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Nexus of Cash Crop Production Using Improved Varieties and Household Food Security

**Aseres Mamo Eshetie[1] · Eunice Matafwali[2] ·
Gershom Endelani Mwalupaso[1,2] · Jie Li[3] · Aijun Liu[1]**

Abstract

This study evaluates the impact of adopting improved sesame varieties on farm household food security using the data collected in 2018 from potential sesame-growing districts in northwestern Ethiopia. Selectivity and endogeneity probleSms were addressed by endogenous switching regression and the propensity score matching approach. Thus, we estimated the influence of technology adoption on different food security indicators. Our findings indicate that the adoption of new sesame varieties significantly reduced the propensity of food insecurity through increased food consumption expenditures, improved nutritional food intake (consumption scores), and the probability of food security of a household. The finding supports that there is a positive relationship between cash crops and food security. Access to improved sesame seeds, a cash liquidity advantage, extension service efficiency, and farmers' networking have a significant and positive effect on the adoption of improved sesame varieties. Hence, development policies should be established to motivate cash crop seed multipliers and research institutes to satisfy the seed demand, improve extension service efficiency, and support rural farmers' primary cooperative. The study enriches the current debate on the subject and provides new empirical evidence of the synergy between cash crops and food security.

Keywords Sesame varieties · Cash crop · Consumption expenditure · Food security · Ethiopia

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Aseres Mamo Eshetie, Eunice Matafwali, Gershom Endelani Mwalupaso, Jie Li and Aijun Liu have contributed equally to this work.

✉ Aijun Liu
   liuaj@njau.edu.cn

[1]   China Center for Food Security Studies, Nanjing Agricultural University, Nanjing, Jiangsu, China

[2]   Prince G Academy and Consultancy, Kabwe, Zambia

[3]   Dyson School of Applied Economics and Management, Cornell SC Johnson College of Business, Cornell University, New York, USA

Résumé

Cette étude évalue l'impact de l'adoption de variétés de sésame améliorées sur la sécurité alimentaire des ménages agricoles à l'aide des données collectées en 2018 dans les districts qui pourraient se mettre à la culture de sésame, au nord-ouest de l'Éthiopie. Les problèmes de sélectivité et d'endogénéité ont été résolus par la régression de commutation endogène et par l'approche d'appariement par score de propension. Ainsi, nous avons pu estimer l'influence de l'adoption de la technologie sur différents indicateurs de sécurité alimentaire. Nos résultats indiquent que l'adoption de nouvelles variétés de sésame a considérablement réduit la propension à l'insécurité alimentaire en augmentant les dépenses de consommation alimentaire, en améliorant l'apport nutritionnel (les scores de consommation) et la probabilité de sécurité alimentaire d'un ménage. Les résultats confirment qu'il existe une relation positive entre les cultures commerciales et la sécurité alimentaire. L'accès à des graines de sésame améliorées, l'avantage d'une trésorerie en espèces, l'efficacité des services de vulgarisation agricole et la mise en réseau des agriculteurs ont un effet significatif et positif sur l'adoption de variétés de sésame améliorées. Par conséquent, des politiques de développement devraient être établies pour motiver les multiplicateurs de semences de cultures commerciales et les instituts de recherche à satisfaire la demande en semences, pour améliorer l'efficacité des services de vulgarisation agricole et pour soutenir la coopérative primaire des agriculteurs ruraux. L'étude vient enrichir le débat actuel sur ce sujet et apporte de nouvelles preuves empiriques de la synergie qui existe entre cultures commerciales et sécurité alimentaire.

Introduction

Currently, policies and studies have been enacted to mainly focus on the cereal crop intensification of smallholders through improved technology adoption, household (HH) welfare, and food security (Asfaw et al. 2012; Bezu et al. 2014; Cunguara and Darnhofer 2011; Dilley et al. 2021; Mathenge et al. 2014; Mendola 2007; Shiferaw et al. 2014). However, high-payoff input adoption such as sesame can also have a substantial impact on increasing resource-poor farmer's income and reducing the propensity to experience food insecurity (Govereh and Jayne 2003; Murray et al. 2016; Verkaart et al. 2017).

In Ethiopia, Sesame (*Sesamum indicum* L.), an ancient oilseed crop, is the second major exportable commodity, accounting for over 90% of all oilseed export value at the national level, right behind coffee (Bekele et al. 2017; Kuma Worako 2015). Interestingly, the economic values of sesame crop, the amount of export quantity and area harvested, have been increasing. Although considerable achievements have been made regarding increasing sesame yield and obtaining a satisfactory export price in international markets, the productivity per hectare remains low and has declined drastically (Kuma Worako 2015). A low supply of improved varieties is one of the problems attributed to long-lasting lower sesame production and occurs because of the nature of Ethiopia's centralized seed production system, where only a few seed enterprises produce and provide high-quality seeds such as sesame, groundnut, soya bean, and chickpea (Asfaw et al. 2012).

Cash crop for a household (HH) may increase food security through higher income and stored grain to be consumed later or sold at a high price. Moreover, a cash crop can attract potential buyers who provide loans in the form of inputs and credit to cash crop growers and help avoid credit-market failure (Twine et al. 2019). Notably, declining farmer's purchasing power, seasonal food price fluctuation and demand, and limited market access adversely associate with cash cropping and exacerbate food insufficiency problems (Anderman et al. 2014).

Unlike cereal crop adoption, the decision to grow a cash crop such as sesame requires sensible decisions and strategies to compensate for food grain failure and ex-ante risk management of food supply shocks. The HH needs a strategy to avoid feelings of deprivation, choice restrictions, and anxiety associated with the amount and quality of food provision for their families. In reality, the unpredictable climate, seasonal fluctuation in food prices and demand, limited market access, and market inefficiency are challenging to smallholder livelihood improvement and food sufficiency. Additionally, access to an improved variety affects a farmer's decision to grow cash crops. For instance, according to Shiferaw et al. (2014) HH access to improved seed is positively associated with adoption decision and benefits obtained from the adoption process.

Because 90% of smallholders allocate their farming areas to cereals and majority are grain-deficit HHs, the synergy between cash crops and food security might be another reason for the weak performance of sesame adoption. For the past four decades, a number of empirical studies have been conducted in east African countries on the adoption of common staple crops such as hybrid maize, rice, wheat, pigeon peas, and groundnut, and its impact on welfare and food security (Asfaw et al. 2012; Bezu et al. 2014; Cunguara and Darnhofer 2011; Kassie et al. 2011; Mathenge et al. 2014; Murray et al. 2016; Sall et al. 2000; Shiferaw et al. 2014). By contrast, there is dearth of empirical evidence on cash crop adoption and its effect on subsistence farmer's food security to warrant effective policy formulation (Kassie et al. 2011; Verkaart et al. 2017). These investigations are partly ascribed to the long-held belief regarding the logical paradox that cash crop production comes at the expense of cereal cropping relay HHs as a food source. Thus, empirical evidence on cash crop adoption benefits has been scrutinized not only from the aspects of income but also from food security. Moreover, the tradeoffs between the cash cropping and food security literature differ based on geographical and agroecological conditions, farming system and crop choice, market infrastructure and time of the study (Anderman et al. 2014; Govereh and Jayne 2003; Maxwell and Fernando 1989; Murray et al. 2016). The findings and conclusions of the studies by most scholars on cash crop adoption are not similar and support the positive effect of income and food security logic entirely. Therefore, geographical area and crop-specific empirical investigation are critical in advocating and formulating appropriate poverty reduction strategies and policies to transform cash crop commercialization.

The objectives of this study are twofold: 1) to investigate the determinants of the adoption of improved sesame seed varieties in smallholder farmers, 2) to estimate the association of adoption and HH food security. Our investigation results indicate that sesame seed adoption is associated with increased food consumption expenditure, food availability, and dietary diversity intake. Given the sustainable

development goals purviews of rethinking agriculture to improve food security amidst a burgeoning world population, the results of this study offer pivotal policy and scholarly implications capable of ensuring sustainable food security.

This paper makes several contributions to the literature. First, according to our review of the literature, this paper would become the most recent paper to introduce a new cash crop type (sesame) and examine the causal effects of cash crop adoption on food security at the HH level in the region. Second, we consider the trade-off between improved seed uses and food security, whereas most cash crop adoption and synergy studies primarily focused on conventional seed varieties. Third, we use different food security measurement indicators to estimate the causal effect of sesame seed adoption and different econometric approaches to cross-check the robustness and consistency of the result. Finally, this study contributes further empirical evidence on the trade-off between a new cash crop (sesame) and food security to identify constraints for variety adoption in Ethiopia.

Sesame Production in Ethiopia

Sesame (*Sesamum indicum* L.) is an important cash crop produced in Ethiopia and the second export earning crop commodity after coffee, ranking the country among the world's top five sesame producers (Bekele et al. 2017). Sesame marketing recorded substantial growth in export quantity in 2013 and generated the export value of $516,206 million from 240,094 metric tons (Kuma Worako 2015). According to Kuma Worako (2015), a trend report on Ethiopian sesame from 2005 to 2013 reported that the total area harvested, production, export quantity, and export value increased by 120%, 91%, 45%, and 149%, respectively. Unlike other agricultural product marketing schemes, sesame has been leading because of a special marketing proclamation and law authorized by the Ethiopian Commodity Exchange (ECX) market opened in 2008 (Andersson et al. 2017). Sesame marketing special law was approved by a legislative authority by 2009 and gave a supervision and controlling power for ECX regarding sesame domestic and export market. ECX has potential to enhance market efficiency through establishing comprehensive system for disseminating information about market price and has, I believe advantage on provision of reliable market information to local trader and producer via SMS, Interactive Voice Response, internet and other media.

The Benishangul, Gumuz, and Oromia regions are the top sesame-producing and exporting regions (Ayana 2015; Aysheshm 2007; Kuma Worako 2015). Because Ethiopia has various agroclimatic conditions, sesame varieties used by producers differ by regions. The varieties adopted by farmers in the study area are T-85 (Humera), Kelafo-74 and Mahado-80, and Setit-1 and Abasena. Sesame is the most drought-tolerant crop that can grow in arid and semi-arid lowland environments but is sensitive to high rainfall, water logging, and salinity. Farmers grow sesame for several reasons. First, sesame grows on farms with soil ranging from less fertile to sandy. Second, sesame is an environmental friendly crop because of its capacity to fix nitrogen, which improves soil fertility, and is a good soil builder when rotated with other cereal crops. Third, instead of farmers selling cereals and livestock for

their required liquid money, sesame is used as a substitute, thereby storing cereals for consumption during the lean season. Finally, sesame has an advantage over other cash crops because it controls angiosperm root, a parasitic weed (*Striga hermonthica*) that causes an adverse effect on cereal crop productivity (Bekele et al. 2017; Hess and Dodo 2004).

The large yield and income gaps among different sesame farmers are due to a lack of improved seed provision, a frequent incidence of plant pest and disease, less experience in quality management and value addition skill. The shortage of certified seed provision to small-scale farmers at a reasonable price in the appropriate place, is a critical problem for the study area (Ayana 2015; Kuma Worako 2015; Walsh et al. 2015). This situation occurred because public and commercial seed enterprises such as the Ethiopian Seed Enterprise focuses approximately 90% of their seed production on cereal varieties such as hybrid maize, wheat, and sorghum (Kuma Worako 2015). Notably, the export potential of the sesame crop has been less considered compared with cereal crops.

Materials and Methods

Data and Description of Variables

Data and Study Area

Data for this study were collected from 322 interviewed farmers in 2018 in Metekel province (zone) in Ethiopia and used to analyze sesame varieties' adoption constraints and impact on smallholders' food security (Fig. 1). Metekel province is one of the potential sesame production areas in western and northern Ethiopia and was selected for four principal reasons. First, sesame is the dominant crop in the
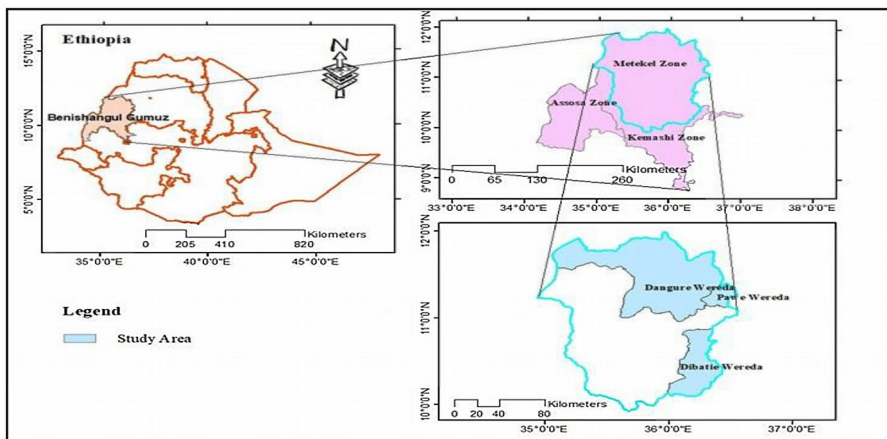

Fig. 1 Study area graphical representation

province, and farmers use improved and conventional varieties. It helps to compare the improved seed adoption constraints and HH food security impact. Second, the province represents other sesame-producing regions regarding rainfall and agro climatic conditions. Metekel has high rainfall (> 1000 mm), fertile soil, and road- and marketing-related infrastructure. Last, despite the province's fertile soil and conducive environment, the population has frequently experienced food shortages and malnutrition (Ayana 2015; Kuma Worako 2015).

Notably, sesame is not produced in all the provinces and districts of the region. In this study, we applied multistage sampling techniques to select the sampled HH. First, a purposive sampling technique was implemented to select Metekel province. Second, based on agroecological suitability and sesame production potential, three districts were purposively drawn from the seven districts in the province: Dangur, Debati, and Pawe. Third, from the targeted districts, 21 villages or peasant administrations were randomly selected as shown in Table 1.

Finally, 322 respondents were selected randomly. We used a properly structured and pre-tested questionnaire as a data collection tool. Trained enumerators and village level agricultural extension workers interviewed the sampled HH. District agricultural experts also closely supervised the data collection along with the authors.

Variable Description

A wide range of variables' information was collected from the field to explain the improved sesame seed adoption and food security status of a HH. Among the variables, a HH's self-report of their food security status (SAFS), list of food consumed in one week, and HH annual food consumption expenditure (amount, type and source) were the fundamental information covered in the outcome variable. Other information such as HH characteristics (education, marital status, family size, age, and gender of HH head), adoption experience and benefit (farming experience, improved seed access, and crop output) were collected for covariate analysis. Additionally, asset ownership (livestock ownership and cropland area), credit availability, access to extension services and social networks, and technical support for farmers are analyzed in the study.

Food security is a multidimensional concept and has no single indicator to capture all food security dimensions. Thus, qualitative and quantitative indicators should be considered. Using more than one indicator is advised (Maxwell et al. 2014). Frequency weighted diet diversity score, or 'food consumption score' (FCS), and food consumption expenditure (FCE) techniques are promising proxy indicators

Table 1 Number of respondents surveyed and their adoption categories by district

Improved sesame seed adoption status	Sampled districts			
	Debati	Dangur	Pawe	Total
Adopters	110	44	19	173
Non-adopters	35	18	96	149

to examine the food security status of a given HH. A dummy variable, namely, a HH's SAFS, was also used as the subjective measurement.

We considered the FCS and FCE in a usual HH behavioral pattern that was practiced in the seven days of the recall period. This information was administered by asking sampled HHs questions related to the amount and types of food consumed over the recall period. This process helped to reduce recall bias that might have come from a respondent's memory-loss–related problems such as underestimation of the less frequently consumed value and overestimation of the new intake (telescopic error) (Gibson 2005). Likewise, HHs usually acquire food from non-purchased sources (e.g., own production, gifts, donation, transfer, food aid, and other activities) and from purchased (bought from a market and consumed inside the HH). In the same manner, the consumption expenditure data is calculated for 12 months from January to December 2018. This study considered expenditure adjusted by an adult equivalent unit (AEU). We used the local market retail price to change the quantity to a monetary value. During the survey period, specific food consumption related to food source, quantity, price, unit of measurement and its monetary value data were collected and analyzed. A detailed discussion was held with both the husband (HH head) and (wife) to collect relevant information.

According to the suggestion in Friedman et al. (2017) and the rule of thumb in Smith et al. (2014), we incorporated eight food groups consumed by a HH for the FCS estimation. Food lists comprised of cereals, pulses, meat/egg/fish, vegetables, fruit, milk, and oil and sugar for a one-week recall period were used (Friedman et al. 2017; Smith et al. 2014). Food items consumed in minimal quantities were treated as condiments (Carletto et al. 2013). The steps for the calculation of FCS were as follows. First, we grouped all the food items into specific food groups and summed all the consumption frequencies of the same group, with truncating no higher than seven. Second, we estimated the new weighted food group scores by multiplying frequency by its weight: Staples $\times 2$, Pulse $\times 3$, Fish, Milk, Meat $\times 4$, Fruits and Vegetables $\times 1$, and Oil and Sugar $\times 0.5$ (Nkomoki et al. 2018). Third, we summed the weighted food group score to obtain the FCS. Finally, the continuous variable value of the FCS was recorded as a categorical variable based on the World Food Programme's appropriate threshold (score 0–21 poor, 21.5–35 borderline and > 35 acceptable) (Mekonnen and Gerber 2017; Wekesa et al. 2018). Moreover, this study used the same SAFS in the same country as Shiferaw et al. (2014). The SAFS of a HH report was classified as chronic food insecurity (food shortage for the whole year), transitory food insecurity (occasional food shortage), breakeven (no food shortage and no surplus), and food surplus.

Empirical Model and Estimation Strategies

Household Adoption Decision and Food Security

According to Maxwell et al. (2014), food security is defined as when all people, at all times, have physical and economic access to sufficient safe and nutritious food to meet their dietary needs and food preferences for a healthy and active life

(Pérez-Escamilla et al. 2017). From the definition, four food security dimensions of food availability, access, utilization and stability should be taken in to consideration during food in/security measurement. However, there is a longstanding debate on how best to measure food security and many indicators and indexes have been proposed. Among different food security measurement tools, most scholars were mainly interested to use three core indicators—Food Consumption Score (FCS), Food Consumption Expenditure (FCE) and Self-assessment measurement (SAFS) techniques (Cafiero et al. 2018; Mabiso et al. 2014; Maxwell et al. 2014; Pérez-Escamilla et al. 2017; Zezza et al. 2017). Consistent measurement tools have been adopted in this study for robust results. For instance, FCS captures the amount of foods the household accesses and consumes which impliedly suggests that food secure households have a higher score. Also, FCE is more in food secure households given the finding by Mwalupaso et al. (2020) and Sekabira and Qaim (2017) who contend that income is a key driver of food security. Finally, SAFs which is basically a self-reported response on whether households think they are food in/secure must also lead to the same finding as for the other two mentioned above. In this way, our finding is more robust and conclusion reliable for policy interventions.

This study defined an adopter farmer if he used any of the sesame varieties that were initially authenticated by the agricultural research institute, and the type could be fresh (basic seed) or recycled. The seed could be purchased from community seed multiplier farmers, multi-purpose cooperatives, and the agricultural office or gifted from nongovernmental organizations and development projects, but not used for more than three years. Notably, sesame is a self-pollinated plant, and the quality of seed highly depends on surrounding field conditions and insect population.

Smallholder farmers are heterogeneous in their characteristics; thus, not all of them participate in technology adoption. Partial or full substitution of land from cereal to improved sesame seed use can help to increase farm income due to the high-value and liquidity, which could have a substantial positive effect on HH food security (Anderman et al. 2014; Govereh and Jayne 2003; Kassie et al. 2011; Shiferaw et al. 2014). The probability of a HH adopting improved seed varieties is determined by the expected utility gained from the adoption process (Asfaw et al. 2012).

Consider the ith farm HH a decision condition of whether to use an improved sesame seed variety. Let $Ʉ_s$ represent the benefit stream from adopting the improved sesame seed and $Ʉ_0$ indicate the benefit from the use of conventional seed. A utility-maximizing farm HH decides to use improved sesame seed if the utility gained from new seed is higher than that gained from using conventional seed ($I_i = Ʉ_s − Ʉ_0 > 0$) regarding productivity, crop income, and welfare change. Because utility is unobservable and the adoption of an improved sesame seed variety is also a latent variable, the net benefit (I_i^*) is explained by a function of observable characteristics ($ƶ_{ii}$) and the error term (μ_i) and represented as an equation:

$$I_i^* = \alpha ƶ_i + \mu_i, \text{ with } I_i = \begin{cases} 1 & \text{if } I_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $-I_i^*$ is a binary indicator variable that has a value equal to 1 if the farmer uses improved sesame seeds and zero otherwise; α is a vector of parameters to be estimated, Z_i is a vector of explanatory variable, and μ is an error term.

In the literature, we observed no best or gold single-standard indicator to measure 'food insecurity' independently. Because the SAFS estimation is subjective and constructed from a single question, the result may not be reliable and satisfied. Similarly, FCE considers a single year consumption trend of a family; and by contrast, FCS examines one season of food composition. Therefore, applying more than one indicator is advisable and increases the estimation accuracy of the real HH food security level (Maxwell et al. 2014). To validate the result and to avoid single indicator limitation, the study used three food security indicators (SAFS, FCE, and FCS) as earlier stated.

The variables of interest are FCE per AEU, and FCS of a linear function with a dummy variable of improved sesame variety used; the linear regression equation can be specified as:

$$Y_i = \beta X_i + \emptyset I_i^* + e_i, \tag{2}$$

where $-Y_i$ represents HH food security status, which is explained by 'Consumption expenditure' per AEU 'consumption score' or respondents' SAFS; X_i are observable characteristics; I_i^* is the improved sesame seed adoption indicator dummy variable as aforementioned (Eq. 1), and β and $\emptyset$ are a vector of the parameters to be estimated, whereas the coefficient $\emptyset$ measures the impact of improved sesame seed adoption on the outcome variable.

Equation (2), however, might generate biased estimates due to a problem of endogeneity (Hausman 1978) that considers that technology adoption is exogenously determined while being potentially endogenous. Again, another cause for biased estimates is associated with sample selection problem (Heckman 1977) because the technology adoption of a farmer is a self-selection process. Therefore, a model of endogenous switching regression (ESR) can address and avoid both endogeneity and sample selection biases (Noltze et al. 2013) and allow a complete interaction between improved sesame seed participation in the HH food security status: one for adopters and another for non-adopters. To check the consistency of the estimation process we also implemented non-parametric matching (propensity score matching [PSM]) empirical estimation techniques (Asfaw et al. 2012; Chilemba and Ragasa 2019; Coromaldi et al. 2015; Shiferaw et al. 2014). ESR and PSM have widely been used in current literature owing to their user-friendliness in use and ability to satisfactory account for selection bias in technology adoption, and endogeneity issues as guided by Amadu et al. (2020).

Endogenous Switching Regression Model

The ESR approach is used to estimate the adoption decision by standard binary dependent variable and other outcome decision variables of HH food security estimated separately for each group (i.e., for adopters and non-adopters) and represented as follows:

$$I_i^* = \alpha Z_i + \mu_i \tag{3}$$

$$\text{Adopter's regime:} Y_{1i} = \beta_{1i} X_{1i} + e_{i_1} \text{ if } I_i = 1 \tag{4a}$$

$$\text{Nonadopters regime:} Y_{2i} = \beta_{2i} X_{2i} + e_{i_2} \text{ if } I_i = 0 \tag{4b}$$

where I_i^* and I_i are an unobservable and observable latent variable for sesame seeds adoption, respectively, Y_i is HH consumption expenditure per capita for regimes 1 (adopter regime) and 2 (non-adopter regime), X_i represents a vector of the exogenous variable to influence consumption expenditure; and μ_i *and* e_i are a random disturbance associated with adoption of improved technology and the outcome variable. Using ordinary least squares to estimate β_1 and β_2 might lead to sample selection bias (Lee 1982) because the error terms (e_1 and e_2) conditional on the sample selection criterion are non-zero. The error term μ, e_1 and e_2 are assumed to have a trivariate normal distribution with a mean of zero and a nonsingular covariance matrix specified as:

$$\text{Cov}(e_{1i} e_{2i} \mu_i) = \begin{bmatrix} \sigma_{e1}^2 & \sigma_{e1e2} & \sigma_{e1\mu} \\ \sigma_{e1e2} & \sigma_{e2}^2 & \sigma_{e2\mu} \\ \sigma_{e1\mu} & \sigma_{e2\mu} & \sigma_{\mu}^2 \end{bmatrix}, \tag{5}$$

where Var $(\mu) = \sigma_\mu^2$ in the dichotomous selection equation (i.e., sesame seed adoption); Var $(e_1 = \sigma e_2^2)$ and Var $(e_2 = \sigma e_2^2)$ in the consumption expenditure outcome function (4a) and (4b); and Cov $(e_1, e_2) = \sigma e_1 e_2$; Cov $(e_1, \mu) = \sigma \ell_{1\mu}$ and Cov $(e_1, \mu) = \sigma e_{2\mu}$. The variance of the selection equation can be assumed to be equal to 1 because α and β are estimable only up to the scale factor. The covariance between β_1 and β_2 is not defined because the two regimes Y_1 and Y_2 are not observed simultaneously (Maddala 1986). The expected values of e_{1i} and e_{2i} are conditional on the criterion equation, and Eq. (1) is correlated with the error term of the two regimes of food security function are non-zero and equal to:

$$(e_{1i} \mid I_i^* = 1) = \sigma_{e1\mu} \frac{\phi(\alpha Z_i)}{\Phi(\alpha Z_i)} = \sigma_{e1\mu} \lambda_{ie1}, \tag{6a}$$

$$E(e_{2i} \mid I_i^* = 0) = \sigma_{e2\mu} \frac{\phi(\alpha Z_i)}{1 - \Phi(\alpha Z_i)} = \sigma_{e2\mu} \lambda_{ie2}, \tag{6b}$$

where ϕ and Φ denote the probability density and standard normal cumulative distribution function, respectively, λ_{ie_1} and λ_{ie_2} are the inverse mills ratio (IMR) estimated from the adoption equation that was included in 4a and 4b and computed using ESR to correct the selection bias problem. To avoid a heteroskedasticity problem, the adoption of improved sesame varieties and food security were estimated simultaneously in two stages of the ESR to make use of the full information maximum likelihood estimation procedure. And most importantly, probit covariates Z contain at least one variable (valid instruments—Access to new sesame seed and improved seed experience) not in X. As guided by Di Falco et al. (2011), a falsification test was conducted. Given that Sesame variety adoption has a 0.15 and 0.092 correlation with access to new sesame seed and improved seed experience with significance

level at 1% while food security indicators had statistically insignificant correlation with both instruments, the instruments were valid. Such a test was also applied in Magrini and Vigani (2016). Our finding confirms that the instruments have statistically significant effects on adoption of sesame varieties, but not with the indicators of food security.

Following Di Falco et al. (2011), the above framework of conditional expectation from the ESR was used to estimate the average treatment effect on the treated (ATT) and untreated (ATU) by comparing the FCE of adopters with non-adopters in an actual and counterfactual scenario that is presented and defined as follows:

(a) Adopters actual treatment effect

$$E(Y_{1i} \mid I = 1) = \beta_1 X_{1i} + \sigma_{e1\mu}\lambda i_{e1}, \tag{7a}$$

(b) Non-adopters' actual treatment effect

$$E(Y_{2i} \mid I = 0) = \beta_2 X_{2i} + \sigma_{e2\mu}\lambda i_{e2}, \tag{7b}$$

(c) Non-adopters' counterfactual effect

$$E(Y_{1i} \mid I = 0) = \beta_1 X_{2i} + \sigma_{e1\mu}\lambda i_{e2}, \tag{7c}$$

(d) Adopters' counterfactual effect

$$E(Y_{2i} \mid I = 1) = \beta_2 X_{1i} + \sigma_{e2\mu}\lambda i_{e1}, \tag{7d}$$

Equations (7a) and (7d) are observed to be actual food security expectations conditional to the criterion adoption function of adopters when they adopt and non-adopters when they do not adopt, and Eqs. (7c) and (7b) are unobserved counterfactual expected outcomes where adopters did not adopt and non-adopters adopted modern technology. The mean food security outcome difference of Eqs. (7a) and (7d) provides the average treatment effect on the ATT as given below:

$$ATT = E(Y_{1i} \mid I = 1) - E(Y_{2i} \mid I = 1) = X_{1i}(\beta_1 - \beta_2) + \lambda i(\sigma_{e1\mu} - \sigma_{e2\mu}), \tag{8}$$

Propensity Score Matching

According to Bravo-Ureta et al. (2012) bias emanating from observed heterogeneity is the principal econometric problem in the estimation of the treatment effect and results because the observational treated groups differ from the controlled group. Owing to potentially weak IV limitations in exclusion restriction-based methods like ESR, PSM is the desired option for robustness checking in most studies.

As proposed by Rosenbaum and Rubin (1983), we applied the non-parametric econometric approach of score matching techniques as a robustness check to address the counterfactual effect that might occur from the bias problem. PSM has an advantage when constructing a statistical compression group between adopters

and non-adopters that have similar characteristics because PSM helps to assign these groups randomly and is used to make a causal link between technology use and the outcome variable for the study (Cunguara and Darnhofer 2011; Kassie et al. 2011; Mendola 2007; Shiferaw et al. 2014). We employed the most commonly used matching estimators, namely, nearest neighbor matching (NNM), radius-matching and the kernel-based matching (KBM) approach. The major reason and advantage of using all the three matching algorithm is robustness check as indicated by Kelemu et al. (2016).

Rosenbaum and Rubin (1983) define the average treatment effect as:

$$\Delta i = E(Y^1 - Y^0), \tag{9}$$

where Y^1 represents adopters' food security status and Y^0 represents non-adopters who use conventional sesame seed. The problem with estimating the causal effect is that we observe only Y^1 or Y^0 but not both simultaneously. What usually is observed is defined as follows:

$$\gamma_i = I_i Y^1 + (1 - I_i) Y^0 I_i = 0,1 , \tag{10}$$

To generate the outcome results of the average treatment effect, we first generated the score value using a probit model for the improved sesame seed variety users. Second, after we predicted the propensity score, we computed the average treatment effect (ATT) which specified as:

$$ATT = [Y_{1 i} | I = 1, \Pr (X)] - [Y_{2 i} | I = 0, \Pr (X) | I = 1] , \tag{11}$$

Estimation Result and Discussion

Descriptive Food Security Indicators Estimation by Technology Adoption

The unconditional summary statistics in Table 2 presents the sesame variety users and non-users' demographics, farm-level, and socioeconomic characteristics of a HH. In this study, the adopters accounted for 53.73% of the total sample. Adopters are younger than their counterparts, with mean age difference of 4.1 years, and this factor had effect on the variety adoption process. Most of the HH heads had no or less formal education. Adopters had more family members than non-adopters, which affected FCE and food security status among groups. Approximately 98% of sampled heads of HHs had access to extension information and contact with an agricultural development agent. Thus, access to agricultural information is not a critical constraint. Additionally, there was a significant mean difference between farmers in social network membership such as cooperative among groups. Almost 79% of the respondents owned mobile phones, and the adopters' ownership of mobile phones was 10% higher.

The descriptive mean comparison under all food security indicators shows that improved sesame variety adopters realized advantages in the HH and per capita consumption expenditure compared with conventional seed users. The food quantity and quality consumed and the frequency intake difference were also associated with

Table 2 Summary statistics of outcome; key independent and explanatory variables

Variables	Description	Full sample		Adopters		Non-adopters	
		Mean	SD	Mean	SD	Mean	SD
Outcome variables							
Food consumption expenditure	Per capita FCE (in Ethiopian currency ETB)	5711	2651	6724	2793	4536	189
Food security (SAFS)	HH self-response on their food security status (1=food secured; 0=food insecure)	0.68		0.879		0.45	
Chronic insecurity	HH within savior food shortage (yes=1)	0.071		0.012		0.141	
Transitory	HH suffering transitory shortage (yes=1)	0.234		0.099		0.389	
Breakeven	HH has no food shortage or excess (yes=1)	0.537		0.659		0.396	
Surplus	HH has excess food (yes=1)	0.158		0.231		0.074	
Food security by FCS	Food security status based on FCS (1=food secure; 0=food insecure)	38.632		43.581		32.886	
Poor	HH FCS less than 21 (yes=1)	0.065		0.029		0.107	
Boarder line	HH FCS 21.5 to 35 (yes=1)	0.251		0.144		0.376	
Acceptable	HH FCS above 35.5 (yes=1)	0.683		0.826		0.517	
Key independent variable							
Improved sesame seed	Heads of HHs adopted improved Sesame seed varieties (yes=1)	0.537		1		0	
Explanatory variables							
Age_hh	Age of the HH head (years)	40.63	10.1	38.73	9.87	42.83	9.94
Gender	Gender of respondents (male=1)	0.88		0.908		0.852	
Schooling year	HHs schooling years of formal education	3.29	3.5	3.555	3.67	2.986	3.282
Family size	HH family members size	5.95	2.35	6.098	2.408	5.772	2.272
Farm size	The total cropping area in *hectares*	4.26	3.27	5.087	4.097	3.303	1.401
Lives-ownership	Livestock in tropical livestock unit (TLU)	7.12	4.14	7.839	4.937	6.284	2.746
Mobile telephone	HHs who have a mobile phone (yes=1)	0.79		0.84		0.74	
Sesame area	Area covered by sesame seeds in *hectare*	1.12	0.77	1.275	0.925	0.931	0.483
Seed access	HHs access to sesame seed (yes=1)	0.38		0.64		0.06	
Sesame income	Total income from sesame in 000 ETB	17,168	15,477	22,990	17,566	10,408	8680

Table 2 (continued)

Variables	Description	Full sample		Adopters		Non-adopters	
		Mean	SD	Mean	SD	Mean	SD
Crop income	Total crop income in 000 ETB	37,708	40,584	51,028	49,308	22,241	17,280
Buy food	HH buys staple food from market (yes = 1)	0.475		0.457		0.497	
Extension access	HH accessed agri-extension service	0.984		0.994		0.973	
Use ext-info	Heads of HHs apply extension information	0.543		0.642		0.429	
Coop membership	HHs membership of cooperative (yes = 1)	0.416		0.549		0.262	
Access to credit	HH accessed to credit service (yes = 1)	0.397		0.451		0.336	
Market distance	Market distance (human walk in minutes)	100.4	108.7	98.94	108.0	102.1	109.8
Road distance	How far to the main road (walk in minutes)	15.77	10.33	15.16	9.66	16.48	11.05
Pawe district	Paweworeda sesame grower farmers	0.357		0.109		0.644	
Debati district	Debatiworeda sesame grower farmers	0.45		0.636		0.235	
Dangur district	Dangurworeda sesame grower farmers	0.193		0.254		0.121	
Number of observations		322		173		149	

the amount of income generated from improved seed use by a given HH. Adopters had a higher FCS with a mean difference of 10.7 points than their counterparts. Most of the technology users (83%) were under the 'acceptance' food consumption group threshold. Based on the SAFS indicator, 88% of improved seed users were food secure but only 45% of conventional seed users were food secure. Again, conventional seed users (non-adopters) were unable to obtain a sufficient amount of food for two to five months per year compared with improved seed users. Adopters generated excess income and were grouped under food surplus categories: could satisfy their family food needs throughout the year compared with their counterparts.

Moreover, Table 3 shows a significant contribution of improved sesame variety adoption to HH food security improvement. Hence, sesame is produced for marketing and not for direct consumption; farmers diversified their cropping by planting more than three crops to minimize the food deficiency risk of a family. Sesame remains the most important cash crop in the study area regarding crop income, area share, and source of the HH budget to purchase consumable goods from a market. In aggregate, improved sesame variety users generated twofold of non-users' income, which resulted in an estimated higher mean difference of 11,070 ETB.

Because adopting improved sesame seed is not a random choice for a farmer, the aforementioned difference may not only occur due to the adoption but also because of other observable and unobserved characteristics. Therefore, a robust multivariate analysis test was conducted to evaluate the impact of variety adoption on HH food security.

Determinants of Improved Sesame Seed Adoption: Binary Probit Estimates

Table 4 presents the maximum likelihood estimates of improved sesame varieties' adoption of the Probit model. Also, possible factors behind farmers' decision to adopt improved sesame seed varieties where the treatment variable takes the value 1 if the farmers used improved sesame seed and 0 otherwise is presented. The marginal effect in the last column indicated the magnitude of adoption probability for a one unit change in an explanatory variable. The model diagnosed goodness of fit and indicated that the selected covariate provided good estimates on the adoption decision. The Wald chi-square test is statistically significant at the 1% level, and the pseudo-R-squared measures of 0.615 are also reasonably high.

The binary probit estimation result shows that most of the variables hypothesized to influence the adoption of improved sesame seeds had the expected signs. Among the variables representing farmer characteristics, HH head age and marital status were positive, significant factors in the choice of improved sesame varieties' adoption. However, HH heads aged older than 60 years were negatively associated with variety adoption. In support of the aforementioned findings, older age farmers were conservative, allocated fewer resources, and were less likely to adopt improved sesame varieties because of risk-aversion behavior and a technology mistrust problem (Bezu et al. 2014; Emmanuel et al. 2016; Verkaart et al. 2017). A married HH had more social responsibilities than unmarried individuals.

Table 3 Households' food security measurement by technology adoption

Variables	Full sample (N = 322)	Adopter (N = 173)	Non-adopter (N = 149)	Difference (S.E)
Mean HH food consumption score	38.632	43.581	32.886	10.695 (0.933)***
Mean HH consumption expenditure in ETB	25,113.56	30,033.96	19,400.61	10,633.35 (1015.7)***
Mean HH FCE in ETB	16,854.47	20,029.69	13,167.8	6861.89 (699.1)***
Mean per capita annual consumption expenditure in ETB	5711.67	6724.15	4536.11	2188.04 (270.39)***
Mean annual income from sesame production	17,168.34	22,990.49	10,408.38	12,582.11 (1583.4)***
Mean annual cash income from other crops	20,539.80	26,340.89	11,276.75	15,064.14 (1203)***
Mean annual expense for cereals crop purchase	1336.08	1491.84	1087.12	404.72 (183.96)*
HH buys essential staple food items from market in %	48.00	43.00	55.00	− 12 (7.801)*
Mean crop type diversified during farming season	3.74	3.63	3.92	− 0.29 (0.19)
HH family members by AEU (adult equivalent unit (AEU)	4.877	4.985	4.752	0.233 (0.216)

Significance levels: *: at 10%; **: at 5%; and ***: at 1% while figures in parenthesis are standard error of the difference

Table 4 Probit estimation of the decision to adopt improved sesame varieties

Explanatory variables	Coef	Std Err	$P > z$	Marginal effect
HH characteristics				
Gender (dummy variable)	0.159	0.483	0.741	0.024 (0.073)***
HH head age 40 to 60 years	−0.2	0.254	0.432	−0.030 (0.038)
HH head age above 60	−1.355***	0.47	0.004	−0.204 (0.068)***
Marital status (dummy variable)	1.252**	0.506	0.013	0.189 (0.076)**
HH head schooling 2 to 6 grade	−0.820***	0.239	0.001	−0.124 (0.036)***
HH head schooling above grade 6	−0.961***	0.336	0.004	−0.145 (0.049)***
Ln (Family size)	−0.747**	0.33	0.024	−0.113 (0.052)**
HHs Asset and experience				
Ln (Farm size)	−0.169	0.222	0.448	−0.025 (0.033)
Livestock ownership	0.0715*	0.04	0.076	0.011 (0.006)*
Mobile phone	0.441*	0.241	0.067	0.012 (0.033)*
Ln (sesame income)	0.512**	0.2	0.01	0.077 (0.028)***
Liquidity advantage	0.703**	0.284	0.013	0.106 (0.040)***
Access to service and membership				
Access to extension info	0.114	0.523	0.827	0.017 (0.079)
Access to credit	−0.117	0.241	0.626	−0.018 (0.036)
Cooperative membership	0.516**	0.26	0.047	0.040 (0.034)
Distance to main market	−0.001	0.001	0.166	0.000 (0.000)
Buys staple food	0.466	0.308	0.131	0.070 (0.044)
Instruments				
Improved seed experience	1.408***	0.206	0	0.212 (0.021)***
Access to new sesame seed	1.196***	0.294	0	0.180 (0.037)***
Constant	−8.172***	2.203	0	
Model test				
Wald chi2 (20)	107.40***			
Log pseudo likelihood	−85.604			
Pseudo-R2	0.6149			
Number of observations	322			

Significance levels: *: at 10%; **: at 5%; and ***: at 1%; robust standard errors are in parenthesis of marginal effect

By contrast, we found a HH head's formal education and family size were negatively associated with sesame variety adoption. A farmer with a higher number of schooling years preferred to participate in other off-farm activities instead of staying to the usual farming practice. Additionally, the family size of a HH had a significant adverse effect on the adoption decision. Our results concur with the findings of Mariano et al. (2012). Most of the studies have considered family size as labor contribution rather than its dependency on consumption and income. With the fixed land size

and scarce family resources, an additional membership in a family may hurt technology choice behavior and overall HH budget decisions.

The next set of the explanatory variables is the natural logarithm of sesame income and liquidity advantage, and we found they significantly encouraged the likelihood of adoption. Similar studies (Asfaw et al. 2012; Langyintuo and Mungoma 2008; Mariano et al. 2012; Mendola 2007) have demonstrated the same result. Farmers preferred to plant sesame for an immediate cash source and to purchase productive inputs.

The last set of variables is social membership and input accessibility. We found access to improved sesame varieties increased HHs' likelihood of adoption by 18%, which is consistent with other studies, for example, Asfaw et al. (2012), Mathenge et al. (2014), and Shiferaw et al. (2015). Likewise, HH sesame farming experience had a positive effect on the adoption of new varieties. Unexpectedly, access to extension service was insignificant; by contrast, being a member of a farmers' cooperative had a positive and significant correlation with technology adoption. Even if the expansion of the agricultural extension service increased at the national level, the inefficient and poor extension service was unable to promote new technology adoption effectively (Landmann et al. 2020). Abebe et al. (2013) found a similar result about poor and inefficient extension services for potato growers in Ethiopia.

Nexus of Technology Adoption and Food Security

This section explains the impacts of the adoption of improved sesame varieties on the outcome variable through the results obtained from the binary PSM and maximum likelihood estimation of the ESR models.

Estimation of the Treatment Effect with Propensity Score Matching Techniques

Unlike a random experiment, in observational studies, an assignment into the treated and controlled group is not random. In a given program, an individual might decide to participate in the program while others do not. Therefore, observing a technology effect on HH food security status by examining observable characteristics could lead to a biased estimation. Rosenbaum and Rubin (1983) suggested PSM as a tool to reduce the treatment effect bias when using with observational data sets. A non-parametric matching technique allows for arbitrary heterogeneity in casual effect and is able to add common support conditions that focus on the comparison of adoption about the study outcome. Covariates of the propensity score model were selected based on technology adoption, empirical findings, and theory similar to the literature. Only variables that influenced the treatment status and the outcome variables simultaneously were included, and the variable lists are the same as presented in Table 4.

Before discussing the impact of the adoption of sesame varieties, it is essential to discuss the quality of the matching process. The matching result obtained after the matching process passed a quality checking test. Considerable overlap in common support was achieved. The common support assumption was satisfied

in the range of [0.019, 0.99] and there was a substantial overlap in the propensity score distribution of adopters and non-adopters. For the two groups (adopters and non-adopters), the density distributions of the estimated propensity score are clearly visualized in the common support graph (Appendix A; Fig. 2).

The goal of the propensity score estimation is to obtain the same distribution of observable and unobservable characteristics independent of the treated and control groups. The results from the covariate balancing tests before and after matching are presented in Table 5. There was a substantial reduction in the bias of standardizing mean difference from 40.4% before machining to a range of 7.8% to 10% after matching. The percentage reduction is 75% for the first nearest neighbor matching (NNM[1]) and 80.6% for kernel 0.03 bandwidth (KBM[0.03]) matching methods. We achieved a substantial bias reduction and a recommended value using the two approaches, which is greater than 20%, as suggested by Rosenbaum and Rubin (1983). The percentage reduction was from 62 to 70% range.

After matching, no variables showed a significant difference, and the p-values of the likelihood ratio test do not reject the null hypothesis, that is, all the coefficients are equal to zero. The pseudo-R2 also reduced significantly from 40% before matching to 3% after matching. The low pseudo-R2, low mean standardized bias, high total bias reduction, and the insignificant p-values of the likelihood ratio test after matching show the matching quality. The results in Table 6 confirm that the proposed specification of the propensity score is reasonably successful regarding balancing the distribution of covariates between the two groups. Finally, the pseudo-R2 test and the likelihood ratio test on the joint significance of the covariates confirmed that after matching there were no systematic differences between adopters and non-adopters.

We estimated the result of the effect of adopting improved sesame varieties on HH food security status by both a single and five NNM method with replacement, an Epanechnikov kernel estimator with 0.03 and 0.06 bandwidth, and radius-matching techniques. Results are presented in Table 6. The ATT and ATU represent the average treatment effect on the treated and untreated condition, respectively. The ATE Diff column explains the net effect change on the outcome variable.

Overall, the matching estimation found that adopting improved sesame varieties has a positive and significant impact on HH food security.

The matching result also revealed that adoption significantly increased average per capita FCE, FCS (food quality consumed), and the probability of food security of a HH (SAFS). From the ATT we understand that adopters and non-adopters received benefits from the adoption process, but in most cases, HHs that did adopt benefited the most from adoption. Keeping other factors constant, the effect of improved seed on average per capita FCE was significantly positive and in the range of ETB 610 to 928. As we expected, technology adoption also had a positive and significant effect on HH FCS and was higher with a range of 5.26 to 5.68 points. The majority of the adopters were grouped under the acceptable food group threshold, in ranges from 9 to 15%.

Similarly, under the SAFS indicator, the probability of a food secured HH increased by a range of 17%–32%. The adoption of improved sesame seeds reduced

Table 5 Quality test for selection bias: propensity score matching

Matching algorithm	Pseudo-R^2 before matching	Pseudo-R^2 after matching	Mean bias before matching	Mean bias after matching	Total % bias reduction	LR^2 (P-value) before matching	LR^2 (P-value) before matching
NNM[1]	0.408	0.034	40.4	9.0	70.6	181.57 (0.000)	16.35 (0.176)
NNM[5]	0.408	0.041	40.4	10.0	64.3	181.57 (0.000)	19.66 (0.104)
KBM[0.06]	0.408	0.030	40.4	9.9	68.3	181.57 (0.000)	14.22 (0.287)
KBM[0.03]	0.408	0.026	40.4	7.8	62.4	181.57 (0.000)	12.43 (0.493)

the probability of a HH experiencing chronic and transitory food insecurity while improving the likeliness of a HH breaking even by 22%; surplus was 12%. In conclusion, the use of improved sesame varieties substantially improves the food security status of a HH through all three food security measurement indicators.

Our findings are consistent with others related to improved crop variety adoption causal effect studies on HH poverty, income, welfare, and food security. For example, Mendola (2007), Kassie et al. (2011), Asfaw et al. (2012), Verkaart et al. (2017), Cunguara and Darnhofer (2011), Bezu et al. (2014), and Mathenge et al. (2014) have reported similar findings. Moreover, Shiferaw et al. (2014) also used PSM and maximum likelihood estimation of the switching regression model in Ethiopia and found that the adoption of improved wheat varieties significantly increased per capita FCE and food security. Similarly, Magrini and Vigani (2016) obtained a significant positive correlation among improved seed users and food security in Tanzania using ESR and non-parametric PSM models.

Estimation of the Treatment Effect with Endogenous Switching Regression

Table 7 presents the sesame varieties' adoption average treatment effect on food security obtained using a switching regression approach. We found consistent estimation with the PSM estimation approach. The results are the same in terms of magnitude and expected sign among the three food security indicators. Our estimation result shows that most outcome variables are significant at a 99% confidence interval. As we observed from the ATE Diff column, adoption can result in substantial improvement in HHs' food security through increasing FCE, frequency, quality of diet consumed, and food security. For example, a non-adopter HH would have ETB 1063 less consumption expenditure per capita than individuals who adopted a new seed. Additionally, consumption expenditure of adopters at the HH level is higher, ETB 5,495 (1063*5.17), where 5.17 is the AEU of the study.

Likewise, under the counterfactual case of the average treatment effect on the ATU, a non-adopter HH, if they decide to adopt, might have advantages and increase expenditure more than ETB 201 per capita (ETB1039 at the HH level), which is statistically significant to the estimation. Similarly, we found a positive and significant result for the nutritional improvement of FCS of the adopters, that is, 11.6 points higher on the consumption score than non-adopters. Nonetheless, 82% of adopters are grouped under the acceptable category, and 4% are under the poor category. Improved variety adoption increased the HHs' SAFS, and adopters are more food secured (25.5%) than their counterparts.

Overall, our estimation result under PSM and ESR shows that the adoption of improved sesame varieties substantially improves HH food security status by increasing consumption expenditure, nutritional food intake, and the availability of a sufficient amount of food for users. Nevertheless, comparing Tables 6 and 7, there are differences between the ATT of PSM and ESR where the ATT of the latter is larger. The basic reasoning is that unlike PSM, ESR does not drop some observations that are off support but rather makes use of the full information in the data as

Table 6 Improved sesame seed adoption average treatment effect

Outcome variable	Matching algorithm	Outcome variable mean from matched observations		
		Adopter	Non-adopter	ATT
Per capita food consumption expenditure	NNM[1]	4352.229	3467.318	884.91 (493.87)*
	NNM[5]	4352.229	3741.689	610.54 (442.62)
	KBM[0.06]	4352.229	3592.561	759.667 (431.82)*
	KBM[0.03]	4359.306	3431.013	928.29 (467.44)**
	Radius matching	4359.306	3457.355	901.95 (387.176)***
Food consumption score	NNM[1]	42.722	37.459	5.26 (2.15)***
	NNM[5]	42.722	37.037	5.68 (1.92)***
	KBM[0.06]	42.721	37.273	5.45 (2.24)**
	KBM[0.03]	42.721	37.274	5.45 (2.48)**
	Radius matching	42.775	37.258	5.46 (2.64)***
Poor	NNM[1]	0.040	0.011	0.029 (0.049)
	KBM[0.06]	0.040	0.018	0.023 (0.074)
	Radius matching	0.040	0.049	− 0.009 (0.048)
Borderline	NNM[1]	0.139	0.225	−0.087 (0.137)
	KBM[0.06]	0.139	0.267	−0.128 (0.118)
	Radius matching	0.139	0.273	−0.134 (0.117)
Acceptable	NNM[1]	0.821	0.763	0.058 (0.140)
	KBM[0.06]	0.821	0.731	0.090 (0.124)
	Radius matching	0.821	0.664	0.157 (0.076)
Binary food security (SAFS)	NNM[1]	0.847	0.532	0.314 (0.163)**
	NNM[5]	0.847	0.674	0.172 (0.112)*
	KBM[0.06]	0.609	0.768	0.238 (0.147)*
	KBM[0.03]	0.847	0.522	0.325 (0.160)**
	Radius matching	0.847	0.523	0.324 (0.159)**
Chronic food insecurity	NNM[1]	0.017	0.008	− 0. 008 (0.060)
	KBM[0.03]	0.017	0.009	−0.006 (0.070)
	Radius matching	0.017	0.022	−0.004 (0.083)
Transitory	NNM[1]	0.122	0.459	−0.338 (0.162)
	KBM[0.03]	0.122	0.468	−0.345 (0.157)
	Radius matching	0.122	0.466	−0.344 (0.156)
Breakeven	NNM[1]	0.691	0.467	0.224 (0.160)*
	KBM[0.03]	0.691	0.473	0.217 (0.157)
	Radius matching	0.691	0.472	0.219 (0.123)*
Surplus	NNM[1]	0.171	0.064	0.107 (0.104)
	KBM[0.03]	0.171	0.043	0.028 (0.071)*
	Radius matching	0.231	0.052	0.119 (0.091)*

Standard errors are in parenthesis, and *, **, and *** represents the significance level at 10%, 5%, and 1%, respectively

NNM[1] = single neighbor matching with replacement and common support.

NNM[5] = five neighbor matching with replacement and common support.

KBM[0.06] = kernel-based matching with band width 0.06 and common support.

KBM[0.03] = Kernel-based matching with band width 0.06 and common support

it is. Therefore, it is plausible to have such a finding but most importantly is magnitudes and expected sign of estimated variables.

Conclusion and Policy Implication

Conclusion

Sesame is an immediate cash source for farmers in western and northern Ethiopia. However, the substitutability of the production of cash and cereal crops and its comparative advantage for smallholder food security is not clear. This study aimed to address the casual effect of the adoption of improved sesame varieties on food security among subsistence farmers in Ethiopia. Using HH survey data, we attempted to quantify the impact of improved sesame varieties on HH food security. To account for several econometrics concerns, we applied ESR and PSM to reduce biases from observed and unobserved heterogeneity and to test the robustness of the results.

We found a substantial improvement in HH food security status due to sesame variety adoption. A farmer who adopts improved sesame seeds is better off than conventional seed users. Under the SAFS, 85% of the improved sesame seed users are food secured, and only 2% have chronic food insecurity problem. Also, HHs adopting improved sesame varieties benefited more and consumed ETB 4575 which (884.91 X 5.17) than their counterparts.

In line with the adoption constraints' objective, our empirical findings confirmed that sesame income, cash liquidity advantage, availability of improved varieties, social networking, possession of a mobile phone, and farmers experience have a positive association with the adoption of improved sesame varieties. Additionally, based on the HH head characteristics, older age, higher number of schooling years, and larger family size are negatively correlated with the HH sesame variety adoption decision.

The Policy Implication

Our study provides insights into two scholarly and policy questions. First, can sesame production ameliorate smallholder farmers' food security? Second, do innovation and promotion of improved sesame varieties bring substantial change on HH food access, availability and nutritional food intake? Ethiopia provides a useful case owing to its deep-rooted commitment to sesame production, and it makes a suitable learning case in the region especially for countries considering adoption of improved sesame varieties.

Results of the present study confirm that adopters of improved sesame variety can increase per capita FCE by 928–1063 ETB, nutritional dietary food intake by 5.7–12 higher FCS, and propensity to be food secure by 25–32% than their counterparts. The positive impact association between improved sesame varieties and household food security might suggest that the policies targeting food security should consider

and facilitate improved cash crop seed provision for farmer. It may be inter-linked through promoting and strengthening seed multiplier enterprises, research institutes, and community-based seed multiplier farmers to provide high-value seed varieties at an affordable price within a specified time. Moreover, in the long-run cash crop framing could be one of the alternative development strategies for grain-surplus area to increase HH income and livelihood. However, the most important question is why adoption of improved sesame varieties can improve households' food access (FCE), utilization (FCS), and stability (SAFS)?

The possible pathway is that sesame growers, adopters to be specific, have liquidity advantage (more income from sesame than non-adopters as can be seen in both Table 2 and 3 under income). In line with the discourse by Mwalupaso et al. (2020), adopters access and have capacity to spend more on various foods than their counterparts. In addition adopters have more resources to avoid advanced storage facilities. Given that intuitively, sesame production is inextricably linked with adoption of modern storage technology, adopters tend to purchase and store enough food for lean season consumption without much difficulties owing to augmented income (Sekabira and Qaim 2017).
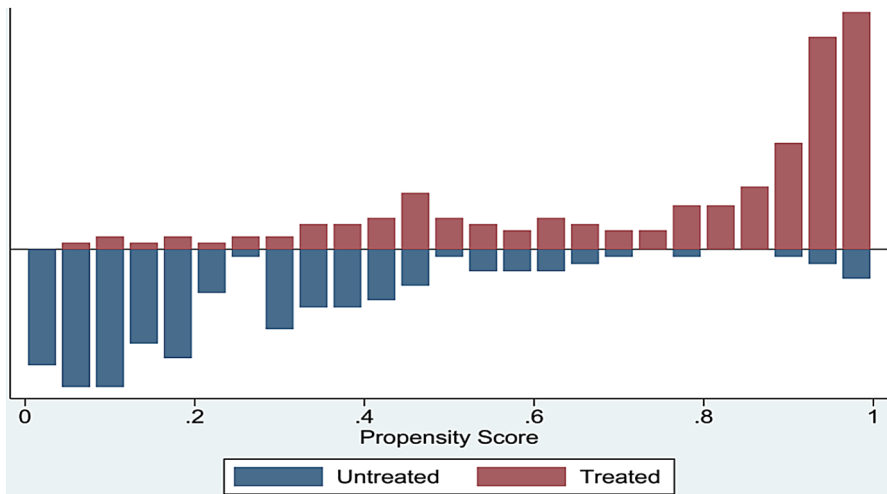
Appendix A

See Fig. 2.

Fig. 2 Predicted value distribution and common support of propensity score. 'Treated on support' denotes a technology adoption group that is a suitable comparison and 'Untreated' denotes non-adopters' group score distribution. The upper part of graph shows the propensity score distribution for adopters and the bottom half refers to the non-adopters. The densities of the score are on the y-axis.

Table 7 Average treatment effect of sesame variety adoption on food security

Treatment effect	Outcome variable	Decision stage		ATE Diff
		To participate	Not to participate	
ATT	Per capita consumption expenditure	4590.458	3527.391	1063.07 (200.75)***
ATU		3101.431	2899.939	201.49 (120.82)*
ATT	Food consumption score	43.580	31.951	11.629 (0.860)***
ATU		33.229	32.905	0.324 (0.565)
ATT	Poor	0.044	0.271	−0.233 (0.020)***
ATU		0.145	0.110	0.035 (0.005)
ATT	Boarder line	0.693	0.374	0.319 (0.033)***
ATU		0.144	0.778	−0.634 (0.032)***
ATT	Acceptable	0.826	0.194	0.632 (0.039)***
ATU		0.394	0.518	−0.123 (0.037)**
ATT	Binary food security (SAFS)	0.878	0.623	0.255 (0.035)***
ATU		0.779	0.449	0.329 (0.037)***
ATT	Surplus	0.873	0.314	0.559 (0.028)***
ATU		0.392	0.173	0.219 (0.051)
ATT	Breakeven	0.903	0.658	0.245 (0.018)***
ATU		0.345	0.395	−0.050 (0.021)
ATT	Transitory	0.393	0.368	0.025 (0.010)
ATU		0.048	0.045	0.003 (0.006)
ATT	Chronic	0.017	0.231	−0.214 (0.024)***
ATU		0.431	0.395	0.036 (0.040)

Robust standard errors in parenthesis: *,**, and *** represents the significance level at 10%, 5%, and 1%, respectively

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