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Impact of Microdosing Practices on Technical Efficiency: An Analysis Accounting for Selection Bias among Smallholder Maize Farmers in Burkina Faso

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Abstract

Smallholder maize farmers are currently confronted with the arduous challenge of managing limited financial resources while incessantly facing the issue of land degradation. To address this issue, an alternative solution has been implemented to optimize the use of chemical fertilizer by adopting microdosing. This innovative system not only helps them enhance their agricultural productivity but also allows them to protect the environment. However, it is unclear how microdosing adoption could increase the technical efficiency (TE) of maize production. Therefore, this research aims to assess how the adoption of microdosing affects the technical efficiency of maize production as well as identify the key factors that influence the technical efficiency of maize production in Burkina Faso. To achieve this goal, farm household survey data was conducted with 210 randomly selected farmers from the Plateau Central and northern regions of Burkina Faso. To account for potential selection biases that could result from both observable and unobservable factors, we used a sample selection stochastic production frontier model and a propensity score matching approach. A stochastic meta-frontier approach was applied to estimate TE differences and the technology gap between adopters and non-adopters. The findings showed that adopters of microdosing have an average efficiency of 68 percent, which is higher than the 53 percent estimated for non-adopters. Adopters of microdosing have been found to have high TE and better agricultural technology than non-adopters. The meta-frontier estimation revealed that the adoption of improved maize varieties would yield better returns. This study contributes significantly to the literature on how fertilizer microdosing affects maize productivity, as well as the policy implications of targeting and encouraging smallholder maize farmers in Burkina Faso to optimize the use of productive inputs and improve maize output by using microdosing.

Keywords: microdosing, technical efficiency, stochastic production frontier, maize production, selection bias, Burkina Faso

1. Introduction

1.1 Background and Purpose

The agricultural sector in Burkina Faso continues to be a critical source of revenue, ensuring food security and serving as a primary means of livelihood. According to the Ministry of Agriculture (2019), the agricultural sector is mainly characterized by smallholder farmers, who make up 60% of the active population. These farmers typically operate farms that span less than 5 hectares and have access to limited resources. However, land degradation poses a significant threat to the majority of these smallholder farmers' livelihoods. Various projects and innovative initiatives have been undertaken by policymakers in response to the urgent problem of land degradation. Their aim is to introduce sustainable land management (SLM) programs that will conserve soil fertility and enhance agricultural productivity (Ministry of Agriculture, 2021). These efforts, spearheaded by both the governmental programs and non-governmental organizations (NGOs), have specifically targeted cereal crops, with a notable focus on maize production, to bolster household resilience.

Maize (*Zea mays* L.) referred to as a staple food in Burkina Faso, is a key crop. It not only serves as a vital food source but also plays a significant role in generating export revenue (INSD, 2017). Maize ranks second in terms of cultivable land and cereal production in the country. However, despite their importance, the revenues generated from maize production have remained stagnant, primarily due to various challenges and constraints faced by smallholder farmers. Improving the technical efficiency of maize adopting innovative technology remains an essential driver of economic growth in developing countries (Lampach et al., 2021).

One alternative method that has significantly enhanced the optimization and efficient use of chemical fertilizer by smallholder farmers is fertilizer microdosing. It has been implemented and promoted by the Ministry of Agriculture and the Ministry of High Education, Research, and Innovation through an *SLM*-initiated research programs, for instance the National Institute for Agricultural Research and Environment (INERA) and the Agriculture Productivity Improvement Program for Smallholder Farmers Projects (SAPEP). This agricultural technology system consists of applying a very small amount of chemical fertilizer necessary for the growth and productivity of the cereal crop (Sawadogo et al., 2023). The benefits of the technology include reducing the amount of fertilizer used per hectare by half. Furthermore, the implementation of microdosing can enhance cereal productivity, minimize costs associated with agricultural inputs, and improve soil fertility (Ouedraogo et al., 2020; Sanogo et al., 2020). Based on the importance of maize production economically, microdosing could be used to enhance maize production while decreasing the amount of chemical fertilizer used. Analyzing the technical efficiency of maize production by adopting microdosing can provide valuable insights into the relationship between agricultural inputs and productivity performance.

Several studies have explored the technical efficiency of maize production in Burkina Faso (Ouedraogo, 2019; Seogo et al., 2021) and Sub-Saharan Africa (Oladeebo & Fajuyigbe, 2007; Olarinde, 2010; Bahta et al., 2020; Tetteh Anang et al., 2020; Ngango & Hong, 2021). None of them has investigated the relationship between the adoption of microdosing and the technical efficiency of maize production. The impact of microdosing on the technical efficiency of maize production has not yet been explored in Burkina Faso. In Sub-Saharan Africa, some authors (Ma et al., 2018; Abdul-Rahaman et al., 2021; Lampach et al., 2021; Ngango & Hong, 2021) have analyzed the technical efficiency using the stochastic production frontier, considering selection bias. Regarding self-selection for adoptive fertilizer microdosing among maize farmers, the sample may not be a random selection (Sawadogo et al., 2023). This stochastic production frontier method adjusts for selection bias to account for biased estimators on observable variables and unobservable factors. Additionally, other studies addressed the bias issue by combining sample selectivity bias-corrected SPF and endogenous switching regression (Aravindakshan et al., 2018; Fu & Zhu, 2023).

Some studies (Mwalupaso et al., 2019; Mzyece & Ng'ombe, 2020; Ankrah Twumasi & Jiang, 2021; Olagunju et al., 2021; Zhu et al., 2021) have employed TE by comparing two groups in order to adjust the efficiency of adopting the technology. Comparing the TE between two groups of farmers is a crucial matter that frequently arises in these studies (Khanal et al., 2021). Farmer groups get self-selected into a specific group (Bravo-Ureta et al., 2012; Ngango & Hong, 2021). Research by Greene (2010) provides an approach from the stochastic production frontier (SPF) that deals with the sample selection problem. Greene's model has been employed in numerous studies to correct the selection bias in the SPF (Abdul-Rahaman & Abdulai, 2018; Ma et al., 2018; Issahaku & Abdulai, 2020; Olagunju et al., 2021; Ankrah Twumasi et al., 2022). Moreover, several studies have integrated Greene's (2010) sample selection bias-corrected SPF with the propensity score matching approach to evaluate the impact of treatments on both treated and control samples (Bravo-Ureta et al., 2012; Abdul-Rahaman et al., 2021; Ngango & Hong, 2021). In this context, this study aims to accurately assess the impact of fertilizer microdosing on the technical efficiency of maize farmers in Burkina Faso, considering the selection bias issues caused by unobservable and observables factors. To address sample selection bias from observable factors, we specifically use a propensity score matching method, and then to correct sample selection bias from unobservable factors, we use Greene's (2010) selectivity-corrected stochastic frontier approach. Then, the technical gaps between adopters and non-adopters were calculated using the stochastic meta-frontier method developed by Huang et al. (2014).

This study aims to make a significant contribution to the literature by exploring the relationship between fertilizer microdosing and the technical efficiency of maize production, bringing a unique and original perspective. Therefore, we controlled the sample selection bias from both unobservable and observable factors to obtain unbiased and consistent estimates on the technical efficiency of maize production using both propensity score matching, and sample selection corrected stochastic production frontier. In addition, we also contribute by accurately assessing the level of the technological gap between fertilizer microdosing adopters and non-adopters.

1.2 Maize Production in Burkina Faso

Maize plays a crucial role in the economy contributing 3% to the gross domestic product (GDP) and accounting for about 10% of total food consumption expenditures (Kaminski et al., 2013). In urban areas, maize is the second most consumed staple after rice. Maize production accounts for 32% of total cereal production (Ouedraogo, 2021).

In order to enhance rainfed maize production (approximately 92%) and overcome the issue of low soil fertility, research institutes have strongly advised farmers to incorporate both chemical and organic fertilizers. Due to limited access to credit, smallholder maize farmers frequently encounter challenges when attempting to use the recommended amounts of fertilizer. However, microdosing technology is a technique for optimizing used application of chemical fertilizer. Microdosing can increase maize production without increasing the amount of chemical fertilizer used compared to non-adopters' farmers. The fact that microdosing is to sow a small amount of chemical fertilizer close to the plant to reduce the waste of fertilizer means that the plant benefits from fertilizer. According to Ouattara et al. (2018), instead of applying a recommended amount of 150 kg of nitrogen, phosphorus, and potassium (NPK) and 100 kg of urea per hectare, farmers can simply employ 2 g of fertilizer per sowing hole, which is equivalent to 62.5 kg/ha of NPK (14-23-14), and 1 g, equivalent to 31.2 kg/ha of urea (46%). This approach not only helps alleviate the burden on farmers' limited resources, but also ensures more efficient use of fertilizers. NPK can be applied 10 days after sowing, and urea can be distributed 45 days after sowing (Ouattara et al., 2018). By adopting microdosing practices, farmers can significantly reduce the amount of chemical fertilizer they use.

In Burkina Faso, drought continues to be a significant challenge to the cultivation of maize (Dao et al., 2015). Agricultural research has successfully overcome environmental constraints by developing improved maize varieties. These new varieties showcase enhanced tolerance to drought, diseases, pests, and have early maturity. Notably, among these drought-resistant varieties are "*Wari*" and "*Barka*", recognized for their early maturation (85–94 days), with "*Barka*" being exceptionally extra-early (70-84 days) (Zoma, 2010). Recently, some improved varieties, such as "*Bondofa*" hybrid, have been introduced to benefit farmers by enhancing maize productivity, which has the potential to yield over 10 tons per hectare. Moreover, a distinct "*Komsaya*" hybrid known as "*The Hunger is Over*," has been introduced with the purpose of making a significant contribution to food security. This variety enhances an average yield ranging from 5 to 8 tons per hectare (Ouedraogo, 2021). In a study conducted by Dao et al. (2015), it was found that 37% of farmers in both the northern and southern regions are adopting improved maize varieties. These varieties possess remarkable characteristics such as high yield potential, early maturity, tolerance to drought, striga resistance, and adaptability to low soil fertility (Dao et al., 2015).

2. Materials and Methods

2.1 Sampling Technique and Sample Size

The study was carried out in the Plateau Central and northern regions (Passore and Oubritenga) of Burkina Faso. We used a cross-sectional dataset from a household farm survey conducted between November 2021 and March 2022 during one cropping season. We chose to conduct our study in the Plateau Central and northern regions for various compelling reasons. Firstly, these regions have been specifically targeted as focal points for Burkinabe government initiatives and local projects aimed at implementing sustainable land management practices and fertilizer optimization, including techniques such as stone lines and microdosing. This strategic focus arises from the heightened levels of land degradation and soil erosion observed in the area. Secondly, the adoption rate of sustainable practices in the study area remains strikingly low, standing at less than 40%. In addition to addressing this issue, targeted efforts in these regions also aim to promote and increase maize production. However, the Ministry of Agriculture (2020) reveals a concerning situation, with rainfed maize production showing 1,354 kg/ha. The urgency of addressing these challenges is underscored by the need for effective measures to enhance productivity of agricultural activities in these regions. Third, these regions have persistently encountered challenges related to food insecurity. In the Plateau Central region, cereal food supply covered only 14.8% of household food needs, while it covered 24.5% in the northern region (MAAH, 2020).

The sampling procedure followed a multi-stage sampling technique to select 9 communes (Absouya, Loumbila, Dapeoloo, Zitenga, Ziniaré, Ourgou-Menaga, Bokin, Arbollé, and Kirsi) and 18 villages from both regions. In the first stage, we selected 6 communes from the northern region and 3 communes from Plateau Central. The selection of these communes was based on their susceptibility to drought shock, their limited ability to adapt to climate change, and the prevailing issue of food insecurity. In the second stage, we conducted a random selection of 18 villages. This included 6 villages from the northern region and 12 villages from the Plateau Central region.

In Plateau Central, 20 smallholder farmers were randomly chosen from each of the 12 villages, while in the northern region, 30 farmers were selected from each of the 6 villages. Then, the entire sample had a total of 420 smallholders, comprising 1,290 plots. From the total sample, we identified 210 maize farmers, including 132 adopters serving as treatment group and 78 non-adopters serving as control group. The treatment group consisted of maize farmers who applied microdosing practices to their plots every cropping season, while the control group consisted of farmers who did not adopt microdosing practices. In the study area, the extension services use to help farmers apply these microdosing practices, and the adopted farmers benefit from these services, including some training, subsidized fertilizer, and improved varieties. The sample adopters and non-adopters' lists were established through the consultation of extension services, and this final list was verified through the questionnaire and a face-to-face interview. Demographic, farm, and institutional characteristics such as age, gender, education, credit, farm income, extension visits, land use, crop production, sustainable land management practices, farm equipment, application of chemicals such as NPK, urea, and diammonium phosphate (DAP), organic fertilizers (manure and compost), and food expenditure were all covered in the data. The total cereal production and total input used were estimated by the farmers themselves. Afterward, the production of each household was adjusted and corrected using the personal data of farmers recorded from local projects, NGO extension agents and research institutes that back farmer production. To ensure the questionnaire's validity and the coherence and consistency of the questions, a pilot survey was conducted. The questionnaire was revised based on the pilot survey feedback to enhance its accuracy and clarity. Interviewers and supervisors received training before and after the pilot survey to familiarize themselves with the field work and survey tools.

2.2 Econometrical Analysis Framework

Figure 1 explains the economic model used and the data analysis in detail. Below, we present a comprehensive overview of the steps involved in econometric methodology.

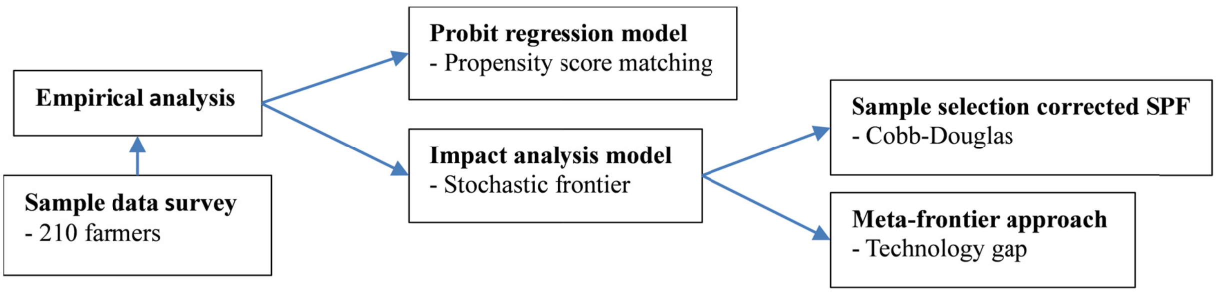

Figure 1. Econometric analysis framework

2.3 Microdosing Adoption Model

The decision of whether to adopt fertilizer microdosing can be effectively modeled within a random utility framework, especially for smallholder maize farmers (Becerril & Abdulai, 2010; Kassie et al., 2015). In our context, we can assume that a maize farmer potentially evaluates the benefits of adopting or not adopting microdosing. In fact, a maize farmer will join the microdosing practices if expected benefits from microdosing practices (M_A^*) outweigh the expected benefits from microdosing non-practices (M_N^*). The difference between the expected benefits from microdosing adoption and non-adoption is represented by the following equation:

$M_i^* = M_A^* - M_N^* > 0$, where M_i^* represents an unobservable latent variable as illustrated below:

$$M_i^* = \delta Z_i + \omega_i \text{ with } M_i^* = \begin{cases} 1 \text{ if } M_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{1}$$

where, M_i^* is a binary indicator of microdosing adoption with a value of one, and zero otherwise. We describe the microdosing adoption model parameters: δ is a vector of parameters to be evaluated; Z_i is a vector of observable attributes that affects an adoption decision: ω indicate the random error, with zero mean with expression variance $\sigma^2 = 1(\omega_i \sim N[0,1])$. The probability to adopt fertilizer microdosing is expressed by:

$$P(M_i^*=1) = P(M_i^* > 0) = P(\omega_i > -\delta Z_i) = 1 - F(-Z_i\delta)Z_i \tag{2}$$

Here, F indicates the cumulative distribution function of ω_i. In terms of motivation, it is clear that every farmer has his or her own special combination of resilience and beliefs, which sets them apart as unique individuals. It should be noted that not all farmers exhibit a natural inclination toward adopting fertilizer microdosing.

2.4 Sample Selection-Corrected Stochastic Production Frontier Model (SPF)

We employ a sample selection-corrected stochastic production frontier approach to address a selection bias that could arise from unobservable factors. In our study, we assume that all farmers are engaged in maize production, regardless of whether they use fertilizer microdosing or not. The sample selection corrected is expressed by:

$$Y_{ij} = f(X, M_i) + \varepsilon_i,\ \varepsilon_i = v_{ij} - u_{ij} \tag{3}$$

Here, Y_{ij} is represent a farmer's maize yield, X indicates a set of inputs variables including independent factors, M_i indicates a binary variable, which shows the impact of fertilizer microdosing adoption, v_{ij} is the two-sided error term and u_{ij} is the one-sided error term estimating efficiency. Farmers can independently adopt fertilizer microdosing, which can lead to selection bias due to factors that are both observed and unobserved.

2.5 Correcting Selection Bias in the Stochastic Production Frontier

When a farmer decides whether to adopt microdosing of fertilizer, some factors (observed and unobserved) influencing the decision to adopt microdosing may also affect yield and the technical efficiency of maize production. To ensure unbiased and consistent estimates related to the effects of adoption in the sample selection-corrected stochastic production frontier model, it is essential to address the potential selection bias diligently. Many previous studies have employed sample selection correction models to correct for selection bias in stochastic production frontier models (Greene, 2010; González-Flores et al., 2014; Azumah et al., 2019; Issahaku & Abdulai, 2020; Ngango & Hong, 2021). Microdosing adoption is not random, whether farmers choose to implement it or not. Both observable and unobservable factors are expected to have an impact on adoption decisions and their resulting outcomes in terms of productivity and technical efficiency. There might be a selection bias because of the correlation between the error terms in the selection model (1) and the SPF model (3). Failure to account for this bias may result in biased and inconsistent parameter estimates (Abdul-Rahaman et al., 2021). To correct for both types of selection bias, we have incorporated the sample selection bias corrected SPF approach proposed by Bravo-Ureta et al. (2012) in our study. The sample selection SPF model developed by Greene (2010) is specified to correct biases caused by unobservable factors. The Propensity score matching (PSM) procedure is applied to correct biases brought on by observable factors. The control group consisted of smallholder maize farmers in our sample who had not adopted any microdosing practices. During that same period, they cultivated small plots of land using basic equipment and focused on growing maize. The final profile list of control groups was established based on these farmers' information in the database.

To implement the PSM in practice, it is crucial to first use a binary choice model. This model generates propensity scores, or p-scores, that serve as indicators of individuals' probability of belonging to either group. Following that, fertilizer microdosing practiced and non-practiced are matched using PSM related to their observed attributes. The following is a description of the error structure and Greene's (2010) selection bias-corrected SPF model:

$$\begin{gathered}
\text{Sample selection: } M_i = 1[\gamma' Z_i + \omega_i > 0],\ \omega_i \sim N[0, 1] \\
\text{SPF: } y_i = \beta' X_i + \varepsilon_i,\ \varepsilon_i N \sim [0, \sigma_\varepsilon^2] \\
(y_i, X_i) \text{ is observed only when } M_i = 1 \\
\text{Error structure: } \varepsilon_i = v_i - u_i \\
u_i = |\sigma_u U_i| = \sigma_u |U_i|, \text{ where, } U_i N \sim [0, 1] \\
v_i = \sigma_v V_i, \text{ where, } V_i \sim N[0, 1] \\
(\omega_i, v_i) \sim N_2[(0, 1), (1, \rho\sigma_v, \sigma_v^2)]
\end{gathered} \tag{4}$$

Here, M_i refers to the adoption variable, assigned 1 for adopters and 1 for non-adopters, Z_i is a set of independent variables in the selection equation, y_i is the maize output, X is a input variables in the stochastic frontier model, v_i is the stochastic error term, and u_i is the inefficiency term. The parameter significant ρ shows a presence of selection bias based on unobservable factors.

2.6 Meta-frontier Approach

An analytical approach suggested in Greene (2010) has a significant flaw. Since the estimated TE scores are based on each group's frontier, it is not possible to directly compare the TE scores of adopters and non-adopters (González-Flores et al., 2014). According to Olagunju et al. (2021), adopters and non-adopters in TE use different technologies that cannot be directly compared. One approach to tackle this limitation is by using the meta-frontier production function technique to establish a common benchmark. This would enable a valid comparison between adopters and non-adopters. The meta-technology ratio (MTE), commonly referred to as the gap between the meta-frontier and each group frontier, can be estimated using this approach. We followed the method proposed by Abdul-Rahaman et al. (2021). A production frontier is estimated for each group of adopters and non-adopters as follows:

$$Y_{ij} = f^j(X_{ij}, \eta_j)e^{v_{ij}-u_{ij}} \tag{5}$$

where, Y_{ij}, X_{ij}, v_{ij}, u_{ij} η_j are as defined preciously above. According to Huang et al. (2014), the both error terms v_{ij} and u_{ij} are assuming to be uncorrelated in a truncated-normal distribution function. We estimated the TE using the production frontier model for both adopters and non-adopters:

$$TE_i^j = \frac{Y_{ij}}{f^j(X_{ij}, \eta_j)e^{v_{ij}}} = e^{-u_{ij}} \tag{6}$$

The function $f^M(X_{ij}, \eta_j)$ represents the meta-frontier (MF), which acts as a common benchmark enveloping the frontiers of both fertilizer microdosing adopter and non-adopter groups. The meta-frontier function for each group of adoption is expressed as:

$$f^j(X_{ij}, \eta_j) = f^M(X_{ij}, \eta_j)e^{-u_{ij}^M}, \forall i, j \tag{7}$$

where, $u_{ij}^M \geq 0$. Thus, $f^M(X_{ij}, \eta_j) \geq f^j(X_{ij}, \eta_j)$. The technology gap ratio (TGR) specifies the ratio of the group frontier to the Meta-frontier:

$$TGR = \frac{f^j(X_{ij}, \eta_j)}{f^M(X_{ij}, \eta_j)} = e^{-u_{ij}^M} \leq 1 \tag{8}$$

The technical efficiency of the meta-frontier production technology (MTE) expressed by $f^M(X_{ij}, \eta_j)$ is then estimated using the following connection by:

$$MTE = \frac{Y_{ij}}{f^M(X_{ij},\eta_j)e^{v_{ij}}} = TGR_{ij} \times TE_{ij} \times e^{v_{ij}} \tag{9}$$

2.7 Empirical Model Specification

As described in the previous section, we estimate a probit model using the PSM technique. Different estimation methods for the PSM approach are used to match samples of microdosing adopters and non-adopters. These methods include k-nearest neighbor matching, kernel matching, radius matching, and stratification matching. The k-nearest neighbor matching yielded a better-matched sample than the other PSM estimates. We used a k-nearest neighbor matching applying a maximum of five matches per group. In addition, we also incorporated a caliper parameter set at 0.01. This matching result output revealed 206 matched observations consisting of 74 adopters and 132 non-adopters. We conducted a balancing test after the matching procedure to verify the quality of matched sample. After obtaining matched sample, we corrected the selection bias from the unobservable factors by estimating selectivity-corrected stochastic production frontier.

Before conducting SPF models, we estimated correlation tests between all the input variables, such as NPK application, urea application, compost, and manure. The findings revealed that the significant correlation between NPK and urea, as well as between compost and manure, influenced the quality of stochastic frontier models. We performed a regression estimation that removed some variables, such as NPK and compost, to resolve this issue of multicollinearity.

From Greene's (2010) approach, we estimated several SPF models from both unmatched and matched samples. For the conventional SPF sample, we estimated two models: (1) a SPF model for an adopter's sample; and (2) a SPF for a non-adopter's sample. We estimated a selectivity-corrected SPF model of (3) for a sample of adopters and a selectivity-corrected SPF model of (4) for a sample of non-adopters as part of our sample selection process. We repeated the exact same procedure for estimation and matching, resulting in four samples of estimated SPF models.

According to Bravo-Ureta et al. (2007), Cobb-Douglas (CD) and Translog (TL) are two of the functional forms frequently applied in technical efficiency studies. The null hypothesis states that the "coefficients of both the squared and interaction terms of the input variables in the TL specification show no statistical difference from zero. If the null hypothesis is not rejected, the CD specification is selected" (Neubauer et al., 2022). We used Stata software to estimate a maximum likelihood ratio (LR) test in order to identify the best production function. The chi-square test revealed that the result of LR value of 6.18 (p-value = 0.1864) was not significant at the 5% level. Thus, we were unable to reject the null hypothesis of CD. As a result, the CD functional form was chosen over the TL functional form since TL does not include CD. The functional form of CD is as follows:

$$\ln(Y_i) = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_{ji} + \sum_{k=1}^{m} \delta_k G_{ki} + v_i - u_i, \text{ if } M_i = 1 \tag{10}$$

where, Y_i indicate maize yield, X_{ji} is quantity of input, G_{ki} is adoption variable, v_i and u_i are the error terms.

3. Results and Discussion

3.1 Descriptive Statistics

Table 1 shows that microdosing adopters have a higher average rainfed maize yield of 1,244 kg/ha than non-adopters (885 kg/ha). This high maize yield among adopters' farmers can be attributed to their performance in optimizing the use of agricultural inputs. From 2015 to 2020, the national average maize yield was 1,354 kg/ha (Ministry of Agriculture, 2020). Concerning the area cultivation, the average maize plot size was 0.748 hectares. The land size was very small mainly due to the loss of arable land from soil erosion, land degradation, and low fertility. The farmers in the study areas experienced a low average maize yield due to the degradation of their land. According to Appendix A, only 37% of the total sample size adopted fertilizer microdosing.

The household heads are on average 49 years; and that showed a relatively young age in the study area among smallholder's maize farmers. According to Guo et al. (2015), younger farmers tend to be more involved in maize farming and increase production suggesting that age may also have a positive effect on agricultural productivity.

The education level reported an average of 1.9 years in school. The findings showed a low level of education among maize farmers. According to Paltasingh and Goyari's (2018) research, farmers' higher education is positively correlated with their agricultural output. Education plays a crucial role in enhancing the farming abilities and productivity capacities of farmers. It empowers them with the knowledge and skills to effectively follow written instructions when applying recommended doses of fertilizers and other necessary inputs (pesticides, herbicides). As a result, education serves as the foundation for improving farmers' practices and ensuring successful agricultural outcomes.

The average household size was 10 members. The findings revealed that the maize farmers had large families, which could be related to their high productivity in maize cultivation. Only 10% of the smallholder's maize farmers had access to credit. This could be attributed to the absence of microcredit facilities and the stringent requirements of some lenders. This is in line with Adom's (2021) study reported that many people in Africa face credit constraints due the unavailability of banks.

On average, farmers applied 68 kg/ha of NPK fertilizer and 29 kg/ha of urea to their crop production. Moreover, the Ministry of Agriculture of Burkina Faso recommends applying 100 kg/ha of urea and 150 kg/ha of NPK as fertilizer for maize cultivation, unless microdosing is used (Ouattara et al., 2018).

Table 1 displays the statistical t-test results for checking the quality of matching, along with the differences in variable means between microdosing adopters and non-adopters. We found that microdosing adopters and non-adopters have significantly different values for most of the variables in unmatched sample. Within the adopters' group, variables such as land ownership, off-farm income, extension visit, improved varieties (dummy), sandy clay soil, hired labor, oxen, urea application, manure, gravelly soil and Absouya location indicate significant differences.

All variables in the matched sample show no difference at the 90% confidence level between both groups, indicating that the PSM method balance (condition region of common support in Figure 2 and balancing of ln yield distribution in Appendix B) is achieved.

Table 1. Descriptive statistics for the study's variables

Variables	Unmatched samples					Matched samples				
	Microd adopters		Microd Non-adopters		T-test value	Microd Adopters		Microd Non-adopters		T-test value
	Mean	St. dev	Mean	St. dev		Mean	St. dev	Mean	St. dev	
Maize yield (kg/ha)	1244.89	791.39	885.83	504.37	4.02***	1225.50	792.59	858.55	501.85	3.41**
Age (years)	50.67	9.33	48.46	10.73	1.51	50.97	9.33	51.77	11.52	-0.46
Gender (female/male)	0.04	0.19	0.08	0.28	-1.26	0.04	0.19	0.07	0.24	-0.76
Education (years)	2.15	2.34	1.80	2.17	1.1	2.12	2.34	2.58	2.18	-1.21
Household size (members)	9.47	3.11	10.62	5.75	-1.63	9.55	3.11	10.50	5.75	-1.28
Land Ownership (yes/no)	0.92	0.27	0.46	0.50	7.52***	0.92	0.27	0.90	0.29	0.41
Off farm income (yes/no)	0.86	0.35	0.74	0.44	2.01***	0.85	0.35	0.91	0.25	-1.02
Access to credit (yes/no)	0.12	0.32	0.09	0.29	0.57	0.12	0.32	0.03	0.17	1.99
Flat Ground (yes/no)	0.32	0.47	0.41	0.49	-1.28	0.34	0.47	0.49	0.50	-1.93
Extension visits (numbers)	3.33	2.38	1.23	1.91	7.01***	3.03	2.38	3.43	2.38	-1.09
Imprd varieties (yes/no)	0.80	0.40	0.57	0.50	4.51***	0.80	0.49	0.57	0.40	3.13**
Group Membership (yes/no)	0.53	0.50	0.51	0.50	0.25	0.50	0.50	0.69	0.44	-1.41
Sandy loam (yes/no)	0.26	0.44	0.19	0.39	1.14	0.24	0.44	0.44	0.50	-1.62
Sandy clay (yes/no)	0.32	0.47	0.20	0.40	1.89*	0.34	0.47	0.20	0.50	-1.90
Hired labor (person days)	12.08	20.60	4.60	18.87	2.68***	11.81	20.60	6.01	26.63	1.54
Oxen (oxen days)	253.02	681.27	92.92	152.61	2.60*	258.20	689.52	118.45	161.93	1.72
Maize land (ha)	0.83	0.70	0.70	0.47	1.55	0.82	0.70	0.53	0.37	3.18**
Urea application (kg/ha)	56.33	75.60	13.84	25.84	5.91***	57.81	76.03	15.57	27.88	4.55***
Manure (kg/ha)	980.54	2432.43	499.54	768.17	2.10**	975.42	2464.44	612.81	835.72	1.21
Family labor (person days)	287.35	261.43	260.54	244.20	0.75	290.17	264.30	289.87	279.29	0.01
Improved varieties (kg/ha)	24.35	38.69	21.48	26.05	0.64	24.73	39.13	30.04	28.37	-0.96
Gravelly (yes/no)	0.46	0.50	0.33	0.47	1.97**	0.43	0.50	0.25	0.42	1.37
Absouya (yes/no)	0.01	0.11	0.34	0.48	5.98***	0.01	0.11	0.04	0.18	-0.09
Loumbila (yes/no)	0.18	0.39	0.12	0.33	1.16	0.19	0.39	0.14	0.33	0.88
Zitenga (yes/no)	0.13	0.34	0.06	0.24	1.69	0.14	0.34	0.20	0.39	-0.98
Sample size	**78**		**132**			**74**		**132**		

Note. St. dev: Standard deviation. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

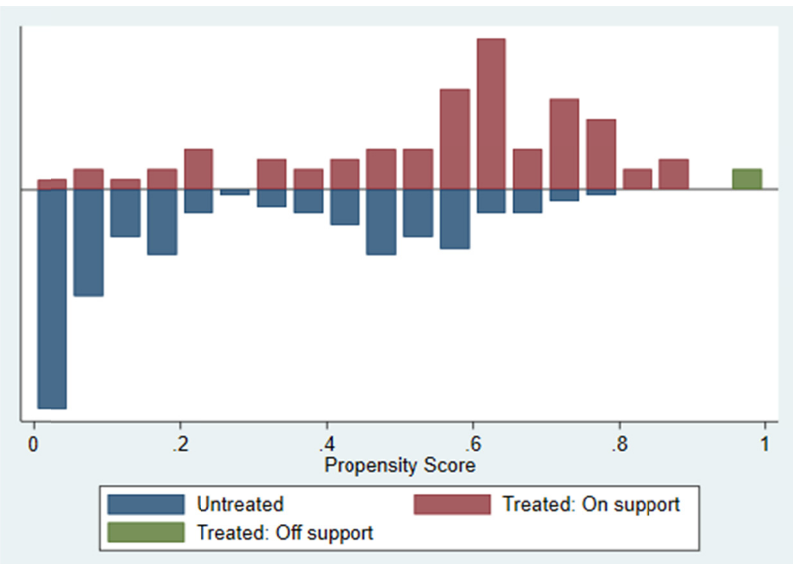

Figure 2. Distribution for propensity score matching and region of common support

Note. Axis y represents a frequency of matched and unmatched for each p-score estimates.

3.2 Determinants for Microdosing Adoption

Table 2 presents the results of estimating the factors that influence the decision to adopt microdosing in matched samples. Following Olagunju et al. (2021), the average marginal effects are additionally estimated and presented to facilitate a clearer interpretation of the findings. Both the Wald chi-square and pseudo-R^2 statistics suggest that the adoption model fits well. Education level, extension visits, household size and land ownership all significantly affect microdosing adoption, according to the probit model results. Furthermore, all these variables have positive and significant marginal effects on microdosing practices.

A relationship exists between the level of education of household heads and the adoption of microdosing. The findings indicate that farmers with a higher level of education were more inclined to adopt fertilizer microdosing in comparison to those without any formal education. Asfaw and Admassie (2004) and Tiwari et al. (2008) pointed out that household head education seems to increase the probability of adopting chemical fertilization. According to Miheretu and Yimer (2017), education is widely recognized as a powerful tool that not only boosts an individual's critical thinking abilities, but also provides them with a deep understanding of the latest technologies and fosters their willingness to adopt these new technologies.

Extension visits have a significant and positive effect on microdosing adoption. This implies that the probability of microdosing adoption increases significantly with the total number of extension visits. According to Beshir et al. (2012), agricultural extension services are the primary source of information for better agricultural technology. They also noted that farmers can get knowledge about these technologies by consulting an extension agent.

The household size seems to be positive and influencing the adoption of microdosing. This can be explained by the fact that microdosing is still labor intensive; the larger the household, the more likely they are to implement microdosing. These results are in line with Miheretu and Yimer (2017), that pointed out households with a larger size are more likely to adopt microdosing.

The marginal effect of land ownership was found to be positive and significant, implying that having land ownership increases the probability of adopting microdosing by 33.5%, consistent with the study by Sawadogo et al. (2023). These findings are also in line with Amsalu and de Graaff (2007), and Bewket (2007) who have found that farmers with property ownership rights are more likely to adopt optimum fertilizer and invest in conservation work in anticipation of long-term benefits.

Table 2. Estimating fertilizer microdosing adoption model

Variables	Probit estimation		Marginal effects	
	Coefficient	Robust St. Er	Coefficient	St. Er
Age	0.014	0.013	0.003	0.002
Gender	-0.543	0.636	-0.110	0.128
Education	0.099**	0.055	0.020**	0.011
Extension visits	0.257***	0.064	0.052***	0.014
Household size	0.068**	0.034	0.014**	0.007
Land ownership	1.655***	0.424	0.335***	0.066
Maize Land	0.329	0.208	0.066	0.041
Off-farm income	0.327	0.308	0.066	0.063
Access to credit	0.406	0.410	0.082	0.080
Flat ground	-0.116	0.294	-0.024	0.059
Gravelly	-0.058	0.264	-0.012	0.053
Sandy loam	-0.060	0.332	-0.012	0.067
Sandy clay	-0.179	0.305	-0.036	0.061
Farm experience	0.068	0.042	0.014*	0.008
Oxen	0.002	0.013	0.000	0.003
Farm membership	-0.046	0.297	-0.009	0.060
Absouya	-1.581**	0.677	-0.320**	0.116
Loumbila	0.246	0.370	0.050	0.075
Zitenga	-0.157	0.473	-0.032*	0.096
Arbollé	-1.028*	0.559	-0.208	0.113
Constant	-2.768***	0.863		
LR chi ^{2}(20)	75.200			
Log likelihood	-74.171			
Pseudo R^2	0.465			
Number of observations	210			

Note. The significance levels of 10%, 5%, and 1% are respectively indicated by the symbols *, **, and ***. St. Er Standard error.

3.3 Selectivity-Corrected Stochastic Production Frontier Estimates

Tables 3 and 4 show the conventional and sample selection-corrected SPF models for the unmatched and matched samples. According to Bravo-Ureta et al. (2012), there is compelling evidence in all cases to reject the null hypothesis that λ equals zero. This leads us to an important conclusion: technical inefficiency is both stochastic and a significant factor in the observed production variability. In addition, we ran a likelihood ratio (LR) test to find out if adopters and non-adopters have different technological preferences. The LR test is expressed by $LR = -2\left[\ln Lp - (\ln La - \ln Lna)\right]$, where $\ln Lp$, $\ln La$ and $\ln Lna$ show the values of log-likelihood obtained from the pooled sample, two separate SPF models for adopters and non-adopters. The null hypothesis of the test reveal that there is no difference between the two group frontiers and the pooled frontier model (Bravo-Ureta et al., 2012). Related to the results of the generalized likelihood ratio test statistic (LR = 70.91, p-value = 0.000), the null hypothesis of similar technology between adopters and non-adopters is rejected at a 5 % level of significance; evidence indicating that the estimation of separate SPF models for adopters and non-adopters is appropriate.

Tables 3 and 4 show a significant result for matched and unmatched samples, the adopter's group has a positive and statistically significant selection bias indicator (ρ). This indicates that unobservable factors cause selection bias. Therefore, the sample selection SPF model (Greene, 2010) may be suitable this study Additionally, Bravo-Ureta et al. (2012) suggests that ignoring selection bias can lead to biased and inconsistent estimates from conventional SPF models. The comparison between adopters and random maize farmers in the area must account for the unobserved selection bias. Adopters may have better farming skills that are not visible such as greater aptitude and motivation. That implies that higher maize productivity and technical efficiency may be connected to their farming skills.

The partial elasticities of all productive inputs can improve technical efficiency of maize production (Table 3 and 4). In the matched sample for the conventional stochastic frontier in the pooled sample, variables such as fertilizer urea, manure, family labor, improved varieties, and gravelly soil positively and significantly impact technical efficiency. These factors significantly increase maize productivity when the same quantity inputs such as fertilizer urea, manure, family labor and improved varieties are maintained.

In the matched sample for the sample selection corrected SPF, the use of urea fertilizers, manure, and improved varieties have a positive and significant impact on adopters' technical efficiency after selection bias is considered. This indicates that, without changing the quantity of these inputs, these practices significantly increase maize production. The results for chemical fertilizer showed that urea improved the performance of maize output. As a result, smallholder maize farmers that use microdosing produce more grain while utilizing fewer agricultural inputs. These findings show that microdosing in maize production remains highly advantageous, even in an environment where the prices of chemical fertilizers are high. The use of manure increases the productivity of maize. The implementation of microdosing with a combination of manure and chemical fertilizer could contribute to a significant increase in maize production.

The technical efficiency of maize production is positively and significantly correlated with urea fertilizer. These findings are consistent with research by Olagunju et al. (2021) on the effects of agricultural cooperative membership in Nigeria, which revealed that fertilizer increases maize yield. The findings are also in accordance with research conducted in Rwanda by Ngango and Hong (2021) on the effects of secure land tenure, which found that fertilizer input has a significant effect on the technical efficiency of maize cultivation. However, the type of fertilizer used in previous studies was not specified. They didn't investigate what type of fertilizer could improve the technical efficiency of maize production. This emphasizes the significance of studying the accuracy and precision of fertilizers in order to maximize production technical efficiency in the context of microdosing practices. Moreover, the findings clearly indicate that smallholders' farmers who adopt microdosing fertilizers can significantly increase their maize harvest without increasing their fertilizer usage, given the current exorbitant prices of chemical fertilizers.

The use of manure has a positive and significant impact on the technical efficiency of maize production. These findings are consistent with Olagunju et al.'s (2021) study, which showed that manure enhances maize yield. These results indicate that maize productivity can be increased without changing the amount of manure applied. Smallholder farmers often encounter difficulties in obtaining sufficient quantities of manure.

The technical efficiency of maize production is also significantly and positively correlated with improved varieties. The results of this study are consistent with the findings of Idris et al. (2015) and Mwalupaso et al. (2019), indicating that the use of improved varieties has a substantial impact on maize production. The strong connection between improved maize varieties, technological advancements, and increased production has been adequately proven. Improved varieties are typically out of reach for smallholder farmers due to their high cost.

Table 3. Estimating parameters SPF models: Unmatched sample

Variables	Conventional SPF estimations				Sample selection corrected SPF estimations			
	Microd adopters		Microd non-adopters		Microd adopters		Microd non-adopters	
	Coefficient	Std. Er	Coefficient	Std. Er	Coefficient	Std. Er	Coefficient	Std. Er
Fertilizer urea (ln)	0.013	0.033	0.054**	0.027	0.107**	0.064	0.081*	0.061
Manure (ln)	-0.003	0.022	0.018	0.017	0.017**	0.029	0.034*	0.021
Family labor (ln)	0.050	0.112	0.248***	0.070	0.072	0.131	0.237***	0.084
Improved varieties (ln)	0.004**	0.002	-0.002	0.002	0.004	0.004	-0.002	0.002
Gravelly	0.283**	0.127	0.096	0.099	-0.243	0.162	-0.118	0.107
Absouya	0.300	0.541	-0.259**	0.113	-0.610	25.230	-0.305*	0.158
Loumbila	0.050	0.170	-0.509***	0.178	0.043	0.252	-0.396	0.283
Zitenga	0.433**	0.204	-0.244	0.201	0.568**	0.246	-0.105	0.273
Constant	6.637***	0.602	6.065***	0.349	6.250***	0.859***	6.051	0.443
λ	0.779**	0.307	3.247***	0.827				
σ^2	0.590***	0.006	0.843***	0.005				
σ(u)					0.549**	0.257	0.758***	0.112
σ(v)					0.505***	0.154	0.319***	0.105
ρ(u,v)					0.933***	0.289	-0.581	0.798
Likelihood	-58.791		-100.991		-102.256		-140.709	
N	78		132		78		132	

Note. The significance levels of 10%, 5%, and 1% are respectively indicated by the symbols *, **, and ***. Std. Er: Standard error.

Table 4. Estimating parameters SPF models: Matched sample

Variables	Conventional SPF estimations				Sample selection corrected SPF estimations			
	Microd adopters		Microd non-adopters		Microd adopters		Microd non-adopters	
	Coefficient	Std. Er	Coefficient	Std. Er	Coefficient	Std. Er	Coefficient	Std. Er
Fertilizer urea (ln)	0.016	0.035	0.054**	0.027	0.087**	0.049	0.077	0.048
Manure (ln)	-0.004	0.023	0.018	0.017	0.016**	0.027	0.011	0.017
Family labor (ln)	0.056	0.115	0.248***	0.070	0.009	0.134	0.314***	0.090
Improved varieties (ln)	0.004**	0.002	-0.002	0.002	0.005**	0.003	-0.003	0.002
Gravelly	0.287**	0.133	0.096	0.099	0.330**	0.163	0.019	0.098
Absouya	0.301	0.556	-0.259**	0.113	-0.433	5.325	-0.441***	0.122
Loumbila	0.056	0.175	-0.509***	0.178	-0.147	0.210	-0.060***	0.221
Zitenga	0.434**	0.209	-0.244	0.201	0.449*	0.250	-0.321	0.215
Constant	6.845***	0.630	6.065***	0.349	6.961***	0.722	5.900***	0.468
λ	0.660**	0.321	3.247***	0.827				
σ^2	0.587***	0.007	0.843***	0.005				
σ(u)					0.729***	0.142	0.901***	0.068
σ(v)					0.406***	0.127	0.224***	0.083
ρ(u,v)					0.998***	0.036	0.680	
Likelihood	-57.574		-100.991		-99.584		-139.785	
N	74		132		74		132	

Note. The significance levels of 10%, 5%, and 1% are respectively indicated by the symbols *, **, and ***. Std. Er: Standard error.

3.4 Technical Efficiency Scores and Technology Gap Ratios

Table 5 reports the results of the mean TE scores, TGRs, and MTE parameters in the matched sample. The average TE scores among microdosing adopters have significantly increased, for matched sample. This result was observed through conventional and sample selection-corrected SPF models, highlighting the impact of microdosing. According to the results from the conventional SPF sample, microdosing adopters reported an average TE score of 0.77, while non-adopters reported a slightly lower score of 0.58. The adopters and non-adopters in the matched sample demonstrated mean TE scores of 0.68 and 0.53, respectively, in the selection-corrected SPF estimation. In terms of performance, these findings indicate that microdosing adopters outperformed non-adopters.

The adoption of microdosing can generate significantly higher returns, as shown by the TGRs from the meta-frontier estimation. TGRs measures the difference between the meta-frontier and the frontiers of the adopter and non-adopter groups, which indicates their level of performance. The MTE, which enables an effective comparison of adopters and non-adopters, is also calculated. The adopting SPF model results in a greater TGR performance of 0.94 for adopters, exceeding the 0.93 performance of non-adopters in a sample from the sample selection.

According to work by Olagunju et al. (2021), if selectivity bias is not adequately addressed, the TE scores are overestimated. It is absolutely crucial to take into account both the observed and unobserved attributes when estimating the effect of microdosing on productivity, in order to accurately address selectivity bias. After correcting the selectivity bias, the results showed that the average technology gap ratio for adopters (0.94) was notably higher than that for non-adopters (0.93). According to these findings, adopters have more advanced technology than non-adopters. MTE reveals that adopters perform better than non-adopters with 0.72 and 0.52, respectively.

Table 5. Estimating of Technical efficiency in matched sample

Variables	Microd adopters		Microd non-adopters		T-test value
	Mean	St. Dev	Mean	St. Dev	
Conventional SPF					
Technical efficiency (TE)	0.77	0.05	0.58	0.19	7.77***
Technology gap ratios (TGR)	0.99	0.01	0.98	0.12	13.19***
Meta-frontier efficiency (MTE)	0.77	0.06	0.59	0.18	18.07***
Sample selection bias-corrected SPF					
Technical efficiency (TE)	0.68	0.06	0.53	0.17	11.40***
Technology gap ratios (TGR)	0.94	0.05	0.93	0.17	2.21**
Meta-frontier efficiency (MTE)	0.72	0.05	0.52	0.20	13.74***

Note. The significance levels of 10%, 5%, and 1% are respectively indicated by the symbols *, **and ***. St. Dev: standard deviation.

We reported the distribution efficiency of the matched sample in the sample selection corrected SPF in Figure 3. The results indicated that 69.42 percent of adopters have shown a mean TE score between 0.71 and 0.8, compared to 9.71 percent of non-adopters. In addition, 19.42 percent of adopters have reported a higher TE score between 0.81 and 0.9. These results suggested that, on average, a large proportion of adopter farmers tend to enhance maize production more efficiently than non-adopters.

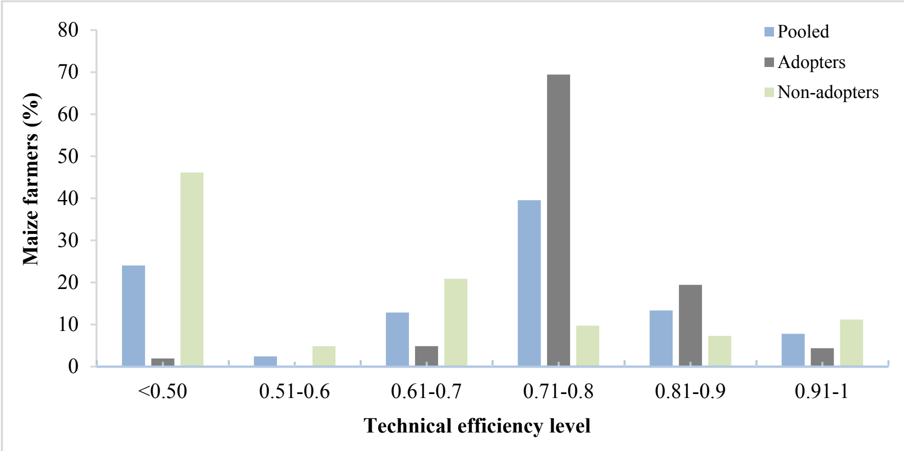

Figure 3. Distribution efficiency on Matched sample and crossing on selection SPF

4. Conclusion and Recommendations

This study investigated the impact of fertilizer microdosing on the technical efficiency of smallholder maize farmers in Burkina Faso. We used a propensity score matching model to address a selection bias issue based on observable attributes, a sample selection corrected scholastic production frontier approach to address a selection bias issue based on unobservable attributes, and a meta-frontier function to analyze the technology gap through the frontier group. The study contributes to providing an evidence-based connection between adoption of fertilizer microdosing and the technical efficiency of maize production. This study provides precise evaluations of the technical efficiency of maize production. It effectively addresses the issue of selection bias related to both observable and unobservable factors. Additionally, it highlights the significant technology gap among adopters and non-adopters of microdosing in Burkina Faso. The study revealed that fertilizer microdosing adoption significantly contributed to increasing the efficiency of maize production. After correcting for selection bias, variables such as urea fertilizer, manure, and improved varieties have a considerable impact on adopters' technical efficiency. This suggests that, without changing the quantity of these inputs, these productive inputs can greatly improve maize production. The meta-frontier production demonstrated that adopters and non-adopters employed different technologies. Without any corrective bias, microdosing achieved a 7.77% higher mean TE level than non-adopters. After adjusting for selection bias due to unobservable variables, adopters had a mean TE level that was 11.40% higher than the non-adopter smallholder farmers. Adopters of microdosing have been shown to have better technology and higher levels of efficiency.

Based on our research findings, we draw policy implications for policymakers and smallholder maize farmers. First, urea fertilizer has been proven to enhance the efficiency of maize production. In order to enhance maize production, it is crucial to implement effective policies that ensure the continuous availability and affordability of this fertilizer.

Second, manure improves the technical efficiency of maize production. To optimize the utilization of manure, farmers need to learn compositing techniques. NGOs and cooperatives can provide educational programs for this purpose.

Third, maize productivity can still be raised by using improved varieties. Agricultural extension services need to enhance the physical and financial accessibility of improved varieties. To provide the best and most effective maize production, farmers need technical documentation on how to use fertilizer effectively. This documentation should specify the dosage and quantity of fertilizer based on the area planted and the type of improved maize varieties. While the Burkinabe National Research Institute has indeed played a role in promoting improved maize varieties, these varieties are often too expensive for smallholder farmers. It is imperative that policymakers empower smallholders by subsidizing and upgrading better maize varieties to make them cheaper and more accessible.

There are some limitations to this study. First, microdosing practices are considered to be high labor-intensive operations and may require more active workers. We did not estimate the labor costs associated with the adoption of microdosing in our study which can affect the net income from smallholder maize farmers, although most maize farmers did not include labor costs in their net income calculation. Future research should estimate the impact of microdosing labor costs on efficiency in maize production. Second, we used cross-sectional data to estimate the technical efficiency of maize production. To fully understand the trend of technical efficiency in maize production, it is essential to examine several years of panel data. A future study should consider panel data on estimating the impact of microdosing on technical efficiency on maize production. In addition, none of these limitations had an impact on the quality of this current research.

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Appendix A

Overview of the main variable statistics

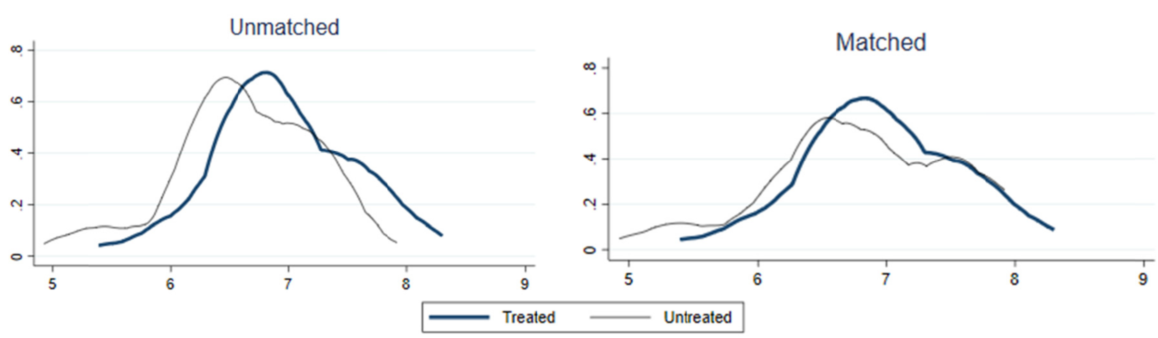
Variables	Description	Sample (N = 210)	
		Mean	St. dev
Maize yield in 2020	Tons per hectare	1.02	0.65
Adoption	Adopting microdosing fertilizer (yes/no)	0.37	0.48
Extension visits	Total number of extensions visits in 2020	2.01	2.33
Age of household head	Age in years	49.3	10.3
Gender	Household head is a female	0.07	0.25
Education level	Number of years in school	1.9	2.2
Household size	Number of persons	10.20	4.96
Land ownership	Farmer owns their land (yes/no)	0.63	0.48
Off-farm income	Household has other income sources (yes/no)	0.79	0.41
Farm credit	Farmer asses to credit (yes/no)	0.10	0.30
Flat ground	Plot is mostly flat (yes/no)	0.38	0.49
Gravelly	The soil at the main plot is mostly gravelly (yes/no)	0.38	0.49
Sandy loam	The soil at the main plot is mostly sandy loam (yes/no)	0.21	0.41
Sandy clay	The soil at the main plot is mostly sandy clay (yes/no)	0.25	0.43
Experience	Number of years in microdosing experience	4.17	4.35
Farm membership	Farmer belongs to farm group (yes/no)	0.51	0.50
Improved varieties[1]	Improved varieties used (kg/ha)	22.55	31.29
Imprd varieties	Improved varieties used (yes/no)	0.62	0.49
Absouya	If household resides in Absouya commune (yes/no)	0.22	0.42
Loumbila	If household resides in Loumbila commune (yes/no)	0.14	0.35
Zitenga	If household resides in Zitenga commune (yes/no)	0.09	0.28

Note. St.dev: Standard deviation; SWC: Soil and Water Conservation; and TLU: Tropical Livestock Unit.

[1] Used improved varieties are mostly "*Wari*" and "*Barka*".

Appendix B

Balancing of ln yield distribution before and after matching



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Authors Contributions

All authors have substantially contributed to this current research work. DS and Prof. IM were responsible for conceptualization, methodology, data collection, and writing the original draft. Prof. ME and Dr. CF validated the findings, conducted a comprehensive review, and contributed to the editing process. Dr. AE diligently reviewed and edited the manuscript, ensuring its overall quality.

Competing Interests

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

Informed Consent

Obtained.

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Data Sharing Statement

No additional data are available.