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Indians Demanding More Plant-Based Protein, but Farmers' Profits Drop: Empirical Evidence to Understand the Dilemma

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This study estimates changes in productivity and profitability and their respective components for two major Indian sse crops, pigeon peas and chickpeas. Results show that average profitability declined during the period under consideration (2009–2014) for both pulse crops. Lower profits are driven by increases in input prices and decreases in total factor productivity, output growth, and output (constant) prices. The reduction in total factor productivity is primarily due to a slow increase in output. Finally, the technical efficiency estimates are lower than for cereal crops like rice and wheat: 72% for chickpeas and 71% for pigeon peas.

Key words: input prices, output prices, scale efficiency, state heterogeneity, technological change, total factor productivity

Introduction

Pulses, a good source of nonanimal protein, occupy a significant place in Indian diets and make up 13% of India's overall protein intake (Umanath, Chengappa, and Vijayasarathy, 2016). Protein from pulses is paramount for Indians, most of whom are vegetarian (Umanath, Chengappa, and Vijayasarathy, 2016). Pulses also contain essential vitamins (vitamins A and C) and minerals (iron, calcium, and phosphorus, see Campos-Vega, Loarca-Piña, and Oomah, 2010). Pulse crops can also fix 30–150 kg of atmospheric nitrogen in the soil per hectare, and pulse crop residues are also major sources of high-quality livestock feed (Lingareddy, 2015). However, for the last few decades, pulses have become less reliably available for average Indians. As a result, daily per capita availability of pulses has declined from 61 g/day in 1951 to about 43 g/day in 2013–2014 (Rampal, 2016; Umanath, Chengappa, and Vijayasarathy, 2016). This decline has led to lower protein intake, greater protein deficiency, and increased malnutrition among Indians (Tripathi and Srivastava, 2011; Srivastava, 2015). Ahlawat, Sharma, and Singh (2016) noted that 15.2% of India's people are undernourished. Even with the decline in per capita consumption, India's demand for pulses has grown considerably over the past 2 decades, making the country the world's largest consumer of pulses. India also remains the world's largest producer of pulses. Still, India has experienced recurring shortages due

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to a decline in its cropped area of pulses and only a marginal increase in pulse yields since the 1960s (Rahman, 2015). Despite growing demand and rising prices in recent years, pulse supplies have not responded adequately (Ahlawat, Sharma, and Singh, 2016).

Further, pulses have not received the same kind of investments in markets and technology as other food grains (Joshi, Kishore, and Roy, 2017). To improve yields and encourage smallholders to pursue pulse farming, the Government of India has introduced high-yielding cultivars, encouraged the adoption of improved production technologies, and enhanced mechanization and grain storage facilities. In addition, policy makers have steadily increased the minimum support prices (MSP) for pulses to spur pulse crop acreage and production growth. Despite these measures, pulse production remains unattractive for many Indian farmers (Ahlawat, Sharma, and Singh, 2016). Pulse producers of all sizes need to balance a complex array of priorities, including increasing pulse yields, reducing input costs, improving crop management practices, and improving farm viability. To encourage smallholders to produce pulses, policy makers need to understand the factors affecting the productivity and profitability of Indian farmers who engage in pulse production. This understanding may be enhanced by decomposing total factor productivity (TFP) into meaningful and preferably independent factors.

The objective of this study is to estimate changes in productivity (i.e., scale components, technical change, and technological efficiency) and profitability (i.e., TFP, output price, output, and input prices) for India's pigeon pea and chickpea crops. The study is significant in three ways. First, it assesses the productivity and profitability of two pulse crops that provide substantial amounts of protein in Indian diets. A better understanding of the factors affecting productivity, technical change, and profitability over time is likely to be associated with smallholder success in achieving more efficient production. Second, the study decomposes productivity and profitability changes that can help policy makers, researchers, and extension agents identify bottlenecks to increased production of pulses in India. Third, findings would help policy makers design policies that increase efficiency and profitability, thus ensuring sustained supplies of these pulses as key protein sources for Indian consumers and improving livelihoods for smallholder farmers. The study uses data collected from 2009–2014 from India by the International Crops Research Institute for Semi-Arid Tropics (ICRISAT) as part of the Village Dynamics Study in South Asia (VDSA) program.

India's Pulse Sector

India is the world's largest producer and consumer of pulses, accounting for about 24% of global production, 27% of consumption, and 34% of food use (Sharma, Kumar, and Mittra, 2016). Pulses are a critical Indian crop,[1] with about 19.3 million tons produced from 25.3 million hectares in 2013–2014. Between 1970–1971 and 2013–2014, average yield of pulses increased by 46%, but wheat and rice yields increased by more than 100% (Government of India, 2018) during the same period. In another study, Lingareddy (2015) noted that rice yields increased 145% and wheat yields increased 270% between the 1960s and 2013–2014, but pulse yields grew by only 28%. However, pulse production in India has been low historically, peaking in 2013–2014 at 19.3 million tons but supply is far less than demand, due to unpredictable weather and unfavorable policies (Sharma, Kumar, and Mittra, 2016). Madhya Pradesh (MP) is India's largest producer of pulses (Government of India, 2018), accounting for about 26% of the nation's total pulse production. Other states with significant output include Maharashtra (14%), Rajasthan (12%), Uttar Pradesh (9%), Karnataka (8%), and Andhra Pradesh (7%). Green Revolution technologies implemented in India were instrumental in bringing about a significant rise in cereal yields, especially in wheat and rice.[2] However, limited agricultural land and limited availability of irrigated farmland have stagnated the domestic supply

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[1] Pulses are used to make dal, a thick, gravy-like dish, as well as in curries and snack foods, such as samosa (a deep-fried pastry stuffed with green peas and potatoes), pakora (vegetables coated in a chickpea-flour batter and deep-fried), and papad (fried or toasted wafers).

[2] The Government of India sets minimum support prices (MSP) for 25 commodities, including five different pulses.

of pulses, with more productive used to grow cereals. The actual yield is low because legumes are grown mainly on unirrigated and drylands.[3] The yield gap for all pulses in India is much higher than for cereals like wheat and rice.

The Government of India has resorted to imports to address the shortages. India has become the world's largest importer of pulses, with imports increasing from 0.3 million metric tons in 1991–1992 to about 6.0 million metric tons in 2015–2016 (Joshi and Rao, 2017). Gulati and Saini (2018) reported that pulses made up about 13% of India's total imports in 2015–2016, up from 9% in 2001. Suppliers include Canada, Myanmar, the United States, Australia, and China, which account for 75% of all global pulse exports. The demand for pulses and other proteins is projected to rise as India's middle class grows. Finally, the Government of India regularly procures commodities in the Public Distribution System to feed the poor.

In this study, we are especially interested in two types of pulses: chickpeas and pigeon peas. Chickpea is a principal pulse crop and account for 40% of total pulse production in India (Joshi and Saxena, 2002). Chickpea is a winter crop planted between September and November and harvested between February and April. It can be grown in various climatic conditions, but it prefers a mild, cool, and comparatively dry climate with temperatures between 20oC and 25oC. These climatic requirements match India's prevailing climate, so many farmers like to grow this crop. India is the world's largest producer of chickpeas, accounting for 65% of global production. Pigeon pea is India's second-most important pulse crop with respect to planted acreage and output (Joshi and Saxena, 2002). Pigeon pea is typically cultivated during the monsoon season (June–September), with planting beginning in June and July and harvest taking place between December and January. India is the world's largest producer of pigeon peas, accounting for 66% of total world production. Over the last 7 decades, India's production area of chickpea and pigeon pea crops has increased steadily, with the increase in pigeon pea acreage higher relative to the increase in chickpea acreage. India's cropped area under chickpeas increased from 7 million hectares (ha) in 1952–1953 to about 9 million ha in 2014–2015. The total cropped area in pigeon peas increased from about 2 million ha to nearly 4 million ha during the same period.

Table 1 shows the area under production, total output, and yield (per hectare) for the chickpea crop between 1990–1991 and 2015–2016 . The table shows a steady increase in the total area, from about 7.5 million hectares to about 8.4 million hectares. Total output increased from 5.4 million tons in 1990–1991 to about 7.2 million tons in 2015–2016. However, the chickpea crop productivity (kg/ha) shows some variability between 1990–1991 and 2015–2016. Table 1 also shows the total area, total output, and yield (kg/ha) for the pigeon pea crop. The total area under production and total output are about half that of the chickpea crop, and yield is much more variable than that of the chickpea crop. Yield growth has emerged as a major challenge for chickpea and pigeon pea crops. In both cases, yield growth has slowed over the last 3 decades. For instance, chickpea output grew by about 3% per year in the 1990s and by about 1.5% per year in the 2000s but fell by 0.5% per year in the 2010s (Table 1). We observe a similar pattern for the pigeon pea crop: Output grew by about 2% per year in the 1990s and about 0.1% per year in the 2000s but fell by 0.5% per year in the 2010s (Table 1).

Literature Review

A comprehensive crop-specific TFP analysis was done by using the farm-level data for all major crops grown in the states of India. Several studies (Rosegrant and Evenson, 1992; Dholakia and Dholakia, 1993; Evenson, Pray, and Rosegrant, 1999; Fan, Hazell, and Thorat, 1999) have shown that TFP growth in agriculture was the primary driving force behind growth in the Indian economy during the 1980s, while Birthal et al. (1999) analyzed the TFP growth trend for India's livestock

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[3] The irrigated area under pulse production increased from about 2 million hectares (ha) to 4 million ha between 1950–1951 and 2011–2012. However, irrigated area under cereals, excluding pulses, increased from about 16 million ha to about 60 million ha during the same period.

Table 1. Chickpea and Pigeon Pea Area, Production, and Yield, 1990–1991 to 2015–2016

	Chickpea			Pigeon Pea		
Year	**Area (million hectares)**	**Production (million tons)**	**Yield (kg/hectare)**	**Area (million hectares)**	**Production (million tons)**	**Yield (kg/hectare)**
1990–1991	7.52	5.36	712	3.59	2.41	673
1991–1992	5.58	4.12	739	3.63	2.13	588
1992–1993	6.45	4.42	684	3.58	2.33	652
1993–1994	6.36	4.98	783	3.53	2.69	762
1994–1995	7.54	6.44	853	3.31	2.14	644
1995–1996	7.12	4.98	700	3.45	2.31	670
1996–1997	6.85	5.57	813	3.51	2.66	756
1997–1998	7.56	6.13	811	3.36	1.85	551
1998–1999	8.47	6.80	803	3.44	2.71	787
1999–2000	6.15	5.12	833	3.43	2.69	786
2000–2001	5.19	3.86	744	3.63	2.26	618
2001–2002	6.42	5.47	853	3.33	2.26	679
2002–2003	5.91	4.24	717	3.36	2.19	651
2003–2004	7.05	5.72	811	3.52	2.36	670
2004–2005	6.71	5.47	815	3.52	2.35	667
2005–2006	6.93	5.60	808	3.58	2.74	765
2006–2007	7.49	6.33	845	3.56	2.31	650
2007–2008	7.54	5.75	762	3.73	3.08	826
2008–2009	7.89	7.06	895	3.38	2.27	671
2009–2010	8.17	7.48	915	3.47	2.46	711
2010–2011	9.19	8.22	894	4.37	2.86	654
2011–2012	8.30	7.70	928	4.10	2.65	661
2012–2013	8.52	8.83	1,036	3.89	3.02	776
2013–2014	9.93	9.53	960	3.90	3.17	813
2014–2015	8.25	7.33	889	3.85	2.81	729
2015–2016	8.35	7.17	859	3.75	2.46	656

Source: Government of India (2018).

sector. Similarly, Fan, Hazell, and Thorat (1999) investigated TFP for the Indian agriculture sector in different states from 1970 to 1995,[4] reporting that TFP grew at an annual rate of 1.75. In another study, Tripathi (2010) found that agricultural growth between 1969 and 2005 was primarily due to increased traditional inputs, while productivity growth was negative during the same period. Joshi et al. (2003) investigated TFP for the rice and wheat crops in the Indo-Gangetic Plains and found that annual TFP growth rate of about 2.43% for rice and 2.99% for wheat between 1970 and 1999. However, these studies failed to document the sources of growth in TFP (e.g., the scale of technical efficiency). Singh and Singh (2012) estimated TFP growth and technological progress in Indian agriculture between 1970 and 2004 and concluded that efficiency change positively contributed to growth in TFP and negative growth in technology detracted from potential productivity growth.

Kalirajan and Shand (1997) investigated the TFP growth in agriculture for 15 states in India. The authors noted that technical efficiency increased in all states throughout the period, but there is still potential to improve technical efficiency. They also reported that Indian agriculture experienced slow rates of technological progress between 1980 and 1990, and output growth in the sector was mainly due to input growth. Using data from Indian national accounts, Rada (2016) constructed

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[4] To measure the output index, the authors used five major crops (rice, wheat, sorghum, pearl millet, and maize), 14 minor crops (barley, cotton, groundnut, pulses, potato, rapeseed, mustard, sesame, sugar, tobacco, soybean, jute, sunflower, and other minor crops), and three major livestock products (milk, meat, and chicken). To measure the input index, the authors used five inputs (labor, land, fertilizer, tractor, and buffalo).

agricultural output data from 1980 to 2008 to examine the spatial and temporal performance of the Indian agricultural sector in the post-Green Revolution period and found that TFP growth diffused away from the northern states of the Green Revolution. The growth has been retributed to yield-enhancing technologies (Chand and Parappurathu, 2012), enterprise diversification (Singh and Pal, 2010; Binswanger-Mkhize and d'Souza, 2012), and farm size expansion, mainly due to irrigation. In a recent study, Mohapatra et al. (2022) used panel data from 571 districts from 1990–1991 to 2015–2016 and found that TFP growth in India averaged around 0.688% between 1990 and 2015 and technical efficiency accounted for most TFP growth. The authors noted that differences in scale components account for annual and cross-state productivity growth disparities.

Several studies in the nonagricultural sector (Fecher-Bourgeois and Perelman, 1992; Domazlicky and Weber, 1998) have identified the source of TFP growth. Aigner, Lovell, and Schmidt (1977) decomposed TFP growth into technical progress and changes in technical efficiency. Kumbhakar and Lovell (2000) decomposed TFP growth into four components—technological progress, allocative efficiency change, change in technical efficiency, and scale effect—using a flexible translog production function. There are numerous studies on farm technical efficiency in developing countries. Most of these studies concentrate on the efficiency of maize and rice farming (Abdulai and Eberlin, 2001; Sherlund, Barrett, and Adesina, 2002). Other empirical studies on the agricultural sector focus extensively on productivity (Baležentis, 2014; Cechura et al., 2015), while a few studies have addressed farm profitability (Kroupová, 2016). In the Indian case, Kalirajan (1981) investigated productivity differences between farms in a sample from Coimbatore, Tamil Nadu; Sidhu and Byerlee (1991) investigated annual TFP growth in Punjab; and Datta and Joshi (1992) studied production efficiency in a district (Aligarh) of Uttar Pradesh for wheat and rice farmers. Other studies (Battese and Coelli, 1995; Evenson, Pray, and Rosegrant, 1999; Shanmugam, 2000; Murgai, 2001; Kumar, Kumar, and Mittal, 2004) have investigated factors affecting TFP growth.

The literature on productivity analysis mentioned above is lacking on several fronts. First, the literature is void of the decomposition of TFP (scale and technical change) for smallholders in an emerging economy like India. Second, no study has investigated Indian pulse crops. Third, an analysis that uses a large sample to analyze TFP and its components is missing. Finally, productivity and profitability remain the primary drivers of farm performance and, thus, of farmers' motivation to cultivate pulse crops. However, there is a lack in the literature addressing changes in the productivity and profitability of farmers specializing in pulses (specifically, pigeon peas and chickpeas). This study fills the gap in the literature by addressing these changes. The dependent and independent variables used in the analysis are mainly derived from previous studies (e.g., Rada, 2016; Mohapatra et al., 2022).

Data

This study is based on farm household-level panel data collected by ICRISAT under the Village Dynamics Studies in South Asia (VDSA) project funded by the Bill and Melinda Gates Foundation. A total of 866-panel households covering 18 villages across six states in India (two villages each in Andhra Pradesh, Madhya Pradesh, and Telangana and four villages each in Maharashtra, Karnataka, and Gujarat) were studied for 6 years (2009–2010 to 2014–2015). These 18 study villages and sample households represent India's diverse agroclimatic context and varied infrastructural and socioeconomic conditions. The VDSA dataset has various modules, including the Household Census Schedule, General Endowment Schedule, plot list, cropping patterns, Employment Schedules, Transaction Schedules, Monthly Price Schedules, Cultivation Schedules, and Livestock Economics Schedule (International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), 2009–2014). The data were collected by resident field investigators who lived in the villages. Enumerators visited the same households monthly and during crop season over the study period. Data from 40 households (10 each from landless, small, medium, and large landholding groups) from each study village were collected, except from the traditional study villages (two communities in Telangana and four in

Table 2. Definition and Summary Variables Used in the Analysis, 2009–2014

	Chickpea (N = 660)		Pigeon Pea (N = 410)	
Item	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Output (kg)	1,790.97	3,133.78	814.27	1,219.71
Price (Rs./kg)	22.95	4.89	32.06	6.23
Seeds (kg)	126.6	217.40	11.62	15.17
Labor (family and hired labor, person-days)	54.68	77.89	31.69	32.61
Fertilizer (kg)	139.00	396.00	131.05	129.90
Bullocks (bullock pair-days)	1.85	3.96	3.78	4.52

Source: International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) (2009–2014).

Maharashtra), which had a larger sample size. This paper focuses on and uses panel data only for farm households cultivating chickpea and pigeon pea crops.

Table 2 shows the description and summary statistics of variables used in the analysis. The average output of chickpeas is about 1,791 kg, higher than the output of pigeon peas (814 kg). However, in both crops, we observe significant variability in production. Indian farmers receive higher prices for pigeon peas than for chickpeas (Rs. 32/kg vs. Rs. 23/kg). The price differential reflects the supply and demand for pigeon peas, which are a staple pulse variety that Indian households use daily. Table 2 reveals that chickpeas have significantly higher seed requirements compared to pigeon peas (126 kg vs. 12 kg), although we also find significant variability (standard deviation) in the amount of seed used by the average farmer in the sample. Chickpeas are a relatively labor-intensive crop, requiring about 55 man-days of labor (both family and hired labor) compared to pigeon peas (32 man-days). The average smallholder uses about 139 kg of fertilizer (diammonium phosphate and urea) in chickpeas and about 13 kg in pigeon pea production. Finally, smallholders in India have small parcels, and animal power (bullocks) is used to plow the fields and substitute for machinery. Bullocks are used in pairs, and their effort is measured in days. Table 2 reveals that, on average, about two bullock-pair-days are used in chickpea farming and about four bullock-pair-days are required for pigeon peas.

Theoretical Framework

Following Kumbhakar, Wang, and Horncastle (2015, p. 294), we consider a single-output cost function for our panel dataset:

$$C_{it} = C\left(\boldsymbol{w}_{it}, y_{it}, t\right) e^{u_i}, \tag{1}$$

where y_{it} is the output for the ith farm ($i = 1, \ldots, N$) in period t ($t = 1, \ldots, T$), $C(.)$ is the cost function, $\boldsymbol{w}_{it}$ is a vector of J input prices, t is a time trend, and $u_i \geq 0$ is input-oriented technical efficiency. The total differentiation of equation (1) gives

$$\dot{C} = \sum_j \frac{\partial \ln C}{\partial \ln w_j}\dot{w}_J + \frac{\partial \ln C}{\partial \ln y}\dot{y} + \frac{\partial \ln C}{\partial t} = \sum S_j \dot{w}_J + \frac{1}{RTS}\dot{y} - TC, \tag{2}$$

where $\frac{1}{RTS} = \frac{\partial \ln C}{\partial \ln y}$, $TC = \frac{\partial \ln C}{\partial t}$, and $S_j = \frac{w_j x_j}{C} = \frac{\partial \ln C}{\partial \ln w_j}$, where x_j is the j input quantity with price w_j.[5] Thus, S_j is a cost share.

Differentiating $C = \sum_j w_j x_j$

$$\dot{C} = \sum S_j \left(\dot{w}_J + \dot{x}_j\right). \tag{3}$$

By equating equations (2) and (3), we obtain

$$T\dot{F}P = \dot{y} - \sum_j S_j \dot{x}_J = \dot{y}\left(1 - RTS^{-1}\right) + TC. \tag{4}$$

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[5] Subscripts i and j are omitted to avoid notational clutter.

Equation (4) is the decomposition of the change in total factor productivity (*TFP*) into scale $\left(\dot{y}\left(1-RTS^{-1}\right)\right)$ and technical change $(-\partial \ln C/\partial t)$ components. Note that the scale effect implies a change in input use leading to output growth. The computation of these components is possible after estimating the cost function. We consider equation (4) to obtain the change in profitability after totally differentiating the profit, $\pi = py - \sum_j w_j x_j$, and dividing both sides by C, where p is output price. Thus, the change in profitability is

$$\frac{1}{C}\frac{d\pi}{dt} = \frac{R}{C}\dot{p} + \left(\frac{R}{C}-1\right)\dot{y} - \sum_j S_j \dot{w}_J + \dot{y}\left(1-RTS^{-1}\right) + TC, \tag{5}$$

where $R = py$. The first three terms in equation (5) are the output price change $(\frac{R}{C}\dot{p})$, the output change $((\frac{R}{C}-1)\dot{y})$, and the input price change $(\sum_j S_j \dot{w}_J)$ components, all computed from the data. The last two terms are the decomposition TFP change.

Empirical Model and Estimation

Computation of the scale and technical change components in equation (5) requires econometric estimation of a cost function. We specify a translog cost function frontier because the functional form is a widely used flexible functional form and approximates any arbitrary functional form local second-order approximation (Christensen, Jorgenson, and Lau, 1971; Apostolakis, 1988; Baltagi and Griffin, 1988; Kumbhakar, 1991). Second, and more importantly, the translog functional form allows technical changes to be factor-augmenting (Mari and Lohano, 2007; Kumbhakar, Wang, and Horncastle, 2015). Thus, a translog cost function frontier with input-oriented technical efficiency and price homogeneity conditions is imposed as

$$\begin{aligned}
\ln\left(\frac{C}{wd}\right)_{it} &= \beta_0 + \beta_y \ln y_{it} + \beta_l \ln\left(\frac{wl}{wd}\right)_{it} + \beta_k \ln\left(\frac{wk}{wd}\right)_{it} + \beta_f \ln\left(\frac{wf}{wd}\right)_{it} \\
&+ \frac{1}{2}\beta_{yy}\left(\ln y_{it}\right)^2 + \frac{1}{2}\beta_{ll}\left(\ln\left(\frac{wl}{wd}\right)_{it}\right)^2 + \frac{1}{2}\beta_{kk}\left(\ln\left(\frac{wk}{wd}\right)_{it}\right)^2 \\
&+ \frac{1}{2}\beta_{ff}\left(\ln\left(\frac{wf}{wd}\right)_{it}\right)^2 + \beta_{lk}\ln\left(\frac{wl}{wd}\right)_{it}\ln\left(\frac{wk}{wd}\right)_{it} + \beta_{lf}\ln\left(\frac{wl}{wd}\right)_{it}\ln\left(\frac{wf}{wd}\right)_{it} \\
&+ \beta_{kf}\ln\left(\frac{wk}{wd}\right)_{it}\ln\left(\frac{wf}{wd}\right)_{it} + \beta_{ly}\ln\left(\frac{wl}{wd}\right)_{it}\ln y_{it} + \beta_{ky}\ln\left(\frac{wk}{wd}\right)_{it}\ln y_{it} \\
&+ \beta_{fy}\ln\left(\frac{wf}{wd}\right)_{it}\ln y_{it} + \beta_t t + \frac{1}{2}\beta_{tt}t^2 + \beta_{lt}\ln\left(\frac{wl}{wd}\right)_{it} t + \beta_{kt}\ln\left(\frac{wk}{wd}\right)_{it} t \\
&+ \beta_{ft}\ln\left(\frac{wf}{wd}\right)_{it} t + \beta_{yt}\ln y_{it} t + u_{it} + v_{it},
\end{aligned} \tag{6}$$

where C, y, wd, wl, and wk are cost, output, price of land, price of labor (hired and family labor), and price of seeds, respectively, for chickpea and pigeon pea production, and wf stands for the price of fertilizers for chickpea production and the price of bullocks for pigeon pea production. Further, $v_{it} \sim N\left(0,\sigma_v^2\right)$ and $u_{it} \sim N^{+}(0,\sigma_u^2)$. Thus, we introduce inefficiency into the model using a half-normal stochastic frontier model (Aigner, Lovell, and Schmidt, 1977; Kumbhakar, Wang, and Horncastle, 2015, p. 117).[6] Additionally, Kumbhakar, Wang, and Horncastle (2015) conclude that half-normal is appropriate for competitive industries because the free entry and exit process would push the predicted values close to the frontier. Model parameters are estimated using the

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[6] For a review of inefficiency error distribution see Kumbhakar and Lovell (2000).

maximum likelihood (ML) approach, and we estimate the panel dataset as a pooled cross-section.[7] The corresponding log-likelihood function for observation i is

$$L = -\ln\left(\frac{1}{2}\right) - \frac{1}{2}\ln\left(\sigma_v^2 + \sigma_u^2\right) + \ln\phi\left(\frac{-\epsilon}{\sqrt{\sigma_v^2 + \sigma_u^2}}\right) + \ln\Phi\left(\frac{\mu_*}{\sigma_*}\right), \tag{7}$$

where $\phi(.)$ and $\Phi(.)$ are the standard normal probability density and the cumulative probability distribution functions, respectively, with $\mu_* = \frac{\sigma_u^2 \epsilon}{\sigma_v^2 + \sigma_{ii}^2}$ and $\sigma_*^2 = \frac{\sigma_v^2 \sigma_u^2}{\sigma_v^2 + \sigma_{ii}^2}$. The summation of equation (7) over all observations is the log-likelihood function of the model. Maximizing equation (7) provides the ML estimates of model parameters. Following Battese and Coelli (1988), we estimate observation-specific efficiency as

$$E\left[\exp\left(-u_{it}\right) \mid \epsilon_{it}\right] = \exp\left(-\mu_{*i} + \frac{1}{2}\sigma_*^2\right)\frac{\Phi\left(\frac{\mu_{*i}}{\sigma_*} - \sigma_*\right)}{\Phi\left(\frac{\mu_{*i}}{\sigma_*}\right)}. \tag{8}$$

Based on Jondrow et al. (1982), observation-specific efficiency is

$$E\left(u_{it} \mid \epsilon_{it}\right) = \frac{\sigma_*\phi\left(\frac{\mu_{*i}}{\sigma_*}\right)}{\Phi\left(\frac{\mu_{*i}}{\sigma_*}\right)} + \mu_{*i}. \tag{9}$$

Using the cost function in equation (6), we can compute TFP and its components. More specifically, the term $\frac{1}{RTS}$ of the scale component is calculated as $\frac{\partial \ln C}{\partial \ln y}$ and provided below:

$$\frac{1}{RTS} = \beta_y + \beta_{yy}\ln y_{it} + \beta_{ly}\ln\left(\frac{wl}{wd}\right)_{it} + \beta_{ky}\ln\left(\frac{wk}{wd}\right)_{it} + \beta_{fy}\ln\left(\frac{wf}{wd}\right)_{it} + \beta_{yt}t. \tag{10}$$

The technical change (or frontier shift) term (TC) in equation (6) is calculated as $-\frac{\partial \ln C}{\partial t}$ and is given by

$$TC = -\beta_t - \beta_{tt}t - \beta_{lt}\ln\left(\frac{wl}{wd}\right)_{it} - \beta_{kt}\ln\left(\frac{wk}{wd}\right)_{it} - \beta_{ft}\ln\left(\frac{wf}{wd}\right)_{it} - \beta_{yt}\ln y_{it}. \tag{11}$$

Results and Discussion

Table 3 presents the maximum likelihood (ML) parameter estimates of the cost function (equation 6) for the chickpea and pigeon pea crops. The Wald chi-squared test based on the Wald statistics is significantly different from 0, indicating that the model's fit is good. The chickpea crop model converged after seven iterations, with a log-likelihood value of −314. For the pigeon pea crop model, estimation converged after 1,345 iterations, with a log-likelihood value of −344. For chickpeas, the estimated variance parameter (σ_u^2) corresponding to inefficiency is statistically significant at the 1% level and is greater than the variance parameter corresponding to the random error ($\hat{\sigma}_v^2$). In contrast, the estimated variance parameter for the pigeon pea crop ($\hat{\sigma}_u^2$) is statistically significant at the 10% level and almost equal to $\hat{\sigma}_v^2$. These results indicate that most of the variation in chickpea costs comes from the inefficient use of inputs rather than from unexpected market effects. In contrast, variation in pigeon pea costs comes almost equally from the inefficient use of inputs and random market effects. However, the overall results suggest inefficiencies in the production of both crops.

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[7] We used two-way fixed effects (i.e., years and villages) and one-way fixed effects (i.e., years or villages) estimation approaches. Appendix Table A1 shows the estimated results of the two-way fixed effects model. Comparing the parameters (betas) between Table 3 and Table A1, we observe that they do not change much. Further, the village and time fixed-effects parameters in Table A1 are statistically insignificant, indicating no gains by including village and year dummies in the estimation. Thus, we use the pooled cross-section estimation approach.

Table 3. Parameter Estimates for the Cost Function (Equation 6) for Chickpea and Pigeon Pea Crops

Cost Parameters	Chickpea (N = 660)	Pigeon Pea (N = 410)
β_0	60.46514	924.2914***
	(169.8313)	(204.4581)
β_γ	32.2263**	−101.3928***
	(15.8688)	(28.9113)
β_l	116.0218**	−205.0553***
	(48.8421)	(71.3568)
β_k	−74.2433	216.0898***
	(48.9840)	(70.4272)
β_f	−0.7074	−6.2676
	(3.3640)	(9.3403)
β_{yy}	0.1548***	0.1963***
	(0.0144)	(0.0221)
β_{ll}	0.0745	0.2709**
	(0.1642)	(0.1345)
β_{kk}	0.1188	0.1745
	(0.1639)	(0.1154)
β_{ff}	0.0148***	0.0326***
	(0.0050)	(0.0084)
β_{lk}	−0.0537	−0.1857*
	(0.1634)	(0.1110)
β_{lf}	−0.0123*	−0.0316**
	(0.006)	(0.0153)
β_{kf}	−0.0063	−0.0008
	(0.0060)	(0.0135)
β_{ly}	−0.0500*	−0.1649***
	(0.0308)	(0.0391)
β_{ky}	0.0707**	0.1777***
	(0.0311)	(0.0381)
β_{fy}	0.0019	−0.0168***
	(0.0019)	(0.0051)
β_t	−0.0308	−0.4589***
	(0.0846)	(0.1017)
β_{lt}	−0.0575**	0.1026***
	(0.0243)	(0.0355)
β_{kt}	0.0369	−0.1080***
	(0.0244)	(0.0350)
β_{ft}	0.0003	0.0033
	(0.0016)	(0.0046)
β_{yt}	−0.0160**	0.0501***
	(0.0078)	(0.0143)
Inefficient term-constant parameter	−1.6087***	−1.4682***
	(0.2189)	(0.5514)
$\hat{\sigma}_u^2$	0.2001***	0.2303*
	(0.0438)	(0.1270)
Random term-constant parameter	−2.5081***	−1.4651***
	(0.1726)	(0.2005)
$\hat{\sigma}_v^2$	0.0814***	0.2310***
	(0.0140)	(0.0463)
Log-likelihood	−313.5908	−344.1461
Wald χ^2 (19)	38, 052.82	8, 646.99
Prob > χ^2	0.0000	0.0000

Notes: Numbers in parentheses are standard deviations. We estimated the two-way fixed effects model and the betas as shown above do not change much. Still, the village and time fixed-effects parameters (shown in Appendix Table A1) are insignificant. Thus, we opted for pooled regression technique.
Source: Authors' calculations.

Table 4. Estimates of Technical Efficiency Indexes (Equation 8) by Year and Crop

	Chickpea			Pigeon Pea		
Year	**Mean**	**Std. Dev.**	**Freq.**	**Mean**	**Std. Dev.**	**Freq.**
2009	0.7247	0.1283	86	0.7086	0.1069	81
2010	0.7395	0.0973	115	0.6991	0.0938	115
2011	0.7024	0.1359	113	0.7256	0.0839	56
2012	0.7239	0.1055	130	0.7129	0.0950	53
2013	0.7376	0.1293	119	0.7140	0.0837	59
2014	0.7170	0.1131	97	0.7027	0.0818	46
Total	0.7245	0.1187	660	0.7089	0.0927	410

Source: Authors' calculations.

Table 5. Descriptive Statistics of Returns to Scale, Total Costs, and Total Factor Productivity (Equation 4), 2009–2014

	Chickpea ($N = 417$)		Pigeon Pea ($N = 207$)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Scale				
2010	−0.02	0.16	−0.18	0.63
2011	−0.06	0.22	−0.32	0.68
2012	−0.02	0.23	−0.09	0.40
2013	−0.04	0.31	0.01	0.47
2014	−0.07	0.29	−0.12	0.36
Average	−0.043	0.254	−0.137	0.533
Total costs				
2010	0.03	0.03	0.03	0.09
2011	0.02	0.02	−0.00	0.08
2012	0.02	0.06	0.01	0.09
2013	0.02	0.03	0.01	0.08
2014	0.03	0.09	−0.01	0.06
Average	0.023	0.054	0.008	0.082
Total factor productivity				
2010	0.01	0.16	−0.14	0.59
2011	−0.05	0.23	−0.33	0.64
2012	−0.00	0.23	−0.08	0.37
2013	−0.02	0.31	0.01	0.47
2014	−0.03	0.29	−0.14	0.35
Average	−0.019	0.258	−0.129	0.508

Source: Authors' calculations.

Table 4 provides technical efficiency (TE) measures for both crops and each year during the 2009–2014 period. The table shows that technical efficiency varies between 70% and 74% for chickpeas and 70% and 73% for pigeon peas (Table 4). On average, the mean technical efficiency level for the 2009–2014 period is about 0.72 for chickpeas and 0.71 for pigeon peas (Table 4, columns 2 and 5). These results suggest that farmers can reduce the use of all inputs by 28% and 29% without reducing current output levels of the chickpea and pigeon pea crop, respectively. The technical efficiency estimate is twice as high in the case of chickpeas as those obtained by Jain et al. (2016), who reported an average technical efficiency of 0.35 for chickpeas and 0.62 for pigeon peas in India. The higher estimates in our study may be attributable to a more extended period and fewer states.[8] The estimated technical efficiencies in this study are similar to the technical efficiency (70%–74%) reported by Abdulai and Eberlin (2001) for farmers in Nicaragua.

Table 5 reports the total factor productivity (TFP) estimates and their components (scale and technical change [*TC*]) for both crops during the 2009–2014 period. The mean TFP of both crops is negative for the entire period: about −0.02 for chickpeas and −0.13 for pigeon peas. Negative TFP may be due to technical change. This result corroborates the Boserup theory.[9] Another reason for negative TFP could be population pressure, which may adversely affect production (James and Roumasset, 1992; Lusigi and Thirtle, 1997; Umetsu, Lekprichakul, and Chakravorty, 2003). Our finding is consistent with Umetsu, Lekprichakul, and Chakravorty (2003), who found periods (the early 1970s and late 1980s) of negative TFP in the Philippine rice sector. Similarly, Kalirajan, Obwona, and Zhao (1996) found negative TFP for aggregate agricultural output in 16 provinces in China for the 1984–1987 period. Interestingly, in our case, the scale component of TFP (top panel of Table 5) for both crops contributed to the overall negative TFP. Note that the scale component is given by $\dot{y}(1 - RTS^{-1})$, which is negative if either $RTS < 1$ or output growth ($\dot{y}$) is negative. The estimated returns to scale, *RTS*, is 1.472 for chickpea production and 3.354 for pigeon peas.

However, output growth for both crops is negative. Thus, we can infer that for the whole period under examination (2009–2014), on average, TFP is negative for both crops due to declines in output (or output growth slows). Technical change (TC) is positive yearly for chickpea production, but the scale component is negative. A negative scale effect means that the average cost of production is still rising. For pigeon pea production, TFP is 0 for 2013 and negative for the other years. The scale and technical change components have been negative for most years. Tables 4 and 5 show that chickpeas perform better in terms of productivity and technical efficiency indicators than pigeon peas. The negative scale component means that chickpea and pigeon pea farmers are unable to exploit existing economies of scale. The negative contribution could be explained by the strong dominance of small farms growing chickpeas. Farmers can benefit from reducing the scale of operations (e.g., Mishra, Rezitis, and Tsionas, 2020). Our finding is consistent with Combary and Savadogo (2015), who found a negative contribution of scale component on TFP growth for cotton farmers in Burkina Faso. Similarly, Houedjofonon et al. (2020) found a scale component in the productivity growth of poultry farms in Benin.

Table 6 reports the four components of changes in profitability (output price change, output growth, input price change, and TFP) for the 2009–2014 period. The first three components are computed directly from the data, and TFP is estimated with the cost function parameters. The average change in profitability (bottom panel, Table 6) is negative for both crops. Note that negative profits are due to lower output price, growth, and TFP. For chickpea production, profitability change was positive in 2014 and negative for the rest of 2009–2013. For pigeon pea production, profitability change is negative for the entire 2009–2014 period. The top panel of Table 6 indicates that the input price change has a substantial negative impact on the change in profitability of both crops, mainly on the chickpea crop. This happens because there is a positive change in input prices (i.e., input prices rise) for each year of the 2009–2014 period and, on average, for the whole period. The positive change in input prices enters the profitability equation (5) with a negative sign, adversely affecting profitability.

Table 7 summarizes the technical efficiency measures for both crops by state for the 2009–2014 period. Technical efficiency varies significantly across states and crops. The technical efficiency of chickpea production ranges from 0.78 in Gujarat to 0.66 in Madhya Pradesh. However, the technical efficiency of pigeon peas is slightly lower, ranging from 0.68 in Andhra Pradesh to 0.76 in Gujarat.

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[8] Jain et al. (2016) used cross-sectional data (2012–2013) and states (12 major pulse-growing states—Andhra Pradesh, Bihar, Chhattisgarh, Gujarat, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal) in their analysis.

[9] The basic idea behind Boserup theory is that population growth is independent of food supply and thus is a positive force behind agricultural innovation. Thus, population growth is a cause driving changes in agriculture. Changes in agriculture are mostly driven by agricultural innovation and technology adoption; as society develops and progresses, it uses farmland more efficiently.

Table 6. Estimates of Output Price Change, Output Growth, Input Price Change, Total Factor Productivity, and Profitability Change, 2009–2014

	Chickpea (N = 417)		Pigeon Pea (N = 207)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Output price change				
2010	0.00	0.01	−0.02	0.01
2011	0.02	0.03	0.00	0.01
2012	0.00	0.02	0.00	0.01
2013	−0.01	0.02	0.00	0.01
2014	−0.01	0.17	0.00	0.00
Average	−0.001	0.081	−0.004	0.011
Output growth				
2010	0.08	0.53	0.13	0.91
2011	0.09	0.65	0.30	0.87
2012	−0.21	0.66	−0.06	0.70
2013	−0.13	0.75	−0.43	0.82
2014	0.23	1.06	−0.04	0.96
Average	−0.004	0.776	−0.033	0.878
Input price change				
2010	0.03	0.15	0.09	0.18
2011	0.26	0.31	0.27	0.34
2012	0.25	0.31	0.18	0.39
2013	0.13	0.28	0.46	0.37
2014	0.13	0.30	0.44	0.40
Average	0.167	0.292	0.286	0.370
Total factor productivity				
2010	0.01	0.16	−0.14	0.59
2011	−0.05	0.23	−0.33	0.64
2012	0.00	0.23	−0.08	0.37
2013	−0.02	0.31	0.01	0.47
2014	−0.03	0.29	−0.14	0.35
Average	−0.019	0.258	−0.129	0.508
Profit change				
2010	0.06	0.44	−0.12	0.57
2011	−0.20	0.59	−0.30	0.56
2012	−0.46	0.62	−0.33	0.48
2013	−0.30	0.64	−0.88	0.59
2014	0.06	0.95	−0.61	1.01
Average	−0.195	0.707	−0.453	0.699

Source: Authors' calculations.

Table 7. Estimates of Technical Efficiency Indexes by State (Equation 8)

	Chickpea (N = 660)		Pigeon Pea (N = 410)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Andhra Pradesh	0.76	0.07	0.68	0.08
Gujarat	0.78	0.10	0.76	0.09
Madhya Pradesh	0.66	0.13	0.72	0.08
Karnataka	0.71	0.12	0.74	0.10
Maharashtra	0.74	0.12	0.69	0.10

Source: Authors' calculations.

Table 8. Estimates of Scale, Total Costs, and Total Factor Productivity by State, 2009–2014

	Chickpea (*N* = 417)		**Pigeon Pea (*N* = 207)**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Scale				
Andhra Pradesh	−0.06	0.19	−0.16	0.46
Gujarat	−0.01	0.18	0.05	0.09
Madhya Pradesh	0.02	0.25	−0.05	0.32
Karnataka	−0.07	0.25	−0.16	0.57
Maharashtra	−0.06	0.35	−0.27	0.75
Total costs				
Andhra Pradesh	0.04	0.02	0.16	0.07
Gujarat	0.00	0.02	0.09	0.03
Madhya Pradesh	0.03	0.07	−0.03	0.06
Karnataka	0.02	0.02	0.05	0.12
Maharashtra	0.03	0.11	0.03	0.06
Total factor productivity				
Andhra Pradesh	−0.02	0.20	0.00	0.44
Gujarat	0.00	0.18	0.15	0.08
Madhya Pradesh	0.04	0.24	−0.08	0.31
Karnataka	−0.05	0.26	−0.11	0.57
Maharashtra	−0.03	0.36	−0.24	0.71

Source: Authors' calculations.

These results suggest that chickpea farmers in Gujarat could reduce their use of all inputs by 22% without lowering output levels. Similarly, pigeon pea farmers in Gujarat could reduce inputs by 24% without sacrificing present output level. These results suggest that farmers in several Indian states have significant scope for improving technical efficiency by adopting enhanced production techniques for pulses. The technical efficiency estimates are much larger than those of Jain et al. (2016), found an average technical efficiency of 0.34 for chickpeas and 0.68 for pigeon peas for farmers in Andhra Pradesh.[10] The authors also found estimates of technical efficiency for chickpeas in Madhya Pradesh (0.33) and Karnataka (0.24) that were lower than our estimates.

Table 8 reports TFP and its components (scale and technical change) for both crops by state for the 2009–2014 period. The mean TFP of both crops is negative across all states and crops, except for Madhya Pradesh in chickpeas and Gujarat in pigeon peas. In addition, TFP is about 0 in Gujarat for chickpeas and in Andhra Pradesh for pigeon peas. The top panel of Table 8 shows that the decrease in TFP may be attributed primarily to scale efficiency. Indeed, due to increasing population and family dynamics, farms in India are getting smaller and more fragmented, reducing productivity (Gaurav and Mishra, 2015; Deininger et al., 2018; Malabayabas and Mishra, 2022). The scale component of TFP is negative for all states in both crops, except in Madhya Pradesh, where it is positive for chickpeas, and Gujarat, where it is positive for pigeon peas. Finally, technological progress (TC) contributed positively to TFP for chickpea production in all states and pigeon pea production in all states except Madhya Pradesh. The above findings show that TFP, technical change, and scale efficiency vary significantly in the production of legume crops across states. Thus, any policy intervention should consider regional and state heterogeneity posed by the landscape, resource availability, and farm size.

Table 9 reports the four components of profitability change (output price change, output growth, input price change, and TFP) by state. As in Table 6, the first three components reported in Table 9 are computed directly from the data, and TFP is estimated from the cost function. The average

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[10] Jain et al. (2016) did not estimate technical efficiency for Gujarat.

Table 9. Estimates of Output Price Change, Output Growth, Input Price Change, Total Factor Productivity, and Profitability Change by State, 2009–2014

	Chickpea ($N = 417$)		Pigeon Pea ($N = 207$)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Output price change				
Andhra Pradesh	0.00	0.02	0.00	0.02
Gujarat	0.02	0.04	−0.01	0.02
Madhya Pradesh	−0.02	0.18	0.00	0.01
Karnataka	0.00	0.02	0.00	0.02
Maharashtra	0.00	0.02	0.00	0.01
Output growth				
Andhra Pradesh	0.07	0.53	0.03	1.05
Gujarat	−0.07	0.50	0.04	0.38
Madhya Pradesh	−0.15	0.97	−0.20	0.76
Karnataka	0.05	0.77	−0.14	1.39
Maharashtra	−0.02	0.89	0.20	0.94
Input price change				
Andhra Pradesh	0.17	0.36	0.08	0.56
Gujarat	0.00	0.11	−0.10	0.05
Madhya Pradesh	0.31	0.38	0.32	0.35
Karnataka	0.11	0.15	0.15	0.18
Maharashtra	0.29	0.38	0.32	0.35
Total factor productivity				
Andhra Pradesh	−0.02	0.20	0.00	0.44
Gujarat	0.00	0.18	0.15	0.08
Madhya Pradesh	0.04	0.24	−0.08	0.31
Karnataka	−0.05	0.26	−0.11	0.57
Maharashtra	−0.03	0.36	−0.24	0.71
Profit change				
Andhra Pradesh	−0.11	0.57	−0.05	0.86
Gujarat	−0.06	0.36	0.27	0.39
Madhya Pradesh	−0.43	0.81	−0.60	0.71
Karnataka	−0.11	0.66	−0.40	1.25
Maharashtra	−0.34	0.92	−0.37	0.52

Source: Authors' calculations.

change in profitability (the bottom panel of Table 9) is negative for all states except for Gujarat's positive change in profitability for pigeon peas. The negative profitability is driven by negative TFP in all states except Madhya Pradesh in chickpeas and Gujarat in pigeon peas. The growth in output slowed in Gujarat, Madhya Pradesh, and Maharashtra for chickpeas and Madhya Pradesh and Karnataka for pigeon peas. The top panel of Table 9 indicates that the output prices did not change during the study period in any state, except for declines in output prices for chickpeas in Madhya Pradesh and pigeon peas in Gujarat. Last, the middle panel of Table 9 shows that changes in input prices have the strongest negative impact on profitability changes of both crops. In particular, input prices rose in chickpea production and all states except for Gujarat in pigeon pea production. Thus, we can infer that rising input prices at the state level have a negative effect on the profitability of chickpea and pigeon pea production in their states.

Policy Implications

In India, legume crops like chickpeas and pigeon peas are highly important for diet and nutrition and are considered critical in addressing the challenge of malnutrition. For most Indians, pulses are a key source of protein in their daily diets. In addition, pulse production complements cereal production because pulses fix nitrogen in soils. Even though pulse production has been improving with increased government support programs, India's pulse production still cannot meet the country's demand. The gap between normative pulse demand, given the current severe deficit in protein consumption and the production of pulses, would be much bigger than expected. Indian farmers face significant yield gaps in these major pulse crops, and policy interventions have produced limited results. Any actions that smallholder farmers take are driven mainly by profitability. Thus, it is prudent to understand the changes in productivity and profitability. This investigation provides a valuable understanding of India's productivity and profitability changes for two legume crops (chickpeas and pigeon peas) from 2009 to 2014.

The study also assessed the impact of changes in the components of productivity and profitability. Results showed that the technical efficiency of chickpea and pigeon pea farmers is about 72% and 71%, respectively, and that chickpeas have better productivity and technical efficiency than pigeon peas. The study found that chickpea and pigeon pea farmers could reduce the usage of inputs by 28% and 29%, respectively, without lowering their production level. The technical efficiency analysis suggests that pulse farmers have greater scope for improving technical efficiency through enhanced technology adoption. Further, the results showing average profitability dropped for both crops in the period under consideration should cause concern among policy makers. Note that the decrease in profitability was greater in pigeon pea production than in chickpea production.

Changes in input prices have the most substantial negative impact on changes in profitability, followed by decreases in total factor productivity (TFP), slowing output growth, and decreases in output prices. This suggests not only the need for productivity increases but also the need for greater efforts to reduce costs to motivate pulse farmers to increase production. Empirical findings are similar at the state level, indicating that profitability dropped for each state in chickpea production and, except for Gujarat, in pigeon pea production. Note that the increasing profitability of pigeon pea production in Gujarat is driven mainly by growth in TFP, followed by decreases in input prices and an increase in output. The decline in Gujarat's input prices in contrast to other states is interesting and might require further investigation to understand its drivers.

The study provides valuable insight into several tools that policy makers could use to design and implement policies encouraging farmers to specialize in pulse production. These policies could result in higher production and greater efficiency, especially chickpeas and pigeon peas. To increase TFP, governments can provide incentives for on-farm investment and access to better seeds and fertilizers (Chand and Parappurathu, 2012; Akber, Paltasingh, and Mishra, 2022). Policy makers can support investments that build farmers' capacity and expand access to irrigation. Smallholders in states with broader and better extension services (O'Donnell, 2010; Food and Agriculture Organization of the United Nations, 2020) and social networks (Varshney et al., 2022) are better equipped to transfer management skills, promote efficient use of inputs, and improve technical efficiency with existing technologies. Understanding the context of irrigation needs, identifying the demand for new solutions—particularly cost-effective ways to harvest and utilize rainwater—and working toward engagement and co-ownerships are paramount to solving the irrigation problem. The Indian government should encourage the transfer of new technologies through extension services and private-sector involvement, perhaps through contract farming. Creating and supporting functional farmer-producer organizations (FPOs) around legumes could also help lower transaction costs, increase access to technology, and improve yields and TFP. To address heterogeneous farm performance across states, due to disparities in resource endowments, environmental and soil conditions, and institutional attributes, policymakers need state-specific policy initiatives that allow smallholders in each state to exploit their full farming potential. States with low technological adoption rates need enhanced resource allocation to encourage technology adoption (Hoda, Rajkhowa, and Gulati, 2017).

To address issues related to input and output prices, policy makers need to encourage policies that lead to the development of the market, value chains, and improved access to credit. Given that smallholders cannot afford the costs of modern inputs and current technologies, Chhetri et al. (2010) and O'Donnell (2010) suggest policies aimed at reducing the transactions cost and improvements in terms of trade that could increase technical efficiency and scale of operation and, subsequently, farm profitability. Contract farming and encouraging farmers to organize FPOs are other methods that could strengthen the linkages between production, marketing, and processing in developing and emerging economies (Mishra, Kumar, et al., 2018; Mishra, Shaik, et al., 2018). These aggregation and collective platforms could be crucial in improving knowledge transfer, farming practices, quality, and competitiveness (Kopp and Mishra, 2022). These platforms help farmers benefit from risk assurances in price, marketing, and other production factors, which improves income stability.

Finally, these institutional arrangements would provide smallholder farmers with inputs, access to credit, the introduction to new and appropriate technology, skill transfers, better pricing structures, and access to reliable markets. This study used older data from 2009–2014, which is a limitation. However, this analysis establishes the importance of addressing the multiple production dimensions of input and output prices, TFP, and profitability to harness legume production's potential to improve nutritional outcomes and farmer welfare.

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Appendix

Table A1. Estimated Parameters of Village and Time Effects, 2009–2014

Cost Parameters	Chickpea (N = 660)	Pigeon Pea (N = 410)
β_0	60.64	924.34***
	(189.93)	(207.85)
β_γ	32.36**	−101.48***
	(15.98)	(29.86)
β_l	116.01**	−205.0553***
	(49.76)	(71.3568)
β_k	−74.42	216.98***
	(48.09)	(72.22)
β_f	−0.70	−6.26
	(3.03)	(10.54)
β_{yy}	0.15***	0.19***
	(0.04)	(0.03)
β_{ll}	0.07	0.27**
	(0.14)	(0.14)
β_{kk}	0.11	0.17
	(0.19)	(0.12)
β_{ff}	0.014***	0.033***
	(0.003)	(0.01)
β_{lk}	−0.05	−0.17*
	(0.15)	(0.112)
β_{lf}	−0.012*	−0.032**
	(0.003)	(0.016)
β_{kf}	(−0.006)	−0.0008
	(0.007)	(0.02)
β_{ly}	−0.051*	−0.159***
	(0.03)	(0.04)
β_{ky}	0.07**	0.18***
	(0.03)	(0.05)
β_{fy}	0.002	−0.017***
	(0.002)	(0.006)
β_t	−0.03	−0.46***
	(0.07)	(0.12)
β_{lt}	−0.06**	0.11***
	(0.02)	(0.036)
β_{kt}	0.04	−0.109***
	(0.03)	(0.037)
β_{ft}	0.0003	0.004
	(0.003)	(0.005)
β_{yt}	−0.016**	0.052***
	(0.007)	(0.015)
Village dummy variables		
Village Babrsol[a]	−0.003	−0.013
	(0.75)	(0.12)
Village Karamdichingariya	−0.034	−0.191
	(0.55)	(0.29)

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Table A1. – continued from previous page

Cost Parameters	Chickpea (*N* = 660)	Pigeon Pea (*N* = 410)
Village Kapanimbargi	0.007	0.371
	(0.95)	(0.79)
Village Markabbinahalli	−0.002	0.004
	(0.02)	(0.09)
Village Kalman	0.007	−0.179
	(0.05)	(0.23)
Village Kanzara	−0.010	0.096
	(0.69)	(0.31)
Village Kinkhed	0.006	0.370
	(0.23)	(0.34)
Village Papda	−0.059	−0.086
	(0.05)	(0.09)
Village Rampur Kalan	−0.011	−0.053
	(0.16)	(0.16)
Village JC Agraharam	0.007	−0.372
	(0.95)	(0.79)
Village Pamidipadu	−0.002	0.171
	(0.02)	(0.12)
Village Shirapur	0.061	−0.045
	(0.43)	(0.04)
Village Makhiyala	−0.089	−0.981
	(0.09)	(0.87)
Year dummy variables		
Year 2010[b]	0.0002	0.0001
	(0.120)	(0.002)
Year 2011	0.0009	−0.0007
	(0.034)	(0.009)
Year 2012	−0.0031	0.0001
	(0.079)	(0.067)
Year 2013	−0.0051	−0.0009
	(0.004)	(0.002)
Year 2014	−0.0001	−0.0003
	(0.091)	(0.004)
Inefficient term-constant parameter	-1.609^{***}	-1.4712^{***}
	(0.219)	(0.526)
$\hat{\sigma}_u^2$	0.2001^{***}	0.2431^{*}
	(0.044)	(0.129)
Random term–constant parameter	-2.508^{***}	-1.50^{***}
	(0.173)	(0.39)
$\hat{\sigma}_v^2$	0.082^{***}	0.241^{***}
	(0.02)	(0.05)
Log-likelihood	−315.9387	−347.6892

Notes: Values in parentheses are standard deviations. We use two-way fixed effects (i.e., years and villages) and one-way fixed effects (i.e., years or villages) estimation approaches. Comparing the parameters (betas) between Table 3 and Table A1 we observe that they do not change much. Further, the village and time fixed-effects parameters in Table A1 are statistically insignificant, indicating no gains by including village and year dummies in the estimation. Thus, we use the pooled cross-section estimation approach (Table 3).

[a] Base village is Pamidipadu.

[b] Base year is 2009.