



Impact of seed producer cooperatives membership on technical efficiency: Evidence from tef farmers in the central highlands of Ethiopia

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ABSTRACT

Farmers in Ethiopia face challenges associated with low efficiency and productivity, primarily due to limited access to improved seeds and complementary inputs. Despite empirical evidence of the vital role played by agricultural cooperatives in providing these basic inputs, there has been no empirical study examining the impact of membership in seed producer cooperatives (SPCs) on agricultural development. This study aimed to assess the impact of membership in SPC on the technical efficiency (TE) of farmers in the central highlands of Ethiopia. Using data from 425 selected tef farmers, the paper employed propensity score matching to match SPC members with non-members and applied a selectivity-corrected stochastic production frontier model to address unobserved biases. In addition, the meta-frontier approach was used to compare TE scores between the two groups of farmers. Results reveal that SPC members achieved a TE of 72 % of their potential output, whereas non-members achieved only 59 %. SPC members achieved meta technical efficiency (MTE) of 67 %, while non-members obtained MTE of 49 %. This indicates that non-members face tef production challenges due to limited access to improved technologies. In conclusion, SPC membership significantly enhances the TE of members compared to non-members indicating that improving TE could greatly boost productivity in the tef sector. The findings of the study suggest that the government of Ethiopia should enhance the skills of SPC members by providing training and promoting knowledge sharing among farmers to improve seed access. Similarly, private seed producers should be strengthened to meet the growing demand for improved seeds.

1. Introduction

Smallholder farmers in Ethiopia depend on cereal farming for their livelihoods, which accounts for over 90 % of the country's food production [1]. However, the cereal sector faces significant challenges in accessing improved seeds. These challenges are exacerbated by the inefficiency of smallholder farmers and recurring shocks [2]. Smallholder farmers are facing technical inefficiencies in tef production stemming from various factors, resulting in a significant gap between their potential and actual production levels [3]. Key obstacles include limited access to high-quality seeds, inadequate information and knowledge, limited access to financial services, climate change, and insufficient extension services [4]. These challenges result in low tef productivity and suboptimal technical efficiency indicating that there is potential for significant improvements in efficiency and productivity [5].

Tef (*Eragrostis tef*) is one of the cereal crops considered as a primary

food source for much of the population [6]. It is a staple food consumed by more than 50 million Ethiopians [7]. The crop serves as a primary source for smallholder farmers and is essential for urban consumers. It plays a crucial role in ensuring food security and supporting the livelihoods of farmers engaged in its production, which has attracted the attention of policymakers [7]. It is prominent for its high production volumes and extensive production area [8]. Tef is recognized internationally for being gluten-free and nutrient-rich, providing significant income for farmers [9]. Over 6 million households cultivate tef on more than 3 million hectares, contributing to 20 % of total cereal production and 30 % of the cereal production area [10,11].

Tef ranks as the second most extensively produced and consumed cereal in Ethiopia [12]. This crop continues to be vital for smallholder farmers in the country for various reasons, including the favorable market price of its grain, its superior performance compared to other cereals in both moisture-stressed and waterlogged environments, and its

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ability to be stored for extended periods without susceptibility to weevil infestations [11,13].

Despite its importance, tef faces a considerable productivity gap, with potential productivity estimated at 6 tons per hectare compared to a national average of 1.97 tons per hectare [14,15]. This productivity gap resulted from limited use of improved seeds, low production efficiency, and high seed costs [2,3]. In addition, the seed sector faces significant challenges such as limited capacity to supply improved tef seeds and complementary inputs, exacerbating the inefficiency of farmers [3,16]. The low productivity of farmers is attributed to the use of poor quality seeds, information asymmetry, limited credit access, climate change effects, and weak extension services [4].

Tef farmers in Ethiopia, particularly in the central highlands, are not fully realizing the potential of their output relative to their inputs and technical efficiency. This is due to limited access to high-quality seeds, low production efficiency, traditional farming techniques, and poor resource management [5,17,18]. Poor institutional services and limited access to improved technologies in the tef sector hinder technical efficiency, preventing farmers from maximizing output from the inputs they use [2,19].

Moreover, the production of tef in the country faces myriad challenges such as limited access to improved seeds and complementary inputs technologies, weak enforcement of institutional frameworks, an often-imperfect market for both output and inputs, and high costs of improved tef seed exacerbated by a limited number of suppliers, which limit its productivity potential of tef [9,19–21].

Poor institutional services and limited access to improved technologies in the tef sector hinder technical efficiency, which maximizes output from given inputs [2,20]. The low adoption of improved varieties and low rate of seed replacement are frequently associated with supply-demand issues within the seed market [22,23].

On the supply side, the availability of improved seed varieties is often inadequate, failing to meet farmers' needs in terms of quantity, timing, or desired traits [2,24]. On the demand side, the performance of the seed market is constrained by factors such as farmers' lack of awareness about seed traits, credit limitations, risk perceptions, climate uncertainty, and other behavioral influences [18,25]. Notably, the demand for improved tef seeds has steadily increased over the years [2, 26]. As a result, researchers, extensionists, development practitioners, and policymakers face significant challenges in meeting this growing demand for improved seeds [16].

To resolve these issues, both the public and private sectors have been involved in improved seed production and supplying improved seeds to farmers. However, they mainly focus on a few crops, such as hybrid maize and vegetables, meeting only a small portion of farmers' demands. As a result, many small-scale farmers face shortages and rely on farmer-to-farmer seed exchange [23,27]. Seed suppliers fail to meet the growing demand across diverse agricultural ecologies, leading to shortages, especially for crops like tef, where seeds are inadequate in quantity, quality, and timeliness [23].

Additionally, both sectors fail to provide seeds cost-effectively, with poor management and high production and marketing costs, limiting availability in rural areas [27]. This weak supply system exacerbates the issue for crops like tef, which remain insufficiently supplied [28]. This is particularly critical, as 43 % of smallholder farmers in Ethiopia cultivate tef [29].

In Ethiopia, the formal seed system has been unable to satisfy the growing demand for improved seed varieties. Currently, this seed sector provides only 20 % of the improved seeds used by farmers, resulting in limited access to high-quality seeds and low technical efficiency among smallholder cereal farmers, including those producing tef [30]. This shortfall in seed availability is further exacerbated by inefficiencies within the seed production and distribution framework, leading smallholder farmers to depend on informal seed systems that offer seeds of inferior quality and limited diversity [24].

Private seed companies, often mainly focus on hybrid seeds driven by

profit motives, resulting in less attention being given to cereal crops like tef in their seed production and supply to markets [31]. The insufficient seed distribution system represents a major obstacle to limiting farmers' access to high-quality seeds, exacerbating the seed shortage and inefficiency among farmers [32]. Furthermore, smallholder farmers face challenges in obtaining credit, which limits their ability to secure necessary resources and inhibits their investment in improved technologies essential for enhancing their technical efficiency [33].

Low technical efficiency among smallholder farmers, coupled with limited access to and availability of improved seeds, significantly reduces agricultural productivity. This situation negatively impacts income generation and the overall economic stability of farming households. In the tef sector, poor institutional services, limited access to improved technologies, and other challenges hinder technical efficiency, preventing the maximization of output from given inputs [2,19]. Moreover, farmers' inadequate technical capabilities and insufficient access to high-quality seeds result in reduced crop yields, which, in turn, adversely affect their farm income [5,20].

To address the poor performance of the agricultural sector, the Ethiopian government formulated and implemented an economic transformation strategy centered on agricultural development-led industrialization (ADLI). This initiative is organized around successive five-year Growth and Transformation Plans (GTP-I and II) [34]. The policy is aimed at enhancing the living standards of rural smallholder farmers [35]. Agricultural cooperatives are mandated to boost farmers' productivity and efficiency [3,35]. The GTP II and the Ten-Year Perspective Development Plan (2021–2030) recognize cooperatives as key stakeholders in agricultural development, highlighting the importance of cooperatives in promoting sustainable practices, improving livelihoods, and fostering rural economic growth [35,36].

Despite the diligent efforts and endeavors of the government, the overall crop production, particularly the tef sector, continues to be characterized by a subsistence production system, low technical efficiency due to limited access to improved seeds, high costs of inputs, and weak institutional services, resulting in low productivity for farmers [21]. Moreover, the level of technical efficiency of tef farmers remains significantly low [7]. The production and value chain of tef predominantly depend on traditional methods [9].

The establishment of farmer cooperatives has proven to be an effective strategy for promoting the interests of farmers and helping them address the numerous challenges associated with smallholder agriculture in Ethiopia [e.g., Refs. [33,37]]. Smallholder farmers can enhance their economic situation by forming cooperatives, which allow them to pool resources, share costs, and access superior services. This collective approach strengthens their bargaining power when acquiring inputs or selling their products. Additionally, cooperatives provide a platform for farmers to market their goods collectively, including seeds [38,39]. As a result, policymakers and development practitioners have shown a keen interest in supporting smallholders who are willing to engage in collective action initiatives, such as seed producer cooperatives, to tackle the challenges related to the supply of improved seeds encountered by smallholders in Ethiopia [34].

Seed producer cooperatives play a crucial role in ensuring farmers have access to high-quality, certified seeds. These seeds are typically more compatible with local environmental conditions and climate, leading to enhanced yields and increased productivity [40,41]. SPCs play a crucial role in promoting sustainable agricultural practices by supplying farmers with seeds that are both high-yielding and resilient to pests, diseases, and environmental challenges. Additionally, SPCs frequently offer training, agricultural extension services, and guidance to farmers [42,43].

The impact evaluation of SPC membership on the technical efficiency of farmers helps improve the productivity of the tef crop, which has significant implications for food security [41]. Comprehending how SPC membership affects the technical efficiency of farmers can help identify ways to increase yields and reduce inefficiencies in tef farming practices.

SPC members have access to better quality seeds, which could improve tef crop performance leading to higher technical efficiency [32]. SPCs often act as platforms for knowledge sharing where farmers can learn from each other about best practices, quality seed production, and management. This information has the potential to greatly improve technical efficiency by optimizing the use of resources, training, and technical services, which can improve their overall seed production and management practices [30,44].

The main goal of seed producer cooperatives is to produce seeds that meet quality standards, resulting in improved yields and increased disease resistance of crops. By facilitating the distribution of improved seeds to smallholder farmers, these cooperatives address the issue of limited access to improved seed varieties. Moreover, the use of improved seeds helps to improve the technical efficiency of farmers [2,8].

In light of the above justifications, smallholder cereal crops farmers in the central highlands of Ethiopia, specifically in the East Shewa zone of Oromia, established seed producer cooperatives (SPCs) with government and practitioner support. This initiative aims to increase the supply of improved seeds and support broader agricultural transformation strategies [34]. East Shewa zone is one of the high-potentials tef-producing zones in the Oromia region of Ethiopia. The climate of the zone is favorable, with appropriate soil types, and has considerable potential for tef production [19]. However, the productivity of the crop is constrained by the low production efficiency of farmers, climate variability, and limited access to improved varieties [26]. Achieving higher yields requires overcoming challenges such as the low efficiency of farmers, ensuring quality seed and providing support to resolve their farming issues collectively [27].

Nevertheless, there is a lack of empirical evidence regarding the impact of SPCs on the technical efficiency of staple cereal farmers, including tef which is the predominant cereal crop in the central highlands of Ethiopia. The long-term sustainability of SPCs remains unclear. It is uncertain whether SPCs can consistently improve access to improved seeds for farmers over time and enhance smallholders' technical efficiency. Furthermore, there is limited information on the effectiveness of using improved seeds to optimize crop output, which highlights a scarcity of empirical evidence to guide policymakers. This lack of evidence makes it difficult to determine the most effective policy interventions to promote the development of SPCs and enhance the technical efficiency of smallholder tef farmers.

However, some empirical studies have examined the impact of agricultural cooperative membership on farmers' well-being [e.g., Refs. [45–48]]. Additionally, some studies have focused on the impacts of cooperative membership on commercialization and marketing [e.g., Refs. [49,50]]. However, only a few studies have explored the impact of cooperative membership on smallholders' farm efficiency, particularly in relation to technical efficiency analysis.

[33] assessed the impact of technical efficiency among cooperative members in Ethiopia based on observable characteristics using propensity score matching techniques. The results of the study found that on average, farmers belonging to agricultural cooperatives were more efficient than independent farmers. The findings of this study indicate a positive impact of cooperative membership on the technical efficiency of farmers. However, it is important to note that a farmer's decision to join a cooperative is not random, which simply implies that such a decision is based on the individual farmer's self-selection for membership. Consequently, cooperative membership is considered endogenous [51].

[5] examined the level and determinants of technical efficiency of smallholder Tef producers in Ethiopia using Stochastic Frontier Analysis (SFA). The findings of this study reveal that productivity increased by 27 % at existing level of technology. Rural organizations, agricultural technologies, and production efficiency impact tef productivity due to the utilization of available inputs and technology, facilitated by investments in enhanced gender-sensitive extension services and infrastructure development in Ethiopia. Additionally, the study revealed that community discussion groups and the proximity to the nearest

agricultural cooperative significantly influenced technical efficiency [19]. These studies conducted on the technical efficiency of tef sectors have employed the traditional stochastic frontier approach which did not control for sample selection bias.

[52] investigated the role of agricultural cooperatives in promoting the adoption of climate-smart agricultural practices (CAPs) among banana farmers in China. Using an endogenous treatment Poisson regression model to mitigate selection bias, the study found that cooperative membership significantly increases the likelihood of CAP adoption. Specifically, the incidence rate ratio indicated that cooperative members are 1.205 times more likely to adopt CAPs, a finding supported by treatment effect estimates.

[53] examined how farmer cooperatives influence the adoption of agricultural technologies in Sichuan, China. Using Propensity Score Matching (PSM) and a two-stage instrumental variable approach, the study revealed that cooperative membership significantly increased the number of technologies adopted—by an average of 1.5 times, or 44.9 %, compared to non-members. While no significant effect was observed on the adoption of production technologies, postharvest technology adoption was substantially higher, with cooperative members adopting over four times more postharvest technologies than non-members.

[54] explored the impact of cooperative membership on off-farm labor decisions among farming couples in China, using data from 595 banana farmers. To address self-selection bias, both a recursive bivariate probit model and an endogenous treatment Poisson regression model were employed. Findings indicated that cooperative membership increased the likelihood of husbands engaging in off-farm work by 38 % and wives by 31 %. Larger household size was associated with a reduced likelihood of off-farm work for husbands but increased likelihood for wives. Cooperative membership also correlated with longer off-farm work hours and higher incomes for both spouses.

[55] analyzed how cooperative membership affects household welfare and poverty levels among maize farmers in Ethiopia, using a three-wave panel dataset from major maize-producing areas. A correlated random-effects regression with a control function was employed to address unobservable heterogeneity and endogeneity. Results indicated that cooperative membership significantly improved maize yields and household income, reducing both income poverty and the poverty gap. However, while yield improvements were pro-poor, the benefits in income and poverty reduction tended to favor wealthier farmers with more land and assets.

In a related study [56], examined the influence of cooperative membership on the intensity and adoption of inorganic fertilizer use among smallholder maize farmers in Ethiopia. Using a double-hurdle model with a correlated random-effects framework and control function, the study found that cooperative membership led to a 5.3 % increase in fertilizer adoption and a 4.2 % increase in usage intensity. Importantly, these benefits were shared by members regardless of their poverty status.

[57] conducted a meta-analysis of 158 yield outcomes from 42 studies across 19 developing countries to assess the impact of cooperative membership on crop and livestock yields. The analysis revealed a positive publication bias, with a tendency among researchers and journals to favor studies reporting significant positive outcomes. After adjusting for this bias, cooperative membership was found to have a minimal and statistically insignificant effect on yields.

More importantly, in the existing a few empirical studies on the impact of cooperative membership on farmers' technical efficiency, the research findings are inconclusive. For example, empirical findings by Ref. [58] showed a positive relationship between cooperative membership and household income and assets. Besides empirical evidence from Mongolia indicates that participation in agricultural cooperatives is associated with increased yields and improved technical efficiency. An analysis of group-specific production frontiers shows that cooperative members consistently outperform non-members. Membership decisions are significantly influenced by various household and farm

characteristics, including education level, engagement in off-farm employment, total land area, proximity to markets, and geographic location [83].

Similarly [59], conducted a study in the West Bank of Palestine to assess the impact of agricultural cooperatives on the efficiency and productivity of olive farms. The findings demonstrate that cooperative membership significantly enhances both technical efficiency and total factor productivity, with improvements ranging from 10.16 to 10.52 percentage points. Contributing factors include access to credit, quality olive seedlings, land, and extension services provided by cooperatives.

Other empirical studies, such as [60] in Ghana and [61,62] in Costa Rica, indicated that cooperative membership had no significant impact. Furthermore, empirical studies reveal methodological shortcomings, failing to address sample selection biases and the non-linear nature of stochastic production frontier models in mitigating sample selection biases and technological gap between members and non-members of cooperatives. For instance, [e.g., Refs. [33,63] used propensity score matching (PSM) and only addressed biases arising from observable farmers' characteristics which potentially leads to biased results.

In contrast, others studies have combined PSM with stochastic production frontier (SPF) modeling to address selection biases from unobservable variables, assuming both cooperative members and non-members use similar technology [e.g., Refs. [64,65]. However, comparing technical efficiency estimates between the two groups may not accurately reflect true differences, as they operate under different benchmarks [66,67]. Addressing both observable and unobservable selection biases and technological heterogeneity between seed cooperative members and non-members is essential for evaluating the impact of SPC membership on the technical efficiency of tef farmers in Ethiopia, where empirical evidence is lacking. To enhance the robustness of its findings, this study critically reviewed relevant literature, including studies that both support and challenge its findings.

This study makes important contributions to understanding cooperatives and technical efficiency, particularly in the Ethiopian context. It focuses on tef, a vital staple crop for food security that is often overlooked in international research but is gaining attention for its gluten-free attributes. The study compares the technical efficiency of Seed Producer Cooperative (SPC) members and non-members, revealing that SPC membership enhances productivity and income by improving technical efficiency.

The significance of this research lies in its shift from traditional economic assessments of cooperatives—such as market access and input provision—to evaluating how SPC membership directly impacts technical efficiency. Smallholder tef farmers in Ethiopia face challenges like limited access to resources, knowledge, and quality seeds. SPCs aim to address these barriers, but their specific impact on efficiency has not been fully explored until now.

The study fills this gap by employing rigorous methodologies to ensure accurate results. Propensity Score Matching (PSM) was used to mitigate selection bias from observable factors, while a sample selection-corrected stochastic production frontier model addressed unobservable factors. Notably, this is the first study to apply a stochastic meta-frontier (SMF) approach in this context, providing a robust framework for identifying technology gaps and comparing efficiency scores between SPC members and non-members. Unlike earlier studies that relied on conventional frontier models, this approach accounts for both selection bias and technological heterogeneity.

Furthermore, the research extends beyond methodological advancements. It highlights the critical role of SPCs in improving efficiency for crops central to food security, such as *tef*. By focusing on seed production, the study illustrates how technology adoption, innovation, and knowledge-sharing within cooperatives can significantly enhance performance. These findings contribute a fresh perspective to cooperative literature and offer practical implications for improving agricultural practices and cooperative models in similar contexts worldwide.

The findings offer several important contributions to the study

population in various aspects. Firstly, they show that smallholder farmers in SPCs have access to high-quality, improved seeds that are well-adapted to their local environments. This highlights the beneficial effects of SPC membership on agricultural practices and technical efficiency. Secondly, the study reveals that SPCs provide basic training to their members on seed production and management techniques, which improves farmers' skills and their capacity to adopt improved agricultural technologies. This training support plays a crucial role in ensuring the long-term viability of the SPCs and enhancing the productivity of their members.

Furthermore, the findings provide valuable insights for independent farmers who may be considering membership in SPCs. These farmers can perceive the benefits of joining SPCs, such as access to improved seeds, technical assistance, and training. This could motivate independent farmers to view SPCs as a viable option for improving their agricultural outputs. Moreover, independent farmers can learn from the experiences of SPC members, adopt improved farming practices, and enhance seed production techniques to increase their productivity.

The results of the study benefited a wide range of stakeholders in Ethiopia's agricultural sector. First, it offers empirical, evidence-based insights for smallholder tef farmers about their access to improved seeds through SPCs. Second, SPC members benefited from training opportunities, enhanced access to technology, and the availability of high-quality seeds. Additionally, the findings are valuable for policymakers, providing evidence to inform the formulation of strategies aimed at boosting agricultural productivity, fostering rural development, and alleviating poverty. The study also serves as a crucial resource for the Ethiopian government, helping to promote SPC models as a sustainable approach to improving seed access and enhancing agricultural productivity among smallholder farmers.

Finally, the study lays the groundwork for further research on the impact of seed cooperatives on agricultural development. Insights gained from this research can assist private seed companies and agribusinesses in improving their products, enabling them to provide high-quality, high-yield seeds tailored to customer needs. This could open opportunities for expansion into other crops or regions within Ethiopia. The article is structured as follows: Section 2 offers the research methodology, including the study areas, sampling procedures, sample size determination, analytical framework, data sources, and models used. Section 3 presents the results and discussion, while Section 4 summarizes the conclusions and their implications.

2. Methodology

2.1. Description of the study areas

The study was undertaken in Adea and Lume districts of the East Shewa Zone of Oromia National Regional State of Ethiopia. Adea district receives a mean annual rainfall of 865 mm with a mean minimum and maximum annual temperature of 15 and 28 °C, respectively. The district is located at 8° 44' N and 39° 02' E, with an altitude of 1880 m above sea level. The district is nationally known for tef production that dominates the agricultural production system in the area. Moreover, the Adea district has 21 primary seed producer cooperatives (hereafter referred to as SPCs) and 63 farmers' service cooperatives registered in the district (DOA, 2015). On the other hand, the Lume district is located between latitudes 8° 12' to 8° 50' and longitudes 39° 01' to 39° 17'. Tef and wheat are the main crops grown in the district. The district has 14 SPCs, 7 marketing cooperatives, 2 dairy cooperatives, and 97 service cooperatives (DOA, 2023). Fig. 1 depicts the study areas.

2.2. Sampling procedure and sample size determination

This research utilized a multi-stage stratified sampling method to ensure a representative sample. Initially, the East Shewa zone in the Oromia region of Ethiopia was **purposively selected due to its**

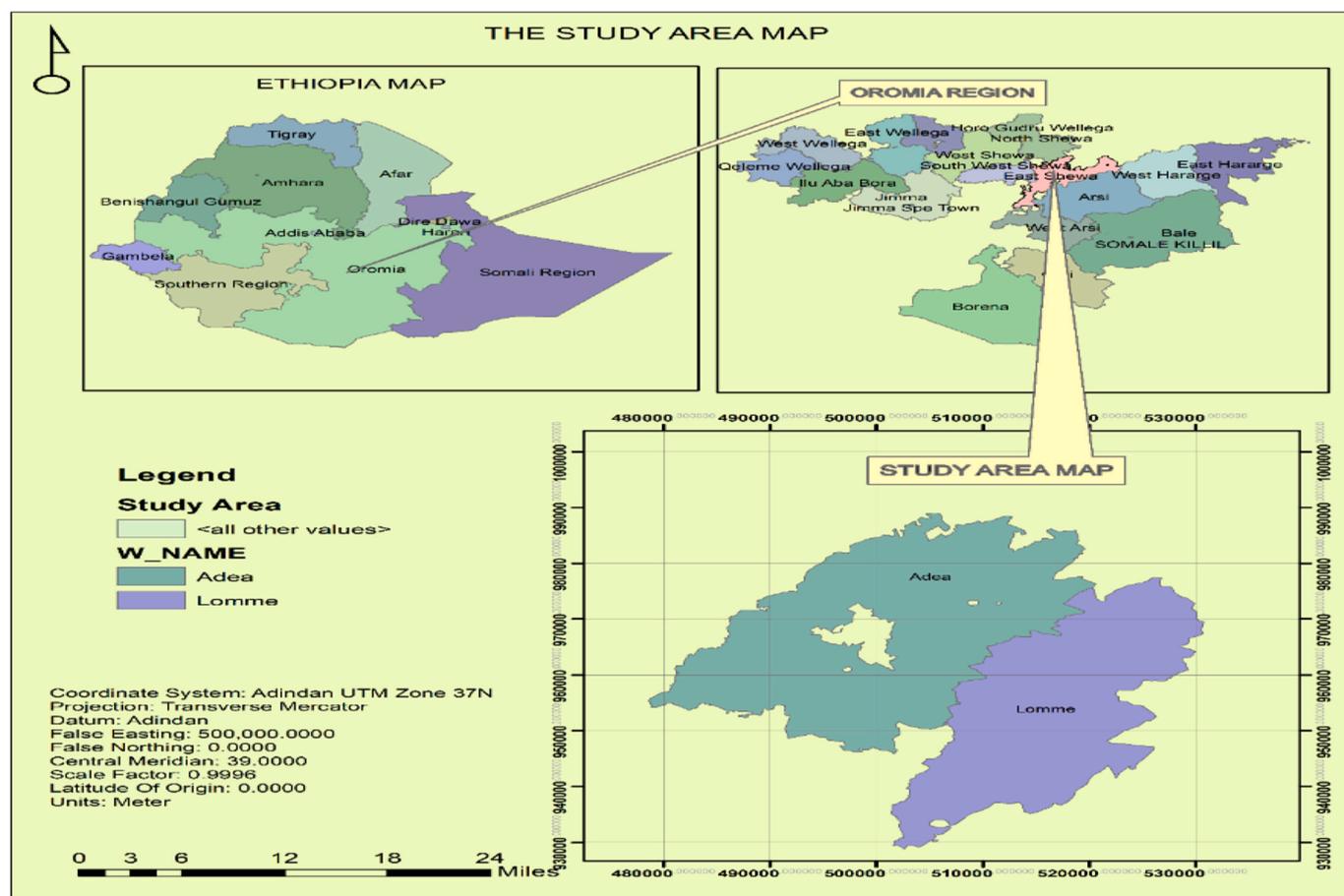


Fig. 1. Map of the study areas Source: Author's owns construct (2024).

prominence in tef production and the existence of many active SPCs. *Subsequently, the Adea and Lume districts were purposively selected based on their tef production potential, the presence of active SPCs, and the availability of active private seed producer companies. The kebeles in the study districts were then stratified into SPCs and independent farmers (control), with the latter serving as out growers for the privately owned improved seed producing companies.* A total of eight kebeles, four from each district, were randomly selected based on the presence of mature and active SPCs. Specially, four SPCs were randomly selected from the 21 SPCs in Adea, and another four from the 14 SPCs in Lume district. Additionally, non-member SPCs residing in the same kebele as SPCs and engaged in seed production as out-growers for privately owned limited seed producer companies were selected. The selected SPC members and non-members were used to create a sampling frame for sampling households. Finally, from the two strata, a total sample size of 425 representative households, 212 SPC members, and 213 non-members were selected to collect cross-sectional data for the study. In addition to the household survey, group discussions and key informant interviews were carried out to enhance the findings from the survey.

2.3. Analytical framework

The researchers are motivated to conduct this study for several reasons. First, there is a significant gap between the potential and actual yields of tef, which is driven by factors such as low production efficiency, limited access to improved inputs, a shortage of high-yielding varieties, and the high cost of improved seeds [2,28]. Given tef's importance for food security and the livelihoods of smallholder farmers, improving its productivity is essential for economic stability in the

country.

Second, this study explores how membership in Seed Producer Cooperatives (SPCs) can contribute to knowledge sharing and the adoption of better farming practices, potentially enhancing farmers' efficiency. Specifically, it examines whether SPC membership can help address technical inefficiencies in cereal production, such as tef. These inefficiencies are often a result of improper use of inputs, limited access to improved technologies, and outdated farming techniques. As noted in studies by Refs. [3,68], these factors significantly contribute to the gap between potential and actual production outputs.

Third, SPCs are crucial in addressing seed supply deficiencies faced by smallholder farmers. However, there is a lack of targeted research on how SPC membership affects the technical efficiency of smallholder farmers in Ethiopia, particularly in cereal production like tef. This study aims to fill that gap by disentangling the effects of improved technology and managerial ability on the technical efficiency of tef farmers. To achieve this, the study employs a multi-stage methodology to mitigate biases from both observable and unobservable variables and to account for technological heterogeneity between SPC members and non-members. The Propensity Score Matching (PSM) technique is chosen over other causal inference methods, such as instrumental variables (IV) and difference-in-differences (DiD), for several reasons. First, PSM addresses selection bias by matching treated and untreated smallholder tef farmers based on similar observable characteristics (e.g., household size, education), thereby approximating a quasi-random treatment assignment. Second, while IV methods require a valid instrument that influences cooperative membership without directly affecting technical efficiency, identifying such an instrument is often difficult. PSM, by contrast, does not rely on an instrument, making it a more practical choice. Finally, DiD methods rely on panel data and the parallel trends

assumption, which may not hold in cases with significant pre-treatment differences. PSM avoids this assumption and offers greater flexibility, making it more suitable for this study, where cooperative membership is non-random, and treated farmers differ from untreated ones.

Additionally, a stochastic frontier model is applied with corrections for self-selection bias. Finally, a stochastic meta-frontier (SMF) model is used to account for technological heterogeneity associated with SPC membership, providing a benchmark for comparing technical efficiency (TE) between SPC members and non-members, as outlined in previous studies [69,70].

The meta-stochastic frontier model (SMF) effectively addresses unobservable factors affecting cooperative membership and productivity using advanced statistical techniques. It tackles key issues like selection bias and endogeneity, while accounting for unobserved heterogeneity by recognizing technological differences between SPC members and non-members. This enables the estimation of a common efficiency frontier for meaningful group comparisons. The model includes individual-specific error terms to capture unobserved factors such as farm-level inefficiencies and variations in technology. By modeling inefficiencies at the farm level, it indirectly controls for hidden attributes like farmer expertise and management skills, assuming these influence the random error component. Additionally, a stochastic production frontier is used to estimate farmers' technical efficiency, distinguishing inefficiency from random noise. Combined with the meta-frontier approach, this allows standardized efficiency comparisons across groups with different technologies and unobserved traits. The integrated model thus provides more consistent and reliable estimates of technical efficiency across diverse farming contexts [70].

Furthermore, robustness checks were conducted using various specifications. This involved altering the model's functional form, accounting for unobserved heterogeneity, and performing tests across different subgroups. These measures enabled a thorough assessment of the validity and reliability of the findings related to the distinct production technologies used by the two groups.

2.3.1. Modeling SPCs membership and PSM

SPC's membership was modeled in the random utility framework. In this framework, a household chooses to be a member of a SPC if the expected utility gained from SPC membership ($MSPC_{i1}$) is larger than the one from non-membership ($NSPC_{i0}$). This means that a household is a member of SPCs if the expected net utility ($MSPC_{i1} - NSPC_{i0}$) is greater than zero. This utility gain can be specified as a function of observed covariates (Z) in a latent variable model as follows:

$$MSPC_i^* = \alpha Z_i + \varepsilon_i, MSPC_i = \begin{cases} 1 & \text{if } MSPC_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where $MSPC_i$ is a binary variable that takes the value 1 for a household if a member of SPCs and 0 otherwise; α is a vector of parameters to be estimated; Z_i is a vector of exogenous farm and household characteristics, and ε_i is an error term. Farmers' decision to join cooperatives may be conditioned by several independent variables based on economic theory and previous empirical literature following [42,43]. To address biases from observed characteristics (such as income, education, and gender), propensity score matching (PSM) was used to create a counterfactual dataset. This method matches SPC member with non-member, resulting in two nearly identical groups differing only in SPC membership [44]. A binary choice model (probit) was estimated to generate propensity scores based on observable characteristics (X), with the propensity score for a farmer i being a member of SPCs (treated = 1) defined in equation (2) [71] (Becker and Ichino, 2002).

$$P_{score} = Z_i = \beta_0 + \sum_{i=1}^M \beta_i X_i + \varepsilon_i \quad (2)$$

Upon completion of the match, the 'balancing hypothesis' is verified

to ensure that the average propensity scores of both members and non-members fall within the same range and have similar or identical averages [71].

2.3.2. Modeling stochastic production frontiers

Empirical evidence has shown that the Stochastic Production Frontier (SPF) approach has been used to evaluate the impact of cooperative membership on smallholder farmers' technical efficiency and well-being [e.g., Refs. [33,72]]. However, these researchers used the traditional stochastic frontier method, failing to address selectivity biases from unobservable factors or the nonlinear aspects of the SPF approach. They assumed no unobserved heterogeneity among farmers [73]. Moreover, they categorized both members and non-members of cooperatives under the same technology framework [74]. To mitigate unobserved selection biases such as risk aversion, farmer expectations, and managerial skills, two main methods of sample selection modeling in the stochastic frontier model were examined [75]. proposed a model where the selection mechanism is influenced by a one-sided error (U_i), while [73] suggested a framework driven by the error term (V_i). The first model involves complex log-likelihood functions [76]. Thus, the current study adopts Greene's approach by constructing two simultaneous equations for Tef farmers: a selection equation and a production function, incorporating the specified error structures.

Selection equation:

$$MSPC_i = 1[\alpha Z_i + \varepsilon_i > 0], \varepsilon_i \sim N[0, 1] \theta \quad (3)$$

$$SPF \text{ function} : Y_i = \beta X_i + \varphi_i, \varphi_i \sim N[0, \sigma_\tau^2] \quad (4)$$

$[Y_i, X_i]$ can only be observed only when $MSPC_i = 1$

The error structure is specified as follows:

$$\varphi_i = v_i - u_i$$

$$u_i = |\sigma_u U_i| = \sigma_u |U_i| \text{ Where } U_i \sim N[0, 1]$$

$$v_i = \sigma_v V_i, \text{ Where } V_i \sim N[0, 1]$$

$$(\varepsilon_i, v_i) \sim N_2 [(0, 1), (1, \rho\sigma_v, \sigma_v^2)]$$

Where $MSPC_i$ represents a binary variable equal to 1 for SPCs members and zero for non-members; Z_i is a vector of independent variables included in the sample selection equation. ε_i is the unobservable error term; Y_i is the output of tef in kilograms; X_i is a vector of inputs in the production frontier; and φ_i is the composed error terms. The unknown parameters α and β are estimated in the selection model and SPF model while the elements in the error structure correspond to those normally included in the stochastic production frontier model. The correlation coefficient ρ measures the relationship between the error term in the selection model and the noise term in the frontier model. A significant estimate of ρ indicates self-selection bias due to unobservable variables impacting both participation and production outcomes.

Following [73], the membership of SPCs was fitted using a probit model in equation (Eq. (1)). **The α estimates were obtained through maximum likelihood estimation and used to compute the conditional simulated log likelihood function for equations 3 and 4. Additionally, separate estimations of stochastic frontier models were conducted for SPCs members and non-members, following [77]. The JLMS approach was used to calculate technical efficiency estimates for each group. These estimates were compared to benchmark values. However, there is still a limitation with the [73] methodological framework that necessitates the implementation of an additional approach.**

2.3.3. Modeling stochastic meta-frontier approach

A key limitation of [73] analytical framework is that it does not allow for direct comparison of technical efficiency (TE) scores between

members and non-members, as these scores are relative to each group's frontier [58]. This issue arises because TE cannot be compared across groups using different technologies. To overcome this, we employ the meta-frontier production function method, which provides a common benchmark for comparing SPC members and non-members, following [69] to estimate the stochastic meta-frontier (SMF) production function. The SMF production function $f_t^M(X_{jit})$ encompasses both the frontiers of SPC members and non-members, $f_t^J(X_{jit})$ [73]. proposed a two-step methodology that first estimates group stochastic frontiers and then pools output predictions from each frontier with the corresponding input data to estimate the SMF. The meta-frontier can then be specified as:

$$\ln f_t^J(X_{ji}) = \ln f_t^M + V_{jit}^M - U_{jit}^M, \forall i, t, j = 1, 2, \dots, J \quad (5)$$

Where $\ln f_t^J(X_{ji})$ is the estimate of each group specific frontier from the first step equation (4) in the presence of selection bias). Given that $\ln f_t^J(X_{ji})$ are specific to each group, the regression is computed separately for both groups: SPCs members and non-member farmers. These estimates from each group are combined to estimate equation (6). Technology gap ratio (TGR) and the meta-frontier technically efficiency (MTE) is defined as:

$$TGR_{it}^J = f_t^J(X_{jit}) / f_t^M(X_{jit}) \quad (6)$$

$$MTE_{jit} = TGR_{it}^J * TE_{it}^J \quad (7)$$

2.4. Data and empirical model

Primary data used in this study came from a household survey conducted across the study areas. Questionnaires were pre-tested on non-sample farmers to check for inconsistencies before embarking on actual data collection. The primary data were collected from members and non-members of seed cooperatives under the supervision of the principal investigator. The household survey was conducted from February to April 2023. Besides, two group and key informant interviews were held to supplement the quantitative data. Furthermore, the secondary data were collected from district and zonal level offices' annual reports, the Oromia Regional Cooperative Agency, the Ethiopian Cooperative Commission, and published journals. The PSM approach was employed to mitigate self-selection biases arising from observable variables using equation (1), following the approaches of [44,77]. Matching techniques such as nearest neighbor, radius, and kernel matching were used to align members with non-members following [78].

After obtaining the matched sample, the sample-selection stochastic frontier model was estimated. Firstly, the selection equation (eq. (3)) was estimated using a probit model. In the second step, the production function was estimated using the sample selection stochastic frontier model. Various functional forms are used in agricultural production economics research, with the most commonly used ones being Cobb-Douglas (CD) and Translog (TL) [79]. Following [62], a log-likelihood ratio (LR) test was conducted using maximum likelihood estimation to choose between the Cobb-Douglas and Translog functional forms and calculate their log-likelihood values. These values were then used to compare the fit of the two models. The calculated likelihood ratio statistic was evaluated against the critical value from the chi-squared distribution table at a significance level of 0.05. In this context, the Cobb-Douglas model consists of six parameters, whereas the Translog model comprises twenty-one parameters. As a result, the degrees of freedom for the chi-squared test are calculated as $21 - 6 = 15$. Referring to the chi-squared table at $\alpha = 0.05$ with 15 degrees of freedom indicates a critical value of approximately 24.996. The Cobb-Douglas likelihood estimate is -221.2 and Translog likelihood estimate is -198.5 .

Based on the likelihoods of the models, the computed likelihood ratio (LR) test was found to be 45.4 using the specification indicated below.

$$LR = -2\{\ln [L(H_0)] - \ln [L(H_A)]\} \quad (8)$$

Where, $\ln [L(H_0)]$ and $\ln [L(H_A)]$ are the null and alternative hypotheses, respectively. Thus,

the findings indicate that the computed likelihood ratio surpasses the critical value, resulting in the rejection of the null hypothesis (CD). The results indicate that the Translog production function model provides a significantly better fit compared to the Cobb-Douglas model based on the likelihood ratio test. Hence, this study used the Translog production function to analyze the data. Following [80], the general Translog functional form for five variables can be specified as follows:

$$\ln Y_i = \beta_0 + \sum_{i=1}^5 \beta_i \ln X_i + \frac{1}{2} \sum_{i=1}^5 \sum_{j=1}^5 \beta_{ij} \ln X_i \ln X_j + V_i - U_j \quad (9)$$

Empirically, the Translog production function model in this study is defined with inputs such as land (L), labor (K), seed (S), fertilizer (F), and herbicide (H) as follows:

$$\begin{aligned} \ln Y_i = & \beta_0 + \beta_1 \ln L + \beta_2 \ln K + \beta_3 \ln S + \beta_4 \ln F + \beta_5 \ln H \\ & + \frac{1}{2} (\gamma_{11} (\ln L)^2 + \gamma_{22} (\ln K)^2 + \gamma_{33} (\ln S)^2 + \gamma_{44} (\ln F)^2 \\ & + \gamma_{55} (\ln H)^2) + \gamma_{12} (\ln L \times \ln K) + \gamma_{13} (\ln L \times \ln S) \\ & + \gamma_{14} (\ln L \times \ln F) + \gamma_{15} (\ln L \times \ln H) + \gamma_{23} (\ln K \times \ln S) \\ & + \gamma_{24} (\ln K \times \ln F) + \gamma_{25} (\ln K \times \ln H) + \gamma_{34} (\ln S \times \ln F) \\ & + \gamma_{35} (\ln S \times \ln H) + \gamma_{45} (\ln F \times \ln H) + \omega D_i + v_i - u_i \end{aligned} \quad (10)$$

Where: $\ln Y_i$ is the natural logarithm of tef output in quintal per hectare.

$\ln L, \ln K, \ln S, \ln F,$ and $\ln H$ are the natural logarithms of the inputs per hectare (land in hectares, labor in man-days, seed in kilograms, fertilizer in kilograms, and herbicide in liters). β_0 is the constant term. $\beta_1, \beta_2, \beta_3, \beta_4,$ and β_5 are the coefficients for the linear terms of the logarithms of the inputs. $\gamma_{11}, \gamma_{22}, \gamma_{33}, \gamma_{44}, \gamma_{55}$ are the coefficients for the squared terms (capturing the quadratic effects of each input). $\gamma_{12}, \gamma_{13}, \gamma_{14}, \gamma_{15}, \gamma_{23}, \gamma_{24}, \gamma_{25}, \gamma_{34}, \gamma_{35}, \gamma_{45}$ are the coefficients for the interaction terms between pairs of inputs (capturing the cross-product effects). D_i denotes different dummy variables such as herbicide use, membership to SPCs, and districts, and v_i is the two-sided error term, and u_i is the one-sided error term (technical inefficiency effects). One issue with the inclusion of input dummy variables is that not all farmers use some inputs such as hired labor, resulting in missing values when applying the logarithm transformation to this input variable. This issue is addressed by including dummies following [66] method. The logarithm transformation of inputs with zero values is executed only if positive, and zero otherwise.

To explain inefficiency, the model below is also specified:

$$\begin{aligned} U_i = & \delta_0 + \delta_1 Sex_i + \delta_2 Age_i + \delta_3 Educ_i + \delta_4 Hoholdsize_i \\ & + \delta_5 livestockown_i + \delta_6 Farmsize_i + \delta_7 Ext contact_i + \delta_8 Training_i \\ & + \delta_9 Farm exp_i + \delta_{10} Mket dist_i + \delta_{11} Soilferti_i + \delta_{12} SPCmem_i + \epsilon_i \end{aligned} \quad (11)$$

Where, Sex_i = Dummy variable for sex of household head (1 if male, 0 if female); Age_i = Age of household head (in years); $Educ_i$ = Educational level of household head (measured in years of schooling); $Hoholdsize_i$ = Number of members in the household in adult equivalent; $livestockown_i$ = Number of livestock owned in tropical livestock unit; $Farmsize_i$ = Size of the farm (in hectares); $Ext contact_i$ = Number of contacts with extension agents per year; $Training_i$ = Dummy variable indicating access to training programs (1 if yes, 0, otherwise); $Farm exp_i$ = Years of farming experience in improved tef production; $Mket dist_i$ = Distance to the nearest market (in kilometers); $Soilferti_i$ = Perceived soil fertility

(categorical); $SPCmem_i$ = Dummy variable for cooperative membership (1 if member, 0 if non-member); ε_i = Random error term for inefficiency. Estimations were conducted using STATA software for PSM and conventional stochastic production frontier, stochastic meta frontier, and NLOGIT software for sample selection stochastic production frontier models. **Table 1 in Appendix A1 display the descriptions of the study variables hypothesized and used in the models.**

3. Results and discussion

The following section presents the descriptive and econometric findings, starting with the characteristics of SPC members and non-members. It includes independent samples *t*-test results comparing the mean values of variables for both groups. The next part assesses the impact of SPC membership on the technical efficiency of tef farmers.

3.1. Descriptive statistics results

The results of the descriptive statistics analysis reveal that 49.9 % of farmers were SPC members, whereas 50.1 % of farmers were non-members. Among SPC members, 93 % are male and only 7 % are female, indicating a significant gender disparity in participation in SPC. One potential reason for the gender gap in SPC is that issues like limited resources, insufficient representation, and family responsibilities limit women's participation, thereby reducing their opportunities to gain from SPCs. These findings align with [81], which noted that female farmers in Ethiopia often face limited opportunities for collective action, like cooperatives.

The average age of SPC members is 50 years, in contrast to an average age of 43.5 years for non-members. This indicates that older farmers tend to be more inclined to join the SPC. In terms of education, SPC members have completed an average of 5 years of schooling, compared to 3.5 years for non-members, indicating a potential association between SPC membership and higher educational attainment. Additionally, SPC member farmers have a larger household size, averaging 5.8 persons compared to 5 for non-members. This shows that SPC membership may foster larger household size units due to social support, economic benefits, and resource availability, contributing to both economic and familial stability. These findings align with [30], which noted that household size, age, and education positively influence cooperative participation. **Table. 1**

Results show that SPC members have an average farmland holding of about 1.5 ha, compared to 0.95 ha for non-members, indicating that SPC membership is associated with larger land holdings. This aligns with [29], who found that land size positively influences the likelihood of engaging in cooperatives. Additionally, 95.5 % of SPC members are affiliated with agricultural cooperatives, while 89 % of non-members also belong to such organizations. This indicates that involvement in other farming groups helps farmers understand the benefits of joining SPCs. **Additionally, the study highlights the importance of the frequency of contact between development agents and tef farmers, as SPC members reported an average of 3.5 days of contact regarding tef seed production. This implies that access to agricultural extension services is crucial in determining farmers' willingness to join SPCs, as well-informed farmers are more inclined to discuss the advantages of membership with the extension personnel. These results are consistent with the study carried out by Ref. [81] who found that farmers who have regular contact with extension agents are in a better position to gather useful information which makes them join a cooperative.**

3.2. Determinants of seed producer cooperatives membership

Table 3 displays the results from the probit model (selection equation) identify the determinants of SPC membership, along with their associated marginal effects. The results generate propensity scores. The model estimates the propensity score to match SPC members with non-

members using observed farmer characteristics. The dependent variable in the model is SPC membership status, with 1 denoting SPC members and 0 for non-members. Goodness-of-fit tests show that the selected covariates offer accurate estimates of conditional membership density. The explanatory variables are jointly statistically significant (LR χ^2 (19) = 309.7; Prob > Chi2 = 0.000), with a pseudo R2 of 0.37 indicating a joint significance of parameters for membership in SPC variables.

The study findings indicate that larger farm landholdings significantly increase the likelihood of farmers joining SPCs, with those owning larger lands being 19 % more likely to participate compared to those with smaller plots. This underscores the importance of land size in determining SPC membership, aligning with [82,83] and, who also found that farmers with larger landholdings are more inclined to join cooperatives. In addition, the study shows that livestock ownership, measured in tropical livestock units, positively influences SPC membership, increase the probability membership by 24 % for those with larger livestock holdings. This supports previous research [84–86] that links livestock ownership to household wealth and cooperative involvement.

As expected, the educational level of the household head increases the probability of joining SPCs. The marginal effect of the variable shows that more educated farm households have a 1 % higher chance of joining SPCs. This finding aligns with results from earlier research [58,87]. Furthermore, the results show that the age of the household head has a positive and significant relationship with the probability of tef farmers participating in SPCs at a significance level of 1 %. This is consistent with a previous study by Ref. [88].

The findings indicate that training farmers increases the likelihood of tef farmers joining SPCs, with a 34 % higher chance for those receiving training on improved seed production. This underscores the importance of equipping farmers with knowledge and skills for better practices. The results align with [77], who found that regular communication with extension agents enhances farmers' knowledge and motivates SPC participation. Additionally, agricultural extension contact positively influences SPC membership, with each extra day of contact increasing the likelihood by 9 %. This shows that the frequent engagement with extension services boosts farmers' motivation to join SPCs, consistent with [45,77], and. Furthermore, membership in other farmers' organizations significantly enhances the likelihood of joining SPCs, facilitating networking and information sharing that raise awareness of SPC benefits, as supported by Ref. [84].

The findings of the study reveal that trust in the leaders and committees of seed producer cooperatives has a positive and significant impact on the likelihood of farmers joining these cooperatives ($p < 0.1$). Trust plays a crucial role in influencing an individual's decision to become a member. Farmers are more inclined to engage when they believe that the cooperative will fulfill its commitments—such as providing access to vital resources, ensuring fair profit sharing, and offering opportunities for knowledge exchange or product marketing. When cooperatives are perceived as transparent, reliable, and accountable, prospective members are more likely to participate, as they feel confident that their expectations will be met [45].

Farm experience emerged as a key factor in the study. The findings show that the agricultural experience of households has a positive and statistically significant effect on the probability of farmers becoming members of seed producer cooperatives ($p < 0.01$). Greater farming experience is associated with enhanced agricultural knowledge, better access to resources, and a stronger motivation to manage farming risks—all of which encourage farmers to join seed cooperatives. The marginal effect estimates indicate that with each additional year of farming experience, the likelihood of participating in a seed producer cooperative increase by 24 %.

Distance to SPC office negatively impacts farmers' participation in SPCs, indicating that establishing seed production clusters at the village level could enhance smallholder involvement. This aligns with [70], who found similar negative effects of distance on SPC membership.

Additionally, the district dummy variable positively influences SPC membership, with farmers in the Adea district more likely to join than those in Lume, likely due to better access to an agricultural research center and information on improved seeds. These findings are supported by Ref. [35], who noted that location can increase the likelihood of farmers participating in cooperatives.

3.3. Propensity score matching

PSM technique was implemented to estimate probability that a farmer in the sample becomes a member of SPC. Then, control (non-member) and member groups are generated using nearest neighbor, kernel, and radius-matching algorithms. Based on its superior performance with better-matched and balanced samples, nearest neighbor was selected as the preferred method. The results indicate that a suitable match between member and non-member is achieved. The propensity scores estimate results for the pooled sample vary between 0.0038 and 0.9993, with an average score of 0.4976. For members, the scores range from 0.0330 to 0.9993, while for non-members, the range is from 0.0038 to 0.9990. Hence, the common support region can be determined by considering the minimum value among treated farmers (SPC members) and the maximum value among comparison groups (non-members of SPCs), which lies between 0.0330 and 0.9990.

From 425 sample observations, the matching process generated 380 matches: 209 SPC members and 171 non-members. However, 41 untreated and 4 treated samples were excluded due to propensity scores falling outside the common support range. Following [60], t-tests were performed before and after matching to test the hypothesis that the means of observed characteristics for members and non-members are equal. The results indicate no significant differences in means after

matching, confirming the balance of the covariates, unlike the unmatched sample in Table 2, which showed significant differences. The post-matching pseudo-squared values for nearest neighbors matching, kernel, and radius matching have significantly decreased, indicating a balance in the residuals. Specifically, the post-matching mean standardized bias, which ranges from 6.1 to 9.2, and the median standardized bias, ranging from 5.1 to 5.7, are both below the widely accepted threshold of 10 % across the chosen algorithms. This demonstrates that the matching process has effectively mitigated confounding factors, thereby reinforcing the validity and reliability of the causal inferences made. Furthermore, the results in Table 4 of Appendix A₂ show that the pseudo-R-squared initially exhibited a higher value but experienced a significant decrease across all algorithms after matching, implying an absence of systematic variation in the distribution of the covariates. Fig. 2 visually supports the common support condition, demonstrating substantial overlap in the propensity score distributions of the two groups. Table 3

3.4. Conventional and sample selection-corrected SPF model estimates using matched samples

Table 5 presents the estimates for both the matched sample models with and without correcting for selection bias. We report the results to compare the estimates between our biased and unbiased models and to analyze the technology difference between SPC members and non-members. In line with common practice, all variables in the Translog production models were normalized using their geometric mean (GM), allowing the first-order coefficients to be interpreted as the partial elasticities of output in relation to inputs at their mean value for the average farmer [58]. Furthermore, the likelihood ratio (LR) test was

Table 2
Descriptive statistics of by SPC membership status of SPCs.

Variables	Pooled sample (N = 425)	SPCs Members (N = 212)	SPCs Non-member (N = 213)	Mean difference	t-test
Variables used in SPF Model					
Tef yield per hectare in kg	1804.35	2324.29	1286.85	-1037.4***	7.79
Land under tef production in ha	1.24	1.53	0.95	-0.58***	6.29
Quantity tef seed per ha in kg	35.8	36.40	35.2	-1.22	1.39
Quantity fertilizer per ha in kg	230.6	297.8	263.9	-33.9***	6.09
labor (man-day/ha) (family and hired)	58.6	70.34	46.9	23.4***	5.3
Quantity of herbicide per ha in lit	0.86	1.1	0.62	-0.48***	3
Quantity of fungicide per ha	0.073	0.108	0.04	-0.070***	3.4
Fertilizer dummy (1 if farmer did not apply chemical fertilizer, otherwise 0)	0.97	0.990	0.967	-0.023*	1.67
Herbicide dummy (1 if farmer did not apply herbicide, otherwise 0)	0.99	1	0.99	-0.005	0.99
Fungicide dummy (1 if farmer did not apply fungicide, otherwise 0)	0.13	0.16	0.09	-0.066**	2.06
Variables used in Probit model					
Age of household head in years	46.7	50	43.5	-6.5***	5.4
Sex of household head (1 = male)	0.93	0.94	0.92	-0.01	0.56
family size in adult equivalents	5.64	5.74	5.55	-0.19***	2.97
Education of household head in years of schoolings	4.1	4.65	3.6	1.07***	2.88
Livestock ownership (TLU)	7.10	8.4	5.8	-2.50***	7.7
Oxen in oxen days for per ha	13.7	14.90	11.7	3.2***	3.78
Training access on seed production	0.49	0.85	0.12	-0.74***	22.4
Average number contact per year in days	2.6	3.53	1.62	-1.91***	5.99
Membership status in other farmers' organizations	0.94	0.99	0.89	-0.103***	4.7
Trust in SPCs committee	3.14	3.14	3.06	-0.075	0.21
Perceived soil fertility status	2.28	2.26	2.29	0.03	0.58
Distance to nearest market in minutes	45.5	43.9	47	3.15	0.80
Distance to SPCs in minutes	28.82	26.8	30.8	4.01	1.30
Total income from tef sales	63542.5	85950.09	41240.2	-44,709.9***	6.62
Off-farm income per household	682.45	123.65	1223.80	1100	2.68
Market availability (if SPCs purchase output and supply inputs, otherwise 0)	0.62	0.63	0.20	-0.43	1.95
Use of basic seed (1 if a farmer uses certified seed obtained known source, otherwise 0)	0.31	0.32	0.25	-0.066	0.28
Adea_dummy (1 = yes)	0.67	0.60	0.73	0.123***	2.73
Lume_dummy (1 = yes)	0.34	0.41	0.27	0.133***	2.91

Notes: ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

Source: Results from own survey in 2023

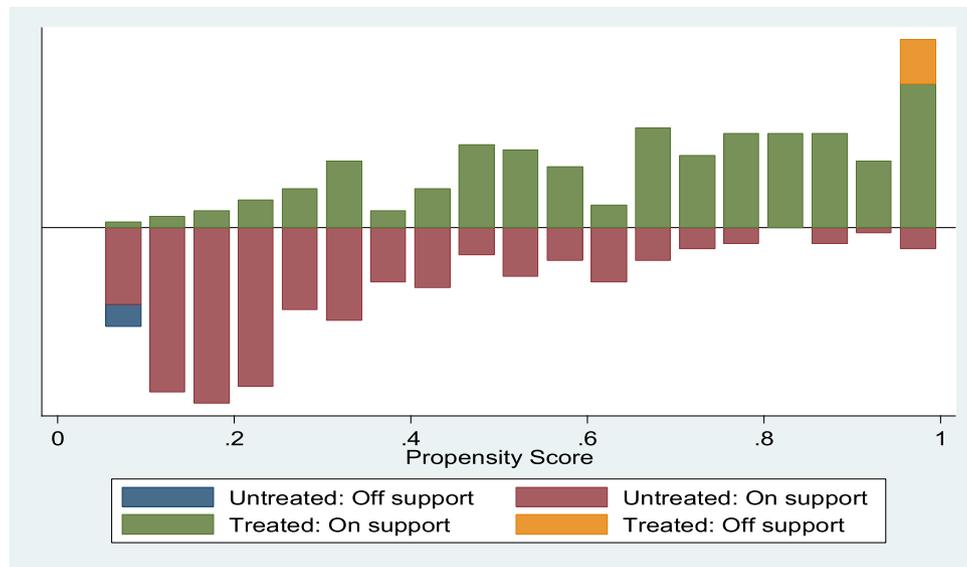


Fig. 2. PSM distribution and common support for propensity score estimation.

Table 3
Probit model results of the determinants of SPC membership.

Variable	Probit estimates				Marginal effects		
	Coef.	Std.Err.	Z	P-value	Coef.	Std.Err.	p-value
Age	0.52***	0.096	5.4	0.000	0.022***	0.0017	0.000
Age square	0.005	0.009	0.55	0.68	0.0047	0.0091	0.69
Sex	0.424	0.231	-1.54	0.11	-0.085	0.051	0.097
Family size	0.56**	0.27	2.07	0.04	0.35***	0.08	0.002
Educational level	0.065***	0.024	2.73	0.006	0.010***	0.0044	0.022
Tef farmland size	0.46***	0.059	7.79	0.000	0.190***	0.034	0.000
Livestock ownership	0.13***	0.033	3.93	0.000	0.24***	0.06	0.001
Access to training	2.00***	0.176	11.33	0.000	0.344***	0.0221	0.000
Extension contacts	0.580***	0.074	7.83	0.0046	0.092***	0.0064	0.000
Soil fertility status	0.041	0.185	0.22	0.825	0.0075	0.034	0.825
Membership in farmer's organization	1.22***	0.503	2.43	0.02	0.225***	0.095	0.018
Total farm income	0.041***	0.013	3.10	0.002	0.0756***	0.0224	0.001
Distance to nearest all weather road	-0.0005	0.0045	-0.11	0.912	-0.00009	0.0008	0.912
Distance from the SPC office	-1.29***	0.247	-5.2	0.000	-0.071***	0.004	0.000
Off farm income	0.0012	0.002	0.06	0.33	0.0025	0.0039	0.95
Experience in tef farming	1.42	0.301	4.72	0.002	0.24***	0.078	0.001
Trust in SPC leadership	0.059*	0.032	1.81	0.070	0.011*	0.006	0.074
Adea	0.707*	0.42	1.68	0.094	0.116*	0.065	1.77
Lume	0.398	0.43	0.93	0.57	0.090	0.16	0.57
_cons	7.13	1.99	3.58	0.000			
A number of obs.			425				
LR chi2(19)			305.82				
Prob > chi1			0.000				
Log likelihood			-140.54				
Pseudo R2			0.41				

Binary outcomes indicating discrete changes from 0 to 1.

Note: ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

conducted to verify whether SPC members and non-members use similar technology using the formula indicated below:

$$LR = (\ln L_p - (\ln L_M + \ln L_{NM})) \tag{12}$$

Where L_p , $\ln L_M$, and $\ln L_{NM}$ denote the log-likelihood function values derived from the pooled model, the members of the SPCs, and the non-members of the SPCs subsamples, respectively. The findings from the log-likelihood ratio test indicate a rejection of the null hypothesis at a 1 % significance level, which posited that SPC members and non-members share similar technology (i.e., the estimation of a common pool). The likelihood ratio test yielded a value of 90.73 ($p < 0.01$), reinforcing the estimation of separate SPFs over the full sample.

The estimates of σ_u and σ_v in both the conventional and sample se-

lection models are significantly greater than zero at the ($p < 0.01$), demonstrating the strong goodness of fit of the model. The findings of the study reveal that the coefficient for SPC membership is both positive and statistically significant at the ($p < 0.01$), indicating a correlation between SPC membership and higher tef yields. This result aligns with earlier research conducted by Refs. [50,89]. The pooled estimation of matched data reveals a positive and statistically significant influence of membership in SPC on the frontier estimates, implying that SPC members tend to operate closer to the production frontier, meaning they are more efficient in their use of resources. This phenomenon can be attributed to the improved access to improved seeds and technical assistance that SPC members typically enjoy through their membership and social networks, leading to increased production levels. The findings

are consistent with the findings reported by Refs. [45,77] in Ghana and in Zambia.

The estimated coefficients for conventional factor inputs are mostly positive, except for herbicide. This indicates that nearly all variable inputs used by both member and non-member farmers align with our expectations, satisfying the monotonicity condition and showing a stable, non-decreasing production function. The negative effect of herbicide on tef yield may stem from excessive use, adversely affecting overall output. These findings are consistent with [76]. Additionally, the pooled estimation of matched data shows that land, labor, seed, and fertilizer significantly influence tef yield at the ($p < 0.01$). The findings from the sample selection bias-corrected model show that the estimated selectivity term ρ for SPC members is -0.56 , negative and statistically significant at the ($p < 0.01$), indicating a strong correlation between unobserved factors affecting membership and the error term in the stochastic frontier model. In contrast, the estimated ρ for non-members is positive and statistically significant at the ($p < 0.01$), suggesting selectivity bias from unobserved factors. These results support the validity of the sample selectivity framework [73].

The estimated partial output elasticities for land, labor, and seeds at the geometric mean in the sample selection model for SPC participants are approximately 0.68, 0.199, and 0.21, respectively. For non-members, the elasticity for land is about 0.44. The coefficients for most variables are smaller in the selectivity-corrected model than in conventional frontier estimates, demonstrating that sample selection bias may have led to an overestimation of average partial elasticities. The selectivity-corrected model indicates that tef yield increases with larger farmland, more labor, seed, and fertilizer at varying significance levels. Specifically, a percentage increase in farmland size in ha, seed (kg per hectare), labor (man-days), and fertilizer (kg per hectare) is expected to result in approximately 0.68 %, 0.2 %, 0.2 %, and 0.11 % increases in tef yield for SPC members, respectively. The beneficial roles of land, labor and fertilizer are corroborated with the research conducted by Ref. [76].

The estimated coefficient for the logarithm of squared land size is positive and statistically significant for both members and non-members, indicating that the partial output elasticity increases with farm size. As the farmland area increases, the output increases at an accelerating rate, indicating that larger farms experience increasing returns to scale, which is consistent with [90]. Additionally, there are significant positive coefficients in the interactions between land-labor, land-seed, and seed-fertilizer for SPC members, showing a complementary relationship among these inputs. This means that increasing one input enhances the elasticity of the others. These findings align with the results of [67], which highlight a positive association between input interactions and TE levels of improved and local maize seed varieties in Ghana.

The return to scale (the sum of all partial output elasticities from the sample selection models) for SPC members is 1.21, while for non-members, it is 0.803, indicating that input use is more productive for SPC members, who benefit from increasing returns to scale (IRS), compared to non-members, who experience decreasing returns to scale (DRTS). The higher sum of partial output elasticities for SPC members suggests advantages in scale, efficiency, and resource use, while non-members face limitations. This indicates members of SPC experience increasing returns to scale, while non-members face diminishing returns as their land size grows. This contrast is largely due to cooperative members benefiting from better resource utilization, improved access to technology, and shared inputs, all of which lead to greater efficiency. In contrast, non-members often face inefficiencies stemming from land fragmentation. This highlights the potential of cooperatives in helping smallholder farmers overcome the challenges associated with fragmented landholdings. By promoting cooperative membership, farmers can pool resources and adopt more efficient practices, enabling them to benefit from economies of scale.

To support this, the government could encourage land leasing or

pooling arrangements, allowing farmers to combine plots and improve productivity. Policies should prioritize cooperative support, facilitate land consolidation, secure land tenure, and invest in infrastructure and technology. These measures would enable smallholders to optimize farm size, enhance efficiency, and contribute to a more sustainable and equitable agricultural sector in Ethiopia. This finding aligns with [90], who found that participants in professional cooperatives had a sum of partial output elasticities greater than 1, indicating IRS for small vegetable farms. Additionally, geographical location significantly influences tef yields, with farmers in the Adea district of the Eastern Shewa zone achieving higher yields than those in the Lume district, the reference district.

Nevertheless, the impact of farmers' locations on yields was not statistically significant in the sample selection SPF for both SPC member and non-member farmers. The differences in yields between the districts are significantly reduced when accounting for both observed and unobserved biases. The findings of the study reveal that access to basic seed has a positive and significant influence on the yield of tef farmers. This influence can be attributed to a combination of factors, including increased access to improved quality seeds, supportive services, affordable cost benefits, and the improved knowledge and resources provided through the cooperative framework. Collectively, these factors contribute to improved technical efficiency and productivity accounted due to seed cooperative, as compared to non-members. This study is consistent with the findings by Ref. [91], who found that critical factors the seed production and marketing effectiveness of SPCs, including improved basic seeds, market stability, high involvement and impact of SPCs within the seed value chain. [Table 4](#)

A potential limitation of the study is the exclusion of farmer risk preferences, which can affect both cooperative membership and productivity. Less risk-averse farmers are more likely to join cooperatives for their risk-sharing benefits, while highly risk-averse ones may avoid them due to perceived uncertainty, especially around management. If risk-tolerant farmers are also more innovative, the study might overestimate the impact of membership on efficiency. However, weather variability is unlikely to bias results, as farmers typically have equal access to weather information, helping mitigate the influence of external shocks on the study's findings. [Table 5](#)

3.5. Determinants of technical inefficiency among tef farmers

The inefficiency component in [Table 6](#) presents the estimates of the determinants of technical inefficiency in tef production. A positive coefficient for inefficiency indicates that the variable has a negative effect on technical efficiency and vice versa. The results indicate that the educational attainment of the household head is negatively correlated with the pooled data, as well as among both SPC members and non-members. This correlation is statistically significant at the ($p < 0.1, 0.01$, and 0.1) levels, respectively. The education variable aligns with our a priori expectation of a negative relationship with inefficiency. These results are consistent with the research by Ref. [67]. Moreover, household size plays a significant role in increasing the technical efficiency of SPC member farmers in tef production. Specifically, the negative coefficient associated with household size suggests that larger households tend to exhibit greater technical efficiency, likely attributable to their ability to augment labor supply during peak farming seasons. A similar result was witnessed by Ref. [83], who indicate that involvement in agricultural cooperatives correlates with increased yield and technical efficiency.

Results indicate that farm size negatively and significantly affects inefficiency, confirming prior expectations. While cooperative membership provides benefits like resource sharing, larger farm sizes enhance technical efficiency for both members and non-members. Additionally, the frequency of extension contacts and access to training also show a negative and significant relationship with inefficiency, indicating that greater engagement with extension services

Table 5
Estimates for conventional and sample selection-corrected SPF model: Matched sample.

Variables	Conventional stochastic production function (SPF)						Sample selection bias corrected SPF			
	Pooled		SPC members		Non-members		SPC members		Non-members	
	Coff.	S. E	Coff.	S. E	Coff.	S. E	Coff.	S. E	Coff.	S. E
Constant	7.21***	2.151	7.80***	0.634	7.80***	0.042	7.831***	0.073	7.644***	0.845
ln land	0.703***	0.112	0.712***	0.143	0.814***	0.101	0.682***	0.163	0.445***	0.050
ln labor	0.232***	0.062	0.242**	0.101	0.285***	0.090	0.199*	0.112	0.233***	0.020
ln seed	0.301***	0.121	0.251***	0.024	0.047	0.102	0.211**	0.090	0.254	0.223
Infertilizer	0.195***	0.07	0.123*	0.071	0.1013*	0.060	0.113***	0.042	0.081***	0.022
ln herbicide	-0.178	0.53	-0.462	0.621	-0.076	0.621	-0.0055	0.972	-0.581	0.45
0.5x(land) ²	0.163***	0.020	0.241***	0.040	0.452**	0.214	0.132**	0.060	0.862***	0.090
0.5x(labor) ²	-0.231*	0.131	-0.260	0.311	-0.401**	0.192	-0.204	0.411	-0.005	0.332
0.5x(seed) ²	-0.852**	0.433	-0.79	0.491	-0.49	0.482	-0.753	0.621	-0.546	0.250
0.5x(Fertilizer) ²	0.084	0.062	0.030	0.192	0.009	0.074	0.025	0.287	0.018	0.365
0.5x(Herbicide) ²	-0.068	0.060	-0.026	0.052	-0.018	0.0511	-0.041	0.225	-0.072	0.573
ln land x ln labor	0.271*	0.021	0.291***	0.080	0.442**	0.194	0.293***	0.040	0.074*	0.393
ln land x ln seed	0.462*	0.164	0.240***	0.031	0.143	0.382	0.212*	0.091	0.639	0.721
ln land x ln fertilizer	-0.596***	0.215	-0.59***	0.152	-0.491	0.321	0.221***	0.047	0.019	0.463
ln land x ln herbicide	0.175	0.131	0.293	0.212	0.199	0.172	0.371	0.245	0.0078	0.621
ln labor x ln seed	-0.293	0.194	0.655	0.502	-0.351	0.245	-0.531	0.353	0.093	0.518
ln labor x ln fertilizer	0.400	0.084	0.131	0.145	0.156	0.101	0.093	0.28	-0.086	0.43 9
ln labor x ln herbicide	-0.177	0.123	-0.47***	0.151	-0.542***	0.133	-0.45**	0.15	0.129	0.34 4
ln seed x ln fertilizer	-0.354***	0.013	-0.58***	0.029	0.124	0.233	0.126***	0.039	0.102	0.10 3
ln seed x ln herbicide	0.056	0.103	0.176	0.183	0.024	0.184	0.196	0.28	-0.29	0.37 1
ln fertilizer x ln herbicide	-0.213	0.154	-0.046	0.155	0.022	0.121	-0.21	0.192	-0.265	0.33 8
SPC membership	0.252***	0.042								
Basic Seeds	0.09**	0.045	0.16***	0.067	0.72***	0.119	0.582***	0.039	0.106***	0.025
Fertilizer dummy	0.21**	0.097	0.69**	0.33	0.053*	0.029	0.055**	0.026	0.027*	0.015
Herbicide dummy	-0.276*	0.14	-0.074	0.056	-0.077**	0.036	-0.34***	0.143	-0.24***	0.027
Fungicide dummy	0.053	0.74	0.084	0.725	0.160	0.227	0.83***	0.060	0.371***	0.056
Adea district	0.205**	0.093	0.185*	0.098	0.142*	0.079	0.0155	0.013	0.014	0.19
SPC x land	0.855***	0.164								
SPC x labor	0.719***	0.117								
SPC x seed	-0.459***	0.157								
SPC x fertilizer	0.064	0.107								
SPC x herbicide	0.133	0.083								
Basic Seeds	0.09***	0.003								
Lambda (λ)	0.34***	0.05	2.9***	0.55	2.57***	0.40	-	-	-	-
Sigma (σ)	0.39***	0.07	0.58***	0.02	0.58***	0.02				
Sigma-u (σ _u)	-	-	-	-	-	-	0.54***	0.06	0.69***	0.07
Sigma-v (σ _v)	-	-	-	-	-	-	0.18***	0.04	0.18***	0.01
Rho (w,v)	-	-	-	-	-	-	-0.56***	0.21	0.345***	0.06
Log likelihood	-219.5		-87.70		-114.7		-110.9		-196.05	
Return to scale	0.824		0.866		0.808		1.209		0.803	
Number of observations	380		209		171		209		171	

Source: survey results, 2023; ***, ** and * means significant at the 1 %, 5 % and 10 % levels, respectively

Table 6
Maximum likelihood estimates of determinants of technical inefficiency.

Variable	Pooled		SPC member		Non- member SPC	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Sex of household head	-0.0062	-0.79	-0.102	-1.07	-0.0017	-0.13
Age of household head	-0.0018***	-2.67	-0.070***	-3.64	-0.0034***	2.89
Educational level	-0.0010*	-1.9	-0.014***	-2.81	-0.0029*	-1.94
Household size	-0.06*	-1.82	-0.044***	-4.18	-0.054	-0.47
Livestock ownership	-0.00071	-1.09	-0.008	-1.31	0.0001	0.08
Farm size	-0.0057	-2.28**	-0.007***	-2.53	-0.003***	-2.41
Extension contacts	-0.065	-10.7	-0.040***	-2.99	-0.335*	-1.95
Access to training	-0.012	-2.80	-0.048***	-3.105	-0.0017	-0.97
Tef farming experience	-0.0002	-0.65	-0.032***	-11.9	-0.009	-0.88
Distance to nearest market	0.000044	0.76	0.04	0.63	0.0011	1.08
Perceived soil fertility	-0.0031	-0.72	-0.05*	-1.96	-0.0012	-0.17
Constant	0.8673	6.09	-0.893	-5.05	-0.84	3.19

Source: Survey results, 2023 *** and ** indicate significance at 1 % and 5 %

improves farming practices, reduces inefficiencies, and boosts productivity. These findings align with [92], who found that factors like access to credit, participation in social organization, participation in field day, farm size and extension contact were marked as best

determinants of technical efficiency.

The inefficiency model results indicate that tef farming experience and perceived soil fertility are significant determinants of technical efficiency. These factors enhance efficiency, as experienced farmers use

Table 7
Parameter estimates of stochastic meta frontier using matched samples.

Variables	Estimated Coef.	Std. Err.	z-value	p-value
ln land per hectare	0.691***	0.27	2.563	0.000
ln labor in man-days	-0.032***	0.011	-2.91	0.0001
ln seed in kg per ha	0.072**	0.035	2.057	0.0400
ln fertilizer in kg per ha	0.106***	0.0107	9.907	0.0010
ln herbicide	-0.020***	0.008	-2.5	0.0054
0.5x(land) ²	0.033***	0.0109	3.027	0.0001
0.5x(labor) ²	-0.286***	0.071	-4.028	0.0001
0.5x(seed) ²	-0.383***	0.142	-2.74	0.0001
0.5x(Fertilizer) ²	0.116***	0.0331	3.52	0.0001
0.5x(Herbicide) ²	0.186***	0.0163	11.41	0.0001
ln land x ln labor	0.309***	0.074	4.18	0.0001
ln land x ln seed	0.206***	0.039	5.31	0.0001
ln land x ln fertilizer	0.193***	0.0161	11.95	0.0001
ln land x ln herbicide	0.129***	0.034	3.794	0.0001
ln labor x ln seed	-0.147***	0.042	-3.5	0.0001
ln labor x ln fertilizer	0.119***	0.024	4.96	0.0001
ln labor x ln herbicide	-0.308***	0.022	-13.90	0.0030
ln seed x ln fertilizer	0.056***	0.0325	17.231	0.0001
ln seed x ln herbicide	0.0204***	0.0023	8.869	0.0001
ln fertilizer x ln herbicide	-0.0385*	0.0202	-1.905	0.0710
Constant	12.33 ***	3.1034	3.9720	0.0001
lambda	1.173***	0.057	20.32	0.0001
sigma_u	0.213***	0.036	5.79	0.0001
sigma_v	0.182***	0.025	7.26	0.0001
Log likelihood	-60.367			
Number of observations	380			

Source: Survey results, 2023 *** and ** indicate significance at 1 % and 5 %

their knowledge to optimize production, while a positive perception of soil fertility helps them make informed decisions that maximize yield and resource use. The findings of the study are similar to the findings of [46,93]. The age coefficient in the inefficiency model is negative and statistically significant at the ($p < 0.01$) level for pooled, SPC members and non-members. This indicates that older farmers in SPCs are more efficient in tef production than younger farmers. Their enhanced efficiency likely stems from greater experience, better resource management, resilience in challenges, established networks, and a long-term farming perspective. These findings align with [33].

3.6. Stochastic meta frontier production function estimation

Table 7 presents an estimate of the parameters for the stochastic meta frontier (SMF) based on [63]. As mentioned in section 3.4, the likelihood ratio test revealed the existence of a potential production technology gap, which justifies the estimation of the meta-frontier production function among farmers. The frontier is used to calculate the meta technical efficiency (MTE) and technological gap ratio (TGR) and to make a comparison between SPC members farmers and non-members. The lambda for the stochastic frontier (i.e. the ratio of the standard deviation values for the inefficiency variable and the symmetric error term) is significant at the 1 % level for both SPC members and non-members. A positive and significant lambda implies that inefficiency is a significant factor contributing to output variability compared to random error. This implies that technical inefficiency is a major factor influencing production performance in addition to random shocks. This finding is consistent with the study by Ref. [69].

The estimated coefficients of the first order indicate the partial output elasticities related to specific inputs, determined at their geometric mean values. The sum of the partial output elasticities is approximately 0.88, indicating a decreasing return to scale along the

Table 8
Tef farmers' efficiency measures for members and non-members of SPCs.

Variable	Pooled		SPC members		SPC non-members		T-test of mean
	Mean	SD	Mean	SD	Mean	SD	
TGR	0.74	0.314	0.93	0.048	0.82	0.204	7.9***
TE	0.648	0.074	0.72	0.139	0.593	0.145	8.9***
MTE	0.469	0.240	0.67	0.138	0.485	0.143	13.6**

meta frontier. This indicates that increasing inputs will lead to less than proportional increases in output overall. Considering the indication of decreasing returns to scale, SPCs should focus on optimizing their current scale to achieve efficient production levels. These results align with the findings of [93].

3.7. Impact of SPC membership on tef farmers' technical efficiency

Table 8 displays the sample statistics of various efficiency scores for SPC members and non-members. The group-specific technical efficiency (TE) scores show that SPC members have a TE of 0.72, while non-members have a TE of 0.59. This means SPC members achieve 72 % of their potential output based on current inputs and available technology, compared to just 59 % for non-members. Thus, members are more technically efficient than non-members. Both groups lose 28 %–41 % of optimal output due to inefficiencies in input use and suboptimal agronomic practices. These study findings are consistent with [67].

SPC members score higher in technology use, with a TGR of 0.93 compared to 0.82 for non-members, indicating better use of available agricultural technologies. A higher TGR score signifies a stronger association between available technology and its practical use. SPC members likely benefit from better resources, training, or support, boosting their adoption of improved methods. In contrast, non-members face barriers to accessing technologies, which limits their use of innovations. Overall, SPC members are more efficient in resource use for output production, achieving a meta-technical efficiency (MTE) score of 0.67, while non-members scored only 0.49.

This suggests that non-members are less efficient, likely due to limited access to basic seed technology, resources, or best practices. The constraints of other factors—such as access training, improved technology, market conditions, and social support—can also explain the observed gap in MTE between SPC members and non-members. Non-members of SPC acquire improved seeds from private companies for production; in turn, the companies purchase seeds from the farmers. However, the type and quantity of improved seeds provided by these companies are insufficient for non-member farmers. These results are in line with the findings of [93], who indicate that adopters are 24 % more technically efficient than non-adopters. If all groups achieved technical efficiency, they could improve output by 7 % for SPC members, 18 % for non-members, and 26 % for the entire tef farming sector by using the most efficient meta-technology available. These results align with the findings of [67,69].

The study's findings align strongly with Ethiopia's agricultural development policies, particularly the Growth and Transformation Plans (GTP I and II) and the 2021–2030 National Agricultural Policy. These frameworks emphasize agricultural modernization, rural development, poverty reduction, and food security.

A key contribution of the study is its demonstration that cooperative membership leads to higher technical efficiency (72 % vs. 59 %) and meta-technical efficiency among farmers. This reinforces the strategic importance of supporting cooperative structures to meet national

development goals.

GTP II identified institutional support for cooperatives as a core pillar, recognizing their role in boosting productivity by enhancing farmers’ access to resources, markets, and technical support. Similarly, GTP I and II stress the value of agricultural cooperatives in achieving large-scale improvements in productivity and rural livelihoods.

By being part of a cooperative, farmers benefit from economies of scale, improved access to inputs like seeds and fertilizers, collective expertise, and market linkages. These findings support GTP II’s emphasis on improving farming practices and strengthening technical capacity through training and collaboration.

The higher meta-technical efficiency among cooperative members also indicates their greater ability to adapt to changing conditions and innovate—an objective echoed in both GTP II and the 2021–2030 policy, which focus on sustainable modernization and resilience in agriculture. The 2021–2030 National Agricultural Policy further prioritizes technology adoption, market integration, and sustainability, emphasizing cooperatives as critical mechanisms for delivering advanced technologies, training, and financial services to smallholders. By leveraging these findings, the government can formulate targeted strategies to establish and strengthen cooperatives, directly contributing to national goals for improved productivity and food security.

Table 9 presents the average treatment effect on the treated (ATT) regarding the average observed and frontier yields in relation to the frontiers of farmers’ own groups. Specifically, the frontier yields are defined as the average expected yield if each farmer group were to improve their efficiency to 100 %. The results indicate that SPC member farmers achieve a 17 % higher observed yield than their non-member counterparts. Additionally, the results reveal that SPC member farmers exhibit an average inefficiency of 26 %, indicating that these farmers could enhance their actual yield from 1857 kg/ha to as much as 2347 kg/ha.

The gap between the frontier yield and the observed yield for non-members of the SPC group is 27 %. This shows that non-member farmers could increase their current average yield of 1593 kg/ha to as much as 2027 kg/ha. The results highlight that membership in SPCs can significantly boost tef productivity since farmers can get technical assistance and improved seeds. There is a significant gap in average frontier yields between member and non-member farmers. This indicates that the productivity gains seen in SPC members are largely due to their affiliation with the SPCs, alongside their managerial capabilities. These results are consistent with the research conducted by Ref. [83].

The findings of the study indicate that membership in a seed producer cooperative (SPC) provides substantial economic benefits beyond technical efficiency. It plays a crucial role in increasing farmers’ incomes, enhancing food security, and improving resilience to climate change, as more efficient farmers tend to be more productive. These benefits align with the broader goals of sustainable rural development and poverty alleviation in Ethiopia, supporting the nation’s long-term agricultural and economic growth objectives.

Findings from key informant interviews and focus group discussions reveal that members of seed producer cooperatives (SPCs) face several significant challenges. These include weak leadership, limited professional management skills, and poor documentation practices, all of which hinder effective planning, auditing, and erode member trust. Governance structures are often dominated by local, better-off farmers,

Table 9
Average observed and frontier yield for members and non-members of SPCs.

Variable	Members of SPCs		Non-members of SPCs		Test of means
	Mean	SD	Mean	SD	
Observed yield (kg/ha)	1857	105.5	1593	109.5	23.8***
Frontier yield (kg/ha)	2347	113.5	2027	118.5	26.7***

Source: Survey results, 2023 *** and ** indicate significance at 1 % and 5 %

limiting inclusivity and potentially marginalizing smaller producers.

The seed certification process is another concern, frequently delayed by bureaucratic procedures. In addition, inadequate storage facilities threaten seed quality, while limited access to credit remains a major constraint. Many SPCs lack collateral or a formal credit history, making it difficult to secure loans for purchasing inputs or investing in infrastructure.

However, farmers noted during group discussions that marketing improved seed is not a major challenge. SPCs typically buy improved seed from members with a markup of 15–18 % over the grain price, providing a relatively reliable outlet for their products.

4. Conclusions and implications

In conclusion, the study underscores the significant impact of SPC membership in enhancing technical efficiency for member farmers, particularly through better access to quality seeds in seed cooperative frameworks. The study reveals that SPC members consistently show higher technical efficiency (TE) than non-members, even when selectivity bias is considered. Matching techniques and sample selection frameworks reduce the TE gap between members and non-members. SPC member farmers achieved 72 % of their potential output, compared to 59 % for non-members, demonstrating the positive impact of group membership on optimizing agricultural practices and resource utilization. The study also found that SPC members exhibit higher meta-technical efficiency (MTE), scoring 67 %, while non-members scored 49 %, underlining the effectiveness of SPC membership in maximizing output relative to input and technology. This gap suggests that non-members face challenges, likely due to limited access to improved seed technology, inadequate technical assistance, and a lack of training in seed production and quality management. The challenges faced by non-member farmers in sourcing adequate improved seeds from private companies underscore the urgent need for increased support and resources to enhance their agricultural efficiency and productivity. Bridging the technological gap for non-members could improve overall tef farming output. The study is limited to the central highlands of Ethiopia due to budget and time constraints. Despite this limitation, it provides robust results and suggests future research in wider areas to capture the overall impacts of SPC membership on seed quality, seed supply, poverty reduction, and smallholder well-being across Ethiopia. Based on these findings, the study recommends that the government of Ethiopia and development partners focus on strengthening the capacity of SPCs to improve seed production within cooperatives. It also advocates for improving seed management skills through farmer training and strengthening private seed producers to meet the growing demand for quality seeds.

CRedit authorship contribution statement

Abera Gemechu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Moti Jaleta:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization. **Lemma Zemedu:** Writing – review & editing, Validation, Supervision, Software, Resources, Methodology, Investigation. **Fekadu Beyene:** Writing – review & editing, Validation, Supervision, Methodology, Investigation.

Declaration of competing interest

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

Appendixes

Table 1

Appendix A₁: Description of variables used in the models

Variables	Description and measurement	Type	Expected sign
SPCs membership	Membership status in the cooperative (1 = yes, 0 = no)	Dummy	
Age	Age of household head (years)	Continuous	+
Sex	Sex of household head (1 = male, 0 = female)	Dummy	+/-
Family size	Number of family size in adult equivalents	Continuous	+
Education level	Education of household head in years of schoolings	Continuous	+
Livestock ownership	Number of livestock in tropical unit	Continuous	+
Training access	Access to training on SPCs services	Dummy	
Extension contacts	Number of extension agent visits to tef farmers per year	Continuous	+
Farm income	Total farm income in Ethiopian income	Continuous	+
Non-farm income	Total non-income in Ethiopian income	Continuous	+
Membership to other farmers' organizations	Membership status in other farmers' organizations	Dummy	+
Perceived soil fertility status	Perceived soil fertility status (1 = good, 0 = otherwise)	Dummy	+/-
Distance to road	Distance to the nearest all-weather road (in minutes)	Continuous	-
Distance to SPCs	Distance to SPCs in minutes	Continuous	-
Market availability	Market availability (if SPCs purchase output and supply inputs, otherwise 0)	Dummy	+
District	District indicates the specific location of a farmer (1 = Adea, 0 = otherwise; 1 = Lume 0 = otherwise)	Dummy	+/-
Input and output variables used in SPF model			
Tef yield (Outcome variable)	Total yield of tef harvested (kg/ha)	Continuous	
Farm land size	Land under tef production in ha	Continuous	+
Labor	labor (man-day/ha) (family and hired)	Continuous	+
Seed	Quantity tef seed per ha in kg	Continuous	+
Fertilizer	Quantity fertilizer per ha in kg	Continuous	+
Herbicide	Quantity of herbicide per ha in lit	Continuous	+

Table 4

Appendix A₂: Summary of the quality matching test for selected algorithms

Algorithms	Sample	Pseudo-squared	Wald chi-square (p-value)	Mean standardized bias	Median standardized bias
Nearest neighbors	Unmatched	0.308	181.25 (0.000)	52.2	37.1
	Matched	0.019	7.9 (1.31)	6.1	5.1
Kernel	Unmatched	0.308	181.25 (0.000)	52.2	37.1
	Matched	0.016	9.17 (0.606)	6.5	5.7
Radius	Unmatched	0.308	181.25 (0.000)	52.2	37.1
	Matched	0.034	9.34 (0.591)	9.2	5.7

Data availability

Data will be made available on request.

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