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A Unitary University, Govt. of Karnataka

BASE University Working Paper Series: 14/2022

Impact of Information on Technical Efficiency of Agricultural Production in India

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January 2022

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Abstract

This paper tries to estimate the impact of information use on technical efficiency of agricultural production in India using propensity score matching method. The study utilises cross-sectional data from the 70th Round of NSSO on Situation Assessment Survey of Farmers (2012-13). Technical efficiency is calculated using a novel technique by Cherchye, et.al. (2013) that acknowledges the presence of multiple outputs, output-specific inputs and joint inputs in the data. The results of propensity score matching method show that users of information have a slightly higher efficiency than non-users but the impacts vary largely across different sources of information. The findings hint at a source effect working at large that tends to dampen the true effect of information. Using information from private sources has the largest impact while media has a smaller impact. Public sources don't show a statistically significant impact, may be due to constraints like lack of infrastructure, manpower and monitoring. Nevertheless, it does not undermine their importance but suggests that they might work through indirect channels that require further exploration.

Keywords: Agriculture, Information Use**,** Technical Efficiency, Data Envelopment Analysis, Propensity Score Matching

JEL Classification: D24, Q12, Q16

Impact of Information on Technical Efficiency of Agricultural Production in India

Aritri Chakravarty [1]

1. Introduction

Agricultural growth is important for poverty reduction and economic growth in developing countries where a large part of the population is dependent on agriculture (Chakravarty, 1987, Timmer, 1988 and Johnson, 2000). The multiplier effect of agricultural growth on the non-farm sector has long been recognised (Byerlee et.al. 2009); especially since the seminal work of Schultz (1964). Thus, development of this sector becomes a core concern for scholars and policy makers in developing countries like India, where almost 60 percent of the population is dependent on it. One of the stylised facts of structural transformation is that during economic development the share of agriculture in output declines as does its share of employment but with a lag. In India, agriculture, with a 15 percent share in GDP remains the mainstay for nearly 60 percent (CSO, 2015) of our population. Indian agriculture is characterised by low productivity and pulling the sector out of this low productivity trap has been of utmost priority to ensure increase in farmers' income and growth of the sector and eventually the growth of the non-farm sector.

Several scholars have tried to address this problem through the lens of efficiency, technological innovation and policy intervention (Kalirajan and Shand, 1985; Kalirajan 1991; Fan 1991, 2000; Coelli and Battesse, 1996; Ghosh 1998; Bhalla, 2006; Fried et.al., 2008; Bardhan et.al. 2012). Some have tested whether agricultural production is efficient or not and also tried to identify the determinants of production and/or cost efficiency. In all this, information has been attributed as one of the key catalysts in increasing productivity by reducing the gap between actual and potential output. Schultz (1968) points out that modern inputs and high skills are complementary in agricultural production and over time tend to substitute for traditional agricultural inputs. When new technology becomes available, farmers do not automatically acquire the requisite skills to use it [Schultz (1964, 1975)]. Government interventions particularly in extension services, general education and rural infrastructure are expected to facilitate this process to speed up the adoption of new technology. In India, the government aims to bring farmers closer to information through

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various channels like Krishi Vigyan Kendras, Extension Agents, Agricultural Universities, veterinary departments and ICTs (newspaper, radio, television and internet). These sources are responsible for supplying the farmers with technical advice on different aspects of cultivation. Agricultural Technology Management Agency (ATMA), introduced in 2005, is one such novel initiative that aims at pluralistic demand-driven (bottom-up) approach to disseminate need-based information to farmers using public, private and non-profit channels. Despite these efforts, use of information remains quite low in India.

The latest round of the National Sample Survey Organisation, a very comprehensive decadal survey that captures various aspects of Indian farming (70th Round, 2012-13) shows access to information stagnated at 41 percent for a decade between 2002-03 to 2012-13 (NSSO, 59th Round, 2005; 70th Round, 2015) while use of information was even lower, only 35 percent. Hence, the focus of this paper is to question the effectiveness of information use by farmers in India. For that I study the impact of information on technical efficiency of agricultural production using NSSO 70th Round (2012-13). Farm outcomes, like profit and returns are subject to market related factors that vary across the country as well as within regions. Since information theoretically improves the production process by increasing its efficiency, using technical efficiency of farming as an outcome variable is justified when studying the impact of information. Higher efficiency would ultimately lead to higher productivity and thus, better farm outcomes. Therefore, I try to understand the impact of information use on technical efficiency of farming. This paper calculates efficiency using a novel technique developed by Cherchye et.al., (2013) and explores the translation of the benefits of information use in terms of higher efficiency gains in farm production using propensity score matching technique. I find that users of information have a slightly higher efficiency than non-users but the effects greatly differ among different channels of dissemination of information. Private channels have a higher average efficiency than public as well as they have a larger and significant impact. Overall, there seems to be a source effect at work which dampens the true effect of information.

Having given a brief background in this section, this paper briefly alludes to the role of information in agriculture and the concept of technical efficiency in section 2. Section 3 elaborates on the data, method and variables used in this study and section 4 discusses the results. The observations and concluding remarks are summarised in section 5.

2. Role of Information, Impact on Agricultural Performance and Technical Efficiency

Role of Information

Productivity gains can be achieved through optimum and correct use of technology and inputs which in turn require information. Information helps in accelerating agricultural development by providing the technical know-how and knowledge on different aspects of cultivation like improved practices, inputs and efficient production methods as well as post-harvest management and marketing (Feder and Slade, 1984; Bertolini, 2004, 2006; Hudson, 1991; Lio & Liu, 2006; Palaskas et.al., 1997; Poole & Kenny, 2003; Sarahelen & Sonka, 1997).

Theoretically, neo-classical economics eliminates inefficiency by assuming perfect and costless information, a condition not met in the real world (Knight, 1921). In reality, systems tend to be inefficient and use of information leads to higher technical efficiency[2] provided agents have the capability to access and adopt it. However, ability to process and use information varies across individuals resulting in different outcomes (Simon, 1959). Many empirical studies have argued that knowledge and information are the most important factors for accelerating agricultural development through appropriate production planning, improved agronomic practices, acquisition of modern inputs, and improved marketing and distribution[3].

Impact of Information

The pioneering studies on the link between information and agricultural performance are offered by Birkhaeuser et al. (1991) and Feder et al. (1999). Studies have used both parametric and non-parametric approaches to isolate the effect of information on agricultural performances. For example, Godtland et al. (2004) estimates a 32 percent increase in income for the participants in farmer field schools of potato farmers in the Peruvian Andes while Davis et al. (2010) found that East African participants in the farmer field schools could realize a 61 percent increase in income. Few studies from India also have assessed the impact of information. Goyal (2010) finds that soybean farmers in the state of Madhya Pradesh have better access to market price information (through the Internet) and achieve 1–5 percent

[2] See Muller (1974) and Shapiro and Muller (1977)
[3] See Poole and Kenny (2003), Bertolini (2004) and Lio and Liu (2006)

higher prices. Birthal et al (2015) found that users of information in India, on an average, realise a 12 percent higher net returns than non-users.

Again, there are studies identifying information as one of the key factors in increasing efficiency. Some of these identify the factors determining efficiency[4] while others specifically see the impact of information on efficiency. Salam and Phimister (2015) find empirical evidence of a significant and positive relationship between farmer ability to access information and farm efficiency of small-scale farmers in Uganda and Aker and Fafchamps (2010) find mobiles are useful in Niger for accessing information. Similarly, the World Bank (2012) finds that access to the internet raises the efficiency of existing processes and makes new production processes possible. Improved access to information could also have more direct efficiency effects associated with cost effective access to agricultural inputs as well as improved managerial practices and farm coordination (De Silva and Ratnadiwakara, 2008) for gherkin farmers in Sri Lanka and for Kerari fishermen in India (Jensen, 2007).

There is also a huge diversity in findings on the impacts of information from different channels on farm outcomes. While very large impacts, as in Davis et al. (2010) for Kenya, Tanzania, and Uganda, Camacho and Conover (2011) and Fafchamps and Minten (2012)[5] do not find significant impacts in Colombia and Maharashtra, respectively. Again, some studies find moderate to low effects like Birthal, et.al. (2015 and Goyal (2010). Thus, it is difficult to conclude whether it is just the "source effect" or the "true effect" of information on farm outcomes. Source effect relates to the efficacy of some channels of information and lack of it in other cases, whereby information could be useful (the true effect), depending on the source dispensing it.

There are several studies, some of which are noted above, that looks into the impact of information either from a specific source (like ICT, extension, mobile phones, radio etc) and/or a specific kind of information like prices of specific inputs, output, production advice etc on farm outcomes. Few studies like Birthal et.al., (2015) look into several information sources jointly but they do not study the impact on farming efficiency. An attempt is made here to bridge this gap since, theoretically information is expected to increase the efficiency

[4] Muller (1974); Kalirajan and Shand (1986); Fan (1991 & 2000); Coelli and Battesse (1996), Kumbhakar (2000),

[5] Fafchamps and Minten (2012) do not find a significant impact from information obtained through mobile phones, either on the quality of farm produce or on the prices in Maharashtra.

of production and thereby improve productivity and farmers' condition.

Technical efficiency

Central to economic theory is the concept of efficiency. In neo-classical economics, the production frontier is defined as the locus of all efficient points of production, that is, points yielding the maximum output for a given quantity of inputs and technology. Hence, inefficient behaviour is assumed away in conventional economic theory, by using a production function in which first-order and second-order optimizing conditions are satisfied. This is the same for cost function where cost is minimized given the output and prices of the inputs and profit function where profit is maximized given output price and input prices. However, the real-world scenario is very different from the theoretical postulations and inefficiency seems to exist in almost all economic activities. It can be seen that firms using identical inputs in same quantity fail to produce equal amounts of output. This is also true for farmers also who use same technology and resources but end up producing different quantities of output. In a theoretical sense, any point lying below the production and profit frontier and above the cost frontier is an inefficient point and the amount by which it lies away from the frontier is a measure of inefficiency (Forsund et al, 1980)**.**

When we talk about the technical efficiency of a producer, in this case, efficiency of a farmer, we mean a comparison between the actual output (input(s)) of the producer and the optimal output (input(s)), given the technology. Thus, efficiency can be a comparison between the minimum inputs required and the actual inputs used to produce the output or, the maximum output attainable compared to the actual level given the inputs or, a combination of the two (Fried, Lovell and Schmidt, 2005). The most widely used measure of degree of efficiency in a multiple input-output setting is the Farrell (1957) measure, more commonly known as the Farrell efficiency. It defines efficiency as the maximum possible proportional reduction in all inputs to produce a given level of output (input efficiency) or the maximum possible proportional increase in the outputs given the level of inputs (output efficiency) respectively. The next section discusses the method applied to calculate technical efficiency and then estimate the impact of use of information on it.

3. Data and Method of Analysis

The latest round of NSSO on Situation Assessment Survey of Agricultural Households in India published in 2015 is used to carry out the analysis. It is decadal survey done with 2 visits, each for six months and the latest round was done for the year 2012-13. The data captures various socio-economic aspects of agricultural households and farming. The survey takes into account the major crops grown by each household and their corresponding inputs. For any household, details of a maximum of four major crops are recorded. For each crop the area on which it is grown and the expenditure for its seeds are recorded. Unlike the last round (59^{th} Round, 2002-03), the other inputs like fertilisers, manures, plant protection chemicals, diesel, electricity, human labour, animal labour, irrigation and other miscellaneous items are recorded jointly for all the crops for each household. The details of the crops grown by households in the first visit (which corresponds to the period between July 2012 to December 2012) are used to calculate technical efficiency and household, farm and famer characteristics derived from the data are used to estimate the impact on efficiency.

3.1 Measuring Technical Efficiency

Since, optimal behaviour is a theoretical concept, in practice, efficiency of individual firms is measured relative to the *best practice*, and hence, in reality we always measure *relative efficiency* rather than absolute efficiency. This is termed as benchmarking. The basic work on efficiency measurement was propounded by Koopmans (1951) and Debreu (1951) and a huge set of literature on estimating production/cost frontiers has developed on its basis. Empirical research on efficiency was carried out by econometricians by average production functions rather than formulating the frontier. However, the pioneering work of Farrell (1957) is the main starting point for estimating frontiers and measuring efficiencies.

The most common tools to calculate efficiency is Data Envelopment Analysis[6] (DEA, henceforth) and Stochastic Frontier Analysis[7] (SFA, henceforth). DEA is a non-parametric deterministic frontier model which uses no functional form to estimate the frontier and is very appealing due to the requirement of very few assumptions. Hence, it is more flexible and adapts closer to the data. However, it can be sensitive to extreme values and outliers which

[6] Charnes, Cooper and Rhodes (1978), and Deprins et al (1984)
[7] Aigner et al (1977), Battese and Coelli (1992), Coelli et al (1998a)

can be otherwise addressed through robustness checks. SFA however, assumes a functional form in estimating the efficiency scores and hence, bound by stricter conditions. Given, the advantages of DEA, it is used here to calculate efficiency. Below DEA is discussed briefly.

Data Envelopment Analysis

Data Envelopment Analysis originates from Farrell's (1957) idea of constructing piece-wise linear convex-hull from observed data points. It was only in 1978 that Charnes et al, reformulated Farrell's approach into a mathematical programming problem and coined the term DEA. Thus, DEA is a mathematical programming technique to estimate best-practice production frontiers and then calculate the efficiency of different decision-making units (farm-households in this case), relative to that best frontier. DEA is constructed on the backdrop of production theory and that decision-making units (DMUs) have a common underlying technology T which is given as,

$$T = \{(x, y) \in \mathbb{R}_+^m \times \mathbb{R}_+^n | \text{x can produce y}\} \quad (1)$$

Here, K farms use m inputs (x_i, i=1,2,...,m) to produce n outputs (y_j, j=1,2,...,n). The inputs belong to a set of non-negative real numbers, $\mathbb{R}_+^m$ and the outputs belong to a set of non-negative real numbers $\mathbb{R}_+^n$.

Since, the production technology is unknown in reality; DEA constructs it on the basis of existing cross-sectional data on actual production activities using the minimal extrapolation principle. The principle extracts the smallest subset from $\mathbb{R}_+^m \times \mathbb{R}_+^n$ containing the data based on the assumptions of free disposability and convexity. Free disposability refers to the fact that more inputs can be used to produce less output and convexity means that a weighted average of two production points is also a feasible point. Hence, the technology estimated through this principle is used as a proxy for the actual (unknown technology) and existing observations are compared to this frontier to yield relative efficiency scores. Thus, the principle of minimal extrapolation combined with Farrell's notion of efficiency generates the notion of mathematical programming used in DEA to calculate efficiency.

Input-oriented technical efficiency (E) is defined as the maximum possible proportional reduction of all the inputs (x) that still allows the farm to produce *y*, and TE for the farm *o* under variable returns to scale (VRS) can be expressed as

$$E^o = E\big((x^o, y^o); T^*\big) = \min\{E > \mathbb{R}_+ | (Ex^o, y^o) \in T^*\} \qquad (2)$$

Where,

$$T^* = \{(x,y) \in \mathbb{R}_+^m \times \mathbb{R}_+^n | \exists \lambda \in \Lambda^K(\text{vrs}): x \geq \textstyle\sum_{k=1}^K \lambda^k x^k \,, y \leq \sum_{k=1}^K \lambda^k y^k \}$$
(3)

and, $\Lambda^k(\text{vrs}) = \{\lambda \in \mathbb{R}_+^K | \sum_{k=1}^K \lambda^k = 1$
(4)

Inserting the formulation of T* yields,

$$\min_{E,\lambda_1,\ldots\ldots,\lambda_K} \quad E \qquad (5)$$

$$\text{s.t.} \quad Ex_i^o \geq \textstyle\sum_{k=1}^K \lambda^k x_i^k \qquad i = 1, \ldots, m \qquad 5(a)$$
$$y^o \leq \textstyle\sum_{k=1}^K \lambda^k y_j^k \qquad j = 1, \ldots, n \qquad 5(b)$$
$$\textstyle\sum_{k=1}^K \lambda^k = 1 \qquad 5(c)$$

Farms with E=1 are efficient and operate on the frontier and farms with E< 1 are inefficient, that is to say that farther a farm's efficiency score is from 1, lower is its efficiency.

λ^k is the weight assigned to the k^{th} farm. The condition 5(c) holds true for VRS. For CRS, $\lambda^k \geq 0$ and for DRS, $\sum \lambda^k \leq 1$. VRS is more flexible and envelops the data more tightly as compared to CRS. Hence, VRS efficiency scores are always greater or equal to CRS scores.[8]

Here, input-oriented technical efficiency is calculated using a novel technique employing DEA developed by Cherchye et.al. (2013). Before moving to the calculation, I briefly discuss

[8] It must also be noted that efficiency estimates under DEA are scale independent with respect to measurement of inputs and outputs. Thus, the results do not change with any positive linear transformation of the inputs and/or outputs. This means that one can use monetary values of the variables instead of their physical values (Bogetoft and Otto, 2011).

the nature of the data and the rationale for using this technique. The survey takes into account the major crops grown by each household and their corresponding inputs. For any household, details of a maximum of four major crops are recorded. For each crop the area on which it is grown and the expenditure for its seeds are recorded. Unlike the last round (59^{th} Round, 2002-03), the other inputs like fertilisers, manures, plant protection chemicals, diesel, electricity, human labour, animal labour, irrigation and other miscellaneous items are recorded jointly for all the crops for each household. Given the nature of the data, the standard DEA method will not yield the best results. To overcome this problem, I use the method developed by Cherchye, et.al (2013) to calculate efficiency of Decision-Making Units (DMUs) specifically to address the issue of DEA calculation in the presence of **multiple outputs**, **joint inputs** and **output-specific inputs**. In our study the DMUs are agricultural households.

This approach is superior to the existing methods because first, it explicitly recognizes that each different output is characterized by its own production technology and simultaneously accounts for interdependencies between the different output-specific technologies. Second, including information on the allocation of output-specific inputs substantially increases the discriminatory power of the efficiency measurement and hence this method has more power to identify inefficient production behaviour. In turn, this should lead to more actions for efficiency improvement and, consequently, higher realized cost reductions. Third, this method allows us to decompose the overall efficiency score of a DMU into output-specific efficiency scores and their respective weights in the DMU's overall efficiency. Such a decomposition is particularly attractive from a practical point of view, because it directly identifies the outputs on which DMU managers should principally focus to correct the observed inefficiency.

In this method, the authors show us how to compute cost efficiency of DMUs producing multiple outputs using joint and output-specific inputs when the prices of both kinds of inputs are available. They call this the primal approach. They also compute input-oriented technical efficiency for the same data in the absence of price information and call it the dual approach. They further show that both the primal and dual yield the same measures of efficiency and can be computed under different returns-to-scale assumption by introducing a linear restriction capturing the returns-to-scale.[9]

I use the dual part of the method to compute technical efficiency of agricultural households under variable returns to scale using the codes created by the authors in the MATLAB software. The assumption of variable returns to scale gives greater flexibility to the data as compared to constant or decreasing returns to scale (Wadud and White, 2010). The efficiency scores calculated under the assumptions of convexity and monotonicity yield the same results as the primal cost efficiency scores. The equality of the primal and dual results is worked out in details in their paper (Cherchye et.al., 2013)[10].

The input oriented technical efficiency is computed as follows.

$$\widehat{TE} = \min_{\theta_t \geq 0, \lambda_s^m \geq 0} \theta_t \tag{7}$$

Subject to

$$\forall m: \sum_{s \in D_t^m} \lambda_s^m Q_s \leq \theta_t \quad Q_t \qquad \text{(Joint Inputs)} \tag{7(a)}$$

$$\forall m: \sum_{s \in D_t^m} \lambda_s^m q_s^m \leq \theta_t \; q_t^m \qquad \text{(Specific Inputs)} \tag{7(b)}$$

$$\forall m: \sum_{s \in D_t^m} \lambda_s^m = 1 \; (\lambda_s^m \text{ is the weight of each DMU} s) \tag{7 (c)}$$

3.1.1 Variables Used to Calculate Technical Efficiency

To calculate technical efficiency, the output variable used is the sum of the value of crops produced by each household. The input variables are of two types – output-specific like land and expenditure on seed and, joint inputs which is the sum of expenditure on labour, natural and chemical fertilisers, fuel, electricity, irrigation and miscellaneous items. The variables used to compute technical efficiency are listed in table 1 below.

Table 1: Variables Used for Calculating Technical Efficiency

[9] Refer to the article for further details.

[10] Even in the absence of prices, the primal part gives the economic efficiency with respect to shadow prices, that is, it estimates the prices for which the DMUs are economically efficient. Therefore, cost efficiency here can be interpreted as technical efficiency since the estimated prices (shadow prices) ensure that inputs are allocated efficiently.

Output (Rs.)	Values of crops produced by each household (maximum four crops)
Output-Specific Inputs	
Land (Hectares)	Land use for cultivating each crop
Seed (Rs.)	Expenditure on seeds for each crop
Joint Inputs	
Labour (Rs.)	Expenditure on labour
Fertilisers (Rs.)	Expenditure on fertilisers, manures and plant protection chemicals
Energy (Rs.)	Expenditure on diesel, electricity and irrigation
Others (Rs.)	Expenditure on machinery, repairing and miscellaneous things

To carry out the calculation, I divide the entire country into 15 agro-climatic zones as identified by the Planning Commission of India (1989)[11]. Calculating efficiency for each zone helps to control the heterogeneity in terms of crop composition and differences in technology arising from differences in climate, geography and topography. Table 2 details out the zones and their composition.

Table 2: Agroclimatic Zones

Zones	Composition
1. Western Himalayan Region	Jammu and Kashmir, Himachal Pradesh and Uttarakhand
2. Eastern Himalayan Region	7 North Eastern States and 3 northern districts of West Bengal (Cooch Behar, Jalpaiguri and Darjeeling)
3. Lower Gangetic Plains	West Bengal except 3 above districts and Purulia
4. Middle Gangetic Plains	Eastern Uttar Pradesh and Bihar
5. Upper Gangetic Plains	Western Uttar Pradesh
6. Trans Gangetic Plains	Punjab, Haryana and Ganganagar district of Rajasthan
7. Easter Plateau and Hills Region	Chhattisgarh, Jharkhand, Western Orissa, Purulia, parts of Madhya Pradesh and Maharashtra
8. Central Plateau and Hills Region	Parts of Rajasthan, Madhya Pradesh and South Western parts of Uttar Pradesh
9. Western Plateau and Hills Region	Rest of Madhya Pradesh and non-coastal Maharashtra
10. Southern Plateau and Hills Region	Non-coastal Andhra Pradesh (undivided), Tamil Nadu and Karnataka
11. East Coast Plains and Hills Region	Coastal Andhra Pradesh (undivided), Pondicherry, Orissa and Tamil Nadu
12. West Coast Plains and Hills Region	Goa, Kerala, coastal Karnataka, Maharashtra and western hilly parts of Tamil Nadu
13. Gujarat Plains and Hills Region	Gujarat, Dadra and Nagar Haveli and Daman and Diu
14. Western Dry Region	Rest of Rajasthan
15. Island Region	Lakshadweep Islands, Andaman and Nicobar Islands

Source: Constructed from various government publications on the composition of the 15 agro-climatic zones of India

To elaborate this, it is important to understand the nature of the data we are dealing with. As already mentioned, the survey records data for a maximum of four crops (outputs) grown by

[11] Khanna (1989) identified 15 resource development regions in the country – 14 in the main land and one in the islands of Lakshadweep and Andaman Nicobar Islands.

each household in each visit and reports land and expenditure on seed as crop-wise inputs and the rest of the inputs as joint inputs. Now, a total of about 150 variety of crops are identified of which for we exclude crops that require more than one season (6 months to grow). Hence, all kinds of trees, plantation crops and sugarcane are not included in our analysis. This is done to avoid the problem of comparing apples with oranges. This reduces the variety of crops to around 100 with each zone reporting 20-25 crops grown in that season. In each zone, the major crops are identified on the basis of their frequency of cultivation. The table below gives the details of the crops grown in each zone (Table 3). Zone 15 is excluded here because it consists of the island regions of Lakshadweep and Andaman and Nicobar Islands and has very few observations.

In each zone the major crops are identified and households not growing any of the major crops are dropped from this analysis. To minimize the loss of observations I have created broad categories of crops like pulses, cereals, vegetables, fodder crops and so on such that the efficiency scores can be identified as representative scores of the zone. A variety of crop combinations and categories were tried before finalising the present categories based on their relative frequency of occurrence.[12] Table 3 below lists the crops and categories used for our analysis. After removing the observations with infrequent crops, plantation crops, missing observations on land used, seed expenditure and zone 15, a total of 20149 households are available for analysis. Paddy is grown extensively in all the zones except zone 14 and takes the largest share among all crops.

Table 3: Major Crops grown in each Agroclimatic Zone

Zones	**Crops**	**No. of Households**
Zone 1	Paddy, Maize and Fodder Crops	698
Zone 2	Paddy, Maize and Leafy vegetables	4746
Zone 3	Paddy and Jute	1606
Zone 4	Paddy, Maize, pulses and Fodder Crops	2198
Zone 5	Paddy, bajra, maize, pulses and fodder crops	1132
Zone 6	Paddy and Cotton	685
Zone 7	Paddy, Maize and Oilseeds	2030
Zone 8	Paddy, Maize, pulses and Oilseeds	1095
Zone 9	Paddy, Jowar, Maize, Pulses, Soyabean, Cotton	1715
Zone 10	Paddy, Jowar, Maize, Pulses, Groundnut, Cotton	1503
Zone 11	Paddy, Groundnut, Pulses, Cotton	1390
Zone 12	Paddy, Banana, Cassava, Tubers	360
Zone 13	Paddy, coarse cereals, pulses, Groundnut and cotton	725
Zone 14	Bajra, pulses, fodder crops	266
Total		20149

[12] The results remain qualitatively same, but this minimises the loss of observations

Source: Calculated using NSSO 70th Round on Situation Assessment Survey of Agricultural Households (2012-2013)

3.2 Estimating Impact of Information on Technical Efficiency

The treatment here is the use of information which is a dummy variable, *D,* denoted by 1 if the household has used information and 0 otherwise. The outcome variable, Y, is the technical efficiency of agricultural production. Assuming Y is a linear function of the treatment dummy and a vector of explanatory variables (*X*), the equation can be written as

$$Y = \delta D + \gamma X + \epsilon \quad (8)$$

δ and γ are vectors of parameters to be estimated, and ε is an error term. The impact of use of information on the outcome variable is measured by the estimates of the parameter δ. However, δ will accurately measures the impact of information use on technical efficiency only if households are randomly assigned to user or non-user groups (Stefanides & Tauer, 1999; Faltermeier & Abdulai, 2009). Use of information is not randomly assigned, farmers themselves decide whether to use information or not; thus there is self-selection. This implies that the decision to use information may be influenced by unobservable characteristics (like managerial skill, motivation, etc) that may be correlated to the outcome of interest. In the regression framework, this is equivalent to saying that ε is correlated with D. In this case, an OLS estimation of Eqn. (8) does not account for this self-selection which may lead to biased results. Observable and unobservable farm and farmer characteristics that are simultaneously correlated with use of information and technical efficiency can lead to biases in estimating the impact of information on efficiency[13].

The standard approaches for dealing with the problem of self-selection is the instrumental variable (IV) method. However, the selection of unobservables in this method is done by imposing distributional and functional form assumptions, such as linearity on the outcome equation and extrapolating over regions of no common support, where no similar user and non-user observations exist. The evidence from Heckman, Ichimura, Smith, and Todd (1998), Dehejia and Wahba (2002), and Smith and Todd (2005) suggests that avoiding functional form assumptions and imposing a common support condition can be important for reducing

[13] There may exist a reverse causality between technical efficiency and use of information that can be addressed by a suitable instrument. However, in the absence of appropriate instruments currently, this remains as a limitation for the current paper and a scope for further research.

selection bias. Moreover, the IV approach crucially depends on the availability of valid instruments, which is a challenge in many empirical analyses (Angrist & Krueger, 2001) like here.

Hence, I use the propensity score matching (PSM) method here which takes into account the problem of self-selection and solves for the impact of information use on technical efficiency of agricultural production. PSM does not require linearity, or parametric or distributional assumptions, and it also does not require exogeneity of covariates to identify the causal effect of interest. They can be all endogenous (Diagne & Demont, 2007; Heckman & Vytlacil, 2007). A limitation of PSM is that it assumes selection is based on observable variables; unobservable variables that may affect both the outcome variables and choice of technology are not accounted for directly (hidden bias). However, in cross-sectional data, the presence of unobserved characteristics in the propensity score estimation can create mismatching and biased estimators (Heckman & Navarro-Lozano, 2004). As noted by Jalan and Ravallion (2003), however, the assumption of selection of observables is no more restrictive than assuming away problems of weak instruments when the IV approach is employed in cross-sectional data analysis. I further use sensitivity analysis to account for hidden bias emanating from unobservables.

Propensity Score Matching

When the study cannot be subjected to random assignment then researchers in the fields of medicine, statistics and economics have opted to using propensity score matching to control for selection-bias in a treatment effect of quasi-experimental designs (D'Agostino, 1998; Grunwald & Mayhew, 2008; Shadish, Luellen, & Clark, 2006). Propensity scores matching technique can be attributed to the seminal work of Rosenbaum and Rubin (1983). It is a mathematical approach to causal inference, based on the Rubin counterfactual framework (West & Thoemmes, 2010). Propensity score matching uses regression techniques to predict group assignment from theoretically relevant covariates and then matches participants on these predicted scores (known as propensity score).

Here also adoption of information is not a random assignment but farmers self-select to adopt or opt out. To understand the impact of information use, we have to estimate the difference in the outcome of the treated individual and the outcome of the same individual had she/he not been treated. This is known as the Average Treatment Effect (ATT). To ensure that treatment effect is identified in quasi-experimental settings, it is important to address the selection bias through some identifying conditions.[14] There are two main conditions.

First is the Conditional Independence Assumption (CIA, also known as unconfoundedness) which says that the potential outcome (here, technical efficiency) is independent of treatment assignment (to use or not to use information) given that the set of observable covariates are not affected by treatment. This implies, that selection is solely based on observable characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed by the researcher.

Second is the Common Support or Overlap condition which suggests that none of the given observable characteristics should predict D perfectly. It ensures that persons with the same observable characteristics have a positive probability of being both participants and non-participants (Heckman, LaLonde, and Smith, 1999).

The above two assumptions are together called "strong ignorability" by Rosenbaum and Rubin (1983). To account for the dimensionality problem arising out of large vector of covariates, Rosenbaum and Rubin (1983) suggest to use *balancing scores*. They explain that if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on a balancing score $b(X)$. The propensity score is one such balancing score.

According to them, propensity score (π) for an individual i is defined as the conditional probability (P) of assigning a participant to a particular treatment or comparison group (D) given a set of covariates (X), expressed as,

$$\mathrm{P}_i(\mathrm{X}) = P(\mathrm{D}_i = 1 | X_i) \tag{9}$$

The choice of covariates is grounded in theory or in stylised facts. For example, we see from the above discussed literature that use of information has been found to be correlated with farm characteristics, household's socio-economic characteristics and farmer's demographic

[14] Estimation of average treatment effects requires that the treatment effect for each individual *i* is independent of treatment participation of other individuals (`stable unit-treatment value assumption'). In randomised experiments the treatment effect is identified due to the random assignment of treatment.

characteristics like age, education and sex among others. The PSM estimator of ATT is given as

$$ATT_{PSM} = E_{P(X)|D=1}\{ E[Y(1)|D = 1, P(X)] - E[Y(0)|D = 0, P(X)]\}$$
(10)

This is nothing but mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

As already mentioned above, the challenge of identifying matches with a multidimensional set of covariates, X, as proved by Rosenbaum and Rubin (1983), can be averted by matching on the propensity score. This eases a multidimensional matching problem to a single dimension. In practice, the true propensity score is unknown, and is estimated using a logit or probit model. Here I use a logit model with the covariates displayed in the next section in Table 4. Different matching algorithms are employed including 1-to-n matching, kernel, and radius matching, all based on the propensity score, and the best algorithm is chosen according to the resulting degree of balance across different covariates.

The validity of this analysis crucially rests on the untestable assumption of CIA, that is the set of observable characteristics alone ensure that potential outcome is independent of treatment assignment and that there is no hidden bias. The first step to justification is the use of covariates extensively used in the literature. The covariates used to undertake matching are indicators of economic status, human capital, and region fixed effects. Nevertheless, it is possible that some unobserved characteristics such as attitude towards risk, motivation and skill influence use of information and its impact on efficiency. Education levels, cropping pattern, sex and age of the household head can act as partial proxies to address these. Still, we cannot fully rule out the possibility of hidden bias from these or other unobservables. Therefore, I check the robustness of the results through sensitivity analyses, both by varying the set of covariates used to calculate the propensity score and by changing different parameters of the matching process. I also checked the sensitivity of the estimated ATT to hidden bias using the Rosenbaum (2002) bounds test. This test suggests how great an effect unobservables would have to have in order to reverse the findings based on matching on observables.[15]

3.2.1 Variables used to Estimate Propensity Score Matching

The outcome variable, Y is continuous and denotes technical efficiency of farming. The treatment variable D is "use of information." D is binary and takes a value of 1 if the household uses information and 0 otherwise. The covariates (shown in Table 4 below) are chosen from the existing literature. and are broadly categorised as farm characteristics, demographic characteristics and household characteristics which covers the socio-economic characteristics of the household.

Table 4: Outcome Variable and Covariates used

Variable	Full Sample	Users	Non-Users	Difference
Outcome Variable				
Technical Efficiency	56	58	54	4***
List of Covariates				
Household Characteristics				
Land owned (hectares)	2.4	2.5	2.3	0.2***
Farmers per household	2	2	1	1***
Cultivation as main source of income (%)	76	80	74	6***
NREGA card holders (%)	52	56	50	6***
Religion (%)				
Hindu	78	80	77	3***
Muslims	9	9	8	1***
Christians	8	6	10	-4***
Others	5	5	5	0
Social Group (%)				
ST	24	18	27	-9***
SC	11	10	12	-2**
OBC	37	40	35	5***
General	28	31	26	5***
House Structure (%)				
Kutcha	9	7	10	-3***
Semi-pucca	33	31	34	-3***
Pucca	58	62	55	7***
Type of Ration Card (%)				
No card	12	9	14	-5***
Antyodaya	4	3	4	-1*
BPL	33	31	34	-3***
Others	51	57	48	9***
Demographic Characteristics				

[15] For more details see the *bounding approach* proposed by Rosenbaum (2002)

Age of head of household (years)	50.7	51.3	50.5	0.8***
Male head of household (%)	93	94	92	2***
Education Level Attained by Head of Household (%)				
Illiterate	33	29	35	-6***
Primary and Below	27	27	28	-1
Middle	16	17	16	1***
Secondary	11	13	11	2***
Above Secondary	12	14	10	4***
Farm Characteristics				
Cropping Pattern (%)				
Food crop	60	56	62	-6***
Non-Food crop	10	11	10	1***
Both	30	32	28	4***
Total	**20149**	**7140**	**13009**	

***, ** and * represent significance at 1, 5 and 10 percent respectively
Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Farm characteristics like the type of crop grown would influence the decision to use of information because non-food crops are generally high risk-high return crops that demand greater information seeking. Farmer characteristics like human capital is an important determinant of information comprehension and use. Gender is also an important factor in the Indian rural economy in shaping several outcomes. Age can act as a proxy for experience and skill. Household characteristics like land owned, social group and occupation are indicators of socio-economic status which shape the decision to use information as well as their efficiency in cultivation. Caste is an important determinant of social capital and economic status in India (Deshpande, 2001). Apart from that there are regional fixed effects corresponding to the agroclimatic zones as identified in Table 2. Table 4 lists the covariates used in this analysis and provides summary statistics for the outcome variable and covariates by treatment status. The last column shows the difference in the means of users and non-users for each variable using the two-sample mean comparison t-test.

4. Results and Discussion

4.1 Efficiency Scores

The average input-oriented technical efficiency is at 56 percent, which means that inputs could be reduced by another 44 percent on average to produce the same value of outputs. Table 5 below shows the efficiency score across the agroclimatic zones and their distribution across users and non-users of information. Agricultural zone 2, the Eastern Himalayan

Region comprising of the north eastern states is an outlier, registering the lowest efficiency at 22 percent. There is no direct explanation this. However certain observations need to be highlighted here. This zone comprises of the entire north east region, a geographically uneven landscape with dispersed political disturbance. In terms of crops, beetle nut is abundantly grown in this region and excluding it from our calculation might have resulted in a lower performance parameter. As mentioned before, it is important to keep in mind that output and expenditure should be for the period under consideration (here, 6 months corresponding to Visit 1 of the survey) and trees do not come under this. However, this is outside the scope of this study. Separate research is required to understand this result which is currently not possible with the data in hand.

The average efficiency rises to 66 percent when we remove zone 2 from our calculation. 8 of the 13 remaining zones record an efficiency score of more than 70 percent while 3 others register more than 60 percent. Except for the outlier, the least efficient zones include the economically poorer regions like middle Gangetic Plains comprising of Bihar and eastern Uttar Pradesh operating at an efficiency level of 53 percent and Eastern Plateau and Hills Region which includes Purulia and drier parts of Chhattisgarh, Jharkhand, Western Orissa, Madhya Pradesh and Maharashtra. Overall, northern states in the fertile Gangetic belts (except the poorer regions of Bihar and eastern U.P), most part of West Bengal in the lower Gangetic belt, north western states with larger land holdings and better irrigation and the southern states show a higher technical efficiency around 70 percent and above.

Table 5: Technical Efficiency across Agroclimatic Zones

Agricultural Zone	**Mean TE**	**Frequency**
Western Himalayan Region	0.72	698
Eastern Himalayan Region	0.22	4,746
Lower Gangetic Plains	0.72	1,606
Middle Gangetic Plains	0.53	2,198
Upper Gangetic Plains	0.73	1,132
Trans Gangetic Plains	0.73	685
Easter Plateau and Hills Region	0.52	2,030
Central Plateau and Hills Region	0.70	1,095
Western Plateau and Hills Region	0.68	1,715
Southern Plateau and Hills Region	0.78	1,503
East Coast Plains and Hills Region	0.64	1,390
West Coast Plains and Hills Region	0.64	360
Gujarat Plains and Hills Region	0.79	725
Western Dry Region	0.77	266
India	**0.56**	**20,149**

TE=Technical Efficiency

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Some Descriptive Statistics

Table 4 showed the that the users of information have a significantly higher mean efficiency than non-users. Here, we try to get an idea about the distribution of mean technical efficiency across some important characteristics. Land is the one of the most important assets in rural India and a crucial determinant of farmers' behaviour. Here, we have 5 land holding classes – marginal (less than 1 hectares), small (between 1 and 2 hectares), semi-medium (between 2 and 4 hectares), medium (between 4 and 10 hectares) and large with more than 10 hectares of land. Table 6 shows the mean technical efficiency of agricultural households across social groups and also the difference in efficiency between users and non-users for each group. We find that efficiency is highest at 76 percent for large land holders followed by medium land holders at 68 percent. It is lower (less than 60 percent) for marginal, medium and semi-medium households. Moreover, users of information have a higher average efficiency than non-users for each group and their difference comes out to be statistically significant (two-sample mean comparison t-test) for each land size class except large land size holding. Large land holdings take the smallest share of less than 1 percent while marginal farmers take the largest share in our sample. Marginal and small farmers together account for about 70 percent of land holdings.

Table 6: Technical Efficiency across Land Holding Classes

Land Holding Classes		**Average Technical Efficiency (%)**			
	Share	**Full Sample**	**Users**	**Non-Users**	**Mean Difference**
Marginal (0-1 hectares)	37	0.58	0.60	0.57	0.03***
Small (1-2 hectares)	32.2	0.53	0.56	0.51	0.05***
Semi-Medium (2-4 hectares)	24	0.54	0.57	0.53	0.04***
Medium (4-10) hectares	6.2	0.63	0.65	0.60	0.05***
Large (> 10 hectares)	0.6	0.76	0.77	0.74	0.03

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Caste, broadly captured by social groups is a major factor in India in determining social capital and economic status (Deshpande, 2001 and Kumar, 2013), access to credit and access to information. The social group is comprised of 4 categories - Scheduled Tribes (ST) who are technically not part of the caste-system but have the lowest socio-economic status amongst, Scheduled Castes (SC) , lowest in the caste hierarchy; Other Backward Classes (OBC) who make the largest share of farmers and are better off than the SCs, and Others or General, which are the upper castes. OBCs account for the highest share in the sample at 37 percent followed by General (28 percent) and ST (24 percent). In terms of average efficiency, SCs have the lowest (43 percent) while all the other groups have an efficiency around 60 percent. The difference in mean efficiencies is positive and significant for all the groups except SCs which takes the smallest share in the sample. Table 7 below shows the same.

Table 7: Technical Efficiency across Social Groups

Social Group		Average Technical Efficiency (%)			
	Share	Full Sample	Users	Non-Users	Mean Difference
Scheduled Tribes	24	0.43	0.45	0.42	0.03***
Scheduled Caste	11	0.61	0.60	0.61	-.01
Other Backward Classes	37	0.59	0.61	0.58	0.03***
General	28	0.60	0.62	0.59	0.03***

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Efficiency also varies with the cropping pattern as shown in Table 8 below. Most households grow food crops or a combination of food and noon-food crops. 34 percent of the households in the sample grow non-food crops only and their efficiency is 66 percent, 10 percent greater than that of food crops. Users of information have a statistically greater efficiency than non-users but users growing non-food crops have an average efficiency of 70 percent while food-crop is 58 percent. By nature, non-food crops generally are high-risk high-return crops while food crops are mainly of subsistence type which might lead to the difference in their average efficiency levels.

Table 8: Technical Efficiency across Cropping Pattern

Cropping Pattern		Average Technical Efficiency (%)			
	Share	Full Sample	Users	Non-Users	Mean Difference
Non-food crop	34	0.66	0.70	0.64	0.06***
Food crop	66	0.56	0.58	0.55	0.03***

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

4.2 Matching

The coefficients of the logit model are given in Table 9 below. The sign of the coefficients corroborates the raw differences in table 4. The dependent variable is the binary choice between use and non-use of information. The estimated coefficients are used to predict the respective probabilities of treatment, that is, the propensity score. Figure 2 shows the distributions of these estimated propensity scores, and establishes that there is overlap in the distribution for treatment and control groups. Figure 2(a) shows the distribution of propensity score before matching between treated and control groups while Figure 2(b) shows the distribution after matching the propensity scores of the two groups scores.

Table 9: Estimation of Propensity Score using Logit Model

Variables	**Dependent Variable Used Information**	
Religion (Base=Hindu)		
Muslim	0.111*	(0.0593)
Christian	-0.351***	(0.0767)
Others	-0.392***	(0.0875)
Farmers in a household	0.0388***	(0.0141)
Size of the household	-0.0130*	(0.00714)
Social Group (Base=ST)		
SC	0.196***	(0.0629)
OBC	0.362***	(0.0504)
General	0.248***	(0.0555)
Land Size Holding (Base=Sub-marginal)		
Marginal	0.240***	(0.0395)
Small	0.471***	(0.0442)
Medium	0.620***	(0.0707)
Large	0.884***	(0.193)
Primary source of income (Base=Cultivation)	-0.163***	(0.0400)
Age of head of household	0.0301***	(0.00753)
Square of age of head of household	-0.000282***	(7.06e-05)
Gender (Base=Female)	0.0833	(0.0623)
Structure of Household (base=Kutcha)		
Semi-Pucca	0.150**	(0.0605)
Pucca	0.151**	(0.0594)
NREGA Card Holder (Base=Yes)	0.0967***	(0.0357)
Type of Ration Card Held (Base=No card)		
Antyodaya	0.318***	(0.0960)
BPL	0.234***	(0.0570)
Others	0.402***	(0.0535)
Educational Attainment of head (Base=Illiterate)		
Primary	0.133***	(0.0416)
Middle	0.250***	(0.0495)
Secondary	0.303***	(0.0555)
Above Secondary	0.368***	(0.0571)
Non-food crop (Base=food crop)	-0.205***	(0.0352)
Constant	-2.569***	(0.233)
Zone Fixed Effects	Yes	
Observations	20,124	
Log-likelihood	-12425.46	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Matching is done using kernel matching algorithm with an Epanechnikov kernel and bandwidth 0.05 as reported in Table 11. However, for robustness I have also run the matching with bandwidth 0.01 and using other algorithms like nearest neighbour (1 to 10), caliper and radius matching. Smith (2000) shows that as sample size grows, all the PSM estimators yield the same results asymptotically since they all become closer to comparing only exact matches. However, the choice of the matching algorithm can be important in small samples (Heckman, Ichimura, and Todd, 1997), where there is typically a trade-off between bias and variance. Since, our sample is substantially large, we do not see any substantial difference in the results from different algorithms. Hence, I only display the results of kernel matching with 0.05 bandwidth in the main section and show the results of other matching algorithms including the common supports and balancing of the covariates in the Appendix (A1, A2 and A4). To check for hidden bias, I use the sensitivity analysis method based on the bounding approach by Rosenbaum (2002) which rules out the same (see Appendix A3).

Table 10: Use of Information by households across Sources

Source	Public	Private/Informal	Media	Total
Used	3,118 [30.4] (15)	4,236 [41.2] (21)	2,911 [28.4] (14)	[100]
Total Sample	20,149	20,149	20,149	

[] denote row percentage - share of use of each source among the total households that used information
() denote column percentage – share of use of each source in the total sample
Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Table 11: Average Treatment effect for users of information and use by sources

Sample	Treated	Controls	S.E.	T-stat
Use of Information				
Matched	0.58	0.57	0.005	2.03**
Unmatched	0.58	0.55	0.005	7.26***
Use of Public Source				
Matched	0.56	0.56	0.005	0.18
Unmatched	0.56	0.56	0.007	0.62
Use of Private/Informal Source				
Matched	0.63	0.60	0.006	3.30***
Unmatched	0.63	0.54	0.006	15.14***
Use of Media (ICT) Source				
Matched	0.56	0.55	0.007	1.79*

Unmatched	0.56	0.56	0.006	0.44
Use of Media and Private				
Matched	0.60	0.54	0.005	11.25***
Unmatched	0.60	0.58	0.005	3.32***
Use of Media and Public (formal Source)				
Matched	0.56	0.56	0.06	-0.40
Unmatched	0.60	0.58	0.005	0.95

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

ATT of these individual sources on the treated are positive and statistically significant for private and public sources at 5 percent and 10 percent levels of significance respectively but statistically non-significant for households accessing public sources. Also, the mean efficiency of private users (63 percent) is higher than that of users as a whole (58 percent) and public and media users (both 56 percent).[16]

Figure 2: Distribution of propensity score of treated and control groups before and after matching

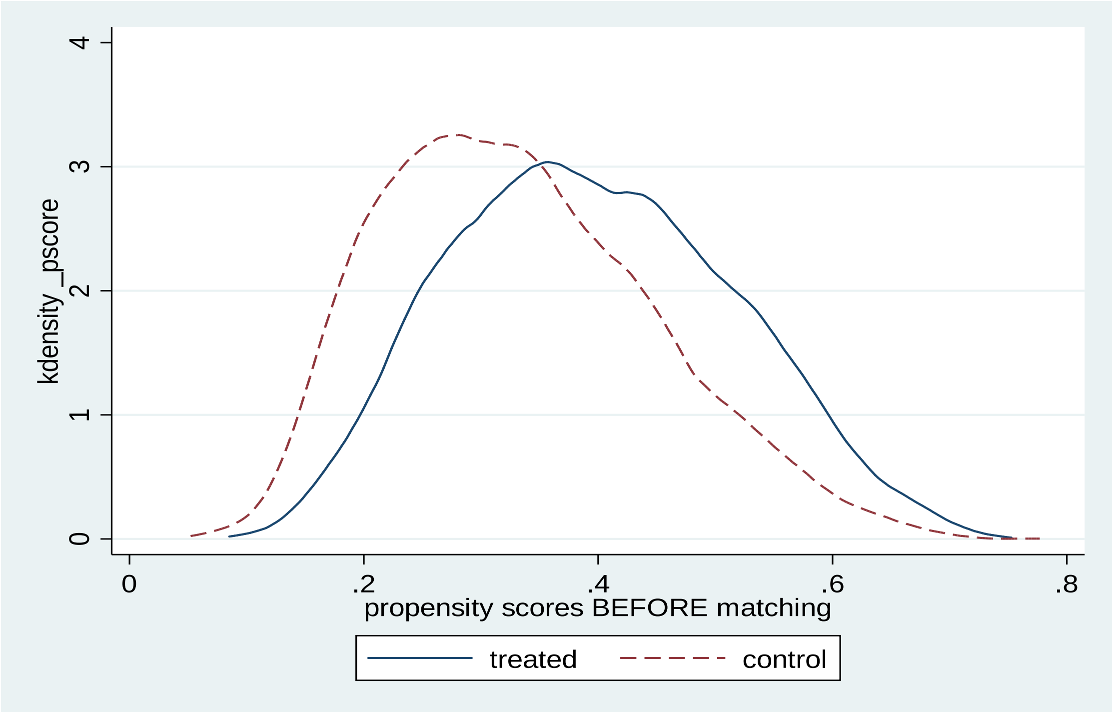

Figure 2(a)- Before Matching

[16] The ATT remains same at 56 percent when we estimate the effect of using formal sources (public and media sources jointly) while ATT increases to 63 percent when we estimate the impact of using private and media jointly. See Appendix (A6).

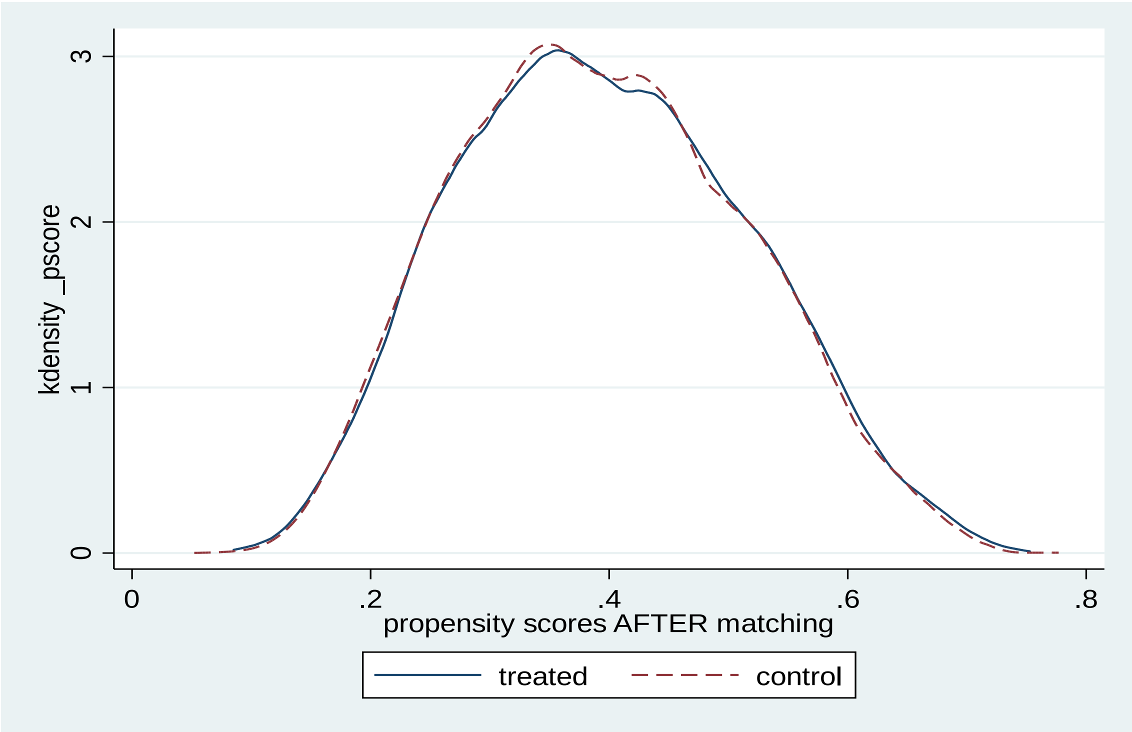

Figure 2(b)- After Matching

In most developing economies, information and knowledge on new agricultural technology and practices are a public good and the most common way of disseminating it is through agricultural extension services (Birkhaeuser, Evenson, & Feder, 1991; Dancey, 1993; Dinar, 1996; Umali & Schwartz, 1994). The formal agricultural extension system has been the government's main channel to disseminate the required information and knowledge to the farmers. However, it has been often argued that government managed extension services suffer from poor planning, formulation and implementation of extension programs. These programmes generally fail to respond to the varying needs of the farming communities (Anderson & Feder, 2004; Rivera, 1991, 1996; Snapp, Blackie, & Donovon, 2003; Umali-Deininger, 1997; Wolf, Just, & Zilberman, 2001). Our results also show that the Indian scenario is no exception to this.

Although the information is generated or transmitted by the government, government policies like Agricultural Technology Management Agency (ATMA) which aims at pluralistic demand-driven (bottom-up) approach towards farmers' need-based information focuses on dissemination using public, private and non-profit organisations. Farmers are more dependent on informal sources like neighbours and input dealers as compared to public extension (Sulaiman and Sadamate, 2000).[17] The efficiency of public extension has been constrained by poor infrastructure, reduction of public funds and poor technical background of the employees. Lack of incentives to the agents/employees and improper monitoring among others are major factors in reducing the efficiency of public sources of information (Babu et.al., 2015). Analysing the Situation Assessment Survey of 2003 (NSSO, 59th Round) Adhiguru *et al*. (2009) found that service delivery by public-sector extension workers was biased against small and marginal farmers; it was lowest for small farmers at 4.8 percent while 12.4 percent for large farmers. Quality and reliability of public extension is also a major concern (Babu, et.al., 2012).

Progressive farmers, mass media and the private sector take the largest share in farmers' sources of information. The impact of information from using private sources, especially progressive farmers is higher. This might mean that progressive farmers and other private sources who get the information from public agents (have a low coverage as seen from our data as well other studies[18]), disseminate it to farmers in their vicinity or community.

Media, however, has the highest access but the lowest use. Media is a human-capital intensive source and scholars like Just, et.al. (2002), Simon (1959), Schultz (1965) argue that human-capital intensive information cannot be comprehended without proper education while informal (private) information which is context-specific and decision-focused (Boehlji, 1998) spreading through oral interaction within a group is easier to comprehend by less educated people. Thus, formal information is more human-capital intensive than informal. More than 60 percent of the heads of households are illiterate, which might have led to lower use of media as well as its weaker impact on technical efficiency. Comparing households that have accessed media and public sources jointly (formal sources) and media with private sources, the effect of the former is 56 percent and not statistically significant while it comes out to be significantly greater among users at 63 percent for the latter (Table 11). Thus, we observe

[17],[14] See Sulaiman and Van den Ban (2003), Birnar and Anderson (2007), Ferroni and Zhou (2012) for more details on the public extension system in India.

that even though impact of information is positive on users, its impact and magnitude vary a lot across different sources of information. The results should not be used to undermine the public channels since the apex entity that generates and disseminates information is the government. It simply suggests further probing into the dissemination pattern because it might be reasonable to argue that the progressive farmers acquire the information from public channels and therefore act as secondary source of information

5. Conclusion

From a global perspective, increasing the productivity of agriculture, given the limited scope of increasing land under cultivation, is necessary for both poverty reduction and the development of the non-agricultural sector. Agricultural productivity gains, poverty reduction, and the growth of the nonfarm sector are complements. In India more than 60 percent of the population is dependent on agriculture and improving agricultural productivity remains the primary concern of policy makers. This paper has tried to estimate the impact of information use on technical efficiency of crop production by agricultural households in India especially after the introduction of pluralistic and demand-driven extension policies like Agricultural Technology and Management Agency in 2005.

It is found that access to information has stagnated at 41 percent for a decade from 2002-03 to 2012-13. Use is even lower at 38 percent and is lowest for formal sources like public and media while highest for private sources, especially progressive farmers followed by private dealers. Overall the average efficiency of farming households is at 56 percent and that of users is 58 percent; slightly higher than non-users. However, this true effect of information seems to be dampened by the source effect. Users of public sources and media have a lower average efficiency than private. Moreover, ATT is significantly higher for private users as compared to media and public users.

Overall use of information has a positive impact which differs greatly across sources. However, access to information still stagnates at 41 percent and also varies considerably across different information sources. The results direct to the fact that on the demand side, the same information might be valued more when it comes through private sources as compared to public sources. However, that should not undermine the public channels since the government is the main entity that generates and disseminates information. It could be that the progressive farmers acquire the information from public channels and therefore act as secondary source of information. Therefore, the results suggest further probing into the dissemination pattern.

On the supply side literature supports that the public extension is limited in its spread and expertise due to several problems in infrastructure, quality of employees and biasedness against poor farmers. The reliability on progressive farmers and informal sources as a whole seems to be much greater than on formal sources. Although the information is generated or transmitted by the government, government policies like Agricultural Technology Management Agency (ATMA) which aims at pluralistic demand-driven (bottom-up) approach towards farmers' need-based information focuses on dissemination using public, private and non-profit organisations. Farmers are more dependent on informal sources like neighbours and input dealers as compared to public extension. The efficiency of public extension has been constrained by poor infrastructure, reduction of public funds and poor technical background of the employees. Lack of incentives to the agents/employees and improper monitoring among others are major factors in reducing the efficiency of public sources of information. Media is a human-capital intensive source which might be difficult to comprehend without proper education while informal (private) information which is context-specific and decision-focused spreading through oral interaction within a group is easier to comprehend by less educated people. More than 60 percent of the heads of households are illiterate, which might have led to lower use of media as well as its weaker impact on technical efficiency. Some of the hurdles to rural welfare are access to credit, infrastructure, farmers' socio-economic conditions and education and these are mostly interlinked with each other. However, a deeper understanding of the reasons for the stagnation of access to information and the variability across sources is required to deliver better extension services to the farmers for higher agricultural gains.

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Appendix

Table A1: ATT for different matching algorithms

Treated	Controls	S.E.	T-stat
Kernel with bandwidth 0.05			
0.58	0.57	0.005	2.03**
Kernel with bandwidth 0.01			
0.58	0.57	0.005	1.80*
Nearest neighbour with 1 neighbour with common support, with replacement			
0.58	0.57	0.007	0.95
Nearest neighbour with 2 neighbours with common support, with replacement			
0.58	0.57	0.006	1.12
Nearest neighbour with 3 neighbours with common support, with replacement			
0.58	0.57	0.006	1.07
Nearest neighbour with 4 neighbours with common support, with replacement			
0.58	0.57	0.006	1.60*
Nearest neighbour with 5 neighbours with common support, with replacement			
0.58	0.57	0.006	1.23
Nearest neighbour with 6 neighbours with common support, with replacement			
0.58	0.57	0.005	1.36
Nearest neighbour with 7 neighbours with common support, with replacement			
0.58	0.57	0.005	1.31
Nearest neighbour with 8 neighbours with common support, with replacement			
0.58	0.57	0.005	1.42
Nearest neighbour with 9 neighbours with common support, with replacement			
0.58	0.57	0.005	1.40
Nearest neighbour with 10 neighbours with common support, with replacement			

0.58	0.57	0.005	1.39
Caliper matching within 0.2 with common support			
0.58	0.57	0.005	2.13**
Radius matching with common support with 0.05 caliper			
0.58	0.57	0.005	2.19**
Abadie and Imbens 2006 method only with Nearest Neighbour (2 neighbours)			
0.58	0.57	0.006	1.16

Source: Computed from NSSO 70^{th} Round, Situation Assessment Survey of Farmers (2012-13)

Table A2: Number of Observation on and off Common Support for different matching algorithms

Treatment Assignment	**Off Support**	**On Support**	**Total**
Kernel with bandwidth 0.05			
Untreated	0	12993	12993
Treated	0	7131	7131
Total	0	20124	20124
Kernel with bandwidth 0.01			
Untreated	0	12993	12993
Treated	2	7129	7131
Total	2	20122	20124
Nearest neighbour with 1 - 10 neighbours with common support, with replacement			
Untreated	0	12993	12993
Treated	0	7131	7131
Total	0	20124	20124
Calliper matching within 0.2 with common support			
Untreated	0	12993	12993
Treated	0	7131	7131
Total	0	20124	20124
Radius matching with common support			
Untreated	0	12993	12993
Treated	0	7131	7131
Total	0	20124	20124
Abadie and Imbens 2006 method only with Nearest Neighbour			
Untreated	0	12993	12993
Treated	0	7131	7131

Total	0	20124	20124

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Table A3: Sensitivity Analysis using Rosenbaum Bounds

Variable	(1) Efficiency
_treated	0.0359***
	(0.00494)
Constant	0.546***
	(0.00294)
Observations	20,124
R-squared	0.003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Estimation of Covariate Balancing

Variable	Treated	Control	Reduction in bias (%)	t-value	p>t
Muslim	.09199	.0929	91.8	-0.19	0.852
Christian	.05665	.05604	98.6	0.16	0.874
Others	.04684	.04476	41.8	0.59	0.552
Farmers in a household	2.463	2.4583	94.9	0.20	0.841
Size of the household	5.4607	5.4595	97.0	0.03	0.979
SC	.10531	.10559	97.4	-0.05	0.957
OBC	.39896	.40272	92.2	-0.46	0.647
General	.31272	.30718	89.3	0.71	0.475
Marginal	.32604	.33102	16.2	-0.63	0.527
Small	.2799	.27763	96.7	0.30	0.762
Medium	.08344	.0781	83.6	1.17	0.242
Large	.00982	.00819	69.1	1.03	0.302
Cultivation as main source of income	.20053	.20022	99.4	0.05	0.962
Age of head	51.258	51.231	96.5	0.12	0.901
Square of age of head	2793.8	2791.7	96.6	0.09	0.925
Female head	.93774	.93789	99.1	-0.04	0.969
Semi-Pucca	.30809	.31166	89.7	-0.46	0.645
Pucca	.62025	.61734	95.7	0.36	0.721
NREGA Card Holder	.56177	.55767	93.5	0.49	0.621
Antyodaya	.03267	.03387	71.4	-0.40	0.690
BPL	.30459	.30845	89.3	-0.50	0.617
Others	.57047	.56681	95.9	0.44	0.659
Primary	.27149	.2709	89.6	0.08	0.937
Middle	.17193	.17171	98.4	0.03	0.973
Secondary	.12845	.13106	88.6	-0.46	0.644

Above Secondary	.13462	.13186	89.6	0.49	0.627
Non-food crop	.56191	.56695	91.9	-0.61	0.544
Eastern Himalayan Region	.20418	.20481	98.7	-0.09	0.926
Lower Gangetic Plains	.10069	.09838	92.9	0.46	0.645
Middle Gangetic Plains	.08344	.08509	95.8	-0.36	0.722
Upper Gangetic Plains	.06156	.0634	77.9	-0.45	0.651
Trans Gangetic Plains	.05006	.04741	89.3	0.73	0.462
Easter Plateau and Hills Region	.09816	.099	80.2	-0.17	0.868
Central Plateau and Hills Region	.04684	.04678	99.5	0.02	0.986
Western Plateau and Hills Region	.07559	.07859	79.9	-0.67	0.501
Southern Plateau and Hills Region	.10237	.1029	98.8	-0.10	0.917
East Coast Plains and Hills Region	.07615	.07891	74.8	-0.62	0.537
West Coast Plains and Hills Region	.01599	.01618	93.4	-0.09	0.927
Gujarat Plains and Hills Region	.05006	.04535	78.3	1.32	0.187
Western Dry Region	.00575	.00475	91.4	0.82	0.411

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.000	8.21	1.000	0.7	0.7	4.8	1.16	50

* if B>25%, R outside [0.5; 2]
The standardised percentage bias is the percentage difference of the sample means in the treated and non-treated (full or matched) sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (formulae from Rosenbaum and Rubin, 1985). Rubin (2001) recommends that B be less than 25 and that R be between 0.5 and 2 for the samples to be considered sufficiently balanced. An asterisk is displayed next to B and R values that fall outside those limits. The null hypothesis is the equality of the values of each variable between treated and control for the matched data.

Table A5: Estimation of Propensity Score by Source of Information using Logit Model

Variables	**Dependent Variable Used Public**		**Dependent Variable Used Private**		**Dependent Variable Use Media**	
Religion (Base=Hindu)						
Muslim	-0.206**	(0.0838)	-0.0442	(0.0724)	0.199***	(0.0746)
Christian	-0.198**	(0.0974)	-0.373***	(0.110)	-0.226**	(0.103)
Others	-0.128	(0.103)	-0.425***	(0.114)	-0.481***	(0.117)
Farmers in a household	0.0568***	(0.0183)	0.0310*	(0.0169)	0.0244	(0.0188)
Size of the household	-0.0127	(0.00954)	-0.0149*	(0.00840)	-0.00489	(0.00953)
Social Group (Base=ST)						
SC	0.112	(0.0850)	0.186**	(0.0747)	0.177*	(0.0935)
OBC	0.245***	(0.0669)	0.338***	(0.0599)	0.458***	(0.0733)
General	0.199***	(0.0733)	0.269***	(0.0668)	0.392***	(0.0782)
Land Size Holding (Base=Sub-marginal)						
Marginal	0.282***	(0.0537)	0.235***	(0.0477)	0.132**	(0.0544)
Small	0.471***	(0.0584)	0.462***	(0.0525)	0.310***	(0.0594)
Medium	0.691***	(0.0866)	0.546***	(0.0800)	0.373***	(0.0915)
Large	0.838***	(0.217)	0.478**	(0.209)	0.942***	(0.212)
Primary source of income (Base=Cultivation)	-0.172***	(0.0545)	-0.101**	(0.0480)	-0.168***	(0.0551)
Age of head of household	0.0604***	(0.0107)	0.0125	(0.00888)	0.0344***	(0.0104)
Square of age of HoH	-0.00054***	(0.0001)	-0.000154*	(8.37e-05)	-0.00026***	(9.6e-05)
Gender (Base=Female)	0.0870	(0.0849)	0.0531	(0.0749)	0.103	(0.0901)
Structure of Household (base=Kutcha)						

Semi-Pucca	0.226**	(0.0879)	0.0948	(0.0724)	0.0312	(0.0861)
Pucca	0.366***	(0.0862)	-0.0279	(0.0706)	0.0779	(0.0841)
NREGA Card Holder (Base=Yes)	-0.00884	(0.0472)	0.00694	(0.0420)	0.287***	(0.0487)
Type of Ration Card Held (Base=No card)						
Antyodaya	0.189	(0.139)	0.210*	(0.115)	0.239*	(0.137)
BPL	0.384***	(0.0805)	0.101	(0.0702)	0.244***	(0.0793)
Others	0.461***	(0.0760)	0.365***	(0.0661)	0.284***	(0.0732)
Educational Attainment of head (Base=Illiterate)						
Primary	0.194***	(0.0559)	0.0881*	(0.0486)	0.304***	(0.0597)
Middle	0.305***	(0.0658)	0.113*	(0.0583)	0.476***	(0.0685)
Secondary	0.363***	(0.0720)	0.0724	(0.0658)	0.719***	(0.0725)
Above Secondary	0.445***	(0.0750)	0.0725	(0.0675)	0.802***	(0.0747)
Non-food crop (Base=food crop)	-0.0787*	(0.0457)	-0.162***	(0.0418)	-0.179***	(0.0466)
Constant	-4.241***	(0.325)	-4.138***	(0.330)	-3.818***	(0.320)
Zone Fixed Effects	Yes		Yes		Yes	
Observations	20,124		20,124		20,124	
Log Likelihood	-8172.57		-9622.37		-7872.48	

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Table A6: ATT by Source and Source-categories using kernel matching (bandwidth=0.05)

Treated	Controls	S.E.	T-stat
Formal (Public and media)			
0.56	0.55	0.006	0.95
Informal (same as private sources)			
0.63	0.60	0.006	3.30***
Progressive Farmers			
0.63	0.60	0.006	4.04***
Media and Private			
0.60	0.58	0.005	3.32***

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

Table A7: Number of Observation on and off Common Support for different sources

Treatment Assignment	Off Support	On Support	Total
Public			
Untreated	0	17,009	17,009
Treated	1	3,114	3,115
Total	1	20,123	20,124
Private (same as Informal)			
Untreated	0	15,890	15,890
Treated	1	4,233	4,234
Total	1	20,124	20,124
Media			
Untreated	0	17,219	17,219
Treated	0	2,905	2,905

Total	0	20,124	20,124
Formal (Public and media)			
Untreated	0	15,324	15,324
Treated	0	4,800	4,800
Total	0	20,124	20,124
Progressive farmers			
Untreated	0	16,565	16,565
Treated	0	3,559	3,559
Total	0	20,124	20,124
Private and media			
Untreated	0	14,268	14,268
Treated	0	5,856	5,856
Total	0	20,124	20,124

Source: Computed from NSSO 70th Round, Situation Assessment Survey of Farmers (2012-13)

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