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Can forage technologies transform Indian livestock sector?: evidences from smallholder dairy farmers in Bundelkhand region of central India

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Abstract The study has analysed the factors affecting adoption of improved forage technologies and its impact on milk yield and feed sufficiency in Bundelkhand region. We used propensity score matching (PSM) technique on cross-sectional data collected from 400 dairy farmers for impact evaluation and also conducted sensitivity analysis to examine the effect of uncontrolled confounders on the estimands. Our findings suggest that, education status, standard livestock unit, animal breed type, off-farm income activities, farm size and access to training, credit and market significantly influence adoption of improved forage technologies and practices. Further the adoption led to a significant increase in annual milk production (over 950 litres) and daily milk yield (1.15 to 2.04 litres) and also reduced time spent in feeding by around 2 hours during *zaid* season and around an hour during *kharif* season.

Keywords Forage technologies, milk productivity, feed sufficiency, PSM, Bundelkhand

JEL Codes Q12, Q16, R58

India has the largest livestock population but of low productivity (Choudhary et al. 2020). Inadequate supply and poor quality of feeds and fodders is one of the major factors for low animal productivity (Ghosh et al. 2016). Feed is also a major cost in dairy production (Mahanta 2017). In India, land allocation to cultivation of green fodder crops is limited and has hardly ever exceeded 5% of the gross cropped area. Therefore, the supply of feed and fodder has always remained short of normative requirement (Ramachandra et al. 2007, Satyapriya et al. 2012), restricting the realization of the true production potential of livestock (Dikshit and Birthal 2010). Presently, the country faces a net deficit of 11.24% in green fodder, 23.4% in dry crop residues and 28.9% in concentrate feed ingredients (Roy et al. 2019).

Nonetheless, there exist regional and seasonal disparities in fodder production. Most of the deficient regions lie in the arid and semi-arid regions. Seasonality in forage availability accentuates the cost of feed and thus the profitability of the livestock production (Gachuiri et al. 2017). Moreover, seasonal scarcity of forages puts additional pressure on common property resources, particularly in the arid and semi-arid tropics; and has always added to the drudgery of farm households especially women in terms of time and energy spent for fodder collection (Dhyani et al. 2013). Therefore, ensuring quality and reliable availability of year-round fodder is prerequisite for enhancing productivity.

One of the main approaches for addressing the feed scarcity has been to develop and promote adoption of improved year-round forage options that include a wide varieties of sown or planted grasses, and herbaceous or dual-purpose cereals and legumes. Integration of forages into mixed cropping systems has been reported to generate significant benefits (White et al. 2013, Paul et al. 2020).

In India, research and development programmes on forages over the past five decades have spread over time and regions. Several experimental field trials have shown the potential of integrating improved forages in enhancing livestock productivity (Sharma et al. 2007, Ghosh et al. 2016); yet comprehensive and quantitative evidences on the driving factors of the adoption of forage technologies and their multidimensional impacts, are lacking in the Indian context.

The present study, therefore, using the example of the KISAN MITrA[1] (Knowledge-based Integrated Sustainable Agriculture Network Mission India for Transforming Agriculture) project seeks to fill the literature gaps on the socio-economic and institutional factors affecting adoption of improved forage technologies and the impacts of forage based interventions on milk yield and feed sufficiency. Under the KISAN MITrA project, a broad set of improved forage technologies and practices like use of quality fodder seeds, grasses on bunds, cultural practises of fodder production and conservation, and ration balancing programmes were promoted making it an ideal context for an investigation of the aforementioned farm-level adoptions and impact analysis of forage based interventions.

Material and methods

Study area

This study was conducted in Lalitpur district located in Bundelkhand region of central India (Fig. 1). Most of the population is dependent on crop/livestock-based activities and around one-third of the geographical area is covered by degraded forests, permanent pastures, fallows and wastelands. Dairy and goat farming are important in the region. The district receives average annual rainfall of around 880 mm, of which 90% occurs in *kharif* season (June-October).

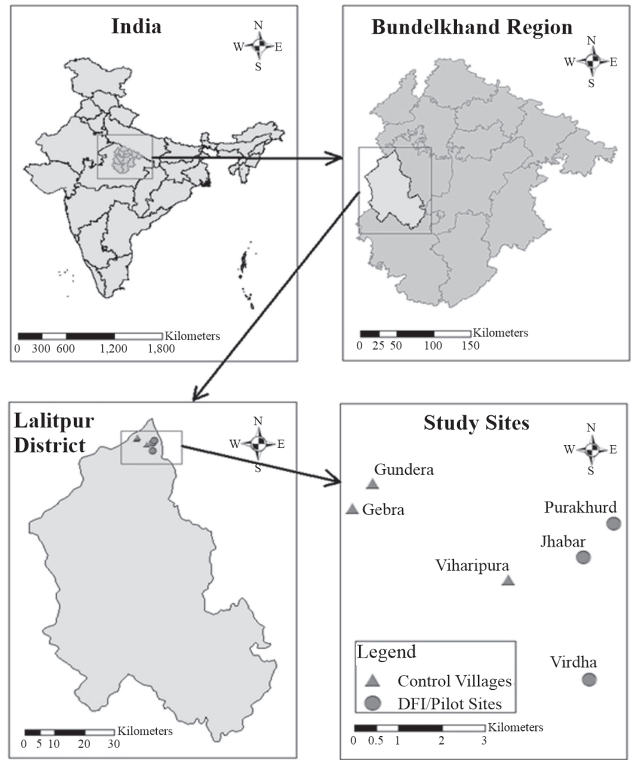

Figure 1 The locale of the study area delineating treated and control villages

Three villages namely *Birdha, Purakhurd, Jhabar* located in Talbehat block of Lalitpur district were the treated villages in our study as all the project activities were focussed within the physical boundaries of these villages. Simultaneously, three contiguous villages namely *Gundera, Gebra and Viharipura* were identified as control villages, with no forage based interventions, but having close similarity with treated villages in their agro-climatic, infrastructural and socio-economic set up. This criterion has been considered in other impact assessment studies to control for any influence (bias) resulting from close proximity with adopters (Gitonga et al. 2013, Marwa et al. 2020).

Analytical framework

Drivers of adoption of improved forage technologies and practices

Following the theory of expected utility, we assumed

[1]The KISAN MITrA project, funded by government of Uttar Pradesh State (India), was started in the Bundelkhand region of India in 2017 by ICRISAT Development Center (IDC), Hyderabad in partnership with ICAR-Indian Grassland and Fodder Research Institute (IGFRI), Jhansi, and ICAR-Central Agroforestry Research Institute (CAFRI), Jhansi. One of important objectives of the project was to implement improved forage technologies on farmer’s field for ensuring year-round quality fodder for livestock.

that a farmer's adoption decision given the risk and uncertainty prospects, is based on the comparison of expected utility (Mercer 2004). Farmers will adopt and practise the interventions if the expected utility from adoption (Ua) is greater than that derived from non-adoption (Un). Profit is used as a proxy and if combined with attitude to risk, farmers are described as maximizing the expected utility of profit rather than expected profit (Borges et al. 2015).

The utility derived from the adoption of improved forage based technology will have a binary choice component determined by observable characteristics X_i and a stochastic error term ε_i.

$I_i^* = \beta X_i + \varepsilon_i$; $I_i = 1$, if $I^* > 0$, and 0 if otherwise

Where, I_i is a dichotomous variable for the adoption of the forage technologies and β is a vector of parameters to be estimated.

Farmers will adopt forage technologies if $I_i^* = Ua - Un > 0$. The probability of adopting the technologies can then be estimated as follows.

$\Pr(I_i = 1) = \Pr(I_i^* > 0) = 1 - D(-\beta X_i)$

Where, $\Pr(I_i = 1)$ is the probability of adoption and D represent the cumulative distribution function for ε_i.

Impact assessment

An empirical challenge in assessing causal impact is to examine the outcome and its counterfactuals (Holland 1986). Ideally, the solution for this would be to randomly assign the treatment (forage interventions in the present case) among farmers, i.e. randomized control trial (RCT), however it is not feasible to implement it practically. Therefore, we relied on Propensity Score Matching (PSM) method, a quasi-experimental technique which is widely used in impact assessment studies to deal with the problem of the missing counterfactual (Imbens and Wooldridge 2009).

The first step in PSM is to estimate the predicted probability values of adoption (propensity scores) using the probit or logit model. We used the standard probit model (0=untreated and 1=treated) to obtain propensity score (Rosenbaum and Rubin 1983).

$P(X_i) = P(Z=1|X_i)$

Where, $P(X_i)$ is the propensity score of the i^{th} household; $P(Z=1|X_i)$ indicates the probability of treatment given the observable covariates (X) of i^{th} household.

To ensure that there is no systematic difference in the covariates of treated and control groups in the matched sample, the balancing test was conducted. After that, three matching algorithms namely nearest neighbour matching (NNM), kernel based matching (KBM) with bandwidth 0.01 and radius matching (RM) with caliper 0.1 were employed. Though these matching procedures differ in creating the counterfactuals and assigning weights to the neighbours, and have their own limitations; using all the three methods provides robustness check of the results.

Finally, the impact of adoption of improved forage technologies on outcome variables indicated by the average treatment effect on the treated (ATT) which is computed by restricting the matches to the households with propensity scores that fall in the area of common support (Caliendo and Kopeinig 2005):

$ATT = E\{ Y1_i - Y0_i \}$

Where, E(Yi) denotes the expected value of the i^{th} outcome variable; 1 represents the treated, 0 otherwise.

We also conducted sensitivity analysis using bounding sensitivity method proposed by Rosenbaum (2002) for the ATT that are significantly different from zero to test whether inference regarding impact were sensitive to 'hidden bias' due to unobservables.

Data

Matching technique requires more observations from control units, preferably in the ratio of around 1:2 (Datta 2015). Hence, we collected information from 150 farm households from the treated villages and from 250 households from control villages. Households were stratified based on land size, and then probability proportional to size method was used to draw sample households from each village. Finally, the respondent household-heads were selected by using random sampling technique.

The primary data collected from transect walk observations, interviews of key informants and detailed household surveys. A team of local enumerators ,who are well acquainted with farming practises in the area, culture, and language of the local inhabitants ,were recruited and trained for data collection. The survey schedule (administered in Hindi for convenience purpose) captured information on various socio-economic, farm-specific and institutional support parameters for the agricultural year 2019-20.

Results and discussion

Covariates and descriptive statistics

Household is the ultimate clientele of farm technology; hence household characteristics like household size, education status and experience in farming are important parameters to be considered in adoption process (Noltze et al. 2013, Ghimire et al. 2015). Further, farm characteristics and institutional factors have also been reported as key influential factors in technology adoption process (Maina et al. 2020). Table 1 depicts the definitions and summary statistics of the selected variables.

It is evident that the households from the treated (adopters) and control villages (non-adopters) are systematically different in of many observed characteristics (Table 1). For instance, relative to control villages, household-heads of treated villages are better educated and have a larger land holding. Moreover, adopters had on average standard livestock

Table 1 Definitions and sample averages of selected variables

Variables	Description	Control (C, n=250)	Treated (T, n=150)	Mean difference (C – T)
	Households characteristics			
Age of HH	Age of household head (years)	47.65	46.63	1.02
HH_Male	% of household headed by male	95	94	1
Experience_HH	Experience of household head in farming (years)	27.63	26.83	0.80
Education_HH	Numbers of years of schooling by household head	3.62	5.27	-1.654**
HH Size	Household size (No.)	6.00	6.19	-0.19
Dependency Ratio	(Household members < 15 and > 65 years)/ household size	0.38	0.35	0.03
	Farm characteristics			
Land holdings	Operational holding in hectares	1.57	1.97	-0.40**
LSU	Standard Livestock unit	3.08	4.16	-1.08*
Buffalo to IC ratio	Buffalo to Indigenous Cattle ratio in dairy herd	0.47	0.69	-0.22*
Off-farm activities	% of household involved in off-farm income activities (%)	37.23	53.45	-16.22*
	Institutional characteristics			
Training	% of households exposed to training and demonstration visit	67.29	93.13	-25.84*
Credit	% of households that has access to farm credit	45.21	49.30	-4.09
Market access	% of households that are able to sale surplus milk	47.36	66.41	-19.05*
	Outcome indicators			
Annual milk production	Total milk production per household per year (litres)	1898.23	2934.28	-1036.05**
Cow productivity	Average milk production (per day per cow)	2.06	3.29	-1.23*
Buffalo productivity	Average milk production (per day per buffalo)	4.81	6.24	-1.43*
Feeding time_Kharif	Daily hours dedicated to feeding during *kharif* season (June to October)	3.14	1.82	-1.25*
Feeding time_Rabi	Daily hours dedicated to feeding during *rabi* season (November to March)	2.15	1.89	-0.26
Feeding time_Zaid	Daily hours dedicated to feeding during *zaid* season (April to May)	4.00	2.07	1.94*

*p<0.01, **p<0.05

Table 2 Indicators of matching quality before and after matching

Test	Before matching	After matching		
		NNM	KBM	RM
Pseudo R^2	0.241	0.002	0.013	0.029
LR χ^2 (P-value)	61.17* (0.00)	4.17 (0.79)	3.26 (0.62)	6.32 (0.59)
Mean Standardized Bias	29.71	7.10	5.90	9.16
Total Bias reduction (%)		76.10	80.14	69.16

Source Authors' estimates based on survey data

unit (LU) of 4.16 units, which is significantly higher than for non-adopters (3.08 units).

Larger proportions of households in the treated village (53.45%) derive income from off-farm sources. Further, adopters are better exposed to training and demonstrations. Consequently, a significant proportion of adopters (66.41%) are able to sell surplus milk.

The significant differences in outcome indicators clearly indicate that adopters of improved forage technology are systematically better off than their non-adopters counterpart in terms of milk yield and daily time spent in sourcing feed during *rabi* and *zaid* cropping seasons (Table 1).

However, as the effects of confounders have not been controlled for, it would be inappropriate to draw any inference regarding the impact of adoption of forage based interventions on these indicators. This further necessitates matching through PSM to analyze factors influencing adoption and to estimate impact thereof.

Matching quality and balancing test

Before discussing the drivers of adoption and its impact, we underline here the quality of the matching through all three algorithms, as the success of PSM lies in matching the observable covariates across treated and control groups (Becerril and Abdulai 2009). Conforming to the requirement of balancing test, the Pseudo R^2 drops significantly to 0.2, 1.3 and 2.9% for NNM, Kernel (KBM) and Caliper matching (RM) respectively, from around 24% before matching (Table 2).

The higher and significant likelihood-ratio (LR) before matching signifies the presence of systematic differences between the treatment and comparison groups. The insignificant p-value for LR after matching indicates that these differences have been removed making the two groups comparable.

Further, the matching procedure led to substantial reduction in bias (69.16-80.14%) and as per the prerequisite criteria (Rosenbaum and Rubin 1983) the Mean Standardized Bias (MSB) is well below 20% after matching. The low Pseudo R^2, insignificant p-values of the LR test, low MSB suggest that the specification of propensity is successful in terms of balancing the distribution of covariates between treated and control groups.

The distribution of propensity scores and region of common support through all the three matching algorithms are depicted in Fig 2. Suitable matches of adopters (treated) and non-adopters (control) are shown as 'treated on support' while, adopters with bad matches from among the control are termed as 'treated off support."

Visual observation of the Fig 2 clearly indicate that there is considerable overlap of the distributions of the propensity scores for adopters and non-adopters of improved forage technology after matching suggesting that the assumption of common support firmly holds.

In case of NNM all the observations from treated unit find a good match and thus there are no treated off-support observations (Fig. 2a). However, in KBM and RM techniques few observations are treated off-support and thus discarded during the analysis (Fig. 2b & 2c). The matching procedure created a clean counterfactual as none of the mean differences of the selected variables between treated and control group are statistically significant (Table 2).

Determinants of improved forage technology adoption

Table 3 presents the probit results on matched sample. Concerning the household characteristics, we find that

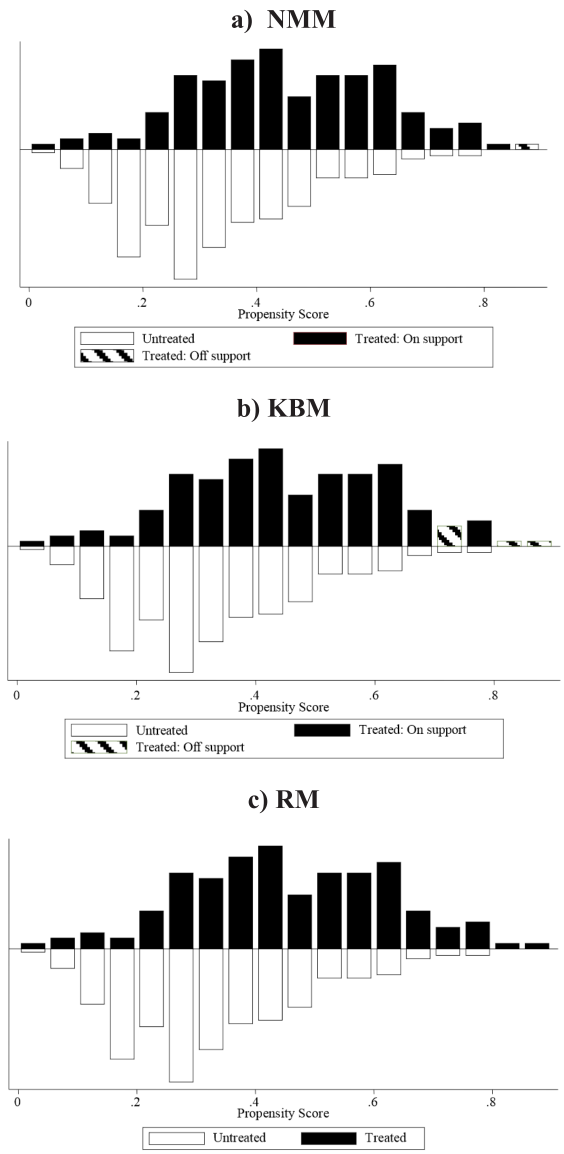

Figure 2 Propensity score distribution and common support

adoption is positively associated with longer formal schooling of the household head. The learning chances of educated farmers from exposure to technical advice, training and farm demonstrations may be higher. The direct relation between inclination towards adoption of improved agricultural technologies and education of household head has good literature support (Kumar et al. 2020). Additionally, households with large farm size are 4% more likely to adopt the improved forage technologies. The larger landholdings accentuate the household's ability to take risks and thus increase the probability of adoption of new technology (Kabir and Rainis 2015).

Table 3 Regression results from probit model on matched sample# for the driving factors of adoption of improved forage technologies/practices

Variables	Coefficients	Std. error	Marginal effect
Age of HH	0.032	0.073	0.0083
HH_Male	0.078	0.139	0.0018
Experience_HH	-0.019	0.027	-0.0037
Education_HH	0.371*	0.016	0.0610
HH Size	0.0071	0.0273	0.0029
Dependency Ratio	-0.1741*	0.0331	-0.0763
Land holdings	0.2382*	0.0914	0.0413
LSU	0.082*	0.0173	0.0991
Buffalo to Cattle ratio	0.6831*	0.2976	0.1329
Off-farm activities	0.0247**	0.0109	0.0571
Training	0.6179*	0.1186	0.2312
Credit	0.3951*	0.1049	0.0361
Market access	0.329*	0.0791	0.1137
Log likelihood	-241.36		
LR χ^2	49.71*		
Sample size†	328		

Source Authors' estimates based on survey data
Note *p<0.01, **p<0.05
† KBM resulted into 150 and 178 observations from treated and control samples respectively, making total sample size of 328.
# We also used NMM and Calliper matching methods, and the results were similar to KBM based estimates. Hence, in the interest of time and space, we present results for KBM method only.

Unsurprisingly, households with higher livestock units and having more buffaloes in their herd are more likely to adopt improved forage based interventions - the probability increases by 0.099 and 0.132, respectively. The finding is in congruence with Kanyenji et al. (2020) and Maina et al. (2020) who observed that households with higher livestock units utilized more crop residue as animal feed and thus more likely to adopt agricultural technologies that yield more forages. Kassie et al. (2018) also reported that ownership of productive breeds increases demands for feed. Moreover, a positive and significant association between off-farm income and the probability of adoption of improved forage technologies was observed. Off-farm income relaxes liquidity constraints faced by the farm households and induces increased use of improved seeds (Diiro 2013, Choudhary and Singh 2019). A significantly higher adoption intensity of agricultural technology among households with off-farm income relative to their counterparts without off-farm income is well acknowledged (Mwangi and Kariuki 2015).

All the three instructional factors considered in this study viz., training, credit and market access have a positive and significant effect on adoption of forage technologies. Exposure to training and demonstrations on improved forage practises increases the probability of adoption by 0.23. Training and demonstrations boost credibility among farmers towards new technologies and counter balance the negative effect of lack of formal education in the adoption decision.

A positive relationship between extension and training, and technology adoption among farm households has been unanimously supported in previous studies (Kumar et al. 2020, Maina et al. 2020). Additionally, access to formal credit and output market is correlated with household's-risk bearing ability and stimulates technology adoption (Ghimire et al. 2015). In the present study, we observed that due to the absence of efficient milk collection centre in the region, the milk vendors or middle men have strong presence for milk marketing, and farmers do not realise remunerative price. However, few farmers disposes the surplus milk in form of dairy products like *Ghee* (clarified butter made from the milk) and *Khoa* (highly condensed milk), which undoubtedly fetches higher prices but also involves considerable drudgery and processing costs.

Impact of forage technologies adoption

The estimated causal impact of improved forage technologies, as average treatment effect on the treated (ATT), on selected outcome variables are presented in Table 4. The estimates of different matching algorithms are though quantitatively different, but qualitatively these are similar. These estimates control for the farmers' endogenous decisions on participating in the KISAN MITrA project and whether to adopt improved forage technologies.

We find that ATT is positive and statistically significant for most of the outcome variables. With regard to annual milk production, adopter households had a higher annual milk yield than non-adopters with matched characteristics and the treatment impact was over 950 litres. The corresponding annual gross return was estimated to hovers between INR 38000 to INR 39000 (Table 5). The impacts on milk yield differ across dairy breeds. While the daily milk yield of cows significantly increased by 1.15 to 1.97 litres; for buffaloes, the improved forage feeding raised daily milk yield by 1.23 litres to around 2 litres.

The assessment of the ATT of adoption improved on feed sufficiency revealed that the project interventions in the study area are associated with increased feed availability, particularly during feed stress periods. After matching, compared to the non-adopters the daily time spent by the adopters in sourcing feed significantly reduced by around 2 hours during the *zaid* season and around an hour during *kharif* season.

The establishment of perennial fodder grasses by the adopters in their forage plots was key sources of cut-

Table 4 Estimates of ATT: Impact of forage technologies

Outcome indicator	Average treatment effect on the treated			Gamma
	NNM	KBM	RM	(Γ)
Total milk production per household per year (litres)	977.13**	959.54**	951.39*	1.25-1.30
	(467.11)	(477.38)	(423.32)	
Cow's daily milk productivity	1.97*	1.15*	1.25*	1.80-1.85
	(0.71)	(0.342)	(0.43)	
Buffalo's daily milk productivity	2.04*	1.23*	1.47*	2.15-2.20
	(0.81)	(0.272)	(1.34)	
Daily hours spent to feeding (*kharif* season)	-1.12*	-1.05*	-0.95**	1.35-1.40
	(0.16)	(0.25)	(0.21)	
Daily hours spent to feeding (*rabi* season)	-0.41	-0.39	-0.37	–
	(0.29)	(0.26)	(0.21)	
Daily hours spent to feeding (*zaid* season)	-1.80*	-1.89*	-1.79*	1.20-1.25
	(0.19)	(0.26)	(0.21)	

*p<0.01, **p<0.05

Note Figures in parentheses indicates standard error

Table 5 Economic benefits of improved forage technologies

Parameters	Economic Gains (INR)		
	NNM	KBM	RM
Annual gross returns* due to increased milk production	39085.2	38381.6	38055.6
Daily gross return per cow	78.8	46.0	50.0
Daily gross return per buffalo	81.6	49.2	58.8
Reduced imputed labour cost (*zaid* and *kharif* season)†	10350.00	10158.75	9371.25

*Gross margin was calculated using milk procurement price (= INR 40/litre) in the study area.

†Imputed labour cost was calculated considering the prevailing labour cost of INR300 for 8 working hours in the study area.

and-carry grass during the *zaid* and *kharif* seasons that saved significant time in sourcing feed than non-adopters that reported spending around 3 to 4 hours sourcing green fodders, mainly weeds and shrubs, from fields and distant areas on a daily basis. In monetary terms, the feed sufficiency due to the project interventions benefited the adopters by reducing the imputed labour cost by around INR 10,000 (Table 5). We did not find significant impact on time saving in sourcing feed during *rabi* seasons due to the plenty availability of traditional feed sources such as crop bi-products and crop residues in these seasons. Our results are consistent with the findings of Ashley et al. (2016) from Cambodia and Maina et al. (2020) from Kenya, who noted that adoption of improved forage technologies resulted in a significant reduction in time spent in sourcing for feed during dry periods.

The result of sensitivity analysis to examine the effect of uncontrolled confounders is also reported in Table 4 (col. 5). The values of critical level of hidden bias (Γ) are well within the acceptable range (Mendola 2007, Keele 2010) and ranged between 1.20–1.25 to 2.15-2.20. The value of $\tilde{A}$ for daily hours spent for feeding during *zaid* cropping season (1.20–1.25) implied that the credibility of a positive impact of adoption on feed sufficiency during the dry season would be questioned if households with similar characteristics differed in their odds of adoption by even 20-25%. The higher the value of Γ, the lower the hidden bias would be and the converse is also true. Therefore, we can conclude that the inference on estimated impact on milk productivity will not be changed even in the presence of large amounts of uncontrolled heterogeneity. In other words, impact of improved forage technology adoption on milk yield of dairy animals is less sensitive to the unobserved bias.

Conclusions

The present study has empirically analysed the drivers as well as farm-level impacts of adoption of improved forage technologies promoted under KISAN MITrA project in Bundelkhand region of central India. We established that the adoption of improved forages is positively influenced by level of education of household head and, various farm and institutional characteristics in a significant way. This necessitates a holistic approach for promoting the uptake of improved forage practises by livestock keepers.

Improving education status of farmers can go long way as it also have multiplier effect on economy, therefore strengthening public education system in rural areas should be the prime policy focus. Besides, mainstreaming practically oriented, participatory and interactive model like farmer field school (FFS) program and encouraging frontline demonstrations by local research institutes, to impart training to the dairy farmers on improved fodder production, conservation and utilization would be imperative to improve farmers' capacity and skills in forage and dairy management.

An urgent policy need in the studied region is to ensure parallel development of supporting market environment for surplus milk encompassing backward and forward market linkages. Promoting farmer's coalition through farmer producer organizations (FPOs) would be crucial in this direction for safeguarding the interest of small dairy farmers. Further, strengthening and streamlining the rural credit networks and other service providers who offer market and input support to dairy farmers will also be a key intervention for increasing the uptake of improved forage technologies.

The kind of rigorous econometric analyses used in this study is crucial for understanding the actual field-level impacts of various sets of improved forage technologies and practices on milk productivity and socio-economic welfare of dairy farmers. Finally, the evidence from Bundelkhand region, with its typical agro-ecological conditions characterized by undulating topography and unique climatic challenges, can offer important lessons for the promotion of improved forage technologies for improving livestock productivity in arid and semi-arid regions around the world which face similar challenges. However, integrating farmer's choices with the suggested policy interventions will be more imperative as the ground implementation of strategies eventually governed by many socio-economic factors prevailing in a region.

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