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ARTICLES

Credit and Efficiency in Indian Agriculture: Evidence from Household-Level Data

Rekha Misra, Pallavi Chavan and Radheshyam Verma*

ABSTRACT

The paper estimates technical efficiency in agriculture for cultivator households applying the Data Envelopment technique to the Rural Economic and Demographic Survey (REDS) database covering 17 major States in India, and analyses its association with agricultural credit along with other household-level economic and demographic variables through a Tobit framework. Agricultural efficiency was observed to have a positive and significant relation with agricultural credit. The impact was positive for all cultivator households including marginal and small cultivator households. Agricultural credit influenced efficiency when directly factored into the model but also in an indirect manner when replaced by various variable and fixed inputs generally purchased by a cultivator using crop and investment credit. Most of these inputs showed positive elasticity with respect to agricultural credit. The paper underlines the need to continue with the policy of providing directed credit support to agriculture with a distinct thrust on marginal and small cultivators.

Keywords: Agricultural Credit, Agricultural Efficiency, Data Envelopment Analysis, Marginal and Small Cultivators.

JEL: Q10, Q14, Q18, N55.

The decade of the 2000s witnessed a striking growth in agricultural credit in India. Several studies have, by now, analysed the patterns of growth and distribution of agricultural credit during this period. Studies have also illustrated the possible triggers for such high growth in agricultural credit, which has been described as a 'revival' from the slowdown that marked the earlier decade (Ramakumar and Chavan, 2007, 2014). An attempt, the first of its kind, was made in 2016 to analyse the linkages between credit and total factor productivity taking a State-level panel and also a district-level panel for Andhra Pradesh, the State with a relatively large share in total agricultural credit in the country (see Misra *et al.*, 2016). The present paper affirmed the point made earlier in the literature for other developing countries of a positive association between bank credit to agriculture, in particular direct bank credit (given directly to agricultural producers instead through any intermediary), and agricultural productivity.

In this paper, we take the exercise further by analysing household-level data to work out technical efficiency for cultivator households and assess its relation with

*Department of Economic and Policy Research, Reserve Bank of India, Mumbai-400 001.
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agricultural credit along with other household-level economic and demographic variables. The main data source used for this exercise is the latest round of 2007 of the Rural Economic and Demographic Survey (REDS) conducted by National Council for Applied Economic Research (NCAER).[1]

The year of the REDS is of special relevance for a contemporary study on agricultural credit. It is expected to appropriately capture the increased flow of credit to agriculture across rural India in the 2000s following the implementation of the "Comprehensive Credit Policy" by the Central Government to double the total flow of agricultural credit in the country. This policy was aimed at stepping up the growth of agricultural credit by 30 per cent per annum between 2004-05 and 2006-07. The policy was a key trigger to raise the growth of agricultural credit significantly during the 2000s (Misra *et al.*, 2016). As shown by Ramakumar and Chavan (2014), the increase in agricultural credit was spread almost uniformly across all geographical regions and states of India.

The paper is divided into five sections. The second section presents the review of similar studies that have attempted an analysis of agricultural productivity and credit. The focus of this section is on past attempts on establishing association of agricultural efficiency and agricultural production with credit at the farm-level in India and other emerging economies. It also summarises the changes in agricultural productivity in India in the 2000s, which provide a backdrop for our existing study. In Section III, the key trends in the growth and intensity of agricultural credit in India between 2000 and 2015 are analysed. Section IV discusses the data sources and econometric methodology used in the paper. Section V provides the findings from the empirical exercise. Section VI concludes with major policy implications.

II

AGRICULTURAL CREDIT AND PRODUCTIVITY – A REVIEW WITH SPECIAL REFERENCE TO HOUSEHOLD-LEVEL STUDIES

The basic link between finance and growth has been an area of extensive research right from the pioneering work by Raymond Goldsmith in the late-1960s. This earlier work was carried forward but with more firm data and methodological framework in the later decades using cross-country panels.[2]

Agriculture, among all economic sectors, has occupied a special role in the literature on finance and growth despite being marred by several data limitations. The importance of agriculture has been due to its centrality in the process of (a) growth and its redistribution being the largest contributor to employment in most developing economies, (b) credit allocation given that most of the directed lending programmes instituted since the 1960s in both advanced and developing economies have focused on agriculture. Needless to say that the research relating to credit and growth linkages in agriculture has been mainly about the developing economies.

The studies on agricultural credit and productivity/efficiency can be broadly categorised in two groups: studies using (a) national/sub-national level data and (b) farm/household-level data. While studies from the first category have primarily looked at the relation between credit and production in agriculture, those in the second category have attempted an analysis of credit and farm-level productivity/efficiency.

The studies in the first category, primarily using macro data, have found a positive impact of agricultural credit on agricultural production: (Armas *et al.* (2010) for Indonesian agriculture, Khandker and Faruquee (2003) for Pakistan and Ammani (2012) for Nigeria.[3] In the Indian context, studies based on aggregated and disaggregated data at the State/district-level by Binswanger and Khandker (1992), Bhalla and Singh (2010), Das *et al.* (2009) and Narayanan (2014) too have found that agricultural credit resulted in higher agricultural production, while controlling for regional factors affecting agricultural production.

Among the recent studies, Deokar and Shetty (2014) analysed the yields of major agricultural crops during 2004-2012 and brought out a quantum jump in crop yields for every crop with the exception of groundnut. The reason for this phenomenal increase was explained in terms of various initiatives undertaken to improve the availability of better inputs and infrastructure as well as credit to farmers.

Most of the studies in the second category have arrived at farm-level productivity/efficiency estimates and then attempted a relation of the same with various economic/demographic determinants including credit. For instance, Nosiru (2010) analysed the relationship between microfinance and agricultural productivity. Productivity was estimated by them using Cobb Douglas production function. They observed that productivity among microfinance beneficiaries was higher than that of the non-beneficiaries.

Taking farm-level data collected from two representative Chinese provinces, Liu and Zhuang (2000) estimated technical efficiency using a stochastic frontier production function model. The key factors explaining the differentials in efficiency were, among others, access to credit, farm size and farming experience. Their study underlined the role of credit in encouraging technological innovations by acting as an insurance mechanism in agrarian economies.[4]

Another study by Guirkinger and Boucher (2008), examining the efficiency of credit-constrained households in Peru, observed that formal credit constraints reduced the efficiency of resource allocation. According to their estimation, the value of agricultural production in the study region would increase by 26 per cent if formal credit constraints were addressed. Helfand and Levine (2004) explored the determinants of technical efficiency, and the relationship between farm size and efficiency in Brazil using farm-level data from 426 counties. The study found that access to credit, access to institutions/public goods, *viz*. electricity, technical assistance, co-operatives and market access, and modern inputs were important determinants of the differences in efficiency across farms. An improved access to credit was found to strengthen the efficiency advantage for small and medium farms.

Rahman *et al.* (2014) investigated the impact of bank credit on agricultural productivity by using a logit model for farmers in Bahawalpur Tehsil of Pakistan. The study concluded that household size, agricultural credit, income of the household, education of the farmers were some of the significant determinants of crop yields. Credit enabled farmers to purchase superior quality or high yielding variety seeds, fertilisers and pesticides and agricultural yields increased because of timely and adequate inputs. Thus, farm/household-level studies conducted in case of various developing economies unequivocally underscored the role of agricultural credit in enhancing productivity/efficiency.

Along with timely provision of credit, farm size was also expected to impact technical efficiency. Intuitively, there exists a direct relationship between farm size and technical efficiency as larger farms have greater access to productivity enhancing inputs. Liu and Zhuang (2000) however found no significant relationship between farm size and efficiency. Helfand and Levine (2004) examined the relationship between farm size and technical efficiency in centre-west Brazil and found it to be a complex one. Their analysis revealed a U-shaped relationship where efficiency fell as farm size rose and beyond a threshold level it started to rise again. The reason underlying the positive relationship was due to preferential access by large farms to institutions and services like credit, technical assistance and rural electricity. They, however, concluded that in an environment wherein small farms had equal access to productivity enhancing institutions, technology and inputs, there would be an inverse relationship between farm size and productivity (*ibid.*).

In the Indian context, studies tracing the linkage between agricultural productivity and credit have been very limited. As noted earlier, one such attempt to analyse the impact of credit on agricultural productivity was made in Misra *et al.* (2016), where we estimated total factor productivity in agriculture using a State-level panel. The paper analysed the relation of productivity with agricultural credit and found that agricultural credit supported improvement in agricultural productivity and this relationship was stronger for direct agricultural credit. A district-level panel model also found a positive relationship between agricultural credit and agricultural production for the (combined) state of Andhra Pradesh (*ibid.*). However, there have not been any study in our knowledge on productivity and credit linkages using farm/household-level data, as has been attempted in this paper.

III

RECENT TRENDS IN THE GROWTH OF AGRICULTURAL CREDIT

Growth in agricultural credit, as illustrated in the literature, showed a distinct increase in the 2000s over the 1990s. Taking the entire time period from 2000 to 2015, agricultural credit, on average, grew at a rate of about 22 per cent (in nominal terms) (Table 1). This was higher than the overall growth in bank credit during this period of about 20 per cent. This implied an increase in the allocation of credit to agriculture as compared to other sectors.

TABLE 1. AVERAGE RATES OF GROWTH OF AGRICULTURAL/TOTAL CREDIT,

(*per cent per annum*)

Period (1)	Total agricultural credit (2)	Direct agricultural credit (3)	Total bank credit (4)
2000-01 = 2014-15	22.3	22.6	20.1
2000-01 = 2006-07	26.1	24.1	23.1
2007-08 = 2014-15	19.0	21.3	17.5

Source: *Handbook of Statistics on Indian Economy*, RBI and Basic Statistical Returns of Scheduled Commercial Banks in India (BSR), RBI.

Breaking down this entire period into two sub-periods with 2007, the survey year and the conclusion of the Comprehensive Credit Policy, as the dividing line, we observe that the growth in agricultural credit was distinctly higher during 2000-07 than the subsequent period. The same could also be said about direct agricultural credit. Further, in each of the two sub-periods delineated in Table 1, growth in total agricultural credit was higher than the growth in total credit.

As a fallout of higher growth in agricultural credit, there was an increase in the credit intensity in agriculture (defined as agricultural credit to agricultural GDP ratio) throughout this period. Notwithstanding a higher average growth of agricultural credit than total credit, the credit intensity in agriculture, however, remained lower than the overall intensity of bank credit during this period. Moreover, it maintained a steady distance with respect to the overall intensity till 2010. However, thereafter, the gap between overall and agricultural credit intensity widened significantly. This implied that even though there was a faster growth in agricultural credit than overall credit, agricultural credit after 2010 could not keep pace with agricultural gross domestic product (GDP). The upturn in 2014 in intensity was largely a reflection of the drought leading to a decline in agricultural GDP in that year.

The rates of growth in both total and direct agricultural credit were above 20 per cent in every geographical region between 2000 and 2015 (Table 2). Moreover, barring the exception of the north-eastern region, the rates of growth of total and direct agricultural credit were significantly higher in the period preceding 2007 than after it. This once again underlined the point that the phase before 2007 was a high growth phase in agricultural credit across most parts of the country.[5]

IV

RESEARCH QUESTIONS, DATA SOURCES AND ECONOMETRIC METHODOLOGY

This paper addresses the following research questions:

(1) What are the various determinants of farm efficiency[6] at the household level? Whether agricultural credit affects farm efficiency at the household level?

TABLE 2. REGION-WISE AVERAGE RATES OF GROWTH IN AGRICULTURAL CREDIT

(*per cent per annum*)

Region (1)	Northern (2)	North-eastern (3)	Eastern (4)	Central (5)	Western (6)	Southern (7)
			Total agricultural credit			
2000-01 = 2014-15	22.9	23.6	23.4	21.9	21.3	22.8
2000-01 = 2006-07	30.5	22.9	29.0	24.3	27.3	23.9
2007-08 = 2014-15	16.3	24.3	18.5	19.8	16.1	21.8
			Direct agricultural credit			
2000-01 = 2014-15	23.3	24.2	23.1	21.8	22.6	23.0
2000-01 = 2006-07	25.7	23.2	27.4	24.1	24.9	22.6
2007-08 = 2014-15	21.2	25.1	19.4	19.7	20.5	23.3

Source: Calculated from data from BSR.

(2) What is the elasticity of various farm-specific fixed and variable inputs with respect to agricultural credit? How far do these inputs that are generally procured with credit affect agricultural efficiency?
(3) How does agricultural credit affect efficiency for marginal and small cultivator households as compared to the rest of the cultivating community?

As discussed in Section II, there has been a conspicuous gap in the literature about studies dealing with agricultural productivity and its possible linkages with agricultural credit in India. One of the reasons for this gap is the lack of availability of credible unit level data on (a) various farm inputs including credit (b) farm outputs.

This study uses data from the REDS of NCAER. REDS is one of the few sources of household-level data for India. The data used for this paper are drawn from the latest round of REDS conducted in 2007.[7] The Additional Rural Income Survey (ARIS)/REDS are being conducted by the NCAER since 1969. So far, there have been four rounds of this survey between 1971 and 2006 (2007 as defined in this paper). The survey provides a comprehensive data on a set of households over longer time horizon and has been the subject of various studies till now.[8] It is a cross-sectional dataset on 8,659 households from 242 villages belonging to 17 major States. It covers not just the households covered in the earlier round of 1999 but also eight newly selected households from each village.

The survey has three components: the first round contains a house-listing which collects basic information on households. The second round collects details about the given village including village finances. The third round, the most intensive of all, collects household level information. It canvasses information on assets, incomes, agricultural inputs and outputs at the household level. In the latest round, the survey also collected crop-wise information on inputs and outputs.

As already stated, while the latest survey round started in 2006, the agricultural details were collected in 2007. Moreover, the information during the third round on households was also collected in 2007 and hence, we, like Binswanger-Mkhize *et al.* (2014), refer to this round as the 2007 round. The selected households were canvassed at the end of each cropping season, which were expected to improve the quality of data collected on agricultural output and inputs. The survey collected data at the level of a fragment, which was taken as the unit of cultivation.[9]

Of the total sample of 8558 households, 3451 households (40 per cent) were considered for our analysis of productivity. Our sample selection was done based on the definition of cultivator households - households that reported operation of land (either owned or leased-in or both) during the survey year.[10] However, our sample of 3451 households had to be further pruned to include only those cultivator households for which data were available on the various data heads that we captured in our empirical exercise. The descriptive statistics of the variables used in the study are presented in Table 3.

TABLE 3. DESCRIPTIVE STATISTICS

Variable (1)	Obs. (2)	Mean (3)	Std. Dev. (4)	Min. 95)	Max. (6)
			All Farms		
vrste	3,449	0.213162	0.170167	0.004	1
logirrig_p~e	1,590	5.662262	1.457621	- 0.80438	9.519702
max_eduhh	3,296	9.476335	4.040093	1	53
hhsize	3,448	5.988399	3.287392	1	36
d_fullfarm~a	3,449	0.298057	0.457471	0	1
logfert_pe~e	3,355	6.621537	0.865138	0.077424	10.30895
logmanure_~e	2,764	3.977759	1.882473	- 1.75493	10.72549
logseed_pe~e	2,789	5.996966	1.128621	1.612157	9.288214
logotherin~e	2,050	5.27555	1.207861	0.430783	9.227198
logmach_pe~e	3,367	6.076292	1.244138	- 1.09272	10.13038
			Small Farms		
vrste	2,502	0.178259	0.147783	0.004	1
logirrig_p~e	1,210	5.895574	1.398363	- 0.80438	9.519702
hhsize	2,501	5.89964	3.241223	1	36
logcredit_~e	2,426	8.277332	1.773099	0.689554	13.43888
max_eduhh	2,382	9.192275	3.893475	1	21
d_fullfarm~a	2,502	0.291767	0.454666	0	1
			Large Farms		
vrste	947	0.305375	0.189919	0.006	1
logirrig_p~e	380	4.919347	1.393905	- 0.73856	7.434943
hhsize	947	6.222809	3.396925	1	25
logcredit_~e	885	7.845275	1.661653	2.295575	13.28599
max_eduhh	914	10.21663	4.314461	1	53
d_fullfarm~a	947	0.314678	0.464633	0	1

Source: Calculations by authors based on REDS database.

As the objective of the study is to understand the overall linkage between agricultural credit and efficiency, we do not delve into the detailed features of the households selected for the analysis. The features of the sample households are already illustrated in earlier studies, including Binswanger-Mkhize *et al*. (2014). However, a noteworthy feature of the sample was that 76 per cent of the households were marginal and small cultivator households (operating up to 5 acres of land) reflective of the general reality in Indian agriculture.

As discussed in Misra *et al.* (2016), any secondary data-based study modelling the relation between credit and production in the Indian context is beset with the limitation that it can only capture formal credit as data on informal credit comes with a lag. However, a study based on household-level data can overcome this limitation as it is possible to capture both formal and informal credit in a household-level survey, as we have done in our study. A primary data-based study can also help in overcoming another limitation relating to credit data in the Indian context, namely, on co-operatives. It is often difficult to capture co-operative credit in any secondary data-based study given the delayed availability of data on these institutions.[11] We use the data on 'credit limit' for agriculture (the maximum amount of credit available to a household for agricultural purposes) provided in the REDS, which relates to credit from all formal and informal sources.[12]

For the estimation of efficiency, we used three inputs and one output variable from REDS: (a) input variables - value of land, total wage bill (includes wages for hired labour and imputed wages for family labour), and expenditure on mechanised inputs.[13] The value of total agricultural output was taken as the output variable. There are two major approaches in the literature for measuring efficiency (a) econometric models - Stochastic Frontier Analysis, Thick Frontier Approach, and Distribution Free Approach and (b) linear programming techniques - Data Envelopment Analysis (DEA) (Havrylchyk, 2006).

In this study, the DEA technique has been employed to measure farm-level technical efficiency of cultivator households. DEA uses a non-parametric technique to estimate production functions and has been used extensively to estimate measures of technical efficiency in a range of industries (Cooper *et al.*, 2000). The origin of DEA can be traced back to Farrell (1957) who introduced a simple method of measuring efficiency of a firm directly from observed data, in a single output and multiple inputs case, which was subsequently extended to multiple inputs and multiple outputs.

DEA has several advantages over other techniques used to measure efficiency. First, a specific functional form of the production process does not need to be imposed on the model unlike in the case of the stochastic production frontiers approach. Secondly, it performs well even in case of small number of observations. Thirdly, it accommodates both multiple inputs and multiple outputs more easily than other techniques. However, a drawback of this method is that it is sensitive to outliers.

The efficiency of a farm consists of both technical and allocative efficiency. Technical efficiency is defined as the ability of a farm to produce the maximum possible output from a given set of inputs and a given technology, or to produce the given level of output by minimising the amount of inputs used for a given level of technology. The former approach is the output-oriented approach, while the latter is the input-oriented approach. Both output and input-orientated models estimate exactly the same production frontier and, therefore, identify the same set of efficient decision making inputs (DMUs). However, the efficiency measures associated with the inefficient DMUs may differ between the two methods (Coelli, 1995). Allocative efficiency is defined as the ability of a farm to optimise on the use of inputs given their respective prices (Coelli, 1995). Technical efficiency is independent of input prices, while allocative efficiency takes into account the input prices.

In the current study, input oriented DEA model has been used to measure the technical efficiency and allocative efficiency of farms using inputs as the primary decision variables. We have modelled efficiency using variable returns to scale.

For this estimation, we use two-step approach following Coelli *et al* (1998). In the first step, DEA has been used to estimate technical efficiencies using traditional inputs and outputs. In the second step, technical efficiency scores obtained from the first stage are regressed upon environmental variables over which the cultivator does not have direct control to explain variations in measured efficiencies.

Following Fare *et al.* (1994) and Dhungana *et al.* (2004) Economic Efficiency (EE) / Cost Efficiency (CE) can be defined as the ratio of minimum cost (MC) to actual cost i.e. EE_j (y_j, x_{ij}, c_{ij}) = MC (y_j, x^*_{ij}, c_{ij}) / ($c_{ij} \times x_{ij}$). If EE_j is equal to one, the farm is considered economically efficient or cost efficient. More formally, assuming constant returns to scale

$$\text{Min}_{\theta,\lambda}\, c_{ij} . x^*_{ij}$$
$$\text{subject to } \sum_{j=1}^{n} y_j \lambda_j - y_j \geq 0;$$
$$x^*_{ij} - \sum_{j=1}^{n} x_{ij} \lambda_j \geq 0;$$
$$\lambda_j \geq 0$$

where, farm j (j = 1, 2, … , 3451) produces a single agricultural output (y_j) using a combination of inputs x_{ij} (i = land, human labour and mechanical inputs). θ is a scalar and λ_j is an n x 1 vector of constants used as multipliers for the input level of the jth farm that it should aim to achieve efficiency. x^*_{ij} is cost minimising vector of inputs for jth farm given the input prices. For all the farms same level of input prices have been used. For lack of availability of per acre rental value of land in the REDS data, the same has been taken from *Cost of Cultivation/Production and Related Data*, Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare for paddy for 2006-07 by taking average for all the states. Labour cost per acre and value of mechanical inputs have been taken from REDS data.

Similarly, technical efficiency score (θ) in case of input oriented DEA with constant returns to scale can be expressed as follows (Charnes *et al.* 1978; Dhungana *et al.* 2004).

$$\text{Min}_{\theta,\lambda}\, \theta$$
$$\text{subject to } x_{ij}\theta - \sum_{i=1}^{m} x_{ij} \lambda_j \geq 0;$$
$$\sum_{j=1}^{n} y_j \; \lambda_j \; - y_j \geq 0;$$
$$\lambda_j \geq 0$$

On solving this problem, if we get $\theta = 1$, the farm is considered on the production possibility frontier and deemed technically efficient. On the other hand, if $\theta < 1$, the farm lies inside the production possibility frontier and will be technically inefficient.

Allocative efficiency has been computed as ratio of economic efficiency and technical efficiency across farms following Farrell (1957).

To estimate the efficiency scores, we have used DEAP V2.1 (developed by Tim Coelli). Overall economic efficiency at the all India level was found at 0.35 with technical efficiency and allocative efficiency at 0.55 and 0.63, respectively. It shows that Indian farms are far from efficient reflecting significant potential to increase their efficiency levels (Table 4).

TABLE 4. DESCRIPTIVE STATISTICS OF EFFICIENCY INDICES

Efficiency measures (1)	Mean (2)	Standard deviation (3)	Minimum (4)	Maximum (5)
Technical efficiency	0.55	0.32	0.11	1
Economic efficiency / Cost efficiency	0.35	0.26	0.05	1
Allocative efficiency	0.63	0.25	0.05	1

The Spearman's rank correlation among different measures of efficiencies suggests a weak negative correlation between technical efficiency and allocative efficiency (Table 5). This indicates that technically efficient farms may not be necessarily allocative efficient too. This may be due to variation in farmers' goals and socio-economic conditions across farms (Dhungana *et al.,* 2004).

TABLE 5. SPEARMAN'S RANK CORRELATION

(1)	TE (2)	AE (3)	EE (4)
Technical efficiency (TE)	1		
Allocative efficiency (AE)	-0.03	1	
	(0.05)		
Economic efficiency (EE)	0.75	0.57	1
	(0.00)	(0.00)	

Note: Figures in parentheses are p-values of rho.

After arriving at the efficiency scores, the determinants of technical efficiency are explained using the Tobit model on similar lines as done in Casu and Molyneux (2003) and Havrylchyk (2006). The Tobit model has been chosen as technical efficiency scores are censored at 1 and their values vary between 0 and 1. If ordinary least squares is used in case of censored dependent variable, it will yield inconsistent estimates.

As mentioned earlier, the manager/cultivator in this case should not have a direct control over the variables used to explain the measured efficiencies. Also, these explanatory variables should not be highly correlated with inputs used in the estimation of DEA. Keeping these considerations, the baseline model was designed as follows:

$$\theta_i = c + \beta_1 \text{AgriCredit}_i + \beta_2 \text{Irrig}_i + \beta_3 \text{Edu}_i + \beta_4 \text{HHSize}_i + \beta_5 \text{PrimActivity}_i + \varepsilon_i \quad \text{....(1)}$$

where,
AgriCredit – Amount of credit for agricultural purposes per acre of land operated;
Irrig –Dummy for irrigated land. If more than 50 per cent of the land of the cultivator is irrigated it takes one, otherwise zero;
Edu – Years of schooling of the head of the household;
HHSize – Size of the household;
PrimActivity – dummy variable suggesting involvement in agricultural activity by the household (1 if household is fully involved in agriculture with no non-farm activity; 0 otherwise)

ε_i – error term

The variables used in the study were winsorised at 5 per cent to overcome the problem of outliers. There are many supply-side/institutional factors that affect the availability of credit, and as such, the cultivator may not have a direct control over it.

Irrigation has increasingly become privately financed with the decline in public investment in irrigation facilities (Government of India, 2007a; Singh, 2014). However, given the long-term character of irrigation investments, the cultivator may not have a direct control over it during the survey year per se. The direct benefits of irrigation include higher farm productivity through increase in crop yield and diversification of cropping pattern. To the extent that irrigation results in higher marketed surpluses and increased employment opportunities, it also indirectly benefits the landless through higher wages. Crop yields have been observed to be consistently higher in irrigated areas than in rainfed areas (Rosegrant and Perez, 1997; Ringler *et al.,* 2000; Hussain and Hanjra, 2004; Lipton *et al.*, 2005). The access to irrigation has been credited to the substantial productivity gains during the Green Revolution in Asia in the 1960s and 1970s (Pingali *et al.*, 1997; Bhattarai *et al.*, 2002).

Education helps in enhancing technological awareness. There is substantial literature documenting the greater propensity of educated farmers to adopt agricultural innovations (Feder *et al.*, 1985). There are not just allocative but also financing effects of education on productivity.[14] Hayami (1969) and Hayami and Ruttan (1970) found that educational level was an important determinant of differences in agricultural productivity among countries.

We also control for the size of the household. *prima facie,* ascertaining the exact impact of size on productivity is uncertain. A large-sized cultivator household may generally provide a larger size of family labour force. However, the role of family labour force in enhancing productivity may depend on various factors, including the size of other fixed and variable investments at the disposal of the household and size of land operated.

The involvement of a household that pursues agriculture as the sole economic activity is also used as an explanatory variable in our model. This involvement too can have a positive or negative impact on productivity. The positive impact can come from the complete involvement of a household in agricultural production in terms of labour and entrepreneurial skills. However, the ability of a household to earn from non-agricultural sources can also open up more avenues for investment in agriculture and can enhance productivity, thus suggesting that the association between this variable and productivity may be negative.

In choosing the explanatory variables, we ensured that the correlation between these variables was low, thus minimising the possibility of multicollinearity in our model (see Table 6A,B,C).

TABLE 6A. CORRELATION MATRIX – ALL FARMS

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. logcredit_per_acre	1.00								
2. irrdummy	0.22	1.00							
3. max_eduhh	0.13	0.19	1.00						
4. hhsize	-0.01	0.03	0.01	1.00					
5. d_fullfarm	0.02	0.02	-0.01	0.00	1.00				
6. logfert_per_acre	0.27	0.37	0.02	-0.03	0.00	1.00			
7. logmanure_ per_acre	-0.09	-0.15	-0.23	-0.01	0.05	0.06	1.00		
8. logseed_ per_acre	0.21	0.34	0.09	0.01	0.00	0.48	-0.09	1.00	
9. logotherin_ per_acre	0.23	0.27	0.05	-0.01	0.01	0.47	0.03	0.30	1

TABLE 6B. CORRELATION MATRIX – SMALL AND MARGINAL CULTIVATOR HOUSEHOLDS

(1)	(2)	(3)	(4)	(5)	(6)
1. logcredit_per_acre	1				
2. irrdummy	0.23	1			
3. max_eduhh	0.17	0.19	1		
4. hhsize	- 0.01	0.02	0.01	1	
5. d_fullfarm	0.01	0.05	- 0.01	0.01	1

TABLE 6C. CORRELATION MATRIX – OTHER CULTIVATOR HOUSEHOLDS

(1)	(2)	(3)	(4)	(5)	(6)
1. logcredit_per_acre	1				
2. irrdummy	0.19	1			
3. max_eduhh	0.06	0.18	1		
4. hhsize	0.01	0.06	0.03	1	
5. d_fullfarm	0.03	- 0.05	- 0.04	- 0.03	1

Source: Calculations by authors based on REDS database.

We then augment the baseline model using State dummies to control for State-specific factors as in (ii). We take Haryana as the base section, as it is a State with one of highest crop yields in India (the dummy variable takes value 1 if the household belongs to a given State, 0 otherwise).[15]

$$\theta_i = c + \beta_1 \text{AgriCredit}_i + \beta_2\ \text{Irrig}_i + \beta_3 \text{Edu}_i + \beta_4 \text{HHSize}_i + \beta_5 \text{PrimActivity}_i + \beta_6 \text{Kar}_i + \beta_7 \text{Mah}_i + \beta_8 \text{Him}_i + \beta_9 \text{AP}_i + \beta_{10} \text{Ors}_i + \beta_{11} \text{WB}_i + \beta_{12} \text{Bh}_i + \beta_{13} \text{UP}_i + \beta_{14} \text{Jh}_i + \beta_{15} \text{Chh}_i + \beta_{16} \text{MP}_i + \beta_{17} \text{Pun}_i + \beta_{18} \text{Guj}_i + \beta_{19} \text{Raj}_i + \beta_{20} \text{TN}_i + \beta_{21} \text{Ker}_i + \varepsilon_i \quad ....(2)$$

The augmented model is further modified to control for the quantum of various purchased farm-level inputs along with state dummies. However, before testing the same, we find out the elasticities of each of these inputs with respect to agricultural credit using the ordinary least squares framework as in (iii).

$$\text{Agriinput}_i = c + \beta_1 \text{AgriCredit}_i + \varepsilon_i \quad ...(3)$$

We then replace the variable of agricultural credit with these inputs to estimate our final augmented model as in (iv), while keeping all controls other than agricultural credit from (ii).

$$\theta_i = c + \beta_1 \text{Irrig}_i + \beta_2 \text{Edu}_i + \beta_3 \text{HHSize}_i + \beta_4 \text{PrimActivity}_i + \beta_5 \text{Fertil}_i + \beta_6 \text{Man}_i + \beta_7 \text{Seed}_i + \beta_8 \text{Other}_i + \beta_9 \text{Kar}_i + \beta_{10} \text{Mah}_i + \beta_{11} \text{Him}_i + \beta_{12} \text{AP}_i + \beta_{13} \text{Ors}_i + \beta_{14} \text{WB}_i + \beta_{15} \text{Bh}_i + \beta_{16} \text{UP}_i + \beta_{17} \text{Jh}_i + \beta_{18} \text{Chh}_i + \beta_{19} \text{MP}_i + \beta_{20} \text{Pun}_i + \beta_{21} \text{Guj}_i + \beta_{22} \text{Raj}_i + \beta_{23} \text{TN}_i + \beta_{24} \text{Ker}_i + \varepsilon_i \quad ....(4)$$

where,
Fertil – Log (Amount spent on fertilisers / acreage of land cultivated);
Man - Log (Amount spent on manures / acreage of land cultivated);
Seed - Log (Amount spent on seeds / acreage of land cultivated);
Other - Log (Amount spent on other agricultural inputs / acreage of land cultivated);

Indian agriculture is dominated by marginal and small cultivators. As per the latest round of Agriculture Census of India 2010-11, about 85 per cent of the total landholdings in India were operated by small holdings of upto five acres and these holdings accounted for 44 per cent of the total area operated in the country (Government of India, 2014). These cultivators also find a prominent place in the allocation of bank credit, as they are included as part of ‘weaker sections’ under the priority sector guidelines of the Reserve Bank of India (RBI). Moreover, as per the change in these guidelines in 2015, a separate sub-target has been laid down for this class of cultivators. Hence, a preliminary attempt has been made by us to identify the impact of agricultural credit on efficiency for this class. We have also estimated the comparable impact of agricultural credit on the efficiency for other cultivator households.[16]

V

EMPIRICAL FINDINGS

5.1 *Estimation of Technical Efficiency*

The mean technical efficiency score for all cultivator households was 0.55 with a standard deviation of 0.32. Furthermore, the distribution of the score suggested that 53.8 per cent of the households were operating below the technical efficiency of 0.50 per cent, while 24.8 per cent reported scores in the range of 0.9-1.0 implying near full efficiency for these households during the sample period. On the whole, the distribution reflected significant scope for improvement in efficiency for these cultivator households as per the model specification (Table 7).

We then estimated efficiency scores separately for small and other cultivator households. The mean score of efficiency using Variable Returns to Scale (VRS) for marginal and small (M and S) cultivator households was slightly lower than that of other cultivator households. However, the standard deviation was relatively high for M and S cultivator households indicating a wide dispersion in the efficiency scores within this category as compared to other cultivator households (Table 7). The concentration of efficiency scores in the lower brackets was also higher, although marginally, for M and S cultivator households as compared to other households; about 52 per cent of the M and S cultivator households had an efficiency score below 0.5, the proportion was 51 per cent for other cultivator households. Similarly, allocative efficiency of other cultivator households was found to be marginally higher than M and S cultivator households (Table 8).

TABLE 7. FREQUENCY DISTRIBUTION OF TECHNICAL EFFICIENCY SCORES OF SAMPLE HOUSEHOLDS

Efficiency scores (1)	All households (2)	Marginal and small cultivator households (3)	Other cultivator households (4)
< 0.20	16.55	12.95	5.63
0.20 - 0.30	14.64	13.99	14.07
0.30 - 0.40	12.55	14.71	16.88
0.40 - 0.50	10.09	10.27	14.29
0.50 - 0.60	7.59	8.31	8.98
0.60 - 0.70	6.09	5.24	7.57
0.70 - 0.80	4.72	5.35	6.93
0.80 - 0.90	3.02	3.12	3.68
0.90 - 1.0	24.75	26.06	21.97
Mean	0.55	0.54	0.56
Minimum	0.11	0.12	0.09
Maximum	1.00	0.31	1.00
Standard deviation	0.32	0.19	0.09

Source: Calculations by authors based on REDS database.

TABLE 8. FREQUENCY DISTRIBUTION OF ALLOCATIVE EFFICIENCY SCORES OF SAMPLE HOUSEHOLDS

Efficiency scores (1)	All households (2)	Marginal and small cultivator households (3)	Other cultivator households (4)
< 0.20	7.91	3.68	4.02
0.20 - 0.30	8.81	7.19	8.59
0.30 - 0.40	11.16	10.59	8.26
0.40 - 0.50	12.03	12.39	9.78
0.50 - 0.60	12.70	11.71	10.22
0.60 - 0.70	10.93	11.63	9.57
0.70 - 0.80	10.87	13.59	16.63
0.80 - 0.90	12.38	14.83	14.13
0.90 - 1.0	13.22	14.39	18.80
Mean	0.63	0.62	0.64
Minimum	0.05	0.09	0.08
Maximum	1.00	1.00	1.00
Standard deviation	0.25	0.24	0.25

Source: Calculations by authors based on REDS database.

5.2 *Determinants of Agricultural Efficiency*

As technical efficiency scores were censored in nature, the Tobit framework was applied to test the models illustrated in equations i, ii and iv. The baseline model (summarised in Column 1 in Table 9) showed that agricultural credit, as intuitively

TABLE 9. DETERMINANTS OF FARM EFFICIENCY

Variable	Technical efficiency in agriculture			
(1)	(2)	(3)	(4)	(5)
AgriCredit	0.003**	0.002	- 0.001	
	(0.001)	(0.001)	(002)	
Irrig		0.016**	0.046***	0.038***
		(0.007)	(0.007)	(0.013)
Edu		- 0.0002	0.002***	0.003***
		(0.0008)	(0.001)	(0.001)
HHSize		0.0009	-0.001	0.0003
		(0.0009)	(0.001)	(0.001)
PrimActivity		0.005	0.004	0.011
		(0.007)	(0.006)	(0.010)
Fertil				0.010
				(0.008)
Man				0.007**
				(0.003)
Seed				0.024***
				(0.005)
Other				-0.008*
				(0.005)
Constant	0.183***	0.178***	0.187***	-0.011
	(0.012)	(0.016)	(0.022)	(0.059)
State dummies	No	No	Yes	Yes
No. of observations	3300	3300	3300	3300
F-Statistic	4.18**	2.21**	22.11***	17.7***

Source: Calculations by authors based on REDS database.

Note: (1) Figures in parentheses are robust standard errors. (2) ***, **, *significant at 1, 5 and 10 per cent level, respectively.

expected, had a positive and significant impact on agricultural efficiency, underlining its role in the adoption of productivity inducing technology, and other fixed and variable inputs.

Irrigation was proxied by irrigation dummy for irrigated land. If more than 50 per cent of the land of the cultivator was irrigated (broadly following the national average irrigation index), the dummy took the value one, otherwise zero. It was found to have a positive and significant impact on efficiency (see column 2). The result was in line with empirical literature in this area discussed earlier.

The years of schooling of the head of the household showed a positive and significant association with agricultural efficiency, signifying greater possibility of educated farmers in adopting modern and efficient technology and inputs (see column 4). Both household size and sole involvement of a cultivator household in agricultural production too had a positive but not significant impact on efficiency. The F-statistic giving the goodness of fit of the model was significant underlining the fact that our model fitted the data.

Under column 4 and 5, we controlled for the state-specific factors using State dummies. From among the State dummies, as expected, the coefficients were significant and negative for majority of the States, including Orissa, West Bengal, Bihar and Jharkhand, Madhya Pradesh, Uttar Pradesh, Rajasthan and Tamil Nadu, suggesting the lower agricultural efficiency among cultivator households in each of these States as compared to Haryana. Some of the States where the coefficient was positive and significant were Gujarat, Karnataka and Himachal Pradesh. This may be due to the fact that these States have higher yield in coarse cereals, pulses, oilseeds and fruits as compared to Haryana (Government of India, 2016).

While choosing the inputs, we avoided including expenditure on labour as the REDS database included both imputed cost on family labour and actual cost in hired labour. While credit is expected to have a positive impact on hired labour, it may not have any effect on the opportunity costs on family labour except through a substitution of family labour by purchased labour, which in all likelihood may be limited given that our sample was predominated by small cultivator households.

We then substituted agricultural credit with the expenditure on each of these variables to test their impact on technical efficiency in our model, while controlling for State specific factors (column 5 in Table 9). We observed that the expenditure on seeds and manures had positive and significant impact on technical efficiency of farms. Though fertilisers were found to be positively associated with technical efficiency, it was not found to be significant. Hence, through the model summarised in column 5 of Table 9, we further reaffirmed the positive role played by agricultural credit in enhancing agricultural efficiency.

We then worked out the elasticities of expenditure on various purchased fixed and variable inputs with respect to agricultural credit after normalising all variables by area of land operated (Table 10). The effect of agricultural credit was observed to be positive and significant for most of these inputs except for the expenditure on manure per acre.

TABLE 10. ELASTICITY OF EXPENDITURE ON VARIOUS AGRICULTURAL INPUTS WITH RESPECT TO AGRICULTURAL CREDIT PER ACRE

Expenditure on agricultural input per acre (1)	Coefficient of elasticity (2)
Expenditure on seeds per acre	0.134***
Expenditure on fertilisers per acre	0.132***
Expenditure on manures per acre	- 0.099
Expenditure on other inputs per acre	0.159***

Source: Calculations by authors based on REDS database.
***, **, *significant at 1, 5 and 10 per cent.

Finally, we split the sample of households into two categories of M and S, and other cultivator households and ran the baseline model on each of these sets of households (Table 11). We observed that agricultural credit had a positive and significant impact on farm efficiency for both sets, but the impact was relatively small for M and S cultivator households than other households. Similarly, irrigation too proxied by irrigation dummy had a positive and significant impact for both these sets of households. In this case also impact of irrigation was found to be higher for other farmers as compared to small and marginal farmers as indicated by size of the coefficients. The years of schooling was also found to be positive and significant for both these sets. However, the size of the household was negatively associated with technical efficiency of farms though not found to be significant. The goodness of fit tests for both models gave a satisfactory result.

TABLE 11. DETERMINANTS OF FARM EFFICIENCY BY SIZE OF LANDHOLDING

	Technical efficiency in agriculture			
Variables	Marginal and small cultivator households		Other cultivator households	
(1)	(2)	(3)	(4)	(5)
AgriCredit	0.003**	0.005**	0.019***	0.004
	(0.001)	(0.002)	(0.003)	(0.003)
Irrig		0.018**		0.103***
		(0.008)		(0.013)
Edu		0.001*		0.003**
		(0.0007)		(0.001)
HHSize		- 0.0003		- 0.001
		(0.001)		(0.002)
PrimActivity		0.004		0.011
		(0.006)		(0.013)
Constant	0.149***	0.115***	0.155***	0.191***
	(0.013)	(0.024)	(0.028)	(0.042)
State dummies	No	Yes	No	Yes
No. of observations	2277	2277	839	839
F-Statistic	3.79**	16.17***	27.41***	17.76***

Source: Calculations by authors based on REDS database.
Note: (1) Figures in parentheses are robust standard errors. (2) ***, **, *significant at 1, 5 and 10 per cent.
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VI

CONCLUSIONS AND POLICY IMPLICATIONS

This paper was an attempt to understand the association between agricultural credit and agricultural efficiency taking household level data. The analysis is of a general relevance given the fact that agricultural credit has been an integral part of the policy of priority sector credit pursued by the Reserve Bank of India (RBI) since 1968. Moreover, the analysis is also of a topical relevance given the fact that the 2000s was a decade of considerable revival in the growth of agricultural credit, particularly following the Comprehensive Credit Policy between 2004-05 and 2006-07. The revival was looked upon as a means of addressing the concerns about agrarian distress and the rising share of informal sources of credit in the Indian agriculture (Government of India, 2007b).

We estimated farm level technical efficiency in this paper using the REDS database for the year 2007. The year of survey is also of relevance given that it marked the conclusion of the Comprehensive Credit Policy, which was aimed at a targeted growth in agricultural credit from all three formal agencies of credit, namely commercial banks, credit co-operatives and Regional Rural Banks. Hence, the analysis in this paper is expected to capture the immediate impact of agricultural credit on technical efficiency.

We observed that technical efficiency of farms estimated using three key inputs of land value, wage bill and investments in mechanised inputs shared a positive and significant relation with agricultural credit. The impact was positive and significant for marginal and small cultivator households as well, although it was slightly smaller in magnitude than other cultivator households. Irrigation, which is often regarded as a common factor affecting agricultural productivity in the literature, also showed a positive impact on farm efficiency. It was found more important in case of other farmers. Moreover, the years of schooling of the head of the households too had a positive impact on agricultural productivity.

The impact of agricultural credit on technical efficiency was reaffirmed by taking various fixed and variable inputs that are commonly purchased through the crop and fixed investment credit by cultivator households and estimating their impact. Most of these selected inputs showed a positive elasticity with respect to agricultural credit. Moreover, these inputs also showed a positive impact on agricultural efficiency, when they replaced agricultural credit in our baseline model.

In sum, the paper underlines the need to continue with the policy of providing credit support to agriculture. While we do not make a distinction between formal and informal credit to agriculture, given the well-known issues relating to informal sources of higher costs and extra-economic coercion, our conclusion relates to providing formal credit to agriculture in order to enhance agricultural productivity. While the credit support needs to be provided to all classes of cultivators, there is a stronger case for giving attention to the credit needs of marginal and small cultivators. This is because agricultural productivity for these cultivators is positively affected by agricultural credit like other cultivators. However, these cultivators are more vulnerable on account of small-sized holdings, low asset base other than land, weaker bargaining power and limited access to various infrastructural facilities, and are generally more credit-deprived.

Apart from credit and irrigation, we do not control for certain key public infrastructural facilities, such as research and development, power and telecommunications, which are important for the enhancement and dissemination of technological inputs in agriculture. However, this is primarily on account of data limitations. It would be thus inappropriate to conclude that mere provision of formal credit will help in increasing agricultural productivity. The investment in public infrastructural facilities is also important in this process.

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NOTES

1. The REDS survey started in 2006 and is therefore often referred to as the 2006 round. However, as noted by Binswanger-Mkhize *et al.* (2014), agricultural data for majority of the States were collected in 2007. Hence, we term the year of the survey as 2007, as in Binswanger-Mkhize *et al.* (2014).
2. See Levine *et al* (2000) and Demirguc-Kunt and Levine (2004).
3. For a more extensive review of literature, see Misra *et al.* (2016).
4. They argued that in the face of uncertain income streams, risk-averse farmers chose to hoard a part of their savings in good states for consumption contingencies, at times, even at the expense of investment. Credit, by mitigating the need to hoard, encouraged innovations and, hence, promoted technical efficiency.
5. There are a number of features about the distribution of agricultural credit, by size classes, location, tenure and month of disbursement. These have already been discussed in the literature and are not directly relevant for the analysis undertaken in this paper and hence, not covered here; see Ramakumar and Chavan (2007, 2014).
6. Availability of time series data is a prerequisite for the estimation of total factor productivity (TFP). As farm level time series data for the computation of TFP is not available, technical efficiency has been used as a proxy for productivity. Most of the studies using farm level data have analysed farm level technical efficiency.
7. Information in this section is drawn from Binswanger-Mkhize *et al.* (2014) and www.ncaer.org
8. See Binswanger-Mkhize *et al*. (2014).
9. A fragment, as illustrated in Binswanger-Mkhize *et al.* (2014), is a collection of adjacent holdings cultivated by a given farmer
10. This definition of cultivator household corresponds closely with the All India Debt and Investment Survey (AIDIS); see NSSO (2006).
11. Also see Misra *et al.* (2016) regarding a discussion on this issue
12. There is, of course, an issue of fungibility of credit. Credit taken from various sources for other purposes can get diverted to agriculture. Similarly, credit taken for the purpose of agriculture can get diverted to other purposes. However, like other primary surveys, it is difficult to capture the difference between 'stated' and 'actual' purpose of credit in the REDS too. We take the purpose of credit as reported against a given household.
13. Although rent is often used by studies as an input in productivity estimation, we could not consider it in our estimation as the information on rent or imputed value of rent was available only for a few households in the REDS database
14. First, education enables one to follow written instructions for chemical inputs and other aspects of modern farm technology (Harma, 1979). Numeracy permits one to calculate correct dosages and may increase the output produced by a given combination of inputs and also enhance allocative efficiency (Chaudhri, 1979). Further, education gives access to more remunerative activities, such as formal non-agricultural employment, and increases the funds available to the household to adopt improved technologies (Collier and Lal, 1986).
15. See Government of India (2016). As the study encompasses households of 17 States, 16 State dummies are used to avoid the dummy variable trap.

16. As already discussed, the REDS sample of cultivator households, reflective of the general reality in the Indian countryside, was dominated by small cultivators. Thus, the number of observations available for other cultivator households was limited. And hence, we chose to run the baseline model for each of these categories and refrained from imposing any further constraints on the model, which could have compromised the robustness of the estimation.

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