Journal of Agricultural and Applied Economics (2023), **55**, 133–150
doi:10.1017/aae.2023.12

CAMBRIDGE UNIVERSITY PRESS

RESEARCH ARTICLE

Does Row Planting Enhance Farm Productivity and Reduce Risk Exposure? Insights From Ethiopia

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Abstract

This study examines the impact of the row planting method on maize productivity and risk exposure using panel datasets from Ethiopia. A flexible moment-based production function is fitted to capture the expected yield, yield variance, and exposure to downside risk. A Mundlak–Chamberlain approach is combined with a switching regression treatment effects model to account for unobserved heterogeneity and endogeneity. The study shows that adopters of the row planting method significantly reduced exposure to downside risk while increasing expected yield. The analysis also identified some household and environmental conditions that affect the gain from the row planting method.

Keywords: Agricultural risk; planting method; production function; switching regression

JEL classifications: D13; Q00; Q12

1. Introduction

Smallholder farmers in developing parts of the world face a range of challenges, including limited access to modern agricultural technologies, market imperfections, abiotic and biotic stress, and weather variability (B.T. Kassie et al., 2015; M. Kassie et al., 2015; Kassie et al., 2020; Shiferaw et al., 2008, 2009; Asfaw et al., 2011; Dillon and Barrett, 2017; Sheahan and Barrett, 2017; Wossen et al., 2015). To withstand the challenges, they adjust their production system by relying mostly on self-defense methods as institutional risk-transfer systems are almost nonexisting. Particularly, since agriculture is the primary source of food and income for the great majority of them, they are mostly reluctant to take downside risks. This motivates them to look for farming practices that boost productivity while reducing risk.

In line with this, numerous studies have demonstrated the benefits of improved crop varieties and other farm inputs (Abebe et al., 2013; Ahmed et al., 2017; Asfaw et al., 2012; Bezu et al., 2014; Khonje et al., 2015; Shiferaw et al., 2014). Researchers also devoted attention to the importance of improved farming practices (ATA, 2013; Anderson, 2010; Berhe et al., 2011; Ponisio et al., 2015; Neumann et al., 2010). [1] Among them, ATA (2013) and Berhe et al. (2011) identified poor farm management practices, including the use of traditional planting methods, to be among the main obstacle to increasing

[1]The role of improved agricultural technologies and practices in the well-being of farming households in developing countries has been well established. Studies have shown that improved agricultural technologies and practices help to boost farm productivity and income (e.g., Khonje et al. (2018); Marenya et al. (2020); Oumer et al. (2020); Tufa et al. (2019)) and enhance food and nutrition security and reduces poverty (e.g., Asfaw et al. (2012); Khonje et al. (2015); Mendola (2007); Shiferaw et al. (2014)). Its indirect effects, including job creation, regulating food prices, and enhancing general economic growth through cross-sectoral collaboration, are also extensively documented (e.g., Evenson and Gollin, 2003; Karanja et al., 2003; Minten and Barrett, 2008; Streeten, 2016). This section discusses only studies that examined how improved agricultural technologies and practices impacted farm productivity and risk exposure.

agricultural productivity in the region. To overcome this, the government of Ethiopia has been encouraging farmers through the national extension system and farm radio partnerships to adopt row planting citing its yield-enhancing benefits since 2012 (ATA, 2013).

According to agronomy literature, planting methods have a considerable impact on crop productivity. Particularly, planting crops in a row with the appropriate distance between rows is expected to improve productivity by improving resource use efficiency, light interception, and photosynthetic potential and tillering capability (Berhe et al., 2011; Mihretie et al., 2021b). By avoiding uneven seed distribution, row planting also enhances yield-attributing qualities, decreases lodging, and lessens plant competition. The method also makes executing productivity-enhancing farm activities like weeding and pesticide application easier. The broadcasting method, on the other hand, is expected to limit farm productivity by increasing competition for light, moisture, and nutrients (Kühling et al., 2017; Matsuyama and Ookawa, 2020).[2] However, the superiority of the row planting method over the broadcasting method that has been established in agronomic studies is rarely investigated using data collected from plots operated by farmers.

Among the few existing studies, Vandercasteelen et al. (2020) uncover a substantial disparity between farmers' fields and agricultural experiment stations, although both employed the row planting method. More precisely, they measured the treatment effects at plots managed by farmers, village demonstration plots, and research plots at experiment stations to demonstrate that row planting had little impact on farm output at farmer-operated plots, but it had a positive impact on village demonstration plots under the supervision of extension agents, even though its size was still smaller than the productivity gains demonstrated on experimental plots. The authors identified that differences in yield across the study groups may be related to levels of farmers' literacy and access to information. Relatedly, Vandercasteelen et al. (2018) could not detect any noticeable increases in profits as a result of row planting. Instead, they demonstrated that the practice raised labor requirements by 30%, which dramatically decreased labor productivity without significantly increasing land productivity. Others such as Alemu et al. (2014) claim that row planting improves farm productivity depending on the agroecology, while Mihretie et al., (2021a, 2021b) argue productivity improvement from row planting depends on the types of farm management practices utilized in addition to it. Gelu and Gebre (2022) and Mossie (2022) showed that the mean yield from plots that adopted row planting was significantly higher than those that used the traditional broadcast planting techniques. The positive effects of practice on yield are shown to increase per capita consumption and agricultural income per hectare while lowering deprivation by Fentie and Beyene (2019), Habtewold (2021) and Martey et al (2020), and others.

In addition to yield benefits, understanding how the use of an improved planting method affects yield stability and avoiding yield reductions can help understand the risk reduction effects of such adjustments. Lyon et al (2009) and Martey et al. (2020) claim row planting may help farmers become more resilient to climatic shocks while simultaneously enhancing agricultural output and earnings. For example, according to Martey et al. (2020), the adoption of row planting is a more efficient way to increase the resilience of farming systems than drought-tolerant seeds However, these existing studies did not thoroughly investigate the risk reduction benefits of the practice.

Among the existing studies that simultaneously investigate the effects of agricultural inputs and practices in enhancing farm productivity and reducing yield variability, Wossen et al. (2017) showed that improved crop varieties increase maize yield by 13% and reduce yield variability and exposure to downside risk by 53 and 81%, respectively. Amondo et al. (2019) and

[2]Row planting in smallholder settings does not require machinery or significant capital investment. In Ethiopia, for example, smallholder farmers manually prepare fields and plant seeds in rows using handheld hoes or simple hand tools. This approach is labor intensive and does not necessitate significant capital investment. Typically, farmers depend on family labor or informal labor sharing for all stages of row planting, including field preparation, weeding, and fertilizer application.

Simtowe et al. (2019) also assessed the effects of the same input and found qualitatively identical results. Wang et al. (2018) claim that irrigation increases rice production while reducing downside risk. Abro et al. (2018) found that tillage intensity is positively connected with agricultural productivity and negatively correlated with reductions in risk exposure. Sarr et al. (2021), on the other hand, discuss how adopting a rain-fed rice intensification system increases yield without altering yield variability.

Some studies explored the effects of the adoption of technologies in combination. Among them, Huang et al. (2015), Shahzad and Abdulai (2020), and Di Falco and Veronesi (2014) show how adaptation to climate change through farm management measures significantly increases yield while reducing the risk of crop losses. Among them, Huang et al. (2015) argue that climate change adaptation measures result in a 14% increase in rice yield and a 43% reduction in production risk. Zhu (2018) studied the impacts of fertilizer use and intercropping and observed that fertilizer use increased both yield and variances; intercropping decreased yield variance but did not increase expected returns, whereas combined adoption of the two led to higher expected returns. Issahaku and Abdulai (2020) demonstrated combining crop choice and soil and water conservation leads to higher crop revenues and reduced riskiness in crop production more than adopting the practices in isolation.

This study contributes to the existing literature by examining the production and risk reduction impacts of the row planting method specifically among maize producers in Ethiopia. This crop-level analysis avoids data aggregation concerns since different crops may respond differently to various farm management practices. Maize is currently one of the most crucial food crops in East and Southern Africa, occupying a significant portion of arable land (Kassie et al., 2018). In Ethiopia, maize is the second most important crop in terms of production volume, land use, and the number of farmers engaged in its cultivation, following teff (Central Statistical Agency of Ethiopia, 2018, 2019). Marenya et al. (2017) highlight that maize sales account for up to 61% of all crop sales made by smallholder farmers in the nation, underscoring its importance for farmers' livelihoods. The crop has benefitted significantly from research development in the country, resulting in the release of more than 40 maize varieties suitable for various agroecologies in the country (Abate et al., 2015). However, national average productivity remains significantly lower than the global average due to recurring droughts, declining soil fertility, poor agronomic practices, limited access to improved farm inputs and credit, and the prevalence of diseases, pests, and weeds (Feleke and Zegeye, 2006; Taffesse et al., 2012; Erkossa et al., 2007; Zeng et al., 2015).

Using extensive plot and household-level data from the two rounds of the World Bank's Living Standard Measurement Study, the study estimates the three central moments of the maize yield distribution (expected yield, variance, and skewness) to be used as indicators of expected maize yield, yield variability, and downside risk. Using the Mundlak-Chamberlain approach combined with a switching regression treatment effects model to account for selection bias caused by observable and unobserved heterogeneities, the study quantified the yield-enhancing and risk-minimizing benefits of row.

The findings of the study help to justify whether the adoption of improved planting methods could be an effective way to reduce exposure to downside risks while boosting agricultural productivity. Such insights are crucial given the scope and importance of agricultural production in emerging countries–both at the micro and macroeconomic levels. The study also documented how household and environmental factors influence the benefits of row planting methods. This will make it easier for decision-makers and other interested parties to develop strategies that will enhance the adoption of improved farming practices.

The remaining sections of the paper are organized as follows. In section two, the methodological strategy of the study is presented. The data source and types are discussed in the third section. The fourth section presents and discusses the findings of the study, and the last section concludes.

2. Estimate Strategy

2.1. Predicting the Outcome Variables

The purpose of this paper is to look into the effects of the row planting method on expected yield, yield variability, and downside risk. Following related works (e.g., Di Falco and Chavas, 2009; Huang et al., 2015; Issahaku and Abdulai, 2020; Ma et al., 2022; Mukasa, 2018), a moment-based approach proposed by Antle (1983) is used to compute the outcome variables. The technique has considerably fewer restrictions on the specification, estimation, and testing of second-and third-order moments as functions of inputs in addition to estimating mean output as a function of inputs.

Therefore, as part of the initial estimating phase, the three sample moments (mean, variance, and skewness) are estimated for each plot. Combining the three central moments provides a more complete picture, which helps to effectively understand the impacts of the planting method since each moment contains information not available from others. Variance, for example, might give useful information about the risk reduction impacts of using the row planting method by showing how effective is the practice in reducing yield variability. However, variance fails to distinguish between unexpected bad and good events (Di Falco and Veronesi, 2014). When variance and skewness are combined, it is possible to assess both the extent and direction of yield variability.

Therefore, the first step is identifying a production function that accurately captures the relationship between inputs and outputs. By following Di Falco and Chavas (2009) and other related studies, a production function that fits the data at hand is chosen using Akaike Information Criteria (AIC) and the Bayesian Information Criterion (BIC). The criteria are used to compare and choose among the Cobb-Douglas, Quadratic, Translog, and Linear-Log production functions, and as shown in Table A1, the test result identified the translog production function to be a more appropriate production function than the alternative functions. From recent studies that used the translog function, Ma et al. (2022) and Mukasa (2018) used it to examine the productivity and risk reduction effects of farm inputs and agricultural institutions, respectively.

The maize production function in the translog functional form is represented in equation (1):

$$\ln\left(y_{itp}\right) = \beta_0 + \sum_{m=1}^{5} \beta_i \ln\left(X_{itp}\right) + 0.5\sum_{m=1}^{5} \beta_i \ln\left(X_{itp}\right)^2 + \sum_{m=1}^{5}\sum_{m=1}^{5} \beta_i \ln\left(X_{itpm}\right)\ln\left(X_{ipk}\right) + \theta R_{ip} * T_t + \sigma Z_{itp} + \varepsilon_{itp} \quad (1)$$

where *ln* denotes the natural logarithm; y_{itp} represents the amount of maize produced on plot *p* by farmer *i*, at year *t*, measured in kg; X_{itp} represents a set of production inputs applied on plot *p* by farmer *i,* at time *t* and *m* represents the number of inputs used on plot *p*. *X* consists of plot size, the amount of labor, fertilizer, and seed, and other variables such as the utilization of agrochemicals, irrigation, soil fertility, and improved seed. By following the related works of Di Falco and Chavas (2009), Mukasa (2018), and Abro et al. (2018), a list of plot attributes (such as soil quality and land slope) are also included in the model and represented by Z_{itp}. Soil fertility is a crucial factor that affects farm productivity. In our analysis, we used two additional indicators of soil fertility, namely Nutrient Availability and Rooting Conditions.[3] To ensure the robustness of our results, we also employed the FAO-GAEZ database, which provides a comprehensive suitability index. This index quantifies how well a given location meets the requirements for different crops by taking into

[3]The LSMS dataset incorporates various environmental data, including information on climate, soil, terrain, and other environmental factors from multiple sources, which are linked to the household survey. To control for soil fertility in our study, we utilized a variable obtained by integrating the survey with the Harmonized World Soil Database. Additional information about this database is available at the following link: https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/.

https://doi.org/10.1017/aae.2023.12 Published online by Cambridge University Press

account several biophysical and climatic factors.[4] $R_{it}{}^{*}T_t$ stands for the interaction between time dummies and state-fixed effects and are expected to absorb any state-level time-varying factors not captured by the observed variables. θ, σ, and β stand for the vector of unknown parameters to be estimated. The definitions and descriptive statistics of variables used in the production function are presented in Table A3.

Some of the farmers in the dataset do not use inorganic fertilizers on their maize plots. To deal with zero values in the functional framework that requires transforming the variables into a logarithmic form, a dummy variable that indicates nonuse of fertilizer is introduced as an additional explanatory variable by following Di Falco and Chavas (2009), and Ma et al., (2021).

An ordinary least squares regression model is used to fit the equation (1). After fitting the production function, the three moments of maize production are computed using the production function. Specifically, the expected maize yield is predicted as *E[ln(y)]*. The risk (variance) and the downside risk (skewness) are computed by taking the square and third powers of the error term, respectively. These three moments are then used as outcome variables in the econometric analysis.

2.2. Estimating Impacts on the Outcome Variables

Farmers' decisions to use or not use agricultural practices such as row planting are expected to be influenced by factors that are linked to the outcome variables. These factors could be observable and/or unobservable factors (such as their innate capacities and skills to gather relevant information about practice). Furthermore, farmers who adopt the row planting practice can be those that have been producing more from the resource they have. In this case, even without adopting the practice, adopters of the practice can produce more than nonadopters. Hence, those two problems need to be properly addressed to estimate unbiased estimates of the impacts of the practice.

As a result, the average treatment effects of row planting are estimated by using an endogenous switching regression (ESR) model.[5] The ESR model is estimated in two steps. The decision to use row planting is estimated at the first stage, and this stage can be specified as

$$R_{itp} = X_{itp}\beta + \varepsilon_{tip} \text{ with } \mathrm{R}_{ip} = \begin{cases} 1 \; if \; R^{*}_{ti} > 0 \\ 0 \; otherwise \end{cases} \tag{2}$$

where R^{*} is the latent variable for the decision to use row planting on plot p at time t and R is its observable counterpart. X_{itp} is vectors of observed plot, household, community, and environmental characteristics determining farmers' decision to use the row planting practice on plot p (The list and descriptive statistics of the variable are presented in Table A4). The interaction of time and state dummies is also included to account for any time-varying state-level characteristics that may not be controlled by the observable factors included in the model. In addition, the mean values of time-varying household and plot-level variables are included to account for unobserved heterogeneity by following (Mundlak, 1978).

In the second stage of the ESR framework, two outcome regression equations faced by the farmer—to use row planting (regimes 1) or not to use (regimes 2)—are estimated conditional on adoption. The equations can be represented as follows:

$$\text{Regime 1(user)}: \mathrm{Q_{1pt}} = \alpha_1 \mathrm{J_{1pt}} + \mathrm{e_{1pt}} \text{ if } \mathrm{R_p} = 1 \tag{3a}$$

$$\text{Regime 2(nonuser)}: \mathrm{Q_{2pt}} = \alpha_2 \mathrm{J_{2pt}} + \mathrm{e_{2pt}} \text{ if } \mathrm{R_p} = 0 \tag{3b}$$

[4]For more detailed information on the FAO-GAEZ database, including types of data used, sources, and estimation approach, interested users can find technical documentation at: https://www.gaez.iiasa.ac.at/

[5]Di Falco et al. (2011), Lokshin and Sajaia (2004), and Asfaw et al. (2012) all provide extensive theoretical and empirical descriptions of the model.

https://doi.org/10.1017/aae.2023.12 Published online by Cambridge University Press

where Q_p denotes the outcome variables in each regime at time t (expected yield, variance, and skewness predicted from the maize production function), J denotes a vector of exogenous variables that are expected to affect the outcome variables at time t, and e denotes random errors. This framework assumes that the error terms have a trivariate normal distribution with zero mean and nonsingular covariance matrix (Asfaw et al., 2012).

Using the aforementioned framework, the average treatment effects of the treated (ATT) and the untreated (ATU) are calculated by comparing the expected values of the outcomes of adopters and nonadopters in actual and counterfactual scenarios. The expected values of the outcomes of adopters and nonadopters in actual and counterfactual scenarios are in equation 4.
Adopters with adoption (observed in the sample)

$$E\left[y_{pit1}|R_{pit}=1;J\right]=J_{pit1}\beta_1+\sigma_{\varepsilon 1}\lambda_{pit1} \tag{4a}$$

Nonadopters without adoption (observed in the sample)

$$E\left[y_{pit2}|R_{pit}=0;J\right]=J_{pit2}\beta_2+\sigma_{\varepsilon 2}\lambda_{pit2} \tag{4b}$$

Adopters had they decided not to adopt (counterfactual)

$$E\left[y_{pit2}|R_{pit}=1;J\right]=J_{pit1}\beta_2+\sigma_{\varepsilon 2}\lambda_{pit1} \tag{4c}$$

Nonadopters had they decided to adopt (counterfactual)

$$E\left[y_{pit1}|R_{pit}=0;J\right]=J_{pit2}\beta_1+\sigma_{\varepsilon 1}\lambda_{pit2} \tag{4d}$$

The impact of the row planting practice on the maize yield and risk exposure of farmers that adopted the practice is then calculated based on the difference between (4a) and (4c). Similarly, we can calculate the average effect of the treatment on the untreated farm households that did not adopt the practice as the difference between (4d) and (4b).

For the endogenous switching models to be identified, it is important to include a selection instrument. Hence, by following Tesfaye et al. (2021), the average village-level households that have adopted row planting excluding the household under consideration is considered as a selection instrument. The importance of social networks on production decisions has been widely examined in studies (e.g. Bandiera and Rasul (2006); Conley and Udry (2010)). Relatedly, the village-level adoption of row planting is expected to impact farmers' adoption decisions due to peer effects or possible learning externality. In other words, a farm household in a village where row planting is widespread is more likely to do so than a farmer in a village where the method is not common. However, village-level adoption rates of row planting are unlikely to be correlated with the household unobserved heterogeneity and the outcome variables. To formalize the admissibility of the exclusion restriction, a simple falsification test is conducted following Di Falco et al. (2011). According to Di Falco et al. (2011), if a variable is a valid selection instrument, it affects adoption decisions but not outcome variables among nonadopters. The test results show that the instruments are significant in explaining the adoption equation but not the nonadopters outcome variables, as shown in Table A2.

Among the control variables used in the analysis, credit and access to extensions could be endogenous. For instance, farmers who adopted new practices may interact with extension employees more frequently than farmers who do not adopt if adopters believe the information they obtain from the extension works helps to boost the productivity of the new practice. Similarly, farmers who obtain credit could be risk-takers and capable to boost production and pay back the loan they receive. The endogeneity of the variables is addressed by using the control function approach (Wooldridge, 2015). More precisely, the endogenous variables are modeled in the first stage as a function of explanatory variables and instruments. The distances from extension agents' offices and microfinance institutions are used as the instrument for access to extension and credit by consulting earlier research. Then, the endogenous

https://doi.org/10.1017/aae.2023.12 Published online by Cambridge University Press

variables' observed values and the residuals predicted from a first-stage regression are added as covariates in the ESR model.

2.3. Data

The data for this study come from the Ethiopian Socioeconomic Survey, which was collected by the World Bank's Living Standards Measurement Study in 2013/14 and 2015/16.[6] The survey generated extensive data at the household, plot, and community levels. The survey, in particular, collected plot-level data on both post-planting and post-harvest agriculture activities, including input use, production techniques, and yield harvested, among other things. It also gathered detailed information on household characteristics such as basic demographic characteristics, as well as access to institutions and infrastructures, whereas the community questionnaire allowed for the collection of socioeconomic indicators from the enumeration areas (EAs) where the sample households reside.

Except for the nonsedentary population, the survey covers the entire parts of the country, allowing for significant geographical variation in agroecology, livelihood options, farming methods, and environmental circumstances. Respondents were chosen from all of the country's regional states using a two-stage random sampling. In the first stage, primary sample units (EAs) were selected using a probability proportional to the total EAs in each of the country's regional states. The respondents who grow maize are the focus of this study.

3. Results and Discussions

3.1. Households' Socioeconomic and Plot Characteristics

Table A4 provides the descriptive statistics and definitions of the working variables based on the adoption status. In terms of the outcome variables, row planting adopters had greater expected yield and skewness and lower yield variance than nonadopters; a simple *t*-test demonstrates that the differences are statistically significant. In terms of control variables, the *t*-test results suggest that adopters are more likely to access credit and extension services. Maize plots that adopted row planting are more likely to be flat and fertile and are located near the farmer's homesteads. In comparison to nonadopters, adopters are also more conveniently situated close to the road and marketplaces. Furthermore, the table shows how adopters and nonadopters differ significantly in terms of environmental factors such as location, rainfall, temperature, and agroecology.

3.2. Econometric Results

3.2.1. Results from Endogenous Switching Regression

The results of the ESR model are shown in Table A5. In column (a), the estimates of the selection equation (equation 2) are presented. In the remaining columns, the estimated coefficients of the outcome equation are shown based on adoption status (equations)(3a) and (3b). Columns (3), (5), and (7) show the coefficient of expected yield, variance, and skewness of maize output, respectively, for row planting adopters. The corresponding coefficients for nonadopters are shown in columns (2), (4), and (6). Column (1) can be interpreted as factors that influence raw planting adoption. In addition to the selection instruments, this study identifies several household, community, and environmental factors as significant determinants of row planting adoption, including the sex of the household head, total livestock, credit utilization, access to extension services, and plot fertility. Although a detailed discussion of these determinants is beyond the scope of the current study, their identification provides valuable insight into the complex decision-making

[6]Detailed information regarding the dataset can be found at: https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA

Table 1. Estimated impacts of row planting

	Outcome	Actual	Counterfactual	Difference (St. err)	Change (%)
ATT	Yield	7.16	7.02	0.14(0.01)***	2.0
	Yield variability	1.04	1.05	−0.1(0.01)	−1.0
	Downside risk	0.20	−1.83	2.03(0.04)***	110.9
ATU	Yield	6.87	6.91	0.04(0.01)***	0.6
	Yield variability	1.23	1.11	−0.12(0.01)***	−10.8
	Downside risk	−0.95	1.16	7.11(0.04)***	181.9

Note: The table presents the average treatment effects of the row planting method on treated (ATT) and the average treatment effects of the method on untreated (ATT) on maize productivity and risk exposure. Standard errors in parentheses; *** $p < 0.01$.

processes of smallholder farmers. Furthermore, while this study does not aim to explore the coefficients of the outcome equations conditional on the adoption decision, the findings indicate significant disparities between adopters and nonadopters, highlighting the presence of heterogeneity between these two groups. Indeed, the ESR model is used for this study to account for such heterogeneity between the two groups and to correct for sample selection bias.

3.2.2. Effects of Row Planting on Mean, Variance, and Skewness of Maize Yield

Table 1 shows the average treatment effects of the row planting method on mean maize yield, yield variability, and downside risk exposure. According to the findings, row planting enhances productivity while reducing yield variability and exposure to downside risk, which is consistent with descriptive statistics. The result implies farmers who planted maize in rows would have produced 14 percent less in the counterfactual case if they had planted using the broadcasting method. Likewise, farmers who used the broadcasting method to plant maize would have produced around 4% more in the counterfactual case if they had switched to row planting. The table also reveals that farmers who used the broadcasting method to plant maize would have reduced their yield variability by 12% if they had switched to row planting. Similarly, farmers who planted maize in rows would have reduced their exposure to downside risk by 111 percentage points if they had planted using the broadcasting method and farmers who used the broadcasting method to plant maize would have reduced their exposure to downside risk by 181.9 percentage points in the counterfactual case.

To see how robust the findings are the impacts of row planting are re-estimated using nearest neighbor matching (NNM) and inverse probability weight (IPW) approaches. Unlike the ESR model, the NNM and IPW account for observable differences between adopters and nonadopters, and they do not correct for unobservable differences. As a result, the results are unlikely to be numerically identical. As shown in Table 2, the results of the robustness test also suggest that the adoption of row planting significantly increases expected maize yield and reduces variance and downside risk.

3.3. Heterogeneous Effects Over the Household and Environmental Characteristics

The treatment effects presented above represent the average effects across all adopters of the practice considered in the study. As a result, the effects may vary depending on household and environmental variables. The heterogeneous treatment effects of the practice across the household and environmental characteristics are estimated following the recent work of Ma et al. (2022). Accordingly, the ATTs of treated plots (plots adopted row planting) are used as dependent variables, to regress on the list of household and environmental characteristics using an OLS model.

Table 2. Estimated impacts of row planting: alternative methods

Approaches	Expected yield	Variance	Skewness
IPW	0.074***	−0.218**	1.265***
	(0.025)	(0.104)	(0.464)
NNM	0.089***	−0.217**	1.181***
	(0.027)	(0.102)	(0.357)

Note: The table presents the average treatment effects of row planting on maize productivity and risk exposure estimated using matching and IPW. IPW: inverse probability weight; NNM: matching based on nearest matching. Standard errors in parentheses; *** $p < 0.01$; ** $p < 0.05$.

Table 3. Determinants of expected yield and production risk: OLS estimations

Variables	Expected yield	Variance	Skewness
Gender HH (1 = male)	0.027	0.057*	0.208
	(0.026)	(0.033)	(0.129)
Education HH	0.041	0.049	−0.085
	(0.026)	(0.037)	(0.127)
Family	0.033***	−0.028***	0.021
	(0.004)	(0.008)	(0.027)
Cultivated land	0.313***	0.144***	0.994***
	(0.013)	(0.017)	(0.030)
ASAL	−0.158**	0.299***	−0.027
	(0.079)	(0.090)	(0.404)
Weekly market in this community (1 = yes)	0.058	−0.113**	0.365**
	(0.036)	(0.053)	(0.161)
Micro-finance institution in this community (1 = yes)	0.011	−0.253***	−0.094
	(0.047)	(0.063)	(0.179)
Rainfall (mm)	−0.000	0.001***	−0.002***
	(0.000)	(0.000)	(0.000)
Constant	0.016	−0.494**	3.119***
	(0.159)	(0.208)	(0.549)
Observations	2,560	2,560	2,560
R-squared	0.560	0.275	0.259

Note: The table presents the determinants of average treatment effects of row planting on maize productivity and risk exposure estimated. Standard errors in parentheses; ***$p < 0.01$; **$p < 0.05$.

As shown in Table 3, the empirical findings show several household and environmental variables to be significantly correlated with the effects of row planting on maize yield, yield variance, and yield skewness.

For example, the positive impact of row planting on the expected yield is found to be stronger for households with larger family and farm sizes and inversely related to being in the Arid and Semiarid agroecological zone. The findings imply that farmers, who are among the adopters

https://doi.org/10.1017/aae.2023.12 Published online by Cambridge University Press

endowed with wealth and labor, benefit more from their adoption choices. This might be connected to the labor-intensive nature of the technique and the farmer's capacity to acquire complementary inputs. Row planting can raise labor requirements to 30%, as discussed by Vandercasteelen et al. (2018), whereas Mihretie et al. (2021a) contend the practice should be utilized in conjunction with other enhanced production techniques to increase yields. The effects of the practice on the yield variance were found to differ depending on various factors such as family size, farm size, agroecology, market access, microfinance availability, and rainfall conditions. The downside risk-reducing effects of the practice are positively correlated with having a larger farm and access to the market while it is inversely related to the amount of rainfall. This implies those farmers facing a shortage of rainfall benefit more from the adoption of row planting. This is understandable since the practice is expected to improve productivity by improving moisture and other input use efficiency.

4. Concluding Remarks

Results from agronomic literature show that row planting methods have a substantial yield advantage over broadcasting. However, this view is rarely verified using data from farmer-operated plots. Understanding the potential contribution of row planting using data from farmers' fields is vital to motivate the adoption of the practice, which is currently quite low.

This study evaluates the impact of the row planting method on productivity and risk exposure by focusing on Ethiopian maize growers. Detailed plots and household-level data are used to estimate a flexible moment-based production function. The ESR treatment effects model is fitted to jointly estimate the decision to adopt the row planting method and its impact on maize productivity, yield variability, and exposure to downside risks.

The study shows that row planting has significant yield and risk-reducing advantages, which is consistent with agronomy literature findings. Therefore, resolving problems that discourage smallholder farmers from adopting the practice contributes to raising agricultural productivity and reducing risk. According to the results of the first stage selection equation of the ESR, the gender of the households, access to credit and extension services, the size of the cultivated land, as well as the proportion of households that have adopted the practice in a village, are some of the important factors that influence the adoption of the practice. Thus, it is essential to take these factors into account when formulating policies and programs that seek to enhance the adoption of the practices.

The findings of this study also show that the benefits from the adoption of row planting may vary depending on household and environmental factors. This underscores the fact that due attention must be given to household and environmental aspects to optimize the advantages of the adoption decision.

The study focused on maize production. As a result, the results may not accurately reflect how the row planting method affects the productivity and risk-reduction of other crops, such as cash crops. Additionally, the study is restricted to looking at how the row planting method affects farm production and exposure to yield variability. More study is required to properly understand the benefits of row planting, including benefits to farm profitability and wellbeing. The study also encountered challenges in controlling the intensity of agrochemical usage and irrigation cost in the production function because precise data on the exact amounts and expenses involved were not collected. As a result, although the objectives of the study did not include estimating the elasticity of production inputs, the accuracy of the results may have been affected by this limitation. Furthermore, it is essential to note that the use of the ordinary least squares (OLS) model to estimate the production function and predict the outcome variables can suffer from omitted variable bias and/or endogeneity bias. Therefore, it is recommended that readers consider these potential limitations when interpreting the study's results. Notwithstanding these limitations, the study makes a valuable contribution to the literature on agricultural productivity by shedding light on the importance of planting methods for farm productivity and risk reduction.

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Appendix

Table A1. Choosing the appropriate production function

Functional form	AIC	BIC
Translog	16517.45	16729.25
Cobb–Douglas	16617.49	16763.1
Linear-log	94179.06	94324.67
Quadratic	94100.66	95273.05

Note: Linear-log functional form has the inputs in log form but the dependent variable is linear.

Table A2. Falsification test

Variables	Selection	Mean yield	Variance	Skewness
EA-level row planting	0.124***	−0.002	0.007	0.026
	(0.020)	(0.002)	(0.008)	(0.033)
Control variables	Yes	Yes	Yes	Yes
Regions#Year Dummy	Yes	Yes	Yes	Yes
Mundluk term	Yes	Yes	Yes	Yes
Observations	5,348	2,733	2,733	2,733

Note: All control variables in table A5 are also included in this analysis. Robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

https://doi.org/10.1017/aae.2023.12 Published online by Cambridge University Press

Table A3. Definition and descriptive statistics of variables used for production function based on LSMS 2013/14 and 2015/16 poled dataset and FAO-GAEZ

Variables	Definitions	Nonadopter (Broadcasting) (n = 3,053)	Adopter (Row planting) (n = 2,656)	Mean Diff
Output	The physical amount of maize produced from the plot in kg	145.66	412.24	−266.583***
Labour	Family and hired labor used for maize production	766.56	1047.20	−280.64
Seed	Amount of maize seed utilized in kg	7.80	31.31	−23.52
Fertilizer	Amount of maize inorganic fertilizer utilized in kg	12.80	79.95	−67.148***
Plot size	Size of land allocated to maize production in ha	0.14	0.24	−0.100***
Irrigation	1 if the plot has irrigation; 0 otherwise	0.05	0.03	0.018***
Agrochemical	1 if the agrochemical is used on the plot; 0 otherwise	0.05	0.08	−0.027***
Seed type	1 if the seed is modern (improved); 0 otherwise	0.04	0.47	−0.425***
Slope	1 if the landscape of the plot is flat; 0 otherwise	0.58	0.65	−0.071***
Soil quality	1 if the farmer considers the plot as fertile; 0 otherwise	0.36	0.41	−0.043***
Nutrient availability	1 if the plot has nutrient availability constraint; 0 otherwise	0.61	0.73	−0.124***
Root condition	1 if the plot has a rooting condition constraint; 0 otherwise	0.52	0.73	−0.208***
Maize suitability	Percentage (with zero the least suitable)	27.42	41.08	−13.26***

Note: Since the values are not standardized, they should not be compared.

https://doi.org/10.1017/aae.2023.12 Published online by Cambridge University Press

Table A4. Definition and descriptive statistics of other working variables based on LSMS 2013/14 and 2015/16 poled dataset

Variables	Definition	Nonadopter (Broadcasting) (n = 3,053)	Adopter (Row planting) (n = 2,656)	Mean Diff
Expected yield	The first moment of the maize production function	6.88	7.156	−0.276***
Variance	The second moment of the maize production function	1.247	1.04	0.207***
Skewness	The third moment of the maize production function	−0.933	0.235	−1.168***
Sex HH	1 if the household head is male; 0 otherwise	0.812	0.824	−0.012
Education HH	1 if the household head can read and write	0.408	0.42	−0.012
Family size	Number of household members in the adult equivalent	4.543	4.618	−0.075
Cultivated land	Size of cultivated land in hectares	0.165	0.184	−0.019
Livestock	Size of livestock owned in tropical livestock unit	5.116	4.461	0.655***
Credit	1 if the household head accessed credit; 0 otherwise	0.171	0.261	−0.090***
Extension service	1 if the maize plot receives an extension service	0.114	0.618	−0.504***
Soil quality	1 if the farmer considers the maize plot fertile; 0 otherwise	0.363	0.406	−0.043***
Filed appearance	1 if the slope of maize plots is flat; 0 otherwise	0.58	0.652	−0.071***
Distance to plot	Distance to the plot from home km	1.314	0.759	0.555***
Distance to market	Distance to the nearest market in km	77.218	49.383	27.835***
Distance to road	Distance to the nearest all-weather road in km	16.261	12.511	3.750***
Agro-ecology	I if Arid and Semiarid Lands; 0 = otherwise	0.401	0.214	0.187***
Temperature	Annual Mean Temperature[7]	19.776	18.916	8.593***
Rainfall	Total rainfall (mm) in the wettest quarter	952.236	1015.141	−62.905***
Tigray region	1 if the household lives in the Tigray region; 0 = otherwise	0.117	0.042	0.075***
Amhara region	1 if the household lives in the Amhara region; 0 = otherwise	0.19	0.265	−0.075***
Oromia region	1 if the household lives in the Oromia region; 0 = otherwise	0.239	0.325	−0.085***
SNNP region	1 if the household lives in the SNNP region; 0 = otherwise	0.268	0.214	0.055***
Other regions[8]	1 if the household lives in other regions; 0 = otherwise	0.186	0.155	0.031***
EA-level row planting	Share of households adopted row planting within EA	0.161	0.684	−0.523***

[7]LSMS provides rainfall and temperature data at the community level by extracting from UC Berkeley and NOAA.

[8]The LSMS technical report notes that the dataset is representative at the regional level of Amhara, Oromiya, SNNP, and Tigray regions and advised that the remaining regions be combined to justify region-specific estimates because they have smaller sample sizes. Hence, we create a variable 'other regions' that encompasses the remaining regions.

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Table A5. Results of the ESR model

		Expected yield		Variance		Skewness	
Variables	Selection	Nonadopter	Adopter	Nonadopter	Adopter	Nonadopter	Adopter
Sex HH	−1.098**	−0.145	−0.276	1.386*	−0.192	−0.134	−2.232
	(0.521)	(0.200)	(0.242)	(0.802)	(1.245)	(3.371)	(4.971)
Livestock	0.047***	0.000	0.000	−0.000	−0.007	−0.090	−0.047
	(0.017)	(0.009)	(0.004)	(0.033)	(0.017)	(0.102)	(0.063)
Extension service	1.922*	−0.238	0.092	−0.077	−1.088	8.384*	1.541
	(0.989)	(0.474)	(0.423)	(1.478)	(2.293)	(5.004)	(7.408)
Soil quality	−0.192***	0.120***	0.165***	−0.043	0.121	−0.029	0.430
	(0.071)	(0.029)	(0.040)	(0.093)	(0.180)	(0.323)	(0.625)
Distance to plot	−0.002	−0.004	−0.014***	0.004	0.005	0.023	0.089
	(0.007)	(0.005)	(0.005)	(0.009)	(0.010)	(0.032)	(0.059)
Distance to market	0.021*	0.002	0.004	−0.028	0.003	0.030	0.051
	(0.012)	(0.004)	(0.005)	(0.017)	(0.027)	(0.067)	(0.107)
ASAL	2.175	0.324	0.474	−3.419	0.768	−0.119	5.284
	(1.457)	(0.524)	(0.617)	(2.144)	(3.310)	(8.816)	(13.482)
Temperature	−0.012	−0.035**	−0.009	−0.066	−0.009	−0.620*	0.127*
	(0.020)	(0.016)	(0.006)	(0.106)	(0.022)	(0.317)	(0.074)
Rainfall	−0.001	0.002*	−0.000	0.005**	−0.001	−0.003	0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.007)	(0.011)
Education HH	−0.944**	−0.142	−0.206	0.986*	−0.167	−0.045	−1.682
	(0.394)	(0.145)	(0.180)	(0.539)	(0.902)	(2.137)	(3.789)
Cultivated land	0.065	−0.211***	−0.551**	0.245***	0.004	−0.327	−1.780
	(0.079)	(0.025)	(0.240)	(0.071)	(0.364)	(0.318)	(1.443)
Credit	20.753**	3.529	4.785	−22.822*	4.278	0.683	41.025
	(8.809)	(3.248)	(4.011)	(13.173)	(20.895)	(54.689)	(85.736)
Filed appearance	0.011	0.115***	0.213***	−0.189	0.085	−0.348	−0.691
	(0.104)	(0.028)	(0.035)	(0.117)	(0.187)	(0.364)	(0.779)
Distance to the nearest road	0.005	−0.001	0.003***	0.001	0.004	0.005	−0.004
	(0.004)	(0.002)	(0.001)	(0.005)	(0.005)	(0.017)	(0.014)
Nutrient availability	−0.000	0.125**	0.007	−0.214	−0.237	0.816	−0.109
	(0.147)	(0.061)	(0.041)	(0.164)	(0.157)	(0.740)	(0.529)
Rooting condition	−0.040	0.299***	0.057	−0.189	0.174	−0.510	0.012
	(0.139)	(0.062)	(0.053)	(0.154)	(0.196)	(0.558)	(0.704)
Family size	−0.041	−0.011	−0.078**	0.085	0.150	−0.050	−0.581
	(0.085)	(0.032)	(0.037)	(0.109)	(0.195)	(0.447)	(0.768)

(*Continued*)

Table A5. (*Continued*)

Variables	Selection	Expected yield Nonadopter	Expected yield Adopter	Variance Nonadopter	Variance Adopter	Skewness Nonadopter	Skewness Adopter
Extension residual	−0.558	0.421	−0.005	0.188	1.121	−8.562*	−2.885
	(0.998)	(0.474)	(0.412)	(1.445)	(2.334)	(4.902)	(7.423)
Credit residual	−20.717**	−3.497	−4.755	22.662*	−4.141	−0.917	−40.584
	(8.828)	(3.248)	(4.007)	(13.173)	(20.834)	(54.658)	(85.317)
EA-level raw planting	0.070***						
	(0.010)						
Rho		−0.044	−0.021	−0.004	−0.063	−0.114*	−0.031
		(0.094)	(0.103)	(0.136)	(0.131)	(0.064)	(0.042)
Regions#Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mundluk term	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−3.055***	6.912***	6.811***	4.623**	1.732	−7.568	−11.033
	(1.180)	(0.536)	(0.510)	(1.868)	(3.071)	(7.339)	(12.473)
Observations	5,246	5,246	5,246	5,246	5,246	5,246	5,246
Robust standard errors in parentheses							

Note: The table presents the results of the ESR models. The dependent variables are indicated as a header of each column. Standard errors clustered at the EA level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6. Estimated impacts of row planting using FAO-GAEZ suitability index to control soil fertility

	Outcome	Actual	Counterfactual	Difference	St. err
	Yield	7.16	7.10	0.06***	0.01
ATT	Yield variability	1.04	1.04	−0.00	0.01
	Downside risk	0.22	−1.82	2.03***	0.04
	Yield	6.87	6.91	0.04***	0.01
ATU	Yield variability	1.24	1.15	−0.91***	0.01
	Downside risk	−0.93	1.36	2.29***	0.03

Note: The table presents the average treatment effects of the row planting method on treated (ATT) and the average treatment effects of the method on untreated (ATT) on maize productivity and risk exposure. Standard errors in parentheses; *** $p < 0.01$.

Cite this article: Ahmed, M.H. (2023). "Does Row Planting Enhance Farm Productivity and Reduce Risk Exposure? Insights From Ethiopia." *Journal of Agricultural and Applied Economics* **55**, 133–150. https://doi.org/10.1017/aae.2023.12