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Agricultural diversification and enhancing farm income: Learning from grassroots

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ABSTRACT

Enhancing the income of farmers is a national priority to address the agrarian issue of distress and improving farmers' welfare. In this context, a network of Krishi Vigyan Kendras (KVKs) was engaged to make interventions on farmers' field. This study carried out in Madhya Pradesh, presents the quantitative assessment on the impacts of KVKs' initiatives in terms of different interventions made to contribute in farmers' income (doubling farmers income, DFI). The structured sampling method was followed using multi-stage random sampling. This has covered selecting 11 agro-climatic regions of the state and 25% of KVKs from each region. Further, 2 treatment (DFI) and 2 control (non-DFI) villages were taken. Finally, from each village, a total of 20 farm households were taken. The results indicated that average treatment effect on the treated (ATT), which is the difference between matched DFI and non-DFI households after accounting for counterfactual, was positive and significant. The value of ATT implies that net income of DFI households was more than that of non-DFI households by 111%. The net income of DFI households has increased by 156% during 2016–17 (the year of launch of KVKs' DFI scheme) to 2020–21. Households with male heads, without any other source of income, owning smaller livestock and land holdings were observed to get benefit from participation in the interventions on DFI made by the KVKs. Recognition and response to the heterogeneity treatment effect can help in optimizing resource allocation, enhancing programme effectiveness and maximizing the potential impact of the KVKs' DFI initiatives. Agricultural diversification shifted to high value crops (e.g., like vegetables, dairying, etc.), has been crucial in enhancing income of DFI households.

Keywords: Agro-climatic zones, Farm household, Farmers income, Socio-economic status

Agriculture serves as the backbone of India's economy, providing sustenance and livelihoods to a significant proportion of its population. However, increasing population pressure has led to average size of landholding per household declining from 0.725 ha in 2003 to 0.512 ha in 2019 (NSS 2021). Inequitable distribution of landholding, with about 87% of marginal or small landholders, accounting for only 57% of total land area is also an important attribute of Indian agriculture. This challenge is further exacerbated by high dependence on rainfed agriculture with only 32% of agricultural households using irrigation water for farming (NSS 2021), which impedes upon the prospect of increasing farmers' income at the desired rate and make farming economically viable. In recent past, initiative [Doubling of Farmers' Income (DFI)] was taken to strengthen farmers' income address the problem of agrarian distress and improve farmers' welfare. The major components in DFI's initiative comprised higher productivity for crops and allied sectors, like horticulture, livestock and fisheries; reduction in cost of cultivation, post-harvest management and value addition; agricultural diversification, promoting supplementary agri-enterprises, ensuring better prices for farmers, promoting non-farm income opportunities and better technical support.

In the efforts of implementing different interventions while influencing DFI, the extension system plays a pivotal role. The extension system serves as a conduit for knowledge dissemination, technology transfer, and skill enhancement. The Indian agricultural extension is pluralistic in nature; however, Krishi Vigyan Kendras (KVKs, Farm Science Centers) have evolved as important district-level model of technology assessment and demonstration for its application at farmers' field and their capacity development. The DFI initiative was undertaken by the KVKs during 2016–17 covering 1416 villages with participation of 1.59 lakh farmers.

The KVKs are considered to be instrumental in undertaking DFI activities, however, there is a lack of

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well tested evidence to support this contention. Studies on impact of KVKs in India have mostly been carried out using small sample size and have been mainly confined to specific locations (Singhal and Vatta 2017) or to specific sectors like dairying (Jena *et al.* 2022). The particularly, the impact of KVKs' initiatives on the farmers' income under the DFI scheme, using a structured sampling design and field level data, to provide statistically valid impact is scant. In this context, it is essential to address questions concerning factors driving farmers' likelihood of participation in KVKs' DFI programmes and the impact of such participation on economic welfare of farmers, measured in terms of net farm household income.

The central state of Madhya Pradesh, located mostly in the central plateau and hills agro-climatic zone of the country, is an agrarian economy in terms of contribution (37%) of agriculture to the state's gross domestic product (Singh *et al.* 2021). 70% of state's population is engaged in agriculture and allied activities. The distribution of land is highly inequitable in the state. About 48% of the farmers are marginal (<1 ha land) and these farmers account for only 17% of total cultivable land area (GOI 2019). Madhya Pradesh is a major producer of pulses and oilseeds (mainly soybean) in the country. The state contributes 12% to the country's food grain production. The state has 52 districts represented by 11 agro-climatic zones.

While the significance of KVKs in promoting agricultural development in the state is acknowledged, the need for rigorous evaluation of their impacts, using advanced econometric techniques, on net farm household income remains crucial. Therefore, in this backdrop, this study was carried out with the following objectives: (i) to identify the factors influencing impact of KVKs' DFI initiatives on farmer's income in the state of Madhya Pradesh; and (ii) to provide quantitative estimates of impact of interventions made while strengthening farmers' income.

MATERIALS AND METHODS

Sampling technique: The study adopted multistage random sampling design to ensure a representative selection of farm households in the state. Initially, a listing of KVKs in each of the 11 agro-climatic zones (ACZ) was undertaken. 25% of KVKs, from each agro-climatic zone, were selected randomly, with the condition to include atleast one KVK from each of the ACZ. Thus, a total of 15 KVKs were selected namely: Balaghat, Betul, Burhanpur, Datia, Dhar I, Dewas, Narsighpur, Jhabua, Sagar I, Jabalpur, Ratlam, Satna, Shahdol, Sheopur, Umaria. From each of the KVK (from state MP) two villages were taken under the initiatives on DFI (Supplementary Table 1 and 2). These two adopted villages were considered as treatment. Additionally, an equal number of non-adopted villages were also taken, as the control, which was comparable in socio-economic characteristics and potential influence of spill-over effects from KVK activities in the adopted villages. In the subsequent stage, a total of 20 farm households were chosen randomly from each of the adopted (hereafter denoted as DFI households) and non-adopted villages (here in after denoted as non-DFI households). After data cleaning and smoothing processes, final sample comprised 1090 farm households (543 DFI and 547 non-DFI households). The statistical validity of the above sample size was tested by considering a confidence interval of 95%, a statistical error of 5%, number of agricultural households in the state (NSS 2019) and the sample proportion of success (50%), following the approach given by Kothari (2004) and Sarma (2021):

$$SS = (Z^2 p.q.N)/(e^2 (N-1) + Z^2.p.q)$$

where SS, Required sample size; Z, Z-value (at 95% confidence interval, 1.96); p, sample proportion of success (0.5); N, No. of agricultural households in the state as per 'Situation Assessment Survey of Agricultural Households and Land and Holdings of Households in Rural India', NSO, 2019 (68,36,000); e, Acceptable sampling error (5%).

The estimated size as obtained on the basis of above equation is 384. The sample size in this study (1090) thus provides a larger dataset for analysis indicating the premise for robustness of the data and the validity of the subsequent analyses in assessing the impact.

Data collection: The primary data were collected in person by face-to-face interview with the head of households. For this, a well-structured interview schedule was developed and pilot tested. Information was collected on the parameters including farm and farmer-specific characteristics, cost and return structure for different components of farming system, including field crops, horticultural crops, livestock and fisheries, and supplementary enterprises like mushroom, vermicompost, beekeeping, etc. The DFI interventions were initiated by KVKs during 2016–17. In order to understand the impacts of interventions made on DFI the year 2016–17, the comparison was made with the baseline survey data collected in beginning at that time in case, where baseline data were not available, the relevant data were collected from the respondents based on recall data and validated by the developmental departments.

Analytical framework: In many cases, the intervention programmes are targeted by the implementing agency, but households may choose even not to participate. So, there could be two cases, the participants who did participate may differ in personal characteristics than those who did not. Under such circumstances, the differences in the parameters of impact, which are of interest, cannot be attributed to the actual intervention. Since we cannot observe the counterfactual, i.e. outcome indicators of a participant (farm household) who did not access the programme, we may encounter the problem of endogeneity bias (independent variable correlated with error term).

Precise estimation of impact requires random selection of individuals or households for treatment. In the absence of random experiments, researchers have resorted to quasi-experimental methods (Kumar *et al.* 2019, Aweke *et al.* 2021). Quasi-experimental methods become essential for mitigating selection bias and confounding factors that may arise from non-random assignment. To deal with this issue, this study adopted the matched Difference-in-Differences (DID) analysis to address the problems of selection bias and endogeneity bias. The matched DID approach helps to address selection bias by creating a comparable control group through matching treated observations (DFI households) with similar control observations (non-DFI households). The first step in matched DID is matching that ensures that the control group (non-DFI households) closely resembles the treatment group (DFI households) on observed characteristics, thereby creating a valid counterfactual. In the next step, DID is performed on matched observations to account for time-varying factors that may differently impact the treatment (DFI households) and control (non-DFI households) groups.

Matching: This study used Propensity Score Matching Method (PSM) to examine the impact of participation in DFI initiative of KVKs on the outcome parameters, viz. net household income. PSM method is one of the more practical ways of estimating impacts using cross sectional data (Hagos 2016). The approach of PSM is to hold all factors constant as much as possible so that the difference in outcome parameter for participating or DFI households and non-participating or non-DFI households is due to the DFI interventions made by the KVKs. Matching across covariates removes the bias associated with differences in the covariates. The correct evaluation of impact of technologies requires identifying the 'average treatment effect on the treated' (ATT). ATT is the difference between the outcome variables of being a beneficiary (DFI household) and its counterfactual (outcome of a beneficiary if it had not been a participant, i.e. non-DFI household).

Assume treated and untreated individuals have potential outcomes in both states. Let y_1 be the outcome in the treated state and y_0 be the outcome in the untreated state. Let d indicate treatment group status. The average impact of the treatment on the treated is:

$$\Delta ATT = E[y_1/d=1] - E[y_0/d=1]$$

$E[y_0/d=1]$, Counterfactual and is not observed.

If we add and subtract $E[y_0/d=0]$ and rearrange,

$$\Delta ATT = \{E[y_1/d=1] - E[y_0/d=0]\} - \{E[y_0/d=1] - E[y_0/d=0]\}$$

where $\{E[y_1/d=1] - E[y_0/d=0]\}$, Observed difference and $\{E[y_0/d=1] - E[y_0/d=0]\}$, Selection bias, which will be equal to zero if the programme was given randomly and at the event where adopter and non-adopters did not differ before the programme implementation.

The estimation procedure was conducted through two main steps. In the first step, the probability of participation in the KVK DFI initiative was estimated through a probit regression model. Before fitting the probit regression, thorough assessment of multicollinearity was conducted using the Variance Inflation Factor (VIF) option to ensure the reliability of parameter estimates and the robustness of the probit model in capturing the true relationships between independent variables and the likelihood of participation. In the second step, matching was done by constructing an artificial comparison group by identifying for every possible observation under treatment and control observation (or set of control observations) that has the most similar characteristics possible. Matching is done on propensity score, which summarizes all of the observed characteristics that affect the likelihood of being in the treatment unit.

Difference-in-difference: The DID method is a quasi-experimental approach that compares the changes in outcome parameters over time between beneficiaries (DFI households) and non-beneficiaries (non-DFI households). After matching, DID was carried out for matched groups by comparing the average change over time in the outcome variable for the treatment group to the average change over time for the control group to account for time varying factors.

To estimate the DID, regression model as ordinary least squares (OLS) model of following type was fitted:

$$y = \beta_0 + \beta_1 T + \beta_2 S + \beta_3 T.S + \varepsilon$$

where T, Dummy variable for time (pre/post intervention); S, Dummy variable for DFI households/non-DFI households (yes = 1; no = 0); T.S, Interaction variable between T and S, i.e. dummy for T = S = 1.

The estimated coefficient associated with the interaction term (T.S) is most important. This is the estimate of the treatment effect, i.e. testing whether the expected mean change in outcome variable y (net household income) before and after the implementation of DFI interventions was different for DFI and non-DFI households (Card and Krueger 1994).

RESULTS AND DISCUSSION

Socio-economic and farm-specific characteristics: The results indicates that average age of head of DFI and non-DFI households were found to be almost same (~45 years) (Supplementary Table 3). Vast majority of farm household's heads were males (86% and 88%, respectively for DFI and non-DFI households). The education level was higher for DFI households with 25% of the household heads having completed high school as against 19% for their non-DFI counterparts. Households having heads with intermediate or graduate levels of education were practically absent for both the groups. Slightly higher proportion (45%) of non-DFI households was nuclear as against DFI households (42%). Average landholding size was higher for DFI households (3 hectares) as compared to their non-DFI households (2.66 hectares). Proportion (48%) of medium and large landholders was higher for DFI households than that of non-DFI households (43%). Livestock holding (measured in terms of total livestock units) was also higher for DFI households (2.67 TLU's) than their non-DFI counterparts (2 TLU's). Proportion (45%) of households with medium and large livestock holdings for DFI households was higher as compared to that for non-DFI households (37%). About 33 and 29% of DFI and non-DFI households reported of having at least one member having non-farm income source.

Factors influencing farmers' participation in KVKs' DFI activities: Probit regression model (binary choice model) was fitted to identify the variables that significantly influence the likelihood of participation in KVKs' DFI initiatives. The examination of VIF values for covariates, included in the probit model, revealed non-significant results, with an overall VIF value of 2.09 (Supplementary Table 4). The non-significance of VIF values of covariates and the overall VIF value indicated that multi-collinearity is not a significant concern in the model. Several factors were identified as significant drivers for the participation of farm households in the KVKs' DFI activities (Table 1). Female headed households have higher likelihood (P<0.1) of participating in the DFI initiatives. Farmers with higher level of education were more likely (<0.01) to be beneficiaries. Joint families have higher probability (P<0.1) of participating KVKs' DFI activities. Source of non-farm income by itself does not influence likelihood of participation, but the significant (<0.1) and positive coefficient of the interaction variable between education and non-farm income shows that households with non-farm income source were more likely to participate when education of heads of those households was high. Land and livestock holding, as well as their interaction variable, are not significant drivers of being beneficiaries of DFI scheme implying lack of scale bias in likelihood of participation in KVKs' DFI activities. In probit model, marginal effects, associated with each covariate, helped quantify the impact of each significant variable on the probability of participation. The marginal effects of significant variables indicated that, on average, the probability of participating increases by 0.083 when the household is headed by a female; by 0.023 for each additional class of education completed; by 0.031 due to the interaction between education and non-farm income. On the other hand probability of participation decreases by 0.088 for nuclear families compared to joint family structure.

Table 1 Factors influencing likelihood of participation in KVKs' DFI initiative (n = 1090)

Beneficiary status (DFI = 1, non-DFI = 0)	Coef.	M.E. (dy/dx)	z	P>z
Gender (Male = 1; Female = 0)	-0.209 (0.117)	0.828	-1.78	0.075
Age (number of years)	0.002 (0.003)	0.001	0.45	0.650
Education level (Number of classes completed)	0.057 (0.021)	0.023	2.72	0.006
Family structure (Nuclear = 1; Joint = 0)	-0.221 (0.109)	-0.088	-2.03	0.043
Non-farm income source (Yes = 1; No = 0)	0.075 (0.085)	0.030	0.89	0.373
Total livestock units	0.006 (0.030)	0.002	0.21	0.835
Landholding size (ha)	-0.004 (0.019)	-0.001	-0.19	0.851
Interaction term (Landholding size × Total Livestock Units)	0.006 (0.006)	0.002	1.07	0.286
Interaction term (Education level × Non-farm income source)	0.077 (0.033)	0.031	2.31	0.021
Constant	-0.178 (0.247)	--	-0.72	0.472
LR chi^2 (9)	35.83			
Prob > chi^2	0.00			
Pseudo R^2	0.024			
Log likelihood	-737.61			

Figures in parentheses indicate S.E.

Impact of DFI initiatives on net farm household income: Propensity score matching method was carried out using single nearest neighbour matching technique. The robustness of the matching results was checked in terms of common support, i.e. overlap in the range of propensity scores across treatment and comparison groups and statistical test for covariate matching. The common support, based on propensity scores, for DFI and non-DFI households implies satisfaction of common support criteria, i.e. implying each treated unit has a comparable control unit (Fig. 1).

The statistical criteria for matching the DFI and non-DFI households for single nearest neighbour matching (NNM) were calculated. The standardized percentage bias across covariates of matched and unmatched observations were recorded (Supplementary Table 5). The lack of significance of bias between the two groups, after matching, indicated similar distribution of confounders between matched results. Thus, the matched treatment and control groups were more similar than their unmatched counterparts, implying similarity of covariate distributions between treated and control groups. The matching was carried out with caliper width of 0.05. Caliper is a critical parameter in PSM that determines how closely the treated and control units must match in terms of their propensity scores. In the pursuit of robustness, sensitivity analysis of the above single nearest neighbour matching was conducted by assuming various

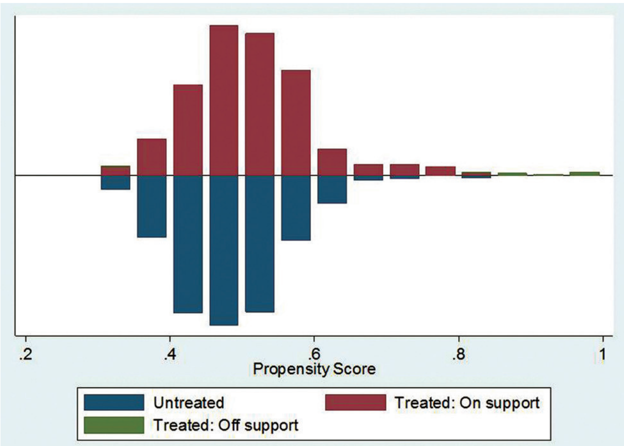

Fig. 1 Common support region.

caliper widths, in spite of caliper width of 0.05 yielding satisfactory results. The results did not vary with different caliper widths, suggesting that the observed treatment effects were not contingent on specific caliper specifications.

To further enhance reliability of matching results, robustness checks by considering different nearest neighbours (NM) specifications ranging from 1–5, were conducted. Table 2 presents the results regarding average treatment effects on the treated (ATT), i.e. the average difference between treated and control observations (on net farm household income) after accounting for the counterfactual, for different sizes of NM's. It was observed that that the ATT's declines with increase in the sizes of NM's considered (decreasing from ₹474 thousand in case of 1 NM to ₹416 in case of 5 NNM). Selection of the number of nearest neighbours can impact the matching process and subsequently influence the estimated treatment effects. This decline in ATT's thus necessitates a closer examination of the trade-off between bias and variance associated with the choice of NM. A low number of nearest neighbours (say NM=1) may lead to higher variance in the estimates as individual matches can be sensitive to outliers. On the other hand, a high number of nearest neighbours (e.g., NM=5) may introduce bias by averaging over a larger pool of potential matches.

The covariance balancing tests run for before and after matching using 5 NM NNM (Supplementary Table 6). The statistical non-significance of difference between the covariates before and after matching, as in case of 1 NM NNM, suggested satisfactory matching for 5 NM NNM also. LR square value, a measure of the joint significance of covariates in predicting treatment assignment, is one validity criteria for covariate balancing tests. The non-significance of this value for both 1 NN and 5 NN specifications implied that there was no significant difference in covariate distributions between treated and control groups for either NNM's. B and R values in matching technique denote measures of bias (average difference in the observed covariates between the treated and control groups after matching). A lower bias value indicated better balance between the treated and control groups in terms of observed covariates. 5 NN specification exhibited slightly lower B and R values, leading to its selection to expect more robust estimation of the treatment effects. While the choice of 5 NN is based on the observed lower B and R values, the robustness of the findings needs to be further assessed on account of marginal differences in the above values between the two approaches.

Thus, alternative matching techniques, including kernel matching, radius matching, and stratification matching were carried out and the results compared with that from 5 NM NNM. Furthermore, to enhance the reliability of our findings, bootstrapping with 1000 replications were applied for all matching techniques. Table 3 elicits the bootstrapped results of above matching techniques. All matching techniques revealed that DFI households had significantly higher annual farm household income compared to their non-DFI counterparts. The ATT's ranged from ₹404 thousand to ₹433 thousand. The results of different matching techniques are more consistent to NNM (5 NM) ATT estimates. The impact of KVKs' DFI initiatives was thus clearly observed for the participating (DFI) households which have higher income by 111%.

Impact of KVKs' DFI initiatives on net farm household income: Data were collected on impact parameter for 2020–21 along with the baseline data (2016–17). This allowed the estimation of the significance of impact of participating in KVKs' DFI activities after accounting for time-varying factors. Matched difference-in-difference method (DID) was used for this purpose. The matched observations (5 NN NNM), as obtained in this study, were used for this analysis. The DID regression was fitted with net household income as dependent variable (Table 4). The coefficient associated with the interaction variable between treatment (participation in KVKs' DFI initiatives) and time (pre/post) variables gave the ATT after accounting for time-varying factors (Table 5). The positive and significant nature of this

Table 2 Results of nearest neighbour matching: Average treatment effect on the treated (ATT)

	Mean Net Household income in ₹ (treatment)	Mean Net Household income in ₹ (control)	Difference	t-cal
NNM (1 NM)	791257.20	317066.30	474190.9 (105381.7)	4.50***
NNM (2 NM)	791257.20	348560.30	442696.9 (104682.5)	4.23***
NNM (3 NM)	791257.20	364263.20	426994 (104517.3)	4.09***
NNM (4 NM)	791257.20	372587.30	418669.9 (105040.2)	3.99***
NNM (5 NM)	791257.20	375153.30	416104 (104888.4)	3.97***

Figures in parentheses indicate S.E.

*** Significant at 1% level of significance. NNM, Nearest neighbour matching; NM, Nearest matching.

Table 3 Average treatment effect on the treated (ATT) in ₹

	ATT	% increase in HH Income	t-cal
NNM (NN = 5) n:treatment = 543 control = 288	416104 (104888)	110.92	3.97***
Radius matching n:treatment = 540 control = 547	433000 (103000)	115.42	4.21***
Kernel matching n:treatment = 543 control = 547	410000 (105000)	109.29	3.90***
Stratification matching n, treatment = 543 control = 547	404000 (100000)	107.69	4.03***

Figures in parenthesis indicates S.E.

*** Significant at 1% level of significance. NNM, Nearest neighbour matching; NN, Nearest neighbour.

Table 4 Results of matched Difference-in-Difference method

	Pre	Post	Difference
Treated	220548.00	791257.20	570709.2
Control	135488.20	360738.50	225250.3
	85059.80	430518.70	345458.9

coefficient suggests net farm income has increased by ₹345 thousand, which is 156% increase when compared with the pre-treatment income level of participant (DFI) households.

Heterogeneous treatment effect: The analysis in Table 5 have revealed significant impact of participation in KVKs' DFI interventions on farmers' net household income. However, the estimated impact of KVKs can vary among different farm households (Kumar *et al.* 2019). Understanding heterogeinity is critical for decisions that are based on knowing how well a treatment is likely to work for a group of similar individuals, and is relevant to policymakers (Varadhan and Seeger 2013). A comprehensive assessment of heterogeneity effects was conducted through sub-group analyses. This involved fitting separate regression models within specific sub-groups (say male or female), associated with each relevant covariate (gender) for matched observations. The results of the sub-group analyses are presented in Supplementary Table 7.

Statistically significant differential impact of KVK access was observed with respect to all variables considered in this study with the exception of age and education of household age and family structure. Households with male heads, no non-farm income source, households with smaller livestock and land holdings were more likely to benefit from participation in KVKs' DFI activities.

Commodity/enterprise wise share and contribution to beneficiary farmers' income: Table 6 elicits the contribution (% share) of different components/commodities to total households' net income for DFI households and their respective contribution to proportionate change in total household's net income. Oilseeds on an average, contributed the highest share (23%) to household's net income in 2020–21. The share increased from 8% in 2016–17, thus registering the highest growth (69% per annum) among all crops (including horticulture). Income from dairying accounted for the next highest share (17%) of net household income for an average DFI households in 2020–21. Vegetables' contribution to net household income increased from 8% in 2016–17 to 15% per annum in 2020–21. Share of income from rice and pulses declined from 20% to 13% and 13% to 10.5% during 2016–17 to 2020–21, respectively. Share of wheat (6.5%) and fruits (6.8%) to average net household income were almost same. As in 2020–21, oilseeds, vegetables and dairying were found to be the most critical components, contributed the highest shares (30%, 18% and 17%, respectively) to additional change in net household income.

Although DFI household heads exhibited a higher level of education among their heads, the absence of intermediate or graduate education levels among household heads in both groups suggested a specific educational profile prevalent among the studied farm households. Higher proportion of medium and large landholders was observed in DFI households. Similarly, greater proportion of DFI households report medium and large livestock holdings, suggesting a potential positive correlation between DFI participation and land and livestock ownership. Similar proportions of DFI and non-DFI households was learned to be non-farm income sources which could reveal similar diversified livelihood strategies employed by the farm households, irrespective of their participation in DFI initiatives.

The results of Probit model regression revealed female headed households had higher likelihood of participation in contrast to earlier findings where bias in favour of male headed households was reported (Kumar *et al.* 2019). Under the KVK DFI initiatives in central zone of India, each KVK had the mandate to adopt two villages for DFI activities; one village was adopted as DFI village, while one more village, where nutrition rich kitchen garden was promoted under 'Gender and Nutrition' initiative of KVKs (named as nutri-SMART village), was selected as the second DFI village in 2016–17. The bias in favour of female headed households, as observed in this study, might be attributed to this village selection bias. The sign of the gender coefficient, thus, needs to be interpreted with caution. In contrast to chi-square analysis, the probit model revealed non-significant influence of land and livestock holding and also the interaction variable between them. This probably implies lack of scale bias in likelihood of participation in KVKs' DFI activities. Education had significant and positive effect, while that of non-farm income source was not significant.

Table 5 Results of matched Difference-in-Difference Regression (n = 2164)

HHNI	Coef.	Std. Err. t	*P*>t	[95% Conf. Interval]	
Treatment	85267.38	73271.20 1.16	0.245	-58422.1	228956.8
Post	225457.9	72863.76 3.09	0.002	82567.47	368348.3
Treat*Post	345251.3	103621.1 3.33	0.001	142043.8	548458.9
cons	135280.6	51522.46 2.63	0.009	34241.86	236319.4
F (3,2160)	31.45				
Prob > F	0				
R^2	0.0419				
Adj R^2	0.0405				

HHNI, Household net income.

Table 6 Commodity/enterprise wise share in household income and compound annual growth rate during 2016–17 to 2020–21 for DFI households (at 2020–21 prices)

Major group	Sub-group	Per cent share in total household's income		Per cent share in additional income
		2016–17	2020–21	
Field crop	Rice	19.86	12.83	9.29
	Wheat	11.89	6.46	3.72
	Maize	2.66	1.74	1.27
	Millets	0.36	0.29	0.25
	Pulses	12.69	10.52	9.42
	Oilseed	8.35	22.91	30.25
	Sugarcane + cotton	2.67	1.72	1.24
Horticulture	Vegetables	8.37	14.73	17.93
	Fruits	6.97	6.74	6.62
	Nutri-garden	5.79	3.00	1.60
Livestock	Dairy animals	18.12	17.31	16.91
	Sheep/Goat	1.03	0.76	0.62
	Poultry	0.00	0.02	0.02
Farm and non-farm enterprises	Vermicompost	0.34	0.29	0.27
	Verms	0.63	0.58	0.55
	NTFP collection and value addition	0.26	0.10	0.02
	Total	100.00	100.00	100

The interaction variable between education and non-farm income was significant. This implies that although non-farm income may not independently influence participation in KVKs' DFI scheme, non-farm income sources may interact with other socio-economic factors, like education in shaping farmers' decisions to participate. The positive influence of the interaction variable indicated farmers with both higher education levels and non-farm income sources may have an increased propensity to participate. Joint families were observed more likely to participate in the DFI activities comparing to the nuclear ones. This might be on account of sharing of common socio-economic dynamics and finding collective benefits in participating.

Rigorous matching techniques for the robustness checks helped identifying an optimal matching technique that is expected to yield stable and reliable treatment effect estimates. The results revealed a substantial and statistically significant ATT of ₹416 thousand, representing a significant 111% increase in average net household income for participants in KVKs' DFI initiatives. By applying matched DID, to account for time varying factors, the ATT was estimated at ₹345 thousand, representing 156% increase in net farm household income. Utilizing a matched control group and application of matched DID allowed the assessment of before-and-after periods and thus concerns related to temporal dynamics were addressed and helped provide a more robust estimate of access of impact of KVKs' DFI initiative. The findings provided quantitative evidence of impact of KVKs' DFI activities and the significant contribution of KVKs' interventions to achieving the ambitious national goal of doubling farmers' income. Further, heterogeneity test, revealed critical insights regarding the differential impact of KVKs' DFI activities across various sub-groups. Positive impact on households with smaller land and livestock holdings imply that not only participation in KVKs' DFI initiatives was scale-neutral, KVKs might have given more focus on small holders improving their management practices so as to get significant impact on income for these household categories. Analyses of shares of different commodities/enterprises to total income and their contribution to additional income during 2016–17 to 2020–21 revealed that agricultural diversification and shift to high value crops like vegetables and ancillary activities like dairying from traditional crops like rice and pulses, has been crucial in enhancing DFI farm household income.

Conclusion and policy implications

The findings suggested that there were significant impact of different activities initiated by the KVKs for influencing the farmers' income. The households with non-farm income source were more likely to participate when education of their heads was higher. As far as land and livestock holding were concerned, there was lack of scale bias in likelihood of participation in KVKs' DFI activities. The application of matched difference-in-difference regression, to account for temporal dynamics, revealed an increase in net income for DFI households. The tailor-made interventions matching to the specific needs and characteristics of households could make considerable change in terms of income. Key insights suggested that there is further need to shift the monocropping system based farming to more diverse farming system with the inclusion of high value horticultural crops and dairying. However, it is also important to recognize the heterogeneity in treatment effects so as to optimize resource allocation in diverse components while enhancing effectiveness of activities on DFI.

The gender was found one of the decisive factors influencing farmers' income due to differential control and power over the resources available locally, and ability to access external resources provided by the KVKs. This necessitated to think how gender sensitive approach may further ease the women's participation in income related activities pursued by not only the KVKs, but also the other agencies. The smallholder farmers got more benefitted from the KVKs' access and DFI. This could imply that equity dimensions, being pursued by the KVKs, could make impact. The factors influencing farmers' income need to be prioritised in order to optimize the investments. The success in terms of DFI indicated that KVKs played important role in motivating farmers to get engage with different interventions, and as a result this could enhance farmers' income. Overall, this could also highlight the potential role of KVKs as one of the institutions in making transformative change while strengthening farmers' livelihoods.

Ethical statement

Before conducting this study, farmers were explained the aim and objectives. They were also briefed the probable outcomes from this study in terms of research publication (digital and hard copy). Accordingly, their consent was obtained for collecting data from them. The farmers wished to participate in this study anonymously, except disclosing some geographic details.

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