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Household nutrition and income impacts of using dairy technologies in mixed crop–livestock production systems

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Technologies like improved breeds of dairy cows and improved forages have the potential to significantly increase dairy cow productivity and farmers' profits in developing countries. However, adoption of such technologies has been low in Ethiopia, despite numerous efforts to disseminate the technologies in the past. Some studies argue that adoption of technologies is low because welfare effects of the technologies could be insignificant or negative to certain groups of farmers. This article employed propensity score matching and inverse probability weighting estimator with regression adjustment to examine the difference in household nutrition and income between adopters and nonadopters of dairy technologies in rural Ethiopia. We find that adoption of cross-bred dairy cows and improved forages increases household nutrition and income. The significant household nutrition and income impact for adopters support the notion that many Ethiopian smallholders have not adopted dairy technologies because adopters and nonadopters of dairy technologies have inherent differences in welfare outcome potentials. The results suggest that interventions that enhance access to farm resources and address barriers to input and output value chains could improve adoption of dairy technologies.

Key words: dairy technologies, impact evaluation, income, nutrition, propensity score.

1. Introduction

The critical role of new technologies and effective institutions in stimulating agricultural productivity and inclusive economic growth is now well established. Intensification of dairy production through the use of agricultural technologies is essential both to meet increasing demand for milk products and to improve household welfare (Delgado *et al*. 2001; McDermott *et al*. 2010). For example, cross-bred dairy cows and improved forages have the potential to improve the welfare of farmers through higher milk yields, better income and improved nutrition. Ethiopian government and

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development partners have dedicated substantial resources to deliver information that encourages farmers to adopt new inputs and practices. Several technological interventions have been promoted in Ethiopia to enhance the productivity of dairy cattle since the early 1960s. For example, crossing indigenous breeds of cattle with exotic breeds of dairy cows has been extensively promoted as a promising option to enhance the productivity of dairy cattle in Ethiopia (Ahmed *et al.* 2004; Rege *et al.* 2011). Several organisations have promoted improved forages in Ethiopia since 1970s (Duncan *et al.* 2013; Ran *et al.* 2013). Despite many research and extension efforts in the past, these technologies have not been adopted by the majority of Ethiopian smallholders and livestock productivity remains very low (Ayele *et al.* 2012; Duncan *et al.* 2013). There may be a good reason why farmers are not adopting technologies and best practice.

It is unlikely the problem is caused by lack of technologies, for technologies that could increase the productivity of dairy animals are available. It is also unlikely that differences in technology adoption or input use across farm households are primarily the result of differences in the fundamental nature of human behaviour across farm households. Smallholders often have heterogeneous access to land, credit and technical advice, basic knowledge of the market system and current information on market prices and conditions - all of which restrict their capacity to invest, expand their market surplus and add value to their produce (Deininger and Jin 2006; Dercon *et al.* 2012). Probably the notion that technologies have different benefits to different groups of farmers could explain why many Ethiopian smallholders have not adopted them (Suri 2011; Kathage *et al.* 2015). Suri (2011) argues that one cannot assume a profitable technology for one farmer will be profitable for every farmer as welfare effects of technology adoption could be insignificant or negative to certain group of farmers. In the case of technologies used by profit-maximising entities, it is clear that technology profitability is the key measure. For technologies that improve an agent's utility, such as dairy technologies that improve household nutrition, measurement of returns is less straightforward. Agents choose to use a technology based on the gain in welfare, which cannot be directly measured. Furthermore, the question of whether adopters and nonadopters of dairy technologies have inherent differences in welfare outcome potentials is an area where relatively little research has been carried out.

Assessing the difference in nutritional and income benefits between adopters and nonadopters of dairy technologies could provide important insights as to why many smallholder farmers have not adopted dairy technologies in Ethiopia. A few studies have estimated the returns to adoption of technologies that are alleged to be underutilised (Ahmed *et al.* 2000; Hoddinott *et al.* 2015; Marshall 2014). The study by Ahmed *et al.* (2000) analysed the impact of introducing cross-bred cows and improved forages on household income and caloric intake using a simultaneous regression model. Ahmed *et al.* (2000) used a pooled model estimation technique which assumed that the set of adoption determinants have the same impact on adopters and nonadopters. Their model also did not account for differences in welfare outcomes between adopters and nonadopters of improved dairy technologies that arise due to unobserved differences between households. This is inappropriate in contexts where farmers have observable differences (e.g. in resources endowment and market access) and unobservable differences (e.g. technical ability, farmers' motivation, attitudes towards work, risk aversion, future orientation and social and other noncognitive skills). Not distinguishing the effect of unobserved differences could lead to misleading conclusions (Heckman *et al.* 2001). Effective impact evaluation methods need to discern the mechanisms by which the beneficiaries are responding to the interventions (Heckman *et al.* 2001; Gibson and McKenzie 2014).

Several studies also have assessed factors affecting adoption of dairy technologies in Africa using logit or probit models (Staal *et al.* 1997; Gebremedhin *et al.* 2003; Abdulai and Huffman 2005; Holloway *et al.* 2008; Burke *et al.* 2015). Such models fail to control for important unobserved heterogeneity effects on farmers' technology adoption decisions. Estimates by nonlinear parametric models such as a probit or logit pivot on the assumption that the effects of unobserved factors do not vary across farm households. Household-specific unobservable factors could be correlated with observable characteristics of households and can affect their adoption decisions. These regression methods may be less successful in dealing with the sample selection problem when subjects in nonexperimental studies cannot be randomly assigned to 'treatment' and 'control' groups (Heckman *et al.* 1997; McKenzie *et al.* 2010).

If technology was randomly assigned to households – as it would be in an experiment for example – we could evaluate the causal effect of technology adoption on household well-being as the difference in average well-being between adopters and nonadopters of the new technology. In the study area, dairy development interventions were not assigned randomly to certain villages or farm households. The study is based on observational data generated by ex post cross-sectional survey on sample households in the study area. Estimation of individual treatment effect in observational data is complicated due to the challenges of confounding and selection bias. Given the study setting, we use quasi-experimental design to conceptualise farmers' choice of dairy technologies as a selection process, where the expected higher nutritional and income outcomes drive farmers' decision of using dairy technologies. Quite limited econometric methods are available to deal with selection problem in quasi-experimental design situations: instrumental variable regression, regression discontinuity design and selection on observable methods. Instrumental variables (IV) regression sometimes provides consistent estimates of causal parameters, given there is credible instrument that affects participation in the treatment sufficiently strongly, but is conditionally uncorrelated with outcomes other than through its effect on participation (Angrist *et al.* 1996; Angrist and Pischke 2009). Because we do not have suitable instruments, we are unable to use IV approach to address the issue of selection bias on unobservable characteristics. Regression discontinuity (RD) data designs can also provide compelling information about impact estimate in situations where assignment to treatment depends on a continuous variable, such as asset holdings, and where the probability of treatment changes abruptly at a particular cut-off value of that continuous variable (Hahn *et al.* 2001). Nevertheless, dairy development interventions in the study area were not assigned based on such criterion, and hence, regression discontinuity designs are not applicable in this context.

Assuming that technology adoption is a function of a wide range of observable characteristics at household level, which rules out potential unobserved explanatory characteristics, propensity score matching (PSM) (Rosenbaum and Rubin 1983) provides a more flexible approach to estimate the potential effects of technology adoption on welfare outcomes using observational data. Inverse probability weighting estimator with regression adjustment (IPWRA) models both the outcome and the treatment to account for the nonrandom treatment assignment (Cattaneo 2010). Given the nature of data generation process and the institutional context governing treatment assignment, this article employs PSM and IPWRA to examine the difference in nutritional and income outcome potentials between adopters and nonadopters of dairy technologies in rural Ethiopia.

2. Dairy production and technology use in Ethiopia

The dairy sector in Ethiopia is characterised by the dominance of smallholder farmers who keep low productive indigenous cattle, hardly use technological inputs and face underdeveloped markets for inputs and outputs (Staal *et al.* 1997). About 81 percent of the total annual milk production is accounted by low-yielding indigenous cattle. The national average daily milk yield from indigenous dairy cows is 1.9 litres per cow (Tegegne *et al.* 2013). As noted above, several technologies such as cross-bred dairy cows and improved forages have been promoted in Ethiopia to enhance the productivity of dairy cattle since 1960s (Staal et al. 1997). Due to their relative importance to the success of improved dairy production, we consider welfare effects of adopting cross-bred dairy cows and improved forages as the two important dairy development interventions in this study.

2.1 Cross-bred dairy cows

Initial efforts on dairy development in Ethiopia were based on the introduction of high-yielding cattle in the highlands (Staal and Shapiro 1996). Various government programs and several projects have distributed cross-bred dairy cattle (Staal and Shapiro 1996; Ahmed *et al.* 2004). Hence, ownership of cross-bred dairy cows is considered an important indicator of dairy technology adoption.

2.2 Improved forages

General scarcity of feeds and poor quality of feeds are the major constraints to livestock production in mixed crop–livestock farming systems (Ayele *et al.* 2012). To alleviate the shortage of livestock feed, improved forage technologies such as planted fodder crops, multipurpose trees, pasture improvement and management, feed conservation technologies and the use of agro-industrial by-products have been promoted (Lenné and Wood 2004). The use of cultivated fodder such as elephant grass, oats-vetch, forage legumes and multipurpose trees by small households is considered as adoption of improved forage technologies in this study.

3. Methodology

3.1 Conceptual framework

Coherent impact analysis needs to view technology adoption within a conceptual framework that treats potential adopters as agents who make decisions in their own best interest (Singh *et al.* 1986; Foster and Rosenzweig 2010). Adoption and input use are the outcomes of optimising by heterogeneous agents. Adopters have characteristics, both observed and unobserved, that make adoption profitable in expectation. This optimisation takes place in the presence of constraints on household's access to farm resources, information, credit and the availability of both the technology and other inputs. We assume that a farmer adopts a dairy technology that maximises utility subject to household demographic characteristics, household resource endowments and other determinants. The marginal utility of technology adoption with respect to technology k can be expressed as follows:

$$\frac{\partial U(x)}{\partial x_k} = \left(\frac{x_k}{\gamma_k} + 1\right)^{\alpha_k - 1} \left\{ \varphi_k + \sum_{m=1}^{k} \theta_{km} \frac{\gamma_m}{\alpha_m} \left[\left(\frac{x_m}{\gamma_m} + 1\right)^{\alpha_m} - 1 \right] \right\} \tag{1}$$

where $\frac{\partial U(x)}{\partial x_k}$ is marginal utility with respect to the adoption of a vector of technologies, x_k ($x_k \geq 0$ for all k), and φ_k, γ_k *and* α_k are parameters associated with technology k.

3.2 Estimation strategy

Because the dairy development interventions were not randomly assigned to households and some households self-selected into adopting the technologies, we use the quasi-experimental research design to estimate the impact on household level outcomes (Imbens and Wooldridge 2009). In a quasi-experimental research design, as is the case with this study, assignment of subjects to the intervention and comparison groups is nonrandom. As it is well known in the program evaluation literature, however, counterfactual outcomes are unobservable as an individual is either in one state or the other at a point in time. A few econometric techniques are available to identify a nontreated group that is statistically and reasonably similar to the treated group to construct the missing counterfactual – what would the economic outcomes have been for technology adopters had they not adopted the technologies. Propensity score matching (PSM) has been widely used to examine the impacts of technology adoption on household welfare using data collected through nonexperimental study designs (Rosenbaum and Rubin 1983; Takahashi and Barrett 2013; Imbens 2014). PSM method strives to overcome the selection bias that may arise due to nonrandom assignment of project participants by creating a comparison group of nonproject participants that are as similar as possible in all relevant preproject participation characteristics to the group of project participants (Rosenbaum and Rubin 1983). PSM method controls for observable characteristics and tests for the robustness of results to handle the unobservable characteristics. PSM approach balances the observed distribution of independent variables across the project participants and nonparticipants based on observables.

More formally, we define two outcomes and a treatment indicator:

Y_{1i}denotes the outcome for a household 'i' with treatment (within the present context, treatment denotes the observed adoption decision);

Y_{0i} denotes the outcome (within the present context, household income or dietary diversity score) for household 'i' without treatment; and

T_i0, 1 indicates treatment status for household 'i'.

Because a given household can only experience one of the two outcomes, we have the observation equation:

$$Y_i = T_i Y_{1i} + (1 - T_i) Y_{0i} \tag{2}$$

where Y_i denotes the observed outcome for household 'i'. We use 'treatment' as a generic term for programs and policies.

For treated household, we observe the treated outcome while the untreated outcome remains counterfactual. For the untreated household, we observe the untreated outcome while the treated outcome remains counterfactual. The difference between the treated outcome and untreated outcome defines the unobserved treated (or causal) effect for each household:

$$\delta_i = Y_{1i} - Y_{0i} \tag{3}$$

The literature focuses on particular average of δ_i, where the choice of which average depends on the policy question of interest, subject to constraints following from the identification strategy and the data. The most common causal estimand is the average treatment effect on the treated (ATT), given by:

$$\text{ATT} = E(Y_1 - Y_0 | T = 1) \quad (4)$$

This parameter informs a cost-benefit analysis that addresses the question of whether to keep or scrap a program in its present form.

Kernel matching (KM) was used in this study as it is known to produce the best balanced statistics (Caliendo and Kopeinig 2008; Becerril and Abdulai 2010). Kernel matches are based on a weighted average of the individuals in the comparison group, and the weight is proportional to the propensity score distance between the treated and untreated. The advantage of kernel matching is greater efficiency, as more information is used; however, the disadvantage is that matching quality may be limited, due to use of observations that may be bad matches (Caliendo and Kopeinig 2008).

To test sensitivity of estimated impacts of the treatment using PSM to unobserved confounding variables, we calculate Rosenbaum bounds. This method relaxes the assumption of selection on observables and assesses how strongly an unmeasured variable must influence selection to undermine the implications of the matching analysis (Rosenbaum 2002).

Inverse probability weighting estimator with regression adjustment (IPWRA)

The PSM method is basically built on a strong assumption that independent variables account for the selection process into the treatment and control individuals' conditions (selection on observed variables assumption). The PSM model could be sensitive to bias when the treatment model or the outcome model is affected by confounding unobservable factors (Imbens 2015). Furthermore, propensity score matching does not perform well in small samples in comparison with other estimators. In light of the emerging literature on these issues (Rosenbaum 2002; DiPrete and Gangl 2004), we had concerns that the estimated treatment effect by PSM may be biased due to unobservable factors. Therefore, we checked the robustness of PSM estimates using inverse probability weighting estimator with regression adjustment (IPWRA) (Cattaneo 2010). The IPWRA estimator has the double-robust property, which means that the estimates of the effects will be consistent if either the treatment model or the outcome model are misspecified (Cattaneo 2010). The doubly robust estimator give us an extra opportunity to achieve correct specification. The IPWRA estimator models both the outcome and the treatment to account for the nonrandom treatment assignment (Abadie and Imbens 2006, 2011; Cattaneo 2010). The IPWRA estimator uses weighted regression coefficients to compute averages of treatment-level predicted outcomes, where the weights are the estimated inverse probabilities of treatment (detailed model expression is given in Cattaneo 2010).

3.3 Data

The data used for this study were derived from a farm-household survey conducted in seven districts in Ethiopia during June–July, 2012. The seven districts were selected purposively based on representativeness of the mixed crop–livestock farming system and suitability to dairy farming. The data were collected using a pretested structured questionnaire by trained enumerators with a good knowledge of the farming systems and fluency in the local languages. The questionnaire was completed using interviews with the household head or in his/her absence, the most senior household member available. The variables of interest included information on household demographic characteristics, household farm resources and household assets, the inventory of crop and livestock production activities, use of modern livestock technologies, household access to extension services, the distance a household resides from input and output markets and household monthly expenditure. In this study, household income and dietary diversity scores are used as welfare indicators in the impact evaluation. We used household monthly expenditure rather than income as a proxy to the measure of household income. Consumption is generally believed to provide better evidence of the standard of living than income. First, by virtue of consumption smoothing, income fluctuates less in the short run compared to income. Second, income provides information over the consumption bundle that fits within the household's budget. Third, an income survey may not capture informal, in-kind or seasonal income and may be more susceptible to under-reporting (Banerjee 2015). The questions on monthly expenditure were based on the template for the categories of goods and services in Ethiopian Rural Household Survey Questionnaire (Dercon and Hoddinott 2004). The total monthly expenditure was computed by aggregating all expense categories (e.g. expenses for food items, clothes, school fees, weddings, funerals, loan repayment, membership fees to local organisations, church donations). Household dietary diversity scores (HDDS) are increasingly used as measures of food security and as a proxy for nutrient adequacy in recent years (Swindale and Bilinsky 2006; Beegle *et al*. 2012; Behnassi *et al*. 2013). The HDDS is defined as the number of food groups consumed during the last seven days (Swindale and Bilinsky 2006; Keding *et al*. 2012). In the questionnaire, we included questions regarding the number of food types or food groups consumed during the last seven days to estimate HDDS. The HDDS is a continuous score from 0 to 12. Food items were categorised into 12 different food groups with each food group counting towards the household score if a food item from the particular group was consumed by anyone in the household in the previous 7 days. The food groups used to calculate the modified HDDS included cereals, roots and tubers, vegetables, fruits, milk and milk products, meat, eggs, fish, pulses and nuts, oils and fats, sugar and condiments (Swindale and Bilinsky 2006; Andrew *et al*. 2010).

Table 1 Mean differences in key farm resources and welfare indicators between adopters and nonadopters of improved dairy technologies in Ethiopia

Variables	Cross-bred dairy cows			Improved forages		
	Adopters (n = 30)	Nonadopters (n = 639)	Diff.	Adopters (n = 49)	Nonadopters (n = 609)	Diff.
Household dietary diversity score (HDDS)	5.63	4.54	1.09***	5.33	4.51	0.82***
Household income(US$)	286.57	66.29	220.28***	141.19	71.62	69.57***
Age of household head (years)	51.90	46.74	5.16	47.47	46.93	0.54
Gender of household head (1 = Male)	0.87	0.84	0.023	0.98	0.83	0.15***
Marital status of household head (1 = married)	0.87	0.84	0.03	0.92	0.83	0.09
Education level of household head (years)	3.97	4.07	−0.11	3.73	4.10	−0.36
Number of family members of working age	5.23	3.63	1.60***	4.16	3.67	0.50
Dependency ratio	0.53	0.85	−0.32**	0.82	0.83	−0.02
Total land holding (ha)	1.22	1.74	−0.53	1.21	1.76	−0.55*
Total livestock holding (TLU)	5.76	5.20	0.54	5.26	5.24	0.03
Oxen holding (TLU)	2.27	1.85	0.42	1.92	1.86	0.06
Access to mobile telephone (1 = yes)	0.70	0.33	0.37***	0.55	0.34	0.22***
Distance to nearest market centre (km)	8.48	9.27	−0.79	11.34	4.26	7.08***
Distance to Farmer Training Centre (km)	3.52	4.84	−1.33	11.7	9.03	2.67**

Notes: ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$

4. Results and discussion

4.1 Descriptive statistics

Summary statistics on equality of means show differences between adopters and nonadopters of cross-bred dairy cows and improved forages with respect to household dietary diversity scores, income, number of family members of working age, dependency ratios and access to mobile telephone (Table 1). Compared to nonadopters of cross-bred dairy cows, farmers who own cross-bred dairy cows and have planted improved forages have a higher dietary diversity score and income. Moreover, adopters and nonadopters of improved forages differ with respect to gender of household head, distance to nearest market centre and distance to farmers' training centre.

The average mean difference in outcome variables presented in Table 1 may mask the actual differences between adopters and nonadopters. For example, when adoption of cross-bred dairy cows is considered, the average household income for adopters is 220 US$ per month. Attributing such a large difference to the use of cross-bred dairy cows could be misleading. In the next section, we present results of the adoption model as a selection process, to assess whether expected benefits of the technologies drive farmers' technology adoption. Simple comparisons of households who adopted dairy

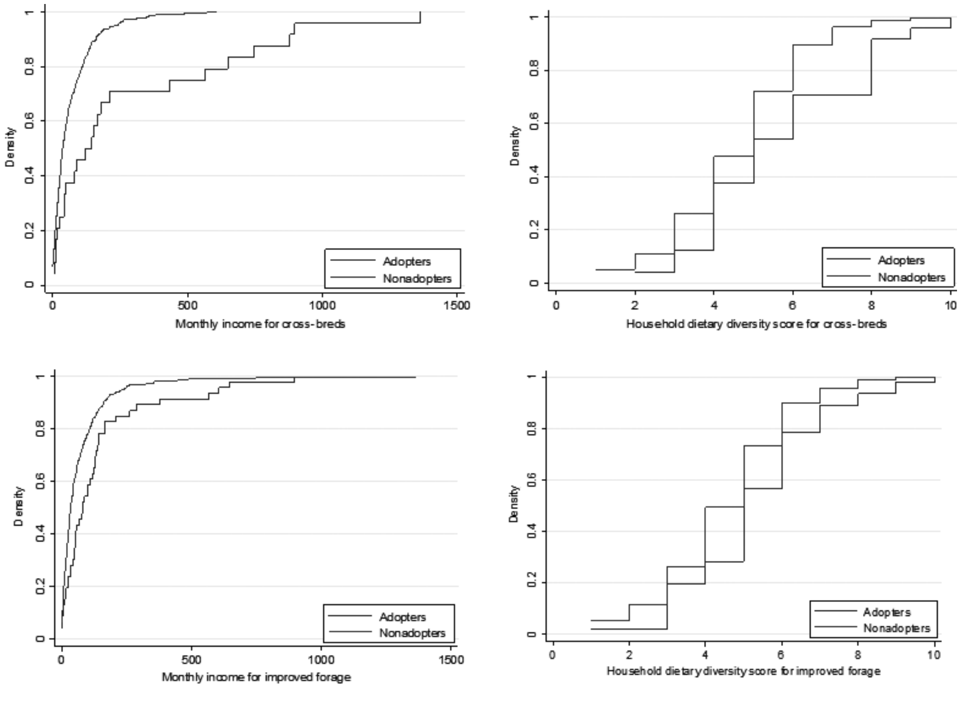

Figure 1 Cumulative distribution functions (CDFs) of income and nutrition for adopters and nonadopters of cross-bred dairy cows and improved forages.

technologies and those who did not suggest that adoption raise the participation rate of their income by 220 US$ per month.

Furthermore, the differences in the outcome distributions of adopting and nonadopting groups produced by stochastic dominance analysis show the income of adopters of cross-bred cows and improved forages in our sample tends to surpass that of nonadopters at income higher levels (Figure 1). Similarly, the differences in the distributions of nutritional adequacy for adopting and nonadopting groups show the nutritional adequacy of adopters of cross-bred cows and improved forages in the sample surpasses that of nonadopters as HDD scores increases. However, comparing the differences in the outcome distributions is not conclusive.

4.2. PSM results

In the logit model used for estimation of propensity scores, the likelihood ratio tests for cross-bred dairy cows [(χ^2 (6) = 23.22, P < 0.00] and for improved forages [χ^2 (6) = 26.30, P < 0.00] indicate that the included independent variables have adequately estimated the propensity scores. The likelihood ratio test results show that the logit model fits propensity scores well using the data. After matching, pseudo-R^2 was 0.13 for cross-bred cows and 0.06 for improved forages, which is fairly low. The number of family members of working age and ownership of mobile telephone had a positive effect on adoption of cross-bred dairy cows. Other independent variables were not significant. In the estimation of propensity scores for improved forages, the number of family members of working age had a positive and statistically significant effect. Education level of household head and the number of livestock owned (TLU) had negative and statistically significant influences on the adoption of improved forages.

Table 2 reports the marginal effects of probit model estimates of household's use of cross-bred dairy cows and improved forages. The estimated effects of using cross-bred dairy cows and improved forages on household income were positive and statistically significant. The significant parameter estimates mean that adopting dairy technologies (cross-bred cows and improved forages) increases household income. This result is consistent with the finding of positive effect of using dairy technologies on household income in the PSM and IPWRA estimates reported below. On the contrary, the effect of using dairy technologies on household dietary diversity score (proxy measure of household food adequacy) was positive but statistically insignificant. The difference in the estimates from the two approaches may occur because, unlike the PSM results, the probit estimates use all nonadopter households (whether good counterfactuals or not) and have no mechanism for dealing with sample selection issues.

Visual inspection of the density distributions of the estimated propensity scores for adopters and nonadopters of cross-bred dairy cows and improved forages showed no significant differences in covariate distributions. The

Table 2 Marginal effects of probit model estimates

Variables	(1) Cross-bred cows	(2) Improved forages
Sex (1 = male)	−0.0180	–
	(0.0285)	–
Age (years)	0.0004	0.0019*
	(0.0008)	(0.0011)
Education (year)	−0.0112*	0.0041
	(0.0060)	(0.0100)
Family labour(adult equivalent)	0.0102**	0.0008
	(0.0049)	(0.0069)
Total cropped area (ha)	−0.0049	−0.0204***
	(0.0059)	(0.0071)
Livestock holdings (TLU)	−0.0003	0.0039
	(0.0018)	(0.0028)
Household expenditure (‘000 USD)	0.0002***	0.0003***
	(8.83e−05)	(9.58e−05)
Household dietary diversity score (HDDS)	0.0128	0.0012
	(0.0080)	(0.0091)
Ownership of mobile telephone	0.0472**	0.0434
	(0.0207)	(0.0294)
Distance to market centre	−0.0001	0.0002
	(0.0002)	(0.0002)
Distance to farmer’s training centre	−0.0002	−3.80e−05
	(0.0003)	(0.0004)
District dummy1	–	−0.1110
		(0.0714)
District dummy2	–	0.0141
		(0.0537)
District dummy3	−0.2410***	−0.0672
	(0.0812)	(0.0742)
District dummy4	−0.3070***	0.0711
	(0.0859)	(0.0504)
District dummy5	−0.1500**	0.0185
	(0.0613)	(0.0487)
District dummy6	−0.1440**	−0.0428
	(0.0632)	(0.0602)
District dummy7	−0.2240***	–
	(0.0757)	–
Observations	307	339

Notes: Standard errors in parentheses; ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$.

density distribution of the estimated propensity scores for adopter and nonadopters of cross-bred dairy cows show overlap in covariate distributions of the adopters and nonadopters. There are observations with identical propensity score values between adopters and nonadopters. Therefore, the common support assumption is fairly satisfied as there was no significant difference in the pretreatment variables or covariate distributions for adopters and nonadopters of cross-bred dairy cows (Figures 2, 3).

The density distribution of the estimated propensity scores for adopters and nonadopters of improved forages also shows overlap in covariate distribution. A visual inspection of the density distributions of the estimated

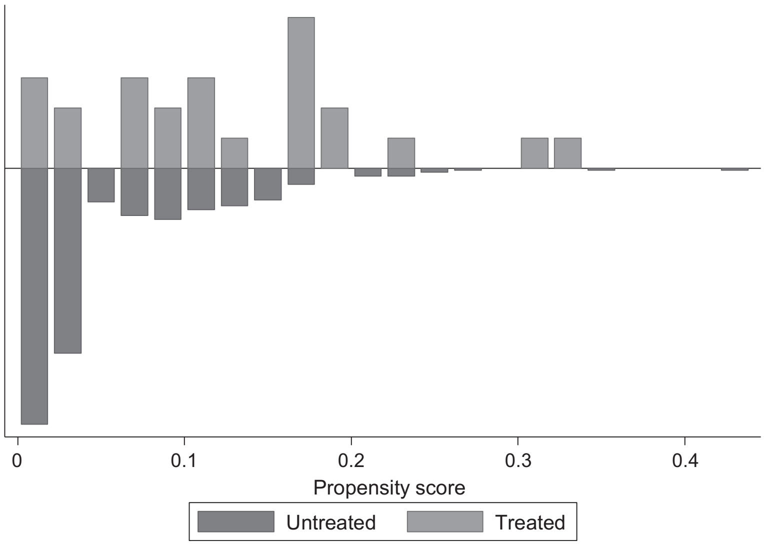

Figure 2 Propensity score distribution and common support for propensity score estimation of cross-bred dairy cows.

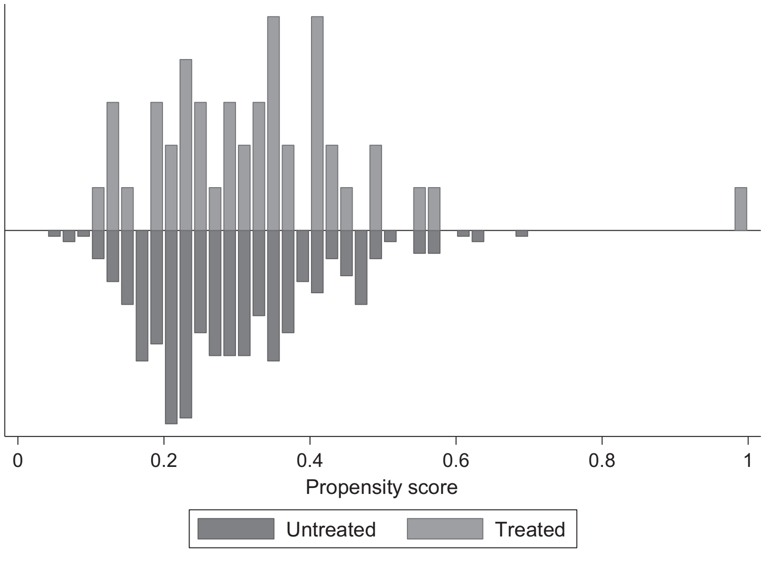

Figure 3 Propensity score distribution and common support for propensity score estimation of improved forages.

propensity scores for the two groups indicates substantial overlap in the distribution of the propensity scores of both adopter and nonadopter groups (i.e. the common support condition is satisfied). The balancing test results also show that the subsample of the original data set is balanced in the independent variables for both cross-bred dairy cows and improved forages.

Rosenbaum bounds sensitivity analysis results

The sensitivity analysis results reported in Table 3 show that PSM impact estimates are mildly robust to hidden bias due to unobserved factors. The estimated causal effects of adopting cross-bred dairy cows on both household dietary diversity score and household income were sensitive to hidden bias due to unobserved factors at gamma level 1 (Table 3). Often, differences in institutional, economic and cultural environments account for the unobserved heterogeneity among households (Kabunga *et al.* 2012, 2014). Counter intuitively, the sensitivity of PSM results implies that the difference in technology adoption and impact among households could be hidden behind unobserved factors. These factors could interfere with determination of the impact of dairy technology adoption. Sensitivity to hidden bias calls for the use of an alternative estimation strategy to check the robustness of the PSM average treatment effect estimates.

On the other hand, estimated causal effects of adopting improved forages on both household dietary diversity score and household income were sensitive to hidden bias due to unobserved factors at gamma level 2 and 3 (see Table 3). This means selection on unobservable characteristics would need to be more than twice as large as the selection on observables to eliminate the estimated causal effects of adopting improved forages on both household dietary diversity score and household income. The results show that bias due to selection on unobservables is not severe enough to invalidate the causal effects of adopting improved forages on both household dietary diversity score and household income.

PSM impact results of dairy technology adoption on household nutrition and income

The PSM results show that adoption of cross-bred dairy cows and improved forage technologies increases household dietary diversity and income (Table 4). Adopting cross-bred dairy cows increases household income for

Table 3 Rosenbaum bounds sensitivity analysis on effect of unobserved factors on dairy technology adoption

Adoption of:	Household welfare indicator	$\Gamma = 1$	$\Gamma = 2$	$\Gamma = 3$
Cross-bred dairy cows	HDDS	1.00	L: 2.00** U: −0.01	L: 2.50*** U: −0.50***
	Income	103.06**	L: 310.96 U: 24.25***	L: 395.00*** U: −2.82
Improved forages	HDDS	0.50	L: 1.00 U: −0.50***	L: 1.50 U: −1.00
	Income	−5.90	L: 28.56 U: −34.41***	L: 51.18 U: −54.01***

Notes: ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$.

Table 4 PSM results of cross-bred dairy cows and improved forages adoption effects on household nutrition and income

Intervention	Household welfare indicator	PSM by Kernel matching	
		ATE	ATT
Cross-bred dairy cow	Dietary diversity score	1.06	0.84***
	Income	268.46	228.46***
Improved forages	Dietary diversity score	0.90	0.66***
	Income	65.65	63***

Note: ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$.

adopters. The results suggest that improved forage adoption has a positive effect on household income but an insignificant effect on household nutrition. The results also show that adoption increases household nutrition. The PSM estimates show that farmers who adopted cross-breed dairy cows have 0.69 higher dietary diversity score and 217 US$ higher household income per annum than their nonadopter counterparts. Similarly, for a randomly selected individual, adoption of improved forages increases household dietary diversity score by 0.66 and household income by 63 US$. Adoption impact of cross-bred dairy cows and improved forage on household nutrition appears to be comparable. The positive impact of using dairy technologies on household nutrition and income is consistent with the perceived role of new agricultural technologies in reducing food insecurity and poverty (Kristjanson *et al*. 2007; Jera and Ajayi 2008).

4.3. Results of IPWRA estimator on effect estimator results of dairy technology adoption impacts on household nutrition and income

The impact estimates by IPWRA show that adopting cross-bred dairy cows and improved forage has a positive and considerable impact on household income. Adoption impact of cross-bred dairy cows on household income appears to be much higher than that of improved forages. A lower magnitude of ATT with PSM as compared to that of IPWRA estimator could be attributed to selection bias arising from unobservable characteristics that may have affected adoption decision and outcome.

These results imply that use of cross-bred dairy cows increases household nutrition and income. Similarly, adoption of improved forages would have increased household dietary diversity score and income by the small amounts shown in the table if they had adopted (Table 5). As compared to PSM, the magnitude of counterfactual dietary impacts with respect to household dietary diversity score and income estimated by the inverse probability weighting estimator with regression adjustment are relatively higher. The difference in the magnitudes of counterfactual impacts between the two methods could be due to bias resulting from unobserved factors that lead to underestimation and overestimation of treatment effects by PSM. The results

Table 5 Results of IPWRA estimator of cross-bred dairy cows and improved forages adoption effect on household nutrition and income

Intervention	Household welfare indicator	Impact	
		ATE	ATT
Cross-bred dairy cow	Dietary diversity score	1.51***	0.85**
	Income	303.08***	213.48***
Improved forages	Dietary diversity score	0.69***	0.65**
	Income	49.99*	61.04**

Notes: ***P < 0.01; **P < 0.05; *P < 0.1.

of inverse probability weighting estimator with regression adjustment are also valid only for a subsample of households more balanced in the independent variables. Given the differences in biophysical, institutional, and economic environments facing different groups of farmers, households' decisions not to adopt technically beneficial technologies could actually be an optimal decision for majority of resource poor farmers (Zewde 2002; Deininger and Jin 2006). Hence, unobserved heterogeneity among smallholders could be the reason why many farmers appear to avoid the technologies promoted for their supposed benefit in sub-Saharan Africa.

5. Conclusion and policy implications

This study examined the difference in household nutrition and income between adopters and nonadopters of dairy technologies using propensity score matching method and inverse probability weighting estimator with regression adjustment. The results show that adopting improved dairy technologies generally increases household nutrition and income. Particularly, adopting cross-bred dairy cows has a substantially higher effect on household income for adopters. The impact is particularly strong for farmers with better resource endowment. The impact estimates using the inverse probability weighting estimator with regression adjustment were consistent and comparable with the impact estimates by PSM.

The significant household nutrition and income impact for adopters supports the notion that many Ethiopian smallholders have not adopted dairy technologies because adopters and nonadopters of dairy technologies have inherent differences in welfare outcome potentials. The result confirms the rationale behind resource constrained farmers' persistent rejection of cross-bred dairy cows despite many years of research and development efforts. Furthermore, other factors, such as supply chain bottlenecks, appear to drive underinvestment in dairy technologies in rural Ethiopia. Missing or incomplete value chains for inputs and outputs and institutional and policy barriers are often overlooked factor affecting the profitability of modern inputs. These findings imply that if the Ethiopian government is serious about increasing the productivity of dairy cows through greater adoption of modern inputs, it should focus on interventions that enhance access to farm resources and lowering the transaction costs arising from bottlenecks in the inputs and output supply chains and institutional and policy barriers.

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