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The impact of adoption of milk safety practices on food and nutrition security: Evidence from smallholder dairy farmers in Ethiopia

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ABSTRACT

Despite the progress observed over the past decades, food and nutritional insecurity remain the prominent challenges in Ethiopia. In this respect, improved farming practices and productivity-enhancing agricultural technologies have been identified as pathways out of these problems; these technologies are the priority agenda of the government policy in Ethiopia. Nonetheless, the impact of the adoption of milk safety practices on dairy farmers' food and nutrition security has not yet been addressed, especially at the smallholder farmers' level. The aim of this study was to evaluate the impact of the adoption of milk safety practices on dairy farmers' food and nutrition security in Ethiopia, using primary data collected from 410 dairy farmers. Generalized propensity score matching was used to evaluate the heterogeneous impact of the adoption of milk safety practices on the household food and nutrition security indicators (per capita food consumption expenditure and food consumption score). The findings reveal that the adoption of milk safety practices had a moderate impact on food consumption expenditure but had no significant impact on food consumption score. An ordered probit endogenous switching regression was also used to account for unobserved bias and check the robustness of the generalized propensity score estimates. Accordingly, the results are similar to the generalized propensity score estimates, and unobserved bias was not a problem. In general, the impact of adoption of milk safety practices on food and nutrition security of smallholder dairy farmers is moderate in Ethiopia. This might be because of the high compliance costs with the adoption of milk safety practices and the lack of quality-based pricing systems. Hence, creating an enabling environment, which in turn, encourages the adoption of milk safety practices would help improve positive effects of the adoption of milk safety practices on food and nutritional security.

1. Introduction

Ethiopia, Africa's second most populous country with over 115 million people according to the 2020 estimates (WB, 2021), is highly dependent on agriculture, which accounts for 32.5 % of the country's GDP (NBE, 2021). Ethiopia is also known for its large number of livestock whose products play a vital role in the national economy, in providing cash for household needs and serving as insurance for smallholder farmers in the times of crop failure (CSA, 2021).

Despite the rapid economic growth observed over the past decades, food insecurity, and malnutrition remain the prominent challenges in Ethiopia (WB, 2021). Before the northern Ethiopia's war started in November 2020, 8 million people in Ethiopia needed food assistance, about 5.9 million people were in acute food insecurity, and over 3.9 women and children were nutritionally insecure (WFP, 2020). Food and

nutrition insecurity problems were made worse by the effects of climate-related shock such as drought, flood and the invasion of desert locusts, which resulted in the loss of livelihoods of millions of people and exacerbated the food and nutrition insecurity problems in Ethiopia (FAO, 2020).

In this respect, climate smart and productivity enhancing agricultural technologies are identified as pathways out of food and nutrition insecurity problems (Feyisa, 2020; Shita et al., 2021; Zegeye et al., 2022). These are currently the priority agenda of the government policy in Ethiopia. As a result, several studies have been conducted on the evaluation of the impacts of improved agricultural technologies on food and nutrition insecurity, poverty, and welfare in Ethiopia (Asfaw et al., 2012; Shiferaw et al., 2014; Kassie et al., 2014; Khonje et al., 2015; Ahmed et al., 2017; Jaleta et al., 2018; Sileshi et al., 2019; Zegeye et al., 2022).

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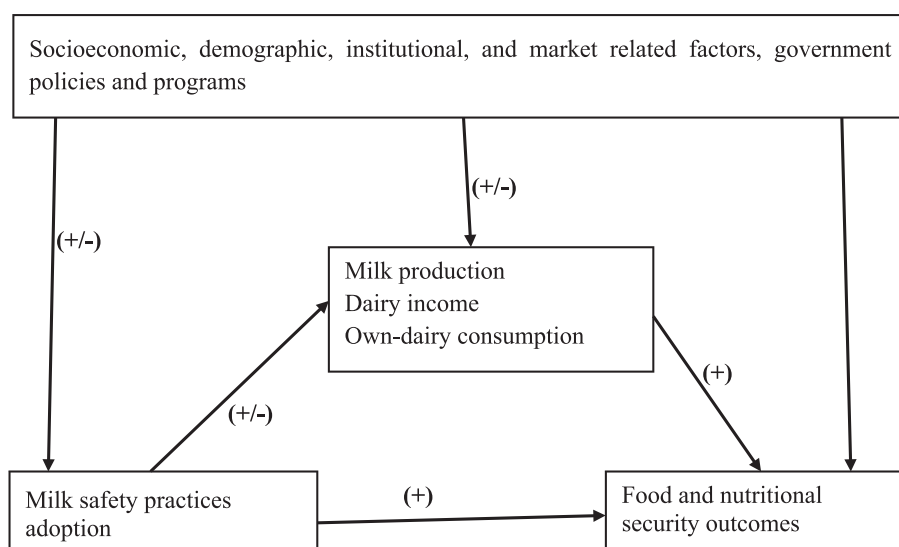


Fig. 1. Conceptual framework linking adoption of milk safety practices with food and nutritional security outcomes. Source: Authors.

Three important things are observed from the growing empirical studies conducted on the impact of agricultural technologies adoption in developing countries in general and Ethiopia in particular. First, most studies have treated agricultural technology adoption as a binary treatment and evaluated the impact of agricultural technology adoption by estimating the average difference in outcome indicators between adopters and non-adopters of agricultural technologies (Asfaw et al., 2012; Khonje et al., 2015; Ahmed et al., 2017). However, it is evident that heterogeneity of the adoption across adopters of a particular agricultural technology leads to heterogeneous impacts on the adopters (Kassie et al., 2014; Jaleta et al., 2018; Letaa et al., 2020). Secondly, though previous studies have focused on the impact of a particular agricultural technology, it is increasingly recognized that farmers adopt multiple agricultural technologies, and evaluation of the impact of multiple agricultural technologies has been receiving greater attention in recent years (Kassie et al., 2018; Biru et al., 2020; Tiruneh and Wassie, 2020; Zegeye et al., 2022). Finally, it is also observed that the impact of the adoption of improved seed varieties, fertilizers, and soil and water conservation practices have dominated the literature. This indicates that little attention has been paid to the livestock sector in general and the dairy sub-sector in particular.

However, the contribution of dairy sub-sector to the country's national income, employments, livelihoods, and food and nutrition security is significant (Shapiro et al., 2015; CSA, 2021; Duguma, 2022). As a result, the government of Ethiopia has identified dairy transformation as one way of pulling smallholder farmers out of poverty, and out of food and nutrition insecurity. Consequently, considerable investments have been devoted to the dairy sub-sector over the last two decades; this is despite that the level of dairy transformation in Ethiopia is yet far from the anticipated level (Minten et al., 2020). Therefore, evaluating the impact of dairy technologies adoption will provide important information for evidence-based policy making in Ethiopia.

Nonetheless, very few empirical studies have been conducted on the evaluation of dairy related technologies (Kebebe, 2017; Lenjiso, 2019; Wordofa et al., 2021; Feyissa et al., 2022). However, the focus of these studies has been limited to the evaluation of a particular technology such as improved breed and/or forage technologies. On the other hand, multiple dairy technologies also known as “good dairy farming practices” are increasingly recommended (FAO and IDF, 2011; Shapiro et al., 2015; Kumar et al., 2017). In addition, previous studies have evaluated the impact of these technologies on intermediate outputs such as productivity and income. However, improvements in productivity and/or income do not necessarily lead to higher food and nutrition security

outcomes (Allen et al., 2019). Hence, the impact of milk safety practices adoption on dairy farmers' food and nutrition security has not yet been addressed.

Therefore, this study has two important contributions to the literature. Firstly, it evaluated the impact of multiple recommended milk safety practices on dairy farmers' food and nutrition security indicators: per capita monthly food expenditure and food consumption score. Secondly, unlike similar studies in other countries (Yang et al., 2019; Kumar et al., 2020), the current study focused on smallholder dairy farmers who contribute the majority (98 %) of the milk produced in Ethiopia (Duguma, 2022). Hence, this study tested the following hypothesis to address these research gaps.

The adoption of milk safety practices has no impacts on smallholder dairy farmers' food and nutrition security outcomes.

The remaining part of this paper is organized as follows: the second section presents the conceptual framework, while the third section presents the research methodology employed in this study. The fourth section presents the main findings and discussion, and the last section concludes with suggested policies emanating from the study.

2. Conceptual framework

The adoption of milk safety practices may affect the household food and nutrition security outcomes in different ways. Studies show that the adoption of milk safety practices could lead to better milk production and productivity (Mekonnen et al., 2010), thereby expected to improve the household consumption of own-produced milk, and marketed surplus. While the improved own-milk consumption as a result of increased production and productivity directly affect the household food and nutrition security, income obtained from milk sold will also indirectly affect the household food and nutritional security if the income is used to purchase food. Previous studies also found the adoption of milk safety practices having a positive impact on selling price, milk acceptance by buyers, profitability and income (Kumar et al., 2017; Dongol et al., 2017). Nonetheless, such a strong positive impact of the adoption of milk safety practices on price and income may not be realized in Ethiopia because of lack of quality-based pricing system (Minten et al., 2020; Minten et al., 2023). In addition, due to lack of organized and effective food safety control mechanism in Ethiopia (GAIN, 2022), dairy producers' income gains from adopting milk safety practices may be obstructed.

The conceptual framework presented in Fig. 1 shows the possible pathways via which adoption of milk safety practices affect the

household food and nutrition security outcomes. As such, it was hypothesized to have a positive effect on milk production and own-dairy consumption. It was also hypothesized to have either a positive or a negative effect on dairy income considering the absence of quality controls and premium pricing systems in the study area, as mentioned above. Fig. 1 also highlights other confounders, which are expected to affect the adoption of milk safety practices and the household food and nutritional security outcomes. Hence, we control for the household demographic and socioeconomic characteristics, market, and institutional factors, which may confound the impact of adoption milk safety practices on the household food and nutrition security.

3. Research methodology

3.1. Description of the study area

The study was conducted in two zones of Oromia region: the Oromia Special Zone Surrounding Finfine and East Hararghe Zone. The Oromia Special Zone Surrounding Finfine is located around the central part of Ethiopia while East Hararghe Zone is located in the eastern part of Ethiopia. Like other zones of the country, smallholder farmers take a lion's share in crop and livestock production in these zones (Feyisa et al., 2023). For instance, smallholder dairy farmers in Oromia Special Zone Surrounding Finfine and East Hararghe zone produced over 81.7 and 86.1 million litres of milk during 2020/2021 production year, respectively (CSA, 2021). According to the same source, milk produced by the smallholder dairy farmers of the two zones during the mentioned production year accounts for 9.36 % of the milk produced by the Oromia region and 3.58 % of the national milk production.

3.2. Sampling and data collection methods

A multi-stage sampling procedure was used to select the sample households. The Oromia Special Zone Surrounding Finfine and East Hararghe Zone were purposively selected due to their milk production performance and proximity to the biggest cities (Addis Ababa, Dire Dawa and Harar). Secondly, the districts were stratified as potential milk producing and non-potential milk producing based on the actual milk production data obtained from each zone. Then, three districts from nine districts of East Hararghe zone and two districts from six districts of Oromia Special Zone Surrounding Finfine identified as potential milk producers were randomly selected. In the fourth stage, fourteen kebeles¹ were randomly selected from these districts based on probability proportional to size. Finally, 424 dairy households were randomly selected from these kebeles based on the proportion of population size (number of dairy households) of each kebele.

On the data collection front, a semi-structured questionnaire was prepared and tested on dairy farmers that were not included in the final survey before the actual data collection. After the questionnaire was updated based on the feedback obtained during the pilot survey, experienced enumerators were recruited from Haramaya University and trained before they embarked on data collection. Finally, the household survey was conducted between February and March 2021.

3.3. Measuring the milk safety practices adopted

Several recommended milk safety practices were included in the survey questionnaire as yes or no questions based on the FAO and IDf's (2011) safe milk production guideline and empirical studies conducted in other countries (Yang et al., 2019; Kumar et al., 2020). In addition, open-ended questions were also included into the questionnaire to explore local specific milk safety practices used by dairy farmers to ensure safe milk production.

Based on this, complete list of milk safety practices adopted in the study areas were identified. Secondly, these milk safety practices were classified under four major milk safety categories, namely, animal health, milking hygiene, milk storage and other general hygienic practices following the guidelines provided by FAO and IDf (2011). The intuition behind this classification is that the adoption of a particular practice improves animal health, milking hygiene, milk storage or has effects that are more general. In order to obtain the percentage of milk safety practices adopted by each dairy household out of the total milk safety practices identified, the weighting approach developed by Kumar et al. (2011) was used to account for differences in the contributions of each milk safety category to the safe milk production. Accordingly, weights of 0.25, 0.35, 0.20, and 0.20 were used for animal health, milking hygiene, milk storage and other general hygienic practices, respectively. Then, the milk safety index was computed as:

$$T_i = \sum_{j=1}^z w_j P_j * 100 \quad (1)$$

where T_i , the treatment variable, is the percentage of milk safety practices adopted by the i^{th} dairy farmer (its value lies between 0 and 100), z is the number of categories, w_j is the weight attached to j^{th} milk safety group, and P_j is the proportion of milk safety practices adopted in j category.

3.4. Food and nutrition security indicators

In order to capture the food and nutrition security, monthly food consumption expenditure per adult equivalent (MFCE) and food consumption score (FCS) are used. The total monthly household food consumption expenditure was computed by adding the money spent on purchased food items and market value of own-produced food consumption during the thirty days preceding the survey. Then, the monthly food expenditure per adult equivalent was obtained by dividing the total monthly food expenditure by total household's family size, measured in adult equivalent.

On the other hand, the FCS of the household was computed based on the past seven days consumption recall. Accordingly, a person responsible for food preparations was asked the types and number of days they have eaten different food items during the seven days. Then, the number of days each food group has been eaten was established with the maximum days being seven and zero when none of the household member has eaten a particular food group. In the next step, the number of days each food group was consumed was multiplied by the standard weight, considering the nutritional value of each food group (WFP, 2008). Finally, the FCS of each household was obtained by adding the results obtained in the preceding step.

3.5. Estimation strategies

In theory, impact evaluation studies seek to estimate the casual effect of an intervention (here; the adoption of milk safety practices) on outcome indicators, but practical application of impact evaluation is challenging especially in non-experimental studies (White and Raitzer, 2017). In general, the contexts and available evidence determine the most appropriate impact evaluation design to be used (Deaton and Cartwright, 2018).

In non-experimental studies, matching has been widely used to establish the non-treated group that is as similar as possible with the treated group. Propensity score matching (PSM) method, developed by Rosenbaum and Rubin (1983), is the most commonly used in empirical studies (Ahmed et al., 2016; Sileshi et al., 2019; Wordofa et al., 2021). However, the use of the PSM is limited to a binary treatment, where one of the groups has access to the treatment while the other has no access to the treatment.

Similar to the PSM, Hirano and Imbens (2004) had developed a

¹ Kebele is the lowest administrative unit in Ethiopia.

similar propensity score matching method known as “Generalized Propensity Score” (GPS) when the treatments take a continuous value. Several studies used the method for evaluating the impact on a continuous scale. For instance, Hofmann (2013) analysed the impact of intensity of export on firms’ productivity. Bekele et al. (2018) evaluated the impact of intensity of Prosopis invasion on household food consumption expenditure. Haji (2022) evaluated the impact of agricultural commercialization on child nutritional outcomes in Ethiopia. Other studies (Shiferaw et al., 2014; Jaleta et al., 2018; Letaa et al., 2020), evaluated the impact of the intensity of the adoption of agricultural technologies on food security using the GPS.

As has been indicated, our treatment variable is the percentage of milk safety practices adopted, which takes the value between zero and hundred. Hence, considering the nature of the treatment and the available data, GPS was employed to estimate the heterogeneous impact of the adopted milk safety practices on dairy farmers’ food and nutrition security outcomes. However, it should be noted that similar to the PSM, the GPS takes into account only the observable covariates in matching households in different treatment intervals (Bia and Mattei, 2008; Shiferaw et al., 2014; White and Raitzer, 2017). In this respect, robustness of the GPS estimates was checked using endogenous switching regression, which captures both observable and unobservable biases and pathway analysis were also conducted.

3.5.1. Generalized propensity score estimation

The GPS approach developed by Hirano and Imbens (2004) is briefly explained as follows. Consider a random sample of households, represented by i where $i = 1, \dots, N$. Let $Y_i(t)$ be the potential outcome for household i under treatment level t , $t \in \Gamma$ where Γ is the treatment interval (t_0, t_1) , and t denotes the dosage (the percentage of milk safety practices adopted). For each i , there is a set of potential outcomes $\{Y_i(t)\}$, $t \in \Gamma$ referred to as the individual level dose response function. The main interest in continuous treatment impact evaluation is an average dose–response function, $\mu(t) = E[Y_i(t)]$, which represents the function of the average potential food and nutrition security outcomes over all possible treatment levels. The observed variables for each household i are vector of covariates, X_i , the treatment received, T_i , and the potential outcome corresponding to the level of the treatment received, $Y_i = Y_i(T_i)$.

Like the binary treatment analysis developed by Rosenbaum and Rubin (1983), Hirano and Imbens (2004) generalized the unconfoundedness assumption to a continuous treatment, where the treatment assignment mechanism is independent of each potential outcome conditional on the covariates: $Y_i(t) \perp T_i | X_i$ for all $t \in \Gamma$. Let $r(t, x)$ be the conditional density of the treatment given the covariates: $r(t, x) = f(T | X(t | x))$. Then the generalized propensity score is defined as $R = r(T, X)$. They argue that GPS has a balancing property similar to that of PSM in the sense that, within the strata with the same value of $X: X \perp 1\{T = t\} | r(t, X)$, the probability that $T = t$ for a given individual does not depend on the value of $X: X \perp 1\{T = t\} | r(t, X)$. Moreover, they showed that if the treatment assignment mechanism is weakly unconfounded given the covariates, then it is also weakly unconfounded given the GPS: $Y_i(t) \perp T_i | r(t, X_i)$ for all $t \in \Gamma$.

Following Hirano and Imbens (2004), the GPS was specified and estimated following three steps.

In the first step, the level of milk safety practices adopted was modelled as:

$$T_i | X_i \sim N(\beta_0 + \beta_1' X_i, \sigma^2) \quad (2)$$

Thereafter, β_0 , β_1 and σ^2 were estimated using a maximum likelihood estimation. The estimated GPS was obtained using β_0 , β_1 and σ^2 estimated in equation (2).

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left(-\frac{1}{2\hat{\sigma}^2}(T_i - \beta_0 - \beta_1' X_i)^2\right) \quad (3)$$

The second step involves estimating the conditional expectation of the outcome (in this study, per capita food consumption expenditure and food consumption score) as a function of observed treatment (T_i) and the estimated GPS (\hat{R}_i). Accordingly, the conditional expectation of the outcome was estimated as a function of treatment level, estimated GPS, and interactions between the two.

$$E[Y_i | T_i, R_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 R_i + \alpha_4 R_i^2 + \alpha_5 T_i R_i \quad (4)$$

In the third step, given the parameters estimated in the second step, the average potential outcome at each treatment level t was estimated as:

$$E[\widehat{Y}(t)] = \frac{1}{N} \sum_{i=1}^N (\hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 \hat{r}(t, X_i) + \hat{\alpha}_4 \hat{r}(t, X_i)^2 + \hat{\alpha}_5 t \hat{r}(t, X_i)) \quad (5)$$

3.5.2. Ordered probit endogenous switching regression

Endogenous switching regression (ESR), a non-experimental evaluation design, is gaining popularity in evaluating the impact of treatment on the outcome variable across different contexts (Jaleta et al., 2018; Teklewold et al., 2022; Sileshi et al., 2022; Ahmed, 2022; Issahaku et al., 2023). Hence, we used this evaluation approach to check the robustness of the GPS estimates. The estimation procedure of the ESR follows two separate stages. In the first stage, the selection outcome is estimated using probit when the treatment is binary (Sileshi et al., 2022), while multinomial logit has been widely used when the selection outcome is discrete with more than two categories (e.g., Teklewold et al., 2022). In the second stage, two separate equations often known as “regimes,” were estimated for the outcomes of interest for both treated and control groups separately. Finally, the average treatment effects were estimated for both treated and control groups by comparing the average treatment effect under real and counterfactual for each group.

In order to employ the ESR in this study, we cut the treatment variable into three categories in such a way that the sample households were divided into three comparable groups. Following the works of Kumar et al. (2017); Bekele et al. (2018); and Haji (2022), the 30th and 70th percentiles were used to classify the households into low, medium, and high adoption categories. As such, 122, 163 and 125 households were classified into low, medium and high adoption categories, respectively. This discrete treatment variable is clearly ordered, and modelling the first stage estimation of the ESR using neither probit nor multinomial logit is plausible. Hence, an alternative model, which captures the ordered nature of the treatment variable, should be used. The ordered logit and ordered probit are commonly used in previous empirical studies under such circumstances (Midingoyi et al., 2019; Aweke et al., 2020; Edeh et al., 2022; Zhou et al., 2023). However, both ordered logit and ordered probit are criticized for their parallel lines assumption, which assume that all the slope coefficients are equal across the outcome variables (Williams, 2009). The Brant test of parallel lines assumption was implemented, and all the explanatory variables met the parallel lines assumption. Hence, the ordered probit endogenous switching regression (OPESR) was used in this study. The two stages of OPESR are specified as follows:

First stage: Ordered probit regression

The ordered probit can be constructed on the latent (unobservable) random variable as follows:

$$P_i^* = X' \beta + \varepsilon \quad (6)$$

where P_i^* is unobserved dependent variable, X' is a vector of independent variables, β is unknown parameters to be estimated, and ε is the error term. Since P_i^* is unobserved, what actually observed is P_i which shows the placement of the household into the three adoption categories. Assume the 30th and 70th percentiles are represented by μ_1 and

μ_2 , respectively; the observed ordered outcome P_i , can be defined as:

$$P_i = 1, \text{ if } P_i^* \leq \mu_1 \quad (7a)$$

$$P_i = 2, \text{ if } \mu_1 < P_i^* \leq \mu_2 \quad (7b)$$

$$P_i = 3, \text{ if } \mu_2 < P_i^* \quad (7c)$$

Then, the probabilities of the household being in each adoption category (low, medium and high) can be written as follow:

$$\Pr(P_i = 1) = \Pr(P_i^* \leq \mu_1) = \Phi(\mu_1 - X'\beta) \quad (8a)$$

$$\Pr(P_i = 2) = \Pr(\mu_1 < P_i^* \leq \mu_2) = \Phi(\mu_2 - X'\beta) - \Phi(\mu_1 - X'\beta) \quad (8b)$$

$$\Pr(P_i = 3) = \Pr(\mu_2 < P_i^*) = 1 - \Phi(\mu_2 - X'\beta) \quad (8c)$$

where $\Phi(\cdot)$ represents the standard normal cumulative distribution function such that the sum of the above probabilities is equal to one.

Second stage: Ordinary least squares

In the second step, the outcome equations are specified following Khonje et al (2018), Sileshi et al. (2022), as follows:

$$\begin{cases} \text{Regime1} : Y_{i1} = \beta_1 Z_{i1} + \sigma_1 \hat{\lambda}_{i1} + \omega_{i1} & \text{if } j = 1 \\ \vdots & (i = 1, 2, 3, \dots, n; j = 1, 2, 3) \\ \text{RegimeJ} : Y_{ij} = \beta_j Z_{ij} + \sigma_j \hat{\lambda}_{ij} + \omega_{ij} & \text{if } j = k \end{cases} \quad (9)$$

where Y_{ij} indicates the food and nutrition security outcomes (in this study; per capita monthly food expenditure and food consumption score) of the i^{th} household in j^{th} adoption category; Z_i is a vector of observed explanatory variables, β_j is unknown parameters to be estimated, ω_i is the error term, σ_j is the covariance between the error terms of selection equation and outcome equations, $\hat{\lambda}_j$ is the inverse mills ratio (IMR) computed from the selection equation, which corrects for the households' self-selection bias into different level of adoption.

Previous studies argue that an exclusion variable should be used to identify the second stage estimation (Jaleta et al., 2018; Sileshi et al., 2022). Access to milk safety information was used as an exclusion variable. Di Falco et al. (2011) noted that the exclusion variable must be strongly correlated with the selection outcome while it must not be correlated with the outcome variables. We used a falsification test to check the validity of the exclusion variable, and access to milk safety information was strongly correlated with adoption of milk safety practices while it was not significantly correlated with both food and nutritional security indicators (see Appendix Tables 2 and 4).

Estimating the average treatment effects (ATE)

Following the second stage of the ESR, the average treatment effects of adoption of milk safety practices on the household food and nutritional security indicators were estimated under two separate scenarios for the households in each adoption category. The average treatment effect on treated (ATT) was estimated for households in the medium and high adoption categories by comparing their observed food and nutritional security outcomes (real) with what would have happened to their food and nutritional security outcomes if they were in low adoption category (counterfactuals). The average treatment effect on untreated (ATU) was also estimated for households in a low adoption category by comparing their observed food and nutritional security outcomes (real) with what would have happened to their food and nutrition security outcomes if they were in the medium and high adoption categories (counterfactuals).

Following Midingoyi et al. (2019), Teklewold et al. (2022) and

Sileshi et al. (2022), the observed food and nutrition security and unobserved expected food and nutrition security outcomes of the households (counterfactual scenarios) were specified as follows:

Observed food and nutrition security outcomes of the households in each alternative adoption category (real scenarios):

$$\begin{cases} E(Y_{i1}|j=1) = \beta_1 Z_{i1} + \sigma_1 \hat{\lambda}_{i1} & (\text{real for low adopters}) \\ E(Y_{i2}|j=2) = \beta_2 Z_{i2} + \sigma_2 \hat{\lambda}_{i2} & (\text{real for medium adopters}) \\ E(Y_{i3}|j=3) = \beta_3 Z_{i3} + \sigma_3 \hat{\lambda}_{i3} & (\text{real for high adopters}) \end{cases} \quad (12)$$

Food and nutrition security outcomes of the households if they were in an alternative adoption category (counterfactual scenarios)²:

$$\begin{cases} E(Y_{2i}|j=1) = \beta_2 Z_{i1} + \sigma_2 \hat{\lambda}_{i1} & (\text{low adopters if they were in medium category}) \\ E(Y_{3i}|j=1) = \beta_3 Z_{i1} + \sigma_3 \hat{\lambda}_{i1} & (\text{low adopters if they were in high category}) \\ E(Y_{i1}|j=2) = \beta_1 Z_{i2} + \sigma_1 \hat{\lambda}_{i2} & (\text{medium adopters if they were in low category}) \\ E(Y_{i1}|j=3) = \beta_1 Z_{i3} + \sigma_1 \hat{\lambda}_{i3} & (\text{high adopters if they were in low category}) \end{cases} \quad (16)$$

Then, ATT was obtained as the difference between Equations 11 and 12 and Equations 15 and 16. The average treatment effect of being in the medium adoption category³ was computed as the difference between Equations 11 and 15 for each outcome variables separately. This implies that:

$$\begin{aligned} ATT &= E(Y_{i2}|j=2) - E(Y_{i1}|j=2) = (\beta_2 Z_{i2} + \sigma_2 \hat{\lambda}_{i2}) - (\beta_1 Z_{i2} + \sigma_1 \hat{\lambda}_{i2}) \\ &= Z_{i2}(\beta_2 - \beta_1) + \hat{\lambda}_{i2}(\sigma_2 - \sigma_1) \end{aligned} \quad (17)$$

In the same manner, ATU was obtained by comparing the expected food and nutrition security of the low adopters (Equations 13 and 14) with the Equation 10 for each outcome variable. The ATU of households in the low adoption category if they were in medium⁴ adoption category was estimated as follows:

$$\begin{aligned} ATU &= E(Y_{i2}|j=1) - E(Y_{i1}|j=1) = (\beta_2 Z_{i1} + \sigma_2 \hat{\lambda}_{i1}) - (\beta_1 Z_{i1} + \sigma_1 \hat{\lambda}_{i1}) \\ &= Z_{i1}(\beta_2 - \beta_1) + \hat{\lambda}_{i1}(\sigma_2 - \sigma_1) \end{aligned} \quad (18)$$

3.5.3. Analysing impact pathways

We have estimated several models to show the possible pathways through which the adoption of milk safety practices could affect the household food and nutrition security. Based on the conceptual framework presented in Fig. 1, we first regressed the logs of milk production, dairy consumption and dairy income on the percentage of the adopted milk safety practices. We also added other confounders highlighted in Fig. 1 into the models subsequently to see how the association between the percentages of the adopted milk safety practices and the logs of milk production, dairy consumption, and dairy income change. Following previous studies, which have evaluated the impact pathways of nutrition sensitive agriculture (Hoddinott et al., 2015; Headey and Hirvonen, 2016; Haji, 2022), the following specifications were estimated using the ordinary least squares:

$$Q_i = \beta_0 + T_i \beta_1 + X_i \beta_2 + \varepsilon_i \quad (19)$$

$$C_i = \omega_0 + T_i \omega_1 + X_i \omega_2 + \zeta_i \quad (20)$$

$$I_i = \delta_0 + T_i \delta_1 + X_i \delta_2 + \eta_i \quad (21)$$

where Q_i , C_i , and I_i represent annual milk produced by the i^{th}

² Equations (13) and (14) represent expected food and nutrition security of the households in the low adoption category if they were in the medium and high adoption categories, respectively.

³ The same procedure was followed to estimate the ATT of the households in high adoption category.

⁴ The same procedure was followed to estimate the ATU of the households in low adoption category if they were in high adoption category.

Table 1
Descriptive statistics of the covariates included in this study.

Variable	Description	Mean	SD
Milk produced	Annual milk produced in litres	2017.83	3097.36
Milk consumed	Monthly milk consumed per AE in litres	6.84	6.53
Dairy income	Annual income obtained from dairy in ETB	29484.95	53857.24
Age	Age of the head in years	43.48	11.88
Education	Highest grade completed by the head	3.55	3.99
Active labour	Number independent family members	3.20	1.57
Experience	Dairy production experience in years	20.30	11.23
Family size	Family size in adult equivalent	4.90	1.75
Total land	Total land owned in hectares	1.35	1.88
Farm income	Annual farm income in 000ETB	56.21	81.32
Lactating cows	Number of lactating cows owned	1.75	1.20
Market distance	Distance from market in walking minutes	80.20	55.51
Road distance	Distance from road in walking minutes	38.93	43.30
Off/non-farm	Annual household income from off/non-farm activities in ETB	8610.15	412160.35
Livestock	Livestock owned in tropical livestock unit	6.30	5.49
Dairy training	Dairy related training (yes = 1)	0.17	0.38
Information	Milk safety information (yes = 1)	0.32	0.47
Extension	Obtained extension services (yes = 1)	0.50	0.50
Credit use	Credit utilization during survey year (yes = 1)	0.18	0.38
Cooperative	Member in agricultural cooperative (yes = 1)	0.25	0.43
Crop loss	Lost crops due to external factors (yes = 1)	0.69	0.46
Inspection	Milk has been inspected for safety (yes = 1)	0.27	0.44
Observations	410		

Source: Authors.

Table 2
Descriptive statistics of the treatment and outcome variables.

Variables	Mean	SD	Minimum	Maximum
Treatment				
Percentage of milk safety practices adopted	58.59	9.16	32.48	82.32
Outcome variables				
Monthly food consumption expenditure per AE	1071.64	477.07	207.02	3100
Food consumption expenditure	59.35	16.89	16	107
Observations	410			

AE means adult equivalent.

Source: Authors.

household, per capita milk consumption of the i^{th} household over the last thirty days, and annual dairy income of the i^{th} household, respectively. T_i indicates the percentage of milk safety practices adopted by the i^{th} household, X_i represents explanatory variables, and ε_i , ζ_i , and η_i are the error terms.

3.6. Covariates selection

The selection of valid and rich covariates is vital in the GPS matching algorithm (Bia and Mattei, 2008). However, the selection of covariates is very challenging and it should be done carefully (Caliendo and Kopeinig, 2005). The main question remains here is the criteria as to which the covariates should be included or excluded.

White and Raitzer (2017) argue that including as many covariates as possible is important in estimating the propensity scores. They highlighted that the significance of the first stage coefficients are not important, and covariates, which could improve the balance, should be included, as long as it is not affected by the outcome variable. Moreover, Gertler et al. (2016) also suggest including all the covariates believed to improve the matching, given that they are not affected by the treatment. On the other hand, other authors suggest that only covariates simultaneously affecting both the treatment and outcome should be included (Caliendo and Kopeinig, 2005). Hence, we relied on the previous empirical studies (Shiferaw et al., 2014; Sileshi et al., 2019; 2022; Kumar et al., 2020), and selected important covariates that affects the treatment and/or outcome indicators, but not affected by the treatment (Table 1).

4. Results and discussion

4.1. Descriptive statistics results

The results of descriptive statistics of important covariates included in the study are presented in Table 1. Accordingly, the mean age of the head of the household, maximum education attained, and dairy production experience were found to be 43.48, 3.55, and 20.30 years, respectively. Regarding the family composition, the mean number of the active labour force (persons between the ages of 15–65) and the total family size in adult equivalent were 3.19 and 4.90, respectively.

On the other hand, results presented in Table 1 reveal that the mean total landholding size, total livestock owned in tropical livestock unit, and the number of lactating cows owned during the survey year were 1.35 hectares, 6.29, and 1.75 respectively (approximately 2 cows). Table 1 reveals further that the mean farm income of the sample households was ETB⁵56210, while the mean annual income obtained from participation in off/non-farm income-generating activities was found to be ETB8610.15. The mean annual dairy income was found to be ETB29484.95, which shows that dairy income had a paramount contribution to the household income. The results also show that the mean annual milk produced by the sampled households was 2017.83 litres, while the average own-milk consumed was 6.84 litres per adult equivalent per month.

Table 1 provides further information about dairy related training,

⁵ ETB (Ethiopian Birr) is an official currency of Ethiopia. During the survey period, 1 United States' dollar was equivalent to ETB40.2314.

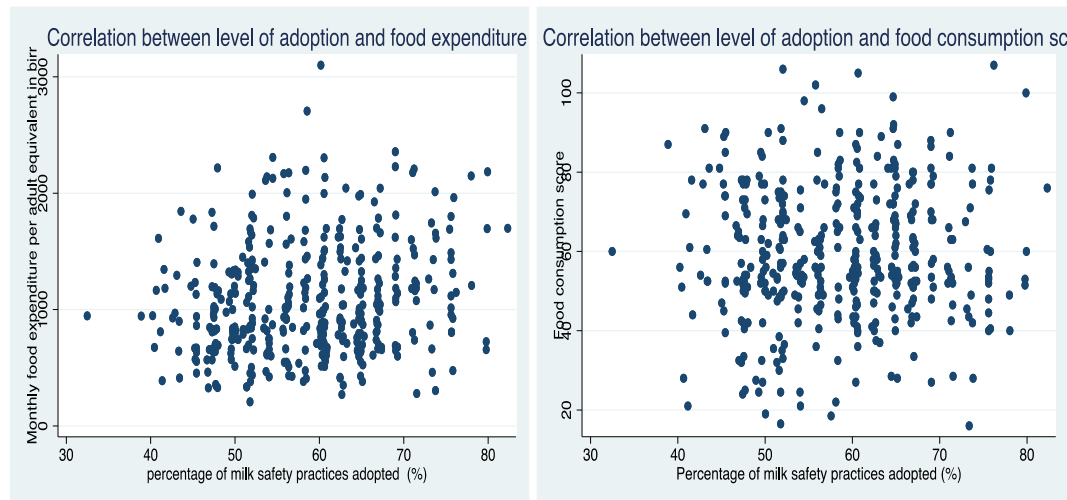


Fig. 2. Unconditional correlation between the treatment and outcome variables. Source: Authors.

Table 3

The estimated GPS: regression of a treatment over the covariates.

Covariate	Coefficient	Standard error
Age	−0.013	1.045
Education	0.502	0.680
Active labour	1.870	3.069
Dairy experience	0.467	0.393
Family size	0.936	3.982
Total land	0.649	1.187
Farm income	−0.011	0.028
Lactating cows	−3.709	3.512
Dairy training	1.925	1.228
Milk safety information	2.854***	1.006
Access to extension	3.512***	0.867
Credit use	0.913	1.108
Cooperative	0.404	1.013
Crop loss	1.178	1.075
Distance from market	−0.002	0.009
Distance from road	0.055**	0.025
Annual off/non-farm income	0.000	0.000
Milk safety inspection	4.066***	0.966
Livestock size	0.215	0.524
Age square	−0.002	0.023
Education square	−0.073	0.138
Active labour square	−0.472	0.655
Dairy experience square	−0.011	0.018
Family size square	−0.329	0.785
Total land square	0.019	0.303
Farm income square	0.000	0.000
Lactating cows square	0.723	1.109
Annual off/non-farm income square	0.000	0.000
Livestock size square	−0.008	0.041
Distance from road square	0.000	0.000
Age cube	0.000	0.000
Education cube	0.005	0.007
Active labour cube	0.029	0.042
Dairy experience cube	0.000	0.000
Family size cube	0.026	0.049
Total land cube	−0.007	0.018
Farm income cube	0.000	0.000
Lactating cows cube	−0.061	0.097
Annual off/non-farm income cube	0.000	0.000
Livestock size cube	0.000	0.001
Constant	49.339***	15.468

*** and ** significant at 1% and 5% significance levels, respectively.

Source: Authors.

milk safety information and dairy producer household experience with milk safety inspection. Accordingly, only 17 and 32 % of the sample households had access to dairy-related training and milk safety information, respectively. Regarding experience with milk safety inspection,

only 27 % of the sample households had reported having their milk inspected for safety during the survey year.

Other essential covariates included are related to institutional variables such as access to extension services, credit utilization and membership in agricultural cooperatives. The result indicates that only 18 % of the sample households had received credit during the survey year while about 50 % of the sample households had received extension services (Table 1). Moreover, about 25 % of the sample households were members of agricultural cooperative. Finally, about 69 % of the sample households had reported crop loss during the survey year due to external shocks, which could highly undermine their food and nutritional security.

Regarding the treatment variable, the summary of milk safety practices adopted is shown in the Appendix Table 1. Overall, 45 milk safety practices were identified in the study areas. However, there is considerable variation in the level of milk safety practices adopted across dairy producer households. On average, only 59 % of the milk safety practices were adopted by dairy producer households (see Table 2). The minimum and maximum milk safety practices adopted by dairy producer households were also found to be 32 and 82 %, respectively. This indicates that the treatment variable takes a continuous value and there were no non-adopters of milk safety practices. As such, the treatment variable satisfies a key underlying requirement for employing the GPS in estimating the causal effects of milk safety practices adopted on dairy producer households' food and nutrition security.

The descriptive statistics of the outcome variables (MFCE and FCS) are also presented in Table 2. The results indicate that the MFCE during the thirty days preceding the survey was ETB1071.64 (\$26.64). The mean FCS computed based on the seven days recall of food consumed by the household was 59.34.

It is also worth indicating the correlation between the treatment and outcome variables before getting into the econometric analysis. As shown in Fig. 2, the correlation between the treatment (percentage of milk safety practices adopted) and the outcome variables looks weak. However, the correlation between the treatment and MFCE (Fig. 2, left) seems stronger than the correlation between the treatment and FCS (Fig. 2, right). Nonetheless, this assures neither the existence nor the absence of causal effects of the treatment on the outcome variables.

4.2. Econometric results

4.2.1. Generalized propensity score estimation results

- The conditional distribution of the treatment given the covariates. The first step in GPS estimation procedures is estimating the

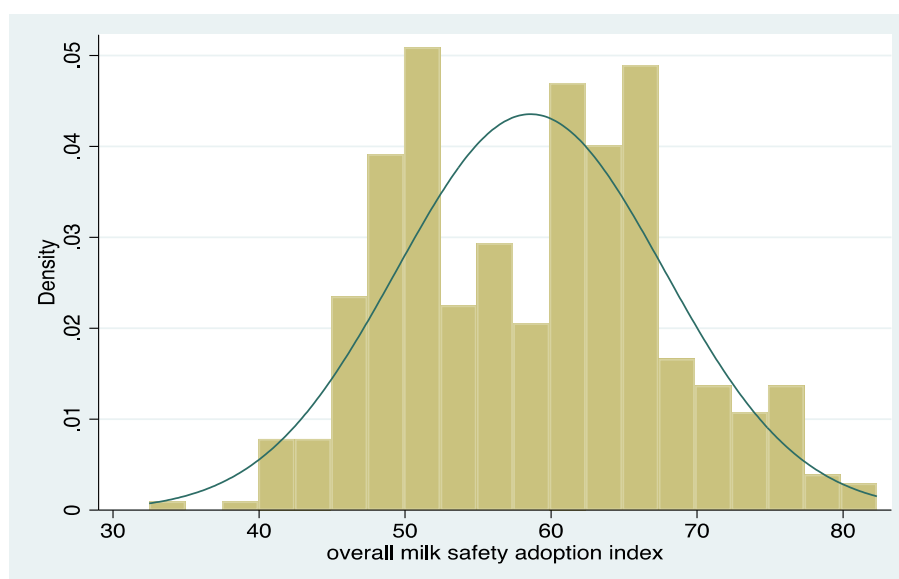


Fig. 3. Distribution of the milk safety practices adopted (%). Source: Authors.

Table 4

Summary of GPS under each treatment interval and common support region.

Treatment interval	Observations	Dosage group	Minimum	Maximum
Treatment ≤ 52.00	410	GPS1	0.0000399	0.0498025
$52.00 < \text{treatment} \leq 64.50$	410	GPS2	0.002453	0.0499232
Treatment > 64.50	410	GPS3	0.0030587	0.0499225
	385	Common support region	0.002453	0.0498025

Source: Authors.

propensity score (the conditional distribution of milk safety practices adopted given the covariates) for each sample household. Hence, in order to estimate the GPS, Equation (2) was estimated by Stata version 17 using “gpscore.ado” Stata package (Bia and Mattei, 2008), and presented in Table 3. The estimated results provide crucial information regarding the fulfilment of the normality assumption of the treatment, the extent to which the covariate balance is achieved given the estimated GPS, and the common support region.

The default test for the normality assumption provided by the “gpscore.ado” Stata package is a Kolmogorov-Smirnov normality test. Accordingly, the treatment variable satisfied the normal distribution assumption at a 5 % significance level. In addition, the values of skewness and kurtosis of the treatment variable were 0.18 and 2.30, which are statistically not different from 0 and 3, respectively. Considering all the evidence provided, the treatment variable is approximately normally distributed (Fig. 3), and further transformation of the treatment variable was not required (Bia and Mattei, 2008).

As the primary purpose of estimating the GPS is obtaining the maximum possible covariate balance and common support region (Bia and Mattei, 2008; White and Raitzer, 2017), squares and cubes of important continuous variables were also included into the model (Table 3). They further highlighted that the multicollinearity and statistical insignificance of the coefficients are not considered as problems. Hence, forty covariates (including the squares and cubes of continuous covariates) were included in Equation (2) in estimating the GPS.

Before turning to the second stage estimation, assessing the covariates balance is critical to see the level of imbalance before and after matching using the GPS. Accordingly, the GPS-unadjusted covariate balance was conducted as follows. The sample households were categorized into three groups based on the level of the treatment received. The 30th and 70th percentiles were used as a cut-off value following Bekele et al. (2018), Kumar et al. (2017) and Haji (2022) to group the

sample households under three groups with comparable sizes. Households whose value of the treatment fall below 30th percentile were classified as low adopters ($n = 122$), and those whose treatment level was between 30th and 70th percentile were classified as medium adopters ($n = 163$), and households with the treatment level higher than the 70th percentile were classified as high adopters ($n = 125$), as indicated before.

Secondly, the mean value of each covariate of low adopters was compared with the mean value of the medium and high adopters combined using t-tests for equality of means. Thirdly, the mean value of each covariate of medium adopters were computed and compared with the mean value of low and high adopters combined. In the fourth step, the mean value of each covariate of high adopters were computed and compared with the mean value of low and medium adopters combined. The results indicate that from the 120 covariates included, the t-values of the twenty-two covariates were greater than 1.68 in absolute value (see Table 5), which indicates decisive evidence against the balancing property according to the rule of thumb (Bia and Mattei, 2008).

In general, the GPS-unadjusted covariates balance indicates the existence of 18 % covariates imbalance. As far as the rule of thumb regarding the maximum acceptable covariate imbalance is concerned, the dose response function (DRF) can be estimated without matching the households based on the estimated GPS. Despite this, it is important to match the households by GPS, see if the GPS improves the matching, and reduce the bias. Previous studies have shown that the GPS has the ability to reduce the covariates imbalance though the pre-matching bias is low (see Kassie et al., 2014; Bekele et al., 2018). Therefore, the households were matched using the estimated GPS, and covariate balancing property of the GPS was checked using the “gpscore.ado” Stata package.

The “gpscore.ado” Stata package tests the covariates balance according to the following steps (see Bia and Mattei, 2008 for details). First, the treatment variable, the percentage of milk safety practices

Table 5

Testing the covariates balance before and after GPS adjustment: t-values for comparison of means.

Covariate	GPS unadjusted			GPS adjusted		
	[32.46–52.00]	[52.00–64.50]	[64.50–82.32]	[32.46–52.00]	[52.00–64.50]	[64.50–82.32]
Age	−0.42	−0.47	0.92	0.76	−0.78	1.08
Education	3.51***	−1.20	−2.17**	1.63	−1.28	−0.04
Active labour	0.00	−0.05	0.04	0.38	−0.20	−0.04
Dairy experience	−0.47	0.26	0.19	−0.11	0.34	0.02
Family size	−0.32	1.06	−0.80	−0.39	1.03	−1.18
Total land	2.20**	−1.35	−0.74	1.68	−1.78*	0.61
Farm income	1.81*	1.16	−3.06***	0.77	0.60	−0.86
Lactating cows	0.32	0.45	−0.81	1.28	0.03	−0.52
Dairy training	2.84***	−0.58	−2.19**	0.77	−0.89	0.26
Milk safety information	4.74***	−0.41	−4.23***	1.70*	−0.90	0.03
Access to extension	4.48***	−0.42	−3.96***	1.51	−0.47	−0.06
Credit use	1.04	−1.57	0.63	1.12	−1.57	1.45
Cooperative	1.08	0.12	−1.21	−0.15	0.13	0.32
Crop loss	−0.48	0.45	−0.00	−1.12	1.21	−1.12
Distance from market	0.71	−0.37	−0.30	1.47	−0.31	−0.35
Distance from road	1.51	0.60	−2.15**	0.85	0.66	−1.28
Annual off/non-farm income	1.08	−0.09	−0.97	0.65	−0.17	−0.00
Milk safety inspection	1.88*	1.53	−3.54***	−0.54	1.17	−0.25
Livestock size	1.56	0.69	−2.29**	1.18	0.21	−1.08
Age square	−0.60	−0.56	1.20	0.77	−0.84	1.23
Education square	3.49***	−1.33	−2.01**	1.91*	−1.53	−0.00
Active labour square	−0.15	0.00	0.14	0.48	−0.13	−0.06
Dairy experience square	−0.83	0.18	0.63	−0.03	0.24	0.22
Family size square	−0.31	1.01	−0.75	−0.27	0.93	−1.23
Total land square	0.95	−0.97	0.09	1.15	−1.23	0.87
Farm income square	1.41	1.15	−2.65***	0.75	0.76	−1.09
Lactating cows square	0.19	0.34	−0.56	1.04	−0.01	−0.34
Annual off/non-farm income square	0.79	0.45	−1.27	0.50	0.35	−0.25
Livestock size square	1.45	−0.02	−1.41	1.37	−0.43	−0.53
Distance from road square	0.94	0.82	−1.82*	0.66	0.86	−1.08
Age cube	−0.78	−0.57	1.39	0.72	−0.82	1.31
Education cube	3.21***	−1.30	−1.77*	1.90*	−1.56	−0.05
Active labour cube	−0.10	−0.01	0.12	0.54	−0.12	−0.08
Dairy experience cube	−1.09	0.27	0.79	−0.08	0.30	0.23
Family size cube	−0.21	0.85	−0.69	−0.12	0.74	−1.22
Total land cube	0.28	−0.73	0.50	0.74	−0.87	0.90
Farm income cube	1.11	1.05	−2.23**	0.66	0.77	−1.11
Lactating cows cube	0.07	0.16	−0.25	0.81	−0.14	−0.08
Annual off/non-farm income cube	0.73	0.63	−1.40	0.47	0.49	−0.33
Livestock size cube	1.22	−0.51	−0.66	1.35	−0.83	−0.10

***, ** and * means statistically significant at 1, 5 and 10% significance levels, respectively.

Source: Authors.

Table 6

Estimated conditional expectations of outcome variables given the treatment and GPS: ordinary least squares.

Variable	Monthly food expenditure		Food consumption score	
	Coefficient	SE	Coefficient	SE
Percentage of milk safety practices adopted	−37.12	40.58	−1.97	1.43
Percentage of milk safety practices adopted square	0.33	0.34	0.01	0.01
GPS	−18590.37	14167.42	−782.07	498.11
GPS square	103547.20	137568.80	−5069.99	4836.75
Percentage of milk safety practices adopted*GPS	240.80	181.52	20.33***	6.38
Constant	2080.89*	1161.36	122.28***	40.83
Observations	385			
F (5, 379)	2.68		2.65	
Probability > F	0.02		0.02	
R-squared	0.03		0.03	

*** and * means statistically significant at 1 and 10% significance levels, respectively, SE means standard error.

Source: Authors.

adopted (Γ) was classified into k groups (where; $k = 1, 2$ and 3). Assume G_1 , G_2 , and G_3 indicate the three treatment intervals. Secondly, for each treatment interval, the GPS was computed at the mean of the treatment and represented by tG_k for each household. Suppose $r(tG_k, X_i)$ indicates the value of the GPS computed at the $tG_k \in G_k$ for each household. Thirdly, in each treatment category, households were further classified into five quantiles called “blocks” based on the GPS estimated in step

two. In the fourth step, the mean difference of each covariate between households belong to a given treatment interval and households belong to other treatment intervals, but belong to the same GPS interval was calculated. Lastly, after weighing the mean difference calculated in the fourth step by the number of observations in each “block,” a t -test value was computed for each covariate and compared against the “bench marks.”

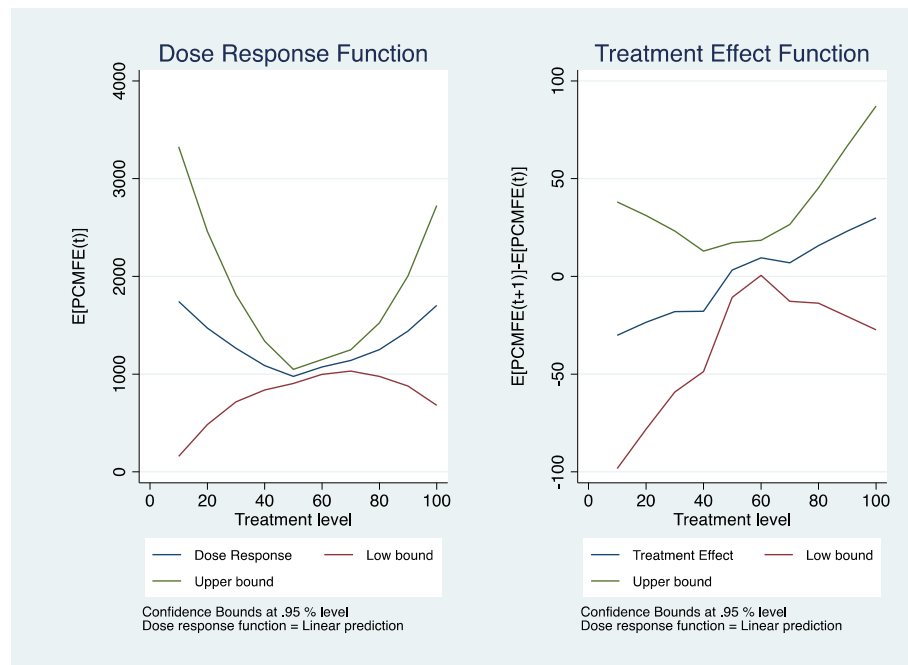


Fig. 4. Dose response function and treatment effect function of the level of milk safety practices adoption on per capita monthly food consumption expenditure Source: Authors.

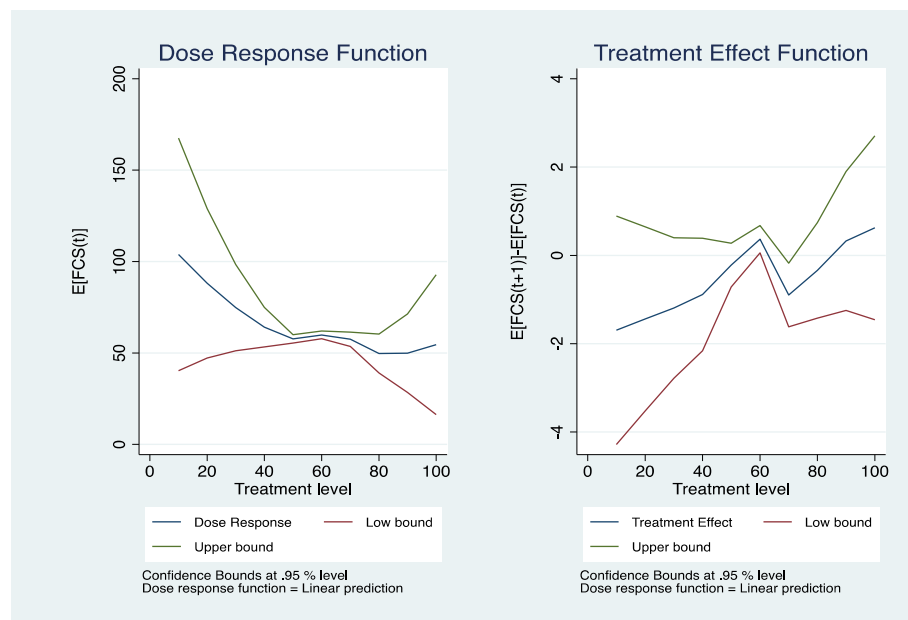


Fig. 5. Dose response function and treatment effect function of the level of milk safety practices adoption on food consumption score Source: Authors.

The result indicates that only four variables were found to have t-values greater than 1.68 in absolute values when GPS was adjusted (see Table 5). Generally, the GPS matching reduced the covariates imbalance by 82 %, which helps ensuring the internal validity of the study. Additionally, checking the region of common support is vitally important before proceeding to the next steps. The descriptive statistics of the estimated GPS for each category and the common support region are provided in Table 4. Accordingly, 25 households were not in the region of common support. As a result, valid sample size was reduced to 385 households after dropping households out of the common support region.

b. Estimating the conditional expectation of the outcomes given the treatment and GPS

In the second step, the conditional expectations of the outcome variables were estimated from the observed treatment (T_i), the estimated GPS (\hat{R}_i), their squares and interactions. The Stata package “dose-response” developed by [Bia and Mattei \(2008\)](#) was used to estimate Equation (4). The estimated results are presented in Table 6, though the coefficients have no useful interpretations ([Hirano and Imbens, 2004](#)).

Table 7

The Average Treatment Effect (ATE) of adoption of milk safety practices.

Outcome	Sample	Treatment	Adoption category				ATE	
PCMFE			Medium		Low			
FCS	Medium	ATT	1087.681	(26.028)	1000.812	(17.649)	85.760***	(31.407)
	Low	ATU	1044.131	(29.889)	969.168	(20.771)	74.764**	36.355
			High		Low			
	High	ATT	1141.002	(29.091)	1039.703	(18.873)	101.206***	(34.677)
	Low	ATU	1006.237	(28.070)	969.168	(20.771)	37.668	(34.884)
			Medium		Low			
	Medium	ATT	59.413	(0.642)	58.559	(0.842)	0.809	(1.059)
	Low	ATU	57.676	(0.883)	57.932	(0.938)	−0.208	(1.289)
			High		Low			
	High	ATT	60.869	(0.874)	59.524	(0.886)	1.237	(1.245)
	Low	ATU	58.740	(0.744)	57.932	(0.938)	0.810	(1.198)

***, and ** signify statistically significant at 1% and 5% significant level, (robust standard errors) are in paranthesis.

Source: Authors.

c. Estimating the average dose response functions

The last step in the GPS estimation is estimating the average dose-response function (DRF) at different treatment intervals (Hirano and Imbens, 2004). Accordingly, the potential treatment level was divided into ten equal parts (at 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100); the average DRF and the average treatment effect function (TEF) were estimated. The “dose-response” Stata package estimates all the first two steps and the final DRFs and TEFs, with 95 confidence intervals, and bootstrapped standard errors were produced through 100 replications (Bia and Mattei, 2008).

The estimated average DRFs and TEFs are presented in Figs. 4 and 5. Fig. 4 depicts the impact of the level of milk safety practices adopted on monthly food consumption expenditure, while Fig. 5 shows the impact

of the treatment on the food consumption score. In general, the graphs have three different lines in which the middle lines indicate the ‘dose response’/‘treatment effect’ while the upper and lower lines indicate 95 % upper and lower bounds, respectively.

The estimated average DRFs and TEFs indicate that the level of the impact of milk safety practices adopted on the household food and nutrition security indicators seems weak, as was suggested by Fig. 2. As shown in the left side of Fig. 4, the average DRF is declining initially, and then slightly increasing at the treatment level of 50 %. Similarly, the right side of Fig. 4 shows that the average TEF is increasing with the level of adoption, and becomes positive when the treatment level reaches around 50 %. As the minimum level of the treatment is around 39 % interpreting the initially declining average DRF and negative value of the average TEF is not appropriate. The DRF starts to increase beyond

Table 8

Pathway analysis: ordinary least squares estimates.

Variables	Log of milk production			Per capita milk consumption			Log of dairy income		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Percentage of MSPs adopted	0.021*** (0.007)	0.017*** (0.005)	0.015*** (0.005)	-0.040 (0.036)	-0.042 (0.035)	-0.057 (0.035)	0.015* (0.009)	0.010 (0.007)	0.007 (0.007)
Zone		0.942*** (0.111)	1.097*** (0.130)		0.594 (0.762)	-1.226 (0.858)		0.824*** (0.148)	0.903*** (0.174)
Number of lactating cows		0.433*** (0.044)	0.423*** (0.047)		1.245*** (0.304)	1.101*** (0.306)		0.479*** (0.057)	0.470*** (0.061)
Sex of the head			-0.273 (0.166)			0.796 (1.091)			-0.534** (0.224)
Age of the head			0.010* (0.006)			0.006 (0.040)			0.014 (0.008)
Education of the head			0.015 (0.012)			0.251*** (0.082)			0.018 (0.018)
Family size			0.039* (0.022)			-0.503*** (0.147)			0.046 (0.032)
Dairy production experience			-0.003 (0.007)			-0.074* (0.043)			-0.010 (0.009)
Total land owned			-0.030 (0.030)			0.275 (0.198)			-0.003 (0.041)
Access to extension services			0.128 (0.099)			-0.460 (0.654)			-0.008 (0.135)
Dairy training raining			0.032 (0.132)			2.711*** (0.870)			0.188 (0.180)
Credit use			0.070 (0.124)			-1.284 (0.819)			-0.024 (0.174)
Distance from the market			-0.002** (0.001)			0.009 (0.006)			-0.002 (0.001)
Distance from water			0.001 (0.003)			0.016 (0.018)			-0.005 (0.003)
Constant	5.566*** (0.413)	4.671*** (0.308)	4.447*** (0.416)	9.127*** (2.120)	6.836*** (2.110)	10.160*** (2.738)	8.618*** (0.504)	7.656*** (0.410)	7.779*** (0.565)
R-squared	0.02	0.49	0.51	0.003	0.07	0.18	0.01	0.38	0.42
Observations	385	383	383	385	385	385	333	333	333

***, **, and * means statistically significant at 1, 5, and 10% significance level, respectively; Standard errors are in parenthesis.

Source: Authors.

Table 9

Summary of milk safety practices identified in the study areas.

Milk safety practices	% of adopters
Overall milk safety practices adopted (mean)	58.59
Animal health	
1 Selected dairy cows well suited to the local environment	93.17
2 Herd size is balanced with available feed, labour and other resources	17.80
3 Vaccinate all animals at least yearly	74.88
4 Buy only animals of known health status	50.49
5 Quarantine immediately if observe sign of diseases on bought animals	49.51
6 Regularly check animals for sign of disease	86.59
7 Sick animals treated immediately by veterinarians	85.85
8 Keep sick animals isolated	61.22
9 Keep written record of all treatments and identify treated animals appropriately	7.32
10 Carefully manage animal disease that can affect the public (zoonosis)	57.32
11 Only use veterinary medicine as prescribed by veterinarians	81.95
12 Store veterinary medicines securely and dispose them responsibly	73.90
13 Calf dehorning	8.05
14 Veterinarians routinely check animals every year	45.12
15 Group feeding for horn cows and hornless cows	53.41
16 No feces seen on the dairy cows	42.44
17 Washing of dairy cows frequently	21.95
Milking hygiene	
1 Washing hands before milking	98.78
2 Drying hands before milking	53.90
3 Washing udder of cows before milking	52.93
4 Udders of dairy cows dried before milking	29.76
5 Use disposable tissue for drying breasts of each dairy cows after washing	18.05
6 Washing milking utensils before milking	100
7 Drying milking utensils before milking	95.85
8 Milking done in separate place from feeding areas	68.29
9 Wearing clean and suitable clothes during milking	46.59
10 Ensure a sufficient supply of clean water during milking	92.93
11 Ensure milking area is kept clean	96.59
Milk storage	
1 Milk storage area is clean	99.27
2 Milk storage area is separate from milking area	96.83
3 Milk storage area is lockable and free from birds, cats, dogs, etc.	95.12
4 Store milk in refrigerator	0.49
5 Fresh milk collection equipment is kept clean when vacant	95.85
6 Equipment washed before bulking	100
7 Bulking equipment dried before used for bulking	97.80
8 Use stainless steel or aluminum milk storage equipment	3.66
Other general milk safety practices	
1 Plan ahead to ensure the herd's feeds and water requirements are met	72.68
2 Buy inputs from known sources for quality inputs	33.90
3 Prepare food mix as directed by feed experts to meet nutritional needs of dairy cows	11.22
4 Discard/ avoid feeding spoiled and contaminated feed by chemical, biological or physical contaminants	73.66
5 Get awareness about disease that affects feed (aflatoxin)	7.07
6 Drain (dry) urine immediately after excretion	10.49
7 Nails of milking person is trimmed regularly	90.73
8 Awareness about gap in milking after treatment	55.61
9 Floor of milking and stall-feeding area is concrete	3.41

Source: Authors.

the treatment level of 50 % and continues to rise and the TEF also increases. However, it should be noted that the maximum level of treatment is about 82 %, and the DRFs and TEFs have no meaningful interpretation beyond that point. Hence, the GPS estimate suggests that the level of the adoption of milk safety practices has a moderate effect on the monthly per capita food consumption expenditure.

Likewise, Fig. 5 indicates the average DRF and TEF on FCS. The average DRF declines until the level of treatment reaches around 45 %, and becomes more or less straight line, which suggests that the treatment has no impact on the FCS. The observed results are intuitively

Table 10

First stage estimation of endogenous switching regression: ordered probit regression.

Variable	Coefficient	Robust standard error
Zone	0.160	0.148
Sex of head	0.055	0.195
Education of head	0.043***	0.015
Children under 5	0.040	0.082
Active labor	0.018	0.042
Experience	0.002	0.006
Total lactating cows)	−0.086	0.057
Milk consumed at	−0.001	0.002
Dairy training	0.197	0.173
Credit use	0.101	0.148
Cooperative membership	−0.033	0.144
Milk safety information	0.503***	0.130
Milk safety inspection	0.358**	0.155
Distance from water	−0.002	0.004
/cut1	−0.088	0.280
/cut2	1.001	0.282
Number of observations	385	
Wald chi2(14)	41.6	
Probability > chi2	0.0001	
Pseudo R-squared	0.054	
Log pseudolikelihood	−397.931	

*** and ** signify statistically significant at 1% and 5% significant level.

Source: Authors.

plausible for two reasons. On the one hand, it has been shown that the cost of compliance with the adoption is high (Kumar et al., 2011), which may reduce the income and other resources available for the household at lower level of adoption. On the other hand, milk is largely sold in the informal market in Ethiopia; and smallholder dairy producers do not have the privilege to receive premium prices for quality products (Minten et al., 2020; Minten et al., 2023). During the survey, dairy producer households were asked to indicate whether they receive higher prices for supplying higher quality milk to the market. However, none of the households indicated the existence of quality-based payments and minimum price guarantee.

4.2.2. Ordered probit endogenous switching regression

The ordered probit endogenous switching regression, which is capable of capturing both observed and unobserved biases was employed to check the robustness of the GPS estimates and reach on a more concrete conclusion.

Before estimating the average treatment effect (ATE) of the adoption of milk safety practices on household food and nutrition security indicators using OPESR, several specification tests were conducted. The parallel lines assumption of the ordered probit was tested using the Brant test. The Brant test result indicates that all the explanatory variables included in the model met the parallel lines assumption (see Appendix Table 3), and the ordered probit was preferred over the generalized ordered probit regression in estimating the first stage of OPESR. The model goodness of fit test presented in the Appendix Table 2 also demonstrates that the ordered probit regression model is significant in explaining the relationship between ordered adoption decision and the explanatory variables included in the model [Wald Chi²(14) = 0.0002]. Furthermore, the validity of the exclusion variable was also tested using a falsification test following previous studies (Di Falco et al., 2011; Sileshi et al., 2022). The test result indicates that access to milk safety information is strongly and significantly associated with the adoption decision at a 1 % significance level (Appendix Table 2), while it is not significant under both the outcome variables (Appendix Table 4).

Table 7 presents the ATE of the adoption of milk safety practices on the food and nutritional security of the household, preceded by the second stage estimations (Appendix Tables 5 and 6). The estimated ATT under the food security indicator reveals that the adoption of milk safety

Table 11
Brant test of parallel lines assumption.

	Chi ²	P > chi ²	Degree of freedom
All	14.1	0.443	14
Zone	0.04	0.846	1
Sex of head	0.76	0.385	1
Education of head	2.16	0.141	1
Children under 5	0.27	0.606	1
Active labor	0	0.962	1
Experience	0.1	0.757	1
Total lactating cows)	0.01	0.934	1
Milk consumed at	0.84	0.358	1
Dairy training	1.02	0.312	1
Credit use	2.37	0.124	1
Cooperative membership	0.85	0.357	1
Milk safety information	0.98	0.323	1
Milk safety inspection	1.36	0.243	1
Distance from water	1.99	0.158	1

Note: A significant test statistic provides evidence that the parallel regression assumption has been violated.

Source: Authors.

Table 12
Falsification test of the validity of the instrumental variable.

Outcome	Per capita monthly food consumption expenditure		Food consumption score	
Variable	Coefficient	R.SE	Coefficient	R.SE
Zone	221.642***	53.319	3.687*	2.045
Sex of head	-137.914*	73.495	2.743	2.819
Education of head	20.617***	5.516	0.385*	0.212
Children under 5	-74.943***	28.887	0.345	1.108
Active labor	-104.162***	14.515	-0.339	0.557
Experience	-3.790*	2.086	-0.249***	0.080
Total lactating cows)	52.899***	20.964	2.670***	0.804
Milk consumed at	-0.142	0.696	-0.070***	0.027
Dairy training	100.247	61.042	5.253**	2.341
Credit use	-50.091	55.526	-1.979	2.129
Cooperative membership	31.987	49.967	-1.640	1.916
Milk safety inspection	30.745	51.717	-2.972	1.983
Milk safety information	41.034	48.695	1.543	1.868
Distance from water	-0.139	1.215	-0.083*	0.047
Constant	1379.213***	103.100	60.814***	3.954
Number of observations	385		385	
F(14, 370)	12.35		6.15	
Probability > F	0.000		0.000	
R-squared	0.318		0.188	

***, **, and * signify statistically significant at 1%, 5%, and 10% significant level; R.SE means robust standard error. Source: Authors.

practices have significantly improved the household's per capita monthly food consumption expenditure (see Table 7). Households in the medium adoption category have on average ETB85.76 more monthly food consumption expenditure per adult equivalent than is the case with their counterfactuals (if they were in the low adoption category). Similarly, households in the high adoption category have on average ETB101.21 more monthly food consumption expenditure per adult equivalent than is the case with their counterfactuals (if they were in the low adoption category). The estimated ATU under the food security indicator also reveals that households in the low adoption category would have achieved significantly higher level of per capita monthly food consumption expenditure than is the case with their current monthly food consumption expenditure if they were in the medium adoption category. Numerically, households in the low adoption category would have an average ETB74.76 higher monthly food consumption expenditure per adult equivalent than is the case with their counterfactuals (if they were in the medium adoption category). The results reveal further that the monthly food consumption expenditure per adult equivalent of the households in the low adoption category is higher than is the case with their counterfactuals (if they were in the

high adoption category), but statistically not significant (see Table 7).

Table 7 also shows the ATE of adoption of milk safety practices on the household nutritional security indicator. The finding reveals that the adoption of milk safety practices has no significant impact on the nutritional security of the households. As the ATT presented in Table 7 indicates, the FCS of the households in both medium and high adoption categories are very similar to their counterfactual estimates, and the differences are statistically not significant. Similarly, the estimated ATU also indicates that households in the low adoption category have similar nutritional security, as is the case with those of their counterfactuals, which also highlights a lack of significant impact of the adoption of milk safety practices on the households' nutritional security.

4.2.3. Impact pathways

To illuminate the pathways via which adoption of milk safety practices may/may not lead to the household food and nutritional security, we estimated several specifications using the ordinary least squares. The estimated models presented in Table 8 show whether the adoption of milk safety practices is significantly associated with milk production, per capita milk consumption and dairy income. The results are presented under columns designed as (1), (2) and (3), which demonstrate what happen to the coefficient of the percentage of milk safety practices adopted (the treatment variable) as additional confounders are added to the models. It should be noted that a statistically significant coefficient shows only the existence of an association between outcome variables (milk production, per capita milk consumption, and dairy income) and explanatory variables, and the results should not be interpreted as causation. Table 9. Table 10. Table 11. Table 12. Table 13. Table 14..

The result shows that the percentage of milk safety practices adopted was statistically significant under log of annual milk produced at a 1 % significance level (see Table 8). Interestingly, the percentage of milk safety practices adopted remains statistically significant even under a full model when other confounders are included into the model. This indicates that the adoption of milk safety practices might have positively contributed to the household food and nutrition security outcomes through increased milk production. On the other hand, the coefficient of the percentage of milk safety practices adopted was negative under all the models estimated for per capita milk consumption. The coefficient becomes statistically significant at a 10 % significance level when other confounders are included (see Table 8). Hence, there is evidence that the adoption of milk safety practices may not lead to improved household food and nutrition security through own-produced milk consumption. On the other hand, the coefficient of the percentage of milk safety practices adopted was found to be positive under all the models estimated for log of dairy income. It was found to be statistically significant at a 10 % significance level when only the adoption of milk safety practices was inserted into the model, but it turned to be statistically not significant when other confounders are inserted into the model.

5. Conclusion, policy implications and limitations of the study

Though the adoption of milk safety practices is identified as a key mechanism for dairy farmers to improve milk production and productivity, which meets the quality and safety standards, the impact of this adoption on dairy farmers' food and nutrition security has not yet been addressed, especially at the smallholder farmers' level in low- and middle-income countries. Therefore, the aim of this study was to evaluate the impact of the adoption of milk safety practices on dairy farmers' food and nutrition security indicators (per capita monthly food expenditure and food consumption score).

Primary data were collected from 410 dairy producer households selected across five districts in Ethiopia, and 385 of them were used in impact evaluation after dropping households beyond the common support region. The treatment variable was constructed based on the recommended milk safety practices adopted by dairy producer households.

Table 13

Second stage estimates of ESR for per capita monthly food consumption expenditure: Linear regression.

Outcome Variable	Low (n = 118)		Medium (n = 149)		High (n = 118)	
	Coefficient	R.SE	Coefficient	R.SE	Coefficient	R.SE
Zone	−7.004	87.596	257.535***	97.758	245.877***	94.064
Sex of head	−36.903	90.221	−215.433	153.499	−237.460**	105.876
Education of head	−1.993	15.400	19.227*	10.092	5.820	11.824
Children under 5	−86.907**	43.585	−90.662	55.423	−99.622**	48.061
Active labor	−95.033***	17.826	−123.621***	26.776	−83.052***	21.912
Experience	−4.920*	2.644	−3.750	4.387	−6.356	3.947
Total lactating cows)	50.758	41.336	80.222**	36.927	71.053**	31.626
Milk consumed at	−0.708	1.230	0.313	1.270	0.391	1.195
Dairy training	84.416	219.912	24.444	98.804	36.182	102.448
Credit use	−259.341***	108.102	−16.417	87.082	−6.523	86.573
Cooperative membership	15.206	98.809	51.092	79.011	−57.144	76.157
Milk safety inspection	−110.152	117.702	−168.046*	99.178	57.075	91.645
Distance from water	1.877	1.429	2.288	3.492	−4.113**	1.851
Inverse Mills Ratio	373.468	307.354	−828.734	683.672	−362.872*	197.674
Constant	1050.596***	328.110	2282.901***	687.980	1995.645***	343.817
F(14, 103)	4.61		6.5		9.67	
Probability > F	0		0		0	
R-squared	0.325		0.358		0.472	

***, **, and * signify statistically significant at 1%, 5%, and 10% significant level, R.SE means robust standard error.

Source: Authors.

Table 14

Second stage estimates of ESR for food consumption score: Linear regression.

Outcome Variable	Low (n = 118)		Medium (n = 149)		High (n = 118)	
	Coefficient	R.SE	Coefficient	R.SE	Coefficient	R.SE
Zone	11.466***	3.674	−6.231	3.770	8.110*	4.216
Sex of head	13.590***	3.954	4.074	3.362	−9.427**	4.718
Education of head	0.389	0.669	0.575*	0.337	0.574	0.399
Children under 5	1.833	1.905	−3.042**	1.510	4.209**	1.992
Active labor	−0.328	1.074	−1.517	0.941	0.716	1.029
Experience	−0.306***	0.123	−0.232	0.147	−0.148	0.131
Total lactating cows)	3.117***	1.287	3.532**	1.590	1.825	1.290
Milk consumed at	−0.078	0.057	−0.033	0.041	−0.053	0.049
Dairy training	−3.568	7.163	4.101	4.269	13.845***	3.246
Credit use	−4.528	3.746	1.943	2.937	−3.194	2.561
Cooperative membership	−4.188	3.465	5.034	3.113	−4.274	3.148
Milk safety inspection	−2.338	4.991	−2.088	3.503	−0.244	3.200
Distance from water	−0.103	0.076	−0.243***	0.085	−0.013	0.070
Inverse Mills Ratio	−3.717	11.353	25.065	27.100	6.997	7.956
Constant	54.694***	13.335	40.347	27.897	52.156***	14.513
F(14, 103)	6.64		3.82		7.12	
Probability > F	0		0		0	
R-squared	0.3337		0.2325		0.3436	

***, **, and * signify statistically significant at 1%, 5%, and 10% significant level, R.SE means robust standard error.

Source: Authors.

The heterogeneous impact of the level of the adoption of milk safety practices on the household food and nutrition security was estimated using a generalized propensity score. The ordered probit endogenous switching regression was also used to account for both observed and unobserved heterogeneity among dairy producer households, while checking the robustness of the generalized propensity score estimates.

Our findings reveal that there is a positive impact of the adoption of milk safety practices on the households' food consumption expenditure. Secondly, the effect of the level of milk safety practices adopted on food consumption score is inconclusive. The ordered probit endogenous switching regression also confirm that the adoption of milk safety practices has a positive impact on only per capita monthly food consumption expenditure. Overall, the findings highlight that creating an enabling environment, which in turn, encourages the adoption of milk safety practices would help improve the positive effects of the adoption of milk safety practices. However, more studies are needed to reach at a more convincing conclusion. Especially, future studies may use panel data to explore the impact of the adoption of milk safety practices on food and nutrition security, to get deep insights.

Despite the efforts made to ensure the internal and external validity of the study, our study has limitations in the following perspectives: First, we relied on the dairy producer households' self-response whether they had adopted each milk safety practices. This could bias our estimates because respondents might have responded as adopter while they did not in reality or the other way. Second, although there is no universally accepted and a single measure of all the dimensions food and nutrition security, using several indicators which capture different dimensions of food and nutrition security may improve the measurement of the household food and nutrition security. However, due to the lack of data on other food and nutrition security indicators, we used the food consumption expenditure and food consumption score as proxies for the household food security and nutrition security, respectively.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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