Impacts of Education and the Adoption of Improved Sesame Seeds on Productivity of Sesame Farms in Burkina Faso

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Abstract

This paper examines the impacts of education and the adoption of improved sesame seeds on productivity of sesame farms in Burkina Faso, using data from a sample of 4,726 sesame farmers. The estimated results from endogenous switching regression and propensity score matching show that education, especially formal primary education and agricultural training, increases productivity through the adoption of sesame technology. The estimated results further show that adoption of improved sesame seeds leads to significant gains in productivity. The study concludes with implications for policies to promote adoption of improved sesame seeds among non-adopters through education, such as formal primary education, agricultural training programs, and productive assets.

Keywords: adoption; productivity; sesame; education; FIML; PSM; Burkina Faso

JEL Classification Codes: C51, Q12

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1. Introduction

One of the persisting problems related to agriculture in Sub-Sharan Africa (SSA) is low productivity. Asfaw et al. (2012), Abdulai et al. (2014), and Ranjan et al. (2018) pointed out that education is necessary to increase farm productivity through the adoption of agricultural technologies. Thus, education offers rural farmers the knowledge, skills, and abilities to make rational choices aimed at improving their production outcomes. Previous applied studies on the impact of farmer education on farm productivity produced mixed and inconclusive results, highlighting two critical issues[1] (Asfaw et al., 2004; Huang et al., 2009; Reimers et al., 2013; Jones et al., 2017; Ranjan et al., 2018). The first is related to the construction of the variable "education" used in empirical models. Most studies ignored the fact that farmers' education is not homogenous, even in the same farm environment. This is likely to confound the true effects of education on farm productivity (Alene et al., 2007). The second issue is related to the importance of formal education in varying farm environments and to different farmers in the same environment (Ranjan et al., 2018). Given these concerns, further analysis of the impact of various forms of farmer education on productivity is warranted.

Sesame is the second major cash crop for export in Burkina Faso, and the country is one of the world's leading producers and exporters. The crop is grown throughout the country for exports[2]. In recent years, the sesame sector has been characterized by tremendous growth in production and export, which is driven by the increasing world demand. The production of sesame in 2016 reached 230,000 tons, with an export value of 170 million USD (Achille et al., 2020). This equaled 21% of the country's agricultural export value. Given the inefficiencies related to the cotton sector[3], sesame production turns out to be a source of agricultural export diversification, an emerging economic sector, and another source of income for many farmers. However, the average sesame yield is relatively lower in Burkina Faso (550 kg/ha) compared to other leading producers such as Ethiopia (1,000 kg/ha), Nigeria (950 kg/ha), Tanzania (800 kg/ha), and China (1,600 kg/ha) (Achille et al., 2020; FAO, 2022). The improved variety of seeds used in Burkina Faso is "*S42*", which has a potential yield of 1,500 kg/ha (MAAH, 2020). This technology is being developed to shorten the growing cycle (90 days), account for irregular rainfall patterns, and increase productivity. Despite the efforts of INERA[4] and its partners to make improved sesame seeds available to sesame producers, adoption remains very low, at less than 15% (MAAH, 2020). To our knowledge, no empirical study has investigated the determinants of improved sesame seed adoption and their causal impact on yields.

Using an endogenous switching regression (ESR) technique, this study attempts to fill the gap in existing knowledge by providing a micro perspective on the adoption of sesame technology and the impact of adoption and education on productivity. Moreover, one of the government's agricultural policies encourages cash crop diversification to increase farmers' income and export

[1] See Ranjan et al. (2018) for an extensive review of the impact of farmers' education on agricultural productivity.
[2] See Achille et al. (2020) for an extensive review on the sesame sector in Burkina Faso.
[3] The cotton industry, the first and biggest industry, alone contributes 60% of agricultural export earnings. However, the cotton sector is facing numerous serious challenges as a result of downward pressure on world prices and internal issues, which has led some farmers to switch to other cash crop production (Achille et al., 2020).
[4] INERA: Institute of Environment and Agricultural Research, Burkina Faso.

earnings. Thus, identifying the factors that influence sesame technology adoption and the various forms of education that boost productivity would inspire conducive and effective policies.

We organize the reminder of this paper as follows: Section 2 shows the methodology and data, while Section 3 presents and discusses the empirical results. Section 4 concludes the study.

2. Methodology and data

2.1. Methodology

Following the expected utility theory developed by Greene (2003), sesame producers' decisions to adopt the improved seeds, given the risk of uncertainty, are based on the expected utility. In other words, sesame farmers will adopt the improved sesame seeds if the utility from adoption is higher than no adoption. In this study, the expected utility would be an increase in yields. The endogenous switching regression (ESR) is suitable for analyzing our objectives, namely the determinants of adoption and the impact of farmer education on productivity through adoption. Analyzing the determinants of agricultural technology adoption and their impact on production outcomes encounters potential endogeneity concerns, which are sample selection bias, unobserved heterogeneity, and reverse relationships (Alene et al., 2007; Asfaw et al., 2012). First, sesame technology adoption may induce productivity enhancement for some farmers. However, at the same time, enhanced productivity also intensifies adoption (Ranjan et al., 2018). As a result of their self-selection, productive farmers will adopt more improved sesame seeds, which is a potential source of endogeneity. Second, the difference in productivity outcomes between the adopters and non-adopters could be due to unobserved heterogeneity caused by unobserved abilities and other farmers' and farm-specific characteristics. Any regression without considering such unobserved heterogeneity would lead to inconsistent estimates. Third, the ESR assumes that the adoption equation and the outcome equation error terms have a tri-variate standard distribution with a covariance matrix and a mean vector zero, which allows for accounting for sample selection bias (Asfaw et al., 2012). Thus, the ESR is the appropriate model to make it possible to avoid selection bias and unobserved heterogeneity among the adopters and non-adopters (di Falco et al., 2011; Asfaw et al., 2012; Wossen et al., 2017).

The ESR uses two stage-treatment frameworks. The first stage involves modeling of the adoption behavior with the limited-dependent variable method. This first stage uses the binary-probit model and allows us to address the first objective. Following Asfaw et al. (2012), Abdulai et al. (2014) and Ranjan et al. (2018), the decision to adopt sesame improved seeds (SIS) can be modeled in the framework of utility maximization. The difference between the utilities from adoption (U_{Ai}) and non-adoption (U_{Ni}) sesame technology can be denoted as ST^*, such that the i^{th} farmer would like to adopt the given improve seeds if (U_{Ai}) is greater than (U_{Ni}). The i^{th} farmer will adopt only if $ST^* = U_{Ai} - U_{Ni} > 0$. Given that ST^* is unobservable, we can express it as a function of observable factors in this latent variable model as follows:

$$ST_i^* = \beta X_i + \varepsilon_i \text{ with } SIS_i = \begin{cases} 1 \text{ } if \text{ } ST_i^* > 0 \\ 0 \text{ } if \text{ } ST_i^* \leq 0 \end{cases} \quad (1)$$

where ST is the dichotomous variable that takes the value of 1 if the farmer is an adopter of sesame technology and 0 otherwise; β is the vector of parameters to be estimated, and X is the vector of farmer, farm, and technology-specific characteristics; and ε is the random error with mean 0 and variance as σ^2. The maximum likelihood estimation (probit) is employed to estimate β. The adoption of sesame technology affects productivity, which is our outcome variable. Conditional on adoption, we specify the switching regression to evaluate the impact of technology adoption and education on productivity as follows:

Regime 1: $Y_{1i} = \theta_1 X_{1i} + \mu_{1i} \; if \; ST_i = 1$ (2)

Regime 2: $Y_{0i} = \theta_0 X_{0i} + \mu_{0i} \; if \; ST_i = 0$ (3)

where Y_1 and Y_0 are the sesame productivity for adopters and non-adopters, respectively. X_1 and X_0 are vectors of covariates including education variables, θ_1 and θ_0 are parameters to be estimated, and μ_1 and μ_0 are the errors terms of the outcome variables (productivity/yield). The errors ε_i, μ_1 and μ_0 are assumed to have a tri-variate normal distribution with zero mean and non-singular matrix. Subject to the selection condition, the estimated errors, μ_1 and μ_0, are non-zero. Because the error term in selection equation (1) is correlated with the error term in outcome equations (2 and 3), applying OLS will bias the prediction of θ_1 and θ_0 (Asfaw et al., 2012). Thus, the selectivity bias is addressed through the use of the ESR by predicting the inverse Mills ratios (λ_{1i} and λ_{0i}) and covariance terms ($\sigma_{\varepsilon 1}$ and $\sigma_{\varepsilon 0}$). These are then included as auxiliary regressions in equations (2) and (3) to correct the bias as follows:

$$E\{\mu_{1i}|ST_i = 1\} = \sigma_{\mu 1\varepsilon} \frac{\phi(\beta X_i/\sigma)}{\psi(\beta X_i/\sigma)} = \sigma_{\mu 1\varepsilon}\lambda_{1i} \qquad (4)$$

$$E\{\mu_{0i}|ST_i = 0\} = \sigma_{\mu 0\varepsilon} \frac{\phi(\beta X_i/\sigma)}{1-\psi(\beta X_i/\sigma)} = \sigma_{\mu 0\varepsilon}\lambda_{0i} \qquad (5)$$

where $\phi(.)$ and $\psi(.)$ are the standard normal probability density function and standard normal cumulative density function, respectively. λ_{1i} and λ_{0i} are the inverse Mills ratio. If the estimated covariances $\sigma_{\mu 1\varepsilon}$ and $\sigma_{\mu 0\varepsilon}$ are statistically significant, it implies that adoption decision and outcome variable are correlated. We find the evidence of ESR and reject the null hypothesis of no sample selection bias if the estimated covariances are significant (Maddala, 1983). The full information maximum likelihood (FIML) is applied to estimate the ESR (Lokshin et al., 2004; Asfaw et al., 2012). It estimates simultaneously the adoption equation (probit model) and the productivity outcome functions to give consistent standard errors. After we obtain the inverse Mills ratio through the ESR framework, we compute the average treatment effect of treated (ATT) following Lokshin et al. (2004). The ATT is defined as the expected difference in farmer productivity between adopters and non-adopters.

2.2. Data

Our empirical analysis relies on data from the "Enquête Permanente Agricole (EPA)", or Continuous Farm Household Survey, collected by the Ministry of Agriculture in Burkina Faso. The survey is designed in two stages, with probability proportional to sample size. The first stage units are the villages in each province, and the second stage units are households. The EPA sample is renewed every five years. EPA data collection takes place over seven months, from June to December each year, using questionnaires grouped into different sections, some of which are administered twice over two different periods. The survey's main objective is to estimate farm input use, production, farming land size, and yield of crops and to provide information about livestock holdings and farming household characteristics. Our study uses five rounds of the survey, that is, from the years 2015, 2016, 2017, 2018, and 2019. Additionally, excluding individual farmers with missing values resulted in an unbalanced panel of 4,726 observations from 45 provinces and 13 regions. Sesame productivity, farmer and farm socioeconomic factors, agronomic factors, and institutional factors are among the variables extracted from this dataset. Since the data cover all the provinces of Burkina Faso, we include province-fixed effects in the empirical analysis to control for observable/unobservable province level variations that affect both institutional factors and technology adoption. Table Table ***1*** below shows the definition of the variables of interest, the covariates employed, and their hypothesized sign.

Table 1.
Definition of variables

Variable	Description	Measurement	Sign
Dependent variable			
SIS	Sesame improved seed adoption	1 if adopted, 0 otherwise	
Productivity/Yield	Sesame yield	kg/ha	
Independent variables			
Gender	Gender of the farmer	1 = male, 0 = female	?
Age	Age of the farmer	Years	?
Marital status	Farmer's marital status	1 if married, 0 otherwise	+
Roof quality	Farmer's home roof	1 if metal sheet, 0 otherwise	+
Wall quality	Farmer's home wall quality	1 if parpaing, 0 otherwise	+
Livestock ownership	Farmer owns livestock	1= yes; 0 = otherwise	+
Literacy[5]	Farmer is literate	1 = yes; 0 = otherwise	+
Primary school	Farmer has attended primary school	1 = yes; 0 = otherwise	+
Secondary school	Farmer has attended secondary school	1 = yes; 0 = otherwise	+
Agricultural training	Farmer has attended agricultural training school	1 = yes; 0 = otherwise	+
Membership	Farmer is a member to a farmers group or association	1 = yes; 0 = otherwise	+
Microcredit access	Farmer has access to any form of credit in the past year	1 = yes; 0 = otherwise	+
Extension service	Farmer contact with an extension agent in the past year	1 = yes; 0 = otherwise	+
NPK application	Quantity of inorganic fertilizer (NPK) applied	kg/ha	+
Pesticides application	Quantity of pesticides applied	cl/ha	+
Organic fertilizer	Quantity of organic fertilizer applied	kg/ha	+
Land ownership	Farmer own the land	1 = yes; 0 = otherwise	?
Restored land	Farm plot has been fallowed	1 = yes; 0 = otherwise	?
Land age	The number of years farm plot is under cultivation	Years	?
Land size	Area under sesame production	Hectare (ha)	+

Notes: The signs in the last column are hypothesized. These are the expected sign between the explanatory variables and the adoption variable (SIS). The question mark indicates the existence of an ambiguous relation between that variable and adoption. The different variables of education i.e., *Literacy*, *Primary school*, *Secondary school*, and *Agricultural training* are our variable of interest in the outcome estimation.

[5] Literacy refers to farmers who attended non-formal schools in order to be able to read. These are rural literacy programs that are either in French or local languages.

3. Empirical results and discussion

3.1. Descriptive statistics

Table 2 below shows that the average yield is 517 kg/ha for the full sample and 549 kg/ha for sesame technology adopters. This is relatively low in comparison to other African producing countries and the potential yield of the "*S42*" variety. The yield difference between the non-adopters and adopters is negative with a significant t-test. This may suggest that adopters have a high yield compared to non-adopters. However, without further econometric estimation, this is a naive comparison that may be misleading, given that other unobserved factors may affect both the adoption decision and yields. According to the descriptive statistics, adopters of improved sesame seeds use more inorganic fertilizer (NPK) and pesticides than non-adopters. Additionally, the proportion of adopters who attended primary school and agricultural training school is higher than that of non-adopters. Furthermore, the proportion of adopting farmers who have access to microcredit (24%), extension services (44.5%), and belong to farming associations is higher compared to the non-adopting farmers. However, these proportions are still low, and improving sesame farmers' access to credit and extension services may enhance the adoption rate of agricultural technologies.

Table 2.
Descriptive statistics

Variable	Full sample	Non-Adopters (N=4093)	Adopters (N=633)	t-test
Yields (kg)	516.83 (322)	511.85 (317.6)	549.02 (346.26)	-37.17***
Gender	.715 (.45)	.709 (.45)	.754 (.43)	-.045**
Age	45.1 (13.32)	45.206 (13.4)	44.4 (12.86)	.81*
Marital status	.956 (.2)	.953 (.21)	.976 (.15)	-.023***
Roof quality	.704 (.46)	.701 (.46)	.724 (.45)	-.022
Wall quality	.112 (.31)	.107 (.31)	.15 (.36)	-.043***
Livestock ownership	.908 (.3)	.901 (.3)	.949 (.22)	-.048***
Literacy	.132 (.34)	.129 (.33)	.155 (.36)	-.026*
Primary school	.075 (.26)	.069 (.24)	.114 (.32)	-.044***
Secondary school	.019 (.13)	.019 (.14)	.016 (.12)	.003
Agri training	.034 (.18)	.032 (.18)	.044 (.2)	-.012
Membership crop	.191 (.39)	.185 (.4)	.231 (.42)	-.045***
Membership other	.107 (.31)	.098 (.3)	.166 (.37)	-.067***
Microcredit	.188 (.39)	.18 (.38)	.239 (.43)	-.06***
Extension service	.349 (.48)	.334 (.47)	.445 (.5)	-.11***
NPK (kg/ha)	2.491 (17.14)	2.18 (16.03)	4.518 (22.9)	-2.34***
Pesticides (l/ha)	4.17 (21.7)	3.76 (16.36)	6.8 (42.23)	-3.03***
Organic fertilizer (kg/ha)	62.483 (821.9)	62.841 (858.6)	60.163 (526.6)	2.68
Land ownership	.585 (.49)	.573 (.49)	.662 (.47)	-.09***
Restored land	.012 (.11)	.012 (.11)	.013 (.11)	0
Land age	13.311 (13.26)	13.12 (12.9)	14.558 (15.53)	-1.44***
Land size (ha)	.772 (1.01)	.781 (1.04)	.712 (.8)	.069*

Notes: The numbers between the parentheses are standard deviations corresponding to the mean values of the respective variables. For binary variables, the t-test value is the chi-square value of the proportion test.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

3.2. Endogenous switching regression: determinants of technology adoption

The FIML estimation of ESR is used to jointly estimate the adoption and outcome equations. Table 3 shows the factors that influence adoption of improved sesame seeds (the adoption equation) in the first stage and the impact of adoption on productivity (the outcome equation) in the second stage. The estimates in the selection equation (column 1 of Table 3) suggest different factors that affect farmers' decisions to adopt improved sesame seeds. Farmers' marital status and livestock ownership have a positive and significant impact on their decision to adopt sesame technology. Agronomic factors such as the use of inorganic fertilizer (NPK) and pesticides increase the likelihood of improved sesame seed adoption. This implies that if farmers use fertilizer and other crop protection practices, such as pesticide application, the likelihood of adopting sesame technology increases. While the size of the sesame-growing land reduces farmers' likelihood of using improved sesame seeds, the age of the land encourages farmers to adopt improved seeds. This result may hold true because larger farms require a greater quantity of improved seeds, resulting in higher seed costs. In this regard, resource constraints may influence farmers' decisions to adopt. This result is consistent with that of Abdulai et al. (2011).

Regarding our variables of interest, namely the various forms of education, only farmers who attended primary school are more likely to adopt sesame technology. This confirms our hypothesis that a certain level of education can positively affect farmers' decisions to adopt new agricultural technologies. This is also supported by many studies, such as Alene et al. (2007), Huang et al. (2009), and Ghimire et al. (2015). However, other forms of education, such as agricultural training, being literate, or having attended secondary school, do not have a significant impact on the decision to adopt. One implication of these results is that implementing rural school programs may enhance farmers' knowledge of agricultural technologies and their adoption.

3.3. Education effects on productivity through adoption of sesame technology

The results of the impact of education on productivity through the adoption of sesame technology are presented in columns 2 and 3 of Table 3 (second stage). In regard to the different forms of education, the dummy variables, i.e., having attended primary school and received agricultural training, are positive and significant for adopters at 5% and 10%, respectively. Thus, under the adoption of modern technologies, farmers' education has a significant impact on farm productivity. This result is supported by studies like Alene et al. (2007) and Asfaw et al. (2012). Farmers who have a minimum education level of formal primary school or have received agricultural training are most likely to adopt improved sesame seeds and experience an increase in productivity. According to the results, farmers who attended primary school, received agricultural training, and adopted the improved variety had productivity levels that were 140 kg/ha and 160 kg/ha higher, respectively, than those who adopted but did not attend primary school or receive agricultural training. This result also supports Schultz's argument that formal education has a significant marginal contribution to farm production only under modern technology (Schultz, 1975). However, being literate or having participated in literacy programs (non-formal schools) is insufficient to experience a significant impact on productivity through adoption (column 3 of Table 3). A similar result was shown by Ranjan et al. (2018) in India. This suggests that obtaining a minimum level of education improves farmers' abilities to collect and analyze data critical to the production process. It fosters an environment conducive to the adoption of modern technology, thereby increasing productivity (Ranjan et al., 2018). Although the coefficient is not statistically significant, the dummy variable having attended secondary school (column 3 of Table 3) did not produce the expected sign. This could be explained by the low proportion of adopters (1.5%) who attended secondary school. Furthermore, the gender of the farmer and the application of inorganic fertilizer (NPK) have positive and significant effects on the productivity of adopters and non-adopters (columns 2 and 3 of Table 3). However, the gender impact is only noticed by adopters.

Although the results are not shown, if the province dummies are grouped into agroecological zones, the zone dummies are significant in both equations, and the most favorable zones are the Sudano-Sahelian and Sahelian zones.

Table 3.
FIML estimates of Endogenous switching regression model

First stage: adoption equation		Second stage: outcome equation	
Variable	(1) Adoption	(2) Non-adopters	(3) Adopters
Gender	.003	8.14	88.225*
	(.07)	(13.138)	(46.211)
Age	-.001	-.245	-.22
	(.002)	(.39)	(1.395)
Marital status	.273*	7.924	41.887
	(.142)	(23.165)	(101.387)
Roof quality	.068	2.013	66.087*
	(.059)	(11.546)	(39.931)
Wall quality	.09	-2.827	66.705
	(.076)	(16.596)	(50.173)
Livestock ownership	.233**	10.862	62.294
	(.106)	(17.639)	(74.747)
Literacy	.091	45.964***	23.896
	(.072)	(14.804)	(48.379)
Primary school	.332***	19.686	139.55**
	(.087)	(19.877)	(58.95)
Secondary school	-.058	9.133	-74.231
	(.191)	(35.682)	(136.132)
Agri training	.179	5.918	159.262*
	(.127)	(27.728)	(85.634)
Membership crop	.06		
	(.056)		
Membership other	.095		
	(.065)		
Microcredit	.021	2.805	31.203
	(.069)	(13.814)	(43.096)
Extension	.028		
	(.049)		
NPK (kg/ha)	.003**	.498*	2.266***
	(.001)	(.302)	(.764)
Pesticides (l/ha)	.001*	.374	.576
	(.001)	(.298)	(.473)
Organic fertilizer (kg/ha)	4.3 e-6	.012**	-.021
	(2e-5)	(.006)	(.026)
Land ownership	.038		
	(.041)		
Land age	.004***		
	(.001)		
Land size (ha)	-.111***		
	(.023)		
Restored land		36.896	78.047
		(44.646)	(104.179)
Constant	-1.154***	235.73	54.7
	(.364)	(307)	(504.33)
Province fixed-effects	Yes	Yes	Yes
Observations	4726	4093	633

Continued

Table 3. FIML estimates of Endogenous switching regression model (continued)

Variable	(1) Adoption	(2) Non-adopters	(3) Adopters
Rho_0		.081	
		(.101)	
Rho_1			.947***
			(.019)
Log likelihood = -35389			
Wald chi^2 (17) = 350.07			
Prob > $chi^{2.}$ = 00000			
LR test of equations independence: chi^2 (2) = 38.65 Prob > $chi^{2.}$ = 0000			

Notes: The numbers between the parentheses are standard errors. Rho_0 and Rho_1 are correlation coefficients between the error terms and the system equation.
See also in the Appendix Table A1 the results using the agroecological zone fixed-effects.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

3.4. The productivity impacts of adopting sesame technology

In this section, we look at the impacts of adopting sesame technology on productivity. The correlation coefficients in Table 3 (Rho_0 and Rho_1) between the error terms and the system equation are positive and significant, indicating the existence of endogeneity and self-selection problems. In other words, there is a selection bias in the decision to adopt sesame technology, so using the ESR to correct the bias is appropriate. Since Rho _1 is positive and significantly different from zero, the model suggests that individuals or farmers who do not adopt sesame technology have lower sesame productivity than a random farmer from the sample, while those who do adopt it have no worse productivity than a random farmer. Moreover, the likelihood ratio test for independence between the selection equation and the outcome equations is significant, indicating dependence between the two systems of equations.

We use the ESR to predict the farm productivity differential between the adopters and their contrafactual. We are especially interested in the average treatment effects on the treated (ATT), which is the difference in average outcome (productivity) between farmers who adopt sesame technology and those who do not. The expected productivity of adopters is 551.35 kg/ha (column 1 of Table 4), while it is 511.85 kg/ha (column 2 of Table 4) for non-adopters. The results in column 3 of Table 4 reveal that the adoption of improved sesame seeds significantly increases sesame productivity by 39.4 kg/ha. In other words, farmers who adopted sesame technology would lose an average of 39.4 kg/ha of sesame if they had not adopted it. This result is consistent with the literature, especially studies conducted by Di Falco et al. (2011) and Khonje et al. (2015) in Ethiopia and Zambia, respectively.

Table 4.
ESR-based average treatment effects of adoption of improved sesame seeds

Productivity (kg/ha)	Adopters	Non-adopters	Treatment Effect
	(1)	(2)	(3)
Adopters	551.35	511.85	39.41***
	(5.425)	(1.416)	(4.186)

Notes: Numbers in parentheses below the coefficients are standard errors. See also in the Appendix Table A2 the results using the agroecological zone fixed-effects.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

3.5. Robustness check

Since results from ESR may be sensitive to its model assumption, i.e., the selection of instrumental variables, we also used the propensity score matching[6] (PSM) approach to check the robustness of the estimated treatment effect results from ESR. The average treatment effects on the treated (ATT) from the PSM can be specified as follows:

$$\text{ATT} = \text{E}(Y_1|P = 1, p(X)) - E(Y_0\,|P = 1, p(X)) \qquad (6)$$

where Y_1 is the value of productivity when the farmer i adopts or is subject to treatment ($P = 1$) and Y_0 the same variable when the farmer does not adopt improved sesame seeds ($P = 0$), and X is a vector of covariates. $Y_1|P = 1$ is observable while $Y_0|P = 1$ is not. Two assumptions should be met in order to avoid bias in the estimates of equation (1). First, conditional on the probability of adoption, given observable covariates and an outcome of interest in the absence of treatment, Y_1 and adoption status, P, are statistically independent. Second, the common support assumption, which requires substantial overlap in covariates between adopters and non-adopters $0 < p(X) < 1$. If these conditions are meet, equation (1) can be estimated.

A visual examination of the density distribution of the estimated propensity scores for the two groups (Figure 1 below) reveals that the common support condition is met: there is significant overlap in the distribution of the propensity scores for adopters and non-adopters. The ATT is the mean difference of the adopters matched with non-adopters that are balanced on the propensity scores and fall within the region of common support. Despite the fact that PSM tries to compare the difference between the outcome variables of adopters and non-adopters with similar characteristics, it cannot correct unobservable bias because it only controls for observed variables. The results presented in Table 5 below also show that adoption of sesame technology significantly increases sesame productivity.

Table 5.
Average treatment effects using the propensity score matching

Variable	ATT	Bias	Total % bias reduction
Adopters	35.76*** (14.253)	-.518	71%

Notes: PSM uses probit model for the selection equation. 87% of the total observation were correctly classified.
Region of common support [.032, .873].
Adopters of improved sesame seeds produce 36 kg/ha more than non-adopters.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[6] See Abadie et al. (2016) for further details on PSM.

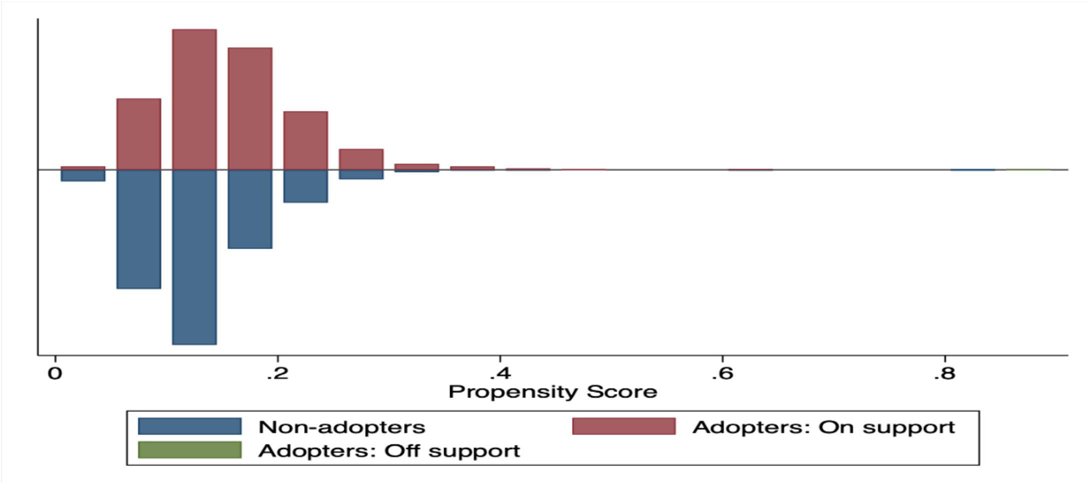

Figure 1. Common support for propensity score estimation
Notes: Adopters on support are farmers who found a suitable match in the adoption group, whereas adopters off support are farmers who did not find a suitable match in the adoption group.

4. Conclusions

This paper analyzes the determinants and productivity impacts of the adoption of improved sesame seeds in Burkina Faso using longitudinal data from a sample of 4,726 sesame farmers. The selection stage of the endogenous switching regression (ESR) revealed that adoption of improved sesame seeds is significantly related to farmers' marital status, livestock assets, fertilizer and pesticide applications, land age, and education, especially formal primary education. The results suggest that adoption of sesame technology can be enhanced through increased farmer education and access to productive assets. The second-stage results of the ESR further showed that adoption of sesame technology leads to significant gains in productivity. More importantly, formal primary education and agricultural training significantly increase sesame productivity through adoption. Therefore, improving or increasing sesame yield depends primarily on the adoption of improved agricultural technologies like improved sesame seeds. This highlights the need for policies and strategies aimed at enhancing adoption of improved sesame seeds among non-adopters through education, such as formal primary education, agricultural training programs, and efficient access to inputs and productive assets.

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