July-
December
2023
Volume 36
Number 2

ISSN 0971-3441
Online ISSN 0974-0279

Agricultural Economics Research Review

Agricultural Economics Research Association (India)

Agricultural Economics Research Association (India)

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. 36 (No.2) 2023

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

Published by:
Dr Anjani Kumar, 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 36 **Number 2** **July-December 2023**

Contents

Author index

Agricultural Economics Research Review 2023, 36 (2), 111-122
DOI: 10.5958/0974-0279.2023.00026.5

Does India have enough feedstock to meet its E20 fuel-blending targets by 2025?[§]

Shweta Saini[1]* and Siraj Hussain[2]

[1]Arcus Policy Research, New Delhi
[2]formerly Ministry of Agriculture (Government of India)

*Corresponding author: ssaini@arcusresearch.in

Abstract The Indian Government has set the target of achieving 20 per cent blending of ethanol (E20) in petrol by 2025-26. This is projected to achieve savings of about $4 billion in country's annual oil import bill. The NITI Aayog projects country's annual ethanol requirement at 10.16 billion litres to achieve the E20 mandate and an additional 3.34 billion litres to meet the demand from other industries. This paper estimates the requirement and availability of feedstock (sugarcane, rice, and maize) to meet these E20 mandates. The study reveals that India is not likely to have enough feedstocks to meet the E20 blending target by 2025-26. Besides, with climate change and growing pressures on land coupled with the country's growing nutritional requirements, the government may do well to rethink its land-use policy, water-use policy and even its climate-related plans. It should define a medium to long-run roadmap of providing enough crops for fuel blending targets.

Keywords E-20 mandate, ethanol, feedstock availability, sugarcane, rice, maize, energy security, atmanirbharta, food security, fuel blending, India

JEL codes Q1, Q4, C6, O44, O53

India depends on imports to meet roughly 86 per cent of its domestic demand for petroleum products (Saini et al. 2023). Such overwhelming dependence on imported crude oil has an adverse impact on India's energy security and makes the country vulnerable to volatility in globalcrude oil prices (Sati et al. 2022, Rogoff 2022). In 2021-22, India's imports of crude oil were worth USD 120 billion. One of the measures taken by the Indian Government to reduce dependence on imported petroleum is the promotion of bio fuels, mainly ethanol-blended petrol. According to the National Institution of Transforming India (NITI Aayog), an annual saving of US $4 billion could be achieved by ethanol blending of petrol. The measure is also expected to reduce greenhouse gas emissions (Kumar 2021 and PIB 2024).

Since 2018, when the National Policy on Biofuels (NPB) was introduced, considerable progress has been made in achieving the Government's fuel blending target. Between the ethanol supply year (ESY)[1] 2019-20 and 2021-22, the availability of ethanol for blending rose from less than 2 billion litres to 4.1 billion litres, increasing the average blending rate in the country from 5 per cent to 9.5 per cent. Having originally set itself the target of achieving a blending rate of 20 per cent

[§]This paper is an updated and abridged version of the Report "Ethanol Blending of Petrol in India: An assessment of raw material availability" authored by Shweta Saini, Pulkit Khatri and Siraj Hussain. The Report can be read here: https://arcusresearch.in/wp-content/uploads/2023/05/Ethanol-blending-of-petrol-in-India-APR-.pdf
[1]The ethanol supply year (ESY) was recently changed from the earlier 12-month period of December 1 to November 30 to a 11-month period from December 1 to October 31.

by 2029-30, the Government has now advanced the target year to 2025-26.

There are three major challenges to achieving the target: first is a realistic assessment of surpluses of Indian crops which can provide the required feed stock for ethanol production from 2025-26 onwards. When ethanol blending policy was promoted in 2018, the country was surplus in its major crops; however, the recent impact of climate change on rains and temperatures has affected these crop surpluses adversely. In the two years of 2022 and 2023, the surpluses in India's staple crops of rice and wheat dwindled, pushing the Government to undertake multiple steps to restrict their trade so as to address the high rates of food inflation. The second is the increase in demand for ethanol from the competing and fast-growing industries like the alcoholic beverages. There is also increasing competition from the feed industry for ethanol feedstock crops like maize. Third is the trade-off between using crops or even resources like land for producing crops for food vs fuel. The country may need to strategically plan how much of its food crops can be diverted towards fuel production. Concerns over undernutrition (one in every third undernourished person in the world is in India) and affordability of balanced diets (FAO's "The State of Food Security and Nutrition in the World" 2023) remain the mainstay in debate.

This paper attempts to answer these questions.

Indian ethanol production and policies

Biofuels are produced from any plant material which can be converted into fuels (e.g., charcoal) or electricity and/or heat. Biofuels used as transport fuels include ethanol, biodiesel, renewable diesel, and bio-jet. The global production of biofuels used in transportation has increased over the years and was about 157.4 billion litres in the triennium ending (TE) 2020 (IEA 2021), with ethanol accounting for about 69 per cent, followed by biodiesel (27%) and renewable diesel (4%). In India, coal is the biggest energy source accounting for 43 per cent, followed by oil (24%) and biofuels (22%) (IEA 2021).

Ethanol can be produced from various sources, including sugarcane, foodgrains, and agricultural or industrial waste, utilizing either first generation (1G) or second generation (2G) technologies. The 1G technology involves the production of ethanol directly from the food crops. The 2G technology is more advanced, as it enables the production of ethanol from Agri- byproducts, non-food crops, industrial wastes, and lignocellulose feedstocks (Susmozas et al. 2020). The NITI Aayog (2021) has strongly advocated the use of 2G technology for producing bioethanol. However, despite some progress, the 2G technology is still commercially unviable (Zhou et al. 2021) in India or even globally. This implies that most of India's ethanol production today is directly from crops.

Blending petrol with ethanol serves two purposes: (i) it reduces the demand for oil without significantly affecting the fuel efficiency of vehicles, and (ii) reduces emissions since blended petrol burns more cleanly than petrol (Kumar 2021 and PIB 2022). The USA and Brazil are the largest global ethanol producers today. For TE 2020, the two countries accounted for 84 per cent of global ethanol production (IEA 2021). In Brazil, the rate of ethanol-blending in petrol in 2022 was 27 per cent (ET 2022).

Although India first permitted ethanol blending in 1948 with the passing of the Power Alcohol Act, it was not until 2003 that the Government launched its Ethanol Blending Programme (EBP), which made it mandatory to blend 5 per cent ethanol with petrol in nine states and four union territories. Subsequently, blending was made optional in 2004 and 2005 because of the shortage of ethanol. The mandate was reintroduced in 2006, when the Government directed oil marketing companies (OMCs) to sell 5 per cent ethanol-blended petrol in 20 states and four union territories; the following year, the mandate was extended all over the country, barring the north-eastern states, J&K and the islands (Ray, Miglani and Goldar 2011).

Ethanol blending received a fillip after the second National Policy on Bio Fuels (NPB) was introduced in 2018, under which 10 per cent blending was to be achieved by 2020-21 and 20 per cent blending (E20) by 2030. On the occasion of the World Environment Day in 2021, the Prime Minister announced the advancement of the E20 target from year 2030 to 2025-26, following which the NPB was amended in 2022 (PIB 2022). To help achieve the target, the Government introduced several measures to increase the production of ethanol, which included the *Pradhan Mantri Ji-Van Yojana* aimed at incentivising investment in integrated ethanol units and allowing the use of surplus rice available with the Food Corporation of India (FCI) for ethanol production. The use of imported denatured ethanol[2] for fuel blending has been restricted. However, the announcement by the Finance Minister of India in her budget speech in 2022-23to exempt imported denatured ethanol from basic excise duty indicates some relaxation of the restriction, at least for non-blending fuel purposes.

In ESY 2021-22 (December to November), India produced 3.76 billion litres of ethanol for blending (MOPNG). The data sourced from the Ministry of Petroleum and Natural Gas (MOPNG) and the Indian Sugar Mill Association (ISMA) indicates that 84 per cent of this ethanol was produced from sugarcane, about 10 per cent from surplus rice from FCI and the remaining 5 per cent from maize, damaged grains, and rice from the open market.

Estimating feedstock requirement for E20

In June 2021, the NITI Aayog in its policy guiding report titled *"Roadmap for Ethanol Blending in India 2020-25"* provided the estimates of the amount of ethanol that would be needed for achieving E20 blending target. It also provided the source of feedstock to produce it. The major feedstocks were sugarcane, rice and maize.

The NITI Aayog has estimated the total annual demand for ethanol in 2025 at 13.5 billion litres, of which 10.16 billion litres is for blending of petrol and 3.4 billion litres for other uses. Of the estimated demand for blending, it projected 5.5 billion litres to come from sugarcane and 4.66 billion litres from grains. As the report did not assign the contribution between grains, we have assumed that rice and maize are the two grains and each of them is to provide 2.33 billion litres of ethanol.

It has been found that different feedstocks provide different yields of ethanol. A tonne of sugarcane can produce 20 litres of ethanol, a tonne of rice around 435 litres and a tonne of maize 380 litres. The high conversion rate of rice makes it a preferred feedstock for ethanol production.

Based on this assumption and using the crop to ethanol conversion ratios, we estimated the total demand for sugarcane, rice, and maize crops to meet the E20 blending target. We found that to produce 10.16 billion litres of ethanol, India will need 275 million metric tonnes (MMT) of sugarcane, 6.1 MMT of maize, and 5.5 MMT of rice (Table 1). Unlike in the case of sugarcane processing, which yields ethanol as a by-product, the diversion of rice and maize to produce ethanol means the diversion of these crops from food to ethanol production.

Using the existing levels of average crop yields, we found that the country will need to earmark 7.1 Mha or roughly 3 per cent of India's gross cropped area to produce the feedstock needed for E20 by 2025-26.

Table 1 Crop area requirement for meeting E20 targets in 2025-26

Feedstock	Supply target (billion litres)	Ethanol yield per tonne feedstock (litres)	Feedstock required (MMT)	Land requirement (Mha.)^
Sugar cane*	5.5	20	275	3.3
Maize	2.33	380	6.1	1.8
Rice	2.33	425**	5.5	2.0
Total	10.16	-	-	7.1

Source Estimated by authors
Notes * Ethanol is assumed to be produced through the B-Heavy molasses route. Ethanol yields have been taken from NITI Aayog's ethanol roadmap, except for sugarcane.
**As per NITI Aayog, ethanol yield from FCI rice and (broken) rice sourced from the open market is 450 litres/tonne and 400 litres/t respectively. Here, we have assumed an average yield of 425 litres/t of rice.
^crop yields have beentaken for year 2021-22 as 8.4 t/ha for sugarcane, 3.4 t/ha for maize and 2.8 t/ha for rice.

[2]Ethanol is of two types – denatured and un-denatured. Denatured ethanol is used as a fuel, or as inputs for medical and industrial purposes while un-denatured ethanol is mainly used to produce alcoholic beverages.

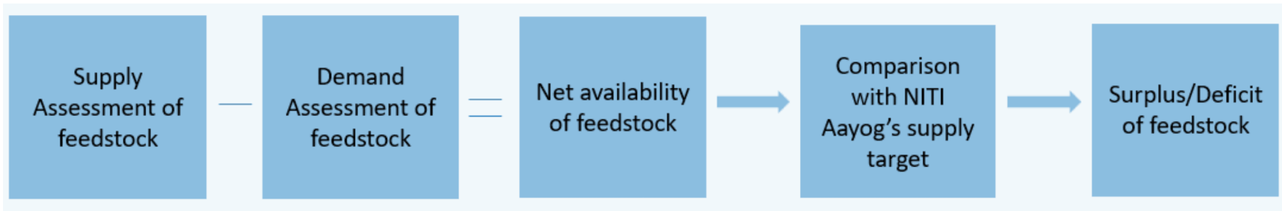


Figure 1 Concept of a crop balance sheet

So, the next question is: can the country spare the required quantities of these crops and resources? To estimate this, we have drawn up the crop-wise annual balance sheets for sugarcane, rice and maize crops for the year 2025-26.

The balance sheet concept involves estimating the residual supply of each crop available for ethanol production after domestic and industrial consumption demand, export demand, stocking requirements if any, and seed and feed requirements are met (Figure 1). The wastage along the crop's value-chain has also been accounted for, which reduces the system's availability. Using income elasticities of demand and supply, each crop's supply and demand are projected for the year 2025-26. To account for several possibilities in future, scenario-wise projections have been made for both demand and supply. Some of the production-side scenarios include, a 5 per cent jump in yields owing to a technology upgrade, a 5 per cent fall in yields because of adverse climate change effects, and a business-as-usual (BAU) scenario that builds on the past performance of the crop. On the demand side, the projections include growth in competing industries such as demand of maize for poultry. The projected demand has been mapped with supplies under different scenarios, and the residuals so estimated have been compared to the demand for feedstock from Table 1.

The crop-wise results have been summarized in the following sections.

Sugarcane: Projected to be the biggest feedstock for E20

The production of ethanol in the country in ESY 2021-22 was 4.1 billion litres. About 84 per cent of this was produced from sugarcane- derived products[3]. As per NITI Aayog's roadmap, in 2025-26 too, out of the 10.16 billion litres required for E20, at least 5.5 billion litres or about 55 per cent would come from sugarcane-based products.[4] As presented in Table 1, India will need at least about 275 MMT of sugarcane every year by 2025-26 to produce 5.5 billion litres of ethanol annually for meeting E20 target.

Using the assumptions listed in Table 2, we have projected 20 possible scenarios of the sugarcane balance sheet.

The sugarcane availability forecast has been done for three scenarios. The first (P1) is the BAU scenario, based on historical data analysis and forecasts of sugarcane area and yield. The projections of area have been made based on data from 2001-02 to 2021-22, using the Auto-regressive Integrated Moving Average (ARIMA) model. Sugarcane yields have been forecast employing the exponential smoothening forecast

[3]After the Government allowed the use of B-Heavy molasses and sugarcane juice/syrup to produce ethanol in 2018-19, there has been an increasing diversion of sugarcane for ethanol production (3.5 MMT equivalent of sugar in 2021-22; expected to rise to around 4 to 4.5 MMT in 2022-23) (ISMA).

[4]Molasses-based ethanol production can be sourced from two main avenues: (i) molasses, could be A, B-heavy, and C-Heavy), and (ii) directly from sugarcane juice as the primary product. The efficiency of ethanol production is positively impacted by a higher sucrose content in the feedstock. For instance, when ethanol is derived directly from sugarcane juice, a mill can yield approximately 62 to 70 litres of ethanol per tonne of sugarcane. On the other hand, if ethanol is produced as a by-product, a tonne of sugarcane is expected to yield around 18 to 20 litres of ethanol.

Table 2 Assumptions made to estimate ethanol supply from sugarcane

Variable	Description
Recovery rates	The conversion rates for sugarcane to cane juice, ethanol, and sugar have been assumed to remain the same as in 2025-26.
Wastages	We have assumed that wastage will be the same as estimated in the latest NABCON 2022 report; it estimates post-harvest losses in the sugarcane value chain at about 7.3 per cent.
Diversion of sugarcane to uses other than sugar/ethanol	Based on industry estimates (ISMA 2021), we have assumed that the diversion of sugarcane for *gur/khandsari* production would decrease from the current 25 per cent to around 17-18 per cent because ethanol production is more profitable.
Stocks of sugar	We have assumed that 6 MMT of carry-over stocks of sugar would be maintained at any time to meet the stocking requirements; this has been added as additional sugar demand.
Opening stocks of sugar	Opening stocks in a year have been assumed to be previous year's closing stocks.
Sugar Exports	Exports have not been taken into account while calculating the demand for sugar in the balance sheet calculation for sugarcane.
Distillation capacity	It has been assumed that there is adequate distillation capacity for ethanol production in the country.

technique. The mean absolute per centage error[5] (MAPE) has been used to estimate the efficiency of the predictions.

The other two scenarios of sugarcane production are:

i) **P2 scenario** — In this scenario production may fall 5 per cent due to lower crop yields attributed to climate change and/or a reduction in the area under the crop because of the relatively higher productivity/profitability of other crops.

ii) **P3 scenario** — For this, estimates have been taken from the OECD-FAO Commodity Outlook Report 2022-31.

The BAU has been assessed as the most likely scenario. Based on these three production scenarios in 2025-26, the sugarcane supply is estimated to be between 442 MMT and 469 MMT (Figure 2).

On the demand side, two scenarios have been considered. The first scenario (D1) uses an extra-polation of sugar demand based on sugar consumption data provided by the Indian Sugar Mills Association (ISMA). The second demand scenario (D2) is based on discussions with the sugar industry.

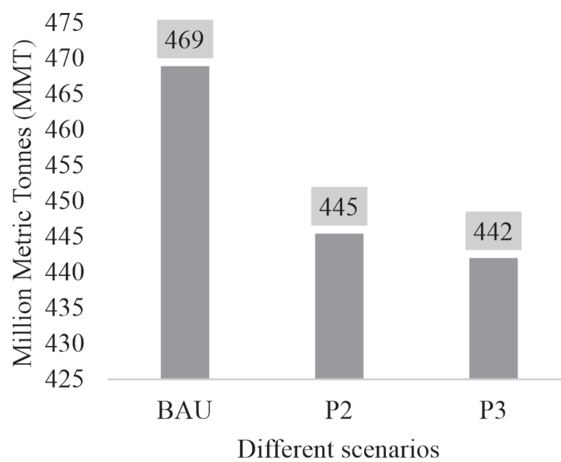


Figure 2 Sugarcane supply forecast for 2025-26
Source Estimated by authors

As per our assessments, the sugar demand in 2025-26 has been estimated to be between 28.8 MMT (D1 scenario) and 29.8 MMT (D2 scenario) and the country at any point in time is assumed to hold inter-year sugar stocks of at least 6 MMT. Based on the existing yields, the amount of sugarcane needed to fulfil this demand (consumption + stocks) would be between 315 MMT and 333 MMT.[6] Table 3 gives the estimates for excess

[5]The mean absolute percentage error (MAPE) is an indicator of the accuracy of a forecast and refers to the average difference between the actual (observed) and forecast values as a percentage of actual value. Percentage errors are summed without regard to the sign to compute MAPE.

[6]The two estimates are based on two possible recovery rates of sugar from sugarcane: 10.75 per cent and 11.04 per cent

Table 3 Estimate of excess sugarcane: After meeting domestic sugar and buffer demand

Scenario	At 11.04 % recovery rate	
	D1	D2
BAU	36	27
P2	19	10
P3	16	7

Source Estimated by authors

sugarcane after fulfilling the aggregate domestic sugar demand, assuming 11.04 per cent recovery rate.

Ethanol production from molasses: Estimates for 2025-26

Since ethanol from sugarcane can be produced as a by-product of sugar manufacturing as well as directly from sugarcane without producing sugar, the total ethanol supply has been estimated as a sum of production through both sources. Using the conversion rates mentioned earlier, a recovery rate of 11.04 per cent and assuming demand scenario D2 (the most likely scenario), it is expected that in 2025-26, between 5.7 and 6.5 billion litres of ethanol as a by-product and between 0.4 and 0.9 billion litres as a direct product of sugarcane would be available. Thus, total production has been estimated between 6.2 to 8.4 billion litres (Figure 3).

This implies that there would be sufficient sugarcane available in 2025-26 to meet the NITI Aayog's projected requirement of 5.5 billion litres. This is be the likely availability of sugarcane even after domestic demand for sugar has been met.

However, if production is lower (P2 and P3 scenarios), the ethanol production from sugarcane is expected to fall short of the requirement of 5.5 billion litres by 0.4 -0.7 billion litres.

Maize: Competition between feed, starch and fuel needs

The third advance estimate (May 2023) of government shows that India produced about 35.9 MMT of maize in 2022-23. The annual domestic consumption of maize is between 28.7 and 30 MMT (OECD Outlook 2022-31). The cattle and poultry industry consumes about 55-60 per cent of this output, mainly for feed. Maize is

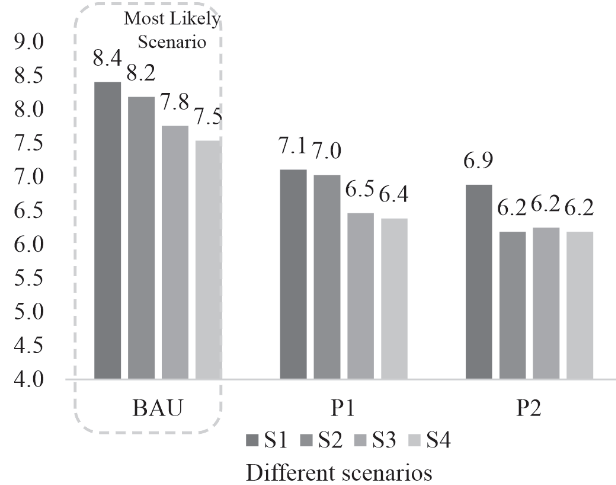


Figure 3 Estimated total ethanol supply from sugarcane in 2025-26

Source Estimated by authors

Notes S1, S2, S3 and S4 are scenarios for different conversion rates where 'S1' – 20 litre/t B-Heavy ethanol and 70 litre/t sugarcane from cane juice scenario. 'S2' – 20 litre/t B-Heavy ethanol and 62 litre/t sugarcane from cane juice, 'S3' – 18 litre/t B-Heavy ethanol and 70 litre/t sugarcane from cane juice and 'S4' – 18 litre/t B-Heavy ethanol and 62 litre/t sugarcane from cane juice.

also used by the starch, pharmaceutical, textile, and cosmetic industries. The consumption of maize as food is low and its exports are not consistent and are residual in nature, although India exported annually about 2.1 MMT of maize in the past three years (2019-20 to 2021-22).

As per our estimates (presented in Table 1), India would need about 6.1 MMT of maize annually to be able to produce about 2.33 billion litres of ethanol to meet the 2025-26 E20 mandate. Like sugarcane, ethanol production from maize has valuable by-products like dried distillers grain solids (DDGS), which can be utilised in animal feed as protein.

In poultry feed, maize is used as a source of energy due to its high starch levels. The DDGS can be used as a substitute for other oil meals like the ones from mustard, cotton seed, and soybean. Therefore, maize diverted for ethanol effectively is likely to compete with its use as poultry feed or in other starch-based industries.

As in the case of sugarcane, various production and consumption scenarios have been considered to assess the net availability of maize to produce 2.33 billion litres of ethanol for E20 in 2025-26 (Tables 4 and 5).

Table 4 Possible scenarios for estimating maize supply

Scenario	Rationale
BAU	Based on ARIMA forecasts
P1	BAU + 5% (likely growth of yields due to technology upgradation, increase in area)
P2	BAU – 5% (impact of climate change, or fall in acreages due to more lucrative competitive crops)
P3	Based on changes in area under maize (using regression coefficients)
P4	Based on OECD projections (Outlook 2022-2031)

Table 5 Potential scenarios for estimating maize demand

Scenario	Rationale
D1	Based on OECD projections (Outlook 2022-2031)
D2	Extrapolated, with Food, Seed and Industrial (FSI) and feed having the same share in production
D3	Extrapolated, with FSI maintaining the same share in production and pegging feed-use to growth in the poultry sector (using regression coefficients)
D4	Extrapolated, with FSI maintaining the same share in production and pegging feed-use to growth in the poultry feed sector (using regression coefficients)

Our estimates have indicated that the supply of maize in 2025-26 is expected to range between 33.7 MMT and 38.6 MMT, while demand is expected to range between 30.5 MMT and 41.3 MMT under different scenarios.

These estimates were made using the following assumptions:

i. Wastage and losses along the maize value-chain were assumed to be the same as that given in NABCON 2022 study of post-harvest losses of 3.8 per cent.

ii. Import and export of maize were assumed to be zero.

The net availability of maize, calculated as the difference between production[7] and demand after adjusting for wastage is depicted in Table 6.

In 19 out of 20 scenarios for which the estimates were made, the availability of maize falls short of the target of 6.1 MMT, required to produce 2.33 billion litres of ethanol (needed to achieve the 2025-26 ethanol blending target). The only scenario where India is projected to generate the required surplus of 6.1 MMT is when the demand for maize does not grow as fast (say, because of slower growth in the poultry sector) and if the yield of maize improves.

Table 6 Net availability of maize for ethanol production in 2025-26 (MMT)

Scenarios	Demand scenarios			
	D1	D2	D3	D4
BAU	4.8	3.2	-5.9	-1.1
P1	6.6	5.0	-4.2	0.6
P2	3.1	1.4	-7.7	-2.9
P3	4.7	3.1	-6.1	-1.3
P4	1.9	0.2	-8.9	-4.1

Source Estimated by authors.

Rice: A water guzzling food crop diverted to manufacture fuel

The high starch content of rice makes it the most efficient of the three feedstocks for ethanol production. One tonne of rice produces, on an average, about 425 litres of ethanol. This compares to 20 litres from one tonne of sugarcane (ethanol as a by-product) and 380 litres from one tonne of maize.

[7]Stocks of maize are assumed to have been exhausted and thus closing stock is taken to be 0.

Table 7 Assumptions made for estimating ethanol supply from rice

Variable	Description
Wastage	NABCON's 2022 report on post-harvest losses estimates a 4.77 per cent loss in paddy. The estimated production has been adjusted downwards to take this into account. (The conversion factor for paddy was taken as 0.67 on the basis of Food Corporation of India (FCI) reports.)
Stocks with FCI in central pool	Based on previous years' data, FCI's minimum stocks have been assumed to be 20.6 MMT (twice the required norm of 10.3 MMT)
Stocks with private trade	Private trade is expected to hold stocks equivalent to three months' domestic rice consumption.
Exports and imports	Export has been assumed between 20 and 21.4 MMT, based on current data, discussions with experts and OECD projections. Imports have been assumed to be 0 MMT.
Opening stock	Opening stock is previous year's closing stock.

Over the past ten years, India's production of rice has increased by about 23 per cent. As per the GOI's third advanced estimate, rice production in 2022-23 was 135.5 MMT (PIB 2023). The area under rice in TE 2020-21 was 44.29 Mha and average yield was 2.69 t/ha (Agriculture Statistics at a Glance 2021).

The availability of rice in 2025-26 has been estimated on the basis of the assumptions are given in Table 7.

Three scenarios were considered to estimate availability of rice. The first, referred to as the business-as-usual (BAU) scenario, is an ARIMA based forecast. Both area and yield of rice were separately modelled to estimate production. The second scenario is based on OECD's rice production projections (OECD-FAO Outlook 2022-31). The third scenario projects a 5 per cent yield loss on account of weather/climatic vulnerabilities. Based on these three scenarios, India's rice production in 2025-26 is projected to be between 131.9 MMT and 138.9 MMT.

The demand for rice has been projected under two scenarios. The first uses consumption projections from the OECD-FAO Outlook 2022-31 report. The second extrapolates NSSO data from 2011-12 household consumption expenditure survey, using IMF's estimate of per capita GDP growth rates, income elasticity of rice consumption (sourced from Kumar 2017) and population projection based on 2011 Census data. These two estimates peg the demand for rice in 2025-26 between 112.4 MMT and 116.6 MMT.

If India continues to export 20 MMT of rice (including 4.5 MMT of basmati) and there is no change in the stocks with the FCI and the private trade, rice output in India may fall short of even the domestic demand of rice in 2025-26. Our estimates have indicated a shortfall 1.2 MMT in 2025-26 against the requirement of about 5.5 MMT of rice (Table 1) for fuel blending in the most likely scenario (BAU-D2) (Table 8). However, if exports decline by 5 MMT, a net surplus of 3.8 MMT would be available to produce about 1.62 billion litres of ethanol.

Table 8 Net availability of rice for diversion to ethanol production

Scenarios	D1	D2
BAU	-7.8	-1.2
P1	-6.2	0.4
P2	-14.5	-7.8

Source Estimated by authors

Putting together the estimates of crop availability for ethanol production for all the three crops, sugarcane, maize, and rice, it is estimated that the total supply of ethanol in 2025-26 would be anywhere between 7.5 and 10.02 billion litres.

Under the most optimistic scenario (ethanol supply of 10.02 billion litres), India may come close to meeting its fuel-blending requirement of 10.16 billion litres. However, it would still be not able to meet the remaining requirement of 3.5 billion litres (13.5 billion litres –10.16 billion litres) for other uses of ethanol.

Assessing the E20 mandate

A reduction in the country's oil import bill is one of the primary triggers for the policy thrust on ethanol

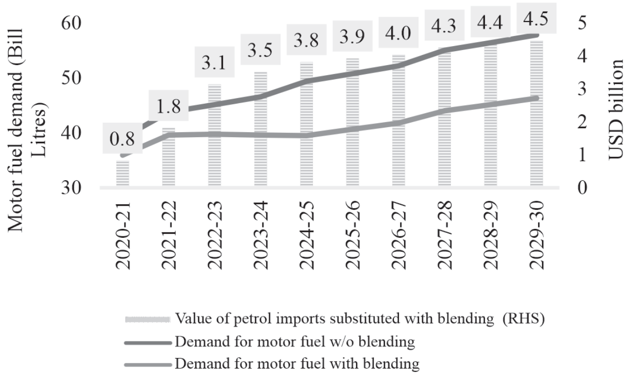


Figure 4 Demand for petrol (litres) and forex savings from blending (billion USD)

Source Estimated by authors based on data from NITI Aayog, World Bank

for fuel blending. Figure 4 shows that in 2025-26, India may annually save about US$4 billion to US$4.5 billion if the World Bank's crude oil price projections are considered[8]. The magnitude of savings estimated is close to NITI Aayog's estimated annual savings of US$4 billion.

Our analysis indicates that it may not be feasible for the country to meet the E20 target of blending under the business-as-usual (BAU) scenario.

Additionally, by creating competition for food crops, ethanol production is likely to squeeze their availability for food and feed related purposes. The Global Human Index (GHI 2022) ranked India 107 out of 121 countries, implying that the incidence of hunger and malnutrition in India remains high. The incidence of stunting and wasting among children under five is 35.5 per cent and 19.3 per cent respectively, with India holding the dubious distinction of having the highest wasting rate in the world. According to India's National Family Health Survey 2019-20, 18.7 per cent of women and 16.2 per cent men in India have a body mass index (BMI) below the normal.[9]

Another major challenge is the shrinking availability of land for cultivation which would have a direct impact on production of food crops. At the current level of productivity, the E20 mandate is understood to require about 7.1 Mha of land (Table 1). Since 1970-71, the operated area under agriculture has declined steadily from 162.3 Mha to about 157.8 Mha in 2015-16 – a decline of 4.5 Mha over a 45-year period. This is mainly due to pressures from urbanisation (Pandey and Seto 2015). According to Hoda (2018), the country is likely to lose at least 10 per cent of cultivated area by 2050. Can India afford to have 7.1 Mha of its land dedicated to producing crops for fuel?

Simultaneously, the per capita availability of water has decreased from 5177 cm^3 in 1955 to 1544 cm^3 in 2011 (CWC 2015). According to a reply in the Lok Sabha by the Minister of State for Jal Shakti, the Central Water Commission in its 2019 report, *"Reassessment of Water Availability in India using Space Inputs"*, had estimated that this would decline further to 1486 cm^3 in 2021 and 1367 cm^3 in 2031. The World Meteorological Organization (2021) ranks the terrestrial water loss in India, particularly in the northern parts of the country, the highest in the world.[10] Gulati and Mohan (2018) have pointed out that water-use for agriculture in India is inefficient. A comparison of water use efficiency for the sugarcane crop, expressed as physical water productivity (PWP),[11] shows that India's PWP was 5.2 kg/cm^3 against the global average PWP of 5.8 kg/cm^3 (Sharma et al. 2018). As per this study, the average PWP for rice was estimated at 0.36 kg/cm^3, with rice accounting for a third of the water used in agriculture. Although, there are geographical areas where there is efficient use of water, PWP for rice is low in several regions with assured irrigation but the region itself is water scarce " for instance, parts of Punjab (Sharma 2018).

Apart from the shrinking availability of land and inefficient resource use in agriculture, a major challenge in the past few years has emerged in the form of climate change impact. This has impacted yield of crops. For example, wheat crop was adversely affected in both 2021-22 and 2022-23 years.

[8]The available data on oil prices is until 2023-24. Beyond this period, the per barrel price of oil is assumed to remain constant, equal to the last five-year average, which includes the projections for 2022-23 and 2023-24. Additionally, the blending rates for oil after 2025-26 are expected to be fixed at 20 percent levels

[9]Normal range of BMI is between 18.5 kg/m^2 to 25kg/m^2.

[10]WMO defines terrestrial water as the sum of surface and sub-surface water.

[11]Physical water productivity, expressed as the ratio of agricultural output to the amount of water used, is usually used to estimate the efficiency of water use.

The FAO (2015) also deems the diversion of crops to biofuels and climate change as the two major threats to long-term food security.

The estimates of this study have shown neither rice nor maize production is likely to be sufficient to yield the surpluses needed to produce ethanol for blending of petrol, even if one ignores the effects of climate change on crop yields.

Conclusions and inferences

The following conclusions are drawn from the analysis:

- A fall in sugarcane yield due to climatic changes is likely to have an adverse impact on its availability for production of ethanol. Given the centrality of cane as feedstock, this is critical for the government to assess.
- Maize production is not sufficient to allow it to emerge as a major feedstock in ethanol production. The alcoholic beverage industry, poultry, and other industries would compete for maize. Besides, lower returns on maize production as compared to other crops and volatile yields have been a major challenge to increasing the acreage under this crop.
- Rice is critical for country's food security and as per calculations, unless FCI stocks lower-than-normal and/or country's rice exports fall over time, rice availability may not be sufficient to meet its requirements under E20. Besides, its diversion towards fuel production appears marred with grave trade-offs in terms of subsidies used to produce rice, the amount of water used for its production and *inter alia*, the crowding-out that such diversion would do for the poorest and malnourished countrymen.
- Both rice and sugarcane are water-guzzling crops and their use in producing ethanol which in turn, would reduce overall emissions in the country, needs to be revisited with a life-cycle-of-the-crop approach. There is an urgent need to improve resource-use efficiency particularly by these two crops.
- Given the availability of feedstocks for ethanol is uncertain, the country would do well by exploring the use of alternate feedstock for ethanol production. Agricultural waste can be an important feedstock and six commercial Second Generation (2G) bio-ethanol projects with a total production capacity of 695 Kilo Litre Per Day (KLPD) in Punjab, Haryana, Odisha, Assam, and Karnataka have been sanctioned.
- At some point in future, the Government may revisit the policy on import of ethanol.
- One of the biggest challenges to the E20 plan is the possibility of a decline in crop yields as a result of climate change. Hence, investment in developing climate-resistant varieties and improving crop yields is imperative for food security itself, irrespective of the country's ethanol requirements.

Increasing incomes and growing urbanization have led to the demand for a more diversified food basket with the demand for plant and animal-based proteins rising. This has led, among other things, to the rapid growth of the poultry sector, which has registered a CAGR of 8 and 10 per cent (APEDA, 2023). Together with the challenges arising from climate change, and the reduction in operated area for cultivation due to increasing urbanization, there is a distinct probability that the outlook for the availability of feedstock for ethanol production, particularly maize, may be far less sanguine than the projections made by NITI Aayog in its roadmap. While E10 has been more or less achieved and is a sustainable level of blending, the E20 mandate may be overambitious.

Way forward

Based on the study, some critical aspects for of government consideration are summarized below:

- **Improvement in crop yields** — Yields of many crops like maize are exceptionally low in many parts of the country. The government needs to invest in technological development that could help raise crop productivity.
- **Development of climate resilient varieties** — 2023 was a El Nino year, from rice to sugarcane, yields of most crops fell. Many like maize are subjected to pest attacks. GOI has to invest in bringing climate resilience to its crops.

- **Strategic land planning** — A proper strategy has to be developed on land-use for arable purpose, both for a short-term as well as long-term, keeping in view the rising food demand and meeting E20 petrol blending targets. The government should adopt measures to revive fallows for sowing crops for fuel.
- **Irrigation water management** — The government to consider the efficiency of water-use in agriculture. Rice and sugarcane, which are the two most important feedstocks for ethanol production, are highly water-intensive. These two crops account for 60 per cent of the total irrigation water supplied to agriculture (NABARD, 2018). In the process several other crops are deprived of water. Therefore, the government should (i) outline a threshold crop area and/or crop size that would be allowed for biofuel production; and (ii) invest in making both rice and sugarcane cultivation more resource-use efficient. Incentivising investment in water conservation techniques like drip irrigation and sprinklers will help increase both cop yields and the productivity of water use.
- The government need to invest in developing 2G technologies that are commercially viable.
- The government should consider the involvement of different states to implement the E20 mandate.
- There is a need to encourage the use of electric vehicles and flexi-fuel vehicles which can take some of the burden off the aggressive ethanol blending target.

References

Box, G E P and G M Jenkins. 1970. Time Series Analysis: Forecasting and Control. San Francisco: Holden-Day.

CWC (Central Water Commission). 2017. Reassessment of water availability in India using space inputs. Basin Planning and Management Organisation, Central Water Commission, New Delhi.

ET (Economic Times). 2022. Brazil's ethanol journey: from 'a fuel of the future' to the 'future of fuel'. Accessed on February 20, 2023.

Gitz, V, A Meybeck, L Lipper, C D Young and S Braatz. 2016. Climate change and food security: risks and responses. Food and Agriculture Organization of the United Nations (FAO) Report, 110(2), 3-36.

Gulati, A and G Mohan. 2018. Towards sustainable, productive and profitable agriculture: Case of Rice and Sugarcane (No. 358). Working paper.

Hoda, A. 2018. Working Paper No. 361 Land use and Land Acquisition.

IEA. 2021. Renewables 2021, IEA, Paris https://www.iea.org/reports/renewables-2021, Licence: CC BY 4.0

Kumar, S. 2021. COP-26 and energy transition: An outlook on India's stance.

NABCONS. 2022. Study to determine post-harvest losses of agri produces in India.

NITI. 2021. Roadmap for Ethanol Blending in India 2020-25. NITI Aayog and MOPNG.

OECD/FAO. 2022. OECD-FAO Agricultural Outlook 2022-2031, OECD.

Pandey, B. and K C Seto. 2015. Urbanization and agricultural land loss in India: Comparing satellite estimates with census data. Journal of Environmental Management, 148, 53-66.

PIB (Press Information Bureau). 2023. Third Advance Estimates of Production of major crops released by Shri Narendra Singh Tomar.

PIB. 2024. ETHANOL 100 fuel launched by Petroleum Minister Hardeep S Puri. Link: https://pib.gov.in/PressReleaseIframePage.aspx?PRID=2015031#:~:text=ETHANOL%20100%20stands%20as%20a,air%20quality%20in%20our%20communities

Ray S, S Miglani and A Goldar. 2011. Ethanol blending policy in India: demand and supply gaps.

Rogoff, K. 2022. Global oil and gas prices have been highly volatile – what will happen next? Accessed on February 2, 2023. Link: https://www.theguardian.com/business/2022/jul/05/global-oil-gas-prices-supply-demand-us-europe

Saini, S, P Khatri and S Hussain. 2023. Ethanol Blending of Petrol in India: As assessment of raw material availability. Arcus Policy Research.

Sati, A, L. Powell and V K Tomar. 2022. Volatility in Global Energy Markets: Implications for India. https://www.orfonline.org/expert-speak/volatility-in-global-energy-markets#:~:text=Every%20US%2410%2Fb%20increase,of%20over%20US%241.9%20billion.

Sharma, B R, A Gulati, G Mohan, S Manchanda, I Ray and U Amarasinghe. 2018. Water Productivity Mapping of Major Indian Crops. Link.

Susmozas, A, R Martín-Sampedro, D Ibarra, M E Eugenio, R Iglesias, P Manzanares and A D Moreno. 2020. Process strategies for the transition of 1G to advanced bioethanol production. Processes, 88(10), 1310.

Von Grebmer, K, J Bernstein, D Resnick, M Wiemers, L Reiner, M Bachmeier, ... and H Fritschel. 2022. Global hunger index: Food systems transformation and local governance. Welt Hunger Hilfe CONCERNWorldwide: Bonn/Dublin, Ireland.

Zhou, Y, S Searle and S Anup. 2021. Techno-economic analysis of cellulosic ethanol in India using agricultural residues. International Council on Clean Transportation, Washington, DC.

Received 12 July 2023 Accepted 25 October 2023

Agricultural Economics Research Review 2023, 36 (2), 123-143
DOI: 10.5958/0974-0279.2023.00027.7

Dynamics of comparative advantage in India's agricultural exports

K Elumalai[1] and Anjani Kumar[2]*

[1]School of Social Sciences, Jawaharlal Nehru University, New Delhi, India
[2]International Food Policy Research Institute, South Asia Regional Office, New Delhi, India

*Corresponding author: anjani.kumar@cgiar.org

Abstract This paper analyses the dynamics of comparative advantage in agricultural exports of India over the period 2001 to 2019. We use the revealed comparative advantage index, and its variant, the revealed symmetric comparative advantage index, to analyze the pattern of export specialization and the Markov transition matrix to examine the product mobility of comparative advantage. The study has shown that the extent of agricultural trade openness has remained constant over time and that there has been little change in the composition of agricultural exports. Analysis of the mobility of comparative advantage reveals little mobility of products from the lowest to the highest decile. There is a 65.8 per cent probability that a product will stay in the first decile even after nearly two decades. A high degree of persistence of export specialization implies a higher probability of starting and ending-up in the highest decile. The study suggests that India should aim at diversification of the agricultural export basket through a product-specific focus based on export demand and the exploration of new global markets.

Keywords Agricultural exports, trade openness, revealed comparative advantage, mobility of comparative advantage, diversification of export basket, India

JEL codes Q17, Q18

Introduction

Between 1996 and 2019, the global agricultural trade increased rapidly, with tripling of agricultural exports and imports (United Nations 2020). However, the degree to which developing economies have shared the benefits of agricultural trade liberalization has been a subject of debate, as has been the question of how much they have been favoured by the direction of trade flows. Although their overall share of agricultural exports and imports has increased over time, it has not been uniform across the developing countries (Aksoy 2005; von Braun and Diaz-Bonilla 2008). Most of the gains from increases in agricultural exports have come from the exporting to other developing economies, while the share of exports to the industrialized countries has actually declined (Aksoy and Ng 2010). The recent literature emerged after Melitz (2003) and Helpman, Melitz, Rubinstein (2008), underline the importance of heterogenous effect of firms on intensifying the existing exports or expanding them to new destinations. The typical argument is that only the most productive firms find it profitable to export and this profitability depends on the characteristics of importing countries. Building on this framework, studies on agri-food trade show that tariff reduction increases the probability of maintaining the existing trading relationship and export of new products along the extensive margin (Debaere and Mostashari 2010; Hejazi, Grant, Peterson 2017; Sun and Li 2018). The trade cost imposed in the form of quality standards on agri-food products reduces firms' export levels and probability of firms entering the new export markets (Eum, Sheldon, Thompson 2021; Fiankor, Haase, Brummer 2021).

It is contended that the expansion of agricultural trade has the potential to reduce poverty and price volatility and improve nutritional outcomes and resource-use efficiency (Martin 2017). Given these complexities, it can be argued that there are geographical variations in the mechanisms by which the trade influences welfare; besides the trade specialization patterns do have a significant effect (Santos-Paulino and Thornquist 2015).

Since 1990s, the waves of trade liberalization have swept most of the developing economies; India at that point also embarked on the promotion of its agricultural exports. From being a net importer of food grains, India has become a net exporter of commodities such as rice, marine products, spices, and cotton. India's agricultural policies have always been weighted in favour of achieving the twin goals of national food security and domestic price stability. Accordingly, in order to regulate exports and imports of agricultural products, restrictive trade policies have at different times been put in place; these have included higher tariffs, export bans, quantitative restrictions, and phytosanitary measures (Pursell and Gulati 1993; Ahmed 1996; Athukorala 2005; Acharya et al. 2012; Saini and Gulati 2016). During the mid-1990s, however, the economic reforms and the World Trade Organization (WTO) Agreement on Agriculture brought down some of these restrictions (Jha and Srinivasan 2004; Mullen et al. 2004). Although trade policies tilted toward a reorientation of agricultural production in favour of generating export surplus, the basic policy approach has continued to support self-sufficiency in foodgrains production (Hoda and Gulati 2013). This notwithstanding, certain agricultural products have gained importance in the export basket, leading to export specialization, while others have lost their prominence and have been dropped from the basket of specialized export commodities.

There is a lack of empirical evidence on these changes in India's agricultural export specialization and no recent systematic study has analysed the dynamics of comparative advantage in the export of agricultural products or its mobility over time. The contribution of this study is threefold: first, it demonstrates the evolving pattern of India's agricultural trade at a disaggregate level; second, it examines changes in trade specialization patterns; and third, it analyzes the extent of mobility of the comparative advantage of agricultural products.

Data sources and methodology

Data

The study is based on the UN Comtrade data on exports and imports (United Nations 2020). This data was compiled for the period 2001 to 2019, using the international six-digit Harmonized System (HS) code for classifying commodities. The coverage of products under agricultural trade is defined as per Annex 1 of the WTO Agreement on Agriculture, with the modification that fish and fish products (Product code 02 at the two-digit level) are included in the present study. The data on national GDP, agricultural value added, and other macro variables were compiled from the World Bank's World Development Indicators (World Bank 2020).

Analytical framework

Measurement of comparative advantage

The theoretical concept of comparative advantage is based on pre-trade relative prices, which are not observable in the post-trade equilibria. Hillman (1980) established an exact relation between the comparative advantage- as indicated by pre-trade relative prices- and the observed direction of trade, with an economy exporting a good that would be relatively cheaper domestically in an autarkic equilibrium.

The empirical studies on comparative advantage grew tremendously after seminal papers of Balassa (1965, 1977). The revealed comparative advantage (RCA), also known as the Balassa index, can be defined as per Equation (1):

$$\mathrm{RCA}_{ij} = \frac{X_{ij} / X_{Wj}}{X_i / X_w} \qquad \ldots(1)$$

Alternatively, RCA in Equation (1) can be written as:

$$\mathrm{RCA}_{ij} = \frac{X_{ij} / X_i}{X_{wj} / X_w} \qquad \ldots(2)$$

where, X is exports, i is country, j is commodity, and w is world total.

The RCA is the normalized measure of international trade specialization. The relative product export share of country i in total world trade is weighted by the total export share of the country in world exports, as in Equation (1). Equation (2) shows the export share of product j in national exports divided by the share of product j in total world exports.

An RCA value of greater than 1 indicates that the relative share of a given product is higher than its share of overall exports in world trade; this reflects the situation of country i specializing in product j. It is expected that a country's exports will include a large share of products whose inputs are found in relative abundance in that country. Balassa's RCA is subject to criticism on the grounds of its lack of theoretical foundation, asymmetric distribution, inconsistency in cross-country comparisons, and failure to capture factors specific to export sectors (Bowen 1983; Yeats 1985; Dalum, Laursen, Villumsen 1998; Hinloopen and Van Marrewijk 2001; Leromain and Orefice 2014). The Balassa index, even so, is widely used as a guide to the measurement of trade specialization patterns. The index is also highly relevant to cross-sector assessments of export performance within a country or cross-country comparison of the export performance of a particular sector (Kowalski and Bottini 2011).

As the value of Balassa's revealed comparative advantage lies between 0 and infinity, this index is considered to be asymmetric in distribution. RCA can be modified, however, as the revealed symmetric comparative advantage (RSCA) index, which can be written as $(RCA_{ij}-1)/(RCA_{ij}+1)$; the RSCA values range from –1 to +1, avoiding the problem of 0 values (Dalum, Laursen, Villumsen 1998). This index has similar properties to the logarithmic transformation of the RCA (Laursen 2015). A positive value of RSCA (above 0) for a commodity indicates that the country has a comparative advantage, while a negative value (below 0) indicates the country's comparative disadvantage in that product.

Following Dalum, Laursen, and Villumsen (1998) and Laursen (2015), a test for stability of export specialization was conducted through regression analysis. This type of regression, called Galtonian regression, was originally developed by Hart and Prais (1956). The equation can be specified as per Equation (3):

$$RSCA_{ij}^{t2} = \alpha + \beta RSCA_{ij}^{t1} + \varepsilon_{ij} \qquad \text{…(3)}$$

The dependent variable RSCA, at time t_2, is regressed against the independent variable RSCA at time t_1. Here, t_1 and t_2 refer to the initial year and the final year, respectively; α and β are standard regression parameters; ε is the error-term. This analysis is comparing two cross-sections at two points in time. The coefficient β measures the stability of the country's export specialization pattern between two points in time.

Mobility of comparative advantage

The persistence and mobility of comparative advantage have been an important subject of research in the international trade literature (Cantwell 1989; Dalum, Laursen, Villumsen 1998; Laursen 2000; Ferto and Hubbard 2003; Laursen 2015; Stellian and Danna-Buitrago 2019). Empirical research focusing on the dynamics of comparative advantage and its endogenous evolution has grown over time, much of it stemming from the work of Proudman and Redding (2000). They developed a theoretical framework for empirical analysis which considers the overall distribution of RCA and the intra-distribution dynamics of individual products. This involves the calculation of Markov transition probability matrices, which provide information about the probability that a product would move from one quantile of RCA distribution to another. We employed decile intervals of the entire distribution of RCA, such that these intervals contained one-tenth of all the product-year observations. With this, the transition matrix provided the probability of a product that was initially in the i^{th} decile at time t moving to the j^{th} decile of RCA distribution at time $t+s$.

If p_{ij} is the probability of moving from state (here decile) i at time t to state j at time $t+s$, the probabilities can be arranged in a sequence to obtain the transition probability matrix depicted in Equation (4):

$$P = \begin{bmatrix} p_{11} & p_{12} \cdots & p_{1m} \\ p_{21} & p_{22} \cdots & p_{2m} \\ \cdots & \cdots\cdots & \cdots \\ p_{m1} & p_{m2} \cdots & p_{mm} \end{bmatrix} \qquad \text{…(4)}$$

If δ_{it} is the fraction of products in the i^{th} decile at time t and δ_t is the initial state of distribution of RCA, then the Markov stochastic process can be written as per Equation (5);

$$\delta_{t+s} = P.\delta_t \qquad \text{…(5)}$$

The above matrix of transition probabilities can be calculated by counting the number of products transitioning into and out of the decile classes. This

Table 1 Average agricultural export and import value, 2001-03 to 2017-19

Period	Value of agricultural exports and imports (US$ million)			
	Export	Import	Total	Trade surplus
2001 to 2003	6,809	3,979	10,788	2,830
2008 to 2010	20,020	11,023	31,043	8,998
2013 to 2015	41,275	20,432	61,707	20,843
2017 to 2019	38,120	25,285	63,405	12,836
	Growth rate (per cent)			
2001 to 2010	15.71	16.96	15.61	20.41
2011 to 2019	7.35	6.44	6.74	11.98

Source United Nations (2020)

implies the extent of mobility of products between different classes of the RCA distribution.

There are summary measures of mobility that reduce the information present in transition matrices to a single average measure. We have used two such mobility indices. The first of these measures of mobility (M_1) was developed by Shorrocks (1978) and the second (M_2) by Bartholomew (1973). They are given as per expression (6) and (7):

$$M_1 = \frac{m - tr[P]}{m-1}, \qquad \ldots(6)$$

where, *m* is the number of classes and *tr*[*p*] is the trace of the matrix.

$$M_2 = \frac{\sum_i \sum_j p_{ij}|i-j|}{m(m-1)}, \qquad \ldots(7)$$

where, M_1 measures the average probability across classes that a product will leave its initial state in the succeeding period. A high value of M_1 shows mobility while a low value indicates the persistence or stickiness of the specialization pattern. M_2 shows the average number of class boundaries crossed by a product.

Results and discussion

Agricultural trade and trade openness

India's agricultural products have gained importance in the global trade basket over time. Its export share increased steadily, from 1.35 per cent in 2001 to 2.61 per cent in 2019. The share of world imports into India also increased, from 0.69 per cent to 1.67 per cent during this period (United Nations 2020). Over the same period, in absolute terms, the value of agricultural exports increased from US$ 6.8 billion in 2001-2003 to a whopping US$ 41.3 billion in 2013-2015 (Table 1). After 2015, however, the value of exports declined marginally to US$ 38.1 billion by 2017-2019. The average annual growth rates, calculated at 10-year intervals, have shown an impressive yearly 15.7 per cent increase in agricultural exports during the period 2001 to 2010 and then, a deceleration to 7.4 per cent per year between 2011 and 2019.[1] The agricultural imports have also decelerated between 2011 and 2019. Despite these observed trends in exports and imports, India's agricultural trade surplus has remained positive, implying that agriculture remains an important contributor to foreign exchange earnings, despite the structural shift in India's economy towards services sector in recent decades.

The domestic economic reforms (e.g., decontrol of fertiliser prices, removal of inter-state grain movement control) and external trade reforms (removal of quantitative restrictions on agricultural exports and imports, decanalization of agricultural exports and imports, tariff reduction under WTO Agreements), introduced by India during the 1990s led to the opening of the agricultural sector to international competition. The degree of openness of agriculture can be assessed through two measures, intrasectoral and intersectoral trade openness.[2]

[1]Kumar (2021) has provided similar evidence on deceleration of India's agricultural exports during the recent years, which is in tandem with a fall in global agricultural exports.

[2]Intrasectoral trade openness is measured as: (agricultural trade/agriculture value added)*100; intersectoral trade openness is measured as: (agricultural trade/national GDP)*100.

Table 2 Measures of agricultural trade openness

Year	Percentage of agricultural trade in agricultural value added	Percentage of agricultural trade in national GDP	Percentage of agricultural export in agricultural value added	Percentage of agricultural export in national GDP
2001	9.30	2.01	6.07	1.31
2002	10.67	2.08	6.86	1.34
2003	9.97	1.95	6.01	1.18
2004	10.87	1.94	6.91	1.23
2005	10.94	1.93	7.08	1.25
2006	11.45	1.92	7.82	1.31
2007	11.79	1.97	8.00	1.34
2008	14.70	2.47	10.50	1.76
2009	12.19	2.04	7.20	1.21
2010	12.67	2.16	7.97	1.36
2011	16.11	2.77	10.84	1.86
2012	20.03	3.37	13.77	2.32
2013	20.44	3.50	14.71	2.52
2014	18.58	3.12	12.48	2.10
2015	16.59	2.68	10.07	1.63
2016	15.06	2.47	8.71	1.43
2017	15.11	2.47	8.84	1.45
2018	15.58	2.40	9.25	1.42
2019	12.97	2.07	8.14	1.30

Source United Nations (2020)

Between 2001 and 2013, the intrasectoral trade openness index showed an increasing trend, and then it declined (Table 2). A similar trend was observed in the intersectoral trade openness index, which was more or less constant till 2009, increased till 2014, and then fell. The decline in the trade openness index, resulted from the restrictions in trade flows that followed from frequent changes in trade policy led to some policy changes in the form of export bans, higher import duties, and quantitative restrictions on agricultural commodities.

In 2015, the Government of India prohibited the import of certain animal products on the grounds of food safety and health. It also applied import quotas on milk powder, butter, maize, sunflower oil and pulses, and imposed licensing restrictions and minimum import prices on certain types of kernels and vegetable products (WTO 2015). Some of these restrictions remain in place even today (India, Ministry of Commerce and Industry 2020).

The outward orientation index—measured as the share of exports in agricultural value added—has not shown a definite trend. It is noteworthy, however, that the share of agricultural exports in agricultural value added peaked at 14.7 per cent in 2013. The alternative measure of the share of agricultural exports in national GDP showed an increasing trend till 2013, indicating an improvement in the outward orientation of India's agricultural sector. The sector's outward orientation, however, has deteriorated in recent years; in fact, the share of agricultural exports in the national GDP has declined steadily from 1.6 per cent in 2015 to 1.3 per cent in 2019, implying stagnation, or even a decline, in India's agricultural export orientation.

Composition of India's agricultural trade

The export composition of agricultural products at the two-digit level is given in Appendix Table A1. There is a slight change in the relative position of products between 2001-2003 and 2017-2019. During 2017-

2019, the four groups of products accounted for 55 per cent of the total value of agricultural exports: cereals; fish, crustaceans, molluscs, and other aquatic invertebrates; meat and edible meat offal; and coffee, tea, mate, and spices. The importance of meat and edible meat offal in the export basket has increased; it now constitutes 10.1 per cent of the total value of agricultural exports.

While the relative position of cereals has improved between 2001-2003 and 2017-2019, there had been a marginal decline in the share of fish, crustaceans, molluscs, and other aquatic invertebrates, and of coffee, tea, mate, and spices. Oilseeds, oleaginous fruits, and miscellaneous grains, seeds, and fruits maintained their position in the export basket, while a reduction was observed in the initial importance of edible fruits and nuts, peel of citrus fruits or melons, sugars and sugar confectionery, and residues and wastes from the food industry. During this period, the share of cotton (not carded or combed) increased from a mere 0.3 per cent in 2001-2003 to 4.3 per cent in 2017-2019, and between 2008-2010 and 2013-2015, there was a significant change in the export share of cereals; fish, crustaceans, molluscs and other aquatic invertebrates; and of residues and wastes from the food industry.

There has been little dynamism over time in the composition of India's imports of agricultural products (Appendix Table A2). Three groups of commodities that constituted 70 per cent of the total import value were: animal/vegetable fats and oils and their cleavage products; edible vegetables, certain roots and tubers, and edible fruits and nuts; and peel of citrus fruits or melons. These commodities remained at the top of the import list for several years. Between 2001-2003 and 2017-2019, there was a marginal increase in the import share of sugar and sugar confectioneries, and of beverages, spirits, and vinegar, each of whose import share constituted about 3.2 per cent. Similarly, the import share of essential oils increased from 0.4 per cent in 2001-2003 to 1.9 per cent in 2017-2019. The import of raw silk (not thrown), wool (not carded or combed) was trimmed down considerably by increasing import duties to protect the interests of domestic industries. Similarly, imports of cotton (not carded or combed) declined from 8.5 percent in 2001-2003 to 2.11 per cent in 2013-2015, but increased to 4.0 per cent during 2017-2019.

An analysis of commodity composition at the aggregate level (two-digit) provides little insight into the nature of India's commodity exports. A perusal of Table 3 shows the export composition of agricultural products at the four-digit level and these products accounted for 75 per cent of the total export value. Between 2001-2003 and 2017-2019, there was a little shift in the relative positions of the top commodities in terms of their export share; in fact, two groups of products accounted for one-quarter of the total export value; these were: rice, and crustaceans (in shell or not, live, fresh, chilled, frozen, dried, salted and related items).

Between 2001-2003 and 2017-2019, except for wheat and meslin, the export of major commodities increased considerably, with cotton (not carded or combed) registering the highest growth rate. In recent years, importance in the export basket has also been gained by the frozen meat of bovine animals, essential oils, other fixed vegetable fats and oils, pepper of the genius Piper, groundnuts, and the seeds of anise and related products. These trends imply that while the traditional agricultural products continued to occupy the top position in terms of export value, the non-traditional commodities, such as raw cotton, meat of bovine animals, and essential oils, could also find a place in the export market.

Further analysis at a disaggregated level (six-digit) has shown the dominance of a few products in the export basket. Table 4 shows the products that accounted for about 70 per cent of the value of agricultural exports. Two groups of products constituted one-quarter of the export value in 2001-2003; these were: semi-milled or wholly milled rice[3], and frozen shrimps and prawns. By 2017-2019, the top position of these two products further improved to the point where they occupied a 32 per cent share in total exports. In recent years, a steep rise in value in the export market has been seen for boneless meat of bovine animals, castor oil and its fractions, cotton (not carded or combed) and essential oils of peppermint and other mints. With the exception of black tea (fermented and partly fermented), the export value of major commodities increased considerably. A sharp rise in the export value was

[3]According to Singh, Anoop and Singh (2020), trade specialization coefficient for basmati rice and rice other than basmati, was equal to one, indicating that India has achieved prominence in the export of rice to the international market.

Table 3 Export of agricultural products at four-digit level in value terms

Product code	Product description	Value (US$ million)		Share of total exports (per cent)	
		2001-2003	2017-2019	2001-2003	2017-2019
1006	Rice	899	7,073	13.06	18.11
0306	Crustaceans (in shell or not, live, fresh, chilled, frozen, dried, salted, etc.)	895	4,566	13.00	11.69
0801	Coconuts, Brazil nuts, and cashew nuts (fresh or dried, shelled or peeled)	392	814	5.70	2.08
2304	Oil cake and other solid residues (ground or not ground) resulting from the extraction of soybean oil	381	824	5.53	2.11
1001	Wheat and meslin	360	52	5.23	0.13
0902	Tea (flavored or unflavored)	354	783	5.14	2.00
1701	Cane or beet sugar and chemically pure sucrose (in solid form)	334	1,202	4.85	3.08
0202	Meat of bovine animals (frozen)	258	3,443	3.74	8.82
0303	Fish (frozen, excluding fish fillets and other fish meat)	227	655	3.30	1.68
0901	Coffee (roasted or unroasted, caffeinated or decaffeinated)	159	552	2.31	1.41
2401	Unmanufactured tobacco, tobacco refuse	147	585	2.14	1.50
1302	Vegetable saps and extracts, pectic substances, agar-agar, and other mucilages	141	922	2.05	2.36
3301	Essential oils (terpeneless or not), including concretes and absolutes	138	1,904	2.00	4.88
1207	Other oil seeds and oleaginous fruits	133	539	1.94	1.38
0307	Molluscs (in shell or not, live, fresh, chilled, frozen, dried, salted, etc.)	125	725	1.81	1.86
1515	Other fixed vegetable fats and oils	122	933	1.77	2.39
0904	Pepper of the genus Piper, dried or crushed or ground fruits of the genus Capsicum	92	866	1.34	2.22
1202	Groundnuts (not roasted or otherwise cooked)	60	584	0.87	1.50
0909	Seeds of anise, badian, fennel, coriander, cumin, or caraway	33	511	0.47	1.31
5201	Cotton (not carded or combed)	19	1,651	0.28	4.23
	Total	5,269	29,186	76.53	74.74

Source United Nations (2020)

observed in the case of raw cotton and boneless meat of bovine animals. These trends at the six-digit level further reinforce the findings at the two- and four-digit levels, which indicated that India's exports have mainly been concentrated in rice, shrimps and prawns, and the meat of bovine animals.

Major export destinations

Having examined the major products exported from India, an analysis was done of destination markets. In 2017-2019, India exported agricultural products worth US$ 11 billion to East Asia and the Pacific region, which was up from US$ 1.9 billion in 2001-2003 (Table 5). This region has remained the largest export destination and accounted for 28.8 per cent of the total exports in 2017-2019. The agricultural exports to the Middle East and North Africa (MENA) have also increased considerably, and in recent years, these regions have emerged as India's second-largest export market. In 2001-2003, the export flows to this region

Table 4 Export of agricultural products at the six-digit level in value terms

Product code	Product description	Value (US$ million)		Share in total exports (percent)	
		2001-2003	2017-2019	2001-2003	2017-2019
100630	Rice (semi-milled or wholly milled)	890	6,691	13.29	18.99
030613	Shrimps and prawns (frozen)	834	4,519	12.44	12.82
230400	Oil cake and other solid residues	381	824	5.69	2.34
080132	Cashew nuts (shelled)	367	724	5.47	2.05
020230	Meat of bovine animals (boneless)	245	3,443	3.66	9.77
170199	Others: cane or beet sugar	244	996	3.65	2.83
090240	Others: black tea (fermented)	221	692	3.30	1.96
030379	Others: fish (frozen)	221	495	3.30	1.40
090111	Coffee (not roasted, not decaffeinated)	156	548	2.32	1.56
090230	Black tea (fermented and partly fermented)	130	70	1.93	0.20
030741 and 030749	Cuttle fish (live, fresh, or chilled)	106	150	1.58	0.37
151530	Castor oil and its fractions	117	861	1.75	2.44
120740	Sesame seeds	111	498	1.66	1.41
130232	Mucilage and thickeners, derived from guar seeds	100	628	1.50	1.78
070310	Onions and shallots	86	403	1.29	1.14
210111	Extracts, essences, and concentrates	72	300	1.08	0.85
240120	Tobacco (partly or wholly stemmed/stripped)	70	533	1.04	1.51
170111	Raw sugar not containing added flavoring or coloring: cane sugar	69	181	1.03	0.51
120220	Groundnuts (shelled, broken or whole)	43	571	0.64	1.62
090420	Fruits of the genus Capsicum or of the genus Pimenta (dried, crushed, or ground)	54	765	0.80	2.17
080450	Guavas, mangoes, and mangosteens	37	164	0.55	0.47
160520	Shrimps and prawns (prepared, preserved)	23	344	0.34	0.98
090930	Cumin seeds	20	423	0.29	1.20
520100	Cotton (not carded or combed)	18	1649	0.26	4.32
330124 and 330125	Essentials oils: peppermint (Mentha piperita) and other mints	66	945	1.01	2.50
	Total	4,680	27,418	69.86	77.22

Source United Nations (2020)

Table 5 Agricultural exports by region in value terms

Region	Value (US$ million)			Share (percent)		
	2001-2003	2008-2010	2017-2019	2001-2003	2008-2010	2017-2019
East Asia and the Pacific	1,897	6,410	10,967	27.8	32.0	28.8
Europe and Central Asia	1,535	3,477	5,836	22.5	17.4	15.3
Latin America and the Caribbean	50	162	352	0.7	0.8	0.9
Middle East and North Africa	1,174	4,871	8,971	17.2	24.3	23.5
North America	1,025	1,623	5,367	15.0	8.1	14.1
Others	75	312	521	1.1	1.6	1.4
South Asia	747	2,464	3,662	11.0	12.3	9.6
Sub-Saharan Africa	317	723	2,461	4.7	3.6	6.5

Source United Nations (2020)

constituted 17.2 per cent of the total exports; this increased to 24.3 per cent in 2008-2010 and remained at that level in 2017-2019 as well.

The importance of Europe and Central Asia as export destination markets declined by 7.2 per cent between 2001-2003 and 2017-2019. Although agricultural exports to this region increased in absolute terms, the rate of increase of export flow was relatively low compared to other regions. The export share to North America was more or less stable, except during the period of financial crisis. Although India is a major economic power among the South Asian countries and even though it has strong cultural affinities with them, it has not been able to significantly tap the region's market potential. India's share of agricultural exports to the South Asian region has declined marginally, from 11.0 per cent in 2001-03 to 9.6 per cent during 2017-19. A rise in export share to sub-Saharan Africa shows it to be an emerging market for India's agricultural products.

The study on the types of commodities exported from India to different regions shows the demand patterns of destination countries as well as the comparative advantage of India in terms of production of these commodities. Rice has been India's top exported agricultural product, with the Middle East and North Africa (MENA) being the largest market for Indian rice. The value of rice exports to this region in 2017-2019 was approximately US$ 4.1 billion, accounting for 11.5 per cent of the total agricultural exports (Table 6). Other export destination markets for Indian rice are: sub-Saharan Africa, South Asia, and Europe and Central Asia. For crustaceans, particularly shrimps and frozen prawns, North America was the major market, followed by East Asia and the Pacific region. East Asia and the Pacific, specifically Vietnam, have been the

Table 6 Export by major products and region, 2017-2019

Product code	Product detail	Region	Export value (US$ million)	Share (per cent)
0202	Meat of bovine animals (frozen)	East Asia and Pacific	2,484	7.05
		Middle East and North Africa	761	2.16
0303	Fish (frozen, excluding fish fillet)	East Asia and Pacific	554	1.57
0306	Crustaceans (in shell or not)	North America	2,100	5.96
		East Asia and Pacific	1,574	4.47
		Europe and Central Asia	622	1.76
0307	Molluscs (in shell or not)	Europe and Central Asia	369	1.05
0901	Coffee (roasted or unroasted)	Europe and Central Asia	388	1.10
0904	Pepper of the genus Piper (dried or not)	East Asia and Pacific	535	1.52
1006	Rice	Middle East and North Africa	4,059	11.52
		Sub-Saharan Africa	1,452	4.12
		South Asia	594	1.69
		Europe and Central Asia	447	1.27
1202	Groundnuts (not roasted or otherwise cooked)	East Asia and Pacific	438	1.24
1302	Vegetable saps and extracts, pectic substances	North America	470	1.33
1515	Other fixed vegetable fats and oils	East Asia and Pacific	479	1.36
1605	Crustaceans, molluscs, and other aquatic invertebrates	North America	352	1.00
1701	Cane or beet sugar and chemically pure sucrose in solid form	Middle East and North Africa	338	0.96
5201	Cotton (not carded or combed)	South Asia	955	2.53
		East Asia and Pacific	631	1.67

Source United Nations (2020)

important destination markets for the meat of bovine animals. From Vietnam, bovine meat is supposedly re-exported to other countries, including to China, where import of bovine meat from India is formally banned. The other export market for the meat of bovine animals is the MENA region. For cotton (not carded or combed), South Asia, East Asia, and the Pacific are the most important destination markets.

The analysis of destination markets by country has revealed that there was little shift in focus for India's agricultural products, implying a lack of diversification of export markets. In 2001-2003, a set of 23 countries accounted for 78.5 per cent of agricultural exports; by 2017-2019, their share declined to 70.36 per cent (Table 7). The United States has been the major destination country for India's agricultural exports. During 2001-2003, the US, along with Japan, Bangladesh, and United Arab Emirates, accounted for one-third of total exports; this declined to less than one-fourth share in 2017-2019. After a jump in the value of exports to the United Arab Emirates in 2008-2010, the period 2017-2019 saw a decline to the levels of 2001-2003. The exports to Saudi Arabia remained more or less stagnant.

India's attempts to diversify its export markets after the global financial crisis seem to have achieved some success, as is evident from the expansion of exports to East Asia and the Pacific region. It is noteworthy that India's exports to Vietnam have increased consistently from 1.3 per cent in 2001-2003 to 10.4 per cent in 2017-2019, with the meat of bovine animals constituting an important export item. The exports to China have also increased and the Islamic Republic of Iran has emerged as an important export destination for Indian agricultural exports.

Table 7 India's major export destinations by country

Country	Percentage of export value		
	2001-2003	2008-2010	2017-2019
United States	14.08	7.34	12.88
Japan	6.89	3.91	2.10
Bangladesh	6.64	5.49	4.09
United Arab Emirates	5.51	8.02	5.23
Saudi Arabia	4.67	5.70	4.22
United Kingdom	4.17	2.59	2.04
Malaysia	3.99	3.92	2.40
Indonesia	3.72	2.59	2.13
Russian Federation	2.74	1.35	1.54
Netherlands	2.64	2.31	2.26
Philippines	2.63	1.14	0.77
Germany	2.53	1.73	1.54
Sri Lanka	2.48	1.59	1.28
China	2.27	8.08	4.81
Singapore	2.02	1.11	0.78
Spain	1.77	1.12	0.92
Belgium	1.73	1.84	1.39
France	1.66	1.48	1.26
Italy	1.66	1.51	1.25
South Africa	1.60	0.71	0.51
Thailand	1.37	1.77	1.83
Vietnam	1.34	5.47	10.41
Iran, Islamic Republic	0.45	2.45	4.72

Source United Nations (2020)

Export specialization pattern of agricultural products

A broad pattern of export specialization of agricultural products has been captured using Balassa's revealed comparative advantage index. The revealed symmetric comparative advantage index was also calculated to provide benchmark results on the changes in comparative advantage to export. The analysis at a broad sectoral level has provided a general pattern of RCA values but revealed little about developments at the disaggregated level. Given the large number of products at the four-digit level, the distribution of product-level RCA and RSCA has been shown in Table 8.

As per the percentile distribution of RCA, the 50th percentile occurs at 0.126, indicating that 50 per cent of products had an RCA value below 0.126. The 75th percentile occurs at 0.760, implying that 75 per cent of products had an RCA value below 0.760. The 90th percentile of RCA and RSCA occur at 4.120 and 0.609, respectively; this implies that 90 per cent of the products have an RCA value of less than 4.120 and an RSCA value of less than 0.609. These patterns indicate that there is little change in the percentile distribution of RCA and RSCA at different points of time and that the pattern of distribution of RCA implies a concentration of its values on the right side of the tail. This is also evident from the skewness and kurtosis values. The coefficient of variation (CV) shows the degree of unevenness/variation of the RCA measured. The CV of RCA values remains more or less constant, suggesting some degree of stability in the export specialization of products at the four-digit level.

Table 8 Cumulative distribution of revealed comparative advantage and revealed symmetric comparative advantage at the four-digit product level

Percentile	Revealed comparative advantage (RCA)			Revealed symmetric comparative advantage (RSCA)		
	2003	2010	2019	2003	2010	2019
5	0.0002	0.0002	0.0004	-0.9996	-0.9996	-0.9991
10	0.0009	0.0011	0.0012	-0.9982	-0.9979	-0.9977
25	0.0147	0.0216	0.0024	-0.9711	-0.9577	-0.9952
40	0.0536	0.0841	0.0260	-0.8982	-0.8449	-0.9493
50	0.1267	0.1619	0.0634	-0.7751	-0.7214	-0.8808
75	0.7604	0.8203	0.5285	-0.1361	-0.0987	-0.3085
90	4.1197	4.5907	3.2625	0.6094	0.6423	0.5308
95	7.7518	7.4818	5.5359	0.7715	0.7642	0.6940
99	18.4062	14.013	11.5733	0.8969	0.8668	0.8409
Max	34.8412	24.540	24.2342	0.9442	0.9217	0.9207
Mean	1.3752	1.400	1.0010	-0.4868	-0.4349	-0.5466
Standard deviation	3.5498	3.229	2.5064	0.6132	0.6113	0.5779
Skewness	5.2358	4.264	4.7124	1.0306	0.8572	1.1355
Kurtosis	40.172	26.074	33.7211	2.5666	2.3112	2.9382
Number of observations	241	234	269	241	234	269

Source Authors' estimates

Though there are about 240 products at the four-digit level, Table 9 includes only the top 20 products that had a comparative advantage in terms of their RCA and RSCA values and their export share during 2001-2003. These 20 products have been arranged in descending order according to their RCA value, and together they account for 50 per cent of exports. At the top of the list, with the highest value of RCA and an export share of 5.79 per cent, are coconuts, Brazil nuts, and cashew nuts (shelled or unshelled); these are followed by oil cake and other solid residues resulting from the extraction of groundnut oil, and fruit and nuts (provisionally preserved), which together had an export share of less than 1 per cent.

Among the products whose export share was negligible but ranked among the top 20 products having a comparative advantage to export are: bones and horn-cores; vegetable materials used in brooms or in brushes; silk waste; seeds of anise, badian, fennel, coriander, cumin; groundnuts; nutmeg, mace, and cardamoms, and silkworm cocoons. Although the export share of these products has been low, they have registered a high RCA value, implying that their relative product export share is higher than the country's overall share in world exports for those products; this further suggests, intuitively, that they enjoy abundant domestic advantages which favour their production.

The study examined the status of comparative advantage of products and their relative positions as recorded in 2001-2003 and in 2017-2019. A slight change was observed in the ranking of products and their export share (Table 10). With an increase in the export share of rice in the world market, its ranking shifted from the sixth position in 2001-2003 to the third position in 2017-2019. The top two products with high RCA values are: seeds of anise, badian, fennel, coriander, or caraway, and human hair (unworked). With the entry of new products such as meat of bovine animals, and cotton (not carded or combed) into the list of top 20 products, the export share of these 20 products increased to 60 per cent, an increment of 10 per cent from 2001-2003. Barring these minor changes, there was only a small structural transition in the export specialization of India's agricultural products.

Stability of export specialization pattern: Galtonian regression analysis

The changes in distributions of RCA and RSCA, captured by density functions are depicted in Figure 1. It shows the stark differences in the evolution of RCA

Table 9 Top 20 products with revealed comparative advantage (>1) at the four-digit level in 2001/2003

Product code	Product description	Revealed comparative advantage (RCA)	Revealed symmetric comparative advantage (RSCA)	Export value (US$ million)	Percentage share of exports
0801	Coconuts, Brazil nuts, and cashew nuts (shelled or unshelled)	70.35	2.75	392.5	5.79
2305	Oil cake and other solid residues resulting from extraction of groundnut oil	64.54	2.69	8.5	0.13
812	Fruit and nuts (provisionally preserved)	63.30	2.69	47.4	0.71
1301	Lac, natural gums, resins, gum-resins, and oleoresins	62.47	2.72	93.4	1.38
506	Bones and horn-cores (unworked, defatted, simply prepared)	40.86	2.59	20.7	0.31
1006	Rice	32.50	2.46	899.5	13.12
1207	Other oil seeds and oleaginous fruits	30.78	2.45	133.5	1.97
902	Tea (flavored or unflavored)	29.11	2.44	353.5	5.24
910	Ginger, saffron, turmeric (curcuma)	27.22	2.40	71.2	1.05
1403	Vegetable materials used primarily in brooms or brushes	23.72	2.30	2.9	0.04
904	Pepper of the genus Piper (dried or crushed)	22.85	2.30	92.4	1.36
1515	Other fixed vegetable fats and oils	22.33	2.27	121.6	1.80
5003	Silk waste (including cocoons unsuitable for reeling, yarn waste, and garnetted stock)	19.12	1.98	4.9	0.08
909	Seeds of anise, badian, fennel, coriander, cumin, or caraway	17.65	2.08	32.7	0.49
306	Crustaceans (in shell or not, live, fresh, chilled, frozen, dried)	17.28	2.11	895.0	13.15
1202	Groundnuts (not roasted or otherwise cooked)	17.11	2.05	59.7	0.88
1302	Vegetable saps and extracts, pectic substances, agar-agar	16.98	2.10	140.8	2.06
908	Nutmeg, mace, and cardamoms	16.60	2.07	16.2	0.24
1211	Plants and parts of plants (including seeds and fruits) used primarily in perfumes, pharmaceuticals, and insecticides	15.83	2.04	72.4	1.07
5001	Silkworm cocoons suitable for reeling	15.64	1.59	0.3	0.00

Source United Nations (2020)

and RSCA for the period 2015-19. The distribution of RCA is seen as asymmetric, with the bulk of products concentrated in the direction of low RCA values. This indicates a high incidence of products with a comparative disadvantage in terms of exports. Although RCA provides guidance on the direction of export specialization, lack of normality in its distribution results in unreliable *t*-statistics when it is used in a regression analysis (Laursen 2015). The alternative measure, RSCA, is seen less skewed, however, and it has overcome non-normality problem and has eliminated 0 value. These properties make RSCA useful in regression analysis.

The regression results on the stability of export specialization are reported in Table 11. The degree of export specialization was measured as the ratio of the estimated regression coefficient ($\hat{\beta}$) to the regression correlation coefficient (R^*). If $\hat{\beta} = R^*$, the export specialization remains unchanged, that is, the distribution of the RSCA remains unchanged between the two time periods. If $\hat{\beta} / R^* > 1$, the export specialization increases; $\hat{\beta} / R^* < 1$ suggests a decrease in export specialization.

It was observed that export specialization did not change during the two sub-periods of analysis, 2001

Table 10 Top 20 products with revealed comparative advantage greater than 1 at the four-digit level, 2017-2019

Product code	Product description	Revealed comparative advantage (RCA)	Revealed symmetric comparative advantage (RSCA)	Export value (US$ million)	Percentage share of exports
0909	Seeds of anise, badian, fennel, coriander, cumin, or caraway	71.08	2.76	510.96	1.34
0501	Human hair (worked or unworked)	45.40	2.60	28.77	0.08
1006	Rice	35.67	2.53	7,072.68	18.55
0904	Pepper of the genus Piper (dried or crushed)	28.71	2.42	866.42	2.28
1515	Other fixed vegetable fats and oils	27.72	2.41	933.41	2.45
1202	Groundnuts (not roasted or otherwise cooked)	26.37	2.38	583.91	1.53
5003	Silk waste (for reeling, yarn waste, and garnetted stock)	25.26	2.36	15.92	0.04
5202	Cotton waste (including yarn waste and garnetted stock)	25.05	2.31	96.37	0.25
0306	Crustaceans (in shell or not, live, fresh, chilled, frozen, dried)	21.78	2.27	4,566.30	11.98
0910	Ginger, saffron, turmeric (curcuma), thyme, bay leaves, curry, and other spices	21.61	2.25	402.51	1.06
1302	Vegetable saps and extracts, pectic substances, agar-agar	18.32	2.15	922.27	2.42
0902	Tea (flavored or unflavored)	18.16	2.05	782.53	2.05
1207	Other oil seeds and oleaginous fruits	18.02	2.11	539.28	1.42
0202	Meat of bovine animals (frozen)	17.23	2.08	3,442.94	9.03
0711	Vegetables (provisionally preserved)	16.45	2.07	79.31	0.21
1301	Lac, natural gums, resins, gum-resins, and oleoresins	15.86	2.03	75.02	0.20
0908	Nutmeg, mace, and cardamoms	14.43	1.89	105.20	0.28
5201	Cotton (not carded or combed)	14.29	1.89	1,648.62	4.31
5103	Waste of wool or of fine or coarse animal hair	13.24	1.89	11.10	0.03
1211	Plants and parts of plants (including seeds and fruits), used primarily in perfume, pharmaceuticals, or insecticides	12.90	1.86	294.84	0.77

Source United Nations (2020)

Table 11 Stability of export specialization pattern

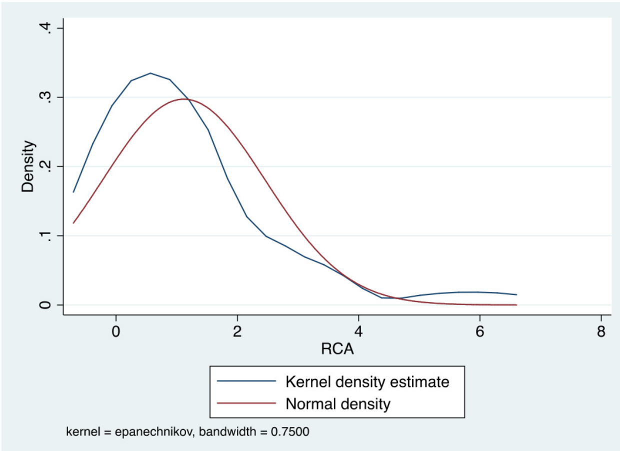
Parameters	2001-2009	2010-2019
$\hat{\alpha}$	-0.044	-0.024
	(0.031)	(0.026)
$\hat{\beta}$	0.821***	0.888***
	(0.040)	(0.033)
$\hat{\beta}/R$*	1.032	1.049
No. of observations	241	287
F (1, 239)	414.06	
F (1, 285)		723.65
Prob > F	0.000	0.000

Source Authors' estimates
Note Figures within the parentheses are standard errors; *** = significance at the 1 per cent level

to 2009 and 2010 to 2019 (Table 11), suggesting the stability of India's export specialization over time. This also means that there is stickiness (persistence) in India's agricultural exports. It was verified through mobility analysis of the comparative advantage of products using Markov transition matrices.

Markov transition and RCA distributional mobility

Transition probability matrices provide information about the persistence and mobility of comparative advantage when the overall distribution of the RCA values of products are considered jointly. The transition matrices show the probability that a product that was



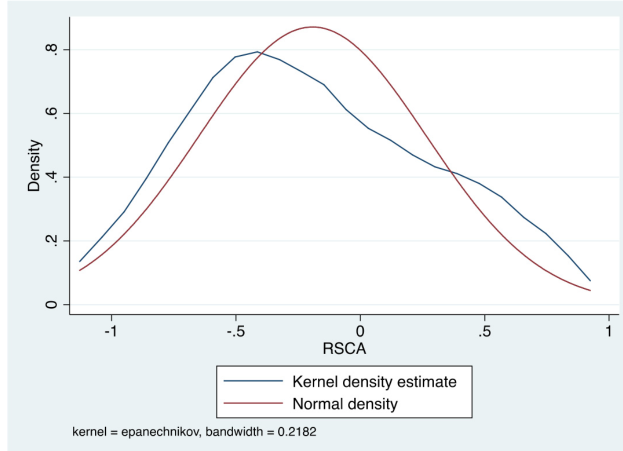


Figure 1 Density distribution of revealed comparative advantage and revealed symmetric comparative advantage, 2015 to 2019
Source Authors' estimates

initially in a particular class of distribution of RCA will move to another class of distribution of RCA in the next period. This mobility depends on the innate mobility of the system and the length of time period during which movements between classes are measured (Shorrocks 1978). Hinloopen and Van Marrewijk (2004) showed that the analysis of dynamics of comparative advantage at the four-digit level should classify the data endogenously into 10 different classes. Accordingly, we used decile classes to analyse the mobility of comparative advantage of products in an average year between 2001 and 2019. With these groupings of data and time periods, the transition matrices can show the probability of a product in the i^{th} decile of the RCA distribution in the year *t* moving to the j^{th} decile of the distribution in the year *t+s*.

The transition probabilities for revealed comparative advantage for the period 2001-2019 are given in Table 12. In this transition table, the rows are associated with decile class to which the product belonged in 2001. By reading across the rows, each cell shows the fraction of products from rows in that decile that are observed in that column's decile in 2019. Accordingly, the values in rows have been appropriately scaled down to unity or hundred. The mobility is observed when there is movement of products between the decile groups. The probability of movement between the decile classes can be captured by the off-diagonal elements of the matrix. The diagonal elements measure the degree of persistence of products in the same decile.

A perusal of Table 12 revealed that the highest values were around the diagonal of the matrix, indicating either the persistence of products in the same decile or movement up or down to the adjacent deciles. If the product is in the first decile of distribution in the study period, there is 65.8 per cent probability that it would stay in the first decile after 19 years, 23.0 per cent probability that it would move to the second decile of the distribution, 5.6 per cent probability that it would move to a third decile, and so on. The diagonal elements show that the persistence of export specialization is high in the first decile, then it declines to reach a minimum (barring the fifth decile) in the sixth decile. Thereafter, it increases to reach the maximum level of persistence (85.3 %) in the tenth decile. These results suggest a high degree of persistence of export specialization at the extreme ends of RCA distribution, which means that there is a much higher probability of starting and ending-up in the highest decile.

The information present in the transition matrices can be compressed and provided in the form of a mobility index, that is, as a summary measure of the overall mobility of products. We have used two popular mobility indices, the Shorrocks index and the Bartholomew index. While the Shorrocks index measures the average probability across all decile groups that a product will leave the initial state in the next period, the Bartholomew index captures the average number of decile classes crossed by all products.

Table 12 Transition matrix for revealed comparative advantage: Average annual change between 2001 and 2019

Starting interval	Ending interval 1	2	3	4	5	6	7	8	9	10
1	**65.83**	22.97	5.60	3.36	0.84	0.84	0.28	0.28	0.00	0.00
2	25.73	**49.87**	17.24	4.51	1.86	0.53	0.27	0.00	0.00	0.00
3	6.25	19.01	**48.18**	19.53	3.91	2.08	0.78	0.00	0.00	0.26
4	3.12	6.23	20.52	**47.01**	17.40	4.16	1.04	0.52	0.00	0.00
5	1.04	1.57	6.27	16.45	**51.44**	16.71	4.70	1.83	0.00	0.00
6	0.00	1.29	2.06	5.14	19.54	**46.02**	20.31	4.63	0.77	0.26
7	0.51	0.77	0.26	2.31	3.59	24.10	**50.51**	15.38	1.54	1.03
8	0.26	0.00	0.52	0.52	0.52	4.94	17.14	**60.26**	13.77	2.08
9	0.00	0.00	0.00	0.52	0.00	0.52	2.84	14.73	**71.32**	10.08
10	0.00	0.00	0.26	0.00	0.26	0.00	0.79	1.58	11.84	**85.26**

Source Authors' estimates

The estimates of mobility indices, along with their bootstrap standard error and number of observations have been reported in Table 13. Bootstrap procedure allows to make statistical inference about the estimated value of indices. Bootstrapped standard errors are generated while estimating the mobility scores. The Shorrocks index value of 1 indicates the perfect mobility of products, while a 0 value indicates that there is a 100 per cent chance that a product will remain in its original decile (immobility). The average value of the Shorrocks index during the entire study period was 0.46, implying a low mobility and suggesting that the transition of products to the highest decile is far from complete. The low mobility has suggested that India's agricultural export structure has evolved little over time. The values of the Shorrocks index and the Bartholomew index have shown an overall declining trend. The Shorrocks index has shown a decline between 2002 and 2005 and then an increase to a peak in 2009; thereafter, the index shows a continuous

Table 13 Trend in revealed comparative advantage mobility index, 2002-2019

Year	Shorrocks index		Bartholomew index		Number of observations
	Estimate	Bootstrap standard error	Estimate	Bootstrap standard error	
2002	0.528	0.048	0.088	0.010	206
2003	0.567	0.054	0.084	0.010	209
2004	0.522	0.048	0.074	0.008	215
2005	0.514	0.050	0.070	0.008	216
2006	0.452	0.054	0.060	0.008	214
2007	0.463	0.045	0.068	0.009	213
2008	0.518	0.052	0.076	0.009	218
2009	0.607	0.057	0.086	0.009	214
2010	0.475	0.051	0.071	0.009	213
2011	0.409	0.042	0.059	0.008	212
2012	0.501	0.054	0.062	0.007	211
2013	0.430	0.052	0.053	0.007	212
2014	0.369	0.044	0.044	0.006	211
2015	0.391	0.063	0.054	0.010	213
2016	0.421	0.058	0.056	0.008	211
2017	0.381	0.044	0.048	0.006	210
2018	0.360	0.041	0.043	0.005	209
2019	0.392	0.042	0.046	0.005	210

Source Authors' estimates

decline until 2019, when it reaches a minimum value of 0.39. These trends suggest that products are spread out in the deciles of distribution and that there is little mobility in their comparative advantage to export.

The mobility of export specialization is influenced by relative factor abundance, technological developments, changes in demand patterns, and economic incentives such as subsidies and trade protection measures (Dalum, Laursen, Villumsen 1998; Laursen 2000). We have also analysed to see whether there was any relationship between the mobility of products (four-digit level) and their share in the national agricultural exports. It is expected that the higher the degree of mobility of a product, the greater is its share in national agricultural exports; the relationship has not, however, shown a definite pattern (Figure 2).

Among the products that showed greater mobility in transitioning out of their initial state, the most were found to have a low share of exports in an average year between 2002 and 2019. The products that had a high export share, however, experienced relatively low mobility across the decile groups, implying persistence of the export specialization of the top commodities in the highest deciles.

One can also expect that products that have a higher share of world agricultural exports will tend to have high mobility in the comparative advantage; however, the pattern of relationship between the mobility of a product and its share of world agricultural exports appeared to be similar to the relationship between mobility and the share of national agricultural exports (Figure 3). Between 2002 and 2019, the bulk of the products that experienced high mobility were found to have a low world export share and products that had a high export share were far from perfectly mobile.

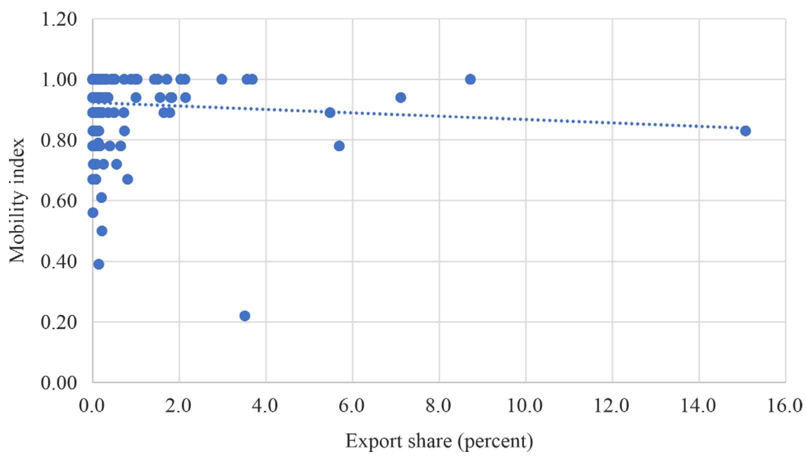


Figure 2 Relationship between mobility index and national agricultural export share
Source Authors' estimates

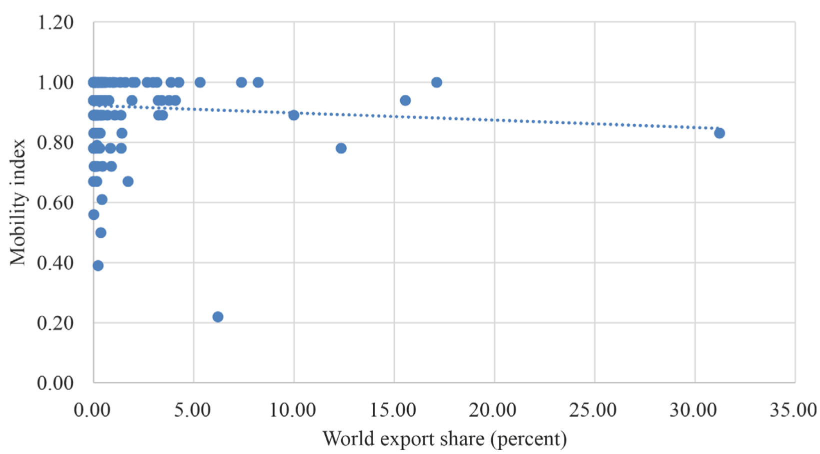


Figure 3 World export share and mobility index
Source Authors' estimates

Conclusions and policy implications

To conclude, the study has found that India's agricultural exports registered an appreciable growth between 2001 and 2019, while the trade openness index remained constant. This is probably due to the contradictory policy stance which has been aimed on the one hand at pushing agricultural trade and on the other at imposing arbitrary trade restrictions to protect the interests of consumers. Since 2015, the outward orientation index has shown a declining trend, indicating a fall in the degree of openness. Except for the export of meat and edible meat offal, whose share increased between 2001-2003 and 2017-2019, there has been little change in the composition of agricultural exports. There is also little dynamism in the import composition of agricultural products. The analysis of export composition at the four-digit level, however, has shown some improvements in the relative importance of products such as rice and crustaceans. The analysis at the six-digit level has also shown that two products (semi-milled or wholly milled rice, and frozen shrimps and prawns) accounted for about one-third of the total exports in 2017-2019, an increase of 8.0 per cent from 2001-2003.

On an average, 20 per cent of products at the four-digit level have shown a comparative advantage to export and these products accounted for over 80 per cent of the total exports. The pattern of a few products accounting for a consistently large share of exports over time implies persistence in comparative advantage among these products and stability in their contribution to the export basket. The mobility of the revealed comparative advantage has shown 65.8 per cent probability that a product would remain in the first decile even after 19 years. There is a high degree of persistence in export specialization at the extreme ends of RCA distribution, meaning thereby that there is a much higher probability of starting and ending up in the highest decile. These findings confirm that there is little mobility of products from the lowest decile to the highest decile and that there is a high degree of persistence in the highest decile of RCA distribution. The policies should aim at the diversification of the agricultural export basket through a product-specific focus that is based on export demand and the exploration of new markets.

References

Acharya, S S, R Chand, P S Birthal, S Kumar and D S Negi. 2012. *Market Integration and Price Transmission in India: A Case of Rice and Wheat with Special Reference to the World Food Crisis of 2007/08*. Rome: Food and Agriculture Organization. http://www.fao.org/3/an034e/an034e.pdf.

Ahmed, R. 1996. Agricultural Market Reforms in South Asia. *American Journal of Agricultural Economics* 78(3): 815-819.

Aksoy, M A. 2005. The Evolution of Agricultural Trade Flows. In *Global Agricultural Trade and Developing Countries*, edited by M A Aksoy and J C Beghin, 17-35. Washington DC: The World Bank.

Aksoy, M A and F Ng. 2010. *The Evolution of Agricultural Trade Flows*. Policy Research Working Paper 5308. Washington, DC: The World Bank.

Athukorala, P-C. 2005. Agricultural Trade Policy Reforms in India. *South Asia Economic Journal* 6(1): 23-36.

Balassa, B. 1965. Trade Liberalization and 'Revealed' Comparative Advantage. *Manchester School of Economic and Social Studies* 33: 99-123.

Balassa, B. 1977. "'Revealed' Comparative Advantage Revisited: An Analysis of Relative Exports Shares of the Industrial Countries, 1953–1971." *Manchester School of Economic and Social Studies* 45: 327–44.

Bartholomew, D J. 1973. *Stochastic Models for Social Processes*. London: Wiley.

Bowen, H P. 1983. On the Theoretical Interpretation of Indices of Trade Intensity and Revealed Comparative Advantage. *Weltwirtschaftliches Archiv* 11: 464-472.

Cantwell, J. 1989. *Technological Innovation and Multinational Corporations*. Oxford: Blackwell.

Chor, D. 2010. Unpacking Sources of Comparative Advantage: A Quantitative Approach. *Journal of International Economics* 82: 152-167.

Costinot, A, D Donaldson and I Komunjer. 2012. What Goods Do Countries Trade? A Quantitative Exploration of Ricardo's Ideas. *Review of Economic Studies* 79: 581-608.

Dalum, B, K Laursen and G Villumsen. 1998. Structural Change in OECD Export Specialisation Patterns: De-specialisation and 'Stickiness'. *International Review of Applied Economics* 12(3): 423-443.

Debaere, P and S Mostashari. 2010. Do Tariffs Matter for the Extensive Margin of International Trade? An

Empirical Analysis. *Journal of International Economics* 81: 163-169.

Eaton, J and S Kortum. 2002. Technology, Geography and Trade. *Econometrica* 70(5): 1741-1779.

Eum, J, I Sheldon and S R Thompson. 2021. Product Quality in Food and Agricultural Trade: Firm Heterogeneity and the Impact of Trade Costs. *Journal of Agricultural and Resource Economics* 46(1): 1-19.

Ferto, I and L J Hubbard. 2003. Revealed Comparative Advantage and Competitiveness in Hungarian Agri-Food Sectors. *World Economy* 26(2): 247-259.

Fiankor, D D, O Haase and B Brummer. 2021. The Heterogenous Effects on Standards on Agricultural Trade Flows. *Journal of Agricultural Economics* 72(1): 25-46.

Gnidchenko, A A and V A Salnikov. 2015. Net Comparative Advantage Index: Overcoming the Drawbacks of the Existing Indices. WP BRP 119/EC/2015. Moscow: National Research University Higher School of Economics.

Hart, P E and S J Prais. 1956. The Analysis of Business Concentration; A Statistical Approach. *Journal of the Royal Statistical Society Series A* 119: 150-191.

Hejazi, M, J H Grant and E Peterson. 2017. Tariff Changes and the Margins of Trade: A Case Study of U.S. Agri-Food Imports. *Journal of Agricultural and Resource Economics* 42(1): 68-89.

Helpman, Elhanan, Marc Melitz and Yona Rubinstein. 2008. Estimating trade flows: trading partners and trading volumes. *Quarterly Journal of Economics* 123(2): 441-487.

Hillman, A L. 1980. Observations on the Relation Between 'Revealed Comparative Advantage' And Comparative Advantage as Indicated by Pre-trade Relative Prices. *Weltwirtschaftliches Archiv* 116(2): 315-321.

Hinloopen, J and C Van Marrewijk. 2001. On the Empirical Distribution of the Balassa Index. *Weltwirtschaftliches Archiv* 137: 1-35.

Hinloopen, J and C van Marrewijk. 2004. *Dynamics of Chinese Comparative Advantage*. Tinbergen Institute Discussion Paper TI 2004–034/2. Amsterdam: Tinbergen Institute, University of Amsterdam.

Hoda, A and A Gulati. 2013. *India's Agricultural Trade Policy and Sustainable Development*. Issue Paper No. 49. Geneva: International Centre for Trade and Sustainable Development.

India, Ministry of Commerce and Industry. 2020. Notification of ITC (HS), 2017–Schedule-1 (Import Policy). Notification No.38/2015–2020. New Delhi: Ministry of Commerce and Industry.

Jha, S and P V Srinivasan. 2004. *Achieving Food Security in a Cost Effective Way: Implications of Domestic Deregulation and Reform Under Liberalized Trade.* MTID Discussion Paper No. 67. Washington DC: International Food Policy Research Institute.

Kowalski, P and N Bottini. 2011. Comparative Advantage and Export Specialization Mobility. In *Globalisation, Comparative Advantage and the Changing Dynamics of Trade*, 81-119. Paris: Organisation of Economic Co-operation and Development.

Kumar, V. 2021. Trends and Performance of India's Agricultural Trade in the Midst of COVID-19 Pandemic. *Indian Journal of Agricultural Economics* 76(3): 350-370.

Laursen, K. 2000. *Trade Specialization, Technology and Growth: Theory and Evidence from Advanced Countries*. United Kingdom: Edward Elgar Publishing.

Laursen, K. 2015. Revealed Comparative Advantage and the Alternatives as Measures of International Specialisation. *Eurasian Business Review* 5: 99-115.

Leromain, E and G Orefice. 2014. New Revealed Comparative Advantage Index: Dataset and Empirical Distribution. *International Economics* 139: 48-70.

Martin, W. 2017. *Agricultural Trade and Food Security.* ADBI Working Paper 664. Tokyo: Asian Development Bank Institute.

Melitz, M J 2003. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica* 71(6): 1695-1725.

Mullen, K, D Sun, D Orden and A Gulati. 2004. *Producer Support Estimates (PSEs) for Agriculture in Developing Countries: Measurement Issues and Illustrations from India and China*. MTID Discussion Paper No. 74. Washington DC: International Food Policy Research Institute.

Proudman, J and S Redding. 2000. Evolving Patterns of International Trade. *Review of International Economics* 8(3): 373-396.

Pursell, G and A Gulati. 1993. *Liberalizing Indian Agriculture: An Agenda for Reform*. Policy Research Working Paper WPS 1172. Washington, DC: Policy Research Department, The World Bank.

Saini, S and A Gulati. 2016. India's Food Security Policies in the Wake of Global Food Price Volatility. In *Food Price Volatility and its Implications for Food Security*, edited by M Kalkuhi, J von Braun and M Torero, 331-54. New York: Springer.

Santos-Paulino, A U and D Thornquist. 2015. *Estimating the Impact of Trade Specialization and Trade Policy on Poverty in Developing Countries*. Trade and Poverty Paper Series No. 6. Geneva: United Nations Conference on Trade and Development.

Singh, O P, M Anoop and P K Singh. 2020. Revealed Comparative Advantage, Competitiveness and Growth Performance: Evidence from India's Foreign Trade of Agricultural Commodities. *Indian Journal of Agricultural Economics* 75(4): 560-577.

Shorrocks, A F. 1978. The Measurement of Mobility. *Econometrica* 46(5): 1013-1024.

Stellian, R and J Danna-Buitrago. 2019. Revealed Comparative Advantages and Regional Specialization: Evidence from Colombia in the Pacific Alliance. *Journal of Applied Economics* 22(1): 349-379.

Sun, Z and X Li. 2018. The Trade Margins of Chinese Agricultural Exports to ASEAN and their Determinants. *Journal of Integrative Agriculture* 17(10): 2356-2367.

United Nations. 2020. UN Comtrade Database. Accessed September 24, 2020. https://comtrade.un.org/.

von Braun, J and E Diaz-Bonilla. 2008. Globalisation of Agriculture and Food: Causes, Consequences and Policy Implications. In *Globalisation of Food and Agriculture and the Poor,* edited by J von Braun and E Diaz-Bonilla, 1-45. New Delhi: Oxford University Press.

World Bank. 2020. World Development Indicators. Accessed September 28, 2020. https://databank.worldbank.org/source/world-development-indicators#.

WTO. 2015. *Trade Policy Review: Report by the Secretariat*. WT/TPR/S/313/Rev.1. Geneva: World Trade Organization.

Yeats, A J. 1985. On the Appropriate Interpretation of the Revealed Comparative Advantage Index: Implications of a Methodology Based on Industry Sector Analysis. *Weltwirtschaftliches Archiv* 121: 61-73.

Received 17 May 2023 Accepted 5 August 2023

Appendix Tables

Table A1 Agricultural export composition of India (per cent)

Product code	Product description	2001-2003	2008-2010	2013-2015	2017-2019
01	Live animals	0.04	0.07	0.03	0.07
02	Meat and edible meat offal	4.26	6.90	11.46	10.05
03	Fish and crustaceans, molluscs, and other aquatic invertebrates	18.90	8.16	11.75	16.60
04	Dairy products, birds' eggs, natural honey, edible products of animals not elsewhere specified or included	1.11	1.39	1.26	1.11
05	Products of animal origin, not elsewhere specified or included	0.59	0.28	0.27	0.30
06	Live trees and other plants, bulbs, roots, cut flowers, and ornamental foliage	0.53	0.35	0.18	0.21
07	Edible vegetables and certain roots and tubers	3.84	4.07	2.97	3.03
08	Edible fruits and nuts, peel of citrus fruits or melons	8.10	5.42	3.87	4.25
09	Coffee, tea, mate, and spices	10.68	8.77	6.76	8.52
10	Cereals	18.87	16.35	22.43	19.34
11	Products of the milling industry, malt, starches, inulin, wheat gluten	1.02	0.32	0.74	0.75
12	Oil seeds, oleaginous fruits, miscellaneous grains, seeds, fruit, etc.	4.31	4.60	4.50	4.45
13	Lac, gums, resins and other vegetable saps and extracts	3.44	2.50	5.20	2.62
14	Vegetable plaiting materials, vegetable products not elsewhere specified or included	0.25	0.23	0.15	0.14
15	Animal/vegetable fats and oils, and their cleavage products, etc.	2.56	3.05	2.28	3.06
16	Preparations of meat, fish, crustaceans, molluscs, or other aquatic invertebrates	0.45	1.22	0.38	1.41
17	Sugars and sugar confectionery	5.30	4.48	3.13	3.77
18	Cocoa and cocoa preparations	0.05	0.11	0.31	0.48
19	Preparations of cereal, flour, starch/milk, pastrycooks' products	0.79	1.16	1.19	1.38
20	Preparations of vegetables, fruit, nuts, or other parts of plants	1.01	1.34	1.17	1.54
21	Miscellaneous edible preparations	1.93	1.43	1.38	1.99
22	Beverages, spirits, and vinegar	0.41	0.67	0.93	0.82
23	Residues and waste from the food industry, preparations of animal fodder	6.41	10.91	5.50	4.00
24	Tobacco and manufactured tobacco substitutes	2.98	4.08	2.40	2.52
3301	Essentials oils (terpeneless or not), resinoids, extracted oleoresins	1.01	1.65	1.54	2.50
5201	Cotton (not carded or combed)	0.26	9.32	7.43	4.32
	Others	0.91	1.16	0.81	0.77
	Total	100	100	100	100

Source United Nations (2020)

Table A2 Agricultural import composition of India (per cent)

Product code	Product description	2001-2003	2008-2010	2013-2015	2017-2019
1	Live animals	0.01	0.08	0.05	0.04
2	Meat and edible meat offal	0.00	0.01	0.01	0.02
3	Fish, crustaceans, molluscs, and other aquatic invertebrates	0.22	0.46	0.25	0.40
4	Dairy products, birds' eggs, natural honey, edible products of animals not elsewhere specified or included	0.44	0.83	0.22	0.16
5	Products of animal origin not elsewhere specified or included	0.31	0.19	0.18	0.17
6	Live trees and other plants, bulbs and roots, cut flowers and ornamental foliage	0.04	0.10	0.09	0.11
7	Edible vegetables and certain roots and tubers	15.45	16.62	14.23	9.04
8	Edible fruit and nuts; peel of citrus fruits or melons	8.85	10.88	12.60	14.41
9	Coffee, tea, mate, and spices	2.56	2.63	3.03	3.24
10	Cereals	0.03	1.22	0.33	2.04
11	Products of the milling industry, malt, starches, inulin, wheat gluten	0.14	0.22	0.28	0.32
12	Oil seeds, oleaginous fruits, miscellaneous grains, seeds, fruits, etc.	0.87	1.47	1.69	2.17
13	Lac, gums, resins and other vegetable saps and extracts	0.75	0.86	0.90	1.08
14	Vegetable plaiting materials, vegetable products not elsewhere specified	0.04	0.06	0.10	0.20
15	Animal/vegetable fats and oils, and their cleavage products	47.54	43.82	50.38	45.60
16	Preparations of meat, fish, crustaceans, molluscs, etc.	0.01	0.03	0.02	0.03
17	Sugars and sugar confectionery	0.49	6.01	2.73	3.20
18	Cocoa and cocoa preparations	0.31	0.72	1.02	1.05
19	Preparations of cereal, flour, starch/milk, pastrycooks' products	0.46	0.30	0.24	0.35
20	Preparations of vegetables, fruits, nuts or other parts of plants	0.33	0.44	0.37	0.47
21	Miscellaneous edible preparations	0.98	0.58	0.60	0.85
22	Beverages, spirits, and vinegar	0.51	2.22	2.38	3.20
23	Residues and waste from the food industry, preparations of animal fodder	1.35	1.46	1.58	2.58
24	Tobacco and manufactured tobacco substitutes	0.16	0.23	0.22	0.19
3301	Essentials oils (terpeneless or not) resinoids, extracted oleoresins	0.44	0.73	0.75	1.90
5002	Raw silk (not thrown)	3.31	1.77	0.78	0.71
5101	Wool (not carded or combed)	3.82	2.26	1.61	1.19
5201	Cotton (not carded or combed)	8.50	2.32	2.11	3.96
	Others	2.08	1.46	1.27	1.33
	Total	100	100	100	100

Source United Nations (2020)

Agricultural Economics Research Review 2023, 36 (2), 145-154
DOI: 10.5958/0974-0279.2023.00028.9

Rise of Agritech: A landscape of technology driven agricultural sector in India

Haritha K[1], Akriti Sharma[1]*, P Venkatesh[1], Asha Devi[1], P Anbukkani[1] and Abhinandan Kumar[2]

[1]Division of Agricultural Economics, ICAR-Indian Agricultural Research Institute, New Delhi 110012, India
[2]Division of Dairy Economics, Statistics and Management, ICAR- National Dairy Research Institute, Karnal, Haryana 132001, India

*Corresponding author: aakritinankur@gmail.com

Abstract The rising demand for innovation in agriculture and the decreasing last-mile delivery to farmers have led to introduction of new technologies in the agriculture ecosystem. With advancements in and application of information technology in agriculture, agritech has been increasingly gaining attention. The present study has investigated the geographical and funding landscape of agritech companies in India. It has identified the technological and business models that are predominant in the Indian scenario. The study is based on the secondary data of 253 agritech companies in India (till 2022) collected from the CrunchBase database. The study has presented summary statistics, tabular and graphical representation, and content analysis for these business models. The results have revealed that the incorporation trend has increased in India over the past few years. The total funding has also shown an increasing trend over the years. Among states, Karnataka has emerged as the hotspot of agritech companies in India, followed by Maharashtra. With the help of Inductive content analysis of the textual data, the study has identified the supply chain technology and output market linkages, followed by the farm management and analytics as the most promising business models in the Indian context.

Keywords Agritech, agriculture, technology, funding, Agri-tech companies, content analysis, CrunchBase database, India

JEL codes L11, L25, Q16, Q19

Introduction

Agriculture is a sector that sustains life on the Earth, provides food and resources to both humans and animals. With the expanding world's population, there is a corresponding rise in the demand for food. As a result, agriculture encounters a variety of serious problems, such as food instability, water scarcity, and climate change. According to the Food and Agriculture Organization (FAO), the global population is expected to reach 9.7 billion by 2050, necessitating a 70 per cent increase in food production (FAO 2009). Agritech has emerged as a promising solution to these challenges and has received significant attention globally from investors, entrepreneurs, and policymakers in recent years. The global agritech market is expected to grow at a CAGR of 17.3 per cent from its estimated value of US$ 19,542.7 million in 2021 to US$ 46,372.5 million by 2030 (Spherical Insights, 2022). The increased investments in agricultural technology in the developing countries and the implementation of big data analytics have propelled the global agritech market forward. The global agritech industry is predicted to develop rapidly as a result of active government support for technical breakthroughs such as digital content creation, AI specialization, etc.

In the Indian context, agriculture continuous to remain the primary source of livelihood for nearly half of the country's population. With more than half a billion people engaged in the agriculture sector, it still faces numerous challenges, such as fragmented and inefficient supply chains and unorganized retail chains, post-harvest losses, poor access to credit, emerging climate change, increasing input cost, etc. However, with the rise of technological advancements, the Indian agriculture industry is witnessing a significant shift towards adoption and integration of innovative and modern agricultural technologies and this could lead to an increase in productivity, efficiency, and profitability. Growing at a CAGR of 50 per cent over the next five years, the Indian Agritech is expected to lead the next five years decade's technology-first value-creation opportunity, addressing a $34 billion market by 2027 (Avendus 2022).

In recent years, there has been an increasing focus on technologies that boost agritech to revolutionize agriculture (Rathod et al. 2020). The study based objects – Internet of Things (IoT) has brought tremendous benefits to the population and agriculture in India. Goh (2021) studied how Agritech was transforming traditional agriculture in the emerging markets in Indonesia. Farm advisory, Peer to Peer lending, traceability, Digital Market place, and Mechanization platforms are the major business models identified in the study area. Ganeshkumar and Khan (2021) have mapped Agritech companies in the Indian Agricultural Value Chain and 163 agritech companies have been listed according to their area of operation in this chain. The number of Agritech companies operating or serving the 'storage and trading' and 'distribution and retail' sectors has been found less compared to other actors of the value chain. The landscape of the agritech ecosystem for smallholder farmers in Latin America and the Caribbean has revealed Columbia to be a regional hub of digital agriculture innovation for smallholder farmers (Loukos and Arathoon 2021). While governments, research institutes, and NGOs were behind most of the first generation of digital advisory services, agritech companies are leading the latest generation of smart advisory services. The volume of investment in Agri-tech sector has grown exponentially over the past few years. The digital procurement tools are increasingly using satellites and drones to improve data collection. Using CrunchBase database, Florez et al. (2022) studied how French agritech start-ups contribute to the sustainability of food value chains.

While several studies have focused on the specific aspects of agritech companies in India, such as IoT and smart agriculture, and mapping of agritech companies in the agricultural value chain, there is a need for the holistic understanding of geographical, structural, and funding landscape of agritech companies in India. Some studies have looked at specific technologies, such as precision agriculture or mobile apps, but there is a lack of comprehensive research that provides an overview of the technological business models that are prevalent in the Indian context. Moreover, most of these studies have relied on the publicly available data, which is likely to be less comprehensive compared to the data obtained from a database like Crunchbase. Therefore, this study aims to bridge this research gap by providing valuable insights into the dynamics of agritech companies in India.

To fully comprehend the effect and potential of this industry, it is necessary to identify the type of companies and the trend in formation of new companies along with their geographical and funding landscape. Identification of technological and business models prevalent in Indian agritech firms is also significant to obtain insights into their potential for scalability and sustainability.

Materials and methods

The secondary data of 253 agritech companies in India till 2022 was collected from the CrunchBase database, which is considered as one of the most comprehensive databases of high-tech companies in the world. It has over 1,000,000 company profiles and has over 55 million users. An "Agritech" filter was first applied to the database to locate agritech companies worldwide; it provided an initial sample of around 3000 firms. Then, the 'Country filter' was applied to locate Agritech companies in India which reduced the number to 253 companies and the study is based on these companies.

Being an exploratory study on this evolving ecosystem, the study has confined to a broad delineation of the functions and interoperability mechanism without going deeper into the technological products and associated marketing strategies. The study has encompassed summary statistics, and tabular and graphical representation for understanding the geographical, structural, and funding landscape of

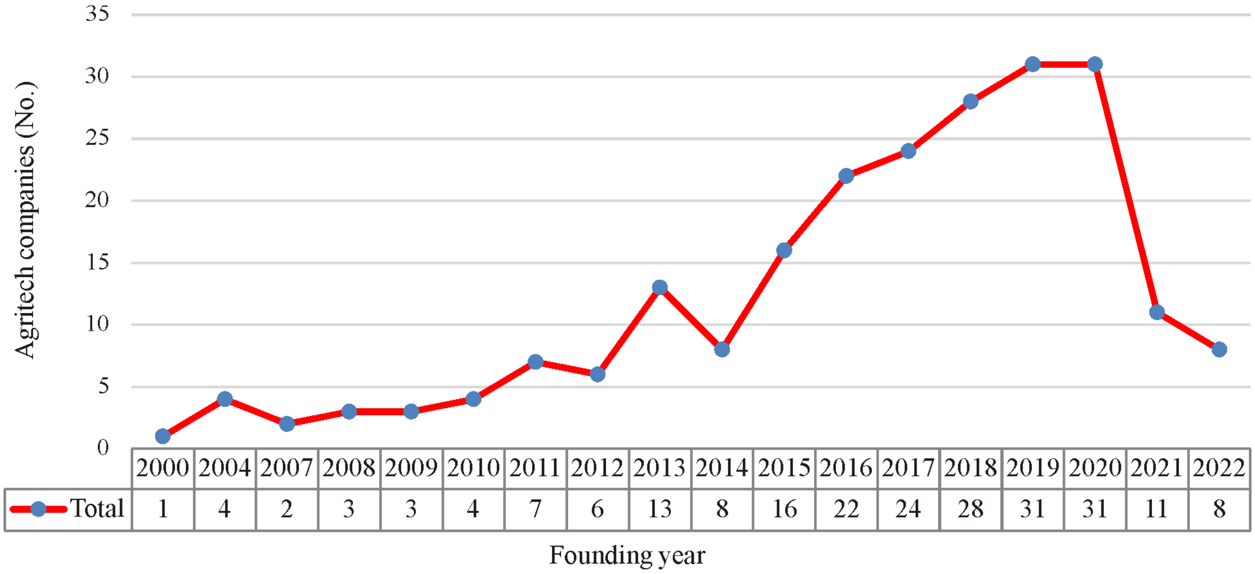


Figure 1 Trend in establishment of new Agritech companies in India: 2000-2022

Agritech firms in India. To identify the sector's major business models, inductive content analysis of the textual data was conducted. It involved systematic analysis and coding of data to identify the recurring themes, categories, and concepts. Then, inductive content analysis approach was adopted which provided a more flexible and exploratory analysis to capture the nuances and complexity of the data.

Result and discussion

The results have been presented in two parts: (i) geographical and funding landscape of agritech companies in India, and (ii) business models predominant in agritech companies of India.

Geographical and funding landscape of agritech companies in India

The trend in formation of new agritech companies in India has been shown in Figure 1. We have found a significant increase in the number of agritech companies in India during 2017 and 2020. In 2019 as well as 2020, 31 agritech companies were operating in India. This represents a growth rate of around 10 per cent. This could be due to several factors, including increased government support to agricultural technology, increased investments in the industry, and rising demand for sustainable and efficient agricultural technologies. After 2020, a decrease has been noted in the number of new agritech companies. The COVID-19 pandemic, as well as the associated lockdown measures, had a severe impact on the world economy, including India. The economic uncertainty and upheavals in different sectors might have discouraged the entrepreneurs from launching new agritech companies (Bhooshan et al. 2022).

The geographical distribution of agritech companies in India is depicted in Table 1. Karnataka has been found to be the leading state in agritech companies with a count of 51, followed by Maharashtra with a count of 49. The Agritech companies are more prevalent in Karnataka due to factors such as a well-developed tech sector, strong research culture, government support, and a thriving startup ecosystem. These factors have created a favourable environment for the emergence of agritech startups that are developing innovative solutions for the sector, making Karnataka a leading hub for innovation in agritech in India.

The trend in total funding of agritech companies in India from 2012 to 2022, shown in Figure 2, reveals a steady increase over the years. This rise in funding is a sign of investors' rising interest in the agritech market and their understanding of the potential of new technologies to transform agribusiness. The major investors in agritech are: Caspian Equity, Caspian Debt, Asha Impact, Ankur Capital, Omnivore, etc. The agritech sector has expanded as farmers and

Table 1 Geographical dispersion of Agritech companies in India

State	Number of companies
Andhra Pradesh	4
Assam	2
Bihar	6
Chandigarh	2
Chhattisgarh	3
Delhi	22
Gujarat	15
Haryana	21
Himachal Pradesh	1
Jharkhand	1
Karnataka	51
Kerala	4
Madhya Pradesh	5
Maharashtra	49
Meghalaya	1
Orissa	3
Rajasthan	8
Tamil Nadu	14
Telengana	18
Uttar Pradesh	18
Uttarakhand	1
West Bengal	3

agribusinesses look for innovative ways to boost productivity, reduce wastes, and enhance yields.

The Agritech enterprises may require capital at various phases of their development, based on their individual business strategy and growth ambitions. The following are the typical stages of funding in agritech sector

(i) Angel Funding — It is a method of financing in which individuals (known as angel investors) invest their personal assets in a startup or early-stage business in exchange for an equity share. The Angel investors contribute funding, coaching, and expertise to the startups and frequently invest at the early stage of development.

(ii) Convertible Notes — These are a type of debt financing in which investors lend money to a company with the option of eventually converting the debt into equity. The convertible notes are commonly utilized in early-stage investment rounds when the company's valuation is unknown.

(iii) Corporate Round Funding — It is a type of financing in which a large corporation invests in a startup or early-stage company. The corporate investors can contribute substantial financial resources, strategic advice, and access to industry experience and networks.

(iv) Debt Financing — It is a type of fundraising in which a company borrows money from investors or financial institutions and promises to repay the principal plus interest over a certain time period. The debt financing can provide a source of funding to a firm while allowing the founders to retain ownership and control of the company.

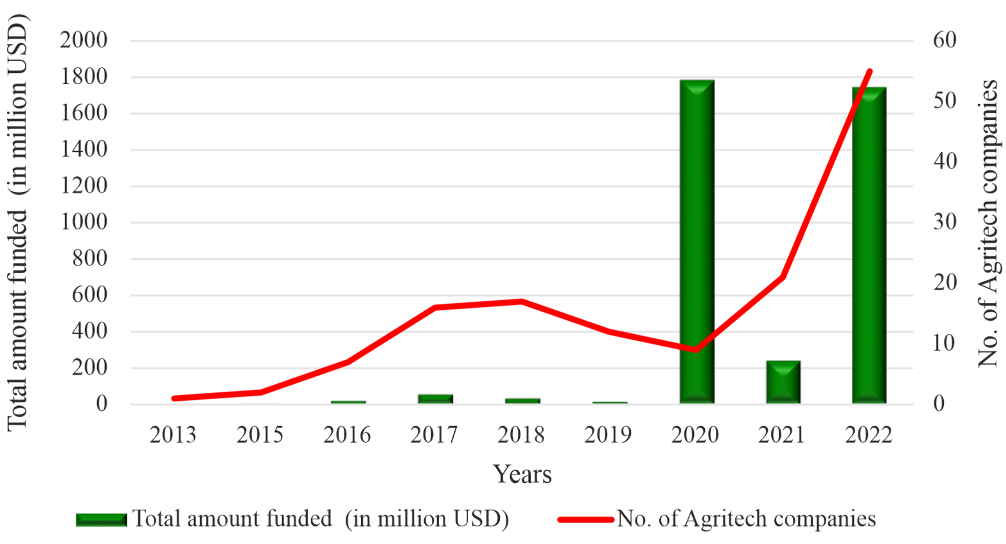


Figure 2 Trend in total funding of Agritech companies in India: 2013-2022

(v) Grant — It is a type of funding in which money is granted to a business or individual in order to support a certain project or activity. A grant, unlike a loan, does not have to be repaid, although it frequently comes with specified stipulations or restrictions.

(vi) Pre-Seed Funding — It is a type of early-stage funding that occurs before a company has significant traction or a minimum viable product (MVP). This sort of finance is typically provided by friends and family or angel investors to cover initial expenses, such as product development, market research, legal bills, etc.

(vii) Seed Funding — Seed funding is the first step of funding for a firm, and it is often used to fund product development or early-stage market research. The angel investors or early-stage venture capital firms usually provide the seed funding.

(viii) Series A — Once a company has developed its product and is ready to market it, it may require more financing to hire a marketing and sales team, build out the infrastructure, and develop additional features as well. Typically, venture capital firms provide this funding in the form of a Series A round.

(ix) Series B — After the company has gained some initial momentum and has an established market, it may require more funding to penetrate into the new markets or develop new products. Series B funding is often utilized for this purpose and is supplied by large venture capital companies.

(x) Series C and beyond — Once the company has achieved significant growth and has established a strong market position, it may require additional funding to continue its expansion or to make strategic acquisitions. Series C funding and subsequent rounds of funding are typically provided by large venture capital firms or private equity firms.

(xi) Post-IPO Equity — The Post-IPO equity is the ownership stake in a company that is offered to investors after the firm has gone public. This sort of equity can be purchased on public stock markets and gives investors a stake in the company's profits and growth prospects.

The aforementioned are the typical stages of agritech funding, but the actual stages and investment amounts may differ based on the particular firm and its needs. The availability of funds and market rivalry also influence the funding stages and amounts for investment.

The trend in total funding in agritech companies in India, across various company stages over the years is shown in Figure 3. It reveals that the series D funding was highest because of the requirement of Agritech sector to scale up operations and bring new products to the market. By Series D, the Agritech companies

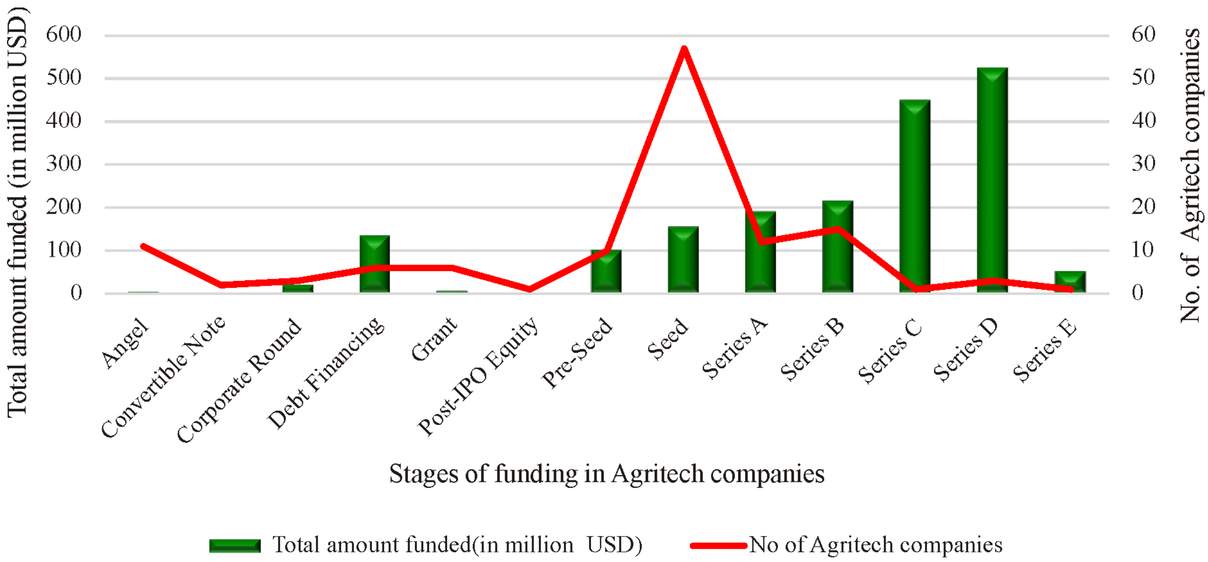


Figure 3 Trend in funding across various development stages in Agritech companies in India

often build a powerful market presence and validate their business strategy, making them more appealing to investors. Further, as the demand for sustainable and efficient agricultural technologies grows, agritech companies face increased competition and need larger funding to remain competitive in the market. The number of companies in seed-stage funding has been found highest in our analysis. The Agritech market in India is still in its early phases and according to NASSCOM (2021), 'the agritech entrepreneurial ecosystem in India is still evolving, with a majority of companies still in the early stages of development'. Many agritech firms in India are still developing and refining their business models and may require additional funding to bring their products to the market. Moreover, India's Agritech sector is highly fragmented, and because of this fragmentation, agritech companies toned more funding at the initial stage to grow their solutions and obtain a widespread adoption.

Technological and business models predominant in Agritech companies of India

To identify the prominent agritech business models in India, this study has employed inductive content analysis. For this a list of agritech companies was gathered from the CrunchBase database. The content of each business model provided by the database was categorized using an inductive method. Each statement was studied by one investigator, who then created a code for each statement based on the text's meaning and content. Every time a new business model text was coded after the previous one, the current codes were examined and revised, and new codes were added, as per need. The same investigator re-studied each document and coded it after all the business model texts had been coded to ensure consistency. Then, using one of the codes that the first investigator had filled in or a brand-new code they created, a second investigator independently classified each business model text. Any difference in the code given to the statements was discussed and resolved. Different sources of data such as CrunchBase database, company websites, press releases, industry reports, news articles, etc. were used to gather further information to confirm their classification as per the category codes.

The quantitative methods such as frequency counts were used to describe the distribution of the different types of Agritech business models in the sample. The major business models identified in the Indian context were: supply chain tech and output market linkage, farm management and analytics, agribiotech, finance and insurance, input market linkage, farm advisory platforms and consultancy services, allied sector services, and integrated services. The prominent Agritech business models identified in the Indian context and their functions are indicated in Table 2 and the number of companies distributed across each business model is depicted in Table 3, along with examples.

Table 2 Prominent Agritech business models identified in the Indian context and their functions

Sl.No	Agritech business model	Functions
1	Supply chain tech and output market linkage	Digital platform and physical infrastructure to handle post-harvest supply chain and connect farm output with the customers
2	Farm management and analytics	Use of geospatial or weather data, IOT, sensors, robotics, automation, etc. to improve productivity; farm management solutions for resource and field management, etc.
3	Agribiotech	Research on plant and animal life sciences and genomics
4	Finance and insurance	Tech-driven credit facilities for input procurement, equipment, etc. as well as for insurance or reinsurance of crops
5	Input market linkage	Digital marketplace and physical infrastructure to link farmers to inputs
6	Farm advisory platforms and consultancy services	Online platform for agronomic, pricing, market information, etc.
7	Allied sector services	Tech-enabled farm-to-fork services in the allied sector
8	Integrated services	Combination of one or more business models

Table 3 Number of companies with some examples across agritech business models identified in India

Major categories	No. of companies	Examples
Supply chain tech and output market linkage	96	Dehaat Waycool Ninacart
Farm management and analytics	71	Intello labs Cropin Fyllo
Agribiotech	3	Greenpod labs
Finance and insurance	12	Jai Kisan Unnati
Allied sector	10	Dhoodwala Aquaconnect
Farm advisory platforms and consultancy services	21	Krishify Farmbee
Input market linkage	18	Bighaat Gramaphone
Integrated services	22	Innoterra Napanta

Table 3 reveals that, in the Indian context, supply 'chain tech and output market linkage' category has the highest number of companies (96), followed by farm management and analytics category (71). The supply chain technology and output market linkage agritech business model has emerged as a popular business model in India due to several reasons. The agriculture industry in India is highly fragmented, with small and marginal farmers accounting for a substantial portion of the population. Due to the presence of middlemen, these farmers frequently encounter challenges in reaching markets and securing a fair price for their produce. The supply chain technology and output market connection linkage attempt to address these challenges by connecting farmers directly with purchasers and providing real-time market demand information for their products. As a result, it has become an appealing business model for the entrepreneurs and investors seeking to make a positive influence in the agriculture sector.

Figure 4 indicates the trend of funding across various business models in India. Over the past few years, **t**he Indian agritech sector has witnessed a surge in funding. Amongst investors, the supply chain technology and output market linkage, followed by farm management and analytics have emerged as the most popular business models. The main reason for this trend is the critical pain points that these business models address in the agricultural value chain. The supply chain technology solutions help the farmers connect with output markets, such as processors, exporters, and retailers, and create value for all stakeholders, while the farm management and analytics solutions enable the farmers in optimizing their operations and improving farm productivity. The funding landscape across business models also signifies the higher expected rate of return promised by the companies having a particular business model. The major investors

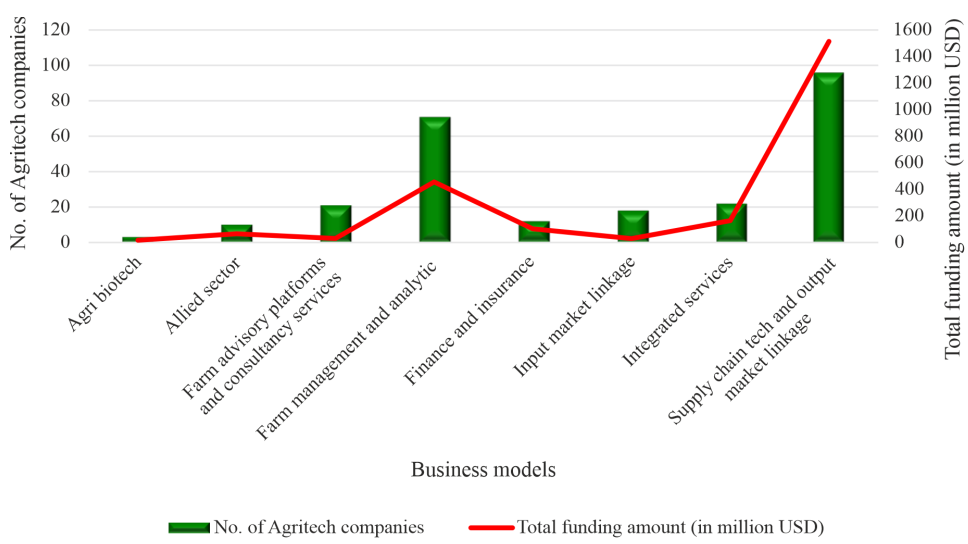


Figure 4 Trend in funding across various business models in India

present in this ecosystem are: Omnivore, Sequoia, Nexus, Ankur Capitals, Tiger Global, and Accel venture partners.

The favourable regulatory environment provided by Government of India is another element contributing to the adoption of these business structures. Several initiatives have been launched by the government to promote the use of technology in agriculture, and creating an environment conducive to the growth of agritech companies. Finally, given the size of India's agriculture sector and the need for technology-driven solutions to improve farm efficiency and productivity, the growth potential for these business models is significant. The domestic and international investors are eager to capitalize on this growth opportunity, which has resulted in an increase in funding for supply chain technology and output market linkage, followed by farm management and analytics business models.

The major technologies employed by the promising business models were also identified using inductive content analysis. The technologies being used by supply chain tech and output market linkage companies include Artificial Intelligence (AI), Internet of Things (IoT), Software as a Service (SAAS), and a combination of AI/IoT/SAAS. The farm management and analytics employs satellite and remote sensing, blockchain, Drones, AI, IoT, and SAAS.

The satellite and remote sensing technologies have transformed the agriculture by providing farmers essential data on crop health, soil moisture, and weather patterns, allowing for precise resource allocation as well as informed decision-making for optimal crop management. The blockchain allows for secure, immutable transaction records, certifications, and traceability, empowering the consumers to make better choices and encouraging fair trade practices in the sector. As a result, blockchain improves transparency and confidence in the agricultural supply chain. The artificial intelligence (AI) supports agriculture by utilizing machine learning algorithms to analyze massive information, enabling predictive analytics for crop disease diagnosis, yield forecasting, and intelligent decision-making based on real-time insights. The Internet of Things (IoT) connects agricultural sensors, equipment, and devices to enable real-time monitoring of soil health, animal health, and agri-equipment performance. This facilitates resource management, increases productivity, and promotes proactive decision-making. The Software as a service (SaaS) systems offer farmers user-friendly, cloud-based agricultural management software that promotes efficiency and production in farming by facilitating streamlined operations, data-driven decision-making, and improved cooperation regardless of technical proficiency.

Figures 5 and 6 depict the trend in funding across various technologies employed in supply chain tech output-market linkage and farm management and analytics companies, respectively. In the case of supply chain tech and output market linkage, SAAS-based technology receives a higher amount of funding and

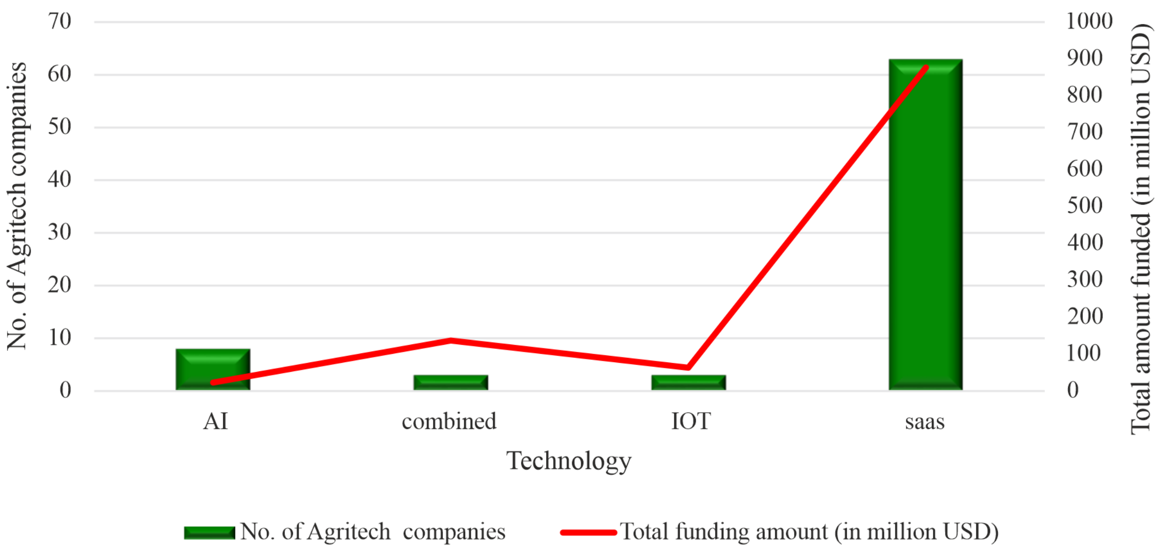


Figure 5 Trend in funding across various technologies employed in the supply chain tech and output market linkage

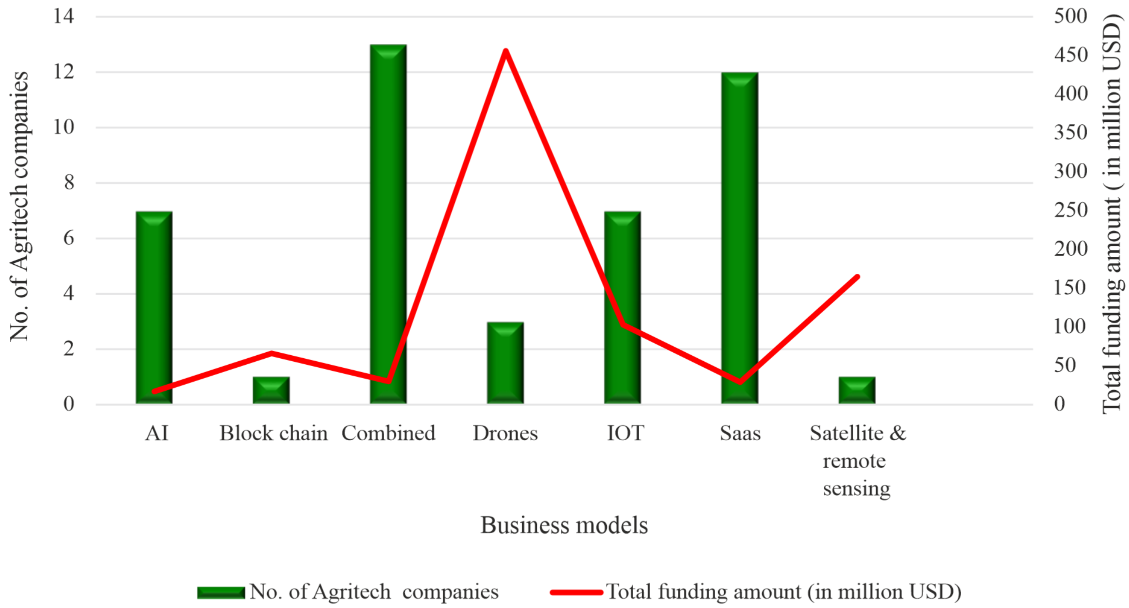


Figure 6 Trend in funding across various technologies employed in farm management and analytics companies

attract more companies compared to other technologies. In the case of farm management and analytics, the companies that employ AI receive a higher amount of funding and most of the companies use a combined version of all the available technologies.

Conclusions and policy implications

Agritech has been increasingly gaining attention in India in recent years. The study has found that the generation of companies were more during 2019 and 2020 in India. Across states Karnataka has been found to be the hotspot of agritech companies with a count of 51, followed by Maharashtra (49). The total funding has shown a surge over the years in India. The companies in Series D round have attracted a significant amount of funding, with a greater proportion of companies choosing for seed stage funding. In India, the Agritech sector has seen a boom in funding, with supply chain technology and output market linkages emerging as the most attractive business models among investors, followed by farm management and analytics. The government is encouraging innovation and entrepreneurship in the sector through a variety of measures. The Indian government's measures to promote the use of modern technologies in agriculture have produced a favourable atmosphere, which has accelerated the expansion of Agritech sector in the country.

Overall, the advent of agritech has potential to alter the agricultural sector by increasing efficiency, production, and sustainability. However, there are issues that must be addressed, such as the digital divide and the need for more localized and context-specific solutions. The future of agritech sector will be determined by how these difficulties are solved, as well as how the sector continues to innovate and evolve to satisfy the demands of farmers and the entire agricultural value chain. The governments might provide financial incentives, such as tax exemptions or subsidies, to encourage agritech companies to establish operations in the non-hot spot areas. The government can encourage venture capital firms to invest in companies in order to assist them progress from seed funding to later levels of funding. The governments should encourage public-private partnerships that foster connection between agritech firms and local farmers, cooperatives, and other stakeholders in order to create a more sustainable and equitable agricultural ecosystem.

Acknowledgment

This paper is emanated as a part of a seminar funded by ICAR-Indian Agricultural Research Institute, New Delhi. The authors thank the Zonal Technology Management and Business Promotion Development (ZTM-BPD) Unit for the help in data compilation.

References

Avendus. 2022. Agritech leading next decade's tech-first value creation. Avendus Capital Private Limited.avendus-agritech-leading-next-decades-tech-first-value-creation-img-639884363031b-.pdf

Bhooshan, Neeru, P C Ranjith, Amarjeet Singh, Diksha Sharma, and Anjani Kumar. 2022. Impact of covid 19 on Agri-startups in India. *International Research Journal of Humanities and interdisciplinary studies*. 3(1), 55-73. https://doi-ds.org/doilink/01.2022-67918817/IRJHIS2201006

FAO. 2009. *Global agriculture towards 2050.*High level expert forum, Food and Agriculture Organization, Rome. https://www.fao.org/fileadmin/templates/wsfs/docs/Issues_papers/HLEF2050_Global_Agriculture.pdf

Florez, Mauro, Isabelle Piot-Lepetit, Isabelle Bourdon, and Karine Gauche. 2022. How do French agri-tech start-ups contribute to the sustainability of food value chains?. *Journal of the International Council for Small Business*. 3(1), 79-93. https://doi.org/10.1080/26437015.2021.1989993

Ganeshkumar, C, and Abrar Khan. 2021. Mapping of Agritech Companies in Indian Agricultural Value Chain. In D. Goyal, A.K. Gupta, V. Piuri, M. Ganzha, & M. Paprzycki (Eds.), Lecture Notes in Networks and Systems. Proceedings of the Second International Conference on Information Management and Machine Intelligence. https://www.researchgate.net/profile/HimanshiBabbar2/publication/348684774_Software

Goh, Lesly. 2021. How Agritech is transforming traditional agriculture in emerging markets. In H. Kharas, J.W. Mcarthur & I. Ohno (Eds*), Breakthrough:The promise of frontier technologies for sustainable development.* Washington: The Brookings Institution. https://www.brookings.edu/wp-content/uploads/2021/12/Chapter-Seven_Breakthrough.pdf

Loukos, Panos, and Leslie Arathoon. 2021. Landscaping the agritech ecosystem for smallholder farmers in Latin America and the Caribbean. Inter American Development Bank, Felipe Herrera Library. https://publications.iadb.org/en/landscaping-agritech-ecosystem-smallholder-farmers-latin-america-and-caribbean

NASSCOM .2021. NASSCOM IDC Report - Technology Sector in India- Building Capabilities to Win in the New Normal. https://www.nasscom.in/knowledge-center/publications/nasscom-idc-report-technology-sector-india-building-capabilities-win

Rathod, Rita, Darasing R Rathod, Prashant R Shingote, Khushal Rathod, Shyam D Jadhav, Gajanan D Chandankar, Meghraj T Chavan, Sandip Gogate, Nitin W Raut, and Dilip T Dhule. 2020. Internet of things (iot) in indian agriculture: New opportunities and perspectives. *Current Updates In Life Sciences* 699-724 https://www.researchgate.net/publication 347736349_INTERNET_OF_THINGS_IoT_IN_INDIAN_AGRICUL TURE_NEW_OPPORTUNITIES_AND_PERSPECTIVES

Spherical insights. 2022. *Global Agritech Market Report.* Spherical Insights LLP. Rertieved from https://www.sphericalinsights.com/reports/agritech-market

Received 22 August 2023 Accepted 3 November 2023

Agricultural Economics Research Review 2023, 36 (2), 155-168
DOI: 10.5958/0974-0279.2023.00029.0

Livestock and transitional poverty in rural India

Shweta Bijla[1]*, P S Birthal[2], R Malhotra[3], A K Dixit[3], Gopal Sankhala[3], Pawan Singh[3] and Sanjit Maiti[3]

[1]ICAR- Directorate of Mushroom Research, Solan, Himachal Pradesh 173213, India
[2]ICAR- National Institute of Agricultural Economics and Policy Research, New Delhi 110012, India
[3]ICAR- National Dairy Research Institute, Karnal, Haryana 132001, India

*Corresponding author: shwetabijla2@gmail.com

Abstract With high economic growth, poverty in India has declined from 35 per cent in1993-94 to 22 per cent in 2011-2012, and further to 10 per cent in 2020-21. The majority of poor reside in the rural regions for whom agriculture is the main source of livelihood. The growth in agriculture has been identified more pro-poor than the growth in other economic sectors. The livestock is an important component of agriculture, and its contribution to agricultural gross domestic product has been growing faster than the overall agricultural growth. The reduction in rural poverty is driven by the growth in livestock. Nevertheless, the evidence on the relationship between livestock and poverty is scarce. Using a panel data on 28205 households, this paper assesses the impact of livestock on the rural poverty. The findings show that ownership of livestock, specifically bovine, significantly contributes to poverty reduction in rural India.

Keywords Livestock, herd size, bovine, ovine, poverty, India

JEL codes C20, Q01, Q19

Introduction

Over the past three decades, the head-count poverty rate in India has declined considerably, from 35 per cent in 1993-94 to 10 per cent in 2020-21 (Sinha Roy and Van Der Weide 2022). Nevertheless, as usual the incidence of poverty remains higher in the rural areas. About 11 per cent of the rural population lives in poverty as against 5.8 per cent of the urban population (Sinha Roy and Van Der Weide 2022). In rural areas, 80 per cent of the population depends on agriculture and allied activities for their livelihood. Agriculture, however, is a low-producing and faces several constraints in improving its productivity (Chand 2022). It is dominated by small landholders possessing landholding size of not exceeding one hectare (Department of Agriculture, Cooperation & Farmers' Welfare 2020). If the farming were the sole source of income, most of the smallholders would have remained stuck in poverty (Chand et al. 2011).

The rural people have diversified income sources, which include animal husbandry and fisheries. Compared to the cultivation of crops, these activities are more remunerative, provide a regular income stream, and also act as a cushion against climatic shocks; hence, comprise an important pathway out of poverty. Globally, about three-fourths of the poor people maintain livestock as part of their livelihood portfolios (FAO 2009). Hence, the income from livestock is likely to help them escape poverty (Holmann et al. 2005; Pica-Ciamarra et al. 2011).

The evidence from several developing countries has suggested livestock development as one of the important pathways for poverty reduction (Dolberg 2003; Maltsoglou and Taniguchi 2004; Kristjanson et al. 2004; Heffernan 2000). Kristjanson et al. (2006) have shown that in Kenya the probability of escaping poverty is 17-times higher for the households having quality herd, and 57 per cent households escaped poverty through this route.

A few studies have also analyzed the relationship between livestock income and poverty in India. Ojha (2007) from a causal analysis of dairy ownership and poverty transition in Uttar Pradesh identified dairying as the third major escape route from poverty. In Andhra Pradesh, Akter et al. (2008) found that 75 per cent of the households escaping poverty had livestock as an important component of their livelihood portfolio. Several authors (Birthal and Ali 2005; Birthal and Taneja 2012; Birthal 2022) have argued that because of more egalitarian distribution of livestock than the land, and the higher income elasticity of livestock products, a similar rate of growth, livestock has a more pronounced effect on poverty reduction than the crop income. Birthal and Negi (2012) have estimated that livestock income has a 1.4-times larger effect on poverty reduction than crop income.

Nevertheless, most of these studies have relied on either the cross-sectional small samples or lack a rigour in their analytical procedures for deriving inferences regarding the impact of livestock on poverty reduction. There are several factors other than households' livestock endowments that influence the poverty decline. This paper uses a large panel dataset on rural households to examine the impact of livestock on poverty, controlling for the effects of other covariates. The study addresses the following questions:

- Does ownership of livestock help reduce incidence of rural poverty?
- Is there a scale effect of livestock on poverty reduction?
- Do different animal species differentially impact poverty reduction?

Data

The data has been extracted from the nationally representative Indian Human Development Survey (IHDS) conducted in 2004-05 and 2011-12 jointly by the University of Maryland, USA, and the National Council of Applied Economic Research (NCAER), New Delhi, India. Both the rounds of IHDS covered a panel of 41,554 households in 971 urban locations and 1503 rural villages. Our dataset comprises a panel of 28,205 rural households.

The poverty status of a household was decided on the basis of monthly per capita consumption expenditure. The expenditure cut-off was considered as recommended by the Tendulkar Committee for knowing poverty status of the household (Planning Commission 2009). The household consumption expenditure in 2011-12 was deflated to make it comparable with their consumption expenditure in 2004-05. The IHDS also contains information on the livestock owned by a household by its type, viz. bovine and ovine.

Empirical framework

The dynamic nature of the data allows the study of the transitional poverty. Using the expenditure cut-off, as suggested by the Tendulkar Committee, the households were categorized into four dynamic groups: non-poor (NP), escaped poverty (EP), fallen into poverty (FP), and chronically poor (CP). The probability of a household falling into any of these groups has been estimated using a multinomial logit (MNL) framework (McFadden 1973). The response variable Y_j represents the distinctly unordered category of poverty dynamics as explained below:

NP (j=0): A household non-poor in 2004-05 as well as in 2011-12

EP (j=1): A household poor in 2004-05 but non-poor in 2011-12

FP (j=2): A household non-poor in 2004-05 but poor in 2011-12

CP (j=3): A household poor in 2004-05 as well as in 2011-12

The multinomial logit (MNL) is suited for such analysis as it allows estimation of the likelihood of a household being non-poor across more than one category of dynamic poverty (Wooldridge 2002; Deressa et al. 2009). By generalizing the bivariate model, the MNL can be expressed by Equation (1):

$$\Pr ob(Y_i = j) = \frac{e^{\alpha_j + \beta_j X_i}}{\sum_{j=1}^{3} e^{\alpha_j + \beta_j X_i}} \qquad \ldots(1)$$

where, Y_i is the dependent variable denoting the poverty dynamic category to which the household belongs. It takes a value of 1, 2, or 3 if a household has escaped poverty, fallen into poverty, or remained chronically poor, respectively. We considered the non-poor as the base category. X_i is a vector of explanatory variables, including the livestock ownership and socio-economic and institutional factors affecting the likelihood of a household falling into a particular dynamic poverty category. α_j and β_j are respectively the intercept and slope coefficients of the regressors (X_i).

Three poverty regressions were estimated: (i) ownership of any livestock species, (ii) the total number of livestock units (in cattle equivalent)[1] owned, and (iii) the number of bovine or ovine owned.

The land size is an important factor influencing the poverty status. In our regressions, it was included as operational size of landholding (in acres), and proportion of irrigated area.

Explanatory variables

Caste — In India, there are four broad caste groups: general castes , scheduled castes (SC), scheduled tribes (ST), and other backward castes (OBC). General caste is at the top of social hierarchy, and SC and ST are at the bottom. The general castes are considered economically most well-off, and the SC/ST the least. In our analysis, we treated the general castes as the base category.

Education — Education, as a proxy of human capital, is considered an important pathway to poverty alleviation. We considered education level of household-heads and categorized them into five groups: primary, secondary, higher secondary, and graduate and above, and illiterate. Illiterate served as a base category in our model.

Occupation — Occupation plays an important role in determining the economic status and therefore the poverty status of households. There were four main occupations, viz. agriculture including allied activities, labour, salary, and business, in which the households are engaged. Agriculture and allied activities served as a base category in our model.

Household members — It is hypothesized that the more the number of dependents, the greater is the likelihood of a household to be poor. Hence, we included dependency ratio in the set of explanatory variables.

Other variables — These were the household's access to institutional credit represented by the bank account, and membership of any cooperative society or self-help group.

The results have been interpreted as the relative risk ratio (RRR), that is the probability of a household falling in a dynamic poverty category relative to the base category. It was estimated as the exponential of the regression coefficient. An RRR > 1 for a variable implies that the probability of a household falling in a particular dynamic poverty group increases with an increase in that variable.

We tested for the assumption of Independence of Irrelevant Alternatives (IIA) (Dow and Endersby 2004; Mokhtarian and Bagley 2000; Pels et al. 2001), that is the probability of a household being in a specific poverty category remains unaffected by other categories. For this, the Small-Hsiao (SH) test has been performed following Small and Hsiao (1985) (Eq. 2):

$$SH = -2\,[L_r(\beta_{AB}) - L_r(\beta_B)] \qquad \ldots(2)$$

The SH is an asymptotically distributed chi-square with *k* degrees of freedom, where *k* is the number of parameters in the restricted choice set.

Average marginal effects (AME)

Unlike several other estimation approaches (i.e., discriminant analysis and propensity score matching), multinomial model allows estimating marginal effects, that is, magnitude of the change in the probability (Rencher 2002). Thus, to draw valid inferences regarding the direction and magnitude of the relationship between the dependent and independent variables, it is imperative to compute the marginal effects (Bowen and Wiersema 2004). Here, we calculated the change in probability (P_{ij}) of falling in the non-poor category due to the change in the livestock ownership (x_{ik}).

$$\text{Partial derivative of } \pi_{ij} = \frac{\partial P_{ij}}{\partial x_{ik}} \qquad \ldots(3)$$

where, $x_{ik}=1$ if the i^{th} household owns any livestock, 0 otherwise

Predictive probability of being non-poor due to increase in herd size

The predictive probabilities show how much the dependent variable shifts when the independent

[1]Different livestock species were converted into cattle-equivalent units following Sirohi et al. (2019).

variable is changes by a specific amount holding other covariates at their means. We calculated the change in probability of being non-poor (p_{ij}) due change in the number of livestock; bovine or ovine.

$$p_{ij} = \Pr(Y_i = j \mid x_i) = \frac{\exp(x_i'\beta_j)}{\sum_{j=0}^{3} \exp(x_i'\beta_j)} \qquad \ldots(4)$$

where, p_{ij} is the probability of being non-poor (p_{ij}) due change in the number of livestock; bovine or ovine, y_i is the poverty status, x_i is the number of livestock (bovine and ovine), β_j is the coefficient of vector x_i, i is the number of observations, and j is the number of poverty status categories (0 to 3).

Results and discussion

Our results have showed a decline in rural poverty from 24 per cent in 2004-05 to 20 per cent in 2011-12. During this period, 64 per cent households escaped poverty and 16 per cent fell into poverty. Our main interest was in knowing the role of livestock in poverty transition and therefore we categorized households based on their livestock ownership in 2004-05 and 2011-12 as:

NN: Non-owners of livestock in 2004-05 as well as in 2011-12

YN: Owners of livestock in 2004-05 but non-owners in 2011-12

Table 1 Frequency distribution of households by livestock ownership in 2004-05 and 2011-12

Livestock ownership	Frequency	Per cent household (%)
NN	9855	34.94
YN	4767	16.90
NY	3782	13.41
YY	9801	34.75
Total	28205	100.00

NY: Non-owners livestock in 2004-05 but owners in 2011-12

YY: Owners of livestock in 2004-05 as well as in 2011-12

The distribution of households is shown in Table 1 About 35 per cent households did not own livestock in any of the years (NN). On the other hand, approximately an equal number of households owned livestock in both the years (YY). About 17 per cent of households exited animal husbandry but 13 per cent entered into it. Thus, at any point of time about half of the rural households were engaged in animal husbandry.

Figure 1 shows the association between transient poverty and livestock ownership of households. The households who owned livestock in 2004-05 and 2011-12 depicted the least incidence of chronic poverty and

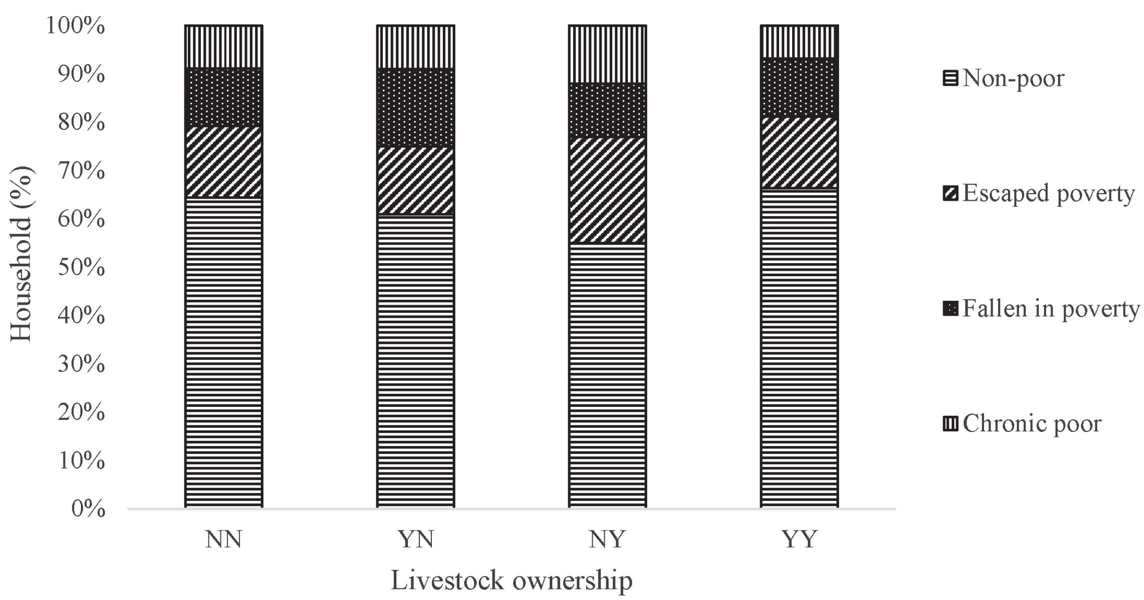


Figure 1 Poverty across livestock ownership groups

the highest incidence was in the non-owning households. This indicates that there is a negative association between the poverty and livestock ownership of a household.

Among the households who entered into animal husbandry after 2004-05, about 22 per cent could escape poverty, but 11 per cent had fallen into it and 12 per cent remained poor. However, the proportion of those who fell into poverty is higher among those who exited animal husbandry after 2004-05. On the other hand, of those households who did not own livestock at any point of time, 9 per cent remained poor, 12 per cent fell into poverty and 15 per cent escaped poverty. These findings give a preliminary indication of the poverty-reducing effect of livestock ownership.

Nevertheless, there are several other factors that influence poverty dynamics. For example, the proportion of non-poor is also equally high among those that did not own livestock in any of the years.

Econometric results

The study examined the effect in terms of livestock ownership, herd size and herd composition on the likelihood of household being consistently non-poor as against being poor in either of the IHDS rounds and being chronic poor, i.e. poor on both the rounds.

Effect of livestock ownership on rural poverty: Ownership

The assumption of IIA was checked using Small-Hsiao test and the results are presented in Table A1 (Appendices). It shows that p-values for all the poverty categories are insignificant, signifying that odds are independent of other alternatives, and hence, the assumption holds. The results of the MNL model are presented in Table 2, where results have been given in terms of relative risk ratios (RRRs) of the associated context predictors i.e. livestock ownership in our case, while controlling for other factors.

Escaping poverty

The risk of being poor is 0.766-times less for livestock owning households, that is livestock ownership is much likely to be consistently non-poor. Similar results have been reported in Andhra Pradesh, wherein 75 per cent of the households escaped poverty through livestock route (Akter et al. 2008). In terms of landholding, an increase of one acre in owned land increases the chances of remaining non-poor by 0.915-times. This is in reference with the finding from Zambia where increase in land size increased the odds of being consistently non-poor by 74 per cent (Chapoto et al. 2011). The irrigated area also mitigates poverty risk to some extent. A 1 per cent increase in the proportion of irrigated area increases the chances of remaining non-poor by a factor of 0.996.

Various controls such as social factors, human capital, access to banks, etc. were also included in the model. In terms of social dimension, OBC, SC, and ST households have depicted a higher risk of being poor in 2004-05 as compared to being non-poor in both the IHDS rounds than general caste houses. Further, the risk of being poor in the initial IHDS round (2004-05) was observed more for households with illiterate heads. In terms of major occupation, the results suggested that households with labour as main occupation have more chances of being poor while salaried and business households have lesser risk of being poor as compared to the farming households, showing the mitigating effect of regular income in the household. The higher the number of earning members in a household, lower is the risk of it being poor. The results also showed that as the number of non-earning fellows in the household increased, the households depicted 1.360-times more risk of being poor in the initial round. Similar findings have been reported by Thorat et al. (2017). Lastly, a better access to finance brings stability to the households. Consistent with our results, households with a bank account have shown nearly 0.782-times lesser risk of being poor. Likewise, households having membership in some credit and saving societies, have revealed 0.938-times lesser risk of being poor.

Falling into poverty

The chances of falling into poverty have been found 0.996-times lesser for livestock-owning households, but these are not significant, showing livestock ownership does not prevent households from falling into poverty. Though, with increase in land area by one acre, chances of falling into poverty decreased significantly by a factor of 0.974 and they are more likely to remain non-poor. The risk of falling into poverty was found less for the general category households. The illiterate and labour households have

Table 2 Effect of livestock ownership on poverty dynamics of households

Variables (Base category: Non-poor)	Relative risk ratio (RRR) (S.E.)		
	Escaped poverty	Fallen in poverty	Chronic poor
Own any livestock (yes)	0.766*** (0.032)	0.996(0.044)	0.642***(0.035)
Area owned (in acres)	0.915***(0.006)	0.974***(0.005)	0.893***(0.010)
Per cent irrigated area	0.996***(0.001)	0.997***(0.001)	0.994***(0.001)
Social groups (Base: General caste)			
Other Backward Classes	1.293***(0.065)	1.312***(0.070)	1.637***(0.126)
Scheduled Castes	1.503***(0.082)	1.882***(0.106)	2.249***(0.178)
Scheduled Tribes	3.156***(0.213)	2.380***(0.180)	9.026***(0.775)
Household-head's education status (Base: Illiterate)			
Primary	0.988(0.052)	0.929(0.053)	0.913(0.060)
Secondary	0.731***(0.034)	0.724***(0.036)	0.519***(0.032)
Higher secondary	0.572***(0.045)	0.677***(0.055)	0.412***(0.047)
Graduates	0.337***(0.036)	0.494***(0.047)	0.173***(0.032)
Main occupation (Base: Agriculture & allied sectors)			
Labour	1.278***(0.064)	1.208**(0.065)	1.206**(0.080)
Salaried class	0.345***(0.031)	0.430***(0.038)	0.256***(0.035)
Others	0.665***(0.044)	0.779***(0.053)	0.543***(0.051)
Number of dependent members	1.360***(0.012)	1.059***(0.011)	1.424***(0.016)
Access to bank account (yes)	0.782***(0.050)	0.761***(0.053)	0.602***(0.059)
Membership of a cooperative society	0.938*(0.027)	0.900***(0.027)	0.912*(0.038)
Region (Base: Northern)			
Hilly region	0.586**(0.072)	1.236*(0.120)	1.224(0.173)
Central region	4.606***(0.301)	1.510***(0.123)	6.327**(0.540)
Eastern region	2.418***(0.146)	2.164***(0.140)	2.705***(0.221)
Northeast region	1.307*(0.142)	1.497***(0.163)	0.790(0.124)
Western region	1.311***(0.083)	1.490***(0.097)	1.230*(0.110)
Southern region	0.756***(0.052)	0.775***(0.056)	0.426***(0.046)
Constant	0.080***(0.007)	0.126***(0.011)	0.034***(0.004)
Model adequacy			
Number of observations (n)		28205	
LR statistics (chi square)		7910.53***	
log likelihood		-24432.88	
Pseudo R square		0.14	

Notes *** p< 0.001, ** p<0.01, * p<0.05 denote level of significance
Figures within the parentheses are respective standard errors (S.E.).

shown more chances of falling into poverty when compared to the salaried and business households. Also, households with more earning hands have depicted a lesser risk of falling into poverty. The households having access to banking facilities have revealed a significantly lesser risk of falling into poverty. So was in the case of households having membership of cooperative credit societies.

Chronic poverty

The risk of remaining chronic poor has been found less by a factor of 0.642 for the livestock-owning households. Thus, livestock-ownership increased the chances of remaining non-poor (Bijla 2018). Further, an increase in land area by one acre lessened the risk of being chronic poor by 0.893-times. Similar findings were reported by Haddad and Ahmed (2003), Chapoto et al. (2011) and Dartanto and Nurkholis (2013). In Indonesia, Chapoto et al. (2011) found that an increase in land size by one hectare improved the odds of being non-poor by around 1.7 per cent. The education improved the likelihood of remaining non-poor. It confirms the previous studies on poverty dynamics reported in the literature (Widyanti et al. 2009; Dartanto and Nurkholis 2013). Further, the labour households have shown more risk of remaining chronic poor, while salaried and business households have revealed significantly lower chances of remaining chronic poor. This is in agreement with the findings that agricultural and wage-earning households have a greater probability of remaining poor (Okidi and Kempaka 2002; Kedir and McKay 2005; Dartanto and Nurkholis 2013). The households with lesser income earning members have 1.424-times more risk of being chronic poor. Access to finance could reduce the risk of remaining chronic poor by 0.602-times.

Average marginal effects of bovine ownership on poverty dynamics

Only directional influence is given by the parameter estimates of the multinomial logit regression. Thus, to get the actual magnitude of change in the probability, we estimated the Average Marginal Effects (AME) from the regression coefficients, which gives the expected change in probability of a particular choice being made due to unit change in the dependent variable i.e. livestock ownership. Table 3 shows the expected changes in probabilities.

Keeping all other variables constant at their mean values, the probability of remaining non-poor has been found higher by 0.04 per cent for bovine owners than non-owners. Also, they have depicted lesser probability of being chronic poor by 0.02 per cent than non-owners of bovine.

Effect of livestock on rural poverty: Total livestock units (TLU)

After estimating the effect of livestock ownership, it was important to know how the size of herd impacts poverty transitions (Table 4). Here, we converted all types of livestock into Standard Animal Units (SAU) following Sirohi et al. (2019).

Effect of livestock on rural poverty: Herd size

Here, herd size was taken in the set of explanatory variables as livestock variable. In order to check the independence of irrelevant attributes (IIA) assumption, results of the Small Hsiao (1985) test have been shown in Table A2 (Appendices). The results of the MNL model are presented in Table 4.

Escaping poverty

It has been found that an increase of one unit increase in livestock-herd size increased the chance of remaining non-poor by 0.935-times. Similarly, an increase in land size by one acre enhanced the chances of remaining consistently non-poor by a factor of 0.922.

Other controls portrayed more or less similar effects as have been discussed earlier.

Falling into poverty

The study has found that one unit increase in herd size

Table 3 Average marginal effect (AME) of livestock ownership on poverty status

Poverty status	Bovine ownership	AME (S.E.)	Z value	Confidence interval	
Non-Poor	Non-owner	0.640*** (0.004)	162.280	0.632	0.648
	Owner	0.676*** (0.004)	185.300	0.668	0.683
Chronic Poor	Non-owner	0.094*** (0.003)	37.680	0.089	0.099
	Owner	0.071*** (0.002)	34.850	0.067	0.075

Notes *** p< 0.001, ** p<0.01, * p<0.05 level of significance. Figures within the parentheses are respective standard errors (S.E.).

Table 4 Effect of total livestock units on poverty dynamics of households

Variables (Base: Non-poor)	RRR (S.E.)		
	Escaped poverty	Fallen in poverty	Chronic poor
Total livestock units	0.935*** (0.009)	0.991(0.008)	0.903*** (0.014)
Area owned (in acres)	0.922*** (0.006)	0.976***(0.005)	0.902***(0.010)
Per cent irrigated area	0.996*** (0.001)	0.997*** (0.001)	0.994*** (0.001)
Social groups (Base: General caste)			
Other Backward Classes	1.304*** (0.065)	1.316*** (0.070)	1.650*** (0.127)
Scheduled Castes	1.506*** (0.082)	1.881*** (0.106)	2.248*** (0.177)
Scheduled Tribes	3.229*** (0.218)	2.391*** (0.181)	9.238*** (0.794)
Household head's education level (Base: Illiterate)			
Primary	0.984(0.052)	0.928 (0.053)	0.909 (0.060)
Secondary	0.727*** (0.033)	0.723*** (0.036)	0.515*** (0.032)
Higher secondary	0.581*** (0.046)	0.679*** (0.055)	0.420*** (0.048)
Graduates	0.338*** (0.036)	-0.493*** (0.047)	0.174*** (0.033)
Main occupation (Base: Agriculture & allied sectors)			
Labour	1.307*** (0.066)	1.204*** (0.064)	1.247** (0.082)
Salaried class	0.351*** (0.032)	0.428*** (0.038)	0.264*** (0.036)
Others	0.683*** (0.045)	0.776*** (0.052)	0.567*** (0.053)
Number of dependent members	1.369*** (0.012)	1.062*** (0.011)	1.431*** (0.017)
Access to bank account	0.771*** (0.049)	0.761*** (0.053)	0.589*** (0.058)
Membership of a cooperative society	0.937* (0.027)	0.901** (0.027)	0.910* (0.038)
Region (Base: Northern region)			
Hilly region	0.592*** (0.073)	1.251* (0.121)	1.221 (0.173)
Central region	4.604*** (0.301)	1.508*** (0.123)	6.340*** (0.541)
Eastern region	2.412*** (0.146)	2.156*** (0.140)	2.701*** (0.221)
Northeast region	1.359** (0.147)	1.488*** (0.161)	0.851 (0.133)
Western region	1.320*** (0.084)	1.489*** (0.097)	1.240* (0.111)
Southern region	0.790** (0.054)	0.773*** (0.055)	0.459*** (0.050)
Constant	0.072*** (0.006)	0.126*** (0.011)	0.029*** (0.003)
Model adequacy			
Number of observations (n)		28205	
LR statistics (chi square)		7921.25***	
log likelihood		-24427.53	
Pseudo R square		0.14	

Notes *** p< 0.001, ** p<0.01, * p<0.05 level of significance. Figures within the parentheses are respective standard error (S.E.).

decreased the risk of falling into poverty by about 0.991-times, but the effect is not significant. Similarly, an increase in land size by one acre reduced the chances of falling into poverty by 0.976-times significantly.

The effects of other control variables were observed directionally similar as have presented in the falling into poverty.

Table 5 Predictive probabilities of being in non-poor group in both IHDS rounds (TLU)

Total livestock units (No.)	Marginal effects	Standard error	Z value
0	0.647***	0.003	218.430
1	0.656***	0.003	258.120
2	0.666***	0.003	251.480
3	0.674***	0.003	211.870
4	0.683***	0.004	172.870
5	0.691***	0.005	143.490
6	0.699***	0.006	122.250
7	0.707***	0.007	106.650
8	0.715***	0.008	94.860
9	0.722***	0.008	85.710
10	0.729***	0.009	78.420

Notes *** $p< 0.001$, ** $p<0.01$, * $p<0.05$ level of significance.

Chronic poverty

It has been found that with one unit increase in herd size, the odds of being chronic poor decreased significantly by 0.902-times. Other controls have more or less same directional effects as given in chronic poverty sub-head earlier.

Predictive probabilities of herd size on poverty dynamics

For a continuous variable, i.e. herd size, predictive probabilities are calculated. It shows the extent to which a household's probability of being non-poor changes when the herd size is varied by a specific amount, while keeping all the other variables constant at their means. The study has found a significant increase in the probability of a household being non-poor with an increase in herd size (Table 5). At a herd size of 10, the probability of household being non-poor has been found to increase from 65 per cent to 73 per cent.

Herd composition and poverty

Different livestock species have different effect on household's poverty status. In this section, we have examined the effects of livestock composition in terms of bovine and ovine on household's poverty dynamics (Table 6).

Effect of livestock on rural poverty: Herd composition

A significant likelihood ratio test statistic indicated a strong explanatory power of the independent variables. An insignificant p values from Small-Hsiao test for all the poverty classes indicated that IIA assumption holds and the multinomial logit specification is apt for determining the impact of herd composition (Table A3 Appendix). The results of the MNL model are presented in Table 6.

Escaping poverty — With an increase of one unit in bovine number, the probability of being poor significantly decreased by 0.821-times. The effect of ovine on poverty escape rate, however, has been found insignificant.

Falling into poverty — With one unit increase in bovine number, the household's risk of falling into poverty decreased by 0.941-times, and the likelihood of its remaining non-poor increased. On the other hand, the households' risk of falling into poverty increased significantly with one unit increase in the number of ovines with the households.

Chronic poverty — The bovines have the tendency to prevent the households from being chronic poor. With one unit increase in the number of bovines in a household, the risk of its being chronic poor decreased by a factor of 0.738. This is in accord with the previous findings in rural Zambia where the number of cattle increased the household's odds of being consistently non-poor considerably by 9.4 per cent (Chapoto et al. 2011). The effects of other control variables have been directionally similar to those presented in different sub-heads earlier.

Predictive probabilities of bovine and ovine numbers on poverty dynamic status

By keeping other explanatory variables constant at their mean level, predictive probabilities have been computed for the number of bovine and ovine animals (Table 7). In the case of bovines, a noteworthy increase has been observed in the household's probability of being non-poor with an increase in the number of bovines, i.e.as the number of bovines is increased from 1 to 10, the probability of remaining non-poor reverberates and increases from 67 per cent to 85 per cent, giving a marginal upsurge of 0.02 to 0.03 per

Table 6 Effect of livestock numbers (disaggregated) on poverty dynamics of households

Variables (Base: Non-poor)	RRR (S.E.) Escaped poverty	Fallen in poverty	Chronic poor
Number of bovine	0.821*** (0.016)	0.941***(0.016)	0.738*** (0.021)
Number of ovine	1.009(0.005)	1.013** (0.005)	1.008(0.007)
Area owned (in acres)	0.929*** (0.006)	0.977** (0.005)	0.911*** (0.010)
Percent irrigated area	0.996*** (0.001)	0.998*** (0.001)	0.994*** (0.001)
Social group (Base: General caste)			
Other Backward Classes	1.320*** (0.066)	1.318*** (0.070)	1.695*** (0.131)
Scheduled Caste	1.494*** (0.082)	1.869*** (0.105)	2.227*** (0.176)
Scheduled Tribe	3.170*** (0.215)	2.370*** (0.179)	9.042*** (0.780)
Household head's education status (Base: Illiterate)			
Primary	0.990 (0.052)	0.923 (0.054)	0.918(0.060)
Secondary	0.742*** (0.034)	0.732*** (0.036)	0.528*** (0.033)
Higher secondary	0.599*** (0.048)	0.690*** (0.056)	0.434*** (0.050)
Graduates	0.348*** (0.037)	0.502*** (0.048)	0.181*** (0.034)
Main occupation (Base: Agriculture & allied sectors)			
Labour	1.261*** (0.064)	1.180** (0.063)	1.191** (0.079)
Salaried class	0.341*** (0.031)	0.422*** (0.038)	0.254*** (0.034)
Others	0.654*** (0.043)	0.759*** (0.051)	0.537*** (0.051)
Number of dependent members	1.375*** (0.012)	1.065*** (0.011)	1.441*** (0.017)
Have bank account (yes)	0.783*** (0.050)	0.766*** (0.053)	0.598*** (0.059)
Membership of cooperative societies	0.940* (0.027)	0.903** (0.027)	0.912* (0.038)
Region (Base: Northern)			
Hilly region	0.597*** (0.074)	1.256* (0.122)	1.254 (0.178)
Central region	4.559*** (0.299)	1.511*** (0.123)	6.179*** (0.529)
Eastern region	2.294*** (0.140)	2.100*** (0.137)	2.516*** (0.207)
Northeast region	1.283* (0.139)	1.450** (0.158)	0.784 (0.123)
Western region	1.249** (0.080)	1.451*** (0.095)	1.152 (0.104)
Southern region	0.747*** (0.052)	0.756*** (0.054)	0.422*** (0.046)
Constant	0.077*** (0.006)	0.130*** (0.011)	0.031*** (0.004)
Model adequacy			
Number of observations (n)		28205	
LR statistics (chi square)		8062.02***	
log likelihood		-24357.15	
Pseudo R square		0.14	

Notes *** p< 0.001, ** p<0.01, * p<0.05 level of significance. Figures within the parentheses are respective standard errors (S.E.).

cent with every unit increase. This is in confirmation with the findings of Chapoto et al. (2011) wherein a marginal increase in the number of cattle increased the probability of household being consistently non-poor by 0.07 per cent. On the other hand, as the number of ovines was raised from 5 to 50, the probability of being non-poor decreased from 65 per cent to 56 per cent.

Table 7 Predictive probabilities of being in non-poor group in both IHDS rounds with respect to bovine and ovine numbers

No.	Marginal effects	Standard errors	Z value
	Bovine		
0	0.635***	0.003	199.160
1	0.665***	0.003	258.090
2	0.693***	0.004	188.150
3	0.719***	0.005	135.160
4	0.743***	0.007	106.750
5	0.765***	0.008	90.150
6	0.786***	0.010	79.560
7	0.804***	0.011	72.340
8	0.821***	0.012	67.180
9	0.836***	0.013	63.370
10	0.850***	0.014	60.480
	Ovine		
0	0.660***	0.003	258.580
5	0.661***	0.004	168.920
10	0.642***	0.007	92.950
15	0.632***	0.010	61.300
20	0.623***	0.014	44.900
25	0.613***	0.018	35.000
30	0.603***	0.021	28.410
35	0.593***	0.025	23.730
40	0.583***	0.029	20.240
45	0.573***	0.033	17.540
50	0.562***	0.037	15.400

Notes *** p< 0.001, ** p<0.01, * p<0.05 level of significance

Conclusions

The study concludes that poverty is a dynamic phenomenon and livestock, particularly bovine ownership and herd size play a significant role in alleviating rural poverty. On the other hand, small ruminants are owned by the extremely poor households for sustenance. The Indian population is mostly vegetarian with dairy products being major components in their daily diet. Hence, dairy sector is well-organized with demand-driven growth. Large investments in the livestock sector, particularly in the bovines and dairy sector are much needed for preventing the rural households from chronic poverty and becoming transient poor.

References

Akter, S, J Farrington, P Deshingkar, and A Freeman. 2008. Livestock, vulnerability, and poverty dynamics in India. Findings from the ODI livelihood options project panel survey. Discussion Paper No 10. Targeting and Innovation. International Livestock Research Institute, Nairobi, Kenya, 43. https://core.ac.uk/download/pdf / 132631045.pdf

Bijla, S. 2018. Dynamic poverty processes in rural India and the role of livestock. *Agricultural Economics Research Review* 31(26): 9-16. http://doi.org/10.5958/0974-0279.2018.00017.4

Birthal, P S. 2022. Livestock, agricultural growth and poverty alleviation. Department of Economic Analysis and Research National Bank for Agriculture and Rural Development. NABARD Research and Policy Series No. 7/2022. ISBN No. ISBN 978-93-5602-931-6. https://www.nabard.org/auth/writereaddata/ tender/1310223010paper-7-livestck-dr-birthal.pdf

Birthal, P S and J Ali. 2005. Potential of livestock sector in rural transformation. In *Rural transformation in India: The role of non-farm sector* eds R Nayyar and A N Sharma, 377-392. Institute of Human Development Publication. https://api.semanticscholar.org/CorpusID:152579202

Birthal, P S and D Negi. 2012. Livestock for higher, sustainable and inclusive Agricultural Growth. *Economic and Political Weekly 47*(26/27): 89-99. http://www.jstor.org/stable/23251727

Birthal, P S and V K Taneja. 2012. Operationalizing the pro-poor potential of livestock: Issues and strategies. *Indian Journal of Animal Sciences 82*(5): 441-447. https://epubs.icar.org.in/ejournal/index.php/IJAnS/article/view/17669/8513

Bowen, H P and M F Wiersema. 2004. Modeling limited dependent variables: Guidelines for researchers of strategic management. In *Research Methodology in Strategy and Management*, eds D J Ketchen and D Bergh, , *1*, 87-134, Oxford, UK: JAI/Elsevier Press. https://doi.org/10.1016/S1479-8387(04)01104-X

Chand, R. 2022. Agricultural challenges and policies for the 21st century. *NABARD Research and Policy Series No*, *6*. https://www.nabard.org/auth/writereaddata/tender/1507223654Paper-6-Agri-Challenges-and-Policies-Dr.Chand.pdf

Chand, R, P A L Prasanna, and A Singh. 2011. Farm size and productivity: understanding the strengths of smallholders and their livelihoods. *Economic & Political Weekly 54*(26/27): 5-11. https://

www.semanticscholar.org/paper/Farm-Size-and-Productivity%3A-Understanding-the-of-Chand Prasanna/3fd702f6ff3aacd0439311858ae127a681f44314

Chapoto, A, D J Banda, S Haggblade, and P Hamukwala. 2011. Factors affecting poverty dynamics in rural Zambia. Working Paper. 10.22004/ag.econ.109888 (No. 1093-2016-87810).

Dartanto, T and Nurkholis. 2013. The determinants of poverty dynamics in Indonesia: evidence from panel data. *Bulletin of Indonesian Economic Studies 49*(1): 61-84. https://doi.org/10.1080/00074918.2013.772939

Deressa, T T, R M Hassan, C Ringler, T Alemu, and M Yesuf. 2009. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change 19*(2): 248-255. https://doi.org/10.1016/j.gloenvcha.2009.01.002

Dolberg, F. 2003. Review of household poultry production as a tool in poverty reduction in Bangladesh and India. Pro-Poor Livestock Policy Initiative Working Paper 6. Food and Agricultural Organization, Rome. 10.22004/ag.econ.23762

Dow, K Jay, and J W Endersby. 2004. Multinomial probit and multinomial logit: A comparison of choice models for voting Research. *Electoral Studies* 23: 107-22. https://doi.org/10.1016/S0261-3794(03)00040-4

FAO. 2009. Livestock, food security and poverty reduction. The state of food and agriculture. Food and Agricultural Organization. Rome. ISBN 978-92-5-106215-9. https://www.fao.org/3/i0680e/i0680e.pdf

Department of Agriculture, Cooperation & Farmers' Welfare, Government of India. 2020. All India Report on Agriculture Census 2015-16.. New Delhi. agcensus.da.gov.in.Haddad, L and A Ahmed. 2003. Chronic and transitory poverty: Evidence from Egypt, 1997–99. *World Development* 31(1): 71-85. https://doi.org/10.1016/S0305-750X(02)00180-8

Heffernan, C. 2000. The socio-economic impact of restocking destitute pastoralists: a case study from Kenya. Sociology, Economics, Environmental Science : 283. https://www.cabidigitallibrary.org/doi/full/10.5555/20036794269

Holmann, F, L Rivas, N Urbina, B Rivera, L A Giraldo, S Guzman, M Martinez, A Medina, and G Ramirez. 2005. The role of livestock in poverty alleviation: An analysis of Colombia, *Forest* 3: 0-9. https://www.lrrd.cipav.org.co/lrrd17/1/holm17011.htm

Kedir, A M and A McKay. 2005. Chronic poverty in urban Ethiopia: panel data evidence. *International Planning Studies* 10(1): 49–67. https://doi.org/10.1080/13563470500159246Kristjanson, P, A Krishna, M Radeny, and J Kuan. 2006. Pathways into and out of poverty and the role of livestock in the Peruvian Andes (No. 1004-2016-78731). International Association of Agricultural Economists Conference, Gold Coast, Australia. 10.22004/ag.econ.25451

Kristjanson, P, A Krishna, M Radney, and W Nindo. 2004. Pathways out of poverty in western Kenya and the role of livestock. Pro-Poor Livestock Policy Initiative Working Paper 14, Food and Agricultural Organization, Rome. 10.22004/ag.econ.23779

Maltsoglou, I and K Taniguchi. 2004. Poverty, livestock and household typologies in Nepal. Pro-Poor Livestock Policy Initiative Working Paper 13, Food and Agricultural Organization, Rome. PPLPIexecsumm _wp13.pdf

McFadden, D. 1973. Conditional logit analysis of qualitative choice behaviour. In *Frontiers of Econometrics,* eds P E Zarembka, , 105-142, New York: Academic Press. https://escholarship.org/uc/item/61s3q2xr

Mokhtarian, P L and M N Bagley. 2000. Modeling employees' perceptions and proportional preferences of work locations: the regular workplace and telecommuting alternatives. *Transportation Research Part A-Policy and Practice* 34: 223-42. https://doi.org/10.1016/S0965-8564(99)00002-6

Ojha, R K. 2007. Poverty dynamics in rural Uttar Pradesh. *Economic & Political Weekly* 42(16): 1453-1458. https://www.jstor.org/stable/4419498

Okidi, J A and G Kempaka. 2002. An overview of chronic poverty and development policy in Uganda. CPRC Working Paper No. 11, University of Manchester, Manchester. http://www.dfid.gov.uk /r4d/PDF/Outputs/ChronicPoverty_RC/11OkidiMugambe.pdf

Pels, E, P Nijkamp, and P Rietveld. 2001. Airport and airline choice in a multiple airport region: an empirical analysis for the San Francisco bay area. *Regional Studies 35*: 1-9. https://doi.org/10.1080/00343400120025637

Pica-Ciamarra, U, L Tasciotti, J Otte, and A Zezza. 2011. Livestock assets, livestock income and rural households: Cross-country evidence from household surveys, FAO, Rome; *ISS, World Bank, The Hague, Washington D.C. https://ageconsearch.umn.edu / record/289004/

Planning Commission. Government of India. 2009. Report of the expert group to review the methodology for estimation of poverty., New Delhi. chrome-extension:/

/efaidnbmnnnibpcajpcglclefindmkaj/https://www.shivajicollege.ac.in/sPanel/uploads/econtent/bf14717bee6fa823982367e94a152ce4.pdf

Rencher, A C. 2002. Methods of multivariate analysis, New York: John Wiley & Sons, Inc. 10.1002/9781118391686

Sinha Roy, S and R Van Der Weide. 2022. Poverty in India has declined over the last decade but not as much as previously thought. World Bank Group, Policy Research Working Paper. https://openknowledge.worldbank.org/handle/10986/37273

Sirohi, S, P Chand, D Sharma, and R Saxena. 2019. Estimation of bovine equalizing units in India: A regional perspective. *Indian Journal of Animal Sciences* 89(9): 1009-1013. https://doi.org/10.56093/ijans.v89i9.93784

Small, K A and C Hsiao. 1985. Multinomial logit specification tests. *International Economic Review* 26: 619-627. https://www.jstor.org/stable/1910997

Thorat, A, R Vanneman, S Desai, and A Dubey. 2017. Escaping and Falling into poverty in India today. *World Development* 93: 413-426. https://doi.org/10.1016/j.worlddev.2017.01.004

Widyanti, W, A Suryahadi, S Sumarto, and A Yumna. 2009. The relationship between chronic poverty and household dynamics: evidence from Indonesia, SMERU Working Paper, SMERU Institute, Jakarta. http://dx.doi.org/10.2139/ssrn.1537080

Wooldridge, J M. 2002. Econometric analysis of cross section and panel data.MIT press. *Cambridge 108*(2): 245-254. https://mitpress.mit.edu/9780262296793/econometric-analysis-of-cross-section-and-panel-data/

Received 30 April 2023 Accepted 1 August 2023

Appendices

Table A1 Small Hsiao test for MNL model of livestock ownership on rural poverty

Variable	lnL(full)	lnL(omit)	chi^2	DF	$P>chi^2$
Non-poor	-4722.59	-4697.03	51.115	48	0.352
Escaped poverty	-6967.37	-6951.33	32.072	48	0.963
Fallen in poverty	-7410.07	-7392.2	35.745	48	0.904
Chronic	-9038.68	-9022.67	32.006	48	0.963

DF: Degrees of Freedom

Table A2 Small Hsiao test for MNL model of aggregated livestock units on rural poverty

Variable	lnL(full)	lnL(omit)	chi^2	DF	$P>chi^2$
Non-poor	-4783.54	-4756.37	54.34	48	0.246
Escaped poverty	-6995.57	-6973.29	44.565	48	0.614
Fallen in poverty	-7492.56	-7472.9	39.327	48	0.809
Chronic	-8952.5	-8937.96	29.086	48	0.986

Table A3. Small Hsiao test for MNL model of disaggregated livestock units on rural poverty

Variable	lnL (full)	lnL (omit)	chi^2	DF	$P>chi^2$
Non-Poor	-4754.65	-4730.59	48.118	52	0.627
Escaped poverty	-6964.15	-6936	56.305	52	0.317
Fallen in poverty	-7454.86	-7442.1	25.526	52	0.999
Chronic	-8973.06	-8943.56	58.995	52	0.235

Agricultural Economics Research Review 2023, 36 (2), 169-176
DOI: 10.5958/0974-0279.2023.00030.7

A cross-sectional estimation of total factor productivity of livestock-based farming systems in tribal areas of Odisha

Tulika Kumari[1]*, A K Chauhan[2] and B S Chandel[2]

[1]Department of Agricultural Economics, RPCAU, Pusa, Samastipur, Bihar 848125, India
[2]DES&M, National Dairy Research Institute, Karnal, Haryana 132001, India

*Corresponding author: tulikakumari42@gmail.com

Abstract The total factor productivity (TFP) of some livestock-based farming systems has been estimated using cross-sectional data and Cobb-Douglas production function. The determinants of TFP in tribal areas of Odisha have also been analysed. The average value of TFP has been observed highest (3.22) for C1 farming system, followed by the C2 (3.19), G1 (3.18), G2 (3.17), P2 (3.14), P1 (3.13) and G3 (3.11) farming systems. It means that the effect of factors other than inputs was more under C1 in comparison to other farming systems. The value of TFP could be increased with a better management of resources and enterprises.The transfer of technology to the farmers could also play a major role in increasing the TFP value of the systems as access to farm extension services has shown a positive and significant effect on TFP. The study has also revealed that the land size has a positive and significant effect on the TFP value. Therefore, collective farming needs to be propagated in this area. For this, farmers should be sensitized through demonstrations and awareness campaigns.

Keywords Total factor productivity, livestock, farming systems, tribal areas, Odisha, cross-sectional data

JEL codes D24, O33, Q10, Q16

Introduction

Odisha is one of the economically poor states in India having highest number (62) of tribal communities. These tribal communities are highly backward and constitute deprived groups in the state. About 94.5 per cent schedule tribe (ST) population of the state resides in the villages (Govt. of India 2011). More than 80 per cent of the rural households own livestock of one or other species or a combination of them to get milk, meat, egg, skin, bone, manure, draught power and employment (Das and Das 2016). The animal husbandry is a major source of livelihood for subsistence economies and the tribal areas are characterized by the presence of such a subsistence economy in the state. Livestock is one of the key resources of the tribal livelihood, apart from land and forest. For the tribal households livestock is an asset. The tribes in the state keep cows and chicks for meeting household requirements. The goat and sheep rearing is largely done for marketing purpose. The pig farming is preferred by these tribes due to its high multiplication rate and more weight and hence better returns. These tribes who own small pieces of land and follow traditional farming and hence farming is not profitable for them. The contribution of factors other than inputs in these farms can be captured by estimating the total factor productivity (TFP) at farm level.

The TFP measures the contribution of factors other than inputs. The portion of output not explained by the amount of inputs used in production is TFP. Several publications are evidence of TFP estimation for the crop (Kumar and Mittal 2006; Chatterjee et al. 2007; Kumar et al. 2008; Elumalai 2011; and Anbukkani et al. 2016) and livestock sector (Elumalai and Pandey 2004; Ohlan 2013; Chand and Sirohi 2015). The temporal data has extensively been used to show TFP growth in the agriculture sector. Only a few studies have been conducted for the estimation of TFP in cross-sectional data. In the present study, the TFP has been estimated for different farming systems by using cross-sectional data. The TFP value obtained through this method has been found to be more meaningful. It measures the performance of productive unit i.e. how efficiently and intensely the inputs are utilized in the production process. The factors which affect the total output other than inputs may be knowledge, infrastructure, scale of operation, technology, management, etc. This paper estimates the total factor productivity for different livestock-based farming systems present in the study area.

Literature review

The review of literature indicated that Tornqvist-Theil index was widely used in the earlier studies (Birthal et al. 1999; Elumalai and Pandey 2004; Chatterjee et al. 2007; Elumalai 2011 and Anbukkani et al. 2016) in the crop and livestock sector. But, only a few studies have been (Armagan and Ozden 2007; Lal and Chandel 2017) conducted on the estimation of TFP at the farm level by using Cobb-Douglas production function.

Armagan and Ozden in 2007 showed that land size has a positive and significant effect on the TFP. It means TFP increases with the increase in farm size. They also indicated that the value of gross output increases with the increase in labour in small farms, land size in medium farms and variable inputs in the case of large farms.

Lal and Chandel (2017) estimated the total factor productivity of milk production and the determinants influencing it in the Sirsa district of Haryana by using Cobb-Douglas production function. They found that the value of TFP was highest on the large category of household and for cross-bred cows. It implies that increased scale of production and adoption of high-yielding breed enhances the TFP. Similar findings were also indicated by Acharya et al. in 2020 among peri-urban dairy farms.

These studies indicate that the TFP value, estimated by using Cobb-Douglas production function, revealed that the TFP of crop in case of cross-sectional data increases with increase in the farm size and TFP of livestock farming in cross-sectional data increases with increase in the herd size.

The earlier researchers have not estimated TFP values for the farming system. The point which needs to be focussed is whether the benefits of technological change have been realized by tribal communities or not and also, what are the factors and how these factors influence TFP values of livestock-based farming system?

Data and methodolgy

Sampling design

The primary data was collected during the year 2017-18 from four districts, viz. Mayurbhanj, Keonjhar, Sundargarh and Koraput in the state of Odisha selected on the basis of highest livestock and tribal population. Then, two blocks were selected randomly from each district, these were: Baripada and Kuliana from Mayurbhanj, Tangarpali and Sadar from Sundargarh, Banspal and Keonjhar from Keonjhar and Koraput and Simliguda from Koraput. From each block, a cluster of villages was selected randomly — three from Mayurbhanj and Sundargarh districts and four from Keonjhar and Koraput districts. The random selection of villages was based on the presence of tribal households. Different farming systems were identified from these areas by considering major contribution of enterprise to the income. Finally, a sample of 240 households was selected on the basis of probability proportional to size from each farming system.

Analytical tool

The following conventional Cobb-Douglas production function (Lal and Chandel 2017) was used to determine the relation between gross production values of farming system obtained from the production of different enterprises as a result of inputs used:

$$Y_i = b_o \prod_{i=1}^{n} X_i^{b_i} \quad \ldots(1)$$

The log linear form of Cobb-Douglas production function obtained by running logarithm on both sides of Equation (1) is:

$$\ln Y_i = \ln b_0 + \sum_{i=1}^{n} b_i \ln X_i \quad \ldots(2)$$

or, $\ln b_o = \ln Y_i - \sum_{i=1}^{n} b_i \ln X_i$

where,

Y_i = Production level (Gross production value of farming system)

b_0 = TFP coefficient

X_i = Inputs used (value of variable inputs), and

b_i = Factor share

For estimating TFP following equation was used;

$$TFP = b_o = \frac{Y_i}{\prod_{i=1}^{n} X_i^{b_i}} \quad \ldots(3)$$

An econometric approach to Equation (2) does not give the average value of TFP at individual farm level. Therefore, to calculate TFP at individual farm level, coefficients were estimated as factor share in the total cost, assuming cost minimization objective function. Thus, b_i for an input on the farm was taken as:

$P_{xi}*X_i/H\ P_{xi}*X_i$

where, P_{xi} = Price of i^{th} input X

The value of intercept term of the equation obtained from the analysis was the average value of TFP.

Determinants of total factor productivity

To find the factors determining the TFP at the farm level, multivariate regression analysis was conducted. Determinants explain the factors that affect total factor productivity of the farming systems. The regression analysis helps to identify the significant factors that may throw light on policy implications. In this process, many factors were included in the step down regression but only land size, herd size, access to farm extension services, age and literacy of the farmer were kept in the final regression analysis. These variables were considered to isolate the effect of technology. The effects of these variables were found by the regression analysis. The linear regression model was selected for analysis on the basis of R^2 value and apriori signs of the economic theory.

$TFP = f(X_i)$

where, X_i = Land size, Herd size, Literacy level of farmer, Age of farmer, Access to farm extension services

The measurement of these variables along with their apriori signs are presented in Table 1.

The positive apriori sign for land size (X_1), herd size (X_2), literacy level (X_4), and access to farm extension services (X_5) means with the increase in land size, herd size, literacy level and access to farm extension services, the TFP value is likely to increase, while, the negative sign for age of farmer (X_3) shows that with the increase in age, TFP declines.

Table 1 Description of variables along with apriori signs

Variables	Measurement	Apriori signs
Land size	Acre	+ve
Herd size	Number in SAU	+ve
Age of farmer	Years	-ve
Literacy level of farmer	Categorical variable (0 – illiterate, 1 – primary school, 2 – middle school, 3 – high school, 4 – higher secondary and 5 – graduate and above)	+ve
Access to farm extension services	Binary response of 0 and 1 (0 for no and 1 for yes),	+ve

Results and discussion

The average values of TFP of different farming systems at the farm level in intercept terms of Cobb-Douglas production function are presented in Figure 1. It revealed that the value of TFP was highest (3.22) for the C1 (cattle + crop) farming system. It could be due to the large herd size and large operational area under crop in the study area. With the increase in herd size and farm size, farmers are likely to follow a more scientific approach leading to proper utilization of resources during the production process. The lowest TFP (3.11) was observed for the G3 (goat + crop + poultry) farming system. It could be due to the small size of farms. Another reason for this was that due to the presence of goat and poultry in the system, farmers were not giving much attention to these enterprises. The frequency distribution of sample households is presented in the Table 2 by using the average value of TFP. It shows how many households had values below and above the average value of TFP. It also indicates, which values (below or above average) have a strong influence on the average value of TFP.

It is clearly evident from Table 2 that the coefficient of variability was highest for C1 (cattle + crop) farming system. It means variation in the value of TFP was more in this system. All the seven systems indicated a similar pattern of frequency distribution of sample

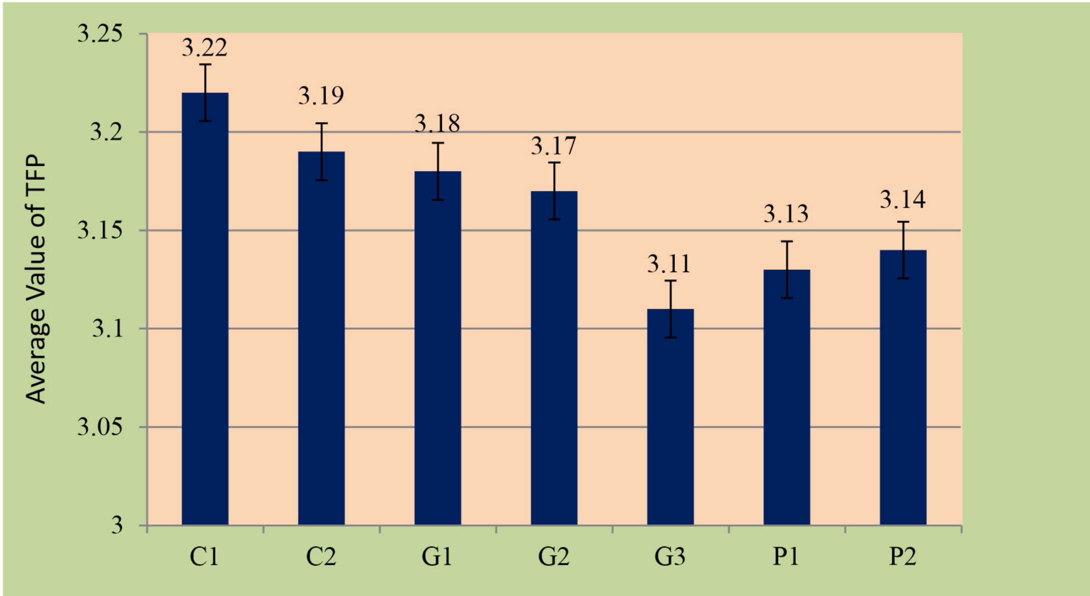


Figure 1 Average value of TFP of farm under different farming systems

(C_1= Cattle+Crop, C_2 = Cattle+Crop+Goat+Poultry, G_1 = Goat+Crop+Cattle+Poultry, G_2 = Goat+Crop, G_3 = Goat+Crop+Poultry, P_1 = Pig+Crop, P_2 = Pig+Cattle+Crop+Poultry)

Table 2 Frequency distribution of sample households according to total factor productivity under different farming systems in Odisha

Farming systems	Average value of TFP	Standard deviation	Frequency of households		Total No. of households
			<Avg	>Avg	
Cattle+Crop (C1)	3.22	0.80	33 (54.10)	28 (45.90)	61 (100.00)
Cattle+Crop+Goat+Poultry (C2)	3.19	0.79	19 (57.57)	14 (42.43)	33 (100.00)
Goat+Crop+Cattle+Poultry (G1)	3.18	0.66	37 (61.67)	23 (38.33)	60 (100.00)
Goat+Crop (G2)	3.17	0.60	22 (48.89)	23 (51.11)	45 (100.00)
Goat+Crop+Poultry (G3)	3.11	0.42	11 (52.38)	10 (47.62)	21 (100.00)
Pig+Crop (P1)	3.13	0.06	6 (60.00)	4 (40.00)	10 (100.00)
Pig+Cattle+Crop+Poultry (P2)	3.14	0.09	5 (50.00)	5 (50.00)	10 (100.00)

Note Figures within the parentheses denote percentage of total households

households for TFP. The majority of households were having less than average TFP in all the systems, which means the value of average TFP was influenced more by these households. The value of TFP could be increased with better management of resources and enterprises. The study carried out by Lal and Chandel (2017) also reported that the value of average TFP was more influenced by the households having TFP value less than the average TFP.

Table 3 Partial regression coefficients of factors influencing the total factor productivity of cattle-based farming systems

Variables	Farming systems	
	Cattle+Crop (C1)	Cattle+Crop+ Goat+Poultry (C2)
	Regression coefficients	Regression coefficients
Constant	2.990*	3.351*
	(0.111)	(0.199)
Land size (in acres)	0.019***	0.017
	(0.010)	(0.016)
Herd size (No./HH)	0.078*	0.017***
	(0.019)	(0.009)
Age of farmer (years)	-0.001	-0.005
	(0.002)	(0.003)
Literacy level of farmer	0.004	0.028**
	(0.008)	(0.130)
Access to farm extension services	0.081** (0.035)	0.180* (0.034)
R^2 value	0.69	0.66
n	61	33

Note Figures within the parentheses are standard errors
*** = P≤0.01; ** = P≤0.05; *** = P≤0.10

Determinants of TFP for different farming systems

The determinants explain the factors that affect the total factor productivity of farming systems. The effect of these factors was studied by regression analysis using different functional relationships. Several functional forms were analysed for regression analysis and finally linear function was found suitable on the basis of statistical (R^2 value) and economic theory. Finally, multiple regression analysis was done using linear function, where TFP of a farming system was taken as the dependent variable. The partial regression coefficients of factors influencing the TFP values of cattle-based C1 and C2 farming systems are presented in Table 3.

Table 3 shows that the values of R^2 were 0.69 and 0.66 for C1 and C2 farming systems, respectively. For the C1 farming system, the factors, land size, herd size and access to farm extension services revealed a positive and significant effect on the TFP value. The values of coefficients for these factors were 0.019, 0.078 and 0.081, respectively. It indicated that the value of TFP increases by 0.019 with the increase of 1 acre in land size, by 0.078 with the increase of 1 unit in herd size and by 0.081 with more access to farm extension services. The effect of land size on TFP was reported positive and significant by Armagan and Ozden, 2007 also. It is clearly seen from Table 3 that land size and age of farmer could not affect the TFP significantly in the C2 farming system. The herd size, literacy level and access to farm extension services have depicted a positive and significant effect on the TFP value for this system. Lal and Chandel (2017) had also reported a positive and significant effect of herd size on TFP value. The values of coefficients for these factors were 0.017, 0.028 and 0.180, respectively. It means that with an increase in these factors, the value of TFP increases. As the literacy level and access to farm extension services increase, the farmers become more aware and efficient for management of their farms.

The partial regression coefficients of factors influencing the TFP value of goat-based G1, G2 and G3 farming systems are presented in Table 4.

Table 4 indicates that the value of R^2 was 0.70 for G_1, 0.66 for G_2 and 0.79 for G3 farming systems. All the factors in the G1 farming system were found significant, except literacy level. The land size, herd size and access to farm extension services have revealed a positive and significant effect on TFP value and the values of their coefficients were 0.040, 0.018 and 0.168, respectively. The age of farmer has shown a negative effect on TFP value and it was turned out significant at 1 per cent probability of error. It indicates that as the age of a farmer increases, the value of TFP decreases by 0.004. The land size and access to farm extension services have shown a positive and significant effect on the TFP value in the G2 farming system. The herd size did not affect the TFP significantly under this system. In the case of G3 farming system, only literacy level and access to farm extension services have shown a positive and significant effect. The other factors, land size, herd size and literacy level have not depicted a significant effect on TFP value. The coefficient of literacy level was 0.093, which means, with the increase in literacy level TFP increases by 0.093. Some similar findings were reported by Elumalai in 2011 who reported that the coefficient associated with public expenditure on education and farm extension services was positive and significant. Thus, an increase in public

Table 4 Partial regression coefficients of factors influencing the total factor productivity of goat-based farming systems in Odisha

Variables	Farming systems		
	Goat+Cattle+Crop+Poultry (G1) Regression coefficients	Goat+Crop (G2) Regression coefficients	Goat+Crop+Poultry (G3) Regression coefficients
Constant	3.250*	3.186*	2.745*
	(0.118)	(0.202)	(0.184)
Land size (in acres)	0.040*	0.053**	0.017
	(0.009)	(0.019)	(0.019)
Herd size (No./HH)	0.018**	0.019	0.010
	(0.009)	(0.013)	(0.012)
Age of farmer (years)	-0.004***	-0.001	0.006
	(0.002)	(0.003)	(0.003)
Literacy level of farmer	-0.012	-0.019	0.093*
	(0.007)	(0.011)	(0.019)
Access to farm extension services	0.168*	0.219*	0.097***
	(0.020)	(0.041)	(0.046)
R^2 value	0.70	0.66	0.79
n	60	45	21

Note: Figures within the parentheses are standard errors
*** = P≤0.01; ** = P≤0.05; *** = P≤0.10

expenditure on education and farm extension services makes farmers more aware and ultimately it accelerates the agricultural productivity.

The partial regression coefficients of factors influencing the TFP value of pig-based P1 and P2 farming systems are presented in Table 5.

Table 5 illustrates that the value of R^2 was 0.60 for P_1 and 0.61 for P2 farming systems. Access to farm extension services revealed a positive and significant effect on the TFP value with regression coefficient as 0.109. Only the literacy level of farmer has shown a positive and significant effect on the TFP value for P2 farming system. The regression coefficient of literacy level was 0.054, which shows that with increase in the level of literacy, the TFP increased by 0.054.

Conclusions and policy implication

The determination of TFP values by Cobb-Douglas production function for different farming systems in the state of Odisha has revealed some significant effects. The average value of TFP has been found high for C1 (3.22) farming system and lowest for G3 (3.11) farming system. It means that some other factors like

Table 5 Partial regression coefficients of factors influencing the total factor productivity of pig-based farming system in Odisha

Variables	Farming systems	
	Pig + Crop (P1) Regression coefficients	Pig+Cattle+Crop +Poultry (P2) Standard error
Constant	3.291* (0.234)	3.417*
Land size (in acres)	0.017 (0.027)	0.012
Herd size (No./HH)	0.005 (0.016)	0.011
Age of farmer (years)	-0.002 (0.003)	-0.006
Literacy level of farmer	0.031 (0.028)	0.054***
Access to farm extension services	0.109** (0.064)	0.048
R^2 value	0.60	0.61
n	10	10

Note Figures within the parentheses are standard errors
*** = P≤0.01; ** = P≤0.05; *** = P≤0.10

proper farming management and utilization of resources were more under the C1 farming system and less in the G3 system. Under the G3 (goat + crop + poultry) farming system, the herd size was small, operational area under crop was small and literacy level of farmer was low. These factors might have caused a relatively low TFP value in comparison to other farming systems. Therefore, awareness campaign related to these factors should be conducted in the region. All the seven farming systems have indicated a similar pattern of frequency distribution of sample households for TFP. The majority of households have shown less than average TFP value in all the systems, which means that the average value of TFP was more influenced by these households. The value of TFP could be increased with the better management of resources and enterprises. The transfer of technology to the farmers could play a major role in increasing the TFP value of the systems as access to farm extension services has shown a positive and significant effect on the TFP value. The study has also revealed that land size has a positive and significant effect on the TFP value. Therefore, to increase the TFP, a large land size is required which can be achieved through the adoption of collective farming. For this, farmers should be sensitized through demonstrations and awareness campaigns.

Acknowledgement

This paper is part of the study conducted for partial fulfilment of the doctoral degree programme of the first author in Agricultural Economics from ICAR-National Dairy Research Institute, Karnal, Haryana. The authors are grateful to all the farmers for providing valuable data which helped in completion of the research work.

References

Acharya, K.K., Malhotra, R., Lal, P., Thakur, A. and Rathore, R. 2020. An Estimation of Total Factor Productivity and its Determinants among Per-Urban Dairy Farmers of Odisha. *Indian Journal of Economics and Development* 16: 489-493. https://doi.org/10.35716/ijed/NS20-047

Anbukkani, P., Nithyashree, M.L., and Kumar, P. 2016. Productivity and Sustainability of Rice-Wheat System in Indo-Gangetic Plains. *Indian Journal of Economics and Development* 12(3): https://doi.org/549-556. 10.5958/2322-0430.2016.00173.6

Armagan, G. and Ozden, A. 2007. Determinants of Total Factor Productivity with Cobb-Douglas Production Function in Agriculture: A Case of Aydin-Turkey. *Journal of Applied Science* 7(4): 499-502. https://doi.org/10.3923/JAS.2007.499.502

Birthal, P.S., Kumar, A., Ravishankar, A. and Pandey, U.K. 1999. Sources of Growth in Livestock Sector. NCAP Policy Paper No. 9, National Centre for Agricultural Economics and Policy Research, New Delhi. pp9.pdf (icar.gov.in)

Chand, P. and Sirohi, S. 2015. Sectoral Priorities for Sustainable Livestock Development in Rajasthan: Lessons from Total Factor Productivity Growth. *Agricultural Economics Research Review* 28(Conference Number): 81-92. https://doi.org/10.5958/0974-0279.2015.00024.5

Chatterjee, S., Saha, M., Samanta, M.K. and Mondal, S.S. 2007. An Economic Analysis of Total Factor Productivity (TFP) of Potato in West Bengal. *Potato Journal* 34(1-2):121-122. Chatterjee%2c+S.%2c+Saha%2c+M.%2c+Samanta%2c+M.K.+and+Mondal%2c+S.S.+2007.+An+Economic+Analysis+of+Total+Factor+Productivity+(TFP)+of+Potato+in+West+Bengal.+Potato+Journal+34(12)

Das, B.C. and Das, J. 2016. Livestock Biodiversity of Odisha. *Odisha Review* 53-58. 54-59.pdf (odisha.gov.in)

Elumalai, K. and Pandey, U.K. 2004. Technological Change in Livestock Sector of Haryana. *Indian Journal of Agricultural Economics* 59(2): 249-258. [PDF] Technological Change in Livestock Sector of Haryana | Semantic Scholar

Elumalai, K. 2011.Total Factor Productivity Growth and its Determinants in Karnataka Agriculture. Working Paper No. 265, Institute for Social and Economic Change, Bangalore. Elumalai%2c+K.+2011.Total+Factor+Productivity+Growth+and+its+Determinants+in+Karnataka+Agriculture.+Working+Paper+No.+265%2c+Institute+for+Social+and+Economic+Change%2=1

Government of India, Ministry of Home Affairs. 2011. Census 2011, New Delhi. *Government+of+India%2c+Ministry+of+Home+Affairs.+2011.+Census+2011%2c+New+Delhi =1*

Kumar, P. and Mittal, S. 2006. Agricultural Productivity Trends in India: Sustainability Issues. *Agricultural Economics Research Review* 19: 71-88. IDEAS/RePEc search

Kumar, P., Mittal, S. and Hossain, M. 2008. Agricultural Growth Accounting and Total Factor Productivity in South Asia: A Review and Policy Implications. *Agricultural Economics Research Review* 21: 145-172. https://doi.org/10.22004/AG.ECON.47669

Lal, P. and Chandel, B.S. 2017. Total Factor Productivity in Milk Production in Haryana. *Agricultural Economics Research Review* 30(2): https://doi.org.in/10.5958/0974-0279.2017.00048.9

Ohlan, R. 2013. Efficiency and Total Factor Productivity Growth in Indian Dairy Sector. *Quarterly J. of International Agriculture* 52(1): 51-77. https://ssrn.com/abstract=2721298

Received 7 September 2023 Accepted 30 November 2023

Agricultural Economics Research Review 2023, 36 (2), 177-188
DOI: 10.5958/0974-0279.2023.00031.9

Understanding price volatility and seasonality in agricultural commodities in India

Md Yeasin[1], Purushottam Sharma[2], Ranjit Kumar Paul[1], Dinesh Chand Meena[2] and Md Ejaz Anwer[2]

[1]ICAR-Indian Agricultural Statistics Research Institute, New Delhi 110012, India
[2]ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi 110012, India

*Corresponding author: Purushottam.Sharma@icar.gov.in

Abstract The volatility in prices of agricultural commodities is a major concern for policymakers, researchers, and value chain participants, including farmers. The study examines the trend and pattern of agricultural price volatility and its seasonality using monthly data from January 2010 to December 2022. The fixed effects model has been used to decipher the effect of market arrivals, rainfall and pandemic shock on the prices. The results have revealed that prices of vegetables were most volatile, followed by oilseeds and pulses. The seasonality pattern of volatility has shown general peaks during the pre-harvest and harvest periods and troughs during the post-harvest period. The rainfall affected the prices of mainly rainfed crops and the effect of the pandemic has been found to be positive for many of the agri-commodities. Strengthening post-harvest value chain institutions and related infrastructure, and increasing of competition in the markets would help integrate markets and reduce price volatility.

Keywords Price volatility, seasonality, food commodities, GARCH, fixed effects model

JEL codes C22, C32, Q11, Q13

Introduction

The price volatility in agricultural commodities is a major concern for value chain actors, including the policymakers. These prices are politically sensitive and several countries have witnessed food riots, demonstrations, and social unrest due to high volatility in these prices (Kalkuhl et al. 2016). The price fluctuations around a smooth and well-established trend, representing market fundamentals, do not pose much risk, but unpredictable and large price variations cause uncertainty for all the stakeholders in the value chain and agricultural markets are characterized by such uncertain price movements. The fluctuations in agricultural prices affect producers, middlemen, and consumers alike, leading to suboptimal outcomes of production and consumption decisions (Díaz-Bonilla 2016).

The poor, who spend a large part of their family income on food commodities, and smallholders who depend on agriculture for their livelihood, are more vulnerable to high volatility in these prices (Minot 2014; Shekhar et al. 2018). Thus, volatility in agricultural prices significantly affects the food and nutrition security of the vulnerable population. The country has experienced significant volatility in food prices, particularly in the prices of vegetables, pulses, and edible oils. The food-price volatility in India is primarily due to the demand-supply imbalances caused mainly by weather variations, inadequate supply chain infrastructure, seasonal and regional concentrations of supply and demand, international scenarios, input costs, and government policies. Sometimes, even small shocks in supply or demand may lead to high volatility in these prices due to the inelastic nature of food commodities in the short run (Gilbert and Morgan 2010). The extent of price volatility varies across seasons, markets, time epochs, etc.

The pieces of evidence have shown mixed results on the effect of the Covid-19 pandemic on price volatility in agricultural commodities. The perishable commodities like tomatoes, onions, and potatoes, were most affected due to the Covid-19 shocks, the prices of which increased by 60 per cent in some markets compared to their prices in the pre-pandemic year (Paul and Birthal 2021). Narayanan and Saha (2021) and Mahajan and Tomar (2021) have also reported that prices of pulses and most edible oils registered significant increases during the period of pandemic-induced lockdown in India. On the contrary, Emediegwu and Nnadozie (2023) have found structural instability in the prices of storable food products due to Covid-19 pandemic, and the prices of perishable food products did not experience structural instability. Weather aberrations and extreme weather events also affected the production of crops and in turn their prices (Kishore and Shekhar 2022). Similarly, crop arrivals also affect the prices in the markets.

Many studies have analyzed the effect of shocks on prices of agricultural commodity in India, but studies regarding changes in price volatility are rare (Paul and Yeasin 2022). A change in prices may not necessarily imply a change in price volatility. Moreover, a change in prices depends on several factors, which affect the supply and demand of the commodity, including the amount of precipitation received during crop growth and harvest periods. The market power or anti-competitive trade practices in major markets may also cause higher price volatility (Birthal et al. 2019). The study of volatility in the prices of different commodities due to different exogenous factors helps policymakers and other supply chain actors in minimising the risk.

The paper aims to analyze the changes in price volatility over time for different agricultural commodities and markets. Quantifying the change in prices due to season, rainfall, and Covid-19 shock is also investigated for different groups of food commodities, viz. Cereals, Pulses, Oilseeds, Vegetables, and Spices for the present analysis.

Data and methodology

The data on monthly arrivals and prices for 19 agri-commodities from 143 markets of India were collected from the AGMARKNET portal for the period January 2010 to December 2022 and were used for the analysis. The monthly data on rainfall for the districts representing markets were collected from the website of India Meteorological Department, Govt of India. First, the missing values in the data were imputed using Kalman filter technique (Harvey and Pierse 1984) and then these were transformed to log return series. The aggregated price has been computed for each agri-commodity as weighted average price of all markets of that specified commodity, where weight assigned to each market is determined by the inverse of the arrival quantity.

$$\text{Aggregated price}_t = \frac{\sum_{i=1}^{k} \text{quantity}_{i,t} * \text{price}_{i,t}}{\sum_{i=1}^{k} \text{quantity}_{i,t}} \quad \ldots(1)$$

where, k is the number of markets for that commodity and t is the time period.

The log returns were measured by the difference in the logarithms of price at a point to the next. Let, $\{y_t\}_{t=1}^{T}$ be the time series data at point t, then the log return of the series are measured by Eq. (2).

$$\text{lr}_t = \ln y_t - \ln y_{t-1} \quad \ldots(2)$$

GARCH model

The Generalised Autoregressive Conditional Heteroscedastic (GARCH) model, developed by Bollerslev in 1986 (Bollerslev 1986), is the most widely employed approach for measuring price volatility in agri-commodities. The GARCH model of the log returns can be expressed as Eq (3):

$$\text{lr}_t = \mu + \epsilon_t \quad \ldots(3)$$

$$\epsilon_t = \sqrt{\sigma_t^2}.\, e_t \,; \quad \epsilon_t \sim N(1, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

where, $\omega > 0$, $\alpha_i \geq 0$ for $i = 1, 2, ..., p$, and $\beta_j \geq 0$ for $j = 1, 2, ..., q$ and satisfy the condition $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j$. Here e_t is the error-term, independent and identically distributed with zero mean and constant variance and σ_t^2 is the conditional variance of the series. The key benefit of the GARCH model lies in its ability of expressing the conditional variance of returns (volatility) as a linear function, dependent on both lagged squared residuals and its own past lags.

The unconditional volatility represents the standard deviation of a time series data and can be measured as $\sigma = \sqrt{E[(y_t - E(y_t))^2]}$. Conversely, the conditional volatility denotes the volatility of a time series at a particular time point, considering the information available up to that moment. The σ_t of the GARCH model has been considered as the conditional volatility. In simpler terms, the conditional volatility pertains to the volatility of time series data considering its previous values, whereas unconditional volatility pertains to the volatility of time series data without considering its historical values. The seasonal volatility of each commodity has been computed using month-wise standard deviation of log return series.

Test of volatility

To determine whether the variances of two or more groups are significantly different from each other, Bartlett's test has been used. This test has been employed to find the difference in volatility among different markets of each commodity (Bartlett's and Kendall 1946). The null hypothesis of Bartlett's test states that the variances of all groups are equal. The test statistics can be defined as per Eq. (4)

$$T = \frac{N-k}{3(k-1)} \sum_{i=1}^{k}(n_i - 1) * \log {s_i}^2 - \sum_{i=1}^{k}(n_i - 1) * \log S^2 \qquad \text{…(4)}$$

where, N is the total number of observations, i.e., $\sum_{i=1}^{k} n_i = N$; n_i is the number of observations in the ith group; s_i^2 is the variance of the ith group; and S^2 is the overall variance.

Moving averages

The moving average (MA) of a series provides a smoothed trend over time, reducing noise and highlighting underlying patterns in the data. The 13-month moving average of log return and 13-month moving standard deviation of log return series have been computed to provide a clear picture of the price volatility over time in the data.

The 13-month moving average of log return series at each time point can be calculated as per Eq. (5)

$$13\ \mathrm{MA_t(lr)} = \frac{\mathrm{lr_t + lr_{t-1} + \cdots + lr_{t-12}}}{13} \qquad \text{…(5)}$$

The 13-month moving standard deviation of log return series at each time point can be expressed as per Eq. (6)

$$13\ MA_t(sd) = \frac{1}{13}\sqrt{(lr_t - MA_t)^2 + (lr_{t-1} - MA_t)^2 + \cdots + (lr_{t-12} - MA_t)^2} \qquad \text{…(6)}$$

Distribution of absolute change

The distribution of absolute percentage change from month-to-month has been calculated to depict the behaviour of changes in level of price.

Absolute percentage change in log returns has been calculated using formula (7)

$$\text{Percentage change} = \left|\frac{\mathrm{lr_t - lr_{t-1}}}{\mathrm{lr_{t-1}}}\right| * 100 \qquad \text{…..(7)}$$

To find the distribution of absolute percentage change, frequencies of bin of size 5 for each commodity have been calculated and presented.

Contribution of seasonality

To estimate the contribution of seasonality to the volatility, trigonometric approach has been implemented due to its parsimonious nature. The simplest trigonometric seasonality with two parameters can be represented as per Eq. (8)

$$s_m = \alpha \cos\left(\frac{m\pi}{6}\right) + \beta \sin\left(\frac{m\pi}{6}\right) \qquad \text{…(8)}$$

where, m is the representation of months (m=1, 2, 3.., 12); $\lambda = \sqrt{\alpha^2 + \beta^2}$ measures the seasonal amplitude, and $\omega = \tan^{-1}\frac{\alpha}{\beta}$ the phase of the seasonal cycle. The seasonal gap is estimated as 2λ. In conjunction with the stochastic trend, the seasonal parameters, λ and ω, can be estimated using Ordinary Least Square (OLS) technique from regression model (9):

$$lr_{mt} = \gamma + \alpha \cos\left(\frac{m\pi}{6}\right) + \beta \sin\left(\frac{m\pi}{6}\right) + \varepsilon_{mt} \qquad \text{…(9)}$$

where, is the stochastic trend. The coefficient of determination of the above model can be considered as the contribution of the seasonality to the total volatility of the series.

Fixed effect model

To estimate the effect of arrival, rainfall (including its 3 lags), and COVID shock in a panel data setting, fixed-effect model has been implemented. The model can be specified as per Eq. (10):

$$y_{it} = \beta_0 + \beta_1 \text{Arrival}_{it} + \beta_2 \text{Rainfall}_{it} + \beta_3 \text{Rainfall}_{i(t-1)} + \beta_4 \text{Rainfall}_{i(t-2)} + \beta_5 \text{Rainfall}_{i(t-3)} + \beta_6 \text{Covid}_{it} \quad \ldots(10)$$

where, y_{it} is the dependent variable for entity i at time t, Arrival_{it} represents the arrival variable for entity i at time t, Rainfall_{it} represents the rainfall variable for entity i at time t, $\text{Rainfall}_{i(t-1)}$, $\text{Rainfall}_{i(t-2)}$, and $\text{Rainfall}_{i(t-3)}$ are the lagged values of the rainfall variable for entity i at times t-1, t-2, and t-3, respectively, Covid_{it} represents the COVID shock variable for entity i at time t. Covid_{it} is taken as 0 and 1 for pre-covid and post-covid periods, respectively, and β_0 is the intercept and β_1 to β_6 are the coefficients to be estimated for the corresponding independent variables. To estimate this fixed-effect model, OLS estimation technique has been implemented.

Results and discussion

Price volatility in agricultural commodities

The volatility in prices of agricultural commodities, conditional (SD of the return series) and unconditional [GARCH (1,1)] model on return series, were estimated on arrival weighted aggregate prices of selected commodities and are presented in Table 1. The results indicated that the prices of perishable vegetables are highly volatile among all crops considered for analysis, while prices of rice and wheat were least volatile. The price stabilization efforts through procurement at minimum support prices (MSP) during the harvest period (Cummings 2012) and open market sales during the lean season are in place in the case of rice and wheat, leading to a less volatile market prices. The price volatility was higher in tomato prices among vegetables which could be due to its high perishable nature. Among pulses, the prices of gram, and urad were slightly more volatile as compared to other pulses. In

Table 1 Price volatility in agricultural commodities in India

Commodity	No. of markets	Unconditional volatility			Conditional volatility		
		Mean volatility	F Statistic	ρ-value	Mean volatility	F Statistic	ρ-value
Paddy	22	0.06	22.44***	< 0.01	0.05	19.27***	< 0.01
Wheat	14	0.04	2.53***	< 0.01	0.04	33.49***	< 0.01
Maize	7	0.08	6.26***	< 0.01	0.08	8.69***	< 0.01
Gram	5	0.12	3.13***	0.01	0.09	3.08**	0.02
Urad	6	0.10	5.12***	< 0.01	0.10	30.66***	< 0.01
Lentil	5	0.06	0.45	0.77	0.06	5.84***	< 0.01
Mung	5	0.09	0.85	0.49	0.08	5.41***	< 0.01
Arhar	10	0.08	10.98***	< 0.01	0.08	44.43***	< 0.01
Potato	7	0.23	0.67	0.68	0.23	4.77***	< 0.01
Onion	10	0.31	2.03**	0.03	0.31	85.43***	< 0.01
Tomato	7	0.51	7.56***	< 0.01	0.50	48.40***	< 0.01
Soybean	9	0.09	2.00**	0.04	0.08	6.62***	< 0.01
Sunflower	6	0.08	3.86***	< 0.01	0.07	5.62***	< 0.01
Groundnut	9	0.14	44.40***	< 0.01	0.13	84.59***	< 0.01
Safflower	3	0.05	13.68***	< 0.01	0.04	7.71***	< 0.01
Mustard	9	0.05	0.35	0.94	0.05	6.87***	< 0.01
Turmeric	2	0.11	6.24***	0.01	0.11	17.65***	< 0.01
Coriander	4	0.10	2.72**	0.04	0.10	31.21***	< 0.01
Cumin	3	0.08	1.38	0.25	0.07	5.04***	0.01

Note *, **, and *** denote significance at 10 per cent, 5 per cent and 1 per cent levels, respectively.

the case of oilseeds, the price volatility was higher in groundnut than in other oilseeds. The prices of cumin were found to be the least volatile among spices.

The 13-month moving average (MA) and 13-month moving standard deviation (SD) of the log return series have also been computed to see the changes in prices as well as patterns in volatility over time for the selected commodities (Figure 1). The pattern of volatility also indicated that cereals prices are less volatile than other commodities throughout the study period. The volatility in rice prices was higher in 2014-15, lower from 2015-end to 2017, started increasing again, and continued to trend up. In the case of wheat, the price volatility was higher in 2012, 2016-17, and 2020 onwards. Maize price volatility was relatively low from 2010 to 2012, increased in 2013 and 2014, decreased briefly in 2015, and continued to trend up afterwards. Overall, with the Covid-19 led restrictions in 2020, there is an upward trend in the 13-month moving SD of the log return series, indicating the increase in volatility of cereals prices post-pandemic.

The price volatility in pulses was higher during 2015-2017, except in mung prices which were more volatile during 2012-2014 period. The 13-month moving SD of the log return series of all pulses was found to be quite consistent from 2020, with a brief increase in the first half of 2020 and declining thereafter. The declining trend in the 13-month moving SD indicates the declining volatility in prices of pulses. The price volatility in soybean and sunflower (soybean and sunflower oils are mainly imported in India other than palm oil), was low until 2019, started increasing thereafter and peaked in 2021. The prices of groundnut, safflower and mustard witnessed volatility peaks and

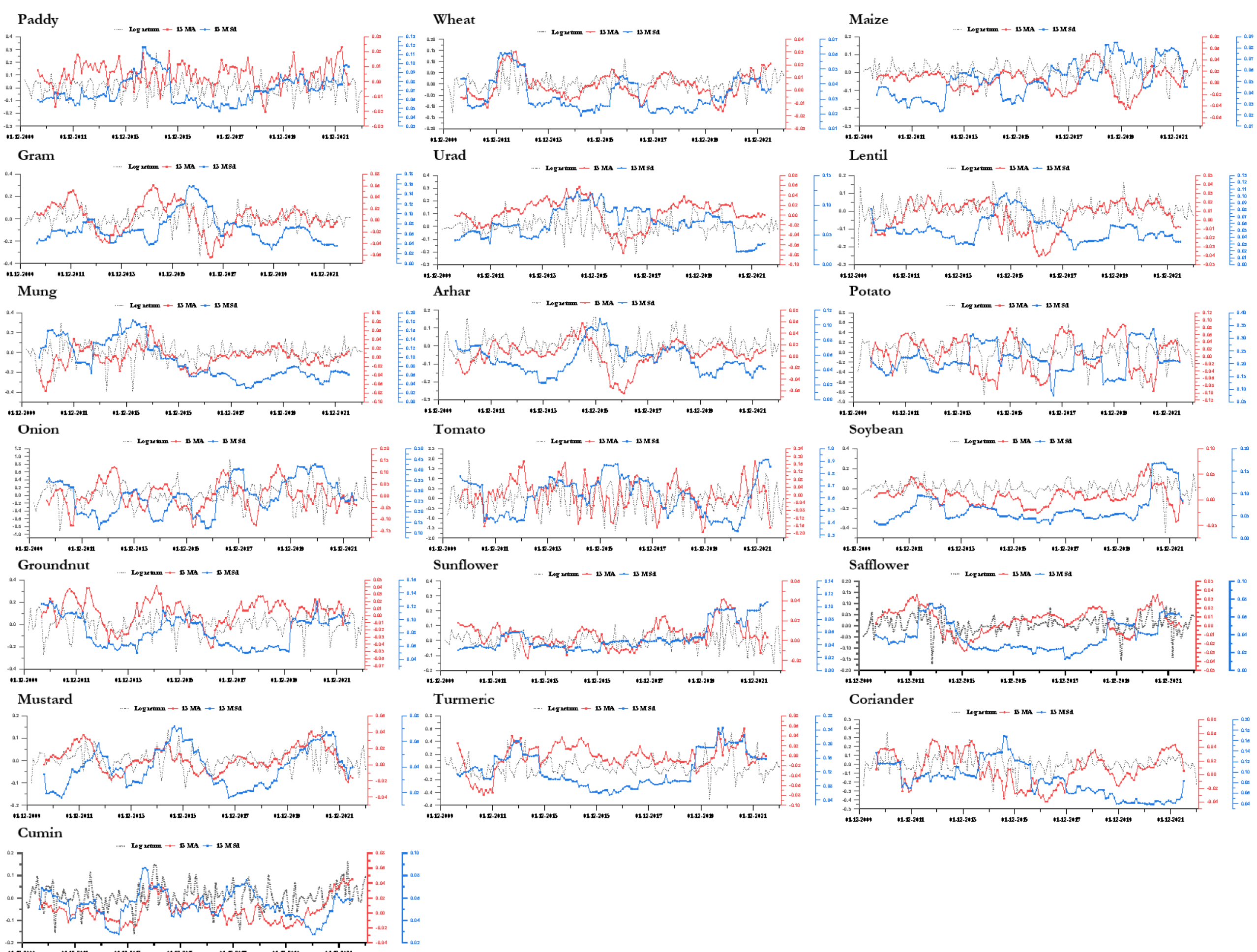


Figure 1 Volatility in agricultural commodity price series (log return, 13-month MA and standard deviation of log price returns series)

troughs during different periods. The 13-month moving SD of the log return series for oilseeds has shown an upward trend post-2020 for all the oilseeds, except mustard. In mustard, there is a decline in the 13-month moving SD. The 13-month MA of the log return series has shown a declining trend after 2020 for sunflower, soybean, and mustard. The price of groundnut looks consistent even after 2020.

The volatility in prices of perishable vegetables has been found to be high as compared to other crops. In vegetable crops, the pattern and trend in price volatility, and 13-month moving SD of the log return series, indicate many peaks and troughs. The price volatility in onion and tomato witnessed an opposite trend after 2020; an increasing trend for tomato and a decreasing trend for onion. The 13-month MA of the log return series for potato showed an increasing trend after 2020. The price volatility in spices witnessed peaks during 2012-13 and 2019 to 2021 in turmeric, 2014-15 in coriander and cumin. The 13-month MA and 13-month moving SD of the log return series for turmeric and cumin have depicted a significant increasing trend after the onset of Covid-19, whereas for coriander, though the 13-month MA of log return series has shown a slightly increasing trend, but not the 13-month moving SD of log return series.

The regional and seasonal concentrations of production, particularly of perishable vegetables, prone to biotic and abiotic stresses, that lead to supply shocks through weather aberrations, coupled with the inadequate supply chain infrastructure and symmetric information flow may result in high volatility in prices of perishables.

Changes in agricultural commodity prices and seasonality

The level of price changes provides an important perspective on volatility in the Indian agricultural markets. There may be small changes day-to-day, sometimes large price swings, or infrequently, there may be large changes in prices of agricultural commodities. These price changes may be due to unforeseen events like weather aberrations or distortions in the supply chain. This is illustrated in Figure 2 based on monthly price changes of different agri-commodities in the Indian markets. In nearly a quarter to half of all the months (January 2010 to December 2022), the monthly absolute percentage change in cereals prices was not more than two per cent. It was below six per cent for half to four-fifths of the months. The month-to-month changes in cereal prices went up to 20 per cent, though very infrequent.

The frequency of month-to-month price changes for pulses, oilseeds, and spices was below 6 per cent for nearly half to three-quarters of all the months, and price changes went up to 25 per cent, 20 per cent, and 30 per cent, respectively for less than 5 per cent of all the months (Figure 2). In the case of vegetables, higher month-to-month price changes were observed, with less frequency of small changes below 5 per cent for fewer than 15 per cent of all the months, the equally higher frequency for larger changes of 15 per cent to 45 per cent monthly changes, and reached up to 80 per cent for a fewer months. Though, looking only at the size of price changes is not sufficient, because, the large monthly changes in the same direction for several successive months may upset the market prices.

The price volatility has been found to be higher during pre-harvest or harvest months, in general, and lower during the post-harvest months (Figure 3). The seasonal pattern of agri-commodities prices, and thus price volatility, are inherent due to seasonality in production, farmers' holding capacity, transport and storage infrastructure availability, and liquidity constraints. The efficient markets are expected to smoothen out high fluctuations through trade and storage, i.e., spatial and temporal arbitrage. The fragmented and long supply chain for the agricultural produce in India and asymmetric market power coupled with asymmetric access to market information add to the high volatility (Birthal et al 2019) and larger seasonal gaps in agri-commodity prices.

In India, agricultural production and consumption may vary seasonally, leading to seasonal peaks and troughs in their prices. A parsimonious but more restrictive functional approach, such as trigonometric functions, has been followed to characterize seasonality (Ghysels and Osborn 2001). The results presented in Table 2 revealed that wholesale prices of rice, wheat, and maize were estimated to be 4.9 per cent, 5.2 per cent, and 8.85 per cent higher than those during troughs (on average across 22, 14, and 7 major markets). In the case of pulses, the peak prices have been estimated to be 13.93 per cent and 9.10 per cent higher than those

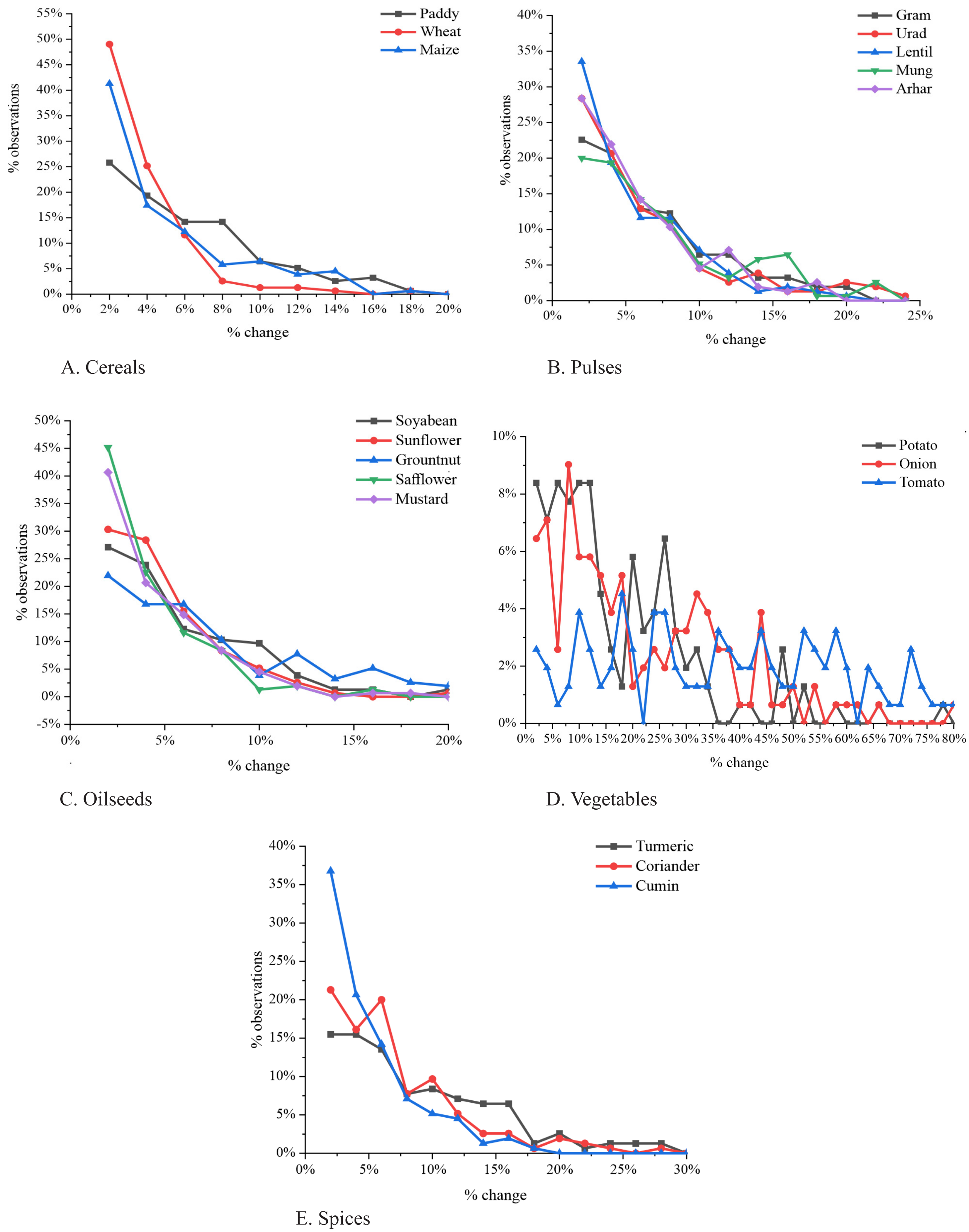


Figure 2. Distribution of absolute percentage change from month-to-month in selected agricultural commodities

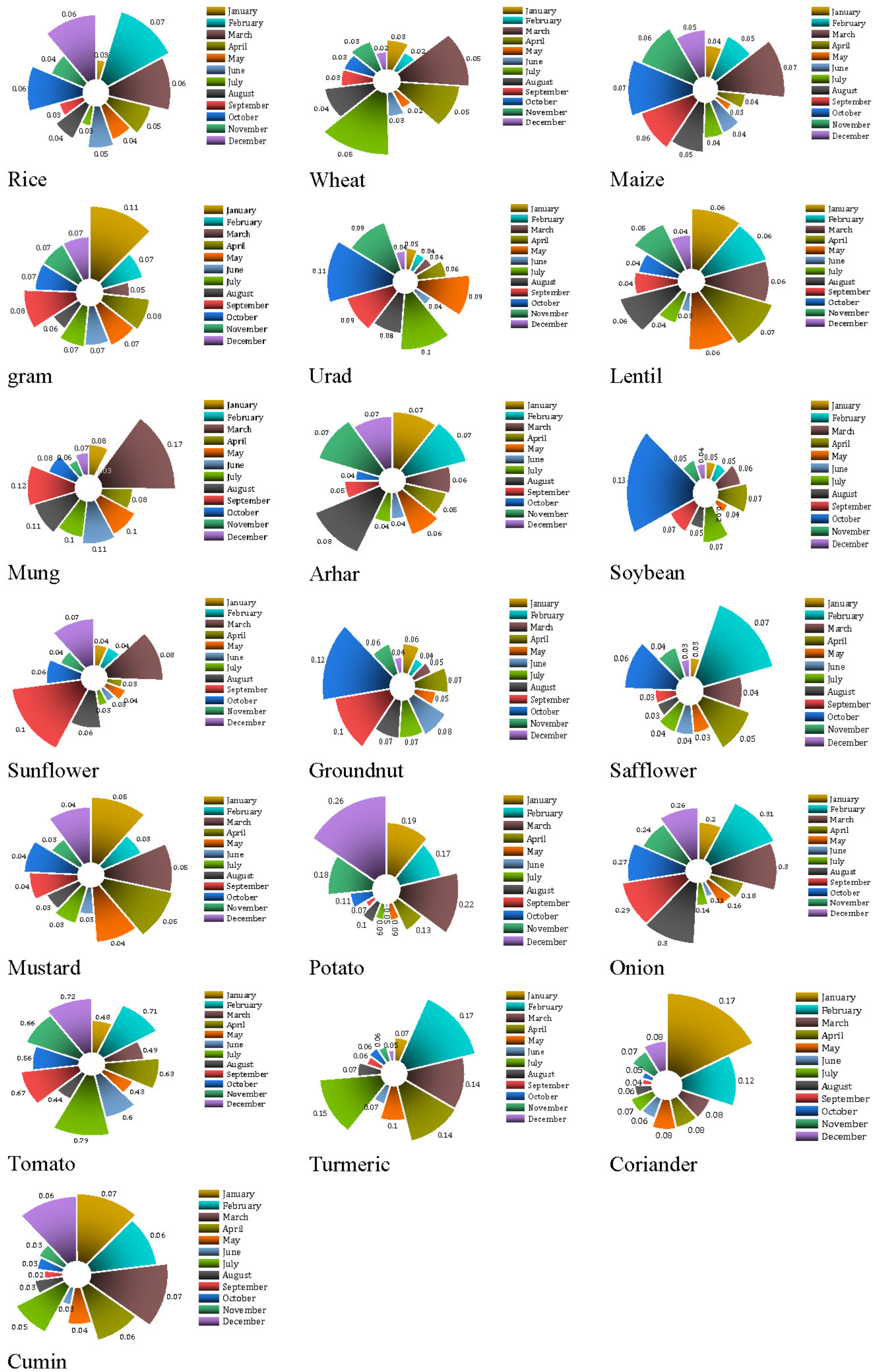


Figure 3. Months of high and low price volatility in different agricultural commodities in India

Table 2 Price seasonality in agricultural commodities

Commodity	Estimated seasonal gap (%)	Seasonal R^2 (%)	Commodity	Estimated seasonal gap (%)	Seasonal R^2 (%)
Paddy	4.90	0.79	Groundnut	18.84	7.71
Wheat	5.20	0.95	Safflower	3.56	0.23
Maize	8.85	1.84	Mustard	13.65	2.67
Gram	13.93	2.50	Turmeric	36.48	19.99
Urad	4.84	0.25	Coriander	4.43	0.17
Lentil	9.10	1.35	Cumin	6.39	1.32
Mung	3.87	0.40	Potato	70.43	25.54
Arhar	2.19	0.08	Onion	80.21	26.33
Soybean	9.58	1.13	Tomato	55.82	16.19
Sunflower	2.86	0.15			

of troughs in gram and lentil, respectively. Similarly, for vegetables, the price seasonality in onion, potato, and tomato was higher at 80.21 per cent, 70.43 per cent, and 55.82 per cent, respectively. In the case of oilseeds, groundnut, mustard and soybean witnessed 18.84 per cent, 13.65 per cent and 9.58 per cent higher prices, respectively during peaks; and in spices, turmeric has depicted 36.48 per cent higher prices in peaks than in troughs.

The contribution of seasonality to overall price volatility, as measured by seasonal R^2, indicated that the contribution of seasonality ranges from 0.15 to 26.33 and it was highest in vegetables (TOP) and turmeric (Table 2). This highlights that there are other sources of domestic price volatility in agricultural commodities.

Effect of arrivals, rainfall, and Covid-19 on prices of agricultural commodities

It is important to understand the effect of market arrivals and rainfall shocks on the prices of agricultural commodities. The fixed effect regression on panel data of market prices for different commodities was estimated to decipher the effect of rainfall shocks, market arrivals, and the Covid-19 pandemic on the prices of selected commodities. The results are presented in Table 3.

The results of the fixed effect model (panel of 22 paddy markets, 14 wheat markets, and 7 maize markets) revealed that the coefficient of arrivals, though very low, has a significant impact with a negative sign on paddy (-0.060) and maize (-0.007), as expected, indicating that the prices of cereals decrease with increase in their arrivals. The coefficient of three-month lag rainfall has shown a significant positive impact on the prices of paddy (0.011) and wheat (0.005), reflecting that the shock of 3-month lagged rainfall increased the paddy and wheat prices. More importantly, the effect of shock due to Covid-19 has been found significant and positive on the prices of agri-commodities, indicating that prices of cereals increased post-pandemic. The maize prices were not affected by rainfall shocks. Among the three cereals, the magnitude of coefficient due to Covid-19 shock was highest in paddy (0.220), followed by wheat (0.196) and maize (0.150). Thus, the volatility in prices of foodgrain crops has increased briefly post-pandemic.

The results of the fixed effect model for oilseeds revealed that rainfall of the current month has a significant positive effect on the prices of soybean (0.011) and groundnut (0.030) and three-month lag rainfall has depicted a significant positive impact on the prices of mustard (0.009). The rainfall has shown no significant effect on the prices of sunflower and safflower. The market arrivals have revealed a significant and negative effect on the prices of soybean and mustard, while the coefficient turned out to be positive and significant in the case of sunflower and groundnut. The shock due to Covid-19 has been found significant and positive for the prices of all oilseeds, indicating increases in oilseeds prices post-pandemic. It is seen that the prices of soybean, sunflower, and mustard increased by more than 40 per cent; the prices

Table 3 Fixed effect model estimates for prices of agricultural commodities

Variables	Cereals			Pulses				
	Paddy	Wheat	Maize	Gram	Urad	Lentil	Mung	Arhar
Intercept	7.879***	7.347***	7.217***	8.033***	8.465***	8.438***	8.545***	8.178***
	(0.023)	(0.021)	(0.031)	(0.047)	(0.037)	(0.047)	(0.028)	(0.033)
Rainfall	0.004	0.001	0.001	0.009	-0.001	0.013	0.001	0.012
	(0.003)	(0.002)	(0.004)	(0.007)	(0.006)	(0.004)**	(0.005)	(0.004)**
Rainfall Lag 1	-0.0004	0.0003	0.0004	0.0095	-0.0014	0.0029	-0.0009	0.0059
	(0.0036)	(0.0025)	(0.0053)	(0.0079)	(0.0074)	(0.0048)	(0.0059)	(0.0049)
Rainfall Lag 2	0.001	0.001	0.005	0.010	0.005	0.006	0.005	0.003
	(0.004)	(0.003)	(0.005)	(0.008)	(0.007)	(0.005)	(0.006)	(0.005)
Rainfall Lag 3	0.0109***	0.0045*	-0.0075	0.0159*	0.0132*	0.0039	0.0074	0.0057
	(0.0031)	(0.0022)	(0.0043)	(0.0065)	(0.0062)	(0.0043)	(0.0052)	(0.0044)
Arrivals	-0.060***	-0.004	-0.007*	0.011	-0.020**	-0.042***	-0.019***	0.019***
	(0.003)	(0.002)	(0.003)	(0.007)	(0.006)	(0.007)	(0.005)	(0.004)
Covid-19 shock	0.220***	0.196***	0.150***	0.122***	0.177***	0.354***	0.201***	0.226***
	(0.015)	(0.010)	(0.017)	(0.033)	(0.031)	(0.021)	(0.024)	(0.020)
R^2	0.2114	0.1656	0.0834	0.12	0.0643	0.3497	0.1164	0.1094
Adj-R^2	0.2099	0.1631	0.0777	0.1124	0.0577	0.3441	0.1088	0.1056

	Vegetables			Oilseeds				
	Potato	Onion	Tomato	Soybean	Sunflower	Groundnut	Safflower	Mustard
Intercept	6.492***	6.890***	5.698***	8.130***	8.033***	8.075***	7.951***	8.209***
	(0.106)	(0.12)	(0.162)	(0.04)	(0.018)	(0.042)	(0.034)	(0.033)
Rainfall	0.021**	-0.006	0.019	0.011**	0.001	0.030***	0.005	0.001
	(0.008)	(0.009)	(0.017)	(0.004)	(0.004)	(0.008)	(0.006)	(0.003)
Rainfall Lag 1	0.029***	0.033**	0.039	-0.001	-0.001	0.002	0.004	0.002
	(0.009)	(0.010)	(0.020)	(0.004)	(0.004)	(0.009)	(0.008)	(0.003)
Rainfall Lag 2	0.032***	0.058***	0.021	0.003	-0.0004	-0.001	0.001	0.006
	(0.009)	(0.010)	(0.020)	(0.004)	(0.0042)	(0.009)	(0.008)	(0.003)
Rainfall Lag 3	0.025**	0.076***	-0.008	-0.003	0.001	0.004	0.003	0.009**
	(0.008)	(0.009)	(0.017)	(0.004)	(0.004)	(0.008)	(0.007)	(0.003)
Arrivals	-0.019	-0.036**	0.152***	-0.013**	0.008*	0.023***	-0.011	-0.016***
	(0.01)	(0.012)	(0.019)	(0.005)	(0.003)	(0.005)	(0.008)	(0.004)
Covid-19 shock	0.542***	0.433***	-0.024	0.412***	0.413***	0.363***	0.356***	0.446***
	(0.036)	(0.039)	(0.074)	(0.016)	(0.013)	(0.033)	(0.026)	(0.014)
R^2	0.306	0.363	0.117	0.356	0.532	0.132	0.361	0.497
Adj-R^2	0.302	0.360	0.110	0.352	0.528	0.127	0.352	0.495

	Spices		
	Turmeric	Coriander	Cumin
Intercept	8.918***	8.295***	9.396***
	(0.076)	(0.091)	(0.029)
Rainfall	-0.026*	0.010	-0.0001
	(0.011)	(0.008)	(0.005)
Rainfall Lag 1	-0.009	-0.002	0.004
	(0.014)	(0.009)	(0.006)
Rainfall Lag 2	-0.014	0.005	-0.0004
	(0.014)	(0.009)	(0.006)
Rainfall Lag 3	-0.008	0.017*	0.006
	(0.011)	(0.008)	(0.005)
Arrivals	0.014	0.023	0.010*
	(0.010)	(0.012)	(0.004)
Covid-19 shock	-0.066	0.158***	-0.060**
	(0.045)	(0.036)	(0.023)
R^2	0.1808	0.0705	0.029
Adj-R^2	0.1629	0.0589	0.0149

Notes Standard errors are shown within the parentheses. *, **, and *** denote significance at 10 per cent, 5 per cent and 1 per cent levels, respectively.

of groundnut and safflower increased by more than 35 per cent after 2020 as compared to the average prices before 2020, despite the increase in production of oilseeds in the country, maybe due to high and volatile international prices of edible oils.

The fixed effect model results have shown that rainfall of the current month has a significant positive effect on the prices of lentil (0.013) and arhar (0.012) and the rainfall of lag three has a significant positive impact on the prices of gram (0.0159) and urad (0.0132). The rainfall has shown no significant effect on the mung prices. As expected, the market arrivals have revealed a significant negative effect on the price of pulses, except for arhar. The shock due to Covid-19 has been found significant and positive for the prices of all the pulses, with the highest effect on lentil (0.354) and the lowest on gram (0.122).

For explaining variations in potato prices, the rainfall for the current and past three months has shown a significant positive impact. For onion, rainfall of the past three months has a significant positive impact, but the rainfall of the current months has shown no effect on its prices. Neither the current month nor lagged rainfall has shown any significant impact on the prices of tomato. As far as Covid-19 shock is concerned, prices of onion (0.433) and potato (0.542) were highly affected, but there was no effect on tomato prices. The market arrivals of onion had a significant and negative effect on its price (-0.036), while a positive and significant effect in the case of tomato (0.152).

The fixed effect model results have revealed a negative effect of rainfall of the current month (-0.026) on the prices of turmeric. For coriander, rainfall of lag three months (0.017) has shown a significant positive effect. Though, cumin prices were not at all affected by the rainfall. Interestingly, due to Covid-19 shock, the coriander price increased, the cumin price decreased, but the turmeric price had no effect.

The results revealed that the price volatility was higher for perishable vegetables and, in general, has increased over time. Shekhar et al. (2018) have reported a high volatility in the prices of fruits and vegetables, having high income elasticity of demand, but with limited processing and storage facilities, as compared to the commodities with steady imports. High volatility in perishables may be due to weather aberrations affecting more to the supply dynamics of perishables (Kishore and Shekhar 2022). Seasonality in production and consumption also plays a role in the price dynamics of food commodities. Although, commodity prices respond to market arrivals, rainfall (up to three lags) also affects the prices of many food commodities, particularly *kharif* crops which are grown mainly under the rainfed conditions. Seasonality in prices drives the intertemporal price wedge, and depends on the storage cost and inter-temporal arbitrage in storable commodities (Gilbert et al. 2017; Burke et al. 2019). Inter-temporal arbitrage may vary, depending on the storage and transaction cost, market power, credit & liquidity constraints, and infrastructure availability which derives a price wedge between two time periods. The market prices are affected by weather shocks through traders' expectation channel and supply shocks (Letta et al. 2022). These prices have become more volatile after covid-19 pandemic. Kishore and Shekhar (2022) have also reported that price volatility increased during 2019-21, despite record production of foodgrains and horticultural commodities.

Conclusions and implications

The price volatility pattern has indicated the periods of ups and downs in prices of agricultural commodities, however, it differs across commodities. The volatility in prices of vegetables has been found higher, followed by oilseeds and pulses. The price volatility is high in the commodities having higher income elasticity of demand, and limited storage and processing facilities (Shekhar et al. 2018). The seasonality pattern shows the peaks during the pre-harvest and harvest periods and troughs during the post-harvest period. The three-month lag rainfall has shown a positive effect on the prices of many commodities and the current month rainfall on prices of some oilseeds and pulses. Breeding and popularising abiotic stress-tolerant varieties of crops would help stabilize production and reduce market price volatility.

The market arrivals have been found to be negatively affecting the prices of most of the agri-commodities. The improved infrastructure and competition at *mandies* may tempt farmers to bring more produce to these markets rather than selling to village traders. The Covid-19 shock has affected the prices of the majority of commodities briefly, vegetables were most affected, followed by oilseeds, pulses, and cereals. The Covid-19 shock had induced a sudden change in the prices of almost all the crops, but the effect on the volatility was not that significant. Also, the effect of shock persisted for a short-term and the prices became consistent in the long-run.

Integration and strengthening of post-harvest value chain institutions and related infrastructure, and increasing of competition in the markets would help integrate markets and reduce price volatility. Easy access to symmetric market information to all the stakeholders, including farmers, monitoring the markets and commodity uses would help make informed decisions and manage price volatility. This calls for the strengthening of the agricultural market intelligence system in the country.

References

Bartlett's, M S and D G Kendall. 1946. The Statistical Analysis of Variance Heterogeneity and the Logarithmic Transformation, *Journal of the Royal Statistical Society* 8(1):128–138.

Birthal, P, A Negi and P K Joshi. 2019. Understanding causes of volatility in onion prices in India. *Journal of Agribusiness in Developing and Emerging Economies* 9(3): 255-275. https://doi.org/10.1108/JADEE-06-2018-0068.

Bollerslev, T. 1986. Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics*, 31(3): 307-327. https://doi.org/10.1016/0304-4076(86)90063-1.

Burke, M, Lauren F Bergquist and E Miguel. 2019. Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets. *Quarterly Journal of Economics* 134(2): 785–842. https://doi.org/10.1093/qje/qjy034.

Cummings, R W. 2012. Experience with managing foodgrains price volatility in Asia. *Global Food Security* 1(2): 150-156. https://doi.org/10.1016/j.gfs.2012.10.005.

Díaz-Bonilla, E. 2016. *Volatile Volatility: Conceptual and Measurement Issues Related to Price Trends and Volatility*. In: *Food Price Volatility and Its Implications for Food Security and Policy,* eds. M Kalkuhl, J von Braun, and M Torero. Springer, Cham. https://doi.org/10.1007/978-3-319-28201-5_2.

Emediegwu, L E and O O Nnadozie. 2023. On the effects of COVID-19 on food prices in India: a time-varying approach, *European Review of Agricultural Economics* 50(2): 232–249. https://doi.org/10.1093/erae/jbac015.

Ghysels, E. and D R Osborn. 2001. *The Econometric Analysis of Seasonal Time Series*, Cambridge University Press, Cambridge.

Gilbert, C L and C W Morgan. 2010. Food price volatility. *Philosophical Transactions of the Royal Society B* 365: 3023–3034. https://doi.org/10.1098/rstb.2010.0139.

Gilbert, C L, L Christiaensen and J Kaminski. 2017. Food Price Seasonality in Africa: Measurement and Extent. *Food Policy* 67: 119–32. https://doi.org/10.1016/j.foodpol.2016.09.016.

Harvey, A C and R G Pierse. 1984. Estimating Missing Observations in Economic Time Series. *Journal of the American Statistical Association* 79:125-131. https://doi.org/10.1080/01621459.1984.10477074.

Kalkuhl, M, Joachim von Braun and M Torero. 2016. *Food Price Volatility and Its Implications for Food Security and Policy*. Springer Cham. https://doi.org/10.1007/978-3-319-28201-5.

Kishore, V and H Shekhar. 2022. Extreme weather events and vegetable inflation in India. *Economic and Political Weekly* 57(44-45): 65-74.

Letta, M, P Montalbano and G Pierre. 2022. Weather Shocks, Traders' Expectations, and Food Prices. *American Journal of Agricultural Economics 104(3):* 1100–1119. https://doi.org/10.1111/ajae.12258.

Mahajan, K and S Tomar. 2021. COVID-19 and Supply Chain Disruption: Evidence from Food Markets in India. *American Journal of Agricultural Economics* 103:35-52. https://doi.org/10.1111/ajae.12158.

Minot, N. 2014. Food Price Volatility in sub-Saharan Africa: Has it Really Increased? *Food Policy* 45: 45–56. doi:10.1016/j.foodpol.2013.12.008.

Narayanan, S and S Saha. 2021. Urban food markets and the COVID-19 lockdown in India. *Global Food Security* 29:100515. https://doi.org/10.1016/j.gfs.2021.100515.

Paul, R K and Md Yeasin. 2022. COVID-19 and prices of pulses in Major markets of India: Impact of nationwide lockdown. *PLoS ONE* 17(8): e0272999.

Paul, R K and P S Birthal. 2021. The prices of perishable food commodities in India: the impact of the lockdown. *Agricultural Economics Research Review* 34(2):151-164

Shekhar, C S C, D Roy and Y Bhatt. 2018. Food inflation and volatility in India: trends and determinants. *Indian Economic Review* 53: 65-91.

Received 30 June 2023 Accepted 12 September 2023

Agricultural Economics Research Review 2023, 36 (2), 189-199
DOI: 10.5958/0974-0279.2023.00032.0

Income diversity of agricultural households in Punjab and its determinants: Evidence from the NSSO surveys

Souradipta Das[1], Kamal Vatta[2]* and Laishram Priscilla[2]

[1]Institute of Rural Management Anand (IRMA), Anand, Gujarat 388001, India
[2]Department of Economics and Sociology, Punjab Agricultural University, Ludhiana, Punjab 141004, India

*Corresponding author: kmlvatta@yahoo.com

Abstract The present study has identified the extent and pattern of income diversification, the factors affecting it, and the impact of income sources on inequality among agricultural households in the state of Punjab. The study has found widespread income inequality among various categories of rural households. The relationship between income diversification and rural household income has pointed towards distress diversification by the relatively poor households. During the period 2002-03 to 2018-19, the semi-medium agricultural households have diversified more. From 2002-03 to 2012-13, the large and small farmers became more specialized, but from 2012-13 to 2018-19, they diversified again. The diversification of rural household income has been found to be significantly influenced by non-farm income, landholding size, and irrigation facilities. The crop income has been found to be inequality inducing and has contributed maximum to income inequality. However, income from livestock, wages, and salaries are found to be viable options for reducing the income inequality.

Keywords Income diversity, income inequality, NSS Survey, agricultural households, Punjab

JEL codes D31, D63, O15

Introduction

A household usually relies on multiple income sources, which may be the result of several push or pull factors. The push factors emerge from the risks and the declining factor returns from a single income source, and land fragmentation (Barrett, Reardon, and Webb 2001) and force the household to diversify towards less remunerative sources for supplementing their low incomes. Such factors dominate in the rural areas of developing economies, where the poor are unable to generate sufficient income from the farming as their major activity. The pull factors arise from the complementarity between farm and non-farm sectors and generate more remunerative income opportunities. Such factors are essential to realise sustainable and equitable growth of the rural economy. The diversity of income may considerably reduce household income inequality, particularly in the developing economies (Clay, Kampayana, and Kayitsinga 1997; Lanjouw 1998). While such diversification has improved household incomes and lifted households out of poverty line in many cases (Minot et al. 2006; Vatta and Sidhu 2007), it has not happened in others. The poor households with relatively less human capital and physical endowments diversify to less remunerative activities emerging out of distress. However, relatively more affluent households have access to better human and physical capital and could appropriate more productive and lucrative employment and income opportunities (Lanjouw and Lanjouw 2001). The access to less or more productive income sources also varies across caste and land ownership categories (Vatta and Sidhu 2007).

After witnessing a stupendous growth in agricultural production and productivity till the 1990s, the rural economy of the state of Punjab is witnessing a slowdown (Singh and Singh 2002; Vatta and Sidhu 2010). The stagnation in productivity, rising input costs, and a slower rise in output prices are affecting agricultural profitability and thereby household incomes (Srivastava, Chand, and Singh 2017). The state has been unable to diversify fast towards the industrial and service sectors and to shift the rural workers to more profitable non-farm employment. Most of the employment in the past has been distress-driven (Vatta and Sidhu 2007). There is a need to identify the potential employment sources which can boost the economic growth of the rural economy.

The present study aims to examine the pattern and extent of income diversity among the agricultural households in the state of Punjab. It also analyses the determinants of income diversification and their effect on income distribution to help the policymakers to develop a suitable livelihood strategy for the rural Punjab.

Materials and methods

Data

This study is based on the unit-level data from three rounds (59th, 70th, and 77th rounds) of the National Sample Survey Office (NSSO) on the situation assessment of agricultural households. The 59th round of 2002-03 was named 'Situation Assessment Survey of Farmer Households in India' and the later rounds of 2012-13 (70th round) and 2018-19 (77th round) were named 'Situation Assessment of Agricultural Households in India'. These surveys cover all the states and around 43000 agricultural households on an average. Our study used only the unit-level data on the agricultural households in Punjab. The 59th round covered 1279 'farmer households' from 164 villages, the 70th round covered 725 'agricultural households' from 94 villages and the 77th round included 889 'agricultural households' from 122 villages in Punjab. Due to the change in the definition of sampling unit, there are comparability issues between the 59th round and the 70th and 77th rounds. In the 59th round, a 'farmer' is defined as a person who owned land and was engaged in the agricultural activities during the past 365 days and a household with at least one farmer member was classified as a 'farmer household'. However, in the subsequent rounds, an 'agricultural household' had at least one member of the household self-employed in agriculture and had a total value of the produce above ₹ 3000 (70th round) and ₹ 4000 (77th round). As no income cut-off was provided in the 59th survey, we proceeded with making the data comparable by including households with an income corresponding to ₹ 3000 at 2012-13 prices. We calculated that amount to be ₹ 1405.81 at 2002-03 prices using the All India Consumer Price Index - Agricultural Labourers (CPI-AL) as a price deflator and utilized this as the cut-off. This filter droped 52 households from the 59th round survey out of the 1279 households for the Punjab state. Further, to ensure the comparability of income values across the rounds, CPI-AL was used to deflate the 2012-13 and 2018-19 survey values to 2002-03 prices. The data was scrutinized for the errors and outliers and households who had no access to land, either owned or leased-in, but had registered farm incomes and those who reported unusually low or high farm income that was not related to their farm size, were omitted from the study.

Analytical techniques

Income diversification

There were four major income sources: crop farming, livestock, wages and salaries, and non-farm business. To measure income diversity we used the Simpson Index of Diversity (SID) due to its computational simplicity, robustness, and broad applicability. It was estimated as per Equation (1):

$$SID=1-\sum_{i=1}^{n} p_i^2 \qquad \ldots(1)$$

Where, n is the total number of income sources and p_i is the proportion of income derived from the i^{th} source. The value of SID ranged from 0 to 1 with the value of zero reflecting complete specialization and a higher value approaching the unity reflecting income diversification.

Determinants of income diversification

Tobit regression (1958) was used to investigate the determinants of income diversification. The SID has a censored distribution, and it ranges between 0 to 1. The Tobit model (Greene 2004) was estimated as per Equation (2):

$$Y_t^* = X_t \beta + \varepsilon_t \qquad \ldots(2)$$

and $Y_t=0$ if $Y_t^* \le 0$

$Y_t = Y_t^*$ if $Y_t^* \geq 0$

where, ε_t is normally distributed with constant variance and zero mean; Y_t* is the SID; Age, dependency ratio, education, landholding, irrigated land, non-farm income, participation in agricultural training, and agro-climatic zone are the explanatory variables used in the model.

Gini coefficient and vertical decomposition of inequality

The income inequality can be measured using a variety of methods. We used two metrics in this study: the Gini coefficient and the Theil index (Charles-Coll 2011). The inequality can be decomposed vertically (i.e., between individuals and households) and horizontally (i.e., between groups). The vertical decomposition is estimated using Lorenz curves and the Gini coefficient, while the Theil index overcomes the disadvantage of ignoring horizontal decomposition.

Total income (*I*) consists of income from various *k* sources. Hence, the total income (*I*) for each household and also for the sample as a whole is given by Equation (3):

$$I = \sum_{k=1}^{k} I_k \quad \text{... (3)}$$

The Gini coefficient, which ranges from 0 to 1, measures how much a group's income deviates from a perfectly equal distribution. It is widely used and relatively simple to calculate and is more suitable for the visual representation and comparing populations of various sizes. The Gini coefficient can be computed using a Lorenz curve representation that plots cumulative income vs. cumulative population. It can also be measured mathematically by relation (4):

$$G = cov\,(y, F(y)\,\frac{2}{\bar{y}}) \quad \text{... (4)}$$

cov denotes the covariance between income levels *y* and the cumulative distribution of the same income *F(y),* and $\bar{y}$ represents the average income.

As an extension of earlier income decomposition theories, Lerman and Yitzhaki (1985) developed a method to decompose the Gini coefficient as the sum of inequality contributions of all the income sources (Shorrocks 1982) (Equation 5):

$$G = \sum_{k=1}^{k} S_k\, G_k\, R_k \quad \text{...(5)}$$

where, G_k denotes the Gini coefficient of income from source *k*, and R_k represents the correlation coefficient between income from source *k* and the total income *I*. S_k is the share of income source *k* in the total income. G_kR_k denotes the pseudo-Gini coefficient of income source *k* (Shorrocks 1983).

With an increase in the product of these three elements, the contribution of income from source *k* to overall income inequality rises. The value of R_k can fall anywhere on the interval (–1,1), while S_k and G_k are always positive and less than one (Leibbrandt, Woolard, and Woolard 2000).

The partial derivatives of the Gini coefficient for a percentage change *e* in income source *k (ek)* are derived using this Gini coefficient decomposition for total income to estimate the percentage change in overall inequality induced by a modest percentage change in income source *k* as per Equation (6):

$$\frac{\delta G}{\delta e_k} = S_k(R_k G_k - G) \quad \text{...(6)}$$

Then, the marginal effect of income source relative to the overall Gini is obtained by dividing Eq. (6) by the overall Gini coefficient (*G*):

$$\frac{\delta G/\delta e_k}{G} = \frac{S_k R_k G_k}{G} - S_k \quad \text{... (7)}$$

The marginal effect property helps to determine whether each income source has an equalizing or opposite effect on the total inequality (López-Feldman 2006). If an income source favours the rich (R_k is positive and large), it may induce more inequality and if it favours the poor, an inequality-decreasing impact may happen. Bootstrapping methods have been used to measure the marginal effect's robustness (Choudhary and Singh 2019). However, the Gini coefficient does not meet the aggregative and additive decomposability requirements (Bourguignon 1979). Theil index overcomes this limitation by allowing it to measure discrimination within and within-population subgroups (Allison 1978).

Theil index and horizontal decomposition of inequality

Theil (1967) suggested a decomposable metric based on the Lorenz curve that could compare the disparity between groups and within groups. The Theil is a type of entropy indices that is a subset of generalized entropy indices (Bellù and Liberati 2006). Theil has no upper limit and has a lower value of 0 (perfect equality). The index is defined by Equation (8):

$$T = \frac{1}{n}\sum_i \frac{y_i}{\bar{y}} \ln\frac{y_i}{\bar{y}} \quad \ldots(8)$$

where, y_i is the i^{th} observation and $\bar{y}$ is the average income.

Further, assuming m groups, the Theil index is decomposed as per expression (9):

$$T = \sum_{k=1}^{m}\left(\frac{n_k}{n}\frac{\bar{y}_k}{\bar{y}}\right)T_k + \sum_{k=1}^{m}\frac{n_k}{n}\left(\frac{\bar{y}_k}{\bar{y}}\right)\ln\left(\frac{\bar{y}_k}{\bar{y}}\right) \quad \ldots(9)$$

The within-group and between-group components are described by the first and second terms of Eq. (9), respectively. Similarly, the Theil index can be decomposed by the source of income using the following formula (10) for m sources:

$$T = \sum_{k=1}^{m}\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y^k{}_i}{\bar{y}}\right)\ln\left(\frac{y_i}{\bar{y}}\right) \quad \ldots(10)$$

In our study, the Theil index was used to decompose inequality into within and between the landholding categories.

Negative income

The exclusion of negative income has been recommended by several researchers (Mussini, 2013). However, excluding households with negative or zero income from the current sample was not feasible since it would have left out many people or households. The constraint of negative or zero values can be solved, according to Bellù and Liberati (2006) and Vasilescu et al. (2011), by replacing zeros and negative income values with a minimal value, ε > 0. It was taken to be equivalent to 10^{-10} in this study.

Results and discussions

Composition of rural household incomes

On average, the annual income of a rural household (at 2002-03 prices) in Punjab increased from ₹81246 in 2002-03 to ₹98282 in 2012-13, and then to ₹101259 in 2018-19 (Table 1). The share of crop income in the total household income rose from 59.7 per cent in 2002-03 to 62.8 per cent in 2012-13 and then fell to 52.4 in 2018-19 (Table 1). The livestock income rose sharply from 2002-03 to 2018-19. Its share in the total household income was just 5.1 per cent in 2002-03, and it exceeded 18.5 per cent during 2018-19. The percentage of non-farm income decreased from 13.2 per cent to 4.2 per cent and those of from wages and salaries went up from 21.9 per cent to 24.9 per cent over the same period. Between 2002-03 and 2018-19, the household real income grew at the rate of 3.7 per cent per annum (Table 2). The pace of growth for various income sources was not uniform. While growth was the highest for livestock income, followed by wages and salary, it was the least for crops. On the other hand, the non-farm business income declined significantly by more than 14 per cent per annum. Further, the income growth was relatively slower during the second period (2012-13 to 2018-19) as compared to during the first period (2002-03 to 2012-13). This was also emphasized by Chand et al. (2015) and Sendhil et al. (2017). The livestock income, however, rose faster during the second period. The income pattern in Punjab reveals a relatively higher dependence of agricultural households on income from crops and livestock and much less on diversification towards non-farm business income.

Table 1 Real incomes of agricultural households and share of income sources of agricultural households in Punjab

(₹ / household/ annum)

Income source	2002-03	2012-13	2018-19
Crops	48521	61722	53040
	(59.7)	(62.8)	(52.4)
Livestock	4149	9488	18767
	(5.10)	(9.7)	(18.5)
Non-farm business	10736	4320	4268
	(13.2)	(4.4)	(4.2)
Wages and salary	17839	22751	25184
	(21.9)	(23.1)	(24.9)
Total Income	81246	98282	101259
	(100.0)	(100.0)	(100.0)

Figures within the parentheses indicate percentages of total income
Note The unit of income was measured in Indian Rupees at 2002-03 prices.

Distribution of real income of agricultural households

The pattern of relatively less income diversity in the

Table 2 Growth rates of real incomes of agricultural households in Punjab: 2002-2019

Income source	Growth rate		
	2002-2013	2012-2019	2002-2019
Crop	2.4	-2.5	1.5
Livestock	8.6	12.0	28.6
Non-farm business	-8.7	-0.2	-14.3
Wages and salary	2.5	1.7	5.9
Total income	1.9	0.5	3.7

Note The unit of income was measured in Indian Rupees at 2002-03 prices.

agricultural households of Punjab has not depicted much change during 2002-03 and 2018-19 (Table 3). Almost one-quarter the of agricultural households did not earn anything from crop production and lost money on livestock rearing. The livestock income, however, improved sharply from 2012-13 to 2018-19. As these households were unable to earn income from wages and salaries and non-farm business, there seemed a serious issue with the economic viability of such households. It was only the upper strata of the agricultural households, which could derive income from all the sources such as crops, livestock, wages/ salaries, and non-farm business. The non-farm business income was found accessible only to 5 per cent of the richest households, which are likely to possess more land, capital, and other relevant skills for earning such income. The top 1 per cent of the agricultural households earned more than nine times the average income of the bottom 50 per cent of the agricultural households during 2002-03 and 2012-13 but the ratio declined to about 6.5 during 2018-19, which points towards some improvement in the income distribution in recent times.

Household income diversification and its determinants

The income diversification of agricultural households was measured using the Simpson Index of Diversity (SID). The SID for Punjab increased slowly from 0.21 in 2002-03 to 0.22 in 2012-13 and finally to 0.30 during 2018-19 (Figure 1). The low income-diversity of agricultural households in Punjab is due to higher dependence on crop production as a source of income. Vatta et al. (2018) also classified Punjab as a high-income outlier and a low-income diversification state, which is in line with the findings of our study.

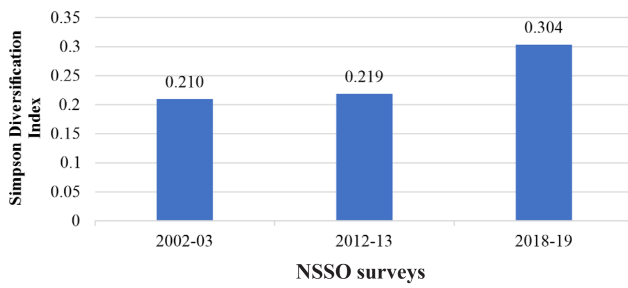


Figure 1 Simpson Index of Diversification for the three rounds of NSSO surveys

Table 3 Percentile distribution of real incomes across agricultural households in Punjab during 2002-03, 2012-13 and 2018-19

(₹ / household/ annum)

Percentile (%)	Crop			Livestock			Non-farm business			Wages and salary			Total income		
	2002-03	2012-13	2018-19	2002-03	2012-13	2018-19	2002-03	2012-13	2018-19	2002-03	2012-13	2018-19	2002-03	2012-13	2018-19
1	-	-2399	-5154	-46860	-35145	-8000	-	-	-	-	-	-	-10849	-25590	1032
5	-	-	0	-23700	-13214	-1053	-	-	-	-	-	-	1920	468	13049
10	-	-	0	-14460	-8641	0	-	-	-	-	-	-	9740	9864	24561
25	-	-	0	-5100	-1077	3172	-	-	-	-	-	-	23400	25906	40081
50	7955	10777	22140	1800	4404	12632	-	-	-	-	-	-	52750	56405	67460
75	58580	83762	63245	9300	15613	24168	-	-	-	25480	29053	36491	101390	117584	119389
90	138940	177769	154665	22800	28608	46316	44736	-	-	52728	58106	63158	179025	250592	231137
95	233529	261471	219460	35700	39597	68140	69456	36082	32561	78000	117150	108772	274310	327553	324709
Mean	48521	61722	53040	4149	9488	18767	10736	4320	4268	17838	22750	25184	81246	98282	101259
S. E	(90562)	(54881)	(96906)	(28242)	(4446)	(26458)	(33183)	(10543)	(25855)	(31947)	(21235)	(48382)	(103126)	(64994)	(111364)

Note Figures within the parentheses are standard errors

The rural household income diversification in Punjab was found to be significantly impacted by factors such as age of household-head, non-farm income, landholding size and irrigated area. The income diversity was directly and significantly correlated with the age of household-head. The number of income sources increased with the age of a household head. It seems that experience and expertise accumulated over time by the head of a household helped him/her to gain from more number of income sources. Similar results were reported by Pavithra and Vatta (2013) and Birthal et al. (2014).

The farm size and irrigated area, which were used as proxies for agricultural capacity, have revealed a significant impact on the degree of income diversification (Table 4). The farm households with larger irrigated area were likely to have less diverse income sources, showing more dependence on agricultural production. Alobo (2012) has also reported similar results. Also, large farm households were more likely to diversify. The income diversification of agricultural households was significantly higher than those in the southwestern and sub-mountainous zones in Punjab.

Contribution of income sources to income inequality

The Gini coefficient (G_k) was the highest for non-farm business (0.90 in 2002-03, 0.97 in 2012-13, and 0.98 in 2018-19), followed by G_k for livestock income in 2003-04 and income from wages and salary in 2012-

Table 4 Determinants of income diversification among agricultural households in Punjab

Particulars	2002-2003	2012-2013	2018-2019	2002-2019
log (Age)	0.08^{**}	0.07	-0.004	0.05^{***}
	(0.03)	(0.04)	(0.03)	(0.02)
Education	0.001	0.001	-0.01^{*}	-0.001
	(0.004)	(0.003)	(0.004)	(0.002)
Dependency ratio	-0.01	0.03	0.01	0.003
	(0.01)	(0.02)	(0.02)	(0.01)
Participation in agricultural training	-0.16^{*}	0.001	-0.05	-0.05
	(0.08)	(0.05)	(0.06)	(0.04)
Non-farm income source	0.17^{***}	0.20^{***}	0.17^{***}	0.18^{***}
	(0.02)	(0.04)	(0.03)	(0.02)
log (Landholding)	0.04^{***}	0.03^{***}	0.02^{**}	0.03^{***}
	(0.01)	(0.01)	(0.01)	(0.003)
log (Irrigated area)	-0.07^{***}	-0.06^{***}	-0.03^{***}	-0.05^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Sub-mountainous zones	0.06^{**}	-0.01	-0.02	0.02
	(0.03)	(0.03)	(0.02)	(0.01)
Central zones	0.07^{***}	-0.01	0.01	0.03^{**}
	(0.02)	(0.03)	(0.02)	(0.01)
Year 2002-03	-	-	-	-0.04
				(0.07)
Year 2012-13	-	-	-	-0.11^{***}
				(0.01)
Constant	0.19	-0.003	0.37^{***}	0.15^{*}
	(0.21)	(0.16)	(0.13)	(0.08)
Sigma value	0.28	0.26	0.22	0.26
Number of observations	1227	724	889	2840

Notes Figures within the parentheses indicate standard errors
Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

13 and 2018-19 (Table 5). It is worth noting that though the non-farm sector enables the poor to enhance their incomes, the barriers to entry into the productive activities lead to unequal distribution of gains. It does not mean that the income component with the highest inequality will contribute maximum to the total income inequality, as the share of income and distribution of the income would matter. Interestingly, although income from crop farming was almost equally distributed, it contributed maximum (68.4% in 2002-03, 80.5% in 2012-13, and 66.7% in 2018-19) to the total inequality, as it was a major source of income (S_k = 0.54 in 2002-03, 0.73 in 2012-13 and 0.28 in 2018-19). A higher correlation of crop farming with total income (R_k = 0.88 in 2002-03, 0.94 in 2012-13, and 0.85 in 2018-19) indicates that households above the total income strata derive more income from the cultivation of crops. The smallest value of Gini coefficient for wages and salaries (R_k = 0.28 in 2002-03, 0.30 in 2012-13, and 0.46 in 2018-19) indicates that the households in the poorest income quintile usually resort to distress activities and it causes a reduction in the overall income inequality. Choudhary and Singh (2019) have reported similar results for the state of Punjab.

Table 5 Decomposition of inequality by sources of income in Punjab during 2002-03, 2012-13, and 2018-19

Income source	NSSO Survey Rounds	S_k	G_k	R_k	Contribution of income source to total inequality	Gini income elasticity	Share in total Gini	Marginal contribution to Gini
Crops	2002-03	0.54	0.76	0.88	0.37	1.26	0.68	0.14^{**} (0.01)
	2012-13	0.73	0.64	0.94	0.44	1.11	0.81	0.09^{**} (0.02)
	2018-19	0.59	0.65	0.85	0.33	1.13	0.67	0.08^{**} (0.02)
Livestock	2002-03	0.11	0.78	0.62	0.05	0.90	0.09	-0.01^{***} (0.01)
	2012-13	0.13	0.72	0.63	0.06	0.83	0.11	-0.02^{**} (0.01)
	2018-19	0.19	0.60	0.63	0.07	0.76	0.15	-0.05^{***} (0.01)
Non-farm business	2002-03	0.14	0.90	0.58	0.07	0.98	0.14	-0.002^{***} (0.01)
	2012-13	0.04	0.97	0.54	0.02	0.95	0.04	-0.002^{***} (0.01)
	2018-19	0.04	0.98	0.68	0.03	1.36	0.05	0.01^{**} (0.01)
Wages and salary	2002-03	0.21	0.72	0.28	0.04	0.37	0.08	-0.13^{***} (0.01)
	2012-13	0.12	0.84	0.30	0.03	0.46	0.05	-0.06^{***} (0.01)
	2018-19	0.18	0.81	0.46	0.07	0.75	0.14	-0.05^{**} (0.01)
Total income	2002-03		0.53					
	2012-13		0.55					
	2018-19		0.49					

Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes Bootstrapped standard error with 50 replications is shown within the parentheses

The sudden increase in the value of Gini coefficient for non-farm income during 2018-19 suggests that such income is usually appropriated more by the higher-income quintile and thus, it increases income inequality. Tables 5 also shows that crop farming is also income inequality enhancing. Other factors being constant, 1 per cent increase in income from crop cultivation, increased the total inequality by 0.14 per cent in 2002-03, which decreased to 0.09 per cent in 2012-13 and then further decreased to 0.08 per cent in 2018-19. The income from livestock, wages and salaries contributed significantly to income inequality reduction in Punjab; it being higher during 2002-03 (Gini of 0.53), increased marginally during 2012-13 (Gini of 0.55), but declined considerably during 2018-19 (Gini of 0.49). The Gini income elasticity value of unity and above reflects inequality increasing income source; its value below unity reflects inequality reducing source and a unit value showing a neutral impact on income distribution. The non-farm income showed an inequality-reducing effect in 2002-03 and 2012-13 and inequality increasing impact in 2018-19. The change in effect may be due to the reduction in entry barriers to capital, knowledge, and education in the rural economy.

The empirical evidence on the effect of nonfarm income on rural income disparity is conflicting. According to Canagarajah et al (2001), this outcome may be related to the heterogeneity of the non-farm sector. According to Reardon and Taylor (1996) and Adams (2001), non-farm income creates inequality since it is unequally distributed in favour of the wealthy. The inequitable land distribution also results in non-farm income disparity. Adams (2001) observed that 'land,' is unevenly distributed and is crucial in determining non-farm income. Figures 2(a), 2(b), and 2(c) depict the uneven income distribution along with a 95 per cent confidence interval from all the four income sources. Pavithra and Vatta (2013) have reported similar results.

Apart from income source, the decomposition of inequality within and between the landholdings category was studied by using the Theil index. The value of Theil index was more for 'within' the periods than the corresponding 'between' values for animal farming, non-farm business, and wages & salary income sources (Table 6). Still, in the case of crop income, the value of Theil index was less for 'within' the periods than the corresponding 'between' values. The value of Theil index was more for 'within' the periods than the corresponding 'between' values for the total income in the year 2002-03 and 2018-19. It indicates that the intra-landholding inequality was the main contributor to total inequality in 2002-03 and 2018-19. So, during 2002-03 and 2018-19, the orientation of efforts within the landholding would be more imperative for smoothening the income inequality of agricultural households in the state of Punjab.

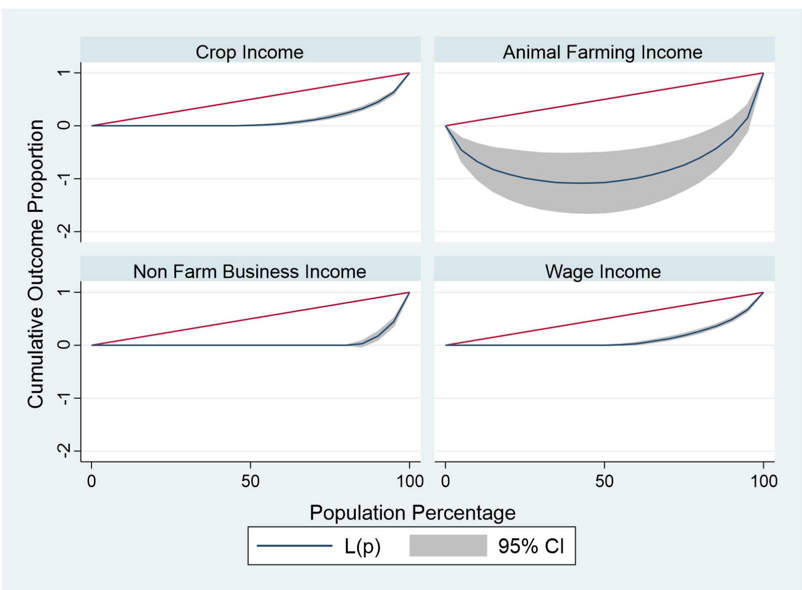


Figure 2 (a) Lorenz curves of income sources in 2002-03

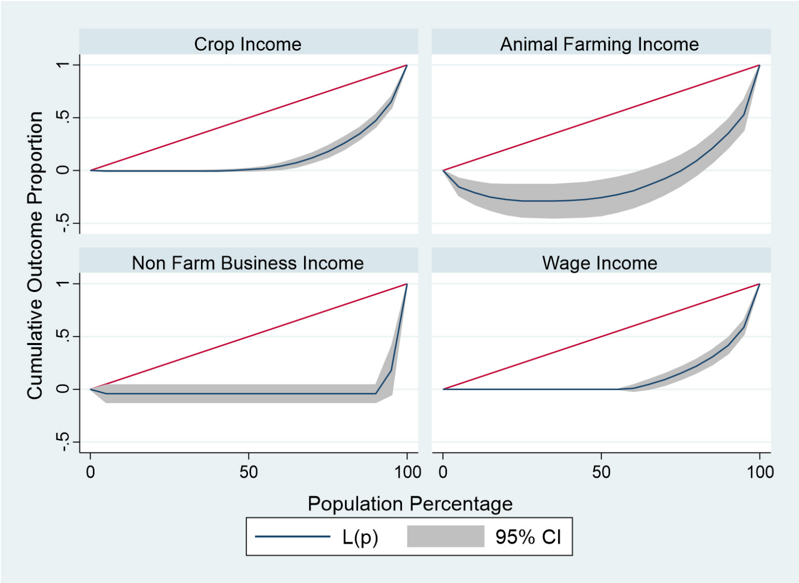


Figure 2 (b) Lorenz curves of income sources in 2012-13

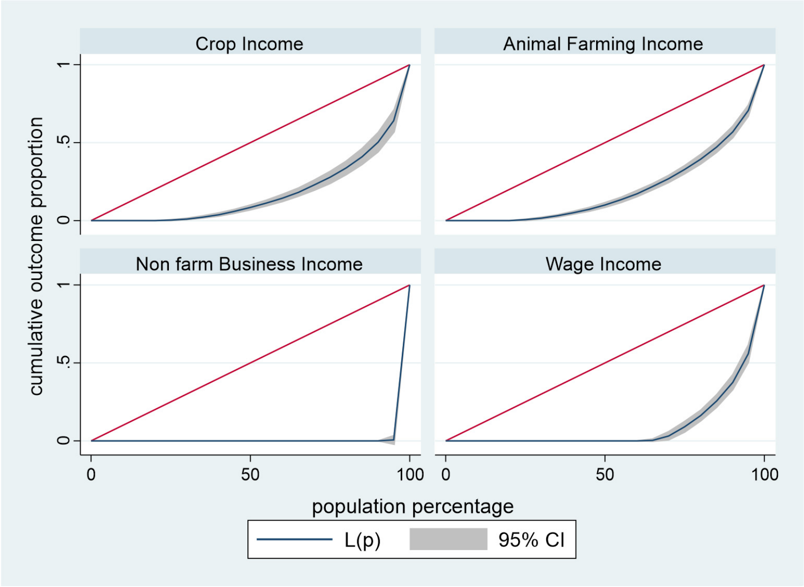


Figure 2 (c) Lorenz curves of income sources in 2018-19

Table 6 Theil index of inequality by different categories of agricultural households in Punjab

Source of income	2002-03		2012-13		2018-19	
	Between	Within	Between	Within	Between	Within
Crops	0.92	0.27	0.50	0.30	0.58	0.33
Livestock	0.15	1.30	0.33	1.10	0.10	0.59
Non-farm business	0.05	2.04	0.45	2.79	0.30	3.52
Wages and salary	0.09	0.95	0.05	1.53	0.06	1.38
Total income	0.26	0.26	0.31	0.27	0.24	0.26

Conclusions and policy implications

Rural households rely on a variety of income sources; the poor tend to sustain their livelihood and the rich try to further increase their already substantial earnings. The landholders depend mainly on crop and livestock income and the poor resort largely to less-remunerative activities. Due to distress, the poor are forced to diversify more than the richer households. The income from crop production is positively correlated with the size of landholding size, large farmers derive more income share from crop farming and hence, this group contributes the maximum to income inequality among agricultural households in Punjab. On the other hand, income from livestock, wages and salaries reduce income inequality.

This study has several important policy implications. As non-farm income is inequality reducing, the promotion of better education and skills in the rural areas, especially amongst the marginal and small farmers will improve access to non-farm employment, enhance household income and reduce income inequality. The strengthening of farm and non-farm linkages will further boost the employment. The rural households should be encouraged to participate more in secondary occupations such as poultry, aquaculture, goat husbandry, and mushroom production. The self-help groups can contribute significantly to the funding of such programs. An emphasis on the development of dairying, construction, manufacturing, and trade in the rural areas can boost employment opportunities and, as a result, income diversification.

References

Adams, R H. 2001. *Nonfarm income, inequality, and poverty in rural Egypt and Jordan*. Vol.2572, World Bank Publications.

Allison, P D. 1978. Measures of inequality. *American Sociological Review* 43(6): 865–880. https://doi.org/10.2307/2094626

Alobo, S. 2012. Determinants of rural household income diversification in Senegal and Kenya. Sfer. https://agritrop.cirad.fr/568230/1/document_568230.pdf

Barrett, C B, T Reardon, and P Webb. 2001. Nonfarm income diversification and household livelihood strategies in rural Africa: Concepts, dynamics, and policy implications. *Food Policy* 26 (4): 315-331. https://doi.org/10.1016/S0306-9192(01)00014-8

Bellù, L G, and P Liberati. 2006. Policy impacts on inequality: Decomposition of income inequality by subgroups. *EASYPol Module* 52. Available online: https://www.fao.org/3/am341e/am341e.pdf (accessed on 22 February 2023).

Birthal, P S, D S Negi, A K Jha, and D Singh. 2014. Income sources of farm households in India: Determinants, distributional consequences and policy implications. *Agricultural Economics Research Review* 27 (1): 37-48. https://doi.org/10.22004/ag.econ.170255

Bourguignon, F. 1979. Decomposable income inequality measures. *Econometrica: Journal of the Econometric Society* 47 (4): 901-920. https://doi.org/10.2307/1914138

Canagarajah, S, C Newman, and R Bhattamishra. 2001. Non-farm income, gender, and inequality: evidence from rural Ghana and Uganda. *Food policy* 26 (4): 405-420. https://doi.org/10.1016/S0306-9192(01)00011-2

Chand, R, R Saxena, and S Rana. 2015. Estimates and analysis of farm income in India, 1983–84 to 2011–12. *Economic and Political Weekly* 50 (22): 139–145. http://www.jstor.org/stable/24482496.

Charles-Coll, J A. 2011. Understanding income inequality: concept, causes and measurement. *International Journal of Economics and Management Sciences* 1 (3): 17-28. https://www.hilarispublisher.com/open-access/understanding-income-inequality-concept-causes-and-measurement-2162-6359-1-018.pdf

Choudhary, B B, and P Singh. 2019. How unequal is rural Punjab? Empirical evidence from spatial income distribution. *Current Science* 117 (11): 1855-1862. https://www.currentscience.ac.in/Volumes/117/11/1855.pdf

Clay, D C, T Kampayana, and J Kayitsinga. 1997. Inequality and the Emergence of Non-farm Employment in Rwanda. In *Changing rural social systems: adaptation and survival*, ed Johnson, Nan E., and Ching-li Wang: 93-130. Michigan State University Press, East Lansing, MI. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=f62ee9d43815c2dba43b890d37d27fd1e182c249

Greene, W. 2004. Fixed effects and bias due to the incidental parameters problem in the Tobit model. *Econometric reviews* 23 (2): 125-147. https://doi.org/10.1081/ETC-120039606

Lanjouw, P. 1998. The rural non-farm sector in Ecuador and its contribution to poverty reduction and inequality. Policy Research Working Paper, Development Economics Research Group, The World Bank, Washington, DC.

Lanjouw, J O, and P Lanjouw. 2001. The rural non farm sector: issues and evidence from developing countries. *Agricultural economics* 26 (1): 1-23. https://doi.org/10.1111/j.1574-0862.2001.tb00051.x

Leibbrandt, M, C Woolard, and I Woolard. 2000. The contribution of income components to income inequality in the rural former homelands of South Africa: a decomposable Gini analysis. *Journal of African Economies* 9 (1): 79-99. https://doi.org/10.1093/jae/9.1.79

Lerman, R I, and S Yitzhaki. 1985. Income inequality effects by income source: A new approach and applications to the United States. *The review of economics and statistics* 67 (1) : 151-156. https://doi.org/10.2307/1928447

Lopez-Feldman, A. 2006. Decomposing inequality and obtaining marginal effects. *The Stata Journal* 6 (1): 106-111. https://journals.sagepub.com/doi/pdf/10.1177/1536867X0600600107

Minot, N, E Michael, A T T Tram, and T L Quang. 2006. Income diversification and poverty in the Northern Uplands of Vietnam. Research reports 145, International Food Policy Research Institute (IFPRI). https://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/32830/filename/32831.pdf

Mussini, M. 2013. A matrix approach to the Gini index decomposition by subgroup and by income source. *Applied Economics* 45 (17): 2457-2468. https://doi.org/10.1080/00036846.2012.667553

Pavithra, S, and K Vatta. 2013. Role of Non-Farm Sector in Sustaining Rural Livelihoods in Punjab. *Agricultural Economics Research Review* 26 (2): 257-266. https://ageconsearch.umn.edu/record/162146/?ln=en#:~:text=The%20non%2Dfarm%20income%20sources,in%20relatively%20less%2Dremunerative%20activities.

Reardon, T, and J E Taylor. 1996. Agroclimatic shock, income inequality, and poverty: Evidence from Burkina Faso. *World Development* 24 (5): 901-914. https://doi.org/10.1016/0305-750X(96)00009-5

Reardon, T, J Berdegué, C B Barrett, and K Stamoulis. 2007. Household income diversification into rural nonfarm activities. In Transforming the rural nonfarm economy: opportunities and threats in the developing world (S. Haggblade, P. B. R. Hazell & T. Reardon, eds.), The John Hopkins University Press, Baltimore. http://barrett.dyson.cornell.edu/Papers/IFPRIbookchapter2006Final.pdf

Sendhil, R, P Ramasundaram, and S J Balaji. 2017. Transforming Indian agriculture: Is doubling farmers' income by 2022 in the realm of reality. *Current Science* 113 (5): 848-850. https://www.currentscience.ac.in/Volumes/113/05/0848.pdf

Shorrocks, A F. 1982. Inequality decomposition by factor components. *Econometrica: Journal of the Econometric Society* 50 (1): 193-211. https://doi.org/10.2307/1912537

Shorrocks, A F. 1983. The impact of income components on the distribution of family incomes. *The Quarterly Journal of Economics* 98 (2): 311-326. https://doi.org/10.2307/1885627

Singh, L, and S Singh. 2002. Deceleration of economic growth in Punjab: Evidence, explanation, and a way-out. *Economic and Political Weekly* 37 (6): 579-586. https://www.jstor.org/stable/4411721

Srivastava, S K, R Chand, and J Singh. 2017. Changing crop production cost in India: Input prices, substitution and technological effects. *Agricultural Economics Research Review* 30, no. conf: 171-182. https://www.cabdirect.org/cabdirect/abstract/20183042842

Theil, H. 1967. Economics and information theory, Chap. 1. North-Holland Publishing Company, Amsterdam.

Vasilescu, B, A Serebrenik, and M V D Brand. 2011. You can't control the unfamiliar: A study on the relations between aggregation techniques for software metrics. In *2011 27th IEEE International Conference on Software Maintenance (ICSM)*, pp. 313-322. IEEE. https://ieeexplore.ieee.org/document/6080798

Vatta, K, and R S Sidhu. 2007. Income diversification among rural households in Punjab: dynamics, impacts and policy implications. *Indian Journal of Labour Economics* 50 (4): 723-736.

Vatta, K, and R S Sidhu. 2010. Rural non-farm employment, income distribution and poverty: Micro level evidence from Punjab. *Indian Journal of Agricultural Economics* 65 (4): 1-17 https://doi.org/10.22004/ag.econ.204720

Vatta, K, G.Singh, N Sharma, and P B Bhoi. 2018. Regional dimensions and determinants of income diversification in rural India. *Agricultural Economics Research Review*, *31*(conf), 33- 46. https://ageconsearch.umn.edu/record/281143

Received 4 August 2023 Accepted 24 November 2023

Agricultural Economics Research Review 2023, 36 (2), 201-212
DOI: 10.5958/0974-0279.2023.00033.2

Harnessing potential of legumes for sustainable intensification of Indian agriculture

Dinesh Chand Meena[1]*, Kiran Kumara TM[1] and Anjani Kumar[2]

[1]ICAR-National Institute of Agricultural Economics and Policy Research (NIAP), New Delhi 110012, India
[2]International Food Policy Research Institute, South Asia Office, New Delhi 110012, India

*Corresponding author: dineshbhu195@gmail.com

Abstract The inclusion of legumes in the cropping systems is recognized as a pathway for sustainable agricultural production with substantial environmental benefits. The legumes provide multiple ecosystem services to societies and agroecosystems, such as providing food, supplying nitrogen to crops through biological nitrogen fixation, reducing greenhouse gas emissions, improving carbon sequestration and soil fertility, and reducing water use and disease and pest infection. Despite these enormous benefits, the adoption level of legume crops is not very inspiring at the field level. The paper has highlighted the potential of legume-based cropping systems through a meta-analysis, using 555 pair observations from 134 studies, in generating additional ecosystem services in terms of physical quantity and monetary terms. Further, the study has identified reasons for the low adoption of legume crops and has provided some policy suggestions to improve the cultivated area under legumes.

Keywords Legumes, pulses, ecosystem services, payment for ecosystem services, India

JEL codes Q51, Q54, Q57

The modern agriculture systems are being confronted with several global challenges, including climate change, food and nutritional security, and sustainable use of natural resources (Stagnari et al. 2017). Adaptation to climate change through reduction of greenhouse gas (GHG) emissions is the most critical challenge for India as its agricultural sector is highly vulnerable to climate shocks (Rao et al. 2016; Birthal and Hazrana 2019). Birthal et al. (2021a) reported that the crop yields would decrease by 1.8 per cent to 6.6 per cent in the medium-term (2041–2060) and from 7.2 per cent to 23.6 per cent in the long-term (2061–2080) under the GHG representative concentration pathway RCP4.5. Thus, climatic change negatively impacts agricultural growth, leading to more challenges in achieving sustainable food security (Bithal et al. 2021b). Similarly, Singh et al. (2019) estimated crop losses at around 0.25 per cent of India's GDP due to extreme weather events. The climate change influences many agroecosystem services, including carbon capture and storage, quality and quantity of water, biodiversity, and pest and disease infestation (Turner et al. 2020). However, at the same time, agroecosystem also helps to mitigate and adapt to climate change impact (Yadvinder et al. 2020).

Agriculture accounts for 16 per cent of the total GHG emissions in India (Panchasara et al. 2021), and the emissions from agriculture are mostly non-energy-related and closely linked to the biological processes (Margini et al. 2016). Within the agriculture, fertilizer application was responsible for 19.1 per cent of emissions, followed by rice cultivation (17.5 per cent) and residue burning (2.2 per cent) (Padhee and Whitbread 2022). Across the globe, nitrogen is the most limiting factor for crop production. As a result, farmers apply large quantities of chemical fertilizers to supply the required nutrients to the plants, contributing significantly to GHG emissions. Nitrous oxide (N_2O) is the major GHG which is produced through the de-nitrification process of nitrogen fertilizer use (Naudin et al. 2014). Rice-wheat cropping system in the Indo-Gangetic plains region in India is one of the significant contributors to the climate change. This cropping system is considered water, capital, and energy-intensive. Thus, long-term cereal-based mono-cropping systems without crop rotation and input-intensive agriculture lead to adverse environmental effects, including soil health deterioration, groundwater depletion, environmental pollution, and biodiversity loss (Power 2010; Campbell et al. 2017) and human health-related issues (Hazra et al. 2018). In addition to adverse environmental impacts, the heavy use of chemical fertilizer has a substantial economic burden on the country, as the Government provides fertilizer subsidies to farmers to ensure fertilizer availability to improve agricultural production further (Bansal and Rawal 2020). The mono-cropping of staple cereal exacerbated the problems of malnutrition, particularly micronutrients and essential vitamins. Desire et al. (2021) reported that a larger percentage of smallholder farming communities in the semi-arid regions are malnourished because of less adoption of legume crops, which are rich in essential micronutrients and vitamins.

The legume crops play a vital role in reducing GHG emissions, particularly nitrous oxide, from agriculture as these crops fix atmospheric nitrogen naturally and do not require external nitrogen application. Jeuffroy et al. (2013) reported that legume crops emit around five to seven times less GHG per unit area than other crops. Further, legumes improve soil health, conserve water, increase the availability of NPK nutrients and microbial activities, reduce runoff and soil erosion, and provide food and nutritional security (Wani et al. 1995; Thilakarathna et al. 2016; Stagnari et al. 2017; Kebede 2020; Dutta et al. 2022; Ladha et al. 2022). Thus, crop diversification by including legume crops in cropping systems is one of the pathways for sustaining agricultural production with reduced inputs and adverse environmental impact. Although numerous studies have highlighted the importance of legume crops, particularly pulses, in achieving food and nutritional security, comprehensive qualitative assessments are not available. Further studies on the evidence of environmental benefits in monetary terms are scarce. Therefore, this study has conducted a meta-analysis to provide a broader conclusion on the role of legume-based cropping systems in sustainable agriculture and their potential to generate agroecosystem services.

Data source

The study is based on a comprehensive literature search on identifying the impact of legume crops on key agroecosystem services using online databases such as Web of Science, Science Direct, and Google Scholar. Different combinations of keywords, including "legume", "pulses", "BNF", " soil fertility", "carbon sequestration", "greenhouse gases", "water use", "crop yield", and "India" were used to find the relevant studies. For broader conclusions, a meta-analysis framework was used for synthesizing evidence of individual studies on the effect of legume-based cropping systems on agroecosystem services. The details of the database used in meta-analysis are presented in Table 1. A total of 555 pair-wise observations from 134 studies were used in the final analysis (A list of included studies in the meta-analysis has been provided in the supplementary file[1]).

Table 1 Summary of studies used in the meta-analysis

Particulars	No. of studies	Observations	Duration[a]
Biological nitrogen fixation	26	118	2.38±1.20
Soil fertility	41	162	2.40±3.17
C-sequestration	24	84	5.62±4.17
Water use	5	18	5.53±3.44
GHG emissions	12	50	2.36±0.77
Crop yield	26	123	2.48±2.64
Total	134	555	-

Note [a]indicates Mean ± Standard Deviation

Results and discussion

Biological nitrogen fixation (BNF)

The legumes have a unique biological trait that allows them to fix atmospheric nitrogen in the soil. The biological nitrogen fixation (BNF) process is essential for sustainable agriculture and is ranked second in importance after photosynthesis (Unkovich 2013), as nitrogen is the most limiting nutrient for plant growth and yield. Before the widespread availability of chemically manufactured nitrogen fertilizers, BNF was the primary source of nitrogen used in agriculture. Meta-analysis results show that legume crops fixed nitrogen through BNF ranging from 4 kg/ha to 190 kg/ha, on average 70 kg/ha (Table 2). However, the BNF process is influenced by the complex interactions between plants and other factors such as soil chemical, physical, and biological properties, temperature, water stress, rhizobial strain, and plant species or varieties (Soussana and Tallec 2010; Das et al. 2011). Often, crops with a deep and dense root system fix nitrogen in higher amounts (Ladha et al. 2022). Kebede (2020) suggested that the BNF capacity of legume crops could be improved by identifying the best legume genotype, seed inoculation with effective rhizobia, and adopting appropriate agronomic practices and agriculture systems.

Soil fertility

The legume-based systems improve soil fertility levels in various ways, such as by increasing soil natural organic matter and microbial activities, supplying biomass, recycling nutrients, solubilizing unsolved phosphorus, improving soil structure and porosity, and reducing soil loss with runoff due to more extensive soil cover (Lithourgidis et al. 2011; Stagnari et al. 2017). We used the available nutrients (NPK) as a proxy for soil fertility, and the results showed that legume-based cropping systems substantially increased available NPK nutrients (11.3 per cent) compared to non-legume cropping systems. (Table 2). The soil fertility can be restored and improved by incorporating legumes and their residues in the soil in cropping systems, despite being totally removed from the field. Further, Thilakarathna et al. (2016) reported that 2-26 per cent of the BNF amount is transferred to the soil by decomposing legume crop nodules and roots.

Carbon sequestration

The soil organic carbon (SOC) stock is a key indicator of soil health and land productivity. It plays a vital role in the sustainability of agroecosystems and in reducing the adverse impact of climate change. The legume-based cropping is an important option for C-sequestration in agriculture, as these crops supply organic carbon to the soil through deep root biomass, leaf litter fall, and decomposing crop residues (Lal 2015). Our meta-analysis results show that the legume-based cropping systems sequestered 16.84 per cent more carbon than the non-legume cropping systems (Table 2). Similar results were reported by Kumar et al. (2018), who found that legume crops could store 30 per cent higher organic soil carbon than other crop species. The legume crops enhance the SOC due to their plant architecture, which has distinct inherent characteristics for carbon sequestration (Hazra et al. 2020). Sexstone et al. (1985) reported that legume crops increase C-sequestration capacity by boosting soil aggregation and inhibiting rapid SOC mineralization.

Greenhouse gas (GHG) emissions

Synthetic nitrogen fertilizers are widely used in modern agriculture to supply nutrients required for plant growth, despite having less usage efficiency by crops. They contribute significantly to greenhouse gas emissions (Li et al. 2023). Continued use of nitrogen fertilizers further harms the climate stability by releasing potent greenhouse gases, such as nitrous oxide, which is 300-times more potent than carbon dioxide on a 100-year scale (Xu et al. 2022). The results

Table 2 Impact of legumes on ecosystem services at farm–level

Ecosystem services	Legume-based system	Non-legumes system	Difference*	Percentage change
BNF (kg/ha)	70.03	NA	70.03	-
NPK availability (kg/ha)	453	407	46	11.30
C sequestration (CO_2 Eq. tonne/ha)	13.69	15.99	2.31	16.84
GHG emissions (kg/ha)	1237	1833	-596	32.52
Water use (mm/ha)	897	1194	-297	24.87
Crop yield$^{\#}$ (t/ha)	5.64	4.42	1.22	27.60

Notes * indicates 1 per cent significance level; $^{\#}$indicates wheat equivalent yield.

of meta-analysis have revealed that legume-based cropping systems reduced GHG emissions by 32 per cent compared to non-legume cropping systems (Table 2). The legume crops emit less GHG than other crops, particularly nitrous oxide, due to their natural ability to fix atmospheric nitrogen and require minimal external nitrogen fertilizer application (Agele et al., 2015; Dequiedt and Moran, 2015). Moreover, these crops supply residual nitrogen to the following crops in the cropping sequence and use less non-renewable energy inputs (Lemke et al., 2007). Therefore, legume-based cropping systems can be promoted as an effective GHG mitigation strategy (Guardia et al. 2016; Oliveira et al. 2021).

Irrigation water saving

The overuse of irrigation water in agriculture production has caused groundwater depletion, worsened water scarcity, and is a threat to the sustainability of agriculture (Gleeson et al. 2012). Therefore, it is crucial to use water judiciously and manage it efficiently worldwide, particularly in the semi-arid tropical countries such as India (Meena et al. 2022). Our study has shown that legume-based cropping systems require 25 per cent less water than non-legume cropping systems (Table 2), which might be due to their large soil coverage and deeper and denser root systems. Therefore, most legume crops are grown under rainfed conditions.

Crop yield

The study found that the yield of legume-based cropping systems was higher by 27.6 per cent than of non-legume cropping systems (Table 2). After decomposition and mineralization of legume crop residues by soil microbes, they release available N for the subsequent crop and increase the nutrient status of the soil. As a result, the yield of subsequent or inter-cropping crops increases (Chu et al. 2004; Thilakarathna et al. 2016). The legume crops also play a significant role in achieving nutritional security, as these crops are known as "poor man's meat" due to their high contents of protein (16-50 per cent), dietary fibre (10-23 per cent), and essential vitamins (Maphosa and Jideani 2017). Therefore, inclusion of legume crops in the cropping systems provides one of the best solutions to protein-calorie and vitamin malnutrition, especially in the developing countries. The inclusion of grain legumes in a regular diet has been linked with reduced risks of coronary heart disease, diabetes, and some forms of cancer (Chibbar et al. 2010). People who consume pulses also have lower rates of obesity and metabolic syndrome. Therefore, it is recommended that individuals should consume pulses as a part of a healthy diet (USDA 2013).

Economic value of ecosystem services

The ecosystem service potential of legume-based cropping systems is estimated by multiplying the relative mean changes in the ecosystem services per hectare, these have been estimated using a meta-analysis, with the legume area of 41.15 Mha (average of the last three years) in the country, including major legume crops, viz. Gram, Pigeon pea, Cowpeas, Black gram, Soybean, and Groundnut. The economic value of ecosystem services (ES) was estimated by employing both direct and indirect valuation methods to express the benefits of legumes to policymakers and farmers.

At the country level, the legume-based cropping systems have the potential to generate additional non-tradable ecosystem services worth ₹ 62,308 crores per year (₹ 15142/ha/year) through biological nitrogen fixation, carbon sequestration, soil fertility, water saving, and reduced greenhouse gas emissions (Figure 1). The BNF is the foremost ecosystem service provided by the legume-based cropping systems, accounting for 51 per cent of the total value of non-marketed legume ecosystem services (Figure 2), followed by soil fertility (18 per cent), water saving (16 per cent), C-sequestration (12 per cent), and reduced GHG emissions (3 per cent).

Scenario of legumes in India

The grain legumes consist of pulses, soybeans, and groundnut oilseed crops. During the Kharif season, the most commonly grown pulses are Green gram (*Vigna radiata*)), Pigeon Peas (*Cajanus cajan*), Black Gram (*Vigna mungo*), and other minor pulses like Cowpeas (*Vigna unguiculata*), Moth bean (*Vigna aconitifolia*), and Kulthi (*Macrotyloma uniflorum*). Similarly, Gram (*Cicer arietinum*), Lentils (*Lens culinaris*), and other pulses like Peas (*Pisum sativum*) and Rajma (*Phaseolus vulgaris*) are cultivated during the Rabi season. The areas under different legume crops

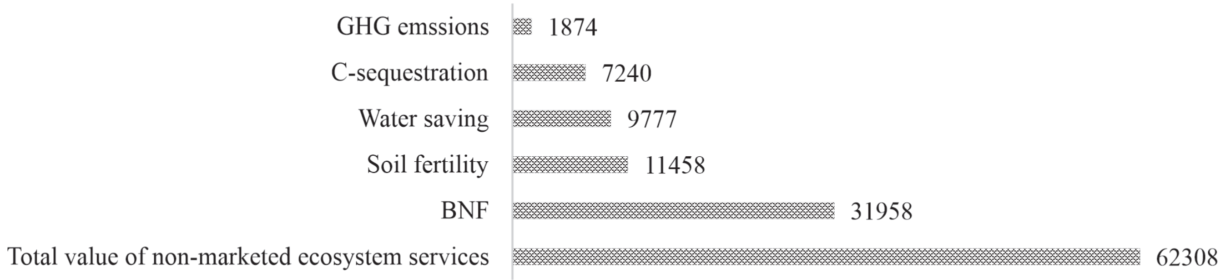


Figure 1 Economic value (₹ crores/ year) of additional non-tradable ecosystem services

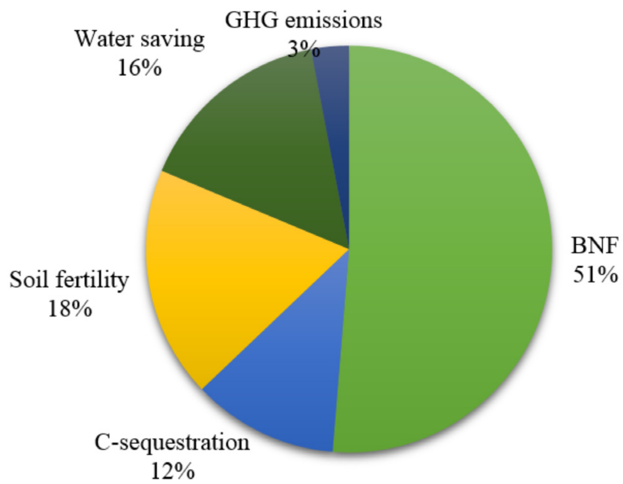


Figure 2 The share of each ecosystem service to the total value of non-marketed legume ecosystem services

and their share in total legume area and major growing states are listed in Table 3. Among the legume crops, soybean and gram occupy nearly half of the total cultivating legume area. Madhya Pradesh, Maharashtra, Rajasthan, and Karnataka are the major legume-growing states that occupy about 70 per cent of the total legume area in the country.

From 1976-77 to 2015-16, the area used for pulse crops remained stagnant at 22-23 Mha. However, there has been a slight improvement since 2015-16, and the area for pulse crops reached 28 Mha in 2020-21 (Figure 3). In the case of oilseed legumes, the area under Groundnut increased from 1976-77 to 1993-94, but has decreased considerably since then. In contrast, the area for Soybean has increased substantially since the launch of technology mission on oilseeds (TMO) in 1985-86. The area expansion, though in small magnitude, under legume crops was also observed since the launch of Integrated Schemes of Oilseeds, Pulses, Oilpalm, and Maize (ISOPOM) in 2004-05. The areas under legume crops have revealed a CAGR of 0.007 per cent during 1980-2000 and of 0.017 per cent during 2001-2021. The proportion of legumes in the total cropped area in 2020-21 was only 22.28 per cent, whereas cereals accounted for 48 per cent area.

Reasons for low adoption of legume crops

Although legume crops are the traditional crops in the Indian cropping systems adopted through crop rotations or intercropping for their nutritional and environmental benefits, farmers have not significantly expanded the area under legume crops, particularly pulses (Figure 3). The major reasons for less adoption of legumes are discussed in the section below.

Specialization in cereals

Arthur's (1994) theory of technological lock-in argued that one technology might become dominant over other alternatives, not necessarily because it is superior, but rather because it has been chosen and adopted by a larger number of people. This theory might be helpful in understanding the less adoption of legume crops despite huge benefits over cereal crops. In Indian agriculture, the cultivation of cereal crops was given higher priority to meet the immediate need for food during the Green Revolution period. Research and development efforts were mainly focused on high-yielding verities (HYV) of rice and wheat, subsidies on inputs, particularly fertilizer and electricity, expansion of irrigated areas under rice and wheat, and the assurance of prices through minimum support prices (MSP). Consequently, these crops have improved their technical and economic performance and have been adopted faster. Meanwhile, legume crops disappeared from the Indian cropping systems, leading to simplified cereal rotation. Unfortunately, this caused a reduction in pulse cultivation, resulting in a deficit

Table 3 Major legume crops grown in India

Crops	Area ('000' ha)	Share in all legumes, %	Major growing states
Soybean	12918	27.1	Madhya Pradesh (51.66%), Maharashtra (33.21%), Rajasthan (8.74%)
Groundnut	6015	12.6	Gujarat (35.96%), Andhra Pradesh (14.46%), Rajasthan (14.23%), Karnataka (11.99%)
Green gram	5130	10.8	Rajasthan (49.77%), Madhya Pradesh (10.60%), Karnataka (8.83%), Maharashtra (7.82%)
Black gram	4143	8.7	Madhya Pradesh (31.72%), Uttar Pradesh (13.37%), Rajasthan (9.93%), Tamil Nadu (9.71%), Andhra Pradesh (9.49%), Maharashtra (8.60%)
Pigeon pea	4724	9.9	Karnataka (34.52%), Maharashtra (26.97%), Telangana (6.89%), Uttar Pradesh (6.27%)
Other *Kharif pulses*	1671	3.5	Rajasthan (61.44%), Odisha (9.08%), Maharashtra (7.38%)
Gram	9996	20.9	Maharashtra (22.32%), Madhya Pradesh (21.61%), Rajasthan (21.14%), Gujarat (8.17%)
Lentil	1468	3.1	Madhya Pradesh (36.91%), Uttar Pradesh (32.15%), West Bengal (10.83%), Bihar (9.30%)
Other *Rabi pulses*	1651	3.5	Uttar Pradesh (21.86%), Chhattisgarh (9.92%), Odisha (9.04%), Karnataka (8.78%),
Legumes	47717	100	Madhya Pradesh (24.8%), Maharashtra (19.1%), Rajasthan (17.0%), Karnataka (8.7%)

Note Values within the parentheses indicate per cent share in the total area of crop
Source Authors' compilation using data from Directorate of Economics and Statistics, MOA&FW, Government of India, New Delhi

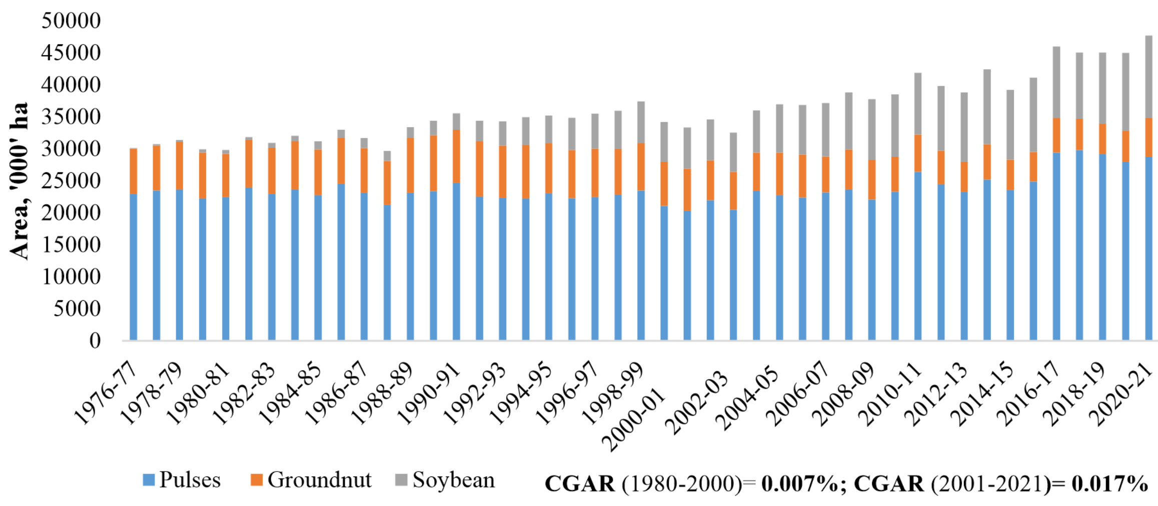


Figure 3 Area under legume crops: 1976-77 to 2020-21
Source Authors' compilation using data from the Directorate of Economics and Statistics, MOA&FW, Government of India, New Delhi

between the demand and supply of pulses in the country. This deficit has led to increased imports, fluctuations in domestic prices, and reduced profitability for pulse growers (Joshi and Saxena 2002).

The infrastructure required for storage, processing, and marketing was also developed only for a few crops due to the economics of scale and the interdependence of upstream and downstream industries. Among legumes, the area under only soybean has increased significantly in the past two decades due to better management of upstream and downstream supply chains through agribusiness, which has highlighted its

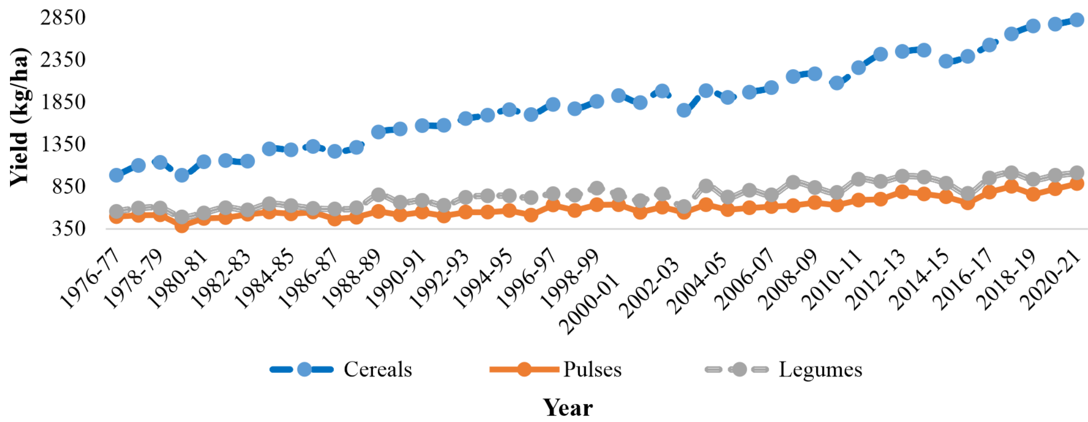


Figure 4 Yield under cereal and legume crops: 1976-77 to 2020-21

Source Authors' compilation using data from the Directorate of Economics and Statistics, MOA&FW, Government of India*,* New Delhi (https://eands.da.gov.in)

multiple uses for feed, food, fuel, and other industrial purposes on a global scale.

Yield and price risk

Our study has revealed that legume yield improved at a slower rate compared to the yield of cereals (Figure 4). From 1980 to 2021, the yield of legumes increased by only 88 per cent, compared to 148 percent in the case of cereals. Additionally, the yield of cereals is about 2.8-times that of legumes. The grain legume production faced significant yield risk due to various biotic and abiotic factors. Some of the biotic factors that contribute to this risk include crop diseases such as yellow mosaic, Cercospora leaf spot, anthracnose, powdery mildew, dry root rot, halo blight, and insect pests like bruchids, whiteflies, thrips, aphids, and pod borers (Singh et al. 2000; Pandey et al. 2018). Abiotic stresses such as waterlogging, salinity, heat, and drought also threaten legume production (Hanumantha Rao et al. 2016). Currently, over 87% of the area dedicated to pulses is rainfed, with the mean rainfall in major legume-growing states below 1,000 mm and a coefficient of variation of 20-25% (Reddy 2009). Further, the limited availability of quality seeds and lack of scientific knowledge about multifaceted legume-based cropping systems are significant factors for the vast yield gap in legumes (Layek et al. 2018). Sharma et al. (2023) reported that the actual yield of different pulses is 10% to 37% lower than the potential yield achievable.

Joshi et al. (2002) found that the variations in yields and price fluctuations are higher in legumes than in cereal crops. Yield and price risk are inter-related and contribute to legume crops' low and unstable income compared to cereal crops, resulting in less adoption of these crops (Joshi and Rao 2017). The lack of assured markets for legume production further exaggerates the price risk. Although the minimum support prices (MSP) of pulses and oilseeds have increased faster than those of cereals since 2010, the procurement of legume crops at MSP is much lower than that of rice and wheat. For example, about 66 per cent and 41 per cent of the total rice and wheat productions were procured at MSP, respectively, during 2020-21, while pulses procurement accounted for 4 per cent only.

Lack of incentives and awareness of environmental benefits

The lack of knowledge and awareness among farmers on environmental benefits or threats is a major barrier to adoption of sustainable agricultural practices. Therefore, increasing farmers' awareness on the legume system's multiple and long-term agroecological benefits is crucial for adopting legumes on farms (Ditzler et al. 2021).

Due to lack of incentives for non-tradable ecosystem services or non-availability of markets, the farmers often overlook or do not fully realize the non-marketed benefits of legumes. The net economic value of marketed ecosystem services at the farm level greatly influences farmers' choice of crops. Our analysis showed a reduction of about 4.5 per cent yield in the legume-wheat cropping system compared to the rice-wheat system in Punjab and Haryana. Similarly, Kumar et al. (2020) reported that the monetary value of expected yield loss was roughly 2-4 times more in pulses than wheat. Therefore, any economic disadvantage in legume crops compared to rice and wheat can result in their exclusion and increase the pressure to specialize in other competing crops. Therefore, providing incentives for increasing non-marketed ecosystem services generated by including legumes in the cropping systems may enhance the profitability of legume-based cropping systems. Unfortunately, translating the non-market outputs of diversified agriculture, such as legumes, into tangible economic returns is rarely achieved.

Government efforts for promoting legume production in India

For area expansion and productivity improvement, the Indian Government launched several schemes or programs, such as pulses development schemes during Fourth five-year plan, the National Pulses Development Project (NPDP) in the VIIth plan, the Technology Mission on Oilseeds (TMO) in 1985-86, Integrated Schemes of Oilseeds, Pulses, and Oilpalm and Maize (ISOPOM) in 2005-2010. However, legume production did not increase as planned in the schemes.

During the past one decade, India has made significant progress towards self-sufficiency in food by implementing several schemes and programs, specifically the National Food Security Mission (NFSM) and Rashtriya Krishi Vikas Yojana (RKVY). To increase legume production through area expansion and productivity improvement, the Government of India has provided several facilities such as making available certified/HYV seeds to farmers, production of foundation seeds and certified seeds, transfer of technology through farmers field schools, and production of inputs component ranging from biofertilizer to seed storage bins. Besides, the minimum support prices (MSP) of pulses and oilseeds have been increased much faster than those of cereals since 2010. Within pulses, chickpea, pigeon pea, black gram, green gram, and lentils have witnessed a substantial increase in MSP. However, these initiatives have not triggered legume cultivation may be due to lack of ensured procurement operations (NASS 2022). Recently, the government has removed procurement ceilings of 40 per cent for tur, urad, and masur at MSP for 2023-24 to motivate the farmers to enhance the sowing area under these crops to enhance production.

Thus, the main focus of all government schemes has been on area expansion and increasing production through technological improvement and price realization. None of them has a focus on providing additional support to legume crop growers for the non-marketed environment benefits (regulating and supporting ecosystem services) of these crops.

Need of a payment mechanism for ecosystem services

For incentivizing farmers to adopt sustainable agricultural practices that generate essential ecosystem services, payment for ecosystem services (PES) is crucial (Garbach et al. 2012; Meena et al. 2022). The main idea behind PES is to offer direct financial incentives to the farmers for implementing and promoting sustainable or conservation practices that enhance important ecosystem services (Development Asia, 2020). The application of PES in the agricultural sector has received significant attention due to its potential for revolutionizing farmer's behaviour and agriculture management practices. Hence, providing incentives to farmers for non-marketed ecosystem services generated by inclusion of legumes in cropping systems through payment for ecosystem services is needed to increase the competitiveness of legume crops. This, in turn, can help mitigate the adverse effects of climate change and minimize the negative effect of chemical fertilizer application on the environment and soil health. Kumara et al. (2023) have suggested a need to repurpose the existing agricultural incentives that promote unsustainable production practices. As part of the repurposing strategy, they have suggested a gradual reduction or phasing out of fertilizer subsidies and providing income support to encourage farmers to adopt sustainable agricultural practices. However, scientific and robust methodologies for the valuation of ecosystem services per unit area are required to develop a PES mechanism (NAAS 2020).

Conclusions and policy suggestions

The meta-analysis results have shown that legume-based cropping systems generate more multiple ecosystems than non-legume cropping systems. The results have underlined the fact that despite huge environmental benefits, the cultivated area under these crops has not increased to the desirable level due to crop specialization, low potential yield and high yield risk, lack of infrastructure for value addition, and, most importantly, lack of institutional supports in terms of quality seed delivery system, guaranteed procurement at MSP and no incentivisation mechanism for non-marketed ecosystem services. The following strategies are recommended to promote legume-based cropping systems:

- Provision of incentives to legume crop farmers for sustaining agroecosystem services and making legume crops competitive with rice and wheat crops.
- Awareness creation among farmers about the non-marketed benefits of legumes.
- Educate farmers on the advantages of seed inoculation with effective microbial rhizobia.
- More focus on R&D for developing high-yielding, insect pest-resistant, disease-resistant, and stress-tolerant varieties of legumes.
- Strengthen quality seed delivery systems and extension services for legume crops.
- Ensure guaranteed procurement of legumes at MSP and strengthen their storage infrastructure.
- Promote pulses through public distribution systems and mid-day meal programs for their multi-level impacts like nutritional security enhancement and mitigation of the negative environmental impacts of monoculture cereal systems.

References

Agele, SO, TO Oladitan, and AT Olarewajul. 2015. Growth and yield performance of sesame (Sesamum indicum L.) in the rainforest and derived savanna agro-ecologies of Nigeria. *International Journal of Agricultural Policy and Research* 3(6): 279–286.

Arthur, WB. 1994. Increasing Returns and Path Dependence in the Economy, University of Michigan Press.

Bansal, P and V Rawal. 2020. *Economic liberalisation and fertilizer policies in India*. SSER Monograph 20/5. Society for Social and Economic Research, New Delhi, India.

Birthal, PS, J Hazrana, and DS Negi. 2021a. Impacts of climatic hazards on agricultural growth in India. *Climate and Development* 13(10): 1–14.

Birthal, PS, J Hazrana, DS Negi, and SC Bhan. 2021b. Climate change and land-use in Indian agriculture. *Land Use Policy 109*, 105652.

Birthal, PS and J Hazrana. 2019. Crop diversification and resilience of agriculture to climatic shocks: evidence from India. *Agricultural System* 173: 345-354.

Campbell BM, DJ Beare, EM Bennet, JM Hall-Spencer, JSI Ingram, F Jaramillo, R Ortiz, N Ramakutty, JA Sayer, and D Shindell. 2017. Agriculture production as a major driver of the Earth system exceeding planetary boundaries. *Ecology and Society* 22(4):8.10.5751/ES-09595-220408

Chibbar, RN, P Ambigaipalan, and R Hoover. 2010. Review: Molecular diversity in pulse seed starch and complex carbohydrates and its role in human nutrition and health. *Cereal Chemistry*, *87*(4), 342-352.

Chu, G, Q Shen, and J Cao. 2004. Nitrogen fixation and N transfer from peanut to rice cultivated in aerobic soil in an intercropping system and its effect on soil N fertility. *Plant and Soil* 263: 17–27.

Das, S, P Bhattacharyya, and TK Adhya. 2011. Impact of elevated CO2, flooding, and temperature interaction on heterotrophic nitrogen fixation in tropical rice soils. *Biology and Fertility of Soils* 47: 25–30.

Dequiedt, B and D Moran. 2015. The cost of emission mitigation by legume crops in French agriculture. *Ecological Economics* 110: 51–60.

Desire, MF, M Blessing, N Elijah, M Ronald, K Agather, Z Tapiwa, MR Florence, and N George. 2021. Exploring food fortification potential of neglected legume and oil seed crops for improving food and nutrition security among smallholder farming communities: A systematic review. *Journal of Agriculture and Food Research 3:* 100117.

Development Asia. 2020. Eco-compensation and what it means for the world. https://de velopment.asia/explainer/eco-compensation-and-what-it-means-world (accessed 30 November 2023).

Ditzler, L, DF van Apeldoorn, F Pellegrini *et al.* 2021. Current research on the ecosystem service potential of legume-inclusive cropping systems in Europe. A review. *Agronomy for Sustainable Development* 41, 26.

Duttaa, A, A Trivedi, CP Natha, DS Guptaa, and KK Hazra. 2022. A comprehensive review on grain legumes as climate smart crops: Challenges and prospects. *Environmental Challenges* 7: 100479.

Garbach, K, M Lubell, and FA DeClerck. 2012. Payment for Ecosystem Services: The roles of positive incentives and information sharing in stimulating adoption of silvopastoral conservation practices. *Agriculture, Ecosystems & Environment 156*, 27-36.

Gleeson T, Y Wada, MF Bierkens, and LP Van Beek. 2012. Water balance of global aquifers revealed by groundwater footprint. *Nature* 488(7410):197-200.

Guardia, G, A Tellez-Rio, S García-Marco, D Martin-Lammerding, JL Tenorio, MA Ibanez, and A Vallejo. 2016. Effect of tillage and crop (cereal versus legume) on greenhouse gas emissions and Global Warming Potential in a non-irrigated Mediterranean field. *Agriculture, Ecosystems & Environment 221*, 187-197.

Hanumantha Rao B, RM Nair, and H Nayyar. 2016. Salinity and high temperature tolerance in mungbean [*Vigna radiata* (L.) Wilczwk] from a physiological perspective. *Frontiers of plant science* 7*,* 1-20.

Hazra, KK, PK Ghosh, MS Venkatesh, CP Nath, N Kumar, M Singh, J Singh, and N Nadarajan. 2018. Improving soil organic carbon pools through inclusion of summer mung bean in cereal–cereal cropping systems in Indo-Gangetic plain. *Archives of Agronomy and Soil Science* 64: 1690-1704.

Hazra, KK, CP Nath, PK Ghosh, and DK Swain. 2020. *Inclusion of Legumes in Rice–Wheat Cropping System for Enhancing Carbon Sequestration*. In: Ghosh, P., Mahanta, S., Mandal, D., Mandal, B., Ramakrishnan, S. (eds) Carbon Management in Tropical and Sub-Tropical Terrestrial Systems. Springer, Singapore.

Jeuffroy, MH, E Baranger, B Carrouee, ED Chezelles, M Gosme, and C Henault. 2013. Nitrous oxide emissions from crop rotations including wheat, oilseed rape and dry peas. *Biogeosciences* 10:1787–97.

Joshi PK, Birthal PS and Bourai VA. 2002. Socio-economic constraints and opportunities in rainfed Rabi cropping in rice-fallow areas of India. International Crops Research Institute for the Semi-Arid Tropics, Patancheru 502 324, Andhra Pradesh, India. p. 58.

Joshi, PK and PP Rao. 2017. Global pulses scenario: Status and outlook. *Annals of the New York Academy of Sciences 1392*(1), 6-17.

Joshi, PK and R Saxena. 2002. A profile of pulses production in India: facts, trends and opportunities, *Indian Journal of Agricultural Economics* 57(3): 326–339.

Kebede, E. 2020. Grain legumes production and productivity in Ethiopian smallholder agricultural system, contribution to livelihoods and the way forward, *Cogent Food & Agriculture*, 6:1.

Kumara, KTM, PS Birthal, and DC Meena. 2023. The Value of ecosystem services from sustainable agricultural practices in India: Implications for Re-purposing agricultural subsidies. Lead paper *In*: *International Conferences on sustainable natural resource management under global climate change*, Indian society of soil conservation, New Delhi, 66-72.

Kumar, S, GK Jha, DR Singh, and H Biswas. 2020. Economic incentives for sustainable legume production in India: A valuation approach internalizing risk sharing and environmental benefits. *Current Science* 119(7): 1184-1189.

Kumar, S, RS Meena, R Lal, GS Yadav, T Mitran, BL Meena, ML Dotaniya, and AEL-Sabagh. 2018. *Role of legumes in soil carbon sequestration*. In: Meena, R., Das, A., Yadav, G., Lal, R. (eds) Legumes for soil health and sustainable management. Springer, Singapore.

Ladha, JK, MB Peoples, PM Reddy, JC Biswas, A Bennett, ML Jat, and TJ Krupnik. 2022. Biological nitrogen fixation and prospects for ecological intensification in cereal-based cropping systems. *Field Crops Research 283:* 108541.

Lal, R. 2015. Restoring soil quality to mitigate soil degradation. *Sustainability* 7:5875-5895.

Layek, J, A Das, T Mitran, C Nath, RS Meena, GS Yadav, BG Shiva Kumar, S Kumar, R Lal, et al., 2018. Cereal+ legume inter cropping: an option for improving productivity and sustaining soil health. In: Meena et al (Ed.), Legumes for Soil health and sustainable management. Springer, Singapore, pp. 347-386.

Lemke, RL, Z Zhong, CA Campbell, and R Zentner. 2007. Can pulse crops play a role in mitigating greenhouse gases from North American agriculture? *Agronomy Journal* 99(6): 1719-1725.

Li, M, L Gao, JC White, CL Haynes, Y Rui, S Ullah, Z Guo, I Lynch, and P Zhang. 2023. Nano-enabled strategies to enhance biological nitrogen fixation. *Nature Nanotechnology 18*(7): 688-691.

Lithourgidis, AS, CA Dordas, CA Damalas, and D Vlachostergios. 2011. Annual intercrops: an alternative pathway for sustainable agriculture. *Australian journal of crop science* 5(4): 396-410.

Magrini, M, M Anton, C Cholez, G Corre-Hellou, G Duc, M Jeuffroy, J Meynard, E Pelzer, A Voisin, and S Walrand. 2016. Why are grain-legumes rarely present in cropping systems despite their environmental and nutritional benefits? Analyzing lock-in in the French agrifood system. *Ecological Economics 126*, 152-162.

Maphosa, Y and VA Jideani. 2017. The role of legumes in human nutrition. *In*: Hueda, M.C. (Ed.), Functional food-Improve health through adequate food. Intech open publishing, Croatia, p. 13.

Meena, DC, S Pal, and P Chand. 2022. Assessment of watershed management ecosystem services in India: a meta-analysis. *Current Science* 123 (11): 1352-1358.

Millennium Ecosystem Assessment (MEA). 2005. Ecosystems and human well-being: A framework for assessment. World Resources Institute, Washington, D.C

NAAS 2022. Sustaining the pulses revolution in India: Technological and policy measures. Policy paper No. 116, National Academy of Agricultural Sciences, New Delhi: 24 p.

NAAS. 2020. Payment for ecosystem services in agriculture. Policy paper No. 94, National Academy of Agricultural Sciences, New Delhi: 20p.

Naudin, C, HM van der Werf, MH Jeuffroy, and G Corre-Hellou. 2014. Life cycle assessment applied to pea-wheat intercrops: a new method for handling the impacts of co-products. *Journal of cleaner production* 73: 80-87.

Oldroyd, GE, JD Murray, PS Poole, and JA Downie. 2011. The rules of engagement in the legume-rhizobial symbiosis. *Annual review of genetics* 45, 119-144.

Oliveira, M, C Castro, J Coutinho, and H Trindade. 2021. Grain legume-based cropping systems can mitigate greenhouse gas emissions from cereal under Mediterranean conditions. *Agriculture, Ecosystems & Environment 313*, 107406.

Padhee, AK and AM Whitbread. 2022. *Indian agriculture: The route post-CoP 26.* DownToEarth.

Panchasara, H, NH Samrat, and N Islam. 2021. Greenhouse gas emissions trends and mitigation measures in australian agriculture sector-A review. *Agriculture* 11:85.

Pandey, AK, RR Burlakoti, L Kenyon, and RM Nair. 2018. Perspectives and challenges for sustainable management of fungal diseases of mungbean [*Vigna radiata* (L.) R. Wilczek var. *radiata*]: A Review. *Frontiers in Environmental Science* 6, 53.

Power, AG. 2010. Ecosystem services and agriculture: Tradeoffs and synergies. *Philosophical Transactions of the Royal Society Biological Sciences* 365(1554): 2959-2971

Rao, CR, BMK Raju, AS Rao, KV Rao, VUM Rao, K Ramachandran, B Venkateswarlu, AK Sikka, MS Rao, M Maheswari, and CS Rao. 2016. A district level assessment of vulnerability of Indian agriculture to climate change. *Current Science* 110(4): 1939-1946.

Reddy, AA. 2009. Pulses production technology: status and way forward. *Economic and Political Weekly* 44(52): 73-82.

Sexstone, AJ, NP Revsbech, TB Parkin, and JM Tiedje. 1985. Direct measurement of oxygen profiles and de-Nitrification rates in soil aggregates. *Soil Science Society of America Journal 49*(3): 645-651.

Sharma, P, BD Pal, and PS Birthal. 2023. *Technology and Policy Option for Sustaining Pulses Revolution.* Policy brief 53, ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi.

Singh, BR, S Chandra, and S Ram. 2000. Evaluation of mungbean varieties against yellow mosaic virus. *Annals of Plant Protection Sciences* 8: 270-271.

Singh, C., CRD Rio, V Soundarajan, V Nath, and V Shivaranjani. 2019. Assessing India's mounting climate losses to financial institutions. Action on Climate Today.

Soussana, JF and T Tallec. 2010. Can we understand and predict the regulation of biological N_2 fixation in grassland ecosystems? *Nutrient Cycling in Agroecosystems* 88: 197-213.

Stagnari, F, A Maggio, A.Galieni, *et al.* 2017. Multiple benefits of legumes for agriculture sustainability: an overview. *Chemical and Biological Technologies in Agriculture* 4(1): 1-13.

Thilakarathna, MS, MS McElroy, T Chapagain, YA Papadopoulos, and MN Raizada. 2016. Belowground nitrogen transfer from legumes to non-legumes under managed herbaceous cropping systems. A review. *Agronomy for Sustainable Development* 368.

Turner, MG, WJ Calder, GS Cumming, TP Hughes, J Anke, SL LaDeau, TM Lenton, BN Shuman, MR Turetsky, Z Ratajczak, JW Williams, AP Williams, and SR Carpenter. 2020. Climate change, ecosystems and abrupt change: science priorities. *Philosophical Transactions of the Royal Society B: Biological Sciences* 375, 20190105.

Unkovich, M. 2013. Isotope discrimination provides new insight into biological nitrogen fixation. *New Phytologist* 198: 643–646.

USDA. 2013. Dietary guidelines for Americans. United States Department of Health and Human Services.

Wani, SP, DP Rupela, and KK Lee. 1995. Sustainable agriculture in the semi-arid tropics through biological nitrogen fixation in grain legumes. *Plant and Soil* 174: 29-49.

Xu, S, R Wang, G Thomas, et al. 2022. Delayed use of bioenergy crops might threaten climate and food security. *Nature* 299–306. ISSN 0028- 0836.

Yadvinder, M, F Janet, S Nathalie, S Martin, MG Turner, FB Christopher, and K Nancy. 2020. Climate change and ecosystems: Threats, opportunities and solutions. *Philosophical Transactions of the Royal Society B: Biological Sciences* 375, 2019010420190104.

Received 10 August 2023 Accepted 2 December 2023

Agricultural Economics Research Review 2023, 36 (2), 213-225
DOI: 10.5958/0974-0279.2023.00034.4

Determinants of rural households' income inequality in India

Ghanshyam Pandey[1]* and Bisla Devi[2]

[1]Department of Economics, ESLA, SRM University, Andhra Pradesh 522240, India
[2]Department of Economics, Shyam Lal Collage, University of Delhi, India

* Corresponding author: ghanshyampndy@yahoo.com

Abstract This study has identified the drivers of income inequality in rural India using IHDS 2011–12 national-level survey. The inequality decomposition methodology developed by Fields (2003) based on a two-way regression methodology has been used. The study has modified on the previous regression-based inequality decomposition technique by accounting for diverse income sources and regimes as well as by effectively correcting for selectivity in the various income regimes. The CLAD model has been used to distinguish the determinants of income inequality in rural India. The study has indicated that income inequality in farm households can be attributed to the level of education, family size, caste/social group composition, and composition in land ownership, and that family size and land ownership are instrumental primarily due to off-farm labour income. The study has shown that education is a significant factor in income inequality due to its impact on off-farm work income. The study has suggested that a continued increase in variability in land distribution may exacerbate income inequality in households in rural India.

Keywords Income, determinants, Gini, inequality, CLAD model, India

JEL codes Q10, Q12, I32, D63

Introduction

The understanding of household livelihood options is critical in reducing rural poverty in the less developed nations of the world (Khatiwada et al. 2017). The concept of poverty is closely associated with income inequality (Pandey 2016). The increase in income inequality across the globe in recent years is a big concern. In several countries, the total income of high-income households has expanded at a faster pace compared to that of low-income households (Rani and Furrer 2016). Since the arrival of new farm technology, the rural development policies in most developing countries have centred around growth and income distribution (Birthal and Singh 1995). Given the disproportionate land distribution, it has been emphasized that while growth in agriculture may not substantially reduce rural poverty, it may adversely affect the distributional equity (Connor 2019; Griffin 1974). Almost two-thirds of the world's poor are concentrated in rural areas of low-income countries and depend primarily on subsistence agriculture and other natural resources for their livelihoods (The World Bank 2020). In addition, rural inhabitants are subjected to the ups and downs of a global economy because if the price of their harvest falls, their ability to survive is compromised (Machel 2004).

To eliminate poverty and inequalities across nations by 2030, one of the major goals of the United Nations Development Program (UNDP) is 'Sustainable Development Goals' (SDGs), but the goal remains elusive (Pandey 2018). Although the fraction of people living below the international poverty line has reduced, a large number of people in the sub-Saharan Africa, South Asia, and East Asia (Krishna 2013b), including two emerging economic superpowers — India and China—continue to live in poverty. Among others, Krishna (2013a) argues that the policies which might have been successful in reducing poverty previously, may not be effective now—as the business-as-usual approach is not going to reduce poverty any further. It is crucial to target income inequality for alleviating poverty. However, it is difficult to estimate how policymaking has impacted income distribution till date since there is a limited quantitative data on household characteristics that determine the level of income inequality and how it has evolved (Naschold 2009).

Income inequality itself is a global issue and has garnered careful examination in economic research in the past few decades. Such inquiry has generally been motivated by the recognition that income inequality is not only an outcome but a determinant of growth also (Kimhi et al. 2014; Perotti 1996). Increasing income inequality is a trend worldwide (Sethi et al. 2021) and is associated with higher crime rates, higher consumer debt, and lower health outcomes (Ranganathan et al. 2017). Despite technological advancements, neoliberal reforms, integration of countries, and advantages of rising incomes and output growth have not been apportioned equally across all the segments of society across the world (Asteriou et al. 2014). Kuznet's hypothesis (1955) explains an inverted U-shape for income inequalities, which predicts that income or consumption differentials would widen in the case of higher economic growth, at least initially, and narrow down eventually. This argument applies in the case of migration of workers from a rural area that has low wages and high-income inequalities to an urban area that has high wages and less income inequalities. When considering emerging economies, such as India and China, income inequality may also be a result of the removal of regulatory control on the economy, which generates growth, increases inequality, and reduces poverty (Borooah et al. 2014). While several developing countries have faced increases in income inequalities, research has challenged Kuznet's hypothesis due to the differences observed in the factors like socio-cultural, historical, religious, and castes that influence income levels and asset possessions of households (Ranganathan et al. 2015).

During 2010s, India's economy grew tremendously faster than in rest of the world. The process of economic reforms, which started in India in 1991, had a positive impact on its economic landscape. Since then, the economy has grown by about 7 per cent per year—nearly twice the growth recorded in the period before the reforms. However, this rapid growth has been concomitant with growing income inequality and the benefits to the poor are hotly debated (Agarwalla and Pangotra 2011; Bhattacharya and Sakthivel 2004; Causa and Hermansen 2020; Devi and Ranganathan 2021; Himanshu 2019; Krishna 2013b; Marmaros and Sacerdote 2002; Nagaraj et al. 2000; Ranganathan et al. 2015; Ravallion 2001; Reddy et al. 2014; Rout and Behera 2022; Sachs and Malaney 2002; Sofi and S. 2017; Thorat and Dubey 2012; Vakulabharanam and Motiram 2012) .

In India, income inequality has been increasing continuously since the 1980s. The top 1% of the population accounted for 11 per cent of total earnings in 1990 and 21 per cent in 2019. The earning share of the wealthiest 10 per cent increased from 30 per cent to more than 56 per cent between 1980 and 2019 (Rout and Behera 2022). Moreover, about 70 per cent of India's total population lives in the rural areas and depends largely on agriculture and related activities. Rawal (2013) has reported elevated levels of income inequality index by 0.76 in the rural India. At the same time, rural India faces challenges on many aspects—tiny landholding size, climate volatility, financial issues, lack of information, rising input prices, and inadequate infrastructure. Thus, it is crucial to understand the scenario of income inequality in the rural areas of India.

Despite growing global interest in income inequality, emerging economies have not been studied sufficiently because of the lack of adequate data and differences in economic and social structures (Himanshu 2007, 2019). Many studies have observed the nature and extent of inequality in India, but, only a few have focused on the determinants of income inequality. Against this backdrop, the purpose of our study is to apply regression-based inequality decomposition methods in assessing multiple income sources and demonstrate their effectiveness using the Indian Human Development Survey (IHDS) data on Indian rural households.

Data and Methodology

Data and sample

For analysis, we have taken data from the IHDS 2011–12, which is a large-scale, nationally representative survey conducted by the National Council of Applied

Economic Research (NCAER), New Delhi, India, in collaboration with the University of Maryland, United States. The survey spans all the states and union territories of India, except the Andaman and Nicobar and Lakshadweep islands. The number of samples collected in the survey in the first and second rounds was 42,551 and 41,471, respectively. After merging the two rounds, the total sample size stood at 32,678 of which 21,041 (64%) were from rural India and the remaining 11,637 (36%) were from urban India.

Methodology

Inequality can be understood as the variance of income or consumption levels among different individuals. It is the relative position different people hold in income distribution. This is a statistical summary of how income is dispersed across the population. The income distribution can be observed at the individual or functional levels.

Gini coefficient

The Gini coefficient has been used widely for measuring income inequality (Manna and Regoli 2012). It measures the degree to which the Lorenz curve deviates from the line of equality. A decomposed Gini coefficient—the product of the Gini coefficient with its share and correlation (G_k, S_k, and R_k, respectively)—provides a consolidated view of the distribution of the income source, its share in the income, and its impact on raising the level of total inequality. Therefore, to analyse how the change in income sources for different income quintiles affects the Gini coefficient, we have used Gini decomposition in this study. In this framework, the Gini index of household income was decomposed as per Equation (1):

$$G = \sum_{k=1}^{k} S_k G_k R_k \qquad \text{...(1)}$$

where, $S_k = \dfrac{\mu_k}{\mu}$ is the ratio of the mean of the income from a particular source, μ_k, and the average household income μ.

Fields decomposition

Several researchers have discussed the regression decomposition of income inequality, but the Fields decomposition model (2003) has been used widely. The Fields model uses an income-generating Equation (2):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon_1 \qquad \text{...(2)}$$

where, y represents the income, β are coefficients and x_i are the independent variables.

The flow of income from an endowment x_k influences the total inequality y as per the Equation (2).

The variance of log of income σ_y^2 to compute inequality can be written as per Equation (3):

$$S_k = \frac{cov\,(\beta_k x_k, y)}{\sigma_y^2} \qquad \text{...(3)}$$

where, S_k is the factor inequality weight which indicates whether the flow from x_k means an increase or decrease in the inequality. Therefore, the relative contribution of resource k to total income inequality can be calculated by Equation (4):

$$s^k = \hat{\beta}\left(\frac{\sum_{i=}^{n} a_i(Y) Y_i^k}{Y}\right) \qquad \text{...(4)}$$

where, a_i is the weight attached to the individual i, income component k, and Y_i^k.

In the regression-based approach, we assume that

$$\hat{Y}_k = X_k \hat{\beta}_k \qquad \text{...(5)}$$

where, X is a vector of the sources of income flows and $\hat{\beta}_k$ is the estimated coefficient. We then calculate the average income shares and income shares for each quartile q as per Equations (6) and (7):

$$\hat{\beta}_k\left(\frac{\bar{X}_k}{\bar{Y}}\right) \qquad \text{...(6)}$$

and

$$\hat{\beta}_k \sum_{i\in q} X_i^k \Big/ \hat{\beta} \sum_{i\forall} X_i^k \qquad \text{...(7)}$$

This approach has the benefit—though at the cost of strong assumptions—that confidence intervals can be constructed for the disaggregated contributions to the inequality index. The standard errors for the estimated contributions of different variables to the aggregate inequality index and variance are obtained by Equations (8) and (9):

$$\sigma(s_k) = \sigma(\hat{\beta}_k)\left[\frac{\sum_{i=1}^{n} a_i(Y)\, x_i^k}{I\,(Y)}\right] \qquad \text{...(8)}$$

and

$$\sigma(s^{\varepsilon}) = \left\{\sigma_{\varepsilon}^2 \sum_{i=1}^{n}\left[\frac{a_i(Y)}{I(Y)}\right]^2\right\}^{\frac{1}{2}} \qquad \text{...(9)}$$

Econometric analysis

In real-world settings, the rural households may have incomes ranging from zero to negative. The ordinary least squares (OLS) regression does not permit the censorship count of a dependent variable with zero value and the Tobit model can cause heteroscedasticity. To overcome these challenges, our study is based on the estimation of the Censored Least Absolute Deviation (CLAD) model.

The CLAD model

Proposed by Powell (1984), the CLAD estimation method assumes that the median is a linear combination of the covariates, but leaves the distribution unspecified otherwise. Consequently, censoring is possible without assuming homoscedasticity. In CLAD, y_i* is the latent variable and is observed in the censored regression model (10):

$$y_i = y_i^* \,(\, y_i^* > 0) \qquad \ldots(10)$$

$$= \begin{pmatrix} 0 & y_i^* \leq 0 \\ y_i^* & y_i^* \geq 0 \end{pmatrix}$$

The latent variable is observed by minimizing deviations from the median-based variations (Equation 11)

$$Med\,(y_i) = Max(\,Med\,(y_i^*), 0) \qquad \ldots(11)$$

According to Powell (1984), the censored regression estimation is:

$$y_i^* = X_i'\beta + \, e_i \qquad \ldots(12)$$

where,

$$y_i = y_i^* \, 1\,(\, y_i^* > 0)$$

The censored regression estimates for β are Maximum Likelihood Estimator when ε_i is independent of X_i and N (0, σ^2), and identifies $X_i'\beta$ as the conditional median of y_i, so we get Equation (13):

$$Med\,\left(\frac{y_i^*}{X_i}\right) = X_i'\beta \qquad \ldots(13)$$

Therefore, the least absolute deviation can be given by Equation (14):

$$S_n(\beta) = \sum_{i=1}^{n}(\,X_i'\beta > 0\,)\,|\,yi - (0, x_i'\beta)| \qquad \ldots(14)$$

The CLAD estimators for β minimize the absolute deviations, assuming conditional medium restrictions on the error-term. Here, y_i is the observable response variable, x_i' is the dimensional vector of explanatory variables (includes demographic, economic, and village-specific characteristics), and β is the dimensional parameter. Estimator $\hat{\beta}$ which minimized $S_n(\beta)$ is called the CLAD.

Results and Discussion

Income and inequality

It is believed that inequalities are more evident in the urban spheres because of their density and heterogeneity (Okatch et al. 2013). Generally, the urban areas are better developed and comprise diverse sectors that require varied competencies and technical skills. This can lead to wage gaps, which in turn lead to higher inequities. We considered income regimes (different sources of income) in India for our analysis, details are given in Appendix 1. Figures 1 and 2 show the breakdown of income from the various regimes and income inequality by regimes in the rural and urban

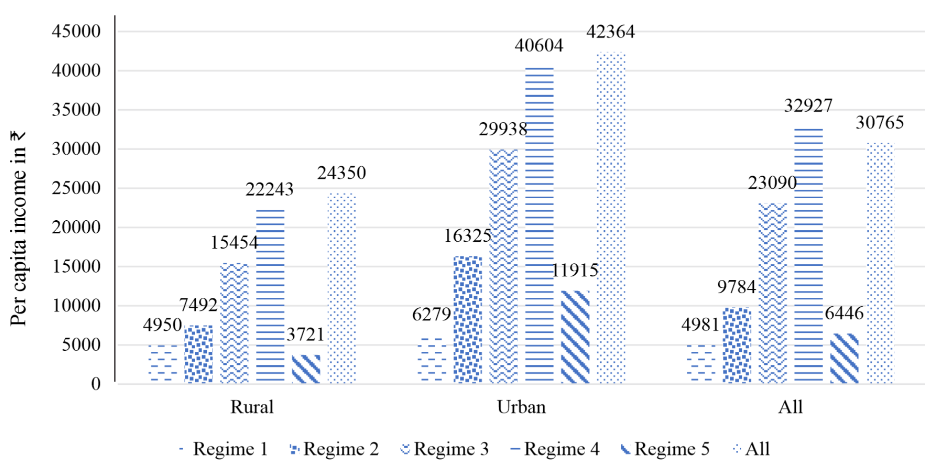


Figure 1 Per-capita income by regimes in India
Source Authors' estimation, IHDS data

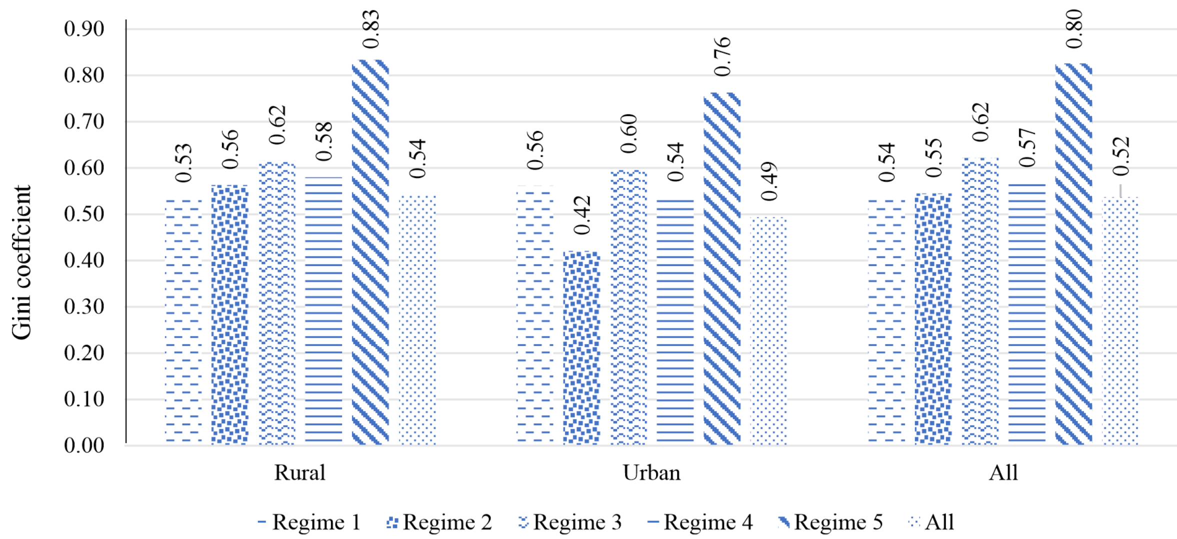


Figure 2 Per capita Gini coefficient for different income regimes in India
Source Authors estimation, IHDS data

India for 2011–12. The overall per capita income in rural India was INR 24,350, relative to income per urban inhabitant of INR 42,364. The major sources of income for the total income as well as for rural and urban income came from regime 4. The overall per capita income of rural India has been found lower than the national average and urban India; the result is similar for the distribution of income (Table 1 Figures 1 and 2). Figure 1 shows that the per capita income was lowest in regime 5, followed by regimes 1, 2, 3, and 4, respectively. This holds for all the three cases—rural, urban, and total. It should be noted that regime 5 recorded the lowest per capita income as well as the highest inequalities across all regions.

Each source's contribution to total income inequality was estimated as the product of the source's Gini index, its share in total income, and its correlation to total income. The most significant factor contributing to the overall income inequality was the maximum value among these estimates. The extent of the income inequality by the regime is depicted in Table 1. Regime 1 is the principal source of income for Indian rural households. It accounts for about half of the inequality, proportional to its share of income. This may be due to the unequal distribution of land and productivity (Birthal and Singh 1995) . While income from other regimes contributes less to inequality than their share of income, regime 4, which represents 18 per cent of total income, accounts for 23 per cent of inequality.

The decomposition of inequalities by income source failed to track the impact of household-level attributes on the level of inequality. It could not capture the

Table 1 Decomposition of income inequality by regime in rural India

Source	Income share S_k	Gini of source G_k	Correlation with rank of total income R_k	Proportional contribution to Gini	Marginal contribution to Gini
Regime 1	0.459	0.717	0.761	0.459	0.000
Regime 2	0.132	0.808	0.304	0.059	-0.072
Regime 3	0.110	0.939	0.685	0.129	0.020
Regime 4	0.182	0.911	0.769	0.234	0.052
Regime 5	0.117	0.878	0.616	0.116	-0.000
Total income		0.544			

Source Authors' estimation

influence of continuous variables. Moreover, analysis becomes complicated when we use multiple discrete attributes. Where the sub-group decomposition has only one criterion, the regression-based inequality decomposition (RBD) captures all household, individual, or regional attributes in a model. As per Table 1, the marginal contribution to Gini shows that with a uniform 1 per cent increase in regime 2, the income of a household is expected to reduce the Gini coefficient by 0.072 per cent, particularly in the rural areas. However, a contrast is observed in the Gini coefficients of other rural household regimes.

The correlation (R_k) between the income source and the rank of total income is the highest in regime 5, suggesting that households with the highest income from other sources, such as remittance and other government transfers, are the ones with the highest total income in the rural India. The overall Gini index is 0.544 (Table 1). Other studies have shown that the Gini index for India is greater than 0.50 (Das and Srivastava 2021; Dev 2017; Himanshu 2007, 2019; Himanshu et al. 2011, 2013)). The Gini coefficient is highest for regime 5, followed by regimes 3, 4, 2, and 1, respectively (Figure 2).

Field decomposition of income inequality in rural India

Since Regression Estimation (RE) estimator and an OLS estimator applied to conveniently transformed variables are equivalent (Wooldridge 2010), we obtained the results of the decomposition analysis as per the Fields method from the OLS regression of the transformed variables. The new variables were deduced by removing from the original ones a fraction of θ of their average over time; θ being the function of the variances of both the error and individual effect terms.

Table 2 reveals the decomposition of income inequality based on specific factors across different income regimes. The last column of Table 2 shows the decomposition of Fields income index of the overall rural income inequality. The results show that around 27 per cent—the value of R^2 for the regression—of income inequality can be explained by the set of explanatory variables as a whole. The remaining 72 per cent can be attributed to the residual term, meaning that much of the inequity is not explained by the variables included in the income determinants. In all the cases, it is the education level, household size, and land-related factors that contribute significantly to the total rural income inequality in India. Table 2 also shows that the southern and western zones of the India contribute the highest to rural income inequality. The southern zone explains income inequality through regime 1, but not another regime. This may be due to the higher agricultural productivity and income in the South Indian states.

The factors, education level and family size are significant contributors to income inequality in the rural India. The education level explains most of the inequality at 8.62 per cent while family size contributes 7.78 per cent, followed by the size of landholding and caste composition of the household in the total rural inequality in India. The influence of education on income inequality has been emphasized by others (Bigotta et al. 2014; Deininger and Olinto 2001; Growth 2016; Londono 1996). Every additional member in a rural household acts as a motivation to be involved in an occupation and earn more money in rural India. Perhaps increased work participation and earnings were favoured by the established rural households, wherein members could exploit more opportunities compared with weaker households, resulting in increased income inequalities (Devi and Ranganathan 2021; Pandey 2018; Pandey 2016; Ranganathan et al. 2015, 2016). The outcome of our study, as anticipated, was that a portion of working-age family members made a modest contribution to the income inequality through their dedication to employment, albeit significantly less to wage earnings.

The spatial factors, which are zones, have only contributed to the income inequalities of regime 1. Under regimes 1 and 2, the household size and marginal farmers have made greatest contributions in terms of inequality. In regimes 3, 4, and 5, higher levels of education, family size, and small classes of landowners have contributed to income inequality. The density of villages, which forces the households to compete for non-agricultural activities, eventually diminishes with incomes, leading to a decreasing inequality effect. The difference in results indicates that when the rural households shift from farming, agriculture wages, and casual wages to non-farm income sources—such as businesses and salaried professions—education acts as a significant barrier, if not accessible to them. A larger family size also plays a powerful motivator. Land ownership acts as a guarantee for business and salaried

Table 2 Regression based regime specific contributions to income inequality

Decomposition	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	All cases
Female household head	-0.08	0.07	0.00	0.00	1.80	0.33
Age of household head	0.11	-0.12	0.02	0.41	10.35	0.07
Age squared	0.11	0.01	-0.29	-0.67	-0.14	-0.74
Education level						
Secondary	0.00	0.50	-0.74	-2.81	-0.84	0.44
Senior Secondary	0.00	0.00	1.77	0.84	0.72	2.49
Higher education	-0.01	-0.05	3.41	14.58	5.53	8.62
Other backward class	0.26	0.03	0.15	0.67	1.06	0.40
Scheduled castes	-0.17	-0.14	0.67	0.40	0.40	0.33
Scheduled tribes	0.65	0.77	2.31	0.00	1.06	1.28
Family size	4.39	2.85	4.26	7.35	9.35	7.78
Marginal farmers	0.34	4.23	1.75	0.55	0.50	0.28
Small farmers	1.82	3.13	0.35	0.22	0.33	0.20
Medium farmers	0.96	2.23	0.13	0.07	0.07	0.95
Semi-medium farmers	0.13	0.36	0.16	0.00	0.08	1.92
Large farmers	-0.02	0.06	0.36	0.00	0.02	1.08
Population density	0.04	0.63	0.03	0.75	0.11	-0.08
East Zone	-0.38	0.00	-0.01	0.48	0.03	0.76
West Zone	2.71	0.15	0.40	0.23	0.16	0.08
South Zone	17.87	0.77	-0.02	0.12	0.98	0.39
Residual	71.27	84.52	85.29	76.83	68.44	73.41

Source Authors' estimation

activities, supported by non-farm activities. Table 2 demonstrates that different explanatory variables have different contributions to income inequality from different sources of income. For example, large farmers contribute positively to inequality in all the regimes except regime 1. This information can be useful for the policymaking efforts.

Determinates of rural inequality in India

Table 3 presents significant variables and their respective coefficients from the various sources by regime, derived using the CLAD model. The coefficient of the estimators represents the influence of various factors on the total rural income and sources. The last column of Table 3 shows the coefficients of overall per capita income for our study. Most of these coefficients have been found statistically significant. Age, which is an explanatory variable, has shown a non-linear effect—first positive and then negative. These two variables i.e., age and age square are significant, as proposed by the human capital theory, and show that income rises with age, but at a decreasing rate. This means that age equalizes income inequality. Other than the fact that age is distributed towards low-income households, why age is associated with lower inequality can be explained by the premise that with age come greater wisdom, knowledge, and experience—all of which enhance one's ability to generate income and improve their quality of life, even in the poor households.

Another important coefficient—the level of education of the household-head was also statistically significant, and positive, except in regimes 1 and 2. The higher education level substantially increases income and the income gap in the population. Accordingly, higher education has contributed the most to income inequality. The influence of training on inequality may be affected by the dissonance between the education sector and the skills demanded by the labour market, as Martins and Pereira (2004) explain. However, education level has shown loss of income among regimes 1 and 2. It equalizes income among heads of

Table 3 Determinates of income inequality: A CLAD model

Variables	Income regime					
	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	All Cases
Female household head	-0.123**	-0.274*	-0.017	-0.207*	0.431*	-0.083*
	(0.055)	(0.049)	(0.076)	(0.042)	(0.044)	(0.014)
Age of household	0.016*	0.007	0.014	0.030*	-0.001	0.039*
	(0.006)	(0.008)	(0.011)	(0.006)	(0.008)	(0.003)
Age^2	-0.000**	-0.000	-0.000	-0.000*	0.000*	-0.000 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education	-0.111**	0.151*	0.070	0.157	0.078**	0.160*
	(0.051)	(0.048)	(0.067)	(0.103)	(0.04)	(0.021)
Secondary education	-0.062	0.292*	0.298*	0.532*	0.251*	0.328*
	(0.046)	(0.052)	(0.063)	(0.072)	(0.037)	(0.016)
Senior Secondary education	-0.085	0.298*	0.555*	0.783*	0.507*	0.525*
	(0.084)	(0.064)	(0.085)	(0.092)	(0.045)	(0.019)
Higher education	-0.110	0.030	0.680*	1.389*	1.052*	0.865*
	(0.096)	(0.077)	(0.079)	(0.097)	(0.09)	(0.022)
Other backward classes	-0.273*	-0.069	-0.202*	-0.265*	-0.411*	-0.264*
	(0.059)	(0.046)	(0.041)	(0.041)	(0.08)	(0.023)
Scheduled castes	-0.111	-0.027	-0.332*	-0.234*	-0.294*	-0.191*
	(0.067)	(0.058)	(0.079)	(0.044)	(0.086)	(0.025)
Scheduled tribes	-0.170**	-0.296*	-0.758*	0.044	-0.480*	-0.425*
	(0.074)	(0.066)	(0.082)	(0.098)	(0.078)	(0.025)
Family size	-0.099*	-0.085*	-0.113*	-0.159*	-0.199*	0.099*
	(0.009)	(0.009)	(0.01)	(0.008)	(0.011)	(0.004)
Marginal farmers	-0.477*	-0.801*	-0.307*	-0.180*	-0.197*	-0.121*
	(0.057)	(0.04)	(0.054)	(0.04)	(0.042)	(0.013)
Small farmers	-0.669*	-1.153*	-0.293*	-0.275*	-0.260*	0.041*
	(0.06)	(0.048)	(0.082)	(0.059)	(0.056)	(0.027)
Medium farmers	-0.697*	-1.365*	-0.115*	-0.174	-0.170**	0.229
	(0.106)	(0.066)	(0.114)	(0.084)	(0.081)	(0.024)
Semi-medium farmers	-0.684*	-1.004*	0.183	0.025	-0.310**	0.592*
	(0.159)	(0.202)	(0.09)	(0.156)	(0.144)	(0.058)
Large farmers	-0.853*	-1.077*	0.966	0.365	0.218	1.125*
	(0.246)	(0.271)	(0.36)	(0.413)	(0.249)	(0.09)
Population density	0.101*	-0.300*	-0.079	-0.238*	-0.055	-0.088*
	(0.023)	(0.061)	(0.049)	(0.083)	(0.038)	(0.024)
East zone	0.359*	0.050	-0.047	0.210*	-0.066	-0.198*
	(0.047)	(0.03)	(0.061)	(0.053)	(0.039)	(0.016)
West zone	0.811*	0.283*	0.111	0.194*	-0.189*	0.048*
	(0.054)	(0.038)	(0.077)	(0.045)	(0.062)	(0.014)
South zone	1.363*	0.145*	-0.068	0.141**	0.476*	0.206*
	(0.046)	(0.051)	(0.07)	(0.064)	(0.056)	(0.017)
Constant	8.111	9.061	9.302	8.813	6.510	9.531
	(0.159)	(0.18)	(0.271)	(0.187)	(0.18)	(0.067)

Source Authors estimation
1. Values in the parentheses presents the standard error
2. *, ** & *** indicate that the values are significant at 10, 5 and 1% level of significance respectively

households without formal education. The equalising effect of primary school is attributed not only to the fact that the variable is distributed in favour of low-income households but also to the fact that primary education enables households to engage in work where advanced skills are not required. More opportunities are offered to people with primary education than those without education in the unorganised sector for unskilled jobs in India. Training has also made a positive and significant contribution to inequality in both income declines. These results are consistent with earlier studies that have used regression-based inequality decomposition (Baye and Ngah 2011; Wan and Zhou 2005). The distribution of land ownership is entirely uneven in the Indian context. Over 86% of farmers are in the small groups. Land size inequality is shaped by the economic, political, social, spatial and environmental factors, which in turn also have an impact. This interdependence means that addressing land inequalities requires a holistic and intersectoral approach. It also means that addressing land inequalities will have a wide range of positive impacts on our planet's wider inequalities and crises.

On the other hand, the female household-head variable has shown no statistical significance in terms of inequality. The coefficient of family size is negative (except for overall income) and statistically significant. Perhaps this reflects the fact that larger households can have multiple nuclear families within one household—a feature of Indian society—and, therefore, possibly more wage earners, or more dependent members, which explains the disparity (Bigotta et al. 2014). Therefore, income per head increases with family size. Increasing the number of paid workers in a one-unit household would lead to an increase in household income for the whole rural area in India. However, it is negative for other sources of income. This may be because lower employment opportunities in rural areas lead to lower per capita income.

The social groups play a critical role in the Indian society and have a significant impact on income, especially in the rural regions. The impact of our reference group—scheduled tribes (ST), scheduled castes (SC), and other backward castes (OBC)—was negative and statistically significant. This indicates that households belonging to lower caste categories experience lower levels of income inequality compared to those from the upper caste households. The disparity in income levels between lower and upper castes may be attributed to the fact that lower castes are frequently relegated to lower-paying and less secure employment positions, while upper castes often have access to higher-paying and more stable job opportunities. Therefore, the gap is larger in absolute terms in rural areas than in urban areas of India. The land ownership also explains inequality in the rural areas. Table 3 shows that there is a positive and statistically significant relationship between the size of land holdings and the per capita income of the households.

The regional factors, as captured by regional dummies have been found integral in explaining the rural income inequality in India, where incomes vary between and within states. This inter-state variation is largely due to differences in the level of development. The family household in the southern region has the highest per capita income than the rest of the country. However, the eastern area is negatively linked to per capita income. The eastern agriculture probably uses old technology, and this compromises agricultural productivity and, ultimately, income.

Conclusions

The study has found that the income inequality in India is high and is on the rise, which may result in inadequate human resource development and subpar economic performance over time. The gap between the poor and the rich is widening continuously in India. The top 1 per cent of the rich dominated in the total income in countries while the income of bottom 50 per cent was not even as much as 1 per cent of the top have. In a society where there is inequality in the distribution of resources, the poor get poorer making the condition of such a society worse. The results of the Field decomposition have shown that most of the rural income inequality in total income in rural India arises from variations in the level of education and number of family members. However, the CLAD model has indicated that the level of education, caste/social group composition, family size, and land ownership composition determine rural income inequality in India. Further, the number of family members and land ownership contribute to income inequality because of varying non-farm incomes. Our findings suggest that a continuous increase in land distribution variability could worsen long-term income inequality among rural households in India.

References

Agarwalla, A and P Pangotra. 2011. Regional Income Disparities in India and Test for Convergence – 1980 to 2006 (No. WP2011-01-04). *Ahmedabad: Indian Institute of Management.*

Asteriou D, S Dimelis and A Moudatsou. 2014. Globalization and income inequality: A panel data econometric approach for the EU27 countries. *Economic Modelling* 36: 592-599. https://doi.org/10.1016/j.econmod.2013.09.051

Baye, Francis Menjo and Boniface Ngah Epo. 2011. "Inequality Decomposition by Regressed-Income Sources in Cameroon" Prepared for the Special IARIW-SSA onference on Measuring National Income, Wealth, Poverty, and Inequality in African Countries Cape Town, South Africa, September 28-October 1, 2011

Bhattacharya, B B and S Sakthivel. 2004. Regional growth disparity in India: comparison of pre- and post-reform decades. *Economic and Political Weekly* 39(10): 1071-1077.

Bigotta, M, J Krishnakumar and U. 2014. Further results on the regression-based approach to inequality decomposition with evidence from India. *Empirical Economics* 48(3): 1233-1266. https://doi.org/10.1007/s00181-014-0819-5

Birthal, P S and M K Singh. 1995. Structure of rural income inequality: a study in western Uttar Pradesh. *Indian Journal of Agricultural Economics* 50(2): 168-175.

Borooah, V K, D Diwakar, V K Mishra, A K Naik and N S Sabharwal. 2014. Caste, inequality, and poverty in India: A re-assessment. *Development Studies Research* 1(1): 279-294. https://doi.org/10.1080/21665095.2014.967877

Causa, O and M Hermansen. 2020. Income redistribution through taxes and transfers across oecd countries. *Research on Economic Inequality* 1453: 29-74. https://doi.org/10.1108/S1049-258520200000028002

Connor, W D. 2019. Equality of Opportunity. *Soviet Social Problems* 81(3): 137-153. https://doi.org/10.9783/9781512817065-003

Das, R and R Srivastava. 2021. Income inequality among agricultural households in India: A regression-based decomposition analysis. *Review of Development Economics* 25(3): 1128-1149. https://doi.org/https://doi.org/10.1111/rode.12758

Deininger, K and P Olinto. 2001. Rural nonfarm employment and income diversification in Colombia. *World Development* 29(3): 455-465. https://doi.org/10.1016/S0305-750X(00)00106-6

Dev, S M. 2017. The Problem of Inequality. *Review of Development and Change* 22(1): 1-43. https://doi.org/10.1177/0972266120170101

Devi, B and T Ranganathan. 2021. Emerging Challenges in Rural Non-Farm Sector and Inequality in Rural India/ : Insight from IHDS Survey. *Finance & Economics Review* 3(1): 88-101. https://doi.org/10.38157/finance-economics-review.v3i1.303

Fields, G S. 2003. Accounting for income inequality and its change: A new method, with application to the distribution of earnings in the United States. *Research in Labor Economics* 35: 679-716. https://doi.org/10.1116/S0147-9121(03)2201-X

Fields, G S. 2006. Economic Mobility Project. *M McGillivray (Ed), UK: Palgrave Macmillan 2006 123*, *The Many Facets of Economic Mobility Inequality*; *Poverty and Well-being*, 123-124. http://www.pewtrusts.org/en/archived-projects/economic-mobility-project

Griffin, K. 1974. The international transmission of inequality. *World Development* 2(3): 3-15. https://doi.org/10.1016/0305-750X(74)90091-6

Growth, E. 2016. *Inequality and Growth in a Panel of Countries Author (s): Robert J . Barro Published by/ : Springer Stable URL/ : http://www.jstor.org/stable/40216021 Accessed/ : 10-06-2016 11/ : 57 UTC Your use of the JSTOR archive indicates your acceptance of the Terms &*. 5(1): 5-32.

Himanshu. 2007. Recent trends in poverty and inequality: Some preliminary results. *Economic and Political Weekly* 42(6): 497-508.

Himanshu. 2019. Inequality in India A review of levels and trends. *United Nations University, UNU- WIDER*, *ISSN 1798*-(Information and requests: publications@wider.unu.edu), 1-26. http://hdl.handle.net/10419/211272%0AStandard-Nutzungsbedingungen:

Himanshu, P Lanjouw, A Mukhopadhyay and R Murgai. 2011. *Non-farm diversification and rural poverty decline: a perspective from Indian sample survey and village study data*. 1-49. http://www.lse.ac.uk/collections/asiaResearchCentre/

Himanshu, P Lanjouw, R Murgai and N Stern. 2013. Nonfarm diversification, poverty, economic mobility, and income inequality: A case study in village India. *Agricultural Economics (UK)* 44(4-5): 461-473. https://doi.org/10.1111/agec.12029

Khatiwada, S P, W Deng, B Paudel, J R Khatiwada, J Zhang and Y Su. 2017. Household livelihood strategies and implication for poverty reduction in rural areas of central Nepal. *Sustainability (Switzerland)* 9(4): 1-20. https://doi.org/10.3390/su9040612

Kimhi, A, Y Arayama and J M Kim. 2014. *Identifying determinants of income inequality in the presence of multiple income sources/ : the case of Korean farm households*. *March 2017*, 1-5.

Krishna, A. 2013a. Making it in india examining social mobility in three walks of life. *Economic and Political Weekly* 48(49): 38-49.

Krishna, A. 2013b. Stuck in Place: Investigating Social Mobility in 14 Bangalore Slums. *Journal of Development Studies* 49(7): 1010-1028. https://doi.org/10.1080/00220388.2013.785526

Kuznets, S. 1955. Kuznets1955.pdf. In *The American Economic Review* (Vol. 1, p. 30). https://www.jstor.org/stable/1811581

Lerman, R I and S Yitzhaki. 1985. Income Inequality Effects by Income Source: A New Approach and Applications to the United States. *The Review of Economics and Statistics* 67(1): 151. https://doi.org/10.2307/1928447

Londono, J L. 1996. *Poverty, inequality, and human capital development in Latin America, 1950-2025*. The World Bank. https://doi.org/10.1596/0-8213-3630-4

Machel, M and U Carleton. 2004. *The Process of Rural-Urban Migration in Developing Countries by Machel McCatty An Honours essay submitted to Carleton University in fulfillment of the requirements for the course ECON 4908 , as credit toward the degree of Bachelor of Arts with Honours in*.

Manna, R and A Regoli. 2012. Regression-based approaches for the decomposition of income inequality in Italy, 1998-2008. *Rivista Di Statistica Ufficiale*, 1998-2008. http://www.istat.it/it/files/2012/10/primocapitolo.pdf

Marmaros, D and B Sacerdote. 2002. Peer and social networks in job search. *European Economic Review* 46(4-5): 870-879. https://doi.org/10.1016/S0014-2921(01)00221-5

Martins, P S and P T Pereira. 2004. Does education reduce wage inequality? Quantile regression evidence from 16 countries. *Labour Economics* 11(3): 355-371. https://doi.org/https://doi.org/10.1016/j.labeco.2003.05.003

Morduch, J and T Sicular. 2002. Rethinking inequality decomposition, with evidence from rural China. *Economic Journal* 112(476): 93-106. https://doi.org/10.1111/1468-0297.0j674

Nagaraj, R, A Varoudakis and M A Véganzonès. 2000. Long-run growth trends and convergence across Indian States. *Journal of International Development* 12(1): 45-70. https://doi.org/10.1002/(SICI)1099-1328(200001)12:1<45::AID-JID586>3.0.CO;2-Z

Naschold, F. 2009. Microeconomic determinants of income inequality in rural Pakistan. *Journal of Development Studies* 45(5): 746-768. https://doi.org/10.1080/00220380902753193

Okatch, Z, A Siddique and A Rammohan. 2013. Determinants Of Income Inequality In Botswana. *Economics Discussion / Working Papers* 13-15.

Pandey, G. 2018. Tackling poverty and inequality among farm households in Bihar: implications for achieving sustainable development goals (SDGs). *Agricultural Economics Research Review 31*(conf), 17. https://doi.org/10.5958/0974-0279.2018.00018.6

Pandey, G K. 2016. Income and Inequality among Farming Community: A Field Based Study of Bihar, India. *Asia-Pacific Journal of Rural Development* 26(2): 97-115. https://doi.org/10.1177/1018529120160205

Perotti, R. 1996. Growth, Income Distribution, and Democracy: What the Data Say. *Journal of Economic Growth* 1(2): 149-187. https://doi.org/10.1007/BF00138861

Powell, J L. 1984. Least absolute deviations estimation for the censored regression model. *Journal of Econometrics* 25(3): 303-325. https://doi.org/10.1016/0304-4076(84)90004-6

Ranganathan, T, A Tripathi and B Rajoriya. 2015. Income and Income Inequality among Indian Rural Households. *Institute of Economic Growth (IEG), New Delhi.*, *April*. https://www.researchgate.net/publication/301355952%0AChanging

Ranganathan, T, A Tripathi and G Pandey. 2016. Income mobility among social groups in Indian rural households: Findings from the Indian Human Development Survey. *IEG Working Paper No. 368*, *368*. https://doi.org/10.13140/RG.2.1.3990.7441

Ranganathan, T, A Tripathi and G Pandey. 2017. Income Mobility among Social Groups. *Economic and Political Weekly* 52(41): 73-76.

Rani, Uma and M Furrer. 2016. *Decomposing income inequality into factor income components/ : Evidence from selected G20 countries*. *July*.

Ravallion, M. 2001. Growth, inequality and poverty: Looking beyond averages. *World Development* 29(11): 1803-1815. https://doi.org/10.1016/S0305-750X(01)00072-9

Rawal, V. 2013. Changes in the Distribution of Operational Landholdings in Rural India: A Study of National Sample Survey Data. *Review of Agrarian Studies* 3(2): 73-104.

Reddy, D N, A A Reddy, N Nagaraj and M C S Bantilan. 2014. Rural Non-Farm Employment and Rural Transformation in India. *Icrisat Cgiar*, *November*. https://doi.org/10.13140/2.1.2047.4569

Rout, S K and R Behera. 2022. Income Inequality and its Important Determinants in India. *Saudi Journal of Economics and Finance* 6(5): 171-187. https://doi.org/10.36348/sjef.2022.v06i05.002

Sachs, J and P Malaney. 2002. The economic and social burden of malaria. *Nature* 415(6872): 680-685. https://doi.org/10.1038/415680a

Sethi, P, S Bhattacharjee, D Chakrabarti and C Tiwari. 2021. The impact of globalization and financial development on India's income inequality. *Journal of Policy Modeling* 43(3): 639-656. https://doi.org/10.1016/j.jpolmod.2021.01.002

Shorrocks, A A F. 1982. Inequality Decomposition by Factor Components Published by/ : The Econometric Society Stable URL/ : http://www.jstor.org/stable/1912537. *Society* 50(1): 193-211.

Sofi, A A and R S D S. 2017. Income convergence in India: evidence from nonparametric panel data. *Journal of Economic Studies* 44(3): 400-411. https://doi.org/10.1108/JES-04-2015-0065

The World Bank. 2020. Poverty and Distributional Impacts of COVID-19/ : Potential Channels of Impact and Mitigating Policies. *Poverty and Equity Global Practice*, 1–10. https://www.worldbank.org/en/topic/poverty/brief/poverty-and-distributional-impacts-of-covid-19-potential-channels-of-impact-and-mitigating-policies

Thorat, S and A Dubey. 2012. Has growth been socially inclusive during 1993-94 - 2009-10? *Economic and Political Weekly* 47(10): 43-53.

Vakulabharanam, V and S Motiram. 2012. Understanding poverty and inequality in urban India since reforms: Bringing quantitative and qualitative approaches together. *Economic and Political Weekly* 47(47-48): 44-52.

Wan, G and Z Zhou. 2005. Income inequality in rural China: Regression based decomposition using household data. *Review of Development Economics* 9(1): 107-120.

Wooldridge, J M. 2010. *Econometric Analysis of Cross Section and Panel Data, second edition*. MIT Press. https://books.google.co.in/books?id=yov6AQAAQBAJ

Received 6 July 2023 Accepted 29 September 2023

Appendix I

The total income of household has been diversified into different sources of income, i.e,

Total income (y) = Own farm income (Fr_y) + Agricultural wage labour + (Aw_y) + Non-farm (including casual + regular employment + self-employment) income (NF_y) + Remittances (R_y) + Other incomes (Oth_y), mathematically

$$Y = Fr_y + Aw_y + NF_y + R_y + Oth_y$$

Own Farm income = Income from cultivation + Income from livestock + Lease of agricultural property

$$Fr_y = Ca_y + Lw_y + Le_y$$

Non-farm Income = Casual labour income + Own- Business income + Salaried employment income, i.e.

$$NF_y = Cl_y + OB_y + Sl_y$$

For a better understanding of the farm and non-farm employment determinants, we have created 5 Regimes of different income sources, as shown Appendix Table 1:

Appendix 1 Categorization of regime by income sources

Regime	Income source
Regime1	Income from agriculture and agricultural labour
Regime2	Income from casual wage labour
Regime3	Income from businesses
Regime4	Income from salary
Regime5	Income from other sources such as remittance and other govt transfers

Agricultural Economics Research Review 2023, 36 (2), 227-235
DOI: 10.5958/0974-0279.2023.00035.6

Nutri-garden for nutritional security and diversity: Some insights from POSHAN Abhiyan

R C Agrawal[1], Lipi Das[2], Rajni Jain[3]*, Prabhat Kishore[3], V R Nikam[3] and Mridula Devi[2]

[1]Division of Agricultural Education, Indian Council of Agricultural Research, New Delhi 110012, India
[2]ICAR-Central Institute for Women in Agriculture, Bhubaneshwar, Odisha 751003, India
[3]ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi 110012, India

*Corresponding author: rajnijain67@gmail.com

Abstract To combat the challenges of malnutrition, the government initiatives such as the POSHAN Abhiyan are emphasized, particularly the introduction of Poshan Vatika (Nutri-Gardens), which is on empowering the women to cultivate nutritious foods and enhance quality of family diets. Data from 1710 farm families across 12 states, has been analyzed through Partial Least Squares Path Modelling and logistic regression, indicates that Nutri-Gardens positively impact the family nutrition. In conclusion, Nutri-Gardens offer a holistic approach to improving nutrition in rural India, empowering women, raising their socio-economic status, and promoting nutrition education and community participation. The collaboration among various stakeholders is essential to disseminate information effectively and ensure the success and sustainability of Nutri-Gardens as a cost-effective and sustainable approach to mitigate malnutrition in the rural households.

Keywords Nutritional security, Nutri-gardens, rural India, malnutrition, women farmers

Globally, the prevalence of triple burden of malnutrition which includes both undernutrition and over-nutrition, is alarming due to coexistence of over nutrition, under nutrition and hidden hunger (micronutrient deficiency). A more comprehensive approach is necessary to optimize agriculture's contribution to good nutrition and make agriculture nutri-sensitive. In India also, nutritional security is a critical concern, particularly in the rural areas where a significant portion of the population is engaged in agriculture. In this connection, women farmers who are important stakeholders in agriculture, can address the challenges of both agricultural development and malnutrition reduction. However, agricultural policies focus on increasing farm production and farmers' income and often overlook the importance of addressing nutritional issues. The majority of farmers in India are small and marginal farmers, and simply increasing overall farm production and income may not adequately address the nutritional needs of the rural population. Hence, at the policy level, achieving inclusive growth in agriculture is important for strengthening the linkages between agriculture and nutrition.

Addressal of nutritional security requires a multi-faceted approach that goes beyond agricultural production. One potential solution is the implementation of Nutri-Gardens scheme, which can contribute to improving the availability and accessibility of nutritious foods at the household level. The Nutri-Gardens comprise the cultivation of a diverse range of vegetables, fruits, and herbs in home gardens or plots. The Nutri-Gardens make the women farmers aware about the quantity of vegetables to be used in daily diet (Kumari et al. 2019). The benefits that can emerge from Nutri-Gardening practices include better health and nutrition, additional income, employment, food security within the household and enhancement in community social life. The increased consumption of fruits and vegetables is one of the simplest and healthier ways of enhancing the nutritional status of population.

Over the past four decades, the Government of India has taken significant measures to provide food security and combat malnutrition through various programs such as the Integrated Child Development Services (ICDS), the Mid-Day Meal program, strengthening the Public Distribution System (PDS), the Eat Right India Movement, the Pradhan Mantri Matru Vandana Yojana, Mission Indradhanush, and the Prime Minister's Overarching Scheme for Holistic Nourishment (POSHAN) Abhiyan.

One unique program under POSHAN Abhiyan is the introduction of Poshan Vatika or Nutri-Gardens. The key principle behind this program is 'Grow what you eat and eat what you grow'.The women, who play a crucial role in family nutrition, are the primary target group for this program. They would be encouraged to cultivate vegetables and fruit plants in their homestead gardens or Nutri-Gardens.

The Indian Council of Medical Research (ICMR) has recommended the consumption of 300 grams of vegetables per person per day, including 50 grams of leafy vegetables, 50 grams of root vegetables, and 200 grams of other vegetables (NIN, 2018). The Nutri-Gardens can help fulfill these recommendations and ensure a diverse and nutritious food intake.

This study aims to provide empirical evidence on enhancement of nutritional security through Nutri-Gardens in the rural India.

Data and methodology

Primary data

This study was undertaken as a part of "Nutri-Smart Village Programme" which was initiated to strengthen the POSHAN Abhiyan. The survey data was collected from 1710 farm families in 12 Indian states involving women respondents relating to their socio-economic profile, nutritional status, knowledge, attitude and practice under the supervision of ICAR-Central Institute for Women in Agriculture, Bhubaneswar. The villages were selected according to the following five criteria:

Nutritional status (Poor consumption pattern and low dietary intake) — Identification of nutrition issues based on the data obtained by regular national monitoring and surveillance of the consumption pattern, dietary intake and nutritional status of the population conducted by the Primary Health Centres.

Accessibility to villages — The selected villages should be located within 50 km radius from the implementing organization for regular monitoring.

Prevalence of mono-cropping and low crop diversification — Adoption of crop diversification increases the dietary diversity at household level and reduce the incidence of malnutrition.

Non-existence or non-overlapping — It didn't overlap with any other nutrition-based programme by other government and non-government agencies.

Scope for conducting nutrition awareness programme — It was conducted at individual as well as household levels through methods like trainings, demonstrations, health camps, Focus Group Discussions on issues like malnutrition, anemia, balanced diets, related health illness, etc.

Analytical tools

Partial Least Squares Path Model

The Partial Least Squares Path Modelling (PLS-PM) is a robust and versatile statistical technique used for structural equation modelling (SEM) in empirical research (Seyyed *et al*. 2012).

In the present study, the interrelationships between the latent variables — attitude, knowledge, nutritional practices, Nutri-Garden and clinical symptoms — were investigated and identified using the partial least squares path model (PLS-PM). The pre-structured questionnaires were used to collect the data pertaining to these five latent variables namely attitude, knowledge, nutrition practices, clinical symptoms and Nutri-Garden (Table 1). The responses were recorded from women farmers on various parameters to capture these latent variables (Appendix A1). The survey used a binary and ordinal data as the response options. SMART-PLS software was used for the analysis (https://smartpls.com). The path coefficients, total effects and p-values were observed and recorded.

Logit Regression Model

The determinants to maintain kitchen garden by the surveyed women were analysed by the Logit regression method, which is used to model the probability of a

Table 1 Summary of latent variables for Partial Least Squares Path Model

Latent variable name	Type	Description*
Attitude	ordinal	Attitude of respondents towards nutrition based on 20 responses
Knowledge	ordinal	Knowledge score of respondents related to nutrition based on 22 responses
Nutrition practices	ordinal	Nutritional practices adoption score of respondents based on 21 responses
Clinical symptoms	ordinal	Measure of nutritional deficiency in the family of respondents-based on 12 responses related to various body parts
Nutri-Garden	binary	Whether respondent practices Nutri-Garden or kitchen garden

*Refer Appendix A1 for more details related to the composition of latent variables

binary outcome or event. In this study, the binary dependent variables- women decision to maintain Nutri-Garden or not, is influenced by several key factors. So, to identify these factors we employed logistic regression model given below:

$$Logit(Y_i) = Ln\left(\frac{P_i}{1-P_i}\right) = \beta X' + \varepsilon$$

where, Y is the indicator variable for maintaining a Nutri-Garden;

$$Y_i = \begin{cases} 1, & \text{if women maintain a Nutri-Garden} \\ 0, & \text{if women don't maintain a Nutri-Garden} \end{cases}$$

P_i indicates the probabilities for Y_i = 1 and 1 – P_i indicates the probabilities for $Y_i = 0$. X' represents vector of predictor variables included in the model, β stands for coefficient to be estimated and ε is random error-term. The predictor variables included in the model were: age of respondent women, education level, family size, annual family income, marital status, primary occupation, landholding category, access to mass media, use of mobile, nutrition extension index and agricultural extension index

Results and discussion

Socio-economic profile of respondents

A survey of 1710 farm families in 12 states was conducted under the supervision of ICAR-Central Institute for Women in Agriculture, Bhubaneswar, to collect data from women respondents related to their socio-economic profile, nutritional status, knowledge, attitude and practice. The summary statistics of socio-economic profile of responding adopters and non-adopters are given in Table 2. The surveyed women who maintained Nutri-Garden were found older and more educated compared to the women who did not maintain it. The primary occupation for the women who maintained Nutri-Garden was not agriculture and they generated higher income than the non-adopters group. The access to the mass media — radio, television, newspaper and mobile phone — was found to be higher among the adopter women (who maintained Nutri-Garden) than non-adopters. Another interesting finding was that the connect with the Anganwadi workers and ANM (Auxiliary Nursing Midwifery) was significantly lower among the women maintaining Nutri-Garden compared to the women who did not maintain it.

Consumption patterns

The per capita daily consumption of vegetables by the adopters and non-adopters of Nutri-Gardens is presented in Table 3. The data clearly indicated a significant differences between the adopter and non-adopter categories of Nutri-Gardens. The total vegetable consumption (kg/day/family) was found to be 0.74 kg by the adopters and 0.62 kg by the non-adopters. This revealed that women who maintained Nutri-Gardens were able to feed more vegetables to their family members than those who did not maintain a Nutri-Garden. Further, there were significant differences in the daily consumption of leafy vegetables and roots & tubers between adopters and non-adopters across the vegetarian and non-vegetarian groups. However, differences in consumption of other vegetables were not found significant for the vegetarians and overall respondent families.

Table 2 Socio-Economic profile of adopter and non-adopter respondents

Variables	Maintenance of Nutri-Garden (Respondents: 1559)		
	Adopters (709)	Non-adopters (850)	Difference
Age of woman respondent (years)	38.90	37.36	1.54***
Education level (illiterate=1, primary school=2, middle school=3, high school=4, intermediate=5, graduation and above=6)	2.85	2.60	0.25***
Family size (small=1, medium=2, large=3)	1.76	1.76	0.01
Annual family income ([1])	152270	136653	15616**
Marital status (married=1; otherwise=0)	0.94	0.95	-0.01
Primary occupation (agriculture=1; otherwise=0)	0.34	0.40	-0.07***
Landholding category (marginal=1, small=2, semi-medium=3, medium=4, large=6)	1.45	1.45	0.00
Access to mass media index score	3.16	2.55	0.60***
Use of mobile (regular=1; otherwise-0)	0.64	0.59	0.05*
Nutrition extension index score	3.26	3.90	-0.64***
Agricultural extension index score	2.35	1.99	0.37***

Note ***, ** and * denote significance at 1 per cent, 5 per cent and 10 per cent levels, respectively
Source Authors' compilation

Table 3 Daily vegetables consumption by adopters and non-adopters of Nutri-Garden

Vegetables	Consumption (kg/day/family)								
	Total responds			Vegetarian responds			Non-vegetarian responds		
	Adopters	Non-adopters	Mean difference and t-stat	Adopters	Non-adopters	Mean difference and t-stat	Adopters	Non-adopters	Mean difference and t-stat
Green leafy	0.19	0.27	-0.08***	0.28	0.24	0.04**	0.26	0.13	0.13***
Other	0.26	0.25	0.01^{ns}	0.27	0.29	-0.02^{ns}	0.26	0.21	0.05***
Roots and tubers	0.26	0.19	0.07***	0.29	0.25	0.04**	0.26	0.13	0.13***
All	0.74	0.62	0.12***	0.83	0.78	0.05^{ns}	0.71	0.46	0.25***

Note *** and ** denote significance at 1 per cent and 5 per cent levels, respectively; ^{ns}- non significant
Source Authors' compilation

Inter-relationships among knowledge, attitude, nutritional practices, Nutri-Garden and clinical symptoms

The partial least square path modelling was conducted using SMART-PLS software to evaluate the relationship between latent variables — attitude about nutrition, knowledge about nutrition, nutritional practices followed, adoption of Nutri-Garden and clinical symptoms arising out of nutrition deficiency. The path coefficients are presented in Figure 1 which revealed that the paths of Attitude→Nutri-Garden, Attitude→Nutritional practices, Knowledge→Attitude, Knowledge→Nutri-Garden, Knowledge→Nutritional practices, Nutri-Garden→Nutritional practices were positive and significant and the path of Nutri-Garden→Clinical symptoms was negative and significant.

The coefficients of total effects showed that Attitude→Clinical symptoms, Knowledge→Clinical symptoms, Nutri-Garden→Clinical symptoms were

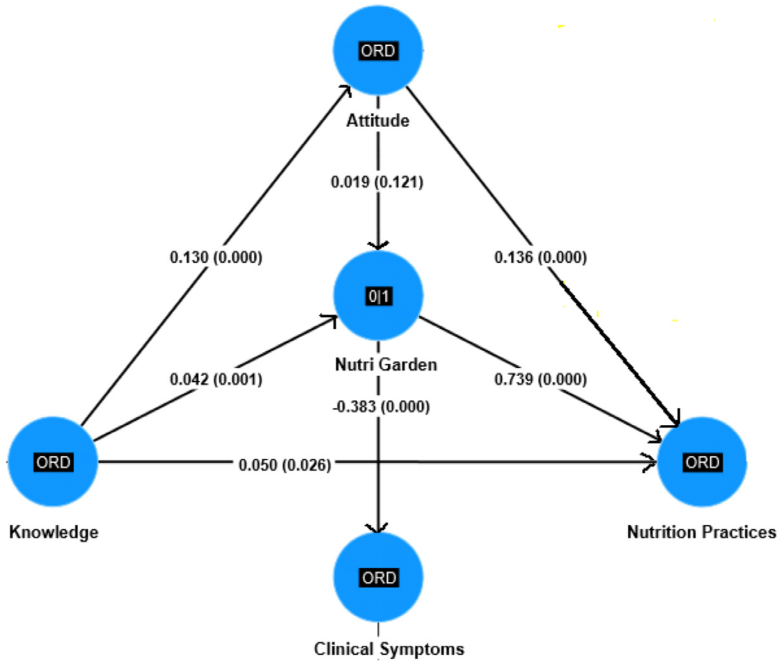


Figure 1 Partial Least Square Path Model for nutritional security through Nutri-Garden
Note The numbers on the arrows between the latent variables are the path coefficients and the numbers written within the parentheses indicate p-values. ORD — Ordinal variable, 0|1— Binary variable
Source Authors' compilation

negative and significant and Attitude→Nutri-Garden, Attitude→Nutritional practices, Knowledge→Attitude, Knowledge→Nutri-Garden, Knowledge→Nutritional practices, Nutri-Garden→Nutritional practices were positive and significant (Table 4). It could be, therefore, inferred that persons having favourable attitude towards nutrition and good knowledge of nutrition had maintained the Nutri-Garden at home. Altogether all these factors resulted in the reduction in clinical symptoms regarding nutritional deficiency of the respondents and thus maintaining their good health.

Table 4 Total effects coefficients in PLS-PM model

Relationships	Coefficients of total effect
Attitude -> Clinical Symptoms	-0.007
Attitude -> Nutri Garden	0.019
Attitude -> Nutrition Practices	0.150***
Knowledge -> Attitude	0.130***
Knowledge -> Clinical Symptoms	-0.017***
Knowledge -> Nutri Garden	0.044***
Knowledge -> Nutrition Practices	0.100***
Nutri Garden -> Clinical Symptoms	-0.383***
Nutri Garden -> Nutrition Practices	0.739***

Note *** denote significance at 1per cent levels
Source Authors' compilation

Factors affecting adoption of nutri-garden

For the binary dependent variables, the use of logistic regression model is consistent in the research literature. In the present case, all the surveyed women were classified into two groups, viz. whether they maintained Nutri-Gardens (adopters) or not (non-adopters). Table 5 displays the estimates of key variables affecting the decision of the women in maintaining a Nutri-Garden across the surveyed 12 states. The elderly women were more inclined to maintain a Nutri-Garden in their homes, as compared to younger women. The education of women has positively and significantly affected the decision of the women farmers in the favour of adoption of a Nutri-Garden. The access to mass media, like TV, radio, newspapers etc. and mobile-use affected the adoption of Nutri-Garden positively and significantly. The frequency of contact with the agricultural extension agencies (scientists, KVKs and Line Departments) influenced the women's decision to adopt a Nutri-Garden in their homes. We had used a control for the

Table 5 Determinants of adoption of a Nutri-Garden by women

Dependent variable: Do you maintain Nutri-Garden (Yes=1, No=0)

Predictor variables	Coefficient	Standard error
Age of respondent (years)	0.019***	0.007
Education level of woman respondent (illiterate=1, primary school=2, middle school=3, high school=4, intermediate=5, graduation and above=6)	0.118***	0.043
Family size of respondent (small=1, medium=2, large=3)	-0.027	0.098
Annual family income (₹)	0.034	0.113
Marital status of respondent (married=1; otherwise=0)	0.247	0.300
Primary occupation of respondent (agriculture=1; otherwise=0)	0.024	0.157
Landholding category of respondent (marginal=1, small=2, semi-medium=3, medium=4, large=6)	-0.025	0.087
Access of respondent to mass media index score	0.327***	0.066
Use of mobile phone by respondent (regular=1; otherwise-0)	0.420***	0.127
Nutrition extension index score	0.005	0.046
Agricultural extension index score	0.203***	0.042
Constant	-1.355	1.263
Likelihood ratio chi-square	696.21***	
Pseudo-R^2	0.3375	
Total number of observations	1494	

Notes *** denote significance at 1 per cent level; the estimate used state fixed effect in the model
Source Authors' compilation

state fixed effect in the model. The log-likelihood ratio (LR) was found to be significant at 1 per cent level of significance that implies that all the explanatory variables included in the model jointly influence the women's probability of maintaining a Nutri-Garden in their homes.

Conclusions and policy implications

A Nutri-Garden can be considered as a holistic farming model that optimizes nutrition supply to the farming families, addresses the nutritional problems, promotes ecological resilience and improves the quality of life. The sensitization on family nutrition through promotion of nutri-farms have made the farming community, especially women farmers to include bio-fortified varieties and nutri-rich vegetables in their daily diet. This has resulted in an increase in the production of fruits and vegetables in the selected 12 states. Also, the gender sensitization approach which was accomplished through several gender sensitization workshops and programmes, has uplifted the socio-economic status of women in these selected states. The farm women have depicted better access to resources and were empowered to take farm-related decisions independently. Conclusively, the inception of this activity could synthesize a kind of awakening among the farm women, creating a sensation among them to upscale their farming to a new height and serve as a catalyst to empower other unreached farm women.

The initiatives like POSHAN Abhiyan can play a significant role in improving the access to nutritious foods and raising awareness about the importance of a balanced diet. To ensure the success and sustainability of Nutri-Gardens, it is crucial to provide training and inputs support to the farmers, especially small and marginal farmers. This includes educating them on the selection and cultivation of nutrient-rich crops, organic farming practices, water conservation techniques, and pest management. As such Nutri-Garden, backyard nutrition gardening or rooftop nutrition or any form of the Nutri-Garden with the farm family as a low cost sustainable approach for mitigating malnutrition especially in rural households need to be promoted at large scale. Collaborative efforts involving government agencies, non-governmental organizations, community-based organizations, and educational institutions can help in disseminating information and implementing interventions effectively.

References

Garrett, J and M Natalicchio. 2011. Working Multi-sectorally in Nutrition: Principles, Practices and Case Studies. International Food Policy Research Institute, Washington DC.

Kumari, P, M Mustaf, S P S Somvanshi, C Singh and P Kumar 2019. Nutri-Garden for sustainable food security and nutritional diversity in Hamirpur district of Bundelkhand Region (UP). *Indian Journal of Extension Education* 55(4): 107-113.

NIN, ICMR-2018. Plate for the day, National Institute of Nutrition, Hyderabad, India: p. 3.

Seyyed, A, A S Baglou, A J Khazri and G Pashavi. 2012. An introduction to structural equation modelling in PLS and its application in behavioral sciences, 126-139.

Received 27 July 2023 Accepted 30 October 2023

Appendix A1 The responses considered for nutritional attitude, nutritional knowledge, nutritional practices and clinical symptoms

Variable	Questions asked from respondents
Attitude towards nutrition	Consumption of super foods is essential for getting phytonutrients
	Millets help in management of life-style disorders
	NutriThali is not essential for all age groups
	We should consume balanced diet
	We should not skip meals
	We should cut nails regularly
	We should maintain personal hygiene
	There is no need to maintain ideal body weight
	We should include green leafy vegetables in daily diet to prevent anemia
	We should avoid drinking direct tap water
	We should not wash hands before food intake
	Morning walk and jogging improve health
	Kitchen garden is necessary to get fresh fruits and vegetables
	Protein-rich food should be included in diet
	We should consume sprouted grains
	Fried, baked foods should be restricted
	Consuming raw vegetables is good for health
	Junk and road-side food are healthy and hygienic
	There is no need for diet diversification
	Diet should include a cup of milk
	Egg should be included in daily diet
	The daily diet should include grains, root and tubers
	Nuts and oilseeds should be avoided in daily diet
Nutritional knowledge score	Are you aware of super foods
	Millets are better for health than rice and wheat
	NutriThali is nothing but a balanced diet
	Balanced diet is essential for good health
	Skipping meals is good for health
	Cutting nails timely is hygienic practice
	Anaemia is due to deficiency of Vit. A
	Ideal body weight is necessary to maintain good health
	Intake of green leafy vegetables enhance Vitamins C
	Drinking tap water is not good for health
	Washing hands before eating food is not a good practice
	Morning walking and jogging are good for health
	Cereals are rich source of carbohydrates
	Sprouting will not improve nutrient availability
	Obesity may be due to excess intake of fat
	Egg is complete protein
	Regular consumption of junk food is good for health
	Milk and milk products enhance calcium and are important for bone health
	Females need more iron in diet than male
	Green leafy vegetables are good source of folic acid
	Supplement diet is necessary to overcome deficiency of nutrients
	Protein is necessary for good Hb status

Contd...

Variable	Response to the questions
Nutritional practices	Do you use Chia seeds, Quinova seeds and flax seeds in your diet
	Do you use millets in your daily diet
	Does your daily diet consist of all five food groups
	Do you consume balanced diet daily
	Do you skip meals
	Do you cut your nails frequently
	Do you keep yourself hygiene
	Do you practice yoga/exercise to maintain ideal body weight
	Do you consume green leafy vegetables daily
	Do you drink direct tap water
	Do you wash your hands before taking food
	Do you maintain a kitchen garden at home
	Do you consume cereals in daily diet
	Do you consume sprouted grains
	Do you consume fried, baked foods daily
	Do you eat enough fruits and vegetables
	Do you consume milk and milk products daily
	Do you consume roots and tubers daily
	Do you take supplement diet
	Do you eat egg daily/frequently
	Do you eat fish & meat
Clinical symptoms	General — Underweight/overweight, short stature, decreased activity level, wasting.
	Hair — lack of natural shine; hair dull and dry; thin and sparse; depigmented, colour changes (flag sign); can be easily plucked, altered texture
	Face — skin color loss (depigmentation); skin dark over cheeks and under eyes; lumpiness or flakiness of skin of nose and mouth; swollen face; enlarged parotid glands; scaling of skin around nostrils.
	Eyes — eye membrane are pale (Pale conjunctivae); Bitot's spots; redness and fissuring of eyelid corners; dryness of eye membranes; cornea has dull appearance; cornea is soft; scar on cornea
	Lips — redness and swelling of mouth or lips (cheilosis); especially at corners of mouth (angular fissures and scars)
	Tongue — swelling; scarlet and raw tongue; magenta (purplish color) of tongue; smooth tongue; swollen sores; hyperemic and hypertrophic papillae; and atrophic papillae
	Teeth — may be missing or erupting abnormally; gray or black spots (fluorosis); cavities (caries)
	Gums — spongy and bleed easily; recession of gums
	Glands — thyroid enlargement (front of neck); parotid enlargement (cheeks become swollen)
	Skin — dryness of skin; sandpaper feel of skin; flakiness of skin; skin swollen and dark; red swollen pigmentation of exposed areas; dermatitis in nasolabial folds, excessive lightness or darkness of skin; black and blue marks due to skin bleeding; lack of fat under skin
	Nails — nails are spoon-shape (koilonychia); brittle, ridged nails
	Muscular and skeletal system — muscles have "wasted" appearance; baby' skull bones are thin and soft; round swelling of front and side of head; swelling of ends of bones; small bumps on both sides of chest wall (on ribs)-beading of ribs; baby's soft spot on head does not harden at proper time; knock-knees or bow-legs; bleeding into muscle; person cannot get up or walk properly
Nutri-Garden	Do you practice nutri-gardening or kitchen garden?

Agricultural Economics Research Review

Guidelines for Authors

The *Agricultural Economics Research Review* (*AERR*) is the journal of the Agricultural Economics Research Association (India) (AERA).

The *AERR* publishes original research articles, review papers, and short communications on agricultural institutions, policies, trade, and infrastructure markets; the adoption and impacts of agricultural technology; and structural transformation.

Authors must be members of the AERA. Please see information on membership at the aera website www.aeraindia.in. To apply for membership, please use the membership form given at the website.

Manuscript preparation

Please submit your article in Microsoft Word only.

Word limit

The length of articles and review articles – including references, footnotes, appendices, tables, and figures – should not exceed 7,000 words. Allow 200 words for each table, graph, or image. Short communications and research notes should be limited to 3,500 words.

Authors

Please provide the complete affiliation of all the authors, along with their email addresses and the postal index number (PIN) of their address.

Acknowledgements

Please provide acknowledgements or declare sources of funding.

Abstract

Please limit your abstract to 100 words, focusing on key motivations, findings, and implications.

JEL classification codes

Please supply the appropriate JEL codes.

Keywords

Please supply four to six keywords.

Footnotes

Please use footnotes only if placing the discussion in the text would impede readability. Please do not insert citations into footnotes.

Tables, graphs, and images

Please do not paste tables, graphs, or images into the Word document; please type into a comment box in the article where you would like these placed.

Please send tables in a separate Word document.

If you have generated graphs in Microsoft Excel, please caption these graphs and attach these in.XLS or.XLSX format to your email. If you have used R, MATLAB, STATA, or another application, please send us the graphs in PDF (along with the captions).

If you need to use images, please caption these and send it to us in the format of the application you used to generate it.

If the appendix of your article contains tables, graphs, or images, please label these consecutively as A1, A2, ….

Title, headings, subheadings, and table, figure, and image captions

Please try to limit headings and captions to 25 characters (including spaces).

Only the first letter should be in capital. For example, *The impacts of information on returns from farming evidence from a nationally representative farm survey in India*

Also provide a short running title. For example, *The impacts of information on returns from farming*.

In headings, subheadings, and table and figure captions, please use Arabic numbers (please do not use letters or Roman numbers). Please try to limit the number of sub-headings to two. Please number figures and tables sequentially.

References

Sources are cited so that readers may look up the documents referred to. To help your readers, please supply the uniform resource locator (URL) for every source you cite, and please consider not citing a source if no URL is available. (However, if you must cite a document that readers cannot look up, insert a note to the Editor to that effect.)

Please look for a URL especially if you cite a state or central government document – laws, bills, ordinances, notifications, parliamentary proceedings and questions, letters, reports, tables, databases. Please link to the document you refer to and not the home page of the website. Please also look for a URL for other published documents (books, working papers, reports by government ministries or private bodies).

For published journal articles, please supply a permanent link, such as a digital object identifier (DOI) or Handle. If it is not available, please supply the URL to the full text or abstract of the article.

The *AERR* uses the author-date system to cite sources: every reference list entry has a corresponding text citation.

Please use the *Chicago Manual of Style*, 17th edition (*CMoS*) to style your references.

Journal article

Agarwal, Bina. 1984. Tractors, tubewells and cropping intensity in the Indian Punjab. *The Journal of Development Studies* 20 (4): 290–302. https://doi.org/10.1080/00220388408421918

Working paper

Hemme, T, O Garcia, and A Saha. 2003. A review of milk production in India with a particular emphasis on small-scale producers. PPLPI Working Paper No 2, Food and Agriculture Organization, Rome. http://www.fao.org/3/a-bp233e.pdf

Book chapter

Lalitha, N and B Ramaswami. 2007. Pesticides use pattern among cotton cultivators in Gujarat. In *Frontiers of agricultural development in Gujarat*, ed R Dholakia, 77–98. Centre for Management in Agriculture, Indian Institute of Management, Ahmadabad, India. https://www.isid.ac.in/~bharat/Research/Pestcides_Use_Pattern_among_Cotton_Cultivation.pdf

Book

Allard, R W. 1999. *Principles of plant breeding*. 2nd edition, John Wiley & Sons, New York.

For edited books, please insert "(eds)" between the names of the authors and the date.

Report

Mayee, C D, P Singh, A B Dongre, M R K Rao, and S Raj. 2002. Transgenic Bt cotton. Technical Bulletin 22, Central Institute For Cotton Research, Nagpur. http://www.cicr.org.in/pdf/transgenic_bt_cotton.pdf

Government report

Department of Animal Husbandry, Dairying and Fisheries, Ministry of Agriculture and Farmers Welfare, Government of India. 2017. Basic animal husbandry and fisheries statistics., New Delhi. http://dadf.gov.in/sites/default/filess/Basic%20Animal%20Husbandry%20and%20Fisheries%20Statistics%202017%20%28English%20version%29_5.pdf

Published conference proceedings

Please treat a paper included in the published proceedings of a meeting like a book chapter in a. If a paper is published in a journal, please treat it as a journal article.

Unpublished documents

If a book or journal article is due to be published, please substitute the year with the word 'forthcoming'.

In-text citation

Single author	(Chaturvedi 2006)
Two authors	(Chaturvedi and Sharma 2006)
Three authors	(Chaturvedi, Sharma, and Jain 2006)
More than three authors	(Chaturvedi et al. 2006)

Please use a semi-colon to separate citations in parentheses; for example, (Chaturvedi 2006; Jain et al. 2018).

Review

Once your article is edited, we will send it to you. When you review the edit, please track your changes, and please address all the comments.

The Guidelines for Authors on the website list recently published articles. Please use these to format your article. That will save us time and help us publish your article quickly.

Submission

Please email your article, along with a cover letter, to ceditoraerr@gmail.com.

In your cover letter, please give the undertaking that your article is original and that it has not been published in another journal or submitted for publication, and that if the AERR publishes your article, the Agricultural Economics Research Association (India) will have the copyright on the full content.

Please mention the title of your article; the names, affiliations, and email addresses of the authors; acknowledgements; and sources of funding.

Processing fee

The *AERR* charges a non-refundable fee of five hundred rupees (Rs 500) for processing articles submitted for publication. You can pay the fee through a demand draft or multicity cheque. Please make it out to the Agricultural Economics Research Association (India), payable at New Delhi, and send the proof to the **Chief Editor,** Agricultural Economics Research Review, F 4, A Block, NASC Complex, Dev Prakash Shastri Marg, Pusa, New Delhi 110 012.

You may alternatively transfer the fee to the bank account of the AERA (Account holder: Agricultural Economics Research Association, Bank Name: Canara, Branch: NASC Complex, Bank Account No.: 90292010018589, IFSC: CNRB0019153, Nature of Account : Saving, MICR No.: 110015508)

AGRICULTURAL ECONOMICS RESEARCH ASSOCIATION (INDIA)

EXECUTIVE COMMITTEE

Regd. No. F2 (A/67)/89

Agricultural Economics Research Association (India)

The Agricultural Economics Research Association (India), a registered society, came into being in 1987, and on date has around 1100 life members, 110 ordinary members, and 120 institutional members from India and abroad. Through it journal *Agricultural Economics Research Review* the Association contributes towards improving quality of research in agricultural economics and rural development. To encourage young professional, the journal also publishes abstracts of the Master's and Doctoral dissertations in agricultural economics. Besides, the Association regularly organizes annual conference on the issues of contemporary importance, and also undertakes sponsored research in agricultural economics and rural development. The Association is now widely recognized for its professional contributions and credibility. Its journal *Agricultural Economics Research Review* is highly rated by the National Academy of Agricultural Science, New Delhi.

Address for correspondence:
Secretary
Agricultural Economics Research Association (India)
F-4, A Block, National Agricultural Science Centre (NASC) Complex
Dev Prakash Shastri Marg, Pusa
New Delhi 110 012, India
Email: aeraindia@gmail.com
Webpage: www.aeraindia.in

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