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The effects of advisory services and technology channeling on farm yields and technical efficiency of wheat farmers in Ethiopia

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ABSTRACT

Improving the performance of low-productivity smallholder farmers is a pathway with great potential for reducing poverty and enhancing food security and nutrition in sub-Saharan Africa. Using experimental data from Ethiopia and a mediated stochastic frontier model that accounts for endogenous treatment status, we examine the impact of advisory services and technology channeling on farm yields and efficiency. Our results show that the impact of improved extension services on yields is positive and statistically significant and that advisory services constitute a significant proportion of the output effect.

1. Introduction

Although many proven agricultural technologies for boosting productivity are available, the yield gaps in sub-Saharan Africa (SSA) are huge compared to other regions in the world (Udry, 2010; Walker and Alwang, 2015). Studies show that low adoption of agricultural technologies is a major contributor to low productivity in SSA (Suri and Udry, 2022) and that adopters of improved technologies are obtaining higher yields (Otsuka and Muraoka, 2017; Kassie et al., 2018). The evidence suggests that improving the performance of low-productivity smallholder farmers has great potential to lift people out of poverty and enhance food security and nutrition in the region. This evidence is also stimulating government agencies and donors to invest in agricultural measures to channel improved agricultural technologies and to encourage smallholder farmers to adopt these technologies and so raise productivity (Bachewe et al., 2018; Maertens et al., 2020). Despite these efforts, the role of "extension" services in improving the low adoption rate of yield-enhancing technologies and low agricultural productivity is still subject to debate (e.g., Becerril and Abdulai, 2010; Krishnan and Patnam, 2014; Ragasa and Mazunda, 2018; Shiferaw et al., 2014). While some researchers have argued that investing in agricultural extension can result in increased adoption and hence improved farm performance (Shiferaw et al., 2014), others believe that access to extension services increases the uptake of yield-enhancing technologies only at an early phase or has trivial impacts at any stage (Krishnan and Patnam, 2014).

Agricultural extension programs in SSA focus on facilitating the adoption of new technologies and promoting better management practices. Extension programs such as the provision of improved seed varieties along with extension services provide a dual goal of inducing an upward shift in the production function and pushing output toward the production frontier (Bravo-Ureta, 2014). The adoption of new technologies induces an upward shift in the production frontier, while promoting improved farming techniques to enhance the technical efficiency of farmers is expected to push output toward the production frontier regions. Hence, building up social resources and fostering innovative technologies can potentially influence both the technological frontier and the efficiency of farmers (Huang and Liu, 1994; Kumbhakar et al., 2009). Due to the weak agricultural input markets in SSA, agricultural extension services play a role in channeling or disseminating inputs to smallholders to enhance the use of improved seeds and fertilizers. For example, in Ethiopia, the government facilitates the supply of about 90% of modern agricultural inputs to smallholders through agricultural extension and rural cooperatives (Tadesse et al., 2018). As noted by Bachewe et al. (2018), increased productivity in Ethiopia partly reflects the efforts taken by development agents (DAs) to promote the use of improved seeds and inorganic fertilizers.

This study aims to investigate the impact of extension services, specifically advisory services and technology channeling, on farm

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performance using data from a field experiment conducted among 1338 farm households in Ethiopia. We use a field experiment to test the significance of extension services delivered by skilled DAs to increase production and enhance the technical efficiency of wheat farmers. We deployed skilled DAs to facilitate smallholders' adoption of a new wheat variety by targeted efforts to promote the new variety, henceforth called "channeling," and to provide the information and services required by smallholders.

While the influence of human capital on the production function is well established (e.g., Kumbhakar et al., 2009; Abdul-Rahaman and Abdulai, 2018), few studies have examined the role of extension services in technology adoption and technical efficiency. For example, Dinar et al. (2007) evaluated the impact of agricultural extension on the performance of farmers in Crete by modeling extension services, an explanatory variable, as a function of both frontier conditions and inefficient work practices. However, their results could suffer from selection bias and endogeneity because the conventional stochastic frontier model (SFM) does not allow for the unobserved features of self-selection into technology adoption and participation in extension programs. Many studies (e.g., Abdulai and Abdulai, 2017; Abdul-Rahaman and Abdulai, 2018; Bravo-Ureta et al., 2021; De los Santos-Montero and Bravo-Ureta, 2017; Villano et al., 2015) have attempted to address the issue of selectivity by using mixed multistage approaches, such as two-step selection bias-corrected SPF models and difference in differences selectivity corrected SPF models. However, these studies fail to account for possible unobserved factors associated with technology and institutions, and hence potentially suffer from endogeneity problems. The SPF model proposed by Chen et al. (2020) addresses this problem. In the present study, we employ this novel approach to examine the impact of the provision of extension services along with an improved wheat variety on farm yields and technical efficiency of farmers.

Previous studies focused on the effectiveness and impact of agricultural extension services (e.g., Abdulai and Huffman, 2000; Wossen et al., 2017; Cawley et al., 2018; Pan et al., 2018; Ragasa and Mazunda, 2018). However, they reported the overall impact of access to extension services on farm productivity and did not disaggregate estimate impacts into an advisory effect and a technology channeling effect, thus masking important policy implications. Specifically, this does not explicitly show the magnitude of the contribution of extension services to farmers' production on the frontier of a given technology because both the adoption of new technologies and improved farmer efficiency tend to influence farm yields. Similarly, the delivery of advisory services and information on best practices to smallholders, whether they use modern or traditional technologies, is likely to increase farm productivity.

Because of the relatively scarce use of agricultural technology in SSA, input supply-led extension is instrumental in increasing productivity in the region. Given the heterogeneity of the production systems, including the use of agroecology and soil nutrients, and responses to policy reforms, the existing extension system needs significant improvement to make it effective and knowledge-driven (Davis et al., 2020). However, evidence on existing extension services is insufficiently disaggregated to guide policymakers concerning alternative extension systems. Empirical analyses of the impact of advisory services and technology channeling effects could provide evidence on extension services' contribution to improving farmer managerial skills, which may inform policy decisions to improve the extension system.

Improving the extension system is relevant to Ethiopia. Although wheat production in Ethiopia has increased by 10% since 2005, it still falls short of the national demand, and one-fourth of domestic consumption is covered by imports (FAO (Food and Agriculture Organization), 2014; Minot et al., 2015; NPC (National Planning Commission)., 2016; CSA (Central Statistics Agency)., 2018). The existing traditional extension service is a model-farmer-based agricultural extension system. The DAs provide extension messages based on agricultural research to the model farmers, expecting them to use this information themselves and to disseminate it to other, non-model, farmers.[1] The DAs specialize in one of the three disciplines of the mixed crop–livestock production system (crop production, animal science, and natural resource management) and operate at the lowest administrative units (*kebele*), providing advice to all 700–1000 farmers in a *kebele* in his/her area of expertise. In each *kebele*, the deployed DAs have no holistic knowledge of all three disciplines of the mixed crop–livestock production system or of advanced communication skills. The in-depth assessment of public extension services in Ethiopia by Davis et al. (2020) suggests generalist DAs should serve specific service areas (villages) within each *kebele*, accordingly a single DA can provide service to only 200–300 farmers in a specific village within the *kebele*. Contextually, this can be achieved through improving the capacity of DAs, without deploying additional expertise.

The rest of the paper is structured as follows. In section 2, we describe the intervention and experimental design of the study. Sections 3 and 4 discuss the empirical specification and the results, respectively. The final two sections present the conclusions and policy implications.

Table 1
Balance test of covariates and the use of inputs across treatment and control groups.

	Treatment group mean (1)	Control group mean (2)	Mean difference (3)	t-value (4)
Mvar	0.267	0.226	−0.041*	−1.75
gender	0.967	0.941	−0.026**	−2.29
age	43.26	42.82	−0.435	−0.630
schooling	1.62	1.62	−0.002	−0.01
experience	1.77	1.89	0.726	1.12
labor	41.10	39.59	−1.50	−1.52
farm size	1.77	1.89	0.118	1.65
fertilizer	161.19	161.77	0.585	0.170
chemical	0.168	0.170	0.002	0.080
chemdummy	0.249	0.259	0.010	0.420
machine	0.131	0.140	0.009	0.500
soil fertility	0.126	0.136	0.009	490
credit constraints	0.477	0.519	0.042	1.52
access to mobile	0.616	0.600	−0.017	−0.620
distmkt	63.18	56.42	−6.76***	−2.92
Z1_inst	0.891	0.841	−0.050***	−2.68
Z2_inst	3.49	3.26	−0.231***	−5.62

Notes: Columns (1) and (2) indicate the mean of the treatment and control groups, respectively, while column (3) indicates the differences in means between treatment and control groups. Column (4) reports the t-value for the test of differences in means. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

2. Intervention and experimental design

We used a multistage sampling approach to select the study area and farming households. First, we purposely selected four adjacent major wheat-growing districts in the Amhara region of Ethiopia. We randomly selected 96 villages from these districts, which were then randomly assigned into treated and control groups.[2] In each of the 96 villages, a

[1] In the current model-farmer-based extension system, identified model farmers tend to better-educated, wealthier, risk-taking, and have access to paved roads (Yitayew et al., 2021). However, most farmers are less likely to participate in the public extension program. This may be associated with their heterogeneous observed characteristics – such as socioeconomic status and unobserved characteristics like innate skills, openness to innovation, and aspiration for change. The estimation model will account for these issues.

[2] Based on this experimental setup, the farmers in the treatment group obtained the extension services directly from trained DAs, not through model farmers, while those in the control village obtained the services following the traditional extension system.

single DA was randomly assigned to provide the extension services.[3] We finally selected and interviewed members of farm households from both treatment and control villages.

Our field experiment involved assigning a single DA with basic but holistic knowledge of all three disciplines of the mixed crop–livestock production system to serve the farmers in only one village. We provided training on the new wheat varieties and the associated agronomic practices to both the DAs in the control and treatment villages. Training on process facilitation and advanced communication skills was offered only to the DAs in the treatment villages. We organized a team of agricultural experts to review profiles of the DAs at the federal and regional levels.[4] Their review indicated that DAs lack information communication skills and are unfamiliar with the most recent research findings. To address this gap, the training module mainly focused on technical aspects of the mixed crop–livestock production system and soft skills for effective facilitation and communication. Because site-specific information on the parameters of the new variety was hard to find, the training module was prepared based on general agronomic recommendations. The major crops grown in the study area such as wheat, maize, and teff (*Eragrostis tef*) were included in the training module.

We organized six days of training before the onset of the 2018 main growing season, divided into two tailored three-day courses. The first three-day training was on the technical aspects of crop production, livestock rearing, and natural resource management; the second three-day training focused on soft skills for process facilitation and effective communication. The training consisted of in-class lectures, group discussions, exercises, and presentations using training materials. A total of 48 DAs received the training and then provided extension services to farmers in the 48 treatment villages. We provided extension services following the traditional model-farmer-based agricultural extension systems to the control villages.

The crop variety used to measure the DAs' channeling role in boosting agricultural productivity is a specific rust-resistant wheat variety called *Kingbird* – a new variety introduced by the research project in the study area.[5] Farmers in both the treatment and control villages had access to *Kingbird* seed. The delivery of inputs including improved seed and inorganic fertilizer was unchanged; *Kingbird* seeds were made available for farmers to purchase from farmers' cooperatives.

Because village-level groups are the unit of randomization, farmers are likely to self-select into participation in the extension program delivered by trained DAs (Bolzern et al., 2018).[6] Although local institutions, namely farmer training centers, are established to promote farmers' learning from demonstration plots, these centers do not function effectively. Therefore, DAs need to visit farmers' fields to improve their managerial skills. However, given the poor rural transport infrastructure, it is not easy for DAs to reach farmers located in remote areas. Farmers' decisions to plant the new variety are also more likely to be endogenous and associated with unobserved characteristics such as their innate skills or conscious decisions for adoption.

Recent advances in production function models – such as the use of a SFM that accounts for mediator variables within the framework of impact evaluation – enable us to separate the effects of technology from managerial performance, and to address the issue of endogeneity, by accounting for unobserved characteristics associated with both farmers' self-selection into technology and the presence of extension programs (Chen et al., 2020).

Table 2
Output effect, technological frontier, and technical inefficiency.

	Output	Technological frontier	Technical inefficiency
Local average treatment effects	0.032*** (0.005)	−0.120*** (0.006)	−0.151*** (0.004)
Direct local average treatment effects	0.036*** (0.006)	−0.290*** (0.008)	−0.326*** (0.005)
Indirect local average treatment effects	−0.004 (0.005)	0.170*** (0.006)	0.175*** (0.003)

Notes: Local average treatment effects represent the average treatment effect conditional on the compliers who act in accordance with the treatment assignment. We present the overall, direct, and indirect effects of extension services in technological and inefficiency frontiers. The inefficiency measures the distance of each individual farmer from the frontier. The standard errors are bootstrapped from 1000 resamples. ***$p < 0.001$.

Table A1
Description of variables.

Variables	Description
Dvar	1 if farmer assigned in the treated village, 0 otherwise
Mvar	1 if farmer planted the new wheat variety, 0 otherwise
gender	1 for male, 0 otherwise
age	Age of farmer in years
schooling	Number of schooling years
experience	Wheat farming experience in years
labor	Labor used in worker-days/acre
farm size	Area of land allocated to wheat in acres
fertilizer	Inorganic fertilizer applied in kg/acre
chemical	Agrochemical used in kg/acre
chemdummy	1 if farmer did not use agrochemicals, 0 otherwise
machine	1 if farmer used thresher machine, 0 otherwise
soil fertility	1 if the soil is infertile, 0 otherwise
credit constraints	1 if farmer is credit constrained, 0 otherwise
access to mobile	1 if farmer owned mobile phone, 0 otherwise
distmkt	Time taken to the nearest market in minutes
Z1_inst	1 if access to paved road, 0 otherwise
Z2_inst	Time taken to rural cooperative in minutes

2.1. Data and descriptive statistics

We collected data using structured and pre-tested questionnaires from 1338 wheat-growing households in January–February 2019. The data include information on wheat production (e.g., input use and production), adoption of new wheat variety, farm and household characteristics (e.g., gender and age of household head, farming experience, mobile ownership, farm size, and soil fertility), as well as institution-related factors (e.g., credit constraints and distance to markets). The inputs include fertilizer, agrochemicals, labor, and machinery.

In the study area, farmers grow wheat in the main production season during April–December. The cultivated wheat varieties are *Kakaba*, *Kingbird*, and *Ogoloch*. The variety *Kakaba* is the most dominant and a

[3] The field experiment, specifically replacing the specialist DAs that serve all households in a *kebele* by the generalist ones to serve a specific village within the *kebele* or deploying DAs in a village within the *kebele*, was implemented in collaboration with the Office of Agriculture. To this end, we organized a two-day workshop on the current agricultural extension system and how to improve it before the onset of the experiment in November 2016. The Federal Ministry of Agriculture, Amhara Region Bureau of Agriculture and Offices of Agriculture from the study districts, Bahir Dar University (Bahir Dar, Ethiopia), BOKU University (Vienna, Austria), International Center for Agricultural Research for the Dry Areas (ICARDA), Ethiopian Institute of Agricultural Research (EIAR), and Amhara Region Agricultural Research Institute (ARARI) attended the workshop.

[4] Their profiles are presented in Table OA1 in the online supplementary appendix. Another important point is that DAs are deployed by the local government in the study area.

[5] Because the variety is newly introduced to the study area, farmers have no access to site-specific information about the inherent features of the new variety.

[6] This problem is less likely to occur if the treatment is randomized to individuals, but this is neither ethically nor politically feasible (Duflo et al., 2008). The cluster Randomized Controlled Trial (RCT) we used will reduce spillover effects and are easy to implement but are more vulnerable to selection bias (Duflo et al., 2008; Bolzern et al., 2018).

relatively traditional variety, while the others are newly introduced. Table A1 in the appendix presents the definition of variables used in the empirical analysis. The treatment variable is a dummy variable that takes the value 1 if the household belongs to the treated villages and 0 otherwise. Adoption of the new variety, which we defined as a mediator variable below, is a dummy variable that takes the value 1 if a household grows the new wheat variety and 0 otherwise. The outcome variable of interest is wheat production. For brevity, we report the summary statistics of the explanatory variables in Table OA1 in the online supplementary appendix.

We also conduct a balancing test of the pre-treatment variables across treatment and control groups. Table 1 presents the balance test of covariates and differences in new technology and inputs use among farmers in the treatment and control groups. Although the values of most of the pre-treatment variables are balanced, some are unbalanced across treatment and control groups. We thus include covariates in the model estimation to improve precision of the estimates. There are also significant differences in the use of the improved wheat variety between treatment and control groups but no significant differences between treatment and control groups in the use of inputs such as inorganic fertilizer, agrochemicals, labor, and machinery. The results in Table A2 in the appendix, however, show that input use varies among adopters and non-adopters of the new variety.

3. Empirical specification

3.1. Mediated SFM

The causal framework of the empirical model used in this study (Fig. 1) shows that extension services may affect both the technological production frontier and the inefficiency frontier. This figure also shows that extension services may have direct and indirect impacts on both frontiers. Specifically, the indirect effect is the effect of extension services that work through the mediator that can explain the change in the production frontier and/or the inefficiency frontier.[7]

Source: Adapted from Chen et al. (2020).

In line with the theoretical framework, to identify the effect of advisory services (direct effect) and technology channeling (indirect effect), we employ a mediated SFM that combines the conventional SFM and mediation analysis model with a special framework of impact evaluation that accounts for potential mechanisms.[8] Following Chen et al. (2020), the mediated SFM, given the observed outcome Y with the causal mechanism M on the subpopulation of compliers,[9] is specified as follows:

$$Y(d, M(d')) = \widetilde{h}(d, M(d'), X) + \upsilon(d, M(d')) - u(d, M(d'), X)$$

$$u(d, M(d'), X) = \widetilde{g}(d, M(d'), X) + \widetilde{u}(d, M(d')) \tag{1}$$

where $\widetilde{h}(\cdot)$ is a potential frontier function, $\upsilon(\cdot)$ is a pure potential random error with mean zero and constant variance, $u()$ is the overall inefficiency component of the model, $\widetilde{g}(\cdot)$ is a non-negative potential inefficiency, and $\widetilde{u}()$ is the error term in the inefficiency component, with mean zero and constant variance. The structural form of the model in (1) comprises many latent variables such as $Y(0, M(0))$, $Y(0, M(1))$, $Y(1, M(0))$, and $Y(1, M(1))$, and a pair of models for $M(0)$ and $M(1)$. Eq. (1) can be re-written based on the conditional mean of $\widetilde{h}()$ and $\widetilde{g}()$ as follows:

$$E[Y(d, M(d'))|X, C] = h_{d'}\left(X, \alpha_m, \beta^h_{d1}, \beta^h_{d0}\right) - g_{d'}\left(X, \alpha_m, \beta^g_{d1}, \beta^g_{d0}\right) \tag{2}$$

where β_d is a parameter vector of the potential-output model and α_m is a parameter vector of the potential-mediator model (for details, see Chen et al., 2020). For methodological convenience, we respecify the structural form of the mediated SFM in (1) as follows:

$$Y = \widetilde{h}(D, M, X) - \widetilde{g}(D, M, X) + U_Y \tag{3a}$$

where Y represents wheat production; X is a vector of inputs;[10] D is the treatment status, which equals 1 if a household is from the treatment villages and 0 otherwise; M is the intermediate variable (causal mechanism or mediator) concerning adoption of the new wheat variety, which is equal to 1 if a farmer adopts the new variety and 0 otherwise; and U_Y is the error term, which is not independent and identically distributed due to unobserved characteristics related to farmers' participation in the extension program and adoption of the new variety, potentially resulting in an endogeneity problem.

The issue of endogeneity associated with omitted variables and unobserved factors requires attention in the stochastic frontier analysis. Endogeneity in SFM potentially stems from (i) input endogeneity because the use of inputs (e.g., farmland size, chemical fertilizers, and agrochemicals) is most likely correlated with the use of improved seed, (ii) farmers' characteristics such as innate skills, conscious adoption decisions, and self-selection to participate in a program, and (iii) endogenous program placement. To address these potential endogeneity problems, we use a strategy that relies on the status of farm roads and the distance of the household to rural cooperatives. We assume that navigable farm roads incentivize DAs to visit farm fields. For example, a

Table A2
Comparison of inputs use between farmers that are adopters and non-adopters of the new wheat variety.

	Adopter (1)	Non-adopter (2)	Mean difference (3)	t-value (4)
labor	37.90	41.19	3.29***	2.88
farm size	2.78	1.52	−1.26***	−16.61
fertilizer	173.64	157.47	−16.17***	−4.06
chemical	0.184	0.165	−0.019	−0.69
chemdummy	0.121	0.297	0.176***	6.48
machine	0.329	0.071	−0.258***	−12.57
soil fertility	0.100	0.141	0.041*	1.94

Notes: Columns (1) and (2) indicate the mean of adopters and non-adopters, while column (3) indicates the difference in mean between adopters and non-adopters. Column (4) reports the t-value for the test of the difference in means. *$p < 0.05$, ***$p < 0.001$.

[7] For brevity, the exposition of the concept of the technical efficiency is presented in Fig. OA1 in the online supplementary appendix, and we describe the link between the causal framework and technical efficiency in the Fig. OA1 footnote.

[8] For brevity, we present the conventional SFM and impact evaluation frameworks in the online supplementary appendix.

[9] Compliers are those farmers who act in accordance with the treatment assignment. In given a binary treatment, we can find four outcomes by dividing the whole population into four mutually disjoint subpopulations: always takers, compliers, defiers, and never takers (for detail, see Imbens and Angrist, 1994).

[10] The input factors (X), such as the area allocated to wheat (in acres) and quantity of chemical fertilizers and agrochemicals (in kilograms), are more likely to be correlated with the given technology (i.e., the variety which farmers grow denoted as M). The estimates in Table A2 in the appendix imply this. Due to unobserved characteristics of farmers (such as farm management skills and ability, individual motivation, aspiration for change, and openness for innovation), the choice of the new variety potentially suffers from selection bias, thus adoption of the new variety (M) is possibly correlated with the two-sided error (υ), leading to inconsistent parameter estimates. This study accounts for M in the SFM by considering it as a mediator variable to capture the effect of DAs in channeling technologies to farmers. In this study, besides the endogenous treatment variable (D), the causal mechanism SFM used enables us to deal with the issue of endogenous mediator variable due to choice endogeneity. The model simultaneously helps to resolve the problem related to input endogeneity.

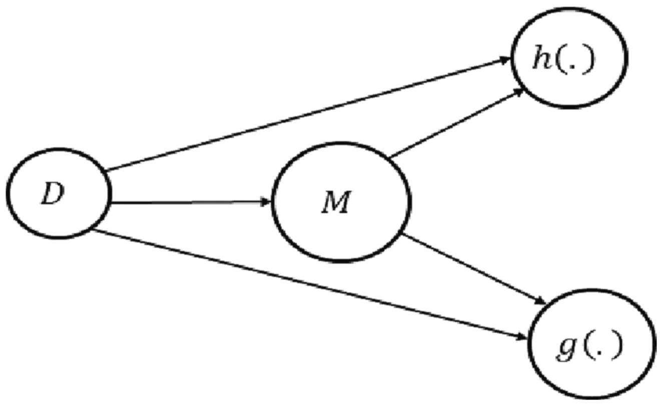

Fig. 1. Causal framework of the SFM with mediator variable. *Notes:* D and M respectively represent the treatment and mediator variables, while $h()$ and $g()$ represent the technological frontier and the inefficiency frontier, respectively. The diagram shows the direct and indirect effects of extension services on both $h(.)$ and g(). The direct link of D and $h()$ in the diagram [$Dh()$] indicates the direct impact of extension services (i.e., advisory services) on $h()$, while $DMh()$ is the indirect effect of the extension services (i.e., technology channeling) on $h(.)$. Analogously, $Dg()$ shows the effect of DAs due to their advisory services on $g()$, and that of $DMg()$ similarly indicates their effect on $g()$ associated with the role of technology channeling to farmers.

study by Abate et al. (2020) revealed that DAs in remote areas put in fewer hours than those in more connected areas. We also assume that the only way that our outcome variable is affected by the status of farm roads is through the treatment status. Non-trained DAs provide first-hand information to model farmers who are expected to use the information themselves and to disseminate it to fellow farmers, while trained DAs directly transfer information to both model and fellow (non-model) farmers in specific villages that are assigned to the treatment group.

Distance to a seed market is the other variable our strategy relies on to deal with potential endogeneity, assuming that the distance of the household to rural cooperatives, the only channel for certified wheat seeds, only affects wheat production through the adoption of the new variety. This is because distance to market, which is associated with cost of acquisition, tends to affect the net benefit of adopting new technologies (Suri, 2011; Abdul-Mumin and Abdulai, 2022).

3.2. Method for addressing identification problem

To account for endogeneity of extension services and technology choice, the structural form of the stochastic frontier framework in Eq. (3a) requires a new method of parameter identification. In this subsection, as suggested by Frolich and Huber (2017), we outline how the parameters are identified from the structural form of the frontier model, and this can be specified as follows:

Causal mechanism:

$$M = 1(\alpha_d D + \alpha_{Z2} Z_2 + X^{\intercal}\alpha_x + U_M \geq 0) \tag{3b}$$

Treatment status:

$$D = 1(\gamma_{Z1} Z_1 + X^{\intercal}\gamma_x + U_D \geq 0) \tag{3c}$$

where the notations are the same as in Eq. (3a). The Z_1 and Z_2 are instrumental variables – the former for delivery of extension services by trained DAs D, and the latter signifying the causal mechanism (the adoption of new variety M). The structural form of the model specification in Eq. (3a) includes endogenous treatment status and the mediator variable, and hence the error term U_M in Eq. (3b) correlates with U_D in Eq. (3c), potentially causing identification problems. Using a bivariate binary response model for $(M,D)|Z_1,Z_2,X$, the bivariate cumulative distribution function (CDF) of (U_M,U_D) [11] provides the necessary conditions for identification. As well as the correlation between the error terms in the structural form of the model in Eqs. (3b) and (3c), we consider the standard instrumental variable approach for the propensity score model to more simply implement the statistical inference (see Chen et al., 2020).[12]

3.3. SFM specification, estimation, and functional form

We use a half-normal specification of the SFM, as characterized by Aigner et al. (1977). The specification for $d,j \in \{0,1\}$ follows:

$$Y = h\left(X,\beta^h_{dj}\right) + \upsilon - u$$

$$u \sim N^{+}(0,\sigma_u^2) \tag{4}$$

where the notations are the same as in Eqs. (1)–(3) and υ is a two-sided zero-mean normal random variable. In estimating β_{dj}, a half-normal specification leads to quadratic minimization of the SFM, assuming that the necessary conditions for identification are satisfied. As noted by Chen et al. (2020), we can then identify β_d shown in Eq. (2) as the minimizer of the weighted mean square error (MSE) of actual outputs in a weighted nonlinear least squares estimator.[13] Specifically, given the assumption that the impact of extension services on farm production can be explained by the adoption of new technologies, the nonlinear least squares estimator is weighted by the households' participation and adoption decisions, as well as by the potential-mediator parameter (α_w).

We employ a Cobb–Douglas functional form for estimating the SFM,[14] specified in Eq. (4):

$$lnY = \beta lnX + \gamma Z + \varepsilon \tag{5}$$

where Y is the natural log of wheat production; X is a vector of production inputs in natural logs; Z is a vector of covariates such as socioeconomic characteristics, institutions, and soil characteristics; β and γ are vectors of parameters to be estimated; and ε is the composite error term, i.e., $\varepsilon = \upsilon - u$, and therefore is used to separate the inefficiency component as the conditional mean function of $E[u|\varepsilon]$. The production inputs are farmland allocated to wheat (in acres), quantity of chemical fertilizer (in kilograms), quantity of agrochemicals (i.e., herbicides and pesticides) (in kilograms), and labor employed in wheat farming activ-

[11] We define the CDF of (U_M,U_D) as $F_{U_{M,D}}(\rho_{md})$, where ρ_{md} is the correlation coefficient of U_M and U_D. In addition to joint estimation, ρ_{md} is used for identification purposes to ascertain whether M and D are endogenous, because treatment and mediation variables are correlated with the "noise" in the structural model in equations (3a)–(3c).

[12] For brevity, we present the bivariate response and parametric instrument propensity score models in the online supplementary appendix.

[13] Non-linear least squares is used to minimize the MSEs subject to some constraints – such as actual output Y is less than or equal to the stochastic frontier $\left[h\left(X,\beta^h\right) + \upsilon\right]$ or $u \geq 0$.

[14] To estimate the nonlinear stochastic model using generalized method of moments, as shown in equation (6), we employ the Cobb–Douglas functional form, as it is simple to use and less likely to face multicollinearity than that of translog functional forms (Mayen et al., 2010).

Table A3
Technological and inefficiency frontiers: weighted nonlinear least squares.

	Treated and adopter (1)	Treated and non-adopter (2)	Non-treated and adopter (3)	Non-treated and non-adopter (4)
Frontier function h(.)				
gender	0.107***	0.094***	0.024*	−0.169**
	(0.041)	(0.026)	(0.013)	(0.080)
age	−0.001	−0.0001	0.019**	−0.005
	(0.005)	(0.006)	(0.010)	(0.005)
schooling	0.002	−0.037	0.006	0.004
	(0.028)	(0.040)	(0.041)	(0.024)
lnlabor	0.331***	0.324***	0.152***	0.277***
	(0.081)	(0.046)	(0.025)	(0.075)
lnfarm size	0.137**	0.072**	0.067***	0.156*
	(0.060)	(0.034)	(0.012)	(0.090)
lnfertilizer	0.307***	0.288***	0.299***	0.405***
	(0.075)	(0.046)	(0.035)	(0.072)
lnchemical	0.077**	0.022	0.040***	0.039
	(0.034)	(0.023)	(0.005)	(0.055)
chemdummy	−0.045	0.104	−0.031***	−0.084
	(0.070)	(0.065)	(0.009)	(0.092)
machine	−0.001	0.062***	0.123***	0.075
	(0.059)	(0.010)	(0.017)	(0.084)
soil fertility	0.073	−0.106	−0.053***	−0.266**
	(0.072)	(0.067)	(0.012)	(0.106)
credit constraints	−0.046	−0.026	0.022	−0.049
	(0.068)	(0.089)	(0.019)	(0.096)
access to mobile	−0.069	0.028	0.036***	0.097
	(0.073)	(0.085)	(0.013)	(0.103)
lndistmkt	−0.047	0.038	0.065*	0.021
	(0.051)	(0.071)	(0.039)	(0.071)
constant	−0.446***	−0.480***	−0.488***	−0.438
	(0.020)	(0.012)	(0.006)	(0.022)
Inefficiency function g(.)				
lnexperience	−0.036	−0.050	0.007	0.014
	(0.030)	(0.055)	(0.028)	(0.041)
constant	0.678***	0.822***	0.794***	0.645***
	(0.050)	(0.057)	(0.011)	(0.078)
observation	696	696	642	642

Notes: Columns (1)–(4) report the mediated SFM of treated and adopter, treated and non-adopter, non-treated and adopter, and non-treated and non-adopter groups, respectively. Columns (1) and (2) are estimates for the treatment group with 696 observations, while estimates in columns (3) and (4) are for the control group with 642 observations. We also report the estimates of technological frontier and inefficiency frontiers. We use a one-step GMM for estimating the mediated SFM. Figures in brackets are bootstrapped standard errors from 1000 resamples. *p < 0.05, **p < 0.01, ***p < 0.001.

ities (in worker-days). To consider those farmers who do not use agrochemicals, we include a dummy variable for agrochemicals in the model. Hence, the natural logarithm of agrochemical use is taken only if it is positive, and is 0 otherwise.[15] As suggested by Battese (1997), this ensures unbiased and efficient parameter estimates.

A one-step generalized method of moments (GMM) estimator provides consistent estimates of the parameter of a nonlinear model with endogenous explanatory variables (Wooldridge, 2001), assuming that the error terms are identically and independently distributed. We estimate both the technical efficiency and farmer-specific inefficiency. The output-oriented measure of technical efficiency is the ratio of the observed output to the frontier output feasible for a given technology, approximately exp $(-u)$. Technical inefficiency (yield gaps) can be estimated as the log difference of the potential outcome and the actual output (i.e., $u = lnY^* - lnY$). Therefore, $u \times 100\%$ is the percentage by which actual output can be increased with the same inputs if a farmer is fully efficient or the percentage loss due to technical inefficiency (Kumbhakar and Wang, 2015).

3.4. Direct and indirect treatment effects

We focus on the subpopulation of compliers to estimate the conditional local average treatment effect (CLATE) (Angrist et al., 1996). Taking into account the mediator variable in the impact evaluation framework following Chen et al. (2020), CLATE is specified as follows:

$$CLATE(\chi) = E[Y(1, M(1))|X = \chi, C] - E[Y(0, M(0))|X = \chi, C] \quad (6)$$

The local average treatment effect (LATE) is then specified:

$$LATE = E[CLATE(X)|C] = E[Y(1, M(1))|C] - E[Y(0, M(0))|C] \quad (7a)$$

As in Chen et al. (2020), to identify the direct and indirect impacts of extension services on farm performance, we decompose LATE into direct effect (direct LATE, hereafter DLATE) and indirect (mediation) effect (indirect LATE, hereafter ILATE). The impacts are specified:

$$DLATE = E[CDLATE(X)|C] = E[Y(1, M(1))|C] - E[Y(0, M(1))|C] \quad (7b)$$

$$ILATE = E[CILATE(X)|C] = E[Y(0, M(1))|C] - E[Y(0, M(0))|C] \quad (7c)$$

where *CDLATE* and *CILATE* are the conditional direct and indirect local average treatment effects, respectively.[16] As we use the stochastic

[15] Cobb–Douglas functional form requires logarithmic transformation. In the case of the agrochemical variable, to retain the value of zero, we add a constant value of 1 on the variable prior to its transformation and the transformed value is generated as $[ln(X + 1)]$, where X is the quantity of agrochemical in kilograms.

[16] We estimate the conditional direct average treatment effect as $CDLATE(\chi) = E[Y(1, M(1))|X = \chi, C] - E[Y(0, M(1))|X = \chi, C]$, and also the conditional indirect average treatment effects as $CILATE(\chi) = E[Y(0, M(1))|X = \chi, C] - E[Y(0, M(0))|X = \chi, C]$.

frontier treatment effect model, the treatment effects such as LATE, DLATE, and ILATE further decompose into technological frontier $h(.)$ and technical inefficiency $g(.)$ levels. These are (i) the output effects at the technological frontier level – $LATE_h$, $DLATE_h$, and $ILATE_h$ – and (ii) the output effects at the technical inefficiency level – $LATE_g$,$DLATE_g$, and $ILATE_g$ (for detail, see Chen et al., 2020).

4. Empirical results and discussion

Before estimating the model in Eq. (2), we estimated a bivariate probit model to ascertain model identification assumptions indicated in Eqs. (3b) and (3c). The results show that both the correlation coefficient (ρ_{md}) and the parameter estimates of the instruments (Z1_inst and Z2_inst) are statistically significant (Table OA2 in the online supplementary appendix). These findings support the assumptions of endogenous treatment status and mediator variable (Eqs. (3b) and (3c)). We also estimate the parameter instrument propensity score model for $Z_1|X$ (Table OA3 in the online supplementary appendix). Like the estimates of the bivariate probit model, the results show that the instrumental variable Z_1 is significant, supporting our assumptions. To the extent that the necessary conditions for parameter identification are fulfilled, we approximate the two normal distributions for Z_2 to estimate the parameter of the potential-mediator model for estimating the model shown in Eq. (2). The results show that the mean and standard deviations of the two normal distributions are significant (Table OA4 in the online supplementary appendix).

We then perform a one-step GMM estimation of the SFM. The estimates are reported in the appendix Table A3. The estimates in Table OA5 in the supplementary online appendix show that all factors of production are positive in the production functions of all models, which satisfies the monotonicity condition of stochastic frontier analysis.

Although the result is consistent with those of Abate et al. (2018), Abdul-Rahaman and Abdulai (2018), and Geffersa et al. (2022), the contributions of the factors of production are quite different. One possible explanation is that the previously cited studies do not account for more than one possible productivity-boosting mechanism in the model estimations. In addition, their strategy to address the potential endogeneity problem, an inherent issue in stochastic frontier analysis, might result in this discrepancy. Previous studies attempted to address the potential endogeneity problem by accounting for unobserved factors associated with farmers' characteristics such as innate skills or conscious decisions for adoption, but not the *unobserved* factors associated with participation in the extension program.

Based on the causal mechanism SFM estimation (Table A3 in the appendix), we estimate the LATE, using the specifications outlined in Eqs. (7a)–(7c). Estimating LATE also allows us to separate the effects of advisory services and technology channeling into production technology and technical inefficiency frontiers.

4.1. Direct and indirect effects of extension services

Table 2 in columns (1)–(3) present estimates of the total, direct and indirect effects of extension services on wheat production, technological frontier, and inefficiency frontier, respectively. We estimate the impact of extension services on wheat production in column (1). The results show that the overall impact of extension services on wheat production is positive and significant. The magnitude of the overall effect of extension services is about 3.2%. We also disaggregate the total effect into direct effect (advisory services) and indirect effect (channeling). The advisory services appear to exert a positive impact representing about 3.6% of the effect, but channeling has a non-significant negative effect (−0.004).

We present the impact of improved extension services on technological and inefficiency frontiers in Table 2. The estimates reveal that improved extension services affect both technological and inefficiency frontiers, but with opposite directions. In particular, extension services improve efficiency of farmers by 15%, but reduce the technological frontier by 12%. We also estimate the disentangled effects of extension services on technological and inefficiency frontiers. The results of the technological frontier reveal that the effect of advisory services in reducing the technological frontier amounts to 29%, but channeling contributes to the technological frontier moving upward to 17% (Table 2). The results of the inefficiency frontier show that advisory services improve efficiency of farmers by 32.6%, but channeling increases their inefficiency by 17.5%.

Our results reveal that channeling contributes to shifting the technological frontier upwards. Consistent with this, Bachewe et al. (2018) revealed that agricultural productivity in Ethiopia is partly due to the efforts of DAs in promoting the use of improved seeds and inorganic fertilizer. Our findings also show that advisory services push output toward the frontier by effecting a change in farmers' technical efficiency. This is because provision of advisory services regarding more effective management options and better farming practices contributes to improving the technical efficiency of farmers.

The estimates of the LATE for technological and inefficiency frontiers reveal that both advisory services and channeling contribute to increased productivity. Specifically, advisory services contribute to pushing output toward the frontier by improving efficiency of farmers, while channeling contributes to moving the technological frontier outward through facilitating technology adoption by farmers. The disaggregated estimates also show that both advisory services and

Table A4
Estimates of input complementarity: multivariate Tobit analysis.

	Chemical fertilizer	Agrochemicals
Mvar	0.044***	0.009
	(0.023)	(0.015)
gender	−0.076*	0.015
	(0.042)	(0.029)
age	−0.003***	−0.000
	(0.001)	(0.001)
lnexperience	0.076***	0.019
	(0.016)	0.012
lnlabor	0.270***	−0.004
	(0.030)	(0.032)
lnfarm size	0.059**	−0.039
	(0.028)	(0.024)
machine	0.161***	0.028
	(0.031)	(0.020)
soil fertility	−0.009	0.033*
	(0.026)	0.017
credit constraints	0.001	0.001
	0.018	0.012
access to mobile	0.004	0.010
	0.018	0.013
lndistmkt	−0.007	−0.008
	0.011	0.007
IMR	–	−0.173***
	–	(0.043)
constant	3.98***	0.173*
	(0.136)	(0.102)
atanhrho	0.150***	
	(0.029)	
Wald chi2	269.26	
Prob > chi2	0.000	
observation	1,338	

Notes: Columns (1) and (2) present the estimates of chemical fertilizer and agrochemicals, respectively. Specifically, we regress the probability of input complementarity for the use of chemical fertilizer and agrochemicals conditional on the adoption of the new variety. The variable "*atanhrho*" represents the correlation between the error terms of these complementary inputs, which is statistically significant. We also control for inverse Mills ratio (IMR), but only in column (2) not column (1). The selection equation of the use of agrochemicals is presented in Table OA6 in the online supplementary appendix. The figures in the bracket are the standard errors. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

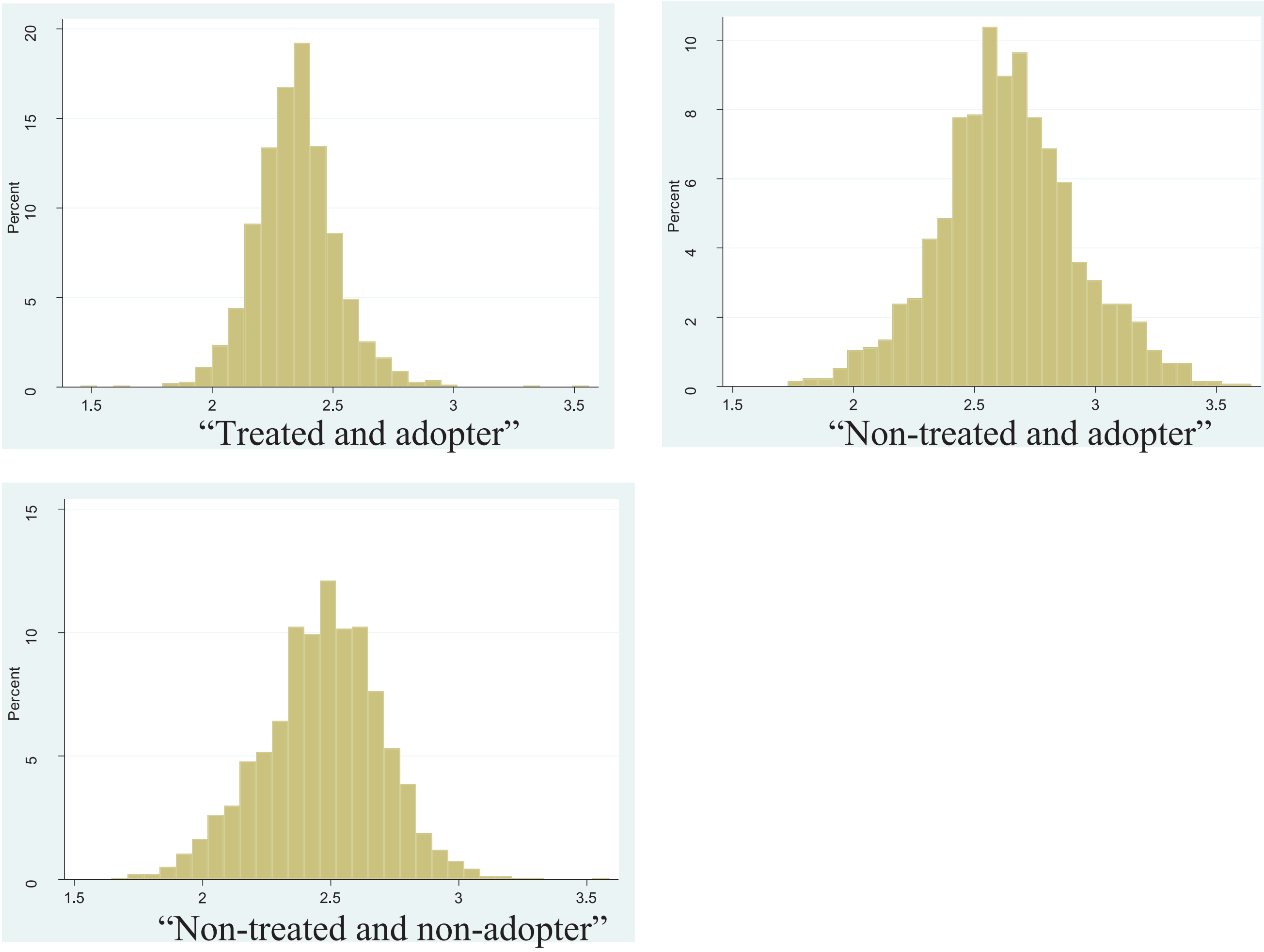

Fig. 2. Distribution of wheat production estimates at the production technology frontier. *Notes*: The figure shows the comparison of wheat production distribution at the technological frontier with adoption of a new variety under improved extension services, adoption of a new variety under traditional extension services, and non-adoption under traditional extension services.

channeling exert a reducing effect on the frontiers. Specifically, the effect of advisory services and channeling appears negative on technological and inefficiency frontiers, respectively.[17]

The estimates of the LATE are also consistent with that of the SFM in Table A3 in the appendix. The results show that deploying trained DAs, with knowledge about agronomic and soil management practices, and teaching them appropriate communication skills, can be effective in increasing the productivity of smallholder farmers. Improved extension services enhance labor productivity and efficiency of farmers' use of fertilizer, as well improve soil management practices. Channeling accompanied by facilitating machinery services also tends to enhance productivity. Moreover, the use of farm machinery for harvest and threshing wheat has a significant positive effect on wheat production. Its effect is higher when the magnitude of the estimate of labor is relatively low.

The estimates of the mediated SFM (Table A3 in the appendix) also show that the effect of chemical fertilizer usage on production is heterogeneous across adopters and non-adopters of the new variety. This evidence is consistent with the estimates of input complementarity (Table A4 in the appendix). We find that chemical fertilizer and agrochemicals are complementary inputs and are correlated with farmers' decisions to adopt the new variety. The recent study on Ethiopia by Abay et al. (2018) indicates that availability of complementary input packages contributes to enhance farm productivity.

4.2. *Wheat production variability and gaps*

Heterogeneity in technical efficiency among farmers and technology choices can drive production variability and production gaps. In this study, we examine whether heterogeneity in technical efficiency among farmers or technology choice drives a large proportion of it. We present the approximately normal distribution of the conditional wheat production estimates at the technological frontier in Fig. 2. The results show that the wheat production variability among the farmers is less likely associated with heterogeneity in their technology choices. The distribution of the conditional wheat production estimates at the inefficiency frontier is skewed either to the right or to the left (Fig. 3), showing that a large proportion of the wheat production variability is driven by

[17] The possible explanation for the reducing effect of advisory services and channeling would be a general recommendation of agronomic practices. Lack of site-specific information on new variety possibly causes ineffective information flow from DAs to farmers and contributes to low productivity (Ayalew et al., 2022; Yitayew et al., 2022). The efficiency of farmers in managing a new variety thus optimally improves in the subsequent growing seasons after they obtain site-specific information on the parameters of the new variety. The recent study on Ethiopia by Yitayew et al. (2022) indicates that farmers need updating on their prior beliefs about the parameters of a new variety. The possible reason is that because of the random effects of the quality of land on variety yield, the optimum input level of the new variety that potentially provides maximum yield is random and ex-ante unknown, irrespective of the features of the new variety.

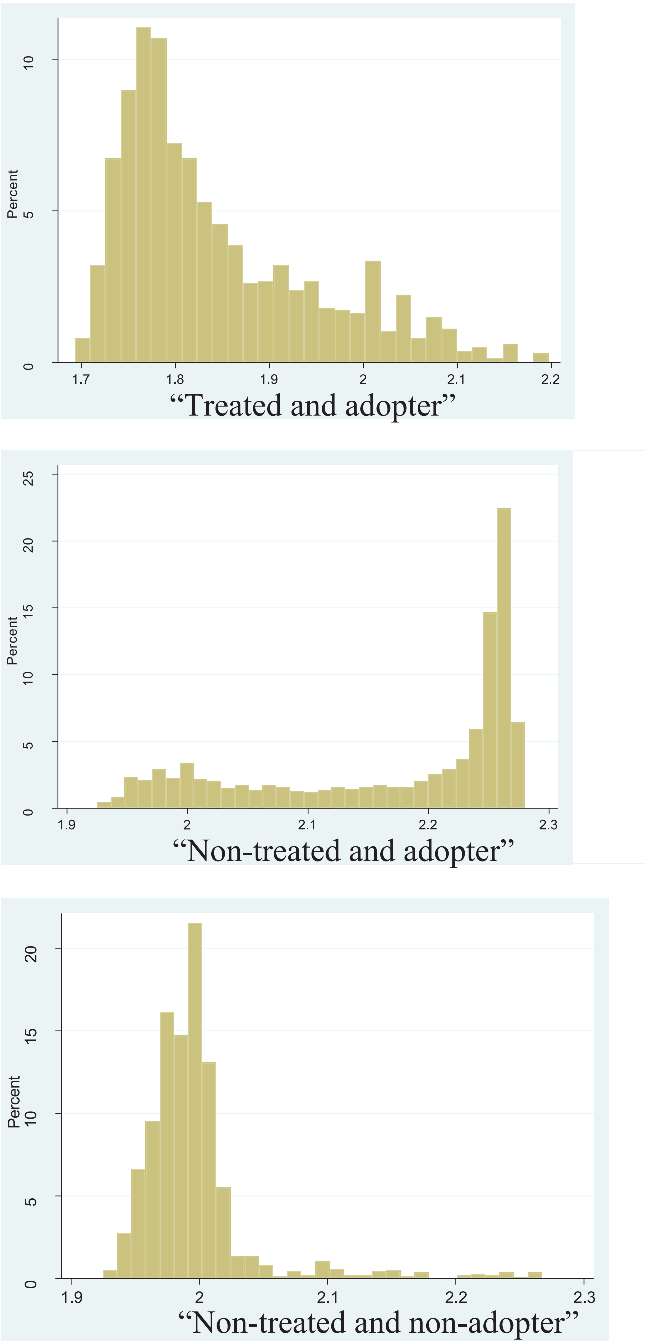

Fig. 3. Distribution of wheat production estimates at the technical inefficiency frontier. *Notes:* The figure shows the comparison of wheat production distribution at the inefficiency frontier with adoption of a new variety under improved extension services, adoption of a new variety under traditional extension services, and non-adoption under traditional extension services.

heterogeneity in technical efficiency among farmers.

Given that the wheat production variability among farmers is predominantly due to heterogeneity in technical efficiency and to a lesser extent to technology choices, we observe wheat production gaps at the technological and inefficiency frontiers. The production gap, or the difference between estimated and actual wheat production (Van Dijk et al., 2017), is based on the conventional form of frontier model (Kumbhakar and Lovell, 2000). Instead, we estimate the conditional average wheat production distance of farmers according to the SFM, considering the treatment status (improved extension services) and mediator variable (farmers' decision to adopt the new variety).

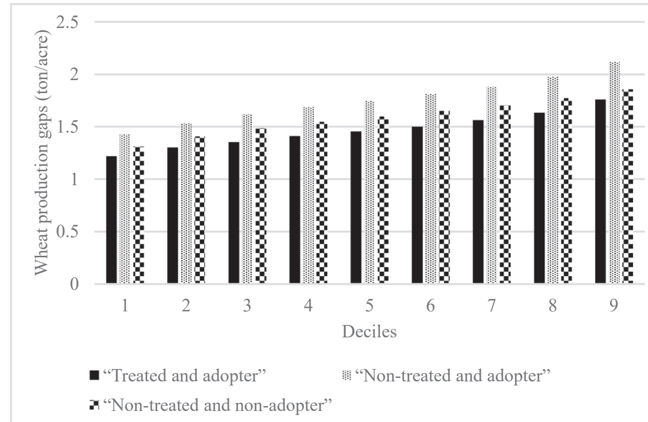

Fig. 4. Average wheat production distance of farmers at the technological frontier. *Notes*: The figure depicts the wheat production gaps in deciles that compare the best-practice performance of farmers with those not producing at the production technology frontier at different levels.

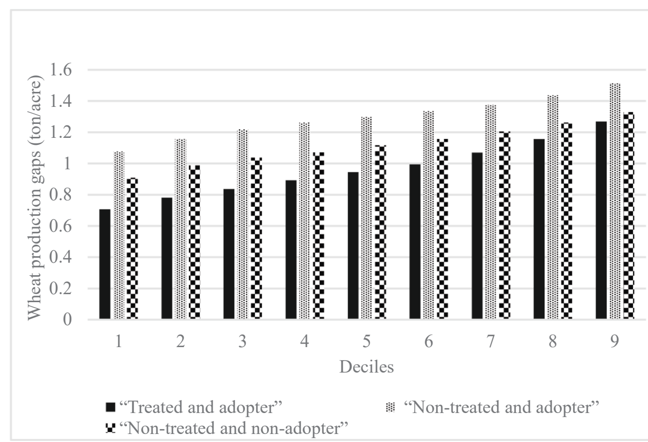

Fig. 5. Average wheat production distance of farmers at the technical inefficiency frontier. *Notes*: The figure depicts the wheat production gaps in deciles that compare technically efficient farmers with inefficient farmers at different levels.

Figs. 4 and 5 present the estimates of the conditional average wheat production gaps at the technological and inefficiency frontiers in deciles, respectively. The estimated wheat production gaps are not zero in any of the scenarios and their patterns in technological and inefficiency frontiers are similar. The average wheat production distance of farmers appears relatively low if they adopt the new variety and obtain extension services from skilled DAs. However, without improved extension services, such as effective information flow from researchers to DAs and then from DAs to farmers, adoption of the new variety at the early stage of the technology diffusion process causes relatively higher yield gaps among farmers. Our results reveal that wheat production can be boosted by narrowing the wheat production gaps among farmers through improving technology uptake and techniques with effective extension services. This implies that if policymakers realize that the effect of extension services in increasing farm productivity is partly dependent on the capacity of DAs, provision of extension services by skilled DAs can contribute to higher productivity.

5. Conclusion

In this study, we hypothesized that extension services not only allow for a change in the technical efficiency of farmers to push output toward the frontier, but also shift the technological frontier upwards through channeling of new technologies to farmers. Using recent experimental data of 1388 smallholder wheat producers in Ethiopia, we examined the impacts of advisory services and channeling on farm production and technical efficiency of smallholder farmers. We employed a mediated SFM, allowing us to capture endogenous treatment status and the mediator variable.

The LATE reveal that the overall impact of improved extension services on wheat production is positive and significant, and advisory services constitute a significant proportion of the effect. Advisory services contribute to pushing output toward the frontier by improving the technical efficiency of farmers, but not shifting the technological frontier upwards. The role of DAs in channeling technology to farmers contributes to moving the technological frontier outwards, but not to pushing output toward the frontier. In summary, there is a trade-off between the impact of advisory services and channeling effects on the technological frontier, as well as on the inefficiency frontier.

Our results also reveal that heterogeneity in technical efficiency causes a larger proportion of variability in wheat production among farmers than that of technology heterogeneity. Delivering effective extension services can boost wheat production, because production gaps are relatively low if farmers adopt the new variety and obtain extension services from skilled DAs, but relatively high if they do not receive extension services from skilled DAs.

Given that the treatment is applied to DAs at the village level, we are assuming the concordance of farmers' and DAs' observations on how farmers interact with extension agents and their changes after the introduction of the new extension approach. However, including specific data on extension involvement with farmers and the changes in their reception of the extension messages from DAs themselves might generate additional insights. Moreover, although the study findings provide useful evidence on the significance of scaling up a new extension approach to increase productivity, it would be helpful to generate more evidence, using similar interventions with different agroecologies, production systems, and socioeconomic conditions. This would be useful in winning the confidence of policymakers, and so influencing policy. Future studies may also consider treatment assignment at the individual level and randomization over both DAs and their clients, as this would ensure robust estimates.

6. Policy implications

The improved extension service delivery system that is tested in this project is effective in helping farmers produce at or close to the production frontier, thereby realizing higher yields. Moreover, by enhancing the quality, quantity, and consistency of information that mixed crop–livestock farmers receive, the improved extension service delivery systems also help in pushing the technological frontier upwards – thereby attaining higher yield levels. The role of extension services in increasing farm productivity partly relies on the capacity of DAs, specifically ability to effectively communicate new research findings and agronomic practices to farmers.

The findings suggest that policymakers need to consider improving the access of farmers to extension services and agricultural information. Investing in an extension service delivery system that improves communication skills and motivation of the extension agents and their contact with farmers, would enhance the impact of extension services on the spread of new research findings and agronomic practices. Efficiency in the system could be improved by reducing the time taken to reach farmers and by creating the opportunity for extension agents to establish trust with farmers. Although the current budgetary allocation to the extension system in SSA countries is quite substantial, the on-the-job DA training necessary for implementing the new extension approach can be accommodated within current budget allocations. Moreover, the revision of the curriculum of technical and vocational education and training can also easily be realized by deploying practitioners as well as professionals from higher education institutions who are already paid by the government, and if needed, qualified experts can be hired as consultants for minimal fees to guide the revision.

Delivery of extension services for farmers with heterogeneous characteristics requires changes in the existing "one size fits all" extension approach. The extension system should be flexible in catering for the demands of smallholder farmers. For example, as argued by Yitayew et al. (2021), lead (model) farmers possibly need improved technologies, while fellow (non-model) farmers require effective advisory services to improve their technical efficiency. This implies that a "variety of available sizes" extension approach enables lead farmers to push the technological frontier upwards, whereas fellow farmers can narrow the average yield distance. Context-specific extension approaches specifically enable farmers to increase productivity and farm output.

7. Authors' statement

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Dr. Asresu Yitayew, and Prof. Dr. Awudu Abdulai and Dr. Yigezu A. Yigezu extensively edited the manuscript and supervise the research study. The first draft of the manuscript was written by Dr. Asresu Yitayew and all authors commented on previous versions of the manuscript. All authors reviewed and edited the final version of this manuscript.

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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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2023.102436.

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