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Research article

Non-farm income and environmental efficiency of the farmers: Evidence from India

Anviksha Drall [a], Sabuj Kumar Mandal [b,*]

[a] T A Pai Management Institute, Manipal Academy of Higher Education, Karnataka, India
[b] Department of Humanities and Social Sciences, Indian Institute Of Technology Madras, Chennai, Tamil Nadu, India

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ABSTRACT

In the face of various agro-climatic shocks when agricultural income becomes highly volatile, farmers often undertake multiple jobholding and engage in non-farm activities for income smoothing. The earnings from these activities are often used to purchase productivity enhancing agricultural inputs. In this context, the impact of non-farm income on intensification of agricultural inputs and the consequent impact on over-all farm efficiency is well documented in the literature. However, with a rapid rise in usage of agricultural inputs with environmentally detrimental impact, very little is known about whether non-farm income has any impact on farmers' environmental efficiency-ability to reduce the amount of polluting inputs to the largest extent possible without reducing the amount of agricultural production. Our study fills the gap in the literature by analysing the impact of non-farm income on environmental efficiency of the farmers. We first estimate the environmental efficiency scores adopting the non-parametric data envelopment analysis (DEA) method and using a household level panel data from Village Dynamics of South Asia project on Indian states for a span of five years (2010–2014). We then estimate the impact of non-farm income on environmental efficiency using Instrumental Variable Tobit Model. Our results show that average environmental efficiency of the Indian farmers was 46 % during the study period indicating the fact that a reduction in polluting agricultural inputs by 54 % was possible without compromising the level of farm production. We also find that for 1 % increase in non-farm income, environmental efficiency of farmers rises by around 4 %. This reflects the environment friendly behaviour of farmers as a channel through which non-farm activities affect usage of environmentally linked inputs. These results provide vital policy insights in terms of how non-farm activities could be integrated with policies related to farming, in order to ensure sustainable agricultural practices.

1. Introduction

With a massive increase in population across the globe, food security has become a major concern. The rise in demand for food along with the domestic support/incentives provided to farmers has led to intensification of farm inputs and output. This phenomenon is especially true for under-developed and developing countries like India. India is one of the major producers of necessary food items like cereals, pulses, fruits, and vegetables, and also accounts for around 2.2 % of global agricultural exports [1]. Nevertheless, this

* Corresponding author.
E-mail address: sabujecon@gmail.com (S.K. Mandal).

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increase in agricultural output can be attributed to intensification of productivity enhancing inputs like chemical fertilizers. On one hand, intensification of chemical fertilizers boosts agricultural output thereby ensuring food security and enhancing rural income. Recent studies like Moring et al. [2] suggest that with a rapid increase in population coupled with a massive rise in food demand, India is expected to double the usage of synthetic fertilizers by 2050. However, an increase in usage of such inputs inevitably has an adverse impact on environment via water pollution, soil erosion and emissions of NO_2 in the air which further has hazardous impact on biodiversity [3–5]. In fact, agricultural sector is observed to contribute around 18 % to the overall Indian Greenhouse gas (GHG) emissions. Interestingly, as shown by Vetter et al. [6] highest GHG emissions come from paddy rice production in India, where CH_4 is a significant emission source. Also, Moring et al. [2] shows that the usage of Nitrogen based fertilizers by Indian farmers has been rapidly increasing leading to growing losses of N_r indicating important implications for environmental quality. At the same time, uncertainties due to agro-climatic fluctuations experienced by farmers prompt them to undertake activities that could stabilize their flow of income [7,8].

In this regard, participation in non-farm activities has become a wide-spread strategy among farmers in general and smallholders in particular. The existing literature [9–11] shows that there are multiple channels through which engagement in non-farm activities can affect the quality and quantity of farm inputs used by the farmers. On one hand, researchers like Kilic et al. [7] and Phimisters and Roberts [11] assert that non-farm earnings might be used to purchase productivity enhancing polluting inputs which could act as a substitute to the declining labour supply on the farm, thus discussing the plausibility of positive income effect of additional earnings from non-farm work. However, a rise in use of polluting inputs could have detrimental impact on environmental quality, food quality and human health. In this context, the popular Environmental Kuznets Curve discusses the possibility of a reduction in usage of polluting inputs with a rise in total income due to non-farm earnings. This decline could be attributed to preference for clean environment and good health with a rise in income [12,13]. Thus, considering the intricate linkages between non-farm activities and usage of environmentally related inputs, the net-impact of non-farm earnings on usage of polluting inputs has been explored in previous studies like Lamb [9], Phimister and Roberts [11], and Amare and Shiferaw [14].These studies, nevertheless, pay less attention to the trade-off between benefits of an increased food production and the negative environmental effects that occur due to the usage of these polluting inputs.

In this context, we add to the existing literature by exploring if non-farm earnings can make farmers more environmentally efficient (due to preference for a clean environment) to investigate if it is possible for the farmers to increase agricultural output while decreasing environmental degradation. In line with mechanisms discussed in the previous paragraph, the objective of the current study is to analyse the net impact of non-farm sector earnings on environmental efficiency of farmers. Even though, studies by Guesmi and Serra [15], Tothmihaly et al. [16] and Karnasuta and Laoanantana [17] explore the environmental efficiency of farmers focussing on input-oriented efficiency of polluting inputs. Nonetheless, these studies do not focus much on the relationship between environmental efficiency and engagement in non-farm activities which plays a vital role in determining the usage of polluting inputs [12].

We undertake this analysis for Semi-arid tropics (SAT) and Eastern regions of India because these regions are a good example of farmers' participation in non-farm activities and environmental deterioration due to attempts to increase agricultural yield via adopting polluting inputs. Recently, Michler [18] noted that the use of complex fertilizers like DAP has increased rapidly in SAT and Eastern regions of India. Furthermore, his analysis suggests an overuse of fertilizers in the study areas. In this regard, reviewing prior studies in the Indian context, we conclude that studies so far either examine how participation in non-farm activities affects overall efficiency of farmers [19] or analyse environmental efficiency of farmers without focussing much on the role of non-farm activities [20, 21]. To the best of our knowledge, however, none of the studies in Indian context so far have explored participation in non-farm activities and its concomitant impact on environmental efficiency in this fashion.

Thus, as a means of fostering sustainability, our research investigates if environmental efficiency is affected by activities unrelated to farming, in order to understand if non-farm activities can be aligned with appropriate use of polluting inputs, thereby ensuring environment friendly agricultural practices. Based on the household level information from Village Dynamics of South Asia (VDSA) data set, we estimate the environmental efficiency of farming activities using the Data Envelopment analysis (DEA) [22] for eight Indian states (Andhra Pradesh, Bihar, Gujarat, Maharashtra, Madhya Pradesh, Jharkhand, Karnataka and Odisha) for a five year span (2010–2014). We analyse the impact of non-farm earnings on environmental efficiency using the DEA scores estimated in first part of the paper. In the second part of the paper, we assess the effect of non-farm earnings on environmental efficiency using instrumental variable Tobit model. Robustness of our results are checked using alternative empirical model – Vella-Verbeek Model [23].

Our results show that average environmental efficiency of the Indian farmers was 46 % during the study period indicating the fact that a reduction in polluting agricultural inputs by 54 % was possible without reducing the agriculture output. The results thus provide vital policy insights on how non-farm activities can be promoted to ensure sustainable agriculture practices.

The paper proceeds as follows: Section 2 briefly discusses the literature shedding light on plausible mechanisms through which non-farm earnings impact farmer's environmentally pro behaviour. Section 3 provides the details of the methodologies used to fulfil the study's objectives followed by details of the data source in Section 4. The empirical results and robustness checks are presented in Section 5 and 6, respectively. Section 7 summarizes the study's findings along with some policy recommendations.

2. Literature review

There are multifarious channels by which engagement in non-farm activities can affect usage of environmentally polluting inputs. The prominent channels focussed upon so far [11] are the positive income effect and labour substitution effect. Particularly, positive income effect captures the rise in purchasing power due to additional earnings from non-farm activities, such that farmers are able to purchase productivity enhancing inputs like agro-chemicals, modern machinery, HYV seeds etc. This is often undertaken in order to compensate for a decline in farm labour supply [24], so as to transition from being highly labour intensive to being less labour intensive and more dependent on labour-saving inputs like chemical fertilizers, HYV seeds, machinery etc. Additionally, positive income effect can exist in cases of migration activities, where consumption requirements of those staying at home in terms of local food, fuel etc. falls freeing up resources for investment in farm inputs which could be polluting in nature [25]. However, since adoption of polluting inputs like agro-chemicals has important implications in terms of environmental degradation, studies by Zhang et al. [13], Ma et al. [26], and Liu et al. [27] in line with Environment Kuznets Curve for pollutants, have found a negative income effect of non-farm earnings such that additional earnings from non-farm activities are invested in environment friendly organic inputs, away from the polluting ones. The negative income effect can also occur if a rise in income disincentivises adoption of environment harmful inputs, particularly due to a higher priority for good health [28]. Also, researchers like Feng et al. [24] focus on non-farm activities undertaken by migrants so that they rent out land and hire workers to take care of their farming activities. In such cases, the overall impact of non-farm earnings is dependent on productivity and decisions of hired workers who may sometimes overuse the polluting inputs. Thus, the net impact of non-farm activities on usage of agro-chemical inputs is ambiguous and difficult to quantify. This is because the impact depends on interaction between various factors like farmers' behaviour and preferences related to time allocation, consumption decisions, farm input decisions and inseparability of production and consumption decisions of farm households.

3. Methodology

The estimation of efficiency has been undertaken in the literature [29,30] either by utilizing parametric approaches like Stochastic Frontier Analysis (SFA) or non-parametric approaches like Data Envelopment Analysis (DEA). The famous DEA approach by Charnes et al. [31] is based on the linear programming optimization problem, which enables the estimation of the piecewise linear best practice production frontier in a multi-output and multi-input scenario. Thus, DEA estimation is undertaken without imposing any restrictions on the functional form of the production function [32]. Nevertheless, Coelli et al. [29] recommend using this approach only in scenarios of multi-output production, low random effects and inconsistency of price data. In this regard, researchers like Kelly et al. [33], Toma et al. [34], and Houngue et al. [35] utilized DEA to estimate the efficiency of farmers, as the sub-vector analysis used in DEA is capable of quantifying input and outputs of interest in contrast to SFA which provides us with efficiency scores based on all inputs [36].

As noted by Wu and An [37], efficiency scores based on traditional DEA models are unable to account for undesirable outputs and inputs. This becomes important especially in today's scenario where the farm sector alone in developing countries like India contributes about 10–14 % to global anthropogenic greenhouse gases (GHG) emissions [38]. Additionally, the residuals of agricultural input-based chemicals have been reported in the soil, air, and water, thereby hampering environmental quality and human health [39]. To incorporate issues like these, Färe et al. [40] put forth a DEA model that incorporates minimization of environmental pollutants during estimation. To fulfil the objective of current study, we thus proceed with Färe's model that accounts for environmentally detrimental farm inputs. Even though there is no clear rule guiding on whether to use DEA or not, the choice of model depends on the objective of the study. The following paragraph discusses why DEA is considered most suitable for current study.

In the Indian farm sector, majority of farmers are smallholders facing issues like inaccessibility to loans. Also, most production resources are subsidised, and farmers generally produce for state procurement [41].In this scenario, ensuring profitability requires the farmers to maximise their efficiency which can be achieved if the inputs are utilized judiciously. Furthermore, as noted by Ma et al. [42], decisions related to agricultural inputs are under farmers' control vis-à-vis decisions on farm produce prone to agro-climatic fluctuations. Based on this, various researchers have estimated input-oriented efficiency (where inputs are minimised while maintaining the same level of outputs) of the Indian farmers [43,44]. Since the current study aims at finding out environmental efficiency of farmers such that farmers can contract the usage of polluting inputs to largest extent possible, at the same time producing at least the observed level of output, we proceed with DEA model that accounts for environment degrading farm inputs [45]. This is in line with previous studies, like Yadav et al. [20] and Gathala et al. [21], estimating environmental efficiency of the Indian farmers while accounting for the harmful environmental impacts of inputs like chemical fertilizers, pesticides etc.

Nevertheless, the environmental efficiency in the Indian context has always been estimated without focussing much on the role of non-farm earnings. Since, the objective of this paper is to integrate the notion of multiple-job holding with environmental efficiency in the Indian context, we analyse how non-farm earnings could affect environmental efficiency. For the purpose of this, we proceed with the empirical estimation in two stages. In the first stage, we calculate the environmental efficiency scores using Data Envelopment Analysis. In the second stage, we use a Tobit Model to regress these efficiency scores on non-farm income [46–48]. The following sections entail description of these two stages.

3.1. Estimation of environmental efficiency

Since we are interested in knowing what the maximum possible reduction in only environmentally detrimental inputs is, we define environmental efficiency as the ability of the farm household to contract the usage of polluting inputs to largest extent possible, which at the same time allows the household to produce at least the observed level of output. Without requiring any additional quantities of any other inputs, the relevant BCC type DEA [49] model to measure environmental efficiency for a DMU, is given below:

Environmental efficiency $(\beta^*) = \min \beta$.

$$s.t. \sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{i0}, i = 1, 2, \ldots m \text{ (Non} - \text{labour inputs)} \tag{1}$$

$$\sum_{j=1}^{n} L_j\lambda_j \leq L_0 \text{ (Labour inputs)} \tag{2}$$

$$\sum_{j=1}^{n} P_j\lambda_j \leq \beta P_0 \text{ (Polluting inputs)} \tag{3}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{r0}, r = 1, 2, \ldots, s \text{ (Output)} \tag{4}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{5}$$

$$\lambda_j \geq 0, j = 1, 2, \ldots, n; \ \beta \geq 0 \tag{6}$$

In the above LLP problem, n represents the number of DMUs (households in this study) to be evaluated, where each DMU uses m non-labour inputs and produces s farm outputs. Each DMU also uses labour input denoted by L and polluting inputs denoted by P. The jth DMU uses x_{ij} of input i, L_j of labour, P_j of polluting inputs to produces y_{rj} of farm output r. λ_j represent the weights assigned by the linear program. β denotes the values of environmental efficiency calculated by the following Variable Returns to Scale (VRS) linear programming problem [49].

The objective here is to reduce the usage of polluting inputs only. In doing so, it is not required that other non-labour and labour inputs be contracted. Nevertheless, inequality (1) and (2) ensure that these inputs should not be increased at the optimum solution, inequality (3) ensures reduction in polluting inputs and inequality (4) ensures that output produced at the optimum level is no lower than what is actually being produced. The above model provides input-oriented measure of technical efficiency that allows for radial contraction of only the polluting inputs [50]. In line with the study's objective of reducing the usage of polluting inputs to preserve environment, the model is appropriate for measuring environmental efficiency. An efficient farmer will have $\beta = 1$, signifying that no proportionate reduction of polluting inputs is possible, whereas an inefficient farmer will have an efficiency value of less than one.

3.2. Non-farm income and environmental efficiency

As mentioned above, environmental efficiency score can take a value of at most one. Thus, to deal with the censorship at one of the efficiency scores, we estimate a Tobit Model. The model helps us analyse the impact of non-farm income on environmental efficiency. The respective equation is as follows:

$$E^*_{it} = \beta \boldsymbol{X}_{it} + \delta NFY_{it} + c_i + \eta_{it}, i = 1, 2, \ldots, N; \ t = 1, 2, \ldots., T \tag{7}$$

where E_{it} (ith household's environmental efficiency score at time 't') and the latent variable E^*_{it} are related as follows:

$$E_{it} = E^*_{it} \text{ if } E^*_{it} > 0 \tag{8}$$

$$E_{it} = 0 \text{ if } E^*_{it} < 0$$

In equation (7), c_i and η_{it} denote the unobserved heterogeneity and a pure random component, respectively. Also, c_i and η_{it} are assumed to be independent and follow a normal distribution, with zero means and homoscedastic variances.

$\boldsymbol{X}_{it}$ represents the vector of covariates determining E_{it} and a DISTRICT dummy, with β as the vector of respective coefficients; NFY_{it} denotes ith household's non-farm income at tth time period with δ as the respective coefficient.

3.3. Correcting for endogeneity of non-farm income

As argued by Pfeiffer et al. [51] our variable of interest i.e., non-farm income, might be endogenous in nature. This is because some farmers may be self-selected into the non-farm sector because non-farm income is then observed only for those participating in non-farm activities. This leads to a non-zero correlation between NFY_{it} and ε_{it} (combined error term, i.e., $c_i + \eta_{it}$). Equation (7) also grapples with the issue of simultaneity between NFY_{it} and E_{it}. This is because the decision on how much to invest in polluting inputs depends on earnings from non-farm activities, resulting in simultaneity between farm input usage and non-farm income. There is also a possibility of reverse causality from environmental efficiency to non-farm income. For instance, if environmental efficiency rises, it may prompt the farmers to increase non-farm earnings which could help them purchase environmentally friendly inputs. Thus, Equation (7) suffers from endogeneity (arising from two sources) of non-farm income, which must be accounted for.

We account for the endogeneity of non-farm income using Instrumental Variable Technique, carried out by estimating a reduced form equation for non-farm income as given below:

$$NFY_{it} = \beta \boldsymbol{X}_{it} + \alpha Non - farmincome_{Average} L_{it} + v_{it} \tag{9}$$

Equation (9) depicts the linear projection for non-farm income. The exclusion restriction for the instrumental variable approach is that a subset of explanatory variables in equation (9) appears in the structural equation i.e., equation (7). Equation (9) is thus estimated using $\boldsymbol{X}_{it}$ as the vector of explanatory variables. Additionally, average non-farm income at village level is used an instrument while estimating (9). Here, average non-farm income is used as an exclusion restriction as it directly affects non-farm income, but not necessarily the environmental efficiency scores. This is because average non-farm income is expected to have a positive impact on decision to participate in non-farm work and associated earnings. Therefore, the variable chosen satisfies the condition of instrumental relevance. Also, it is improbable that average non-farm income asserts a direct impact on environmental efficiency because average non-farm income could be a potential determinant of only non-farm income. Thus, considering that average non-farm income can only indirectly influence environmental efficiency, we relied on average non-farm income as a perfect instrument for the study.

existence of endogeneity issue and. To confirm whether endogeneity actually exists, we used Durbin-Wu-Hausman Test, where residuals from reduced form equation (9) were used as regressors to estimate structural equation (7). As per eatimated results, coefficients of residuals were found be significant at 1 % (p-value = 0.00). Thus, Null Hypothesis that Non-farm Income is exogenous gets rejected, thereby confirming endogeneity of non-farm income. The estimation results of Equation (9) are shown below in Table 1.

The results above show that the average non-farm income has a positive and significant impact (p-value = 0.000) on household-level non-farm income. Furthermore, we estimated equation (9) with and without instrument (average non-farm income). The partial R-squared for the instrument used is found to be around 20 %, significantly increasing overall fit of the model. This indicates that average non-farm income (instrument) significantly explains changes in household-level non-farm income (endogenous variable). Additionally, we used partial F-test to assess significance of average non-farm income in (9). Results of the test showed a very high level of significance rejecting the Null hypothesis that Average non-farm income doesn't improve the reduced form equation model (9). Lastly, overall significance of the model is found to be very high. Thus, using Stock-Yogo Test, we reject the Null Hypothesis that Instrument used is weak. Therefore, we ensure that the instrumental variable used by us is reliable.

Next, we used falsification test to ensure validity of average non-farm income as the instrument. This is because instrument validity isn't ensured if instrumental variable has a direct impact on dependent variable. The falsification results for current study are given below in Table 2.

Our results show an insignificant impact (p-value = 0.646) of average non-farm income on environmental efficiency scores. This ensures that instrument used is valid.

Since, our instrument is both valid and strong, we proceed with second stage regression.

In the second step, the structural equation (7) is estimated after excluding average non-farm income variable, where fitted values of non-farm income from (9) are used as an explanatory variable. Thus, the final estimable equation is as follows:

$$E_{it}^{*} = \beta \boldsymbol{X}_{it} + \delta \widehat{NFY}_{it} + c_i + \eta_{it}, i = 1, 2, \ldots, N;\ t = 1, 2, \ldots., T \tag{10}$$

In the above equation, our coefficient of interest is δ, which captures the impact of non-farm income on environmental efficiency.

4. 4. data source and descriptive statistics

The current study is based on a novel panel dataset based on the Village Dynamics Studies in South Asia, 2013 project [52] implemented in 2009 by ICRISAT (International Crops Research Institute for the Semi-Arid Tropics), in collaboration with the Bill and Melinda Gates Foundation. The objective of the project was to provide (i) micro-data on individuals and households, and (ii) meso-data providing vital information at district level – to foster the process of eliminating poverty in rural households of the survey areas. The survey households belonged to semi-arid and humid tropics of India and Bangladesh.

However, for the purpose of this study we focus on household level panel data for India. The data is based on rural households from eight Indian states: Andhra Pradesh, Bihar, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra, and Odisha, spanning a period of five years (2010–2014). Although, the dataset covers only eight Indian states, these semi-arid tropics and humid tropics states experience drastic fluctuations in monsoon and temperature. Thus, compared to other Indian states, households of these states are more likely to engage in multiple jobs like non-farm activities. At the same time, studies like Lamb [9], based on the same data set have found that adoption of productivity enhancing inputs (like chemical fertilizers) is greatly increased by investing non-farm earnings in farm inputs. Since, the dataset provides micro-level information on multiple job holding decisions and investment in various agricultural inputs, particularly the polluting inputs, we found it appropriate to fulfil the objective of this study. To the best of our knowledge, ours is the first study that uses the VDSA dataset to investigate the impact of non-farm earnings on environmental efficiency of farmers in the study areas.

Table 1
First Stage regression- Estimation of Non-farm income Equation (9).

Variables	Coefficient	Standard Error
Average non-farm income	2.17***	(0.250)
Controls (Refer to Section 4 on details of these variables)	Yes	
Locational Dummy	Yes	
Year Dummy	Yes	
Wald Chi^2: 444.51		
Prob > Chi^2: 0.00		
R^2 Overall: 0.17		

Note: ***, ** and * denote statistical significance at 1 % 5 % and 10 %, respectively.

Table 2
Falsification test and Instrument validity

Y = Environmental Efficiency Scores (Outcome variable)	Coefficient (Standard Error)
X = Average Non-farm income at Village level (Instrumental Variable)	−0.004 (0.0103) *P-value* = 0.646
Wald Chi2 = 146.90 Prob > Chi2 = 0.00	

Source: Authors' estimation based on VDSA dataset.

4.1. Descriptive statistics

In order to estimate the environmental efficiency, the DEA model is conceptualized based on a single output and three input production function for the farm sector in the study areas. The farm output is measured by the value of the crops (in Rupees) produced in an year by a household. The inputs include land, labour, and operating expenses by the household for the same year. The land variable is measured by the area of cultivated land (in acres) while labour is measured by the wage bill, comprising of the expenditure on family as well as hired labour (in Rupees). Following Anriquez and Diadone [47], operating expenses on non-labour inputs are also considered as an input for farm production, which are measured by the sum of expenditure (in Rupees) on principal inputs such as machinery, seeds, irrigation etc. The usage of polluting inputs is captured using expenditure (in Rupees) on fertilizers, pesticides, and weedicides From VDSA data set, we investigated the components of these inputs. The major components were found to be DAP, Urea, Potash, Sulphate, Phorate, Acephate and Potassium nitrate etc., use of which is hazardous for environment [2,6]. Thus, expenses on inputs comprising these components were used in order to capture intensity of polluting inputs.

Descriptive statistics of these variables are presented below in Table 3.

Before proceeding with the empirical assessment of how non-farm income affects environmental efficiency, we use data insights to assess how participation in non-farm activities affects environmental efficiency. In this regard, Table 4 provides definitions of the vector of variables ($\boldsymbol{X}_{it}$) used for empirical estimation of equation (7) and descriptive statistics of the variables as per the participation status of households in the non-farm sector.

Table 4 shows that those engaged in non-farm activities managed to take more credit and to be members of various organizations, societies, groups etc. than those who participated only in farm activities. The value of assets owned by those participating in non-farm sector was higher than that of those involved only in farming. Households participating in non-farm activities had a larger household size than their counterparts. It was also observed that 94 % of households involved only in farming were headed by males. On the other hand, 92 % of non-farm sector participant households were headed by males. Lastly, farm families engaged in non-farm activities could more easily access the nearby markets than those involved only in farming.

In the following section, we present DEA based efficiency scores of households and insights based on same.

4.2. Environmental efficiency and non-farm income

The objective of the DEA Model in the current study is to minimize the usage of polluting inputs to largest extent possible without increasing the use of other non-polluting inputs or reducing farm output. The results of this model are presented above in Table 5 The average environmental efficiency of the farm households for the five-year span (2010–2014) is found to be 0.46. Although the calculated efficiency, on an average, is quite low, we see an improvement in average efficiency over the years. For instance, in 2010, average efficiency of households was 0.41 indicating that around 59 % reduction in polluting inputs is possible without reducing the farm output. However, the environmental efficiency score of 0.50 in the year 2014 reflects that it is possible for the households to decrease the usage of polluting inputs by almost 50 %. The rise in environmental efficiency scores, thus, reflect the role of farmers preference towards a clean environment. At the same time, average non-farm income also exhibited an increasing trend as shown in Column 3 (Table 5).

Considering the potential role of multiple jobs undertaken by farmers, and in order to explore if there is a significant impact of non-farm income on environmental efficiency, we resorted to some descriptives for the data. These are mentioned below.

A Correlation

First, we calculated the correlation coefficient between non-farm income and environmental efficiency. We found a strong and

Table 3
Descriptive Statistics of the variables used for DEA

Variables	Mean	Standard Deviation
Farm Output	110565.5	217461.1
Land	7.343578	11.03065
Labour	1796.484	4116.787
Operating expenses (non-labour inputs)	18513.39	33675.65
Polluting inputs	9597.404	18000.16

Table 4
Definitions and descriptive statistics (2010-14)

Variable	Description	RNFS non-participants (n = 1343)		RNFS participants (n = 5375)		Mean Difference
		Mean	SD	Mean	SD	
Non-farm income	Log of one plus total income earned by the household members by working in the RNFS (in Rupees)	0	0	10.86	1.34	−10.86***
Total Credit	Log of value of loans taken by household members (in Rupees)	9.99	1.69	10.22	1.55	−0.22***
General Education	Average education of household members) (in Years)	5.27	2.85	5.29	2.9	−0.017
Technical Education	Proportion of members in the household which possess technical education	0.06	0.14	0.07	0.14	−0.005
Membership in organizations and societies	Proportion of household members associated with various forms of organizations such as self-help groups, cooperative banks, caste groups and cultural groups.	0.09	0.19	0.11	0.21	−0.02***
Farm size	Land area cultivated for farm production (in Acres)	8.80	9.30	6.58	11.10	2.22***
Non-land Asset Value	Log of Value of livestock, durables, farm implements, and stock inventory (in Rupees)	11.7	1.19	11.5	1.34	018***
Gender of Household Head	Dummy, = 1 if male, 0 else	0.94	0.24	0.92	0.27	0.01*
Age of Household Head	Age of the household head (in Years)	49.72	13.13	49.45	12.65	0.26
Household size	Number of members belonging to a household	4.76	2.13	5.47	2.66	−0.71***
Distance to the market/ nearest town	Distance to the market/nearest town (in Kilometres)	12.24	6.83	11.03	6.7	1.22***

Note: Mean differences are based on paired *t*-test between RNFS participants and RNFS non-participants ***,** and * denote statistical significance at 1 %, 5 % and 10 %, respectively.
Source: Authors' estimation based on VDSA dataset.

Table 5
Average environmental efficiency based on ability to minimize usage of polluting inputs

Year	Average Efficiency	Average Non-farm income
2010	0.41	61152.8
2011	0.43	77896.35
2012	0.44	86995.09
2013	0.52	91360.21
2014	0.50	100418.7
2010–2014	0.46	83564.64

positive correlation between the two variables, indicated by a high value of correlation coefficient of 0.83. Fig. 1 provides a diagramatic representation of this correlation between non-farm income and environmental efficiency.

Given below, is the scatter plot between the two variables, showing their co-movement in the same direction.

B Paired *t*-test

In order to test whether environmental efficiency scores are determined by non-farm income, we calculated the average environmental efficiency scores of households as per their participation status in non-farm activities. Using a paired *t*-test, we found that the environmental efficiency of the households who participated in the non-farm activities is significantly higher, i.e., 0.48, vis-à-vis

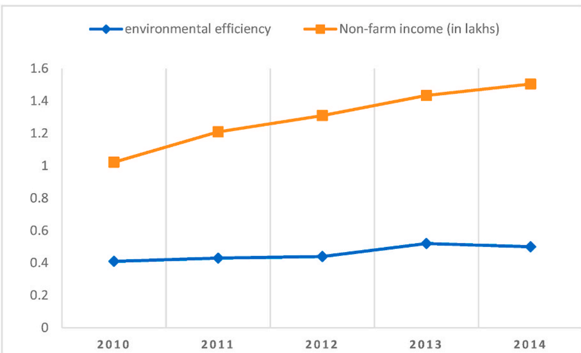

Fig. 1. Correlation between non-farm income and environmental efficiency.

the households engaged in only farming activities. The value of environmental efficiency of households involved in only farming activities is found to be 0.39 indicating that it is possible for these households to reduce the usage of polluting inputs by around 60 % compared to those engaged in multiple jobs like non-farm activities.

C State-level variation

Lastly, we explored if the hypothesised relationship exists at the state level or not. We calculated the average non-farm income and average efficiency scores of the eight Semi-arid and humid tropics states. The variation in the considered variables across these states is shown in the maps below.

Fig. 2 shows that for time period 2010-14, average non-farm income earned by Bihar, Jharkhand and Odisha, is higher compared to other states. Fig. 2 also shows that average efficiency scores are very high for Bihar, Jharkhand and Odisha for the same time period. Thus, the state-level data also indicates that non-farm income and environmental efficiency are related in a positive manner.

Nevertheless, to quantify if there is any significant contribution of income earned from non-farm activities on environmental efficiency, we look into our final empirical results based on Tobit Model, which are presented in the following section.

5. Empirical results

5.1. Non-farm income and environmental efficiency

The results in Table 6 reveal that a 1 % increase in non-farm income increases environmental efficiency by 4 %. This implies that non-farm income plays a vital role in determining how much farmer a is concerned about environment quality given his participation in both farm and non-farm activities. In particular, a positive coefficient of non-farm earnings shows that among various competing effects (as discussed in Section 2) of non-farm income on environmentally linked inputs, the positive effect of non-farm income outweighs various negative impacts of non-farm income. In addition, we found that when non-farm income rises by 1 %, usage of chemical fertilizers and pesticides rises by around 2 %. Surprisingly, usage of organic fertilizers rises too by 2 % with a 1 % rise in non-farm income. This reflects that with a rise in non-farm earnings, even though farmers continue to purchase harmful chemical inputs, at the same time they are investing in environment friendly inputs and processes.

Our results on environmental efficiency and how it is influenced by non-farm income are similar to a study in context of China by Bai et al. [53]. Our average efficiency score of 0.4 is akin to Bai's results, where chemical fertilizer use efficiency of apple producing farmers is found to be 0.47. Moreover, Bai et al. [53] show that fertilizer use efficiency is extremely sensitive to changes in non-farm income. In a similar study by Bai et al. [54], average regression coefficient of non-farm employment on fertilizer use efficiency was found to be 0.424 for a span of ten years. However, our findings contradict the findings of Lamb [9] and Nasrin et al. [55] where engagement in non-farm sector increases the demand for of chemical fertilizers making farmers less environmentally efficient.

As expected, the value of non-land assets owned by households affect environmental efficiency negatively. This could be attributed to the fact that non-land assets act as a coping mechanism making farmers being more risk-averse. Our results reveal that household head's age has a negative effect on environmental efficiency. This is consistent with the hypothesis stating that young farmers are more knowledgeable about the environmentally friendly techniques compared to their older counterparts [56,57]. It is also found that higher the number of family members belonging to a household, lower is the environmental efficiency. This could be attributed to the higher consumption spending by the households making it difficult for them to purchase environmentally friendly fertilizers. We also found that as the distance to nearest market increases, the farmers become more environmentally efficient. This could be because of farmers procuring and storing farm inputs in large quantities because of markets located far away [58]. This could also be attributed to a lower likelihood of farmers participating in non-farm activities (from results on non-farm income equation) and being more efficient on the farm.

The empirical results in Table 6 show the net impact of non-farm earnings on environmental efficiency. However, we in order to explore if this impact varies across various groups of farmers as per landholding size, we undertook heterogeneity analysis. The analysis is presented and discussed below in Section 5.2.

5.2. Non-farm income and environmental efficiency as per landholding size

In this section, we conduct sub-sample analysis to test whether variation in landholding size plays role in determining environmental efficiency of farmers. The heterogeneity analysis is based on the same empirical model explained in Section 3, except the estimation of equation (10) which is now estimated for various sub-samples based on above-mentioned characteristics.

As shown below in Table 7, the analyses provide additional insights on environmental efficiency, thereby capturing the differential impact of non-farm income.

The results in Table 7 show a significant differential impact of non-farm earnings on environmental efficiency, across considered sub-samples. Interestingly, in line with Bai et al. [53] we found that non-farm earnings have a higher impact on environmental efficiency for medium and large farmers vis-à-vis small farmers. In fact, a rise in non-farm earnings by small farmers is found to deter environmental efficiency. This shows that the dominant transition mechanism varies across landholding size. In particular, for small farmers the negative coefficient reflects a substitution of labour by a rise in quantity of chemical fertilizers, reflecting the labour substitution effect. In contrast, for medium and large farmers, the positive coefficient reflects a decline in usage of polluting inputs due to a preference for a clean environment with a rise in income level.

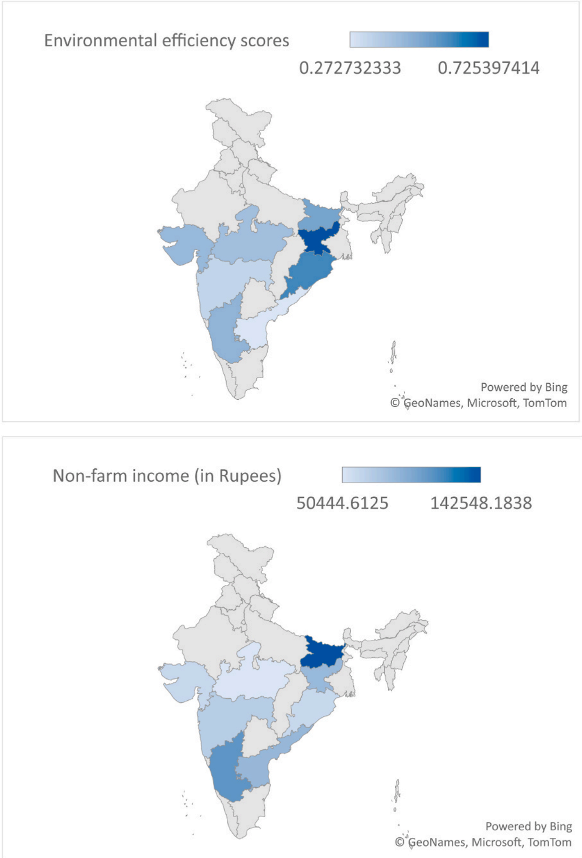

Fig. 2. Non-farm income and environmental efficiency at state-level.

Table 6
Tobit Results on impact of non-farm income on environmental efficiency

Variables	Coefficient	Standard Error
Non-farm income	0.04***	(0.0017)
Total Credit	−0.007	(0.006)
General Education	−0.006*	(0.004)
Technical Education	−0.02	(0.063)
Membership	−0.13***	(0.04)
Non-land asset	−0.06***	(0.009)
Gender of household head	0.13	(0.04)
Age of household head	−0.0008**	(0.001)
Household size	−0.02***	(0.006)
Distance to market	0.005***	(0.001)
District Dummy	Yes	
Year Dummy	Yes	
Log-likelihood: 964.59		
Wald Chi^2: 785.33		
Prob > Chi^2: 0.00		

Note: ***, ** and * denote statistical significance at 1 % 5 % and 10 %, respectively.
Source: Authors' estimation based on VDSA dataset.

6. Robustness check and sensitivity analysis

To ensure that our results are robust, we estimated the impact of non-farm income on environmental efficiency using an econometric approach and conducted a small sensitivity analysis. The details of analyses are discussed as follows.

Table 7
Non-farm income and environmental efficiency: Sub-sample Analysis

Y = Environmental efficiency scores from DEA	Sub-sample estimates of marginal effects based on Tobit Model		
Samples based on Landholding Size:	Small farmers	Medium farmers	Large farmers
Coefficient (S.E.)			
Non-farm income	−0.09***(0.03)	0.03***(0.01)	0.01*(0.008)
Total Credit	0.03*(0.02)	−0.009* (0.005)	0.003 (0.005)
General Education	0.01 (0.01)	−0.002 (0.003)	0.002 (0.004)
Technical Education	0.25 (0.24)	0.02 (0.07)	−0.1**(0.04)
Membership	−0.08 (0.14)	−0.09** (0.05)	−0.04 (0.04)
Non-land asset	−0.07***(0.02)	−0.04***(0.009)	−0.02**(0.008)
Gender of household head	−0.09 (0.001)	0.0001(0.04)	0.02 (0.04)
Age of Household head	−0.0003 (0.001)	0.0004(0.0006)	−0.0005 (0.0005)
Household size	0.03* (0.02)	−0.02***(0.005)	−0.004 (0.004)
Distance to nearest market/town	0.009* (0.004)	0.005***(0.001)	−0.001 (0.001)
Log-likelihood	−344.06	−392.05	300.31
Wald Chi^2	110.95	262.19	293.61
Prob > Chi^2	0.00	0.00	0.00

Note: Standard errors (S.E.) in the parentheses. ***, ** and * denote statistical significance at 1 % 5 % and 10 %, respectively.
Source: Authors' estimation based on VDSA dataset.

6.1. Robustness check using an alternative empirical model

As discussed previously for equation (7), non-farm income is an endogenous variable attributable to self-selection and simultaneity. To combat endogeneity of non-farm income we used the Vella-Verbeek model [23] as it addresses the issue of sample selection by accounting for censoring of non-farm income at zero and for simultaneity between non-farm income and environmental efficiency. Estimation of Vella Verbeek Model proceeds in two stages. In first stage factors affecting non-farm income (NFY_{it}) are estimated using a Tobit Model, followed by the second stage which allows for interaction between non-farm income and environmental efficiency. In Stage 1, the censoring of non-farm income at zero is accounted for by using a random-effects Tobit model, as follows:

$$NFY^*_{it} = \boldsymbol{\beta X_{it}} + c_i + \eta_{it}, i = 1, 2, ..., N;\ t = 1, 2, ..., T, \text{where:} \tag{10}$$

$$NFY_{it} = NFY^*_{it} \text{ if } NFY^*_{it} > 0 \tag{11}$$

$$NFY_{it} = 0 \text{ if } NFY^*_{it} < 0$$

c_{it} and η_{it} are as defined previously in Section 2. $\boldsymbol{X_{it}}$ represents the same set of variables used to estimate equation (9) with $\boldsymbol{\beta}$ as the respective coefficients.

In stage two, the effect of non-farm income on environmental efficiency (E_{it}) is estimated using the equation below:

$$E_{it} = \delta NFY_{it} + \boldsymbol{\beta X_{it}} + c_i^{'} + \eta_{it}^{'} \tag{12}$$

For the reasons aforementioned, $\boldsymbol{X_{it}}$ includes the same explanatory variables used to estimate Equation (10), except average non-farm income at village level. This is because Equation (10) must include at least one variable not included in Equation (12) for proper identification of the model.

The unobserved components of Equations (10) and (12) are defined as v_{it} and $v_{it}^{'}$, where $v_{it} = c_i + \eta_{it}$ and $v_{it}^{'} = c_i^{'} + \eta_{it}^{'}$. Equation (12) is estimated after accounting for the simultaneity between environmental efficiency and non-farm income. This is done by allowing a correlation[1] between v_{it} and $v_{it}^{'}$.

Finally, Equation (12) is estimated by OLS, where v_{it} and $v_{it}^{'}$ are used as the additional explanatory variables, the significance of which provides a direct test of the endogeneity of non-farm income. Table 8 below shows the estimation results of equation (12):

As the results in Table 8 indicate, non-farm income has a positive and significant impact on environmental efficiency. The results in Table 8 concur with the results in Table 5 and ensure that our empirical results are robust in nature. Also, the significance of correction term - v_{it}, proves that non-farm income is an endogenous variable. This justifies that use of Vella-Verbeek Model is appropriate.

6.2. Sensitivity analysis

We used the Wilcoxon rank sum test by Wilcoxon [59] to ensure that efficiency scores of households engaged in non-farm work are higher because of treatment (positive non-farm income earnings) and not due to other factors. It is a non-parametric approach to

[1] Particularly, it is assumed that the conditional expectation of v_{it} is a linear function of $v_{it}^{'}$, i.e..$E(v_{it}|\boldsymbol{z_{it}}, \boldsymbol{z_{it}^{'}}) = w_1 v_{it}^{'} + w_2 \overline{v_{it}^{'}}$ (9)where $\overline{v_{it}^{'}} = \frac{\sum v_{it}^{'}}{T}$, where $v_{it}^{'}$ and $\overline{v_{it}^{'}}$ are referred to as the correction terms.

Table 8
Robustness Check: Non-farm income and environmental efficiency using Vella-Verbeek Model

Stage I (Y= Non-farm labour supply)	Estimates of coefficients based on Tobit Model	
	Coefficient	Standard Error
Average Non-farm income	2.9***	(0.34)
Other controls	Yes	
Locational Dummy	Yes	
Year Dummy	Yes	
Log-likelihood	−8849.77	
Wald Chi^2	397.35	
Prob. > *Wald Chi*^{2}	0.00	
Stage II (Y = Environmental efficiency scores)	**Estimates based on Pooled OLS Model**	
Non-farm income	0.37***	(0.006)
Other controls	Yes	
v_{it}	0.27***	(0.08)
v'_{it}	(0.0003)	(0.07)
Locational Dummy	Yes	
Year Dummy	Yes	
F Statistic: 54.22		
Prob > *F*: 0.00		
R^2:0.33		

Note: ***, ** and * denote statistical significance at 1 % 5 % and 10 %, respectively.
Source: Authors' estimation based on VDSA dataset.

establish significant difference between two sample groups using magnitude-based ranks. We found this test to be appropriate for our study as DEA based efficiency scores are relative in nature, justifying use of ranks. As per the test, if the ranks of the two sample groups are significantly separated, then the test statistic identifies significant difference. The test examines the null hypotheses that the treatment effect is zero which in this context would be 'H_o: Non-farm income has no effect on efficiency scores. The results test revealed that there was a statistically significant difference at 1 % in efficiency scores (z = - 7.34, p = 0.00). Thus, we rejected the Null Hypothesis, indicating that non-farm income had a significant effect on the efficiency of farmers.

7. Concluding remarks and direction for future research

This paper is aimed at analysing the role of non-farm income in determining environmental efficiency of farmers. We used the unique household level panel dataset created by VDSA, where micro-level information on labour allocation decisions along with the expenditure on productivity-enhancing inputs like chemical fertilizers, pesticides and organic inputs was available.

Our empirical results based on Data Envelopment Analysis revealed that farmers in the study areas were not quite environmentally efficient with an average environment efficiency score of only 46 % for the five-year span (2010–2014). However, a rise in environmental efficiency of farmers was observed in 2014 compared to previous years. Using a Tobit Model, we found that 1 % increase in non-farm income resulted in 4 % increase environmental efficiency of farmers. These results indicate that even though non-farm income might be invested in both polluting and non-polluting inputs, there could be a possibility of farmers using less of environmentally detrimental inputs. This could happen because of farmers' increased preference towards a clean and healthy environment due to a rise in non-farm earnings. Furthermore, we observed a larger impact of non-farm income for medium and large farmers compared to the smallholder farmers. This unveils preference of these farmers towards better environment quality [60]. In contrast, for small farmers non-farm was found to have a negative effect on environment as they are highly dependent on chemical fertilizers and pesticides.

These results are specifically important for designing public policies motivating farmers to engage in multiple jobs apart from farming but with a caution. This is because for large scale farmers, non-farm earnings prompt them to use less of harmful inputs making them more environmentally efficient. However, for the small farmers, non-farm earnings could motivate excessive usage of environmentally harmful inputs due to higher participation in non-farm work and a decline in farm labour. Thus, non-farm activities should be promoted carefully for small farmers in a manner that harmful inputs are not used in large quantities. This can happen if non-farm activities are available near to place of residence. This would ensure complementarity between labour and other inputs, so that labour is not substituted by large quantities of harmful inputs and manage the production process efficiently. Thus, providing education/skills, financial resources, and enhancing participation in various social groups should be undertaken so as to motivate participation in non-farm jobs [61]. This should be carefully done by creating jobs in non-farm sector at local level too, considering vicinity of small farmers. Alternatively, as suggested by Sabasi et al. [62], for small farmers programs that enable them to rely less on non-farm work and help them efficiently reallocate some labour back to farm, may boost environmental efficiency of farmers. This study also found that young farmers are more likely to be environmentally efficient. In this context, policies aimed at promoting environment specific education for the young farmers could unleash their potential in maintaining a clean environment.

Although our results unveiled some interesting findings, further research work is needed to uncover some of the issues that were not captured in this study. First, primary research on behavioural factors such as preferences for environmental quality and health [63,64], underlying farmers' decisions on inputs, could isolate the role of farmers' preferences for a clean environment. Second, future works should account for intra-household decisions related to labour supply, consumption expenditure, and other farm inputs, reflecting the contribution of family members. This could provide reflections on role of individual-specific consumption patterns, risk preferences and other characteristics like information on farm inputs etc [65,66]. Third, environmental efficiency could be better captured by a direct measure of pollution levels arising from agricultural activities. This further requires inter-disciplinary research based on data on emissions as undertaken by Lal [67]. The availability of data on variables like preferences for good health, clean environment and consumption patterns would capture individual level behaviour unveiling the transition mechanism. The information on exact transition mechanism, in turn would help in better policy recommendations. Lastly, DEA based polluting inputs-oriented efficiency scores capture relative efficiency and these scores might not always indicate absolute efficiency – which depends on nature's carrying capacity [45]. This requires constructing a polluting inputs-oriented efficiency measure independent of peer group comparisons.

Data availability

The data used in this study is publicly available from the website of International Crop Research Institute in Semi-Arid Tropic under Village Dynamics Studies in South Asia (VDSA). The web-link for the data is: https://vdsa.icrisat.org/vdsa-database.aspx.

CRediT authorship contribution statement

Anviksha Drall: Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Sabuj Kumar Mandal:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

None of these authors have any conflicting interest with any individual or organization that can prevent publishing the research output of this paper.

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