	345.6	281.21	63.11
	(15.98)	(9.22)	(1.18)	(26.82)	(14.17)	(1.23)	(22.73)	(15.12)	(1.59)	(19.3)	(12.81)	(1.03)	(25.52)	(11.91)	(1.1)	(11.08)	(7.14)	(0.39)	(18.01)	(11.41)	(2.85)

Contd...

Model	Agra			Burdwan			Ahmedabad			Azadpur			Mumbai			Bangalore			Jalandhar		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
4:5s:11	624.76	570.29	50.61	476.94	377.9	26.07	652.91	562.23	47.5	539.18	463.43	47.19	405.92	342.38	22.87	404.23	343.02	12.14	623.47	496.95	101.21
	(8.35)	(4.38)	(0.53)	(15.36)	(7.58)	(0.61)	(12.78)	(8.81)	(0.96)	(12.92)	(6.55)	(0.54)	(10.46)	(4.38)	(0.41)	(3.33)	(2.12)	(0.11)	(13.91)	(8.18)	(2.01)
4:6s:11	381.75	269.5	20.12	415.3	357.59	28.35	518.14	382.85	27.37	447.23	386.79	35.7	383.01	317.15	11.05	375.86	313.26	10.86	430.16	373.68	68.66
	(5.47)	(2.33)	(0.29)	(9.56)	(4.16)	(0.34)	(10.69)	(6.68)	(0.71)	(8.83)	(4.51)	(0.37)	(8.63)	(4.15)	(0.3)	(1.82)	(0.97)	(0.05)	(9.66)	(5.14)	(1.28)
5:2s:11	303.16	221.76	16.27	401.06	343.11	28.74	643.76	473.36	31.6	569.43	470.6	54.88	606.35	230.94	41.23	317.86	283.64	10.24	270.8	224.38	50.26
	(68.47)	(44.13)	(5.74)	(70.82)	(49.87)	(4.69)	(74.23)	(53.16)	(5.55)	(78.13)	(59.3)	(4.53)	(61.5)	(43.2)	(4.13)	(58.15)	(44.3)	(2.35)	(70.34)	(45.16)	(12.83)
5:3s:11	522.54	470.87	43.97	417.08	351.41	28.56	416.13	338.53	32.76	424.13	322.64	33.09	300.41	256.12	17.27	272.06	233.37	8.32	663.53	531.54	120.38
	(30.86)	(17.07)	(2.17)	(40.16)	(25.47)	(2.41)	(36.87)	(25.26)	(2.69)	(43.76)	(30.48)	(2.43)	(25.76)	(18.51)	(1.72)	(27.15)	(18.67)	(0.99)	(34.14)	(22.33)	(5.89)
5:4s:11	565.79	458.59	40.4	389.94	303.88	20.39	462.35	375.61	35.01	396.42	283.74	22.23	288.96	239.94	14.63	336.66	272.24	24.47	586.39	435.07	82.96
	(15.62)	(6.65)	(0.81)	(16.21)	(9.24)	(0.72)	(21.09)	(13.29)	(1.46)	(19.83)	(12.36)	(0.99)	(13.65)	(7.55)	(0.69)	(8.21)	(5.29)	(0.28)	(14.84)	(9.56)	(2.41)
5:5s:11	904.94	785.87	68.48	453.94	366.39	25.05	511.92	454.38	38.03	459.62	354.91	42.14	361.57	315.72	20.94	465.72	410.65	14.92	459.08	401.19	77.13
	(8.67)	(3.09)	(0.38)	(9.78)	(5.41)	(0.43)	(11.46)	(6.32)	(0.65)	(11.05)	(5.13)	(0.4)	(3.35)	(2.17)	(0.19)	(3.43)	(2.04)	(0.11)	(7.42)	(4.5)	(1.1)
5:6s:11	733.89	521.29	39.11	440.94	350.98	23.32	459.94	369.39	34.32	340.7	262.43	27.92	400.39	308.92	17.14	309.1	258.3	8.89	380.76	314.98	70.13
	(4.58)	(2.03)	(0.25)	(7.24)	(3.31)	(0.25)	(9.51)	(5.11)	(0.52)	(9.69)	(4.3)	(0.34)	(3.41)	(1.78)	(0.16)	(1.62)	(1.02)	(0.05)	(6.07)	(3.54)	(0.78)

Note The figures in parentheses are the error measures of the training group

Agricultural Economics Research Review 2022, 35 (2), 135-150
DOI: 10.5958/0974-0279.2022.00036.2

Value chain analysis of Kadaknath chicken in Madhya Pradesh and Chhattisgarh

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Abstract This paper identifies the production and marketing systems of Kadaknath poultry breed by mapping and analyzing the value chains in Madhya Pradesh and Chhattisgarh, the former considered as the cradle of Kadaknath rearing. Qualitative and quantitative data regarding type of chain actors and their interactions were gathered through personal interview method. Farmers/producers, traders, retailers, road-side restaurants/Dhabas and Krishi Vigyan Kendras (KVKs) are the major chain actors involved in identified value chains in the study area. Quantitative mapping reveals that majority (38%) of the birds is sold by farmers to traders and to ultimate consumers at the farm gate (33%).About 39% of the birds procured by traders are exported to other districts, while 31% and 22% of the birds are sold by traders to road side Dhabas and ultimate consumers, respectively. Of the total value added, traders in fresh/raw chicken chains and restaurants/Dhabas in value added chains capture significant shares. Some policy suggestions have been made to streamline the Kadaknath value chains towards integrated and inclusive production and marketing systems so as to benefit resource-poor farmers in the study area.

Keywords Value chain, economics, poultry production, backyard poultry, price spread

JEL codes Q11, Q13, Q18

Introduction

Livestock production in India is intrinsically linked to agriculture and the sector plays a crucial role for the nation's overall food and nutritional security. *In the context of union government's mandate of doubling farmers' income by 2022,* livestock and poultry have been considered as one of the flagship enterprises for farm diversification, which in turn helps in mitigation of farmers' income fluctuation and income enhancement. According to the estimates of the Central Statistics Office (CSO) livestock sector contributed 27.40 per cent of the gross value added (GVA) from agriculture and allied sector in 2018 at 2012 prices (GOI 2019).

Indian poultry sector

Poultry sector in India plays a vital role in alleviating rural poverty and enhancing women empowerment.

The paper is drawn from Master's Thesis of the first author submitted to ICAR-Indian Veterinary Research Institute (Deemed University), Izatnagar, 243122,Uttar Pradesh, India

This sector has expanded significantly in recent past mainly on account of increased demand for high value animal food products like chicken meat and eggs; the factors driving this increased demand being rising per capita income, increasing trends in urbanization, changing lifestyles and increasing population. In fact, these factors have also contributed, during the same period, to a shift in dietary patterns in favour of animal protein, of which poultry products is a major component. During 2003-2019, the per-annum growth rate (3.05%) in poultry population has been higher that of all other livestock breeds/species, except crossbred cattle. Production of meat and eggs, during 2000-2018, grew at about 10 per cent and 5.6 per cent per annum, respectively, which were higher than the annual growth rate in milk output (4.75%). Also, as a result of significant expansion in poultry production, the percentage change in per capita availability of meat (271%) and eggs (131%) during 2000-2018 has been significantly higher than that of milk (98%). As per estimates from All India Poultry Breeder Association, poultry sector, with a contribution of about USD 17.31 billion to the country's GDP, satisfies hunger of 50 million people through direct and indirect employment (Kolluri, 2020).

Although, the expansion of the poultry sector has mostly been observed in the commercial segment, the backyard poultry farming is also increasing in importance. Commercial poultry segment also has limited implication for poverty alleviation. On the other hand, backyard poultry is practised by mostly the poorer households and are thought to be an excellent tool in poverty alleviation due to their quick turnover and low investment requirement (Permin et al., 2001). Backyard poultry has seen significant growth of over 45.79 per cent per annum during 2012 to 2019, and has reached 317.07 million in 2019 (GOI, 2019). With the contribution of 18.14 billion eggs, backyard poultry, accounted for about 18 per cent of total egg production as in 2019. Within the backyard poultry sector, indigenous fowls contributed 11.52 per cent of total egg production.

Importance of Kadaknath as indigenous breed

The importance of indigenous breeds of chicken in the rural economy can hardly be overemphasized in developing countries, including India. Promotion of indigenous breeds with better adaptability to the local production systems, climatic conditions and higher degree of disease resistance characteristics, will ultimately help in poverty alleviation, women empowerment as well as fulfilling the nutritional requirements of marginalized people (Padhi, 2016.). According to NBAGR (2019), there are 19 registered indigenous poultry breeds in India, which desperately need attention for conservation and improvement of animal genetic resources. Out of these indigenous poultry breeds, one breed is Kadaknath, also known locally as Kalamasi, on account of black colour of its flesh. The breed originated in Alirajpur and Jhabua districts in Madhya Pradesh and is reared mainly by the rural poor and tribal population living in districts in Western Madhya Pradesh and Chhattisgarh.

Kadaknath is popular for its adaptability in village conditions and has claimed aphrodisiac and medicinal properties (Verma et al. 2020). Due to its unique characteristics and high demand, it fetches higher price as compared to other native birds. State and central governments have promoted the rearing of Kadaknath breed, as backyard enterprise, through different schemes in order to improve the livelihoods of resource poor farmers, especially the tribal population. SA PPLPP (2009) conducted a study on the profitability of Kadaknath farming vis-a-vis desi chicken in Jhabua district of Madhya Pradesh and reported that one tribal family can earn around INR 5, 000 per year from a single Kadaknath bird whereas the same figure is around INR 1, 180 for desi bird.According to a study conducted by Mooventhan et al. (2019), Kadaknath birds reach their saleable weight of 1.10 kg in 105-120 days, fetching a price of INR 700-800/kg live body weight in the local market. The authors also reported that this business has helped the farmers to earn a net income of INR 80, 000-90, 000 per year.

However, in spite of the potential inherent in Kadaknath poultry farming in improving farmers' livelihood security, significant challenges are faced in up-scaling this breed, viz. high demand of Kadaknath meat driving the breed under the verge of extinction, endemic nature and regular outbreaks of infectious diseases like Ranikhet disease, indiscriminate breeding with high yielding exotic breeds and unorganized nature of marketing with no systematic linkage among different value chain actors to respond to changes in demand.

Importance of value chain analyses

Value chain can be described as a series of activities essential to bring a product or service from its inception, through the intermediary phases of production, to an ultimate consumer. A simplified version of the value chain includes an input supplier, producer, traders, processors, transporters, wholesalers, retailers and final consumers. Given the role of Kadaknath in poverty alleviation (SA PPLPP 2009; Verma et al. 2020; Mishra et al. 2019) a pro-poor value chain development of Kadaknath is the need of the hour. The first step in this regard is to document the functioning of existing value chains, including the governance mechanism, role of different stakeholders and efficiency of these chains. The results of such analyses would help policy makers to bring positive change in terms of improving their economic efficiency and generate more social benefits like employment generation and gender equity.

In India, studies on value chains in the livestock & poultry sectors are mostly focused on dairy value chains (Birthal et al. 2009; Kumar 2010; Kumar et al. 2011; Wani et al. 2014; Birthal et al. 2017). Some studies are available on the value chain analyses of meat sector (Bardhan et al.2019; Dineshkumar et al.2020). In case of poultry, some studies are found on the role of poultry in livelihood security, poverty alleviation and production & marketing. Studies on comprehensive analyses of poultry value chains, more so for indigenous breeds and focussing on smallholder backyard enterprises, are scant.

As for Kadaknath breeds, there have been few works which have analyzed the economics of Kadaknath rearing at the farm level (SA PPLPP 2009; Sahu et al.2019; Mooventhan et al. 2019) and identified the constraints faced in Kadaknath chicken farming (Verma et al. 2020). However, literature regarding value chain analyses of backyard poultry rearing, with special reference to Kadaknath breed, and focussing on all the value chain stakeholders is scarce.

This paper aims to identify the different stakeholders involved in Kadaknath value chains and map the linkages between them; assess the economics of Kadaknath breed rearing underdifferentrearing systems; and ascertain the performance of value chains in terms of price spread and the distribution of benefits across various stakeholders. The findings are likely to help chain actors to improve the governance and competitiveness of each segment of the chain and help it function efficiently.

Methodology

Study area and sampling

The study was carried out in the states of Madhya Pradesh and Chhattisgarh, located geographically in the central and east-central parts of India. Kadaknath farming has been promoted in this region extensively by different government agencies, given the breed's adaptability to the specific agro-climatic conditions. There are evidences that promotion of this breed as backyard enterprises has helped in changing the lives of tribal farmers in the two states (SA PPLPP 2009; Mishra et al. 2019; Sahu et al. 2019; Mooventhan et al.2019).

Krishi Vigyan Kendras (KVKs), which are typically Farm Science Centres, have the major mandate of technology assessment, validation and refinement at the farmers' fields. They provide a link between various research stations within the national agricultural research system (NARS) and the farmers. KVKs in this region have established hatcheries dedicated to Kadaknath breeds of poultry. The KVKs have not only promoted the breed in these two states, but have also made attempts to popularize the same in adjoining and nearby states. According to Mishra et al.(2019), approximately 2 lakh chicks were supplied to 15 districts of 14 states by KVK of Jhabua in Madhya Pradesh. Apart from KVKJhabua, there are four other KVKs (Chhindwara, Burhanpur, Dhar and Gwalior) in Madhya Pradesh and four KVKs in Chhattisgarh (Dantewada, Kanker, Balrampur and Rajnandgaon), which have established Kadkanath hatcheries. According to Sahu et al. (2019) Dantewada district of Chattisgarh alone produces 4 lakhs of chicks annually by 203 established Kadaknath farms. Mishra et al.(2019) had reported that KVK, Kanker in Chhattisgarh, alone has supplied more than 1.5 lakhs Kadaknath chicks to local farmers as well as to other states.

Nine districts, in which the respective KVKs (five in Madhya Pradesh and four in Chhattisgarh), have established Kadaknath hatcheries and supply Kadaknath Chicks, were categorized into low and high hatchery capacity categories. In the next step, one district was selected randomly from the high and low capacity categories from each state. Thus, two districts were selected from each of the two states. Multi-stage random sampling design was used to select Kadaknath rearing households, the ultimate sampling units for this study. From each selected district, a list of blocks in which Kadaknath breed has been promoted by the concerned KVKs was prepared. Two blocks were selected randomly from each district. From each selected block, list of villages with Kadaknath breed intervention was prepared. Five villages were then selected randomly from these lists from each block. Thus, this study covered two states, four districts, 8 blocks and 40 villages. For selection of Kadaknath rearing households, sampling frame was prepared by listing households having Kadaknath poultry enterprises. Twenty five per cent of the households from this sampling frame from each village were then selected randomly as ultimate sampling units.

For selecting the value chain actors, viz. traders, wholesalers, retailers, etc., the number of such value chain actors operating in the study area was assessed during the survey and 20 per cent of total number of each actor category was selected subject to the number of chain actors not exceeding 50.

Data

Primary data were collected with the help of a structured and pre-tested interview schedule by personally interviewing the farmers and key-value chain stakeholders in the Kadaknath value chains. The actors who were surveyed included officials from the State Animal Husbandry Department, village representatives (Gram Pradhan), Kadaknath farmers, Kadaknath traders/intermediaries, Kadaknath wholesalers, butchers and retailers. The aim of multi-stakeholder interviews was to map the value chains, identify critical sites/infrastructure, identify people and organizations, process/product movement, and analyze price and quantities generated, sold and consumed.

Analytical framework

Mapping of Kadaknath value chains

The primary data collected from different actors involved in Kadaknath value chain were used to map and quantify the value chain as a visual tool to graphically illustrate the actors involved in the value chain & relationships between them and the flow of the product along the chains from the point of inception to final consumer in terms of volume & value.

Economics of Kadaknath rearing

Cost estimation

The overall cost of rearing birds is an aggregate of the expenditure incurred on the fixed and variable items.The fixed costs include depreciation on durable assets like sheds and equipment. The depreciation on sheds and equipment was worked out using the straight-line method considering the useful life of the asset concerned.The interest on fixed capital (shed, equipment and wire fencing) was calculated at 12% per annum. The components of variable cost include the cost of day-old chicks, feed costs, labour expenses and expenditures on veterinary & health care and miscellaneous items. Cost of feeds was estimated by multiplying the quantity fed to the birds by the prevailing market price in the study area. The value of hired labour, as prevailing in the study area, was taken as such and the value of family labour was imputed based upon the prevailing wage rate in the study area. Veterinary expenditures included expenditures incurred on vaccination, medicines, charges made by the veterinary personnel, etc. Miscellaneous expenditures included costs incurred on repairs of sheds, store and equipments, electricity and water charges, if any.

Estimation of returns

The output variable was the live birds & eggs sold, along with sale of dressed chicken & any other value added products. The volume of these products sold was multiplied with the market price in order to obtain gross returns. The gross cost was then subtracted from the gross returns to arrive at the net returns from Kadaknath farming.

Price spread among various stakeholders in the identified value chains

Price spread along the various actors involved in different identified value chains was calculated. Price spread has two components; one is the cost of performing the various marketing functions which include the transaction costs also and the other part is the profit/ net margins of the various market functionaries involved in moving the birds from the producers till it reaches the ultimate buyer. Total cost was calculated by adding standard marketing costs and transactions costs. Here the transaction costs involve the costs of travel, communication, transport and storage, loss in quality and quantity during transportation, credit, extension services, market fee, commission charges, and personnel time (own and hired). The estimation of market actors' net marketing margin was computed in two steps. First, gross marketing margin was calculated by subtracting purchase price from the selling price and then net marketing margin was determined by taking the difference between gross marketing margin and total costs.

Marketing efficiency

Marketing efficiency is the measure of the ability of marketing agencies to move the products from the producer, at the minimum cost by extending maximum service, to the ultimate buyer. It is the ratio of market output to marketing cost. Acharya's modified method (Acharya and Agarwal 2001) of calculating marketing efficiency was used to measure the marketing efficiency. Marketing efficiency was computed by considering the price paid by the consumer (RP), total marketing cost (MC) & net marketing margin (MM). One of the indicators of the increased marketing efficiency is the reduction in the cost of marketing and margins of the intermediaries involved in the marketing and the overall increase in the producer's share. According to Acharya's method, higher the value of the index of marketing efficiency (ME), higher is the marketing efficiency and vice versa.

The formula for calculating marketing efficiency was:

$$ME = [RP/(MC+MM)] – 1$$

Where,

ME = Index of marketing efficiency

RP = Price paid by the consumer

MC = Total Marketing Cost

MM = Net Marketing Margin

Results and discussion

Mapping of value chain

We map the Kadaknath value chain for the combined four districts surveyed in this study by utilizing the information from key informants and group discussions and following the framework developed by Alarcon et al. (2017) (Fig. 1). Private hatcheries and KVKs are the main suppliers of day old Kadaknath chicks to the farmers for their rearing. The 4 KVKs in the surveyed districts supplied 54 per cent of day olds chicks to the farmers while about 10 private hatcheries which

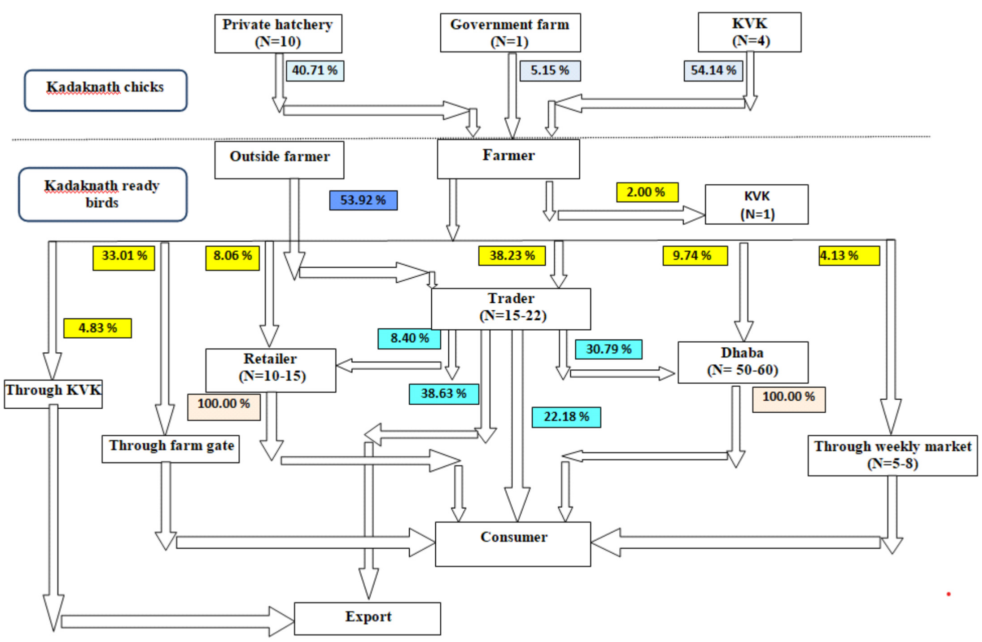

Figure 1 Kadaknath poultry value chain

operated in the study area supplied about 41 per cent of the chicks. One government hatchery farm accounted for remaining (5%) supply. It is estimated that there are about 15-20 traders, 10-15 retailers and 50-60 road side restaurants (Dhabas) operating in the surveyed districts.Majority (38%) of the birds is sold by farmers to traders and at farm gate (33%) to ultimate consumers. About 10 per cent and 8 per cent of the birds are sold by farmers directly to road sideDhabas and retailers, respectively. A small proportion (4%) of birds is sold by farmers to consumers at weekly markets. About 2 per cent of the birds find their way to KVK hatcheries from the farmers, mostly for breeding purpose; and about 5 per cent of the birds are exported to other districts through KVKs. The traders operating in the study area also procure birds from farmers from other districts. Out of the total volume of Kadaknath birds handled by the traders in the four districts, 54 per cent of birds is procured from farmers from other districts, while the farmers from the surveyed districts accounted for 46 per cent of the birds traded. About 39 per cent of the birds procured by tradersareexported to other districts, while 31 per cent and 22 per cent of the birds are sold by traders to road sideDhabas and ultimate consumers, respectively. Only about 8 per cent of birds are sold by the traders to retailers. The entire volume of birds procured by the retailers and Dhabas are sold to ultimate consumers as fresh and cooked meat, respectively.

Functioning of value chains and their governance

Poor chick supply and high chick price are the major constraints faced by the farmers. Present chick supply (from both government and private hatcheries) is not enough to fulfil the demand, which leads to a high waiting period of one to two months for the farmers. Incidence of sale at farm gate is very high on account of apprehensions on the part of farmers regarding contracting infections from other birds at weekly markets. In fact outbreaks of diseases like Ranikhet disease has been frequent in the recent past in districts like Dhar, where significant proportion of the birds are traded at weekly markets. Apart from this, market charges and transportation costs also act as disincentives for the farmers to sell their birds at the markets. In districts, where markets for the breed is well-developed, like Jhabua, sale of birds start mostly at about 5 months of age with all the birds being disposed off within s span of 1-2 months. Demand for the birds by local consumers is low and infrequent, with major demand coming from tourists, educated and salaried individuals. Birds reared are mostly exported to almost all parts of India. Due to lack of organized marketing farmers most often lack market information, in terms of buyers and market prices, which proves to be another impediment. Demand for chicks and birds from Jhabua has increased in recent past from other districts and states, on account of their Geographical Indication (GI) status (GOI 2018). The breed is thus reared in other states also, and as such the demand for ready birds for consumption from the district has decreased. Generally, demand for Kadaknath birds increases from July-August and reaches peak during November-December. Supply remaining fixed the demand-supply gap as such fluctuates during the peak season which reflects in significantly higher prices. In spite of proximity to major centre of demand for Kadaknath (like Indore), the market remains underdeveloped in districts like Dhar. Non-governmental organizations (NGO's) are functional in some districts, like Dhar, where farmers are provided with chicks, feed and built-in sheds free of cost. Large numbers of birds become ready for marketing at the same time, thus resulting in surge in supply. This along with free provision of inputs significantly lowers prices, thus leading to adverse implications for economic sustainability of commercial enterprises. Due to low demand in underdeveloped markets like Dhar and Dantewada, the birds are reared for longer periods, sometimes almost up to 1 year (instead of 6 months by which the birds are ready for marketing) which leads to increased cost of production. Markets for Kadaknath have witnessed significant development in Chhattisgarh, especially in districts like Kanker. The role of KVK and State Animal Husbandry Department has been crucial in this regard in these districts. Chick supply has been streamlined and regularized mostly by establishment of high capacity hatcheries in farms owned by educated farmers. Marketing of Kadaknath chickens has also been promoted through exclusive retail outlets along highways. Self-help groups (SHGs) have also been promoted by NGOs which supply inputs at market price, with the exception of free technical support and subsidy for sheds. In spite of this, demand fluctuation leads to constraints in timely marketing of the birds.

Table 1 Distribution of sample Kadaknath farmers

Sl No.	State	District	Backyard	Commercial	Group*	Total observation
1	Madhya Pradesh	Jhabua	6	27	0	33
2		Dhar	22	8	0	30
3	Chhattisgarh	Dantewada	0	7	11	18
4		Kanker	10	17	2	29
		Total	38	59	13	110

*10 Farmers in each group

Technical parameters of sample farms

Out of the total 110 farms surveyed in this study, majority (54%) of the farms are commercial, while 35 per cent and 12 per cent are backyard and group promoted (each group comprising approximately 10 farmers), respectively (Table 1). Average number of cycles per annum ranged between 1.89 to 2.31 for backyard and commercial farms (Table 2). On the other hand, each group promoted farm raised only 1.31 cycle per year, on an average. Number of birds (255) reared per cycle is highest for group promoted farms, followed by commercial (187) and backyard (46) farms. However, commercial farms, on average, sold significantly higher number (376) of birds per year than that by group promoted (226) farms, on account of higher cycles raised per year. Due to higher number of cycles, the birds are sold earlier in commercial farms at 25 weeks of age. Backyard and group promoted farms, on average, sold their birds at 30 and 43 weeks, respectively. As such, the average live body weight of birds at the time of sale is lowest for commercial farms (1.18 kg) and highest for group promoted farms (1.52 kg). Birds sold by commercial and backyard farms fetch significantly higher price (Rs. 486 and Rs. 477 per kg live weight) as compared to group promoted farms (Rs. 338 per kg live body weight). Kadaknath birds lay eggs after 6 months of age. Since, each cycle runs significantly longer in group promoted farms, significantly higher proportion (84%) of such farms sell eggs than backyard (11%) and commercial farms (20%).

Costand return structure for chain actors

Farmers

Table 3 elicits the average per day costs incurred by farmers and returns earned by them for rearing Kadaknath birds for different farm categories.Average paid-out cost, across all categories, is INR 261 per farm and INR 0.95 per bird. When imputed value of capital invested and family labour is considered, the total cost amounts to INR 281 per farm and INR 1.05 per bird.

Table 2 Farm category-wise basic information about Kadaknath farms

	Backyard	Commercial	Group	Pooled
Average no. of cycle(s) per year	1.89	2.31	1.31	1.70
Average no of Kadaknathbirdsper cycle	45.92	186.68	255.08	146.14
Average no of Kadaknath chicks procured	88.68	429.29	335.85	300.58
Average mortality rate	15.73	14.91	34.96	17.56
Average no. of Kadaknathbirdssold per year	72.55	376.24	226.31	253.61
Average weight ofKadaknath (per bird)	1.37	1.18	1.52	1.28
Average age at the time of sale (weeks)	29.82	25.67	42.66	29.11
Average selling price of Kadaknath (per bird) (Rs.)	658.84	568.15	551.4	597.5
Average selling price of Kadaknath per kg live body weight (Rs.)	476.53	485.82	338.16	465.16
Average price of Kadaknath egg (Per egg)	16.00	17.40	14.00	15.80
% farms selling Kadaknath egg	10.53	20.34	84.62	24.55

Table 3 Farm category-wise cost of Kadaknath rearing and income measures

Item of cost/ income	(Rs./farm/day)				(Rs. / bird/ day)			
	Back-yard	Commer-cial	Group	Pooled	Back-yard	Commer-cial	Group	Pooled
I. Cost concepts								
1. Expenditure on feed	42.33 (59.45)	278.79 (65.01)	159.79 (71)	183.04 (65.07)	0.61 (59.80)	0.70 (64.22)	0.70 (71.43)	0.67 (64)
2. Expenditure on chick	17.98 (25.25)	92.61 (21.60)	34.07 (15.08)	59.91 (21.30)	0.25 (24.51)	0.24 (22.02)	0.13 (13.27)	0.23 (22)
3. Vety. expenditures	1.09 (1.53)	7.5 (2)	4.92 (2.18)	4.98 (2)	0.01 (1)	0.02 (2)	0.02 (2.04)	0.02 (2)
4. Miscellaneous expenditure	1.32 (2)	9.75 (2.27)	5.7 (2.52)	6.36 (2.26)	0.02 (2)	0.03 (3)	0.03 (3.06)	0.02 (2)
5. Hired labour	0 (0.00)	13.02 (3.04)	0 (0.00)	9.18 (3.26)	0 (0.00)	0.01 (1)	0 (0.00)	0.005 (0.48)
6. Imputed value of family labour	8.08 (11.35)	23.31 (5.44)	18.49 (8.18)	17.48 (6.21)	0.13 (13)	0.07 (6.42)	0.09 (9.18)	0.1 (9.52)
7. Depreciation on fixed assets (shed, equipments, etc.)	0.15 (0.21)	2.94 (0.69)	1.33 (0.59)	1.78 (0.63)	0.002 (0.20)	0.007 (0.64)	0.005 (0.51)	0.005 (0.48)
8. Interest on fixed capital	0.25 (0.35)	4.43 (1.03)	1.64 (0.73)	2.66 (0.95)	0.004 (0.39)	0.01 (0.92)	0.004 (0.41)	0.007 (0.67)
9. Cost A (1+2+3+4+5+7)	62.87 (88.30)	401.07 (93.53)	205.81 (91.09)	261.16 (92.84)	0.89 (87.25)	1 (92)	0.88 (89.80)	0.95 (90.48)
10. Cost B=Cost A+8	63.12 (88.65)	405.51 (94.57)	207.45 (91.82)	263.82 (93.79)	0.89 (87.25)	1.01 (92.66)	0.89 (90.82)	0.96 (91.43)
11. Cost C=Cost B+6	71.2 (100.00)	428.81 (100.00)	225.93 (100.00)	281.3 (100.00)	1.02 (100.00)	1.09 (100.00)	0.98 (100.00)	1.05 (100.00)
II. Income measure								
12. Gross income	127.78	603.35	354.99	409.71	1.81	1.56	1.51	1.64
13. Farm labour income=12-9	64.91	202.28	149.19	148.55	0.92	0.55	0.63	0.69
14. Family labour income=12-10	64.66	197.85	147.55	145.89	0.91	0.54	0.62	0.68
15. Net income=12-11	56.58	174.54	129.06	128.42	0.78	0.47	0.53	0.59

Figures in parentheses indicate percentage

Among all the cost components, expenditures onfeed and chicks account for overwhelming shares (65% and 21%, respectively) across all farm categories. Total cost per farm is highest for commercial farms (INR 429 per farm) and lowest for backyard farms (INR 71 per farm). Gross and net income per farm is significantly higher for commercial farms (INR 603 and INR 175, respectively) than that for group promoted (INR 355 and INR 129, respectively) and backyard (INR 128 and INR 57, respectively) farms. Although, gross and net income per farm are significantly higher for commercial farms as compared to backyard farms, the same is however higher for the latter category on per bird basis. The average gross income per bird (INR 1.81) is higher than that for commercial farms (INR 1.51) on account of higher price fetched by backyard farms for their birds (Table 2). Net income per bird is also higher for backyard farms (INR 0.78) as compared to that for commercial farms (INR 0.47).

Agencies for sale by farmers

Five main agencies for sale of Kadaknath birds were identified in the study area, Farmers across all farm categories mainly sold to multiple agencies. Only in case of direct sale to ultimate consumers, significant proportion of backyard and group promoted farms sold to this agency exclusively (29% and 38%, respectively) (Table 4). Apart from exclusively selling to consumers, backyard farmers (39%) mainly sold directly to consumers and road-sideDhabas. Group promoted farmers (38%) also sell to combination of agencies comprising direct sale to consumers and KVKs (who help them in linking to markets in other districts). KVKs also procured birds from group promoted farmers for breeding purpose in their hatcheries as about 8 per cent of this category farm sold to KVKs for this purpose along with direct sale to consumers. Commercial farms mostly sold to multiple agencies comprising traders, retailers &Dhabas (29%) and traders, retailers & direct sale to consumers (24%).

Traders

Table 5 presents the average costs of procurement and sale of Kadaknath birds by traders. Traders were observed to operate in allthe surveyed district except Dantewada. Overall, across the remaining districts, for one kg of carcass, the average cost is estimated INR 741, of which 99 per cent is for the purchase of the live birds; remaining 1 per cent being accounted for by marketing & transaction costs. The total cost incurred by traders is highest in Jhabua (INR 838 per Kg), and lowest in Kanker (INR 688 per kg). Price received by the traders per kg carcass weight is also higher in Jhabua (INR 921) as compared to the same in Dhar (INR 778 per kg) and Kanker (748 per kg). As such, for each kg of carcass weight, the traders in Jhabua earned the highest net profit (INR 84), followed by Kanker (INR 60) and Dhar (INR 57).

Retailers

Retailers are operational in Jhabua and Kanker districts only. The costs to retailers are comprised of the fixed cost of their establishments, utensils and equipment. The variable costs include transport costs of the birds, wages and miscellaneous expenses. Retailers purchase both from the traders and directly from the farmers. Table 6 reveals the average cost incurred and returns earned by

Table 4 Farm category-wise proportionKadaknath birds sold to and farms selling to different agencies

Multiple / exclusive agency	Backyard				Commercial				Group				Pooled			
	No. of birds	% of birds	No. of farms	% of farms	No. of birds	% of birds	No. of farms	% of farms	No. of birds	% of birds	No. of farms	% of farms	No. of birds	% of birds	No. of farms	% of farms
Agency (1+2+3+4)	—	—	—	—	6717	30.26	8	13.56	—	—	—	—	6717	24.08	8	7.27
Agency (1+2+3)	344	12.48	4	10.53	4384	19.75	14	23.73	780	26.51	1	7.69	5508	19.74	19	17.27
Agency (1+3+4)	270	9.79	1	2.63	6139	27.66	17	28.81	340	11.56	1	7.69	6749	24.19	19	17.27
Agency (3+4)	959	34.78	15	39.47	230	1.04	1	1.69	—	—	—	—	1189	4.26	16	14.55
Agency (1+3)	290	10.52	4	10.53	2492	11.23	9	15.25	—	—	—	—	2782	9.97	13	11.82
Agency (2+3)	271	9.83	3	7.89	170	0.77	1	1.69	—	—	—	—	441	1.58	4	3.64
Agency (6+3+5)	—	—	—	—	706	3.18	2	3.39	—	—	—	—	706	2.53	2	1.82
Agency (3+5)	—	—	—	—	212	0.96	1	1.69	174	5.91	1	7.69	386	1.38	2	1.82
Agency (1+2)	—	—	—	—	140	0.63	1	1.69		0.00		0.00	140	0.50	1	0.91
Agency(6+3)	—	—	—	—	668	3.01	4	6.78	950	32.29	5	38.46	1618	5.80	9	8.18
Agency 1	—	—	—	—	340	1.53	1	1.69	—	—	—	—	340	1.22	1	0.91
Agency 3	623	22.60	11	28.95	—	—	—	—	698	23.73	5	38.46	1321	4.74	16	14.55
Grand total	2757	100.00	38	100.00	22198	100.00	59	100.00	2942	100.00	13	100.00	27897	100.00	110	100.00

Agency 1: Traders; Agency 2: Retailers; Agency 3: Consumers; Agency 4: Road-sideDhabas; Agency 5: KVKs for breeding purpose; Agency 6: Export to other districts through KVKs

Table 5 Costs incurred by traders in procurement and marketing of birds

(INR per bird per week)

Particulars	Jhabua		Dhar		Kanker		Pooled	
	Per bird	Per kg effective carcass weight	Per bird	Per kg effective carcass weight	Per bird	Per kg effective carcass weight	Per bird	Per kg effective carcass weight
Purchase price of bird	582.77	828.66	529.19	712.23	475.45	679.56	521.47	731.49
Marketing & transaction cost								
Transportation cost	2.00	2.84	2.05	2.76	2.00	2.86	2.01	2.83
	(31.10)	(31.01)	(31.06)	(31.05)	(35)	(35)	(33)	(33)
Labour cost	0.74	1.06	1.18	1.59	0.52	0.75	0.77	1.07
	(11.51)	(11.57)	(18)	(18)	(9.08)	(9.16)	(12.50)	(12.41)
Misc. expenses	3.69	5.26	3.37	4.54	3.21	4.58	3.39	4.76
	(57.39)	(57.42)	(51.06)	(51.06)	(56.02)	(56)	(54.92)	(55)
Total marketing & transaction cost	6.43	9.16	6.60	8.89	5.73	8.19	6.18	8.66
Total cost	589.20	837.82	535.80	721.11	481.17	687.74	527.65	740.15
Selling price	646.31	921.33	578.73	777.66	524.55	747.76	581.96	815.42
Net margin	57.11	83.51	42.93	56.55	43.38	60.02	54.31	75.27

Table 6 Costs incurred by Retailers in procurement and selling of carcasses/meat cuts

(INR per bird per week)

(Purchase from trader)

Particulars	Jhabua		Kanker		Pooled	
	Per bird	Per kg effective carcass weight	Per bird	Per kg effective carcass weight	Per bird	Per kg effective carcass weight
Purchase price of bird	633.83	876.86	567.00	724.30	600.42	800.58
Fixed cost						
Interest on fixed capital	0.64	0.90	1.54	1.96	1.09	1.43
	(7.74)	(7.83)	(12.37)	(12.35)	(10.54)	(10.43)
Depreciation	0.41	0.57	0.95	1.21	0.68	0.89
	(4.96))	(4.96)	(7.63)	(7.62)	(6.58)	(6.52)
Total fixed cost	1.05	1.47	2.49	3.17	1.77	2.32
	(12.70)	(12.78)	(20.00)	(19.97)	(17.12)	(16.95)
Marketing &transaction costs						
Transportation cost	2.67	3.71	3.67	4.68	3.17	4.19
	(32.29)	(32.26)	(29.42)	(29.44)	(30.56)	(30.62)
Labour expenditures	2.38	3.31	2.18	2.78	2.28	3.04
	(28.78)	(28.78)	(17.47)	(17.48)	(21.96)	(22.22)
Miscellaneous expenses	2.17	3.01	4.13	5.26	3.15	4.14
	(26.24	(26.17)	(33.10)	(33.12)	(30.36)	(30.21)
Total marketing &transaction cost	7.22	10.03	9.97	12.72	8.59	11.38
	(87.30)	(87.22)	(80.00)	(80.03)	(83)	(83.05)
Total cost	642.10	888.36	579.46	740.19	610.78	814.28
Selling price	686.74	946.06	610.42	781.79	648.20	863.93
Net margin	44.64	57.70	30.96	41.60	37.42	49.65

Table 7 Costs incurred by retailers in procurement and selling of carcasses/meat cuts

(Purchase from farmers)

(INR Per bird per week)

	Jhabua		Kanker		Pooled	
Average live weight per bird (in kg)	1.19		1.27		1.22	
Particulars	Per bird	Per kg effective carcass weight	Per bird	Per kg effective carcass weight	Per bird	Per kg effective carcass weight
Purchase price of bird	605.63	832.56	545.00	705.35	585.42	790.15
Fixed cost						
Interest on fixed cost	0.35	0.48	1.15	1.49	0.62	0.82
	(5.31)	(5.30)	(14.89)	(14.89)	(8.88)	(8.73)
Depreciation	0.22	0.31	0.68	0.88	0.38	0.50
	(3.45)	(3.44)	(8.74)	(8.74)	(5.42)	(5.34)
Total fixed cost	0.57	0.79	1.83	2.37	0.99	1.31
	(8.76)	(8.74)	(23.63)	(23.63)	(14.30)	(14.07)
Marketing and transaction costs						
Transportation cost	2.13	2.93	2.00	2.59	2.08	2.82
	(32.57)	(32.59)	(25.82)	(25.82)	(30.05)	(30.16)
Labour expenditures	2.08	2.86	1.58	2.05	1.91	2.59
	(31.85)	(31.85)	(20.44)	(20.44)	(27.60)	(27.76)
Miscellaneous expenses	1.75	2.41	2.33	3.02	1.94	2.61
	(26.82)	(26.82)	(30.12	(30.12)	(28.05)	(28.00)
Total marketing and transaction cost	5.95	8.20	5.92	7.66	5.94	8.02
	(91.24)	(91.26)	(76.37)	(76.37)	(85.70)	(85.93)
Total cost including fixed cost and marketing & transaction costs	6.52	8.99	7.75	10.03	6.93	9.34
Total cost	612.15	841.55	552.75	715.38	592.35	799.49
Selling price	654.26	901.31	591.55	763.59	636.59	855.40
Net margin	42.11	59.76	38.81	48.21	44.24	55.91

retailers, in selling dress Kadaknath meat to consumers after procuring the birds from traders. Purchase price of birds paid by retailers account for overwhelming share of total cost accrued to retailers (99% and 98%, respectively in Jhabua and Kanker).Out of the total offixed costs and marketing & transaction costs, the latter contributed significantly higher shares (87% and 80%, respectively, in Jhabua and Kanker). The selling price per kg carcass weight is significantly higher in Jhabua (INR 946) as compared to the same in Kanker (INR 782). As a result, the net margin accrued to retailers was also significantly higher for retailers in Jhabua (INR 58 per kg carcass weight) than that in Kanker (INR 42 per kg carcass weight). When retailers purchase directly from farmers, the purchase price (INR 833 and INR 705, respectively in Jhabua and Kanker) is lower than the same when purchased from traders (INR 877 and INR 724, respectively in Jhabua and Kanker) (Table 7). As result, the net margin earned by retailers (INR 60 and INR 48 per kg carcass weight, respectively in Jhabua and Kanker) is higher.

Distribution of value addition across chain actors

Tables 8-10 elicit the distribution of benefits per kg effective carcass weight across the Kadaknath value chains. There are two major chains for marketing of Kadaknath chicken in the study area; viz. chain for marketing of fresh/raw chicken for domestic consumers and chain for value added chicken. Roadside restaurants/Dhabas are the only units that sell value-added Kadaknath chicken products in the form of cooked meat.

In regard to marketing of Kadaknath birds as fresh/raw meat, for the farmer-trader-retailer-consumer chain, the net margin (INR 60 per kg carcass weight) is the highest for traders (retaining 55% of total value added). The net margin (INR 105 per kg carcass weight) for traders is even higher when they procure directly from farmers and sell to consumers. When retailers procure from farmers directly, the net margin (INR 56 per kg carcass weight) earned by them is higher than when they purchase from traders (INR 50 per kg carcass weight). Farmers account for the major shares of consumers' Rupee across all the chains for marketing of fresh/raw meat, ranging from 85 per cent to 92 per cent. When consumers of fresh/raw meat purchase directly from farmers at their farm gate, they pay significantly higher price as compared to what they pay to farmers at weekly markets.

In regard to chains for marketing of value added/cooked meat, the road side Dhabas earn higher net margin (INR 244 per kg carcass weight) when they procure from farmers directly than that (INR 233 per kg carcass weight) when they procure from traders. However, even when the birds are procured from the traders, the share of the Dhabas in the total value added is substantial (79%). The shares of farmers in consumers' Rupee come down in the value added chains (65-70%) as compared to the fresh/raw chicken chains as the Dhabas garner a significant share (29-30%).

Table 11 elicits the results regarding marketing efficiency estimates for identified value chains. Marketing efficiency is highest for farmer-consumer chain through weekly market (24.95) and lowest for the value-added chains, viz. farmer-trader-Dhaba-Consumer chain (1.84) and farmer-Dhaba-consumer chains (2.32), implying the benefits of value addition are not channelled back at the back-end of the marketing chains, mostly on account of predominantly unorganized nature of marketing system.

Table 8 Cost and returns (Per kg carcass weight) across the fresh Kadaknath meat value chain for domestic consumers of fresh/raw meat

Marketing channel	Price	Cost	Net margin	PSCR (%)	Marketing channel	Price	Cost	Net margin	PSCR (%)	Marketing channel	Price	Cost	Net margin	PSCR (%)
Farmer →	731.49	482.40	249.09	84.67	Farmer →	731.49	482.40	249.09	86.57	Farmer →	790.15	482.40	307.75	92.37
Trader →	800.58	740.15	60.43	8.00	Trader →	845.01	740.15	104.86	13.43	Retailer →	855.40	799.49	55.91	7.63
Retailer →	863.93	814.28	49.65	7.33	Consumer					Consumer				
Consumer														

*PSCR: Producers' Share in Consumers' Rupee

Table 9 Cost and returns (Per kg carcass weight) across the fresh Kadaknath meat value chain for domestic consumers of fresh/raw meat

Through farm gate					Through weekly market				
Marketing channel	Price	Cost	Net margin	PSCR (%)	Marketing channel	Price	Cost	Net margin	PSCR (%)
Farmer ↓ Consumer	833.32	482.40	350.92	100	Farmer ↓ Consumer	672.76	449.31	223.45	100

*PSCR: Producers'Share in Consumers' Rupee

Table 10 Cost and returns (Per kg carcass weight) across the value added Kadaknath meat value chain

Marketing channel	Price	Cost	Net margin	PSCR (%)	Marketing channel	price	Cost	Net margin	PSCR (%)
Farmer ↓	731.49	482.40	249.04	64.74	Farmer ↓	775.03	482.40	292.63	69.91
Trader ↓	800.67	741.15	60.52	6.12	Dhaba ↓	1108.56	864.98	243.58	30.09
Dhaba ↓	1130	896.77	233.2	29.14	Consumer				
Consumer									

*PSCR: Producers'Share in Consumers' Rupee

Table 11 Marketing efficiency across the different chains for Per Kg. Carcass Meat

	Farmer-Trader-Retailer–Consumer	Famer-Trader–Dhaba-Consumer	Farmer–Trader-Consumer	Farmer-Dhaba-Consumer	Farmer – Retailer-Consumer	Farmer-Consumer (Through weekly market)
Net price received by farmer	731.49	731.49	731.49	775.03	790.15	646.83
Cost incurred by farmer	-	-	-	-	-	25.93
Trader purchase price	731.49	731.49	731.49	-	-	-
Cost incurred by trader	8.66	8.66	8.66	-	-	-
Trader margin	60.43	60.52	104.86	-	-	-
Total cost/kg	800.58	800.67	-	-	-	-
Cost incurred by retailer	13.70	-	-	-	9.34	-
Total cost to the retailer	814.28	-	-	-	799.49	-
Cost incurred by dhaba	-	96.10	-	89.95	-	-
Total cost to dhaba	-	896.77	-	864.98	-	-
Price paid by buyer/ consumer	863.93	1129.97	845.01	1108.56	855.40	672.76
Retailer margin	49.65	-	-		55.91	-
Dhaba margin		233.20	-	243.58	-	-
Gross market margin	132.44	398.48	113.52	333.53	65.25	25.93
Net marketing margin	110.08	293.72	104.86	243.58	55.91	00.00
Marketing efficiency ratio	5.52	1.84	6.44	2.32	12.11	24.95

Conclusion

The study shows how the major Kadaknath value chains - for fresh meat and value-added cooked meat products - function. All the chains originate from mainly three back-end sources, viz. backyard production systems, commercial farms and Kadaknath groups promoted by NGO's and KVKs. Traders, retailers, road-side restaurants/Dhabas and KVKs are identified as major value chain actors operating in either fresh/raw chicken or value added/cooked chicken chains. Majority of the birds is sold by farmers to traders and to ultimate consumers at farm gate.Major proportion of the birds procured by traders is exported to other districts.In the value-added and fresh/raw chicken chains, restaurants/Dhabasand traders, respectively, garner the major share of benefits. The price premium if any, especially in value added chains are not passed at the backend of the chains to the producers, implying overall lack of systematic linkage across the value chains. Overall, this study identified structural deficiencies and vulnerabilities and provided the framework for intervention policies that can improve system efficiency. These may be promoting scientific practices of Kadaknath production, rationalizing the subsidies given to resource poor to encourage efficiency in production & realizing genuine economies of scale, implementation of integrated and inclusive system for Kadaknath production and sale and creation of awareness about the health and other benefits about the breed among consumers. Establishing and strengthening marketing groups or co-operatives would also encourage the farmers to leverage scale economies and bring them closer to the consumers in the value chain thus removing the inefficiencies which impede their bargaining power.

Acknowledgements

Financial support provided by Indian Council of Agricultural Research (ICAR), routed through ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi, for carrying out this study in the form of network research project 'Policy imperatives for promoting value chain for agricultural commodities in India', is duly acknowledged. The authors sincerely acknowledge the support provided by Senior Scientists & Heads of respective Krishi Vigyan Kendras (KVKs) in the districts covered under this study, viz. Dr. B. Sahu, KVK, Kanker; Dr. IS

Tomar, KVK, Jhabua; Dr. GS Gathiye, KVK, Dhar and Dr. N. Sahu, KVK, Dantewada.

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Received 24 November 2021 Accepted 16 February 2022

Agricultural Economics Research Review 2022, 35 (2), 151-158
DOI: 10.5958/0974-0279.2022.00037.4

Export and import of bamboo and bamboo products: Markov chain analysis

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Abstract Bamboo trade has played a vital role in upliftment of socio-economic status of rural communities. This paper used trend analysis, instability index and markov chain analysis for logical inferences of the bamboo products export. The results reveal an incremental trend in area, production and productivity of bamboo, indicating ample scope for entrepreneurship development in bamboo sector. There is growth in export of bamboo products over the years however, India is still a net importer of bamboo products signifying huge scope to harness the global market.

Keywords Bamboo products, export, import, growth, Markov chain analysis

JEL codes Q17, Q23

Bamboo is the fastest growing plant. It belongs to the family *Poaceae* (Graminae) and found in the tropical, sub-tropical and mild temperate regions (FSI 2019). It is one of the most valuable non-wood forest products. Worldwide, more than two billion people depend on bamboos for their basic needs, as a renewable, productive, versatile, low cost or no cost, easily accessed, environment-enhancing resource especially in villages and countryside of the developing world (Sastry 2008). Value-added bamboo has the potential in environment and economy. Its trade has gained importance in upliftment of socio-economic status of rural communities (Sundriyal and Sundriyal 2011). The employment potential of bamboo is very high and the major work force constitutes of the rural poor, especially women and 432 million work days per annum are provided by the bamboo sector in India (Dhurga 2017). It was reported that, over 77 genera and 1,450 species (Hunter 2003) present in the world and most of which are confined to South-East Asia with largest number of species (ca 500) in China (Zhao-hua and Kobayashi 2004) followed by Japan (237) and India (138). In India, there are 125 indigenous and 11 exotic species of bamboos belonging to 23 genera. More than half of the species diversity has been recorded from North-East India with 58 species belonging to 10 genera (FSI 2011). The major bamboo producing countries in Asia are India and China, contributing 70 per cent bamboo of Asia .The largest bamboo producer and exporter in the world is China and there has been a rapid growth in its trade over the past few years. The export value of value-added bamboo products increased faster than the traditional ones (Junqi 2014). The National Bamboo Mission (NBM) is also playing a major role in development of bamboo sector in India. It have special subsidy schemes for the north eastern states to develop the sector right from propagation of quality planting material to establishment of processing industries to marketing of value added products(Government of India 2019). With increasing demand of bamboo products in the world our country has a wide scope to boost up its economy. This paper is an attempt to provide a comprehensive analysis of trends in its production and performance in global trade along with instability analysis of bamboo products.

Methodology

The analysis was based on the data for 10 years (2009 to 2018) of value of exports and imports of bamboo products. The secondary data on export and import of bamboo products was collected from the United Nations Comtrade Database (United Nations Comtrade Database 2020). Study period was guided by the availability of comparable data as India adopted the Harmonized Commodity Description and Coding System (HS) for bamboo products only in 2007. Prior to 2007 there were only ten 6-digit UN HS codes covering bamboo and rattan commodities, including bamboo and rattan vegetable materials, plaiting articles, furniture and seats, and bamboo shoots, of which only two were specified for bamboo and rattan. 14 new codes for bamboo and rattan have been put into effect since 2007, with the efforts of INBAR, the World Customs Organization and Chinese Customs, in which individual codes were given to bamboo and rattan wickerwork, furniture and seats, and bamboo charcoal, flooring, plywood, pulp, paper and preserved bamboo shoots. In 2018, there were 24 HS codes for bamboo and rattan (INBAR 2020). Total twelve bamboo products along with its HS codes are given in Table 1. The category of industrialized bamboo products has high demand in the global trade.

Analytical techniques

The Compound Annual Growth Rate (CAGR) and the instability index of the export and import were calculated. The product concentration was analyzed by estimating the share of values of products in export and import. Three potential bamboo products *viz.* seats prepared from bamboo, bamboo made mats and bamboo shoots, which can be prepared at household or community level of high export quality with less investment in machineries, among others were considered for markov chain analysis to observe their export performance. Major importing countries and other importing countries pooled together as other countries of the particular products from India were considered for the markov chain analysis.

Table 1 Description of bamboo products

Category	HS code	Item Details
Bamboo raw materials	140110	Bamboo used primarily for plaiting
Bamboo shoots	200591	Vegetable preparations; bamboo shoots, prepared or preserved otherwise than by vinegar or acetic acid, not frozen
Industrialized bamboo products	440210	Wood; charcoal of bamboo (including shell or nut charcoal), whether or not agglomerated
	441210	Plywood, veneered panels and similar laminated wood; of bamboo
	440921	Wood (including strips & friezes for parquet flooring, not assembled) continuously shaped (tongued, grooved, rebated, chamfered, V-jointed, beaded, moulded, rounded/ the like) along any of its edges, ends/faces, whether/not planed/sanded/end-jointed, non-con
	460121	Plaiting materials, plaits and similar products of plaiting materials; mats, matting and screens, of bamboo
	470630	Pulp; of bamboo
	482361	Paper and paperboard; trays, dishes, plates, cups and the like, of bamboo paper or paperboard
Bamboo woven products	460192	Plaits & similar products of plaiting materials, whether/not assembled into strips; plaiting materials, plaits & similar products of plaiting materials, bound together in parallel strands/woven, in sheet form, whether/not being finished articles, of bamboo
	460211	Basketwork, wickerwork and other articles; of bamboo, made directly to shape from plaiting materials or made up from goods of heading no. 4601
Bamboo furniture products	940152	Seats of bamboo
	940382	Furniture of bamboo

Source United Nations Comtrade Database, 2020

Markov Chain analysis

The average export of bamboo product to particular country was considered as a random variable following a first order Markov process (Kusuma and Basavaraja 2014), (Satishkumar et al. 2016).

$$E_{jt} = \sum_{i=1}^{n} (E_{it-1}) P_{ij} + e_{jt}$$

Where,

E_{jt} = Exports of bamboo product from India during the year t to j[th] country

E_{it-1} = Exports of bamboo product to i[th] country during the period t-1

P_{ij} = Probability that exports of bamboo product will shift from i[th] country to j[th] country

e_{jt} = The error term which is statistically independent of E_{it-1}, and

n = Number of importing countries of bamboo product

The transitional probability P_{ij}, which can be arranged in a (c x r) matrix, have the following properties.

$0 \leq P_{ij} \leq 1$

$\Sigma P_{ij} = 1$

The expected export share of bamboo product of a country during the period 't' was obtained by multiplying the actual exports in the previous period (t-1) by the transitional probability matrix. The transitional probability matrix is estimated in the linear programming (LP) framework by a method referred to as minimization of mean absolute deviation (MAD).

The linear programming formulation is stated as,

Min $OP^* + I_e$

Subjected to

$XP^* + V = Y$

$GP^* = 1$

$P^* > 0$

Where, O is the vector of zeros

P* is the vector in which probability P_{ij} are arranged

I is an apparently dimensioned vector of area, e is the vector of absolute errors

Y is the vector of export of bamboo product to each country.

X is the block diagonal matrix of lagged values of Y

V is the vector of errors

G is the grouping matrix to add the row elements of P arranged in P* to unity.

Results and discussion

Status of bamboo in India

Bamboo has been traditionally harvested from forest lands in India and the homesteads which have a few clumps of one of the many species of bamboo for household use, but very less intervention in terms of commercial planting has been done in the past (Kumar and Tanya 2015). The total area under the bamboo in India has been increasing (Table 2.) It was observed that there was 12.78 per cent growth in area from 2011 to 2019 touching 16 million ha. India is producing 39.45 thousand million of bamboo culms (woody ringed stems of bamboo are called as culm) giving a total of 277587 thousand metric ton (MT) of bamboo in 2019. Number of estimated culms has increased by 40 per cent and green equivalent weight by 39 per cent between 2011 to 2019. The increasing trend in area and production over the past years shows a better scope for entrepreneurship development in bamboo sector which will generate large scale of employment. As per report of Forest Survey of India 2019, Madhya Pradesh has maximum bamboo bearing area (2.0 m ha) followed by Maharashtra (1.5 m ha), Arunachal Pradesh (1.49 m ha) and Odisha (1.18 m ha). The maximum number

Table 2 Area and production of bamboo in India

Particulars	2011	2017	2019	Change between 2011 and 2019 (%)
Area(million ha)	13.96	15.69	16.00	12.78
No of estimated culms (in million)	23297	28103	39454	40.96
Green equivalent weight ('000 MT)	169312	188759	277587	39.00

Source FSI, 2019

of green culms were found in Arunachal Pradesh (4869 million), followed by Assam (3082 million) and Madhya Pradesh (2406 million).

Bamboo production in north eastern region

Bamboo is one of the traditional economic crop for North-eastern region of India and also it has proven to have tremendous bio-genomic, resilience in combating the brunt of climate change (Basumatary et al. 2015). The north eastern region comprising of eight states along with West Bengal accounts for more than 50 per cent of the bamboo resources which is collectively considered as hotspot of biodiversity' (Upreti and Sundriyal 2001). In terms of bamboo bearing area Arunachal Pradesh stands at 3rd position followed by Assam and Manipur in 2019 (FSI 2019). Similarly, Arunachal Pradesh produces highest number of culms (14.62%), followed by Assam (9.70%), Nagaland (6.45%) and Manipur (3.86%). The weight of green culms was estimated maximum in Arunachal Pradesh (22.6 MT) followed by Nagaland (18.6 MT) and Assam (17.2 MT) as per the report of FSI, 2019. Hence, the statistics shows that there was dominance of north eastern states in terms of production of bamboo resources. It reveals that being the region unexplored has ample scope for intervention to earn more livelihood and income from these bamboo resources through developing entrepreneurship within the country to compete at globally. North Eastern Council (NEC) has also identified bamboo cultivation as a major source of economic gains to the North Eastern Region having potential to provide additional source of income to the small and marginal farmers, which has become priority of the Government (Government of India 2019) in boosting-up the economy of North Eastern Hill Region (NEHR).

Role of National Bamboo Mission in production of bamboo

The major operating scheme in the country for development of bamboo sector is National Bamboo Mission (NBM) which was launched as a centrally sponsored scheme in 2006-07 and was subsumed under Mission for Integrated Development of Horticulture (MIDH) in 2014-15. Maintenance of the bamboo plants were taken care under that and the significant growth of export were observed over the study period. After 2015, value addition along with other propagation activities were also carried out which in turn boosted the bamboo production along with the export of its products. NBM expects to cover more area ensuring adequate stocks of selected genetically superior quality planting material, promotion and diversification of bamboo products through establishment of MSME and development of value chain, setting up and strengthening of bamboo bazaars including promoting online trade and enhanced cooperation within the country related to research, technology, product development, machinery, trade information and knowledge sharing platform particularly for NE States to give a boost to the low key bamboo based industry in the country (Government of India 2019). With the successful achievements of the objectives of the mission will boost the bamboo sector of the country to next level.

Trade of bamboo and its products

The analysis of external trade of bamboo and its products showed a compound annual growth rate of 8.59 per cent (Table 3). On the other hand, the compound annual growth rate of import in its value terms was 15.00 per cent. The balance of trade was negative which signifies that India as a net importer of bamboo products despite of its second position in bamboo production in the world after China (Aniket 2013). It means that there are huge opportunities to harness the international market by increasing its production and ensuring establishment of a proper value chain ecosystem (Government of India 2019).

Table 3 External trade of bamboo products (in US million dollar)

Year	Export value	Import value	Balance of trade
2009	707254	8432635	-7725381
2010	594183	12537839	-11943656
2011	1514309	22791490	-21277181
2012	2114754	23804298	-21689544
2013	1348249	23502757	-22154508
2014	1585595	28895794	-27310199
2015	2599666	34659440	-32059774
2016	1061768	35004466	-33942698
2017	1290261	32962258	-31671997
2018	1959182	35076492	-33117310
CAGR(%)	8.59	15.00***	

*Significant at 10%, ** Significant at 5% and *** Significant at 1% probability level

Source United Nations Comtrade Database, 2020

Growth and instability in global trade of bamboo and its products

The relative shares to the total export value of bamboo products reveals that bamboo furniture products (22.67%) contributed more to total value and the lowest contribution was made by pulp of bamboo (0.44%). The compound annual growth rate was found to be highest in case of bamboo wood (75.09%) (Table 4). All the bamboo products shows a positive CAGR value but only five products shows significant growth in export value. Therefore, there is need to consider the quality of all the products to get a better price in the market. Although the products export value has been found to be increased over the years but there was high instability in the growth which may be due to unstable supply of the products as bamboo is mainly harvested from the reserved forests or community forests.

The import value of bamboo products was found to be much higher than the export. The CAGR of import value of bamboo poles were 60.69 per cent contributed highest among all the products to the total import share. Bamboo paper based products contributed lowest to total share with a value of 0.03 per cent. The instability index of the products in import value shows much less instability compared to export instability. Similar evidence has been reported by Anjum and Madhulika (2018). Therefore, policy makers need to focus on this aspect to reduce the instability in export of bamboo products so as to gain trust of the markets relying on India for its bamboo products.

Product concentration

Technically, lower product concentrations in external trade are indicative of wider product bases with considerable leverage to cushion the adverse effects of individual products. Conversely, higher product concentrations are vulnerable to fluctuations in prices of major product groups and consequently adverse effects on the performance of the sector (Joseph et al. 2006). The product concentrations in exports were covered by bamboo furniture (HS code 940382) with 22.67 per cent, charcoal of bamboo (HS code 440210) with 14.48 per cent, bamboo primarily used for plaiting material (HS code 140110) and bamboo paper based products (HS code 482361) with a total share of 60.92 per cent to the total export value (Table 5). All remaining 8 products contributes only 39.08 per cent to total export. Compared to exports, the product concentration was higher in import during the study period. HS code 140110 alone contributed 56.44 per cent share followed by bamboo charcoal, pulp of bamboo and bamboo wood. Therefore, it was evident that the value added products are more concentrated on the global market of bamboo just after the raw bamboo poles.

Table 4 Relative shares, compound annual growth rates and instability index of bamboo products exports and imports value (2009-2018)

HS code	Export			Import		
	Relative share (%)	CAGR (%)	Instability index (%)	Relative share (%)	CAGR (%)	Instability index (%)
140110	12.04	39.64	142.32	56.44	60.69***	29.52
200591	0.85	16.90*	139.54	0.31	46.98***	22.46
440210	14.48	56.58*	214.28	0.30	40.63	115.19
441210	5.75	44.79*	53.17	29.69	26.20*	41.18
440921	9.35	75.09***	38.24	2.32	40.60**	21.88
460121	8.41	34.40	69.41	2.17	35.60	25.47
460192	1.20	42.53	141.71	1.84	27.81**	51.70
460211	4.92	55.51**	88.80	2.06	44.00***	19.36
470630	0.44	62.08	76.58	2.56	43.97**	33.60
482361	11.73	24.17	137.54	0.03	39.51	99.19
940152	8.16	35.12	139.46	0.16	31.20	59.61
940382	22.67	31.84*	51.70	2.12	30.49*	40.15
Total	100			100		

*Significant at 10%, ** Significant at 5% and *** Significant at 1% probability level

Table 5 Product concentration in exports and import of bamboo products (2009-2018)

Export		Import	
HS code (%)	Share	HS code (%)	Share
940382	22.67	140110	56.44
440210	14.48	441210	29.69
140110	12.04	470630	2.56
482361	11.73	440921	2.32
Total	60.92	Total	91.01

Source United Nations Comtrade Database, 2020

Export analysis of bamboo and its products

In the north eastern region of India, there is lack of industrialization, therefore small scale industries or business are operating in the region. Bamboo products like seats prepared from bamboo, bamboo mats, bamboo shoots etc. are potential products which can be prepared at household or community level of high export quality with less investment in machineries. The major concern to be considered is mainly the market for the products and stability in export from which the stakeholders will not be discouraged. Therefore, export performance of these three potential bamboo based products, *viz.* bamboo shoots, bamboo mats and seats prepared from bamboo which can be prepared at household level in the north eastern region were carried out using markov chain analysis.

The major importers of bamboo made mats from India are Netherlands, Sri Lanka, Bahrain, Germany and Oman. The transitional probability matrix of bamboo made mats from India reveals that Netherlands was the most stable importer of bamboo made mats with highest retention capacity of 74 per cent (Table 6). Oman was the second stable importer from India with 50 per cent retention capacity by losing its share to Sri Lanka (28%) and Bahrain (21%). Other countries together have a retention capacity of 60 percent and likely to gain 100 percent of Bahrain market. The most unstable markets among the importing countries were Bahrain and Germany with the zero per cent retention. . The country like China is giving tough competition in the bamboo product market (INBAR 2019; Aniket 2013) which may be reason for zero retention capacity of Indian products in these markets. Bahrain having zero retention probability was likely to gain from Germany (92%) and Oman (21%). This indicates that India can continue exporting to Bahrain that has strong preference for the bamboo made mat.

The major importers of bamboo made seats from India were Australia, France, USA, Spain and Netherlands. The transitional probability matrix of bamboo made seats from India reveals that USA was the most stable importer of bamboo made seats with highest retention capacity of 63 per cent followed by Australia (45%) as second stable importer (Table 7). Other countries together retention capacity (71%) has shown that although they were importing in fewer amounts but were reliable importer from India. The study is in line with Satishkumar et al. (2016). Retention capacity of Spain was very low (9%) and was unstable importer of seats of bamboo by losing its share to Australia (33%) and other countries (50%). France and Netherland reported zero transitional probability implying that the markets were not stable for India's export. Although retention capacity of France was zero but it was likely to gain from Netherlands (69%) and USA (15%). Netherlands was likely to gain from Australia (32%) and Spain (6%). Similar studies were reported by Shilpa et al. (2017).

New Zealand was found to be the stable importer of bamboo shoot with 72 per cent retention probability

Table 6 Transitional probability matrix of bamboo mats export (2009 to 2018)

	Netherlands	Sri Lanka	Bahrain	Germany	Oman	Others
Netherlands	**0.769**	0.008	0.000	0.000	0.008	0.215
Sri Lanka	0.577	**0.220**	0.000	0.000	0.000	0.203
Bahrain	0.000	0.000	**0.000**	0.000	0.000	1.000
Germany	0.078	0.000	0.922	**0.000**	0.000	0.000
Oman	0.000	0.282	0.213	0.000	**0.505**	0.000
others	0.000	0.000	0.001	0.395	0.000	**0.603**

Table 7 Transitional probability matrix of bamboo made seats export (2009 to 2018)

Countries	Australia	France	USA	Spain	Netherlands	Others
Australia	**0.445**	0.000	0.131	0.000	0.332	0.092
France	0.000	**0.000**	0.000	0.000	0.000	1.000
USA	0.000	0.154	**0.634**	0.199	0.000	0.013
Spain	0.334	0.000	0.000	**0.096**	0.066	0.503
Netherlands	0.310	0.690	0.000	0.000	**0.000**	0.000
Others	0.002	0.003	0.246	0.030	0.000	**0.719**

Table 8 Transitional probability matrix of bamboo shoot export (2009 to 2018)

	United Arab Emirates	Australia	Germany	United Kingdom	New Zealand	Others
United Arab Emirates	**0.498**	0.502	0.000	0.000	0.000	0.000
Australia	0.012	**0.507**	0.000	0.165	0.107	0.210
Germany	0.154	0.000	**0.000**	0.761	0.000	0.084
United Kingdom	0.000	0.000	0.000	**0.000**	0.000	1.000
New Zealand	0.000	0.000	0.030	0.000	**0.728**	0.241
Others	0.000	0.000	0.017	0.056	0.000	**0.927**

losing its 24 per cent share to other countries (Table 8). Besides New Zealand, Australia and United Arab Emirates were the stable markets with retention capacity of 50 per cent and 49 per cent, respectively. The 'other countries' category which was the minor importers of bamboo shoot shows a retention probability of 92 per cent which suggests beneficial trade with these nations. Similar findings were given by Mahadevaiah et al. (2005) where other countries retained highest. Interestingly, the retention capacity of United Kingdom was found to be zero but it was likely to gain from the switch over from Germany and Australia. This shows that export of Indian bamboo shoot have strong preference of United Kingdom.

Conclusion

From the study we observed an increasing growth in bamboo sector in terms of area and production along with high growth in the export of bamboo products. Among all the products, value added bamboo products like furniture has shown more profit. The study also revealed that the bamboo products like bamboo shoots, bamboo made seats and bamboo made mat were having ample scope for its trade to abroad. The product bamboo shoots have scope for its export to New Zealand, USA market for bamboo made seats whereas the product bamboo made mat is preferred more in the market of Netherlands. India is also importing a large amount of bamboo products. Therefore, within our country there are ample scopes for its entrepreneurship development for huge number of unemployed youths. As so many programmes have been launched by state and central government like national bamboo mission (NBM) which need to realize among the society for further to make it more useful for every stakeholder.

Acknowledgement

The paper is a part of doctoral research study. The authors are grateful to the University Grant Commission(UGC), New Delhi for funding the research work.

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Received 7 February 2021 Accepted 14 August 2021

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